SLA Non-compliance Detection and Prevention in Batch Jobs

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Abstract: This paper reports the study done on SLA non-compliance detection and prevention in batch job systems. It sets out the task of determining optimal and the smallest set of levers to minimize SLA non-compliance at minimum impact business requirements. The methodology to address the problem consists of a four-step process that includes inputs, pre-processing, modelling & solving and post processing. This paper uses Integer Linear Programming (ILP) to achieve global optima given a set of varied constraints such as sacrosanct constraints, auxiliary constraints, reach time constraints and SLA non-compliant identifier constraints. Methodology has been tested on two sets of data- synthetic data of small size to corroborate the correctness of approach and a real batch job system data of a financial institution to test the rigor of the approach.

1 INTRODUCTION

Batch jobs have become ubiquitous in enterprise IT of today's organizations. Batch jobs are so called due to a particular mode of processing- execution of jobs in a sequence i.e. batch. The IT infrastructure underlying business processes of modern day organizations are tuned to perform high volume, repetitive tasks/jobs that require little or no human intervention. Most of these tasks/jobs need not be handled in real time. Data integration, compliance checks, analytics, reporting, billing and image processing jobs are some examples of Batch applications.

Typically, a batch system is characterized by jobs and interdependence among jobs. Business processes (streams) are broken down into series of steps referred to as jobs. Each job can only start after its predecessors have completed their execution. Business requirements define these precedence relations among jobs. In addition, business requirements entail various other constraints such as 'start time', criticality, batch completion time etc. These constraints are described in greater detail in subsequent sections.

A vital aspect of batch systems is the Service Level Agreements (SLAs). SLAs are defined by measuring the 'start time' and 'end time' of business critical jobs and processes. In a typical investment bank setting, for instance, bulk of batch applications are scheduled to run after trading hours and are expected to finish before the start of next day's trading. To fulfil this business requirement, SLAs are defined for each batch process separately. However, spikes in workload, inadequately provisioned computational resources along with many other reasons often lead to SLA violations. The onus is on the system administrators to handle such scenarios and ensure that SLA violations are minimized. To do so, it is essential to not only predict potential SLA violations, but also to identify the right set of levers that can be used to minimize SLA non-compliance.

SLAs are critical to businesses. Firms view SLAs as instruments to establish measurable targets of performance with the objective of achieving required levels of service. SLAs for enterprise IT translate the expectations from the business perspective to quantifiable performance targets for various IT systems. Thus enabling them to monitor and steer the engagements from a distance. An important aspect of SLAs is the associated financial penalties with adverse outcomes. A customer having signed such an agreement with a service provider may claim compensation in case of non-compliance. Non-compliance, in the context of batch systems may include reduced throughput, longer wait times, poor Quality of Service (QoS), deadline misses, etc.

In a complex system there could be multiple objectives such as efficiency, cost, compliance etc. In a systemic setting these objectives are often intertwined and there is a trade-off in meeting them. Set of levers available to meet these objectives also overlap and

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Objectives	Job Flexibility	Partition Specs	Preemption	Job Characteristics
SLA Compliance	Rigid Jobs	None	None	None
Processing Time	Moldable Jobs	Fixed	Local	Workload
Throughput	Evolving Jobs	Variable	Migratable	Runtime
Weighted Tardiness	Malleable Jobs	Adaptive	Gang Scheduling	Start time
Flow Response Time		Dynamic		Class

Figure 1: Literature Classification: Dimensions of Scheduling Models.

there is many to many relationships between objectives and levers.

Levers are assessed on their potential impact on the objectives and business logic to arrive at an optimal selection. Postponing the run of a particular job to another day, deleting dependencies between jobs, reducing the 'run time' of a job by provisioning additional capacity or limiting workload and preponing a job's run within the batch are examples of levers. By business logic mean the interrelationships among jobs which are defined by business imperatives at business level and not at the IT level and cannot be arbitrarily changed to meet the objectives.

1.1 Purpose of This Paper

The purpose of this paper is to propose an optimization based approach to determine the smallest set of levers to minimize SLA violations. Considerations such as reducing the overall batch execution time and other issues are not part of the scope of this paper even though these issues are interrelated.

