A Framework for Data Center Scale Dynamic Resource Allocation Algorithms

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***Abstract*—The scale and complexity of online applications and e-business infrastructures has led service providers to rely on the capabilities of large-scale hosting platforms, i.e., data centers. Dynamic resource allocation (DRA) algorithms have been shown to allow server resource allocation to be matched with application workload, which can improve server resource utilisation and drive down costs for service providers. However, research on DRA algorithms has almost exclusively focused on their performance characteristics at small-scale, precluding their useful application in commercial hosting environments, such as those dedicated to supporting cloud computing. In this paper, we show, and subsequently propose a framework to address, the scalability problems of current DRA algorithms. We then build on the proposed framework to develop a highly-scalable algorithm for dynamic resource allocation.**

***Keywords*-Cloud Computing, Data Center, Dynamic Resource Allocation, Server Provisioning, Scalability**

I. Introduction

Online applications and e-business infrastructures are subject to unpredictable fluctuations in workload, not least because application workload is typically demand-driven. These unpredictable fluctuations, which may be orders of magnitude in extent, can make economic resource provisioning difficult. The hosting of such applications in data centers can be seen as a response to this issue. Typically an organisation will agree to pay a provider for a specified level of service, with that service provider then taking responsibility for the allocation of resources to applications. However, as it is generally the goal of any service provider to maximise income and reduce outlay, resource utilisation is a concern.

Dynamic resource allocation (DRA) algorithms allow server resource allocation to be matched with application workload, improving server resource utilisation in situations where workloads are volatile. The potential effectiveness of such DRA algorithms, particularly when compared with static allocation approaches, is well established [1]. The characteristics and benefits of DRA algorithms lend themselves to data center scale resource management. Such DRA algorithms will typically consider many factors when attempting to make informed decisions regarding the allocation of resources, including the number of requests, service-level agreements, current resource utilisation and predicted workload. However, this multiplicity of concerns results in a huge state space which DRA algorithms have to explore in order to provide effective resource allocation. It is this large state space that presents the scalability challenges in the design and development of DRA algorithms.

A. Contributions

In this paper, we make the following specific contributions:

- We formalise the DRA problem and show it to be an NP-hard problem.
- We show that a class of state-of-the art DRA algorithms have exponential complexity.
- We strengthen our system model to develop a framework for the development of scalable DRA algorithms.
- We demonstrate the application of our framework by developing a scalable and efficient DRA algorithm.

B. Paper Structure

The remainder of this paper is structured as follows: In Section 2, we give an overview of related work. Section 3 sets out the adopted system model. Section 4 presents a scalability analysis for a general class of DRA algorithm. An improved, demand-based approach is proposed in Section 5. Section 6 presents the experimental setup used in our analysis, whilst Section 7 shows performance comparisons which illustrate the effectiveness of the proposed approach. Section 8 concludes this paper with a summary of achievements and a discussion of future work.

II. Related Work

Online applications and e-Business infrastructures are subject to large variations in workload. In cases where the applied workload is greater than the system capacity, a system will become overloaded, which will in-turn lead to long system response times and a reduction in throughput. Such situations can have severe consequences for all parties involved, as illustrated by prominent examples such as the CNN outages following the 9/11 terror attacks [2] and the estimated cost of service downtime for Amazon.com [3]. The use of dynamic resource allocation has been shown to improve the performance of individual applications and increase the utilisation of system resources [1].

Work in [4] utilises a mean value analysis approach to maximising the profit obtained from an enterprise system, with resource allocation across all tiers of a 3-tier architecture. The work is extended in [4] to incorporate an admission control policy which further improves results. This work is extended in [5] to include workload predication, which further increases the profits obtained.

In [6] the authors develop an algorithm for profit maximisation of multi-class requests through dynamic resource allocation. The algorithm is developed for two service classes; a best-effort service class and a service class with a guaranteed quality of service (QoS). This work demonstrates a policy which delivers significant improvements in profits, however the algorithm demonstrates poor scalability characteristics as the number of service classes increases. In contrast, work in [7] develops four heuristic policies for dynamic server reallocation which aims to minimise the holding cost of queued jobs within the system. In this paper, the policies are developed for allocating resources across two applications. This work was validated experimentally by work in [1].