1.2 Organization of This Paper

This paper briefly discusses batch job system and its ubiquitous nature in modern business organizations in its introduction in section 1. Section 1 also discusses the background literature and context of this study. Section 2 discusses the methodology and section 3 consists of ILP (Integer Linear Programming) formulation of the problem and the mathematical model. Section 2 & 3 constitute the main body of the paper. Section 4 reports and discusses the results produced by the model on 2 sets of data-synthetic and real. Section 5 concludes the paper with a pointer to the future work as an extension of this study.

1.3 Literature

A part of this study corresponds to the field of parallel job scheduling. The parallel job scheduling literature broadly addresses both the temporal and spatial (processor space) dimensions of job scheduling. We, however, restrict this study to the temporal aspect of job scheduling. Large number of batch jobs, complex dependency structure and large solution space due to multiple lever combinations make this problem challenging despite confining the scope of this study to temporal dimension alone.

The primary purpose of this study is to realign a given batch job system to maximize SLA compliance. Job scheduling is one of the ways to realize the aforementioned objectives. The study of computer architectures with parallel processors has prompted the design and analysis of algorithms for scheduling parallel jobs. The studies in this area differentiate themselves based on the level of indigeneity in their models. Feitelson *et al*, (1997) have characterized studies based on various aspects of batch job systems that are incorporated in scheduling models. These aspects include partition specifications, job flexibility, preemption support, amount of job and workload data available, memory allocation and the optimization objectives.

Models proposed in these studies try to optimize one or more of the following objectives – throughput, deadline misses (SLA non-compliance), completion time (batch processing time), flowtime and tardiness. These objectives are broadly interconnected to each other. Some of these objectives closely follow each other. Optimizing one of them can potentially optimize others in similar conditions. Kellerer *et al* (1996) and Leonardi and Raz (2007) have shown in their work that a batch job system configuration with optimal completion time would also have optimal flow time under the same model constraints. Feitelson *et al* (1997) argue that a good management policy for a batch job system requires optimization of different objectives over different time frames. For example, during working hours, when users wait for completion of jobs, response time might be the most critical objective. However, during non-working hours, system throughput might be the most vital objective. Also, there are a host of studies that consider multi criteria optimization. Zhu and Heady (2000) have addressed the scheduling problem by considering both throughput and completion time as objectives. The model proposed in this paper considers the objective of minimizing the aggregate deadline misses.

The next aspect of batch job systems that has been extensively studied in the literature is partition specifications. Batch jobs are executed on processors which are architected in multiple ways. These architectures have a major bearing on the scheduling. Feitelson *et al* (1997) roughly classifies partition specifications into four types – fixed, variable, adaptive and dynamic. While fixed partitions (Feldmann *et al,* 1994) can only be altered by a system reboot, variable partition sizes can be determined at the time of job submission. Adaptive partitions (Turek *et al,* 1992) consider the job's request for partition along with the overall system load and allot the best possible partition based on a preset distribution policy. Dynamic partition (Deng *et al,* 2000) sizes can change even during the execution of jobs. Some batch job systems have memory along with processing power as a resource constraint. Parsons and Sevcik (1996) and Setia (1995) have taken memory into account in scheduling algorithms. As discussed earlier, our model does not consider the spatial dimension (processor space). The ever dropping costs combined with the ease of leasing processing power and memory over the cloud have made this constraint redundant over the years (Bahl *et al,* 2007, Singh *et al,* 2013, Agarwal *et al,* 2011 and Suter 2014).

Like processors, jobs too are categorized into four kinds (Feitelson et al, 1997) depending on how they are programmed. A rigid job has a processor(s) assigned and it runs on the same processor in every batch. Also the processor requirement is not expected to change during its execution. Moldable job's processor allotment is dynamic and is decided by the system scheduler right before its execution. However, the processor requirement remains constant throughout the execution, similar to a rigid job. An evolving job, as the name suggests, goes through multiple phases where the processor requirement varies based on the incoming workload. A malleable job is low on criticality (Ex: maintenance jobs). It can be starved of processors, if more critical jobs are in need of processors. Turek et al (1994) have studied the aggregate impact of having more rigid jobs on the scheduling efficiency. Mason et al (2002) have studied the positive impact of presence of moldable jobs and the delay in the onset of a bottleneck like scenario. For this study, we consider the first two kinds of jobs – Rigid and Moldable jobs. Rigid jobs are referred to as critical jobs in this paper. Another aspect of batch job scheduling is level of pre-emption supported by the scheduler. No pre-emption indicates that once a job starts its execution, it finishes without interruptions while holding its assigned processors. With local pre-emption, threads of a job may stop and resume their execution albeit on the same processor unlike migratable pre-emption (Deng et al, 2000), where threads may be suspended on one processor and resumed on another. Gang scheduling (Schwiegelshohn, 2004) refers to suspension and resumption of all the threads of a job simultaneously.

Most of the scheduling studies have not considered pre-emption in their models. Motwani *et al* (1994) and Schwiegelshohn (2004) have studied the overheads associated with pre-emption due to which pre-emption is not often seen in actual batch job systems. In our study, we too have assumed that jobs would finish their execution without any pre-emption.

Feitelson *et al* (1997)'s last characteristic to classify studies on batch job scheduling is the amount of job related data used in models. While some of the above mentioned aspects such as level of rigidity and pre-emption support are job characteristics that are vital, any additional details about job can improve the overall scheduling efficiency. Literature has seen the use of job characteristics such as workload, parallelism level and 'run time' in various studies (Agnetis et al, 2004, Janiak et al, 2005). Our model incorporates job characteristics such as 'run time', SLA definitions and 'start time' constraints.

2 THE MODEL

The schema in figure 2 shows the four components of the model - inputs, pre-processing, post processing, modelling & solving and post-processing.

2.1 Inputs

Inputs to the model include job dependencies, run history, SLA definitions, and batch schedule. Job dependencies describe a graph that captures the dependency relationship among jobs. These relationships are defined by underlying business logic and cannot be changed arbitrarily. Run history data comprises of job 'start time', 'end time', 'from time' and 'run time'. 'Start time' is the time when job execution starts while 'end time' is the time when job execution ends. 'From time' is a constraint that restricts the 'start time' of a job and 'run time' is the amount of time taken to complete the job execution. These data are very important for efficient and feasible scheduling of jobs. Batch schedule tells us what jobs of a batch are scheduled to be executed on a particular day. Business critical jobs in a given batch have SLA definition and these jobs should be completed within the specified definition. Failure to do so results in non-compliance.

2.2 Pre-processing

In the pre-processing module, we pool input data from multiple sources such as job and dependency data tables, transaction history, batch schedule and SLA definitions. We clean these data sets to ensure data consistency, completeness and uniformity. This module comprises of the following sub-modules.

2.2.1 Job Profiles

Job profiles are the collection of individual job characteristics that are useful in scheduling. Each job profile includes 'job name', 'run time', 'from time', criticality and SLAs (if defined).

2.2.2 Predecessor List

The predecessor list represents the dependencies among the jobs. A job can only start executing if all of its predecessor jobs are executed. It captures the relationship between jobs.

2.2.3 Dependency Graph

By using job profiles and dependency list, we form a directed graph called dependency graph, where each node represents a job and an edge represents the precedence relationship. This helps in visualising the batch job system as a graph and thereby letting us use graph theoretic approaches to achieve the objectives.

2.2.4 'Reach Time'

We define a metric called 'reach time' for each job. It is defined as the earliest time epoch a job can start execution. This metric helps us identifying the potential SLA non-compliant jobs by comparing 'reach time' and SLAs. For a job (j), the 'reach time' (j) can be calculated from the following equation.

$$reachtime_j = Max\{reachtime_k + runtime_k, fromtime_j\}, \forall\, Jobs(k) \in Predecessors(j) \quad (1)$$

2.2.5 Potential SLA Non-compliance

We identify the jobs that are likely to violate SLAs defined on them using 'reach time' and SLAs. Our objective is to keep the non-compliance as minimum as possible. Once we identify these potential SLA non-compliant jobs, we find the optimal set of levers to minimize SLA non-compliance.

2.3 Modelling and Solving

In this module, we discuss about business objectives, business constraints and solution space. Thereafter we discuss the mathematical model formulation and solving.

2.3.1 Business Objectives

The business objective that we are trying to achieve here is minimization of SLA non compliant jobs with minimum impact on business logic. The SLAs are defined on ''from time'' and ''end time'' of jobs. For a batch job system, it is very important to meet these SLAs as a batch may be dependent on the outcomes of another batch. The subsequent batch cannot be executed if its predecessor batch is not yet completed. Delay in a batch leads to delays in its subsequent batches.