Work in [8] proposed a approach known as cluster-on-demand (COD). This approach is based on dynamic allocation from a common pool to many virtual clusters, each with independently configured environments, access controls and network storage volumes. The experiments associated with this work were performed using a physical cluster composed of 80 servers. This paper serves as a good example of a working dynamic resource allocation scheme, though the number of applications examined is limited.

In contrast to on-demand techniques, [9] explored periodic server provisioning. Here a single application, to which idle servers are added as load increased, was analysed, with short-term and long-term workload prediction being used to guide resource allocation. The work presented differs from [9], as the scale of the environment is fixed, with applications competing for available resources.

Much research in application performance modelling can be applied to resource provisioning. For example, analytical application models were employed in [10], [11], queueing models have been applied in [12] and online measurement has been used for dynamic provisioning in [13].

The greatest limitation of existing DRA algorithms is the limited number of servers and applications that have been used in their evaluation. In this paper, we directly address this limitation, demonstrating that a class of DRA algorithm, which accounts for many established policies, is not suited to the effective management of resources at data center scale. This paper is differentiated from similar work on DRA algorithm analysis [7] by (i) its focus on scalability, an issue that has not received adequate treatment in existing literature, and (ii) the development and validation of a framework for DRA algorithm design and implementation.

III. System Model and Scalability Analysis

We consider the following system model: A large-scale hosting platform consists of a set of servers $S = \{S_1, S_2, ..., S_M\}$ for the processing of a number of applications $A = \{A_1, A_2, ..., A_N\}$, where $M \geq N$. We assume that (i) all servers $S_i \in S$ are homogeneous, i.e., they provide identical resources, and (ii) each server has all the resources required by an application.

The DRA problem is as follows: Given a system with a set $A = \{A_1, \ldots, A_N\}$ of applications, and a set $S = \{S_1, \ldots, S_M\}$ of servers, allocate applications to servers such that overall utility of the system is maximised. Formally, given a set of possible mappings $F = \{F_1, \ldots, F_k\}$ of servers to applications ($F_i : (S \rightarrow A)$), and a corresponding utility function U, find a mapping $F_i \in F$ such that $U(F_i) = max\{U(F_1), \ldots, U(F_k)\}$. In other words, find the allocation of resources that maximises resource utilisation.

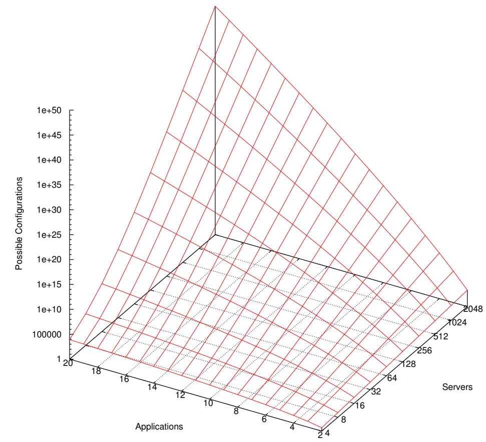


Figure 1. Possible server allocations

The DRA problem can be formalised as follows: Let x_i^j be an allocation of server j to application i. We wish to maximise $U(x_1^1, \ldots, x_N^M)$ subject to the following constraints:

$$x_i^j = \begin{cases} 0, & \text{Server } j \text{ not allocated to application } i. \\ 1 & \text{Otherwise.} \end{cases}$$

$$\sum_{j=1}^{M} \sum_{i=1}^{N} x_i^j \leq M$$

(Applications can not use more than M servers)

$$x_i^j \neq x_k^j, i \neq k$$

(Two applications can not reside on the same server)

This problem is an instance of binary integer programming problem, which is known to be NP-hard. Thus, exponential complexity is unavoidable. Greedy algorithms are typically used to solve approximations to NP-hard problems. The design of algorithms that approximates the DRA problem is normally of the form shown in Algorithm 1, whereby the algorithm examines all possible combinations of allocations and chooses the best allocation, based on its own metric, with the complexity of the algorithm being $O(M^N)$.