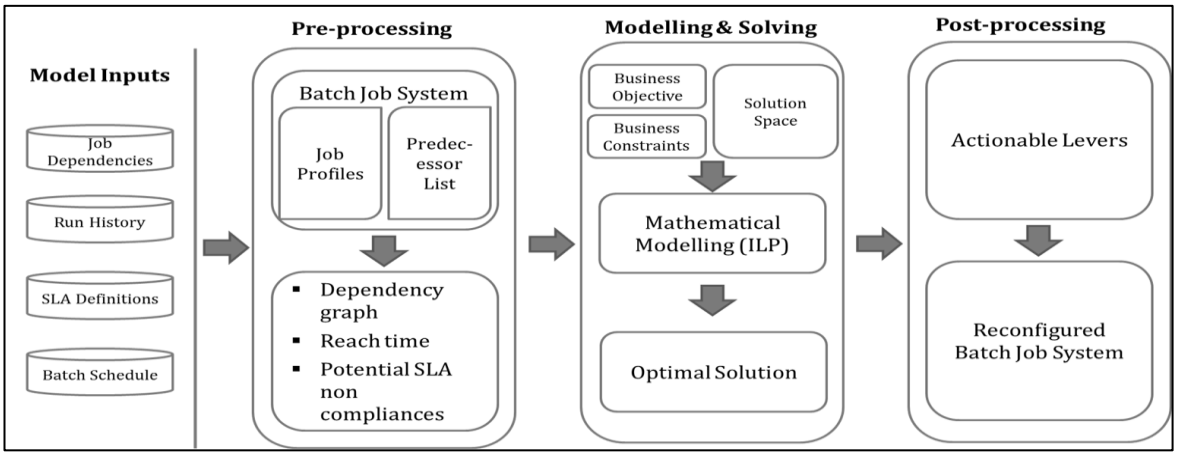


Figure 2: The Methodology Schema.

2.3.2 Business Constraints

Business constraints are generally derived from the jobs relationships and requirements. A typical business constrains could be something like, "a job can start only after its defined 'from time'"; "a job can start only after all its predecessors are completed" etc. If a job or dependency is defined as critical then it cannot be perturbed.

2.3.3 Solution Space and Optimal Solution

The following levers can be used to meet the stated business objective.

- The amount of time by which a job can be preponed.
- The fraction by which a job's 'run time' can be reduced.
- Whether a job needs to be deleted from the current batch.
- Whether a dependency can be removed.

The solution space is comprised of all possible combinations of these levers. For example, if the 'from time' of a job is 1000 seconds the first lever can take any values between 0 and 1000. Similarly, for a given job, the second lever can assume any value between 0 and 100. For the fourth lever, the combinations can go as high as 2^n with 'n' being the number of dependencies in the system. Putting all these together, the size of solution space of 1000 jobs of a batch job system can run into billions. The challenge is to find an optimal solution within reasonable time limits.

3 ILP FORMULATION

The general structure of the proposed optimization model is to minimize SLA non-compliance with least impact on business logic, subject to 'from time' and dependecy constraints. The proposed optimization model is an Integer Linear Program (ILP). An ILP guarantees the global optimal solution if it is feasible (Wolsey *et al*, 2014; Brucker, 2007). Integer Linear Program (ILP) is a tool for solving optimization problems. The first step towards modeling an optimization problem is identifying inputs and decision variables. The nature of the decision variables determines the problem type (continuous, integer or mixed integer). The problem is then formulated by identifying objectives and its constraints. When both objectives and constraints are linear, and decision variables are integer the problem is called ILP. Operations research practitioners have been formulating and solving ILPs since the 1940s (Klotz and Newman, 2013a) However, in recent years, the availability of large computing power and development of powerful optimization solvers has empowered practitioners to be able to solve complex real-world problems(Klotz and Newman, 2013b). This work uses ILP to find the smallest set of levers that minimizes SLA violations. The input parameters of the proposed model are as follows.

$$J = set\ of\ jobs$$
$$cJ = set\ of\ critical\ jobs$$
$$nJobs = total\ no\ of\ jobs$$
$$PL(j) = dependency\ job\ list\ of\ job\ j$$
$$cE = set\ of\ critical\ edges$$
$$rt_j = runtime\ of\ job\ j\ in\ seconds$$
$$et_j = endtime\ SLA\ for\ job\ j\ in\ seconds$$
$$ft_j = fromtime\ of\ job\ j\ in\ seconds$$
$$st_j = starttime\ SLA\ for\ job\ j\ in\ seconds$$

The decision variables of the proposed model are shown in table 1. The objective of the proposed mathematical model is to minimize SLA non-compliance with minimal impact on business logic. So, the objective function has two parts. First part ($SLAnonCompliances$) takes care of the SLA non-compliance and the second part ($ImpactOnBusinessLogic$) ensures minimum possible changes to the existing system configuration. The **objective function** is given below.

$$Minimize\ ([SLAnonCompliances] + [ImpactOnBusinessLogic]) \quad (2a)$$

$$Minimize\ [M * \sum_j (axz_j + s_j)] + [\sum_j \sum_{k \in PL(j)} (-y_{jk}) + \sum_j -(x_j + cnt\_pr_j + rst_j)] \quad (2b)$$

We have two types of SLA non-compliance, 'end time' SLA non-compliance (axz_j) and 'start time' SLA non-compliance (s_j). A very large number 'M' is multiplied to SLAnonCompliances, that ensures that the model will minimize the non-compliance whenever feasible. We have four levers (delete a job (x_j), delete a dependency (y_{jk}), reduce 'run time'/workload (pr_j) and reduce 'from time' (rst_j)) to achieve the objective. We want to use theses levers as minimimum as possible and minimize the SLA non-compliance. The second term ($ImpactOnBusinessLogic$) ensures this objective.

3.1 Constraints

The model needs to consider following set of constraints to obtain optimal set of levers that minimizes SLA non-compliance.

Table 1: Decision Variables.

$\boldsymbol{pr_j = percentage\ runtime\ of\ job\ j, pr_j \in [0,1]\ If\ pr_j = 0, then\ job\ j\ is\ deleted.}$	(3)
$y_{jk} = \begin{cases} 1, if\ dependency\ between\ job\ j\ and\ k\ is\ not\ relaxed \\ 0, otherwise \end{cases}$	(4)
$rst_j = the\ amount\ of\ time, you\ can\ prepone\ the\ fromtime\ of\ job\ j$	(5)
$reachtime_j = the\ time\ when\ job\ j\ can\ be\ started\ at\ the\ earliest$	(6)
$z_j = \begin{cases} 1, if\ reachtime_j + (rt_j * pr_j) > et_j \\ 0, otherwise \end{cases}\ [endtime\ SLA\ non\ complaince]$	(7)
$s_j = \begin{cases} 1, if\ reachtime_j > st_j \\ 0, otherwise \end{cases}\ [starttime\ SLA\ non\ complaince]$	(8)
$cnt\_pr_j = \begin{cases} 1, if\ 0 < pr_j < 1 \\ 0, otherwise \end{cases}$	(9)
$ayp_{jk} = y_{jk} * pr_k = \begin{cases} pr_k, if\ y_{jk} = 1 \\ 0, otherwise \end{cases}$	(10)
$x_j = \begin{cases} 1, if\ job\ j\ not\ deleted\ or\ removed\ from\ the\ batch \\ 0, otherwise\ (pr_j = 0) \end{cases}$	(11)
$rty_{jk} = y_{jk} * reachtime_k = \begin{cases} reachtime_k, if\ y_{jk} = 1 \\ 0, otherwise \end{cases}$	(12)
$axz_j = x_j * z_j = \begin{cases} 1, if\ x_j = z_j = 1 \\ 0, otherwise \end{cases}\ [1, if\ job\ j\ is\ SLA\ non\ compliant\ and\ not\ deleted]$	(13)

3.1.1 Sacrosanct Constraints

There are a few business critical jobs or dependencies, which cannot be altered. Constraints below ensure that we do not delete a business critical job from the current batch or reduce its workload or 'run time'. Constraint (15) puts bound on 'runtime' reduction of a job. Constraint (16) ensures that no business critical dependencies are deleted.