To be suitable for data center scale resource allocation, an algorithm must account for scaling in two dimensions: (i) the number of servers and (ii) the number of applications to be distributed across the servers. Much existing literature has focused on small number of servers, typically with two applications, meaning that little consideration has been given to scalability. However when the number of applications increases, the space of possible combinations increases dramatically. The number of combinations for a given number of servers, s, and applications, a, that wholly allocate all servers can be calculated using $\binom{s+a-1}{s}$. The graph in Figure 1 shows the number of combinations for up to 20 applications and 2048 servers.

To understand the rate at which the states could be examined we developed a benchmark using the C programming language to iterate over the number of states. Testing this on a 2GHz AMD Opteron demonstrates that 1.2×10^8 states can be iterated over each second, excluding the computation of any metric for each state. The time taken for a DRA

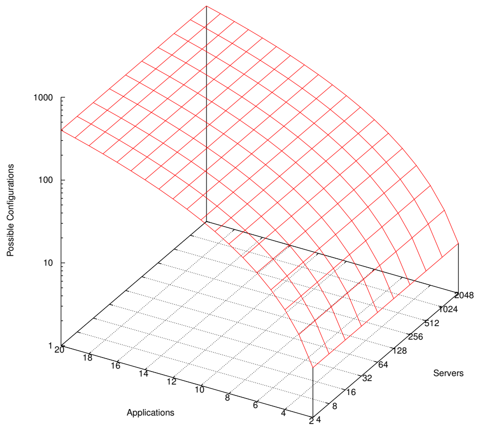


Figure 2. Heuristic framework scaling

Algorithm 1 General class algorithm

```
Let a, ..., z represent servers allocated to each application
Let S represent servers available
Let B represent best allocation
Let V represent the value of the best allocation
Init V, B
for a = 0; a ≤ S; a++ do
    for b=0; Σ_a^b ≤ S; b++ do
        ⋮
        for z=0; Σ_a^z ≤ S; z++ do
            value = metric(a, b, c...z)
            if value > V then
                (a, ..., z) → B
                value → V
            end if
        end for
    end for
end for
return B
```

algorithm to iterate over all possible allocations and select a configuration forms the lowest bound on the interval between allocations.

IV. A Demand Based Approach

To address the exponential complexity illustrated in Section III, we now propose a template for the development of DRA algorithms suitable for the management of applications and resources at large-scale. The template utilises three distinct phases: (i) the first phase is a preprocessing step done at system setup, (ii) the second phase requires knowledge of throughput of each application, and (iii) the third part runs periodically to reallocate servers to applications.

In the first stage, the applications are ranked in accordance with a pre-defined metric. We do not provide a specific metric here, as the framework aims to be adaptable, but suitable examples include business criticality, in the context of a single organisation, or $SLAs$ in the context of a shared hosting provider. For the second stage, throughput may be measured through performance testing on hardware that is equivalent to that of the deployment target, performance modelling, or measured online at runtime. The accuracy of

Algorithm 2 Improved scalability algorithm

```
1:  Let N be the number of applications
2:  Let a_1, ..., a_n be ranked applications
3:  Let m_1, ..., m_n be minimum resource of a_i
4:  Let t_a be the throughout of a server of a
5:  Let n_a be number of servers allocated to a
6:  Let I be idle servers
7:  for i = 1; i < N; i++ do
8:      p = predictedDemand(a_i)
9:      S'_i = p / t_a
10:     if S'_i < S_i then
11:         Append S_i − S'_i servers to I'
12:         S'_i → S_i
13:     end if
14: end for
15: for i = 1; i < N; i++ do
16:     if S_i ≠ S'_i then
17:         if I' > 0 then
18:             if I' > S'_i − S_i then
19:                 Move S'_i − S_i from I' to S_i
20:                 break
21:             else
22:                 Move all servers in I' to S_i
23:             end if
24:         end if
25:         for j = N; j > i + 1; j−− do
26:             if S'_i − S_i ≤ S_j − m_j then
27:                 Move (S'_i − S_i) from S_j to S_i
28:                 Break
29:             else
30:                 Move (S_j − m_j) from S_j to S_i
31:             end if
32:         end for
33:     end if
34: end for
35: Let I = I'
```

the performance analysis undertaken will have an impact on the allocation of resources.