$$pr_j = 1, rst_j = 0\ and\ x_j = 1, \forall\ j \in cJ\ (critical\ jobs\ can\ not\ be\ deleted) \quad (14)$$

$$pr_j \leq x_j, \forall\ j\ (puts\ bound\ on\ 'run\ time'\ reduction\ of\ a\ job) \quad (15)$$

$$y_{jk} = 1, \forall\ e(j,k) \in cE\ (critical\ dependencies\ can\ not\ be\ removed) \quad (16)$$

3.1.2 Reach Time Constraints

We define 'reach time' ($reachtime_j$) of a job *j* as the earliest time epoch, when the job *j* can start executing. Constraint (17) ensures that the job *j* can start executing after it's ''from time'' only. Constraint (18) makes sure that the job *j* can start executing only after all its predecessor jobs are executed.

$$reachtime_j + M * (1 - x_j) \geq ft_j - rst_j, \forall\ j \quad (17)$$

$$reachtime_j + M * (1 - x_j) \geq rty_{jk} + (rt_k * ayp_{jk}), \forall\ j\ and\ k \in PL(j) \quad (18)$$

3.1.3 SLA Non-compliant Identifier Constraints

Constraints (19) and (20) ensure that when a job j violates 'end time' SLA (et_j), it is registered through the decision variable z_j. Simillarly, constraints (21) and (22) ensure 'start time' SLA (st_j) violation is recorded in variable s_j.

$$et_j * z_j < reachtime_j + (rt_j * pr_j) + M * (1 - x_j), \forall j \quad (19)$$

$$reachtime_j + (rt_j * pr_j) - M * (1 - x_j) \leq et_j * (z_j + 1) + M * z_j, \forall j \quad (20)$$

$$st_j * s_j < reachtime_j + M * (1 - x_j), \forall j \quad (21)$$

$$reachtime_j - M * (1 - x_j) \leq st_j * (s_j + 1) + M * s_j, \forall j \quad (22)$$

3.1.4 Auxiliary Constraints

These constraints help in estabilishing the relationships between different variables. Constraint (23) records if 'run time' reduction is required for job *j*. Constraints (24) – (26) are the equivalent of the non-linear constraint, $ayp_{jk} = y_{jk} * pr_k$. The variable, ayp_{jk}, captures the 'run time' reduction for job *j* if dependency between job *j* and *k* are not deleted. This value is required for 'reach time' calculation.

$$cnt\_pr_j \geq 1 - pr_j, \forall\ j \quad (23)$$

$$ayp_{jk} \leq pr_k + M * (1 - y_{jk}), \forall j, k \in PL(j) \quad (24)$$

$$(1 - y_{jk}) * M + ayp_{jk} \geq pr_k, \forall j, k \in PL(j) \quad (25)$$

$$-y_{jk} * M + ayp_{jk} \leq 0, \forall j,k \in PL(j) \quad (26)$$

Constraints (27)-(29) are the equivalent of the non-linear constraint, $rty_{jk} = y_{jk} * reachtime_k$. The variable, rty_{jk}, updates the 'reach time' for job j depending upon the dependency between job k & j.

$$rty_{jk} \leq reachtime_k + M * (1 - y_{jk}), \forall j,k \in PL(j) \quad (27)$$

$$(1 - y_{jk}) * M + rty_{jk} \geq reachtime_k, \forall j,k \in PL(j) \quad (28)$$

$$-y_{jk} * M + rty_{jk} \leq 0, \forall j,k \in PL(j) \quad (29)$$

Constraints (30)-(32) are the equivalent of the non-linear constraint, $axz_j = x_j * z_j$. The variable axz_j captures whether job j is SLA complaint or not.

$$axz_j \geq x_j + z_j - 1, \forall j \quad (30)$$

$$axz_j \leq x_j, \forall j \quad (31)$$

$$axz_j \leq z_j, \forall j \quad (32)$$

We discuss the model solving approach in the following sub-subsection.

3.2 Optimal Solution

The formulated mathematical model is an Integer Liner Program (ILP). We have coded the proposed model using Python-PuLP to create an optimizer consumable input format (.lp file). This LP file is passed to the optimization solver for optimal solution. We have used CBC solver (open source) for our study. More efficient, proprietary solvers (Cplex, Gurobi etc.) can also be used to obtain the optimal solutions.

3.3 Post Processing

The post-processing module is further divided into two sub-modules. Actionable levers and reconfigured batch job systems.

3.3.1 Actionable Levers

We translate the obtained optimal solutions, which is expressed in mathematical terms into implementable actions such as identifying the jobs that can be postponed to another batch, executing batch jobs partially by reducing the workload or running the job on multiple cores simultaneously, identifying the dependencies that can be relaxed or identifying those jobs whose 'from time' constraint can be relaxed.

3.3.2 Reconfigured Batch Job Systems

Once we identify all the actionable levers we reconfigure the batch job system's run to achieve the stated objective by updating the job and dependency tables.

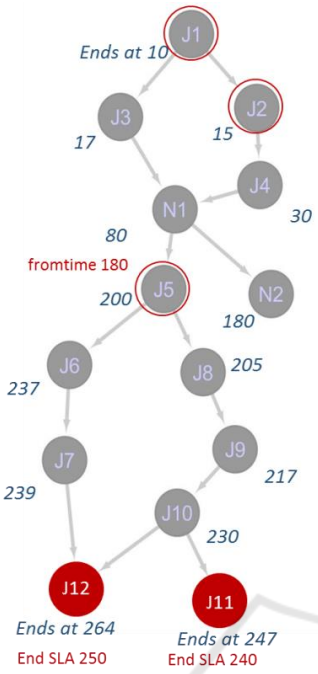
4 RESULTS AND DISCUSSION

4.1 Illustration with Synthetic Data

To illustrate the method presented in the previous section, we use two different sets of data. The first illustration is on synthetic data for demonstrating solution's correctness. The second illustration is on a real batch job system of a large financial institution. The batch job system shown in figure 3 comprises of 14 jobs. These jobs vary in terms of attributes such as 'run time', 'from time', SLA definitions and criticality. 'Run time' of all the jobs and the interdependencies among them are shown in figure 3. For example, job N1 cannot be scheduled for a run unless jobs J3 and J4 are executed. Job criticality is indicated by encircling nodes in red. Jobs J1, J2 and J5 are critical (Figure 3) and cannot be used as levers to perturb the system. Jobs J11 and J12 in red. These jobs have predefined 'end time' SLAs and are not expected to be used as levers. The dependencies between jobs in this case are also considered critical. Next to each node in the dependency graph is the 'end time'.

In the as-is configuration of this system, jobs J11 and J12 are violating their SLA definitions by 7 and 14 time units respectively. Job J5 has 'from time' defined at 180th time unit, which means even if job J5's predecessors finish execution before 180th time unit, it cannot start execution. As seen in this case, job N1 completes execution at 80th time unit but, due to the 'from time' constraint, job J5 had to wait for 100 more time units. Although, such constraints are derived from business logic and often unalterable, it is vital to identify and minimize such slacks to reduce spikes in CPU utilization.

With the objective being minimization of SLA non-compliance, there are multiple feasible solutions. However, the 'Impact on Business Logic' component of the objective function given in section 3 ensures that lever usage is confined. The solution obtained from the model is to reduce the 'run time' of job J5 by 70% (from 20 mins to 6 mins). In cases where there is a cap on the amount of 'run time' reduction, the feasible solution set shrinks. When we set a cap on 'run time' reduction at 50%, the optimal solution would then be to reduce the 'run time' of jobs J5 and



Job	'run time'
J1	10
J2	5
J3	7
J4	15
N1	50
N2	100
J5	20
J6	37
J7	2
J8	5
J9	12
J10	13
J11	17
J12	25

Dependency Graph | *Job run times*

Figure 3: Dependency graph and job 'run time' with synthetic data.

J6 by 50% and 10% respectively. Both these solutions are as expected.

4.2 Illustration with Real Data

We tested the model on a real batch job system with 518 jobs and 738 interdependencies. Due to a pre-scheduled maintenance activity over the weekend batch runs, there might be an adverse impact on SLA compliance. Around 14 jobs are expected to have a 50% increase in their 'run time'. The model has identified 18 SLA violations as a result. Some other important characteristics of this system include- 62 jobs with 'from time' constraints, 21 critical jobs, 137 critical dependencies and 35 jobs with 'end time' SLA definitions.