The periodic stage of the proposed framework is shown in Algorithm 2. Lines 6-13 reclaim resources from applications which are over provisioned for the next stage. Lines 14-32 allocate resources across applications which are under provisioned for the next period. Lines 16-21 allocate resources from the reclaimed servers if any are available. Lines 23-30 allocate resource from the lower ranked applications to higher ranks, subject to their minimum server allocation. Line 33 returns remaining idle servers. There are several options for servers which remain unallocated after all allocations have been made, and we do not specify any actions here. They may be allocated amongst applications either equally or by some weighted metric. Alternatively they may be switched into a low power mode, if the policy is aiming to minimise power consumption.

The migration of serves is not cost-free, as servers are unable to service requests whilst being migrated. The penalty to the applications is the number of requests that are unable to be serviced between the time of the decision to migrate servers and the completion of the migrations. The proposed greedy algorithm satisfies higher priority applications first, which means that servers allocated to these applications are less likely to be migrated to applications of lower priority, thus incurring lower cost.

This framework provides a heuristic to solve the NP-hard allocation problem discussed in Section III. This approach is heuristic-based as (i) it relies on predicted demand to calculate the required resource to be provisioned, and (ii) a ranking of applications to guide resource allocation. We specify a ranking of applications to satisfy the requirements of the most important applications first, thus improving the best-case performance of the algorithm. The worst-case complexity of the framework is $O(n^2)$ when scaling the number of applications. This algorithm is independent of the number of servers. Figure 2 shows the scalability of the framework across 20 applications and 2048 servers.

V. Experimental Setup

In our experiments we use applications with identical characteristics to limit external parameters. Each application is defined as serving four request types, with service durations of 15, 20, 45 and 110ms ,which represent proportions 0.45, 0.3, 0.2 and 0.05 of the requests respectively. The requests received for each application are distributed by a round robin scheduler to all servers dedicated to the application.

The server reallocation process is comprised of the following steps. Firstly, the round robin scheduler server stops dispatching requests to the server being migrated. Next, the server completes all requests currently queued and the application is stopped on the server. The new application is then deployed to the server. Finally, the server is added to the scheduler and begins to service requests for its new application. The time for the un-deployment and deployment of an application is set at 30 seconds.

We also consider the impact of failed requests on the system. A request is considered to fail if the response time exceeds 60 seconds or it is rejected due full server queues. The queued request limit is set at 10000 requests per server.

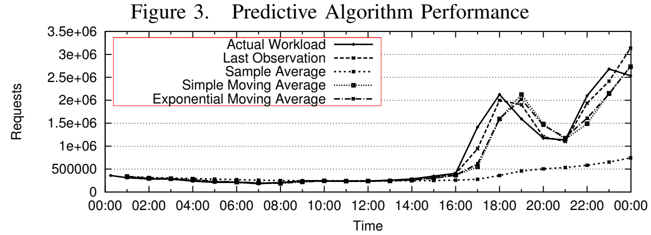
To define a policy using the proposed framework we consider the priority of our applications. Applications are ranked by their identifier such that Application 1 is ranked higher than Application 2. We also require resource performance knowledge. For our experiments the throughput of a single server is calculated as 73 requests per/sec in our simulation environment. In order to select a workload prediction algorithm, we have evaluated several in the context of the 1998 World Cup web traffic data [14]. To select the best prediction algorithm we measure the busiest 24 hour period of June 30th 1998. We examine the following algorithms:

- A last observation approach uses the workload from the previous period as the predicted value for the next period. This works well in situations where the workload does not fluctuate significantly between periods.
- A sample average considers the workload for the next period to be the average of all periods observed. This works well where the workload is constant.
- A simple moving average calculates an average of the previous five periods to make a prediction. Older windows have no bearing on the prediction.
- An exponential moving average is similar to the simple moving average, but it weights the previous periods placing the most weight on the most recent period. In this test we have used five windows.