Figure 4 shows the partial dependency graph of the batch system used in this illustration. The node size depicts the 'run time' of a job. The nodes marked in blue are the jobs affected by the scheduled maintenance activity and are expected to see an increase in their 'run time'. The nodes marked in yellow are the ones expected to violate SLAs. The optimal solution suggested by our model includes deletion of 3 jobs, reduction of 'run time' of 2 jobs while preponing the 'from time' of 2 jobs. However, despite these interventions, the total SLA violations could only be brought down from 18 to 4. This configuration of batch system makes 100% SLA compliance an *unattainable target*.

5 CONCLUSION

In this study, we proposed an optimizer for batch job systems that maximizes SLA compliance with minimum possible impact on the business logic. Although, there exists an extensive body of literature on solutions to achieve this objective, the levers used to do so are mostly focussed on job scheduling. Our study considers a more practical approach wherein a wider range of levers such as Job and Dependency deletion and 'run time' reduction are also considered while designing the optimizer. By taking these additional levers into consideration, the solution space increases many fold. Despite this, our approach finds the optimal set of levers within reasonable time limits as we have modeled the complex optimization problem as an integer linear program (ILP). Linear formulation guarantees the global optimal solution and has better computational efficiency than the non-linear models.

In its current state, the model can handle batch job systems of size around 1000 jobs and 1800 depend

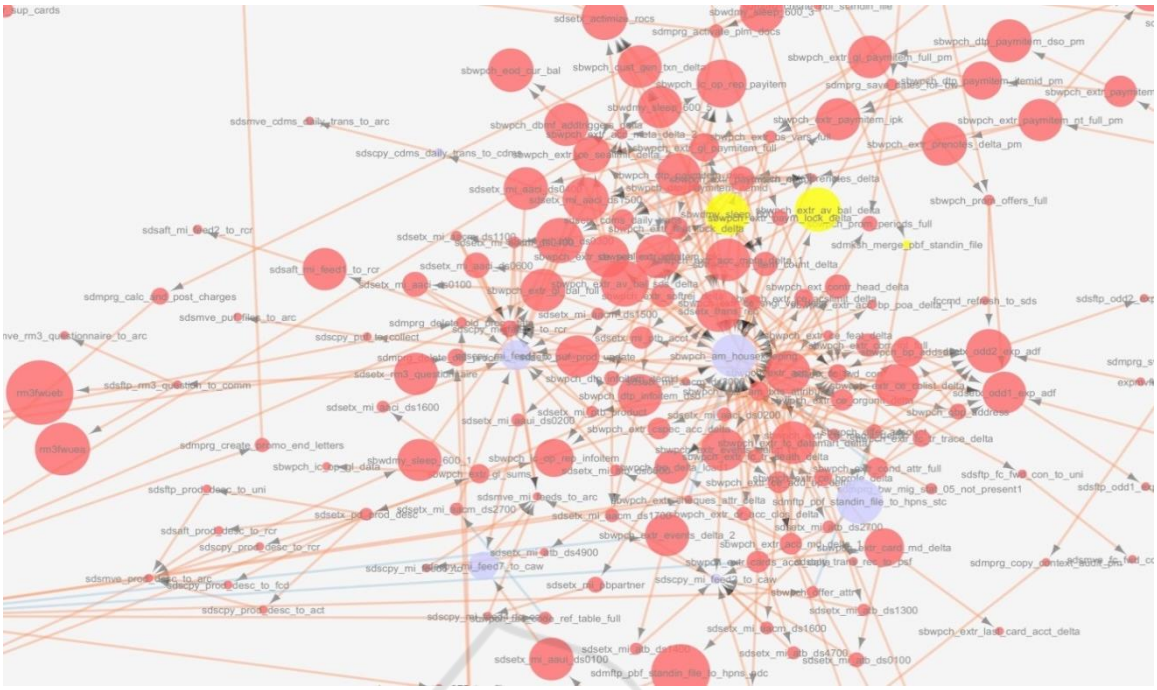


Figure 4: A real batch job system.

encies. Beyond this, the 'run time' shoots up substantially. An interesting direction for future research would be to build heuristics that intelligently prune the solution space without compromising the optimality of the solution.

A major consideration of batch system optimizers is their 'run time'. As described in the previous section, we have programmed this solution on Python-PuLP with CBC solver. When implemented on a 2.6GHz, i5 processor with 4GB RAM, the solution takes less than 2 minutes to handle 1000 jobs and 1800 dependencies batch system to find the optimal solution.

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