Table I
Predictive Algorithm Results

Algorithm	Min Pred. Err.	Max Pred. Err.	RMSE
Last observation	333	601104	142574
Sample average	376	2416625	814575
Simple moving average	805	944556	289467
Exp. moving average	553	815174	258210

Figure 3. Predictive Algorithm Performance



The predictive performance of these algorithms is shown in Table I. The last observation algorithm yields the lowest absolute errors and the lowest RMSE. However, this algorithm is affected by large shifts in application workload. In practice this would mean that the underlying platform my reallocate servers more often. The exponential moving average provides a smoothed prediction of the workload, which allows for clear incremental changes in resource allocation which should remove the potential for significant resource migrations, thus the exponential moving average was chosen as the workload prediction algorithm.

A. *Performance Experiments*

To verify the effectiveness of our framework we now compare the performance of the example policy against a policy from the general class and a static resource allocation. The algorithm we have selected for comparison is the Average Flow Policy, which was derived in [7] and demonstrated practically in [1]. The algorithm is stated in algorithms 3 and 4. To avoid modification of the original algorithm, two applications are used for the performance comparison.

The workload used for the simulations is derived from the log files of the 1998 Football World Cup. The workload selected for each application is an 8 hour section from the 24 hour period. Application 1 is subject to a higher workload than Application 2; 56582546 requests versus 29208765. The time period selected for Application 1 is 16:00 until 24:00 while Application 2 uses requests issued between 12:00 and 20:00. The workload for Application 1 varies between 105 and 3816 requests per second while the workload for Application 2 varies between 202 and 3118 requests per second.

The number of servers used in this experiment is 64, which are initially distributed equally between the two applications. The period between executions of the DRA policies is 15 minutes.

Since the Average Flow Policy allocates all available servers to applications, we do the same for the framework derived policy. Servers which are idle after allocations have

Algorithm 3 Server Allocation

Require: Current server allocation S_1, S_2
Arrival Rates, λ_1, λ_2
Completion Rates, μ_1, μ_2
Queue Lengths q_1, q_2
Switches in progress $w_{1,2}, w_{2,1}$
Switch Rate $r_{1,2}, r_{2,1}$
Job costs c_1, c_2
Switch costs $sc_{1,2}, sc_{2,1}$
Ensure: New server allocation, S_1', S_2'
Let tc_1, tc_2 be total costs for each job queue
$tc_1, tc_2 \leftarrow 0$
Let bdc be best decision cost
$bdc \leftarrow \infty$
if $\mu_1 = 0$ and $\mu_2 = 0$ **then**
  return error
end if
for s in S_1 **do**
  $tc_1 \leftarrow$Algorithm 4 $(s, S, \lambda_1, \mu_1, w_{2,1}, r_{2,1}, q_1)$
  $tc_2 \leftarrow$Algorithm 4 $(s, S, \lambda_2, \mu_2, w_{1,2}, r_{1,2}, q_2)$
  if $(c_1 \times tc_1 + c_2 \times tc_2 + sc_{1,2} \times s) < bdc$ **then**
    $S_1' \leftarrow -s$
    $S_2' \leftarrow s$
  end if
end for
for s in S_2 **do**
  $tc_1 \leftarrow$ Algorithm 4 $(s, S, \lambda_1, \mu_1, w_{2,1}, r_{2,1}, q_1)$
  $tc_2 \leftarrow$ Algorithm 4 $(s, S, \lambda_2, \mu_2, w_{1,2}, r_{1,2}, q_2)$
  if $(c_1 \times tc_1 + c_2 \times tc_2 + sc_{2,1} \times s) < bdc$ **then**
    $S_1' \leftarrow s$
    $S_2' \leftarrow -s$
  end if
end for
return S_1', S_2'

been made will be distributed across applications proportionally by rank.

B. Scalability Experiments

For scalability experiments eight applications were distributed across 64 servers, each of which was subject to a different workload. Applications were initially distributed evenly across servers. Workloads were synthetic, based on sine waves of varying frequency and amplitude, and are shown alongside the respective results in Figures 5 and 8. The workload durations in these experiments were 8 hours, and the periodic reallocation time is 15 minutes.

VI. Results

A. Performance Results

In this section, we compare the performance of the policy derived from the proposed framework against that of the Average Flow Policy and a static allocation. We compare the results based on two criteria; (i) application response times and (ii) the number of requests serviced.

The top graphs in Figures 6 and 7 show the workload for each application, the middle graph shows the server allocations made for the duration of the experiment and the bottom graph gives the 95th percentile response time for each applications. Figure 4 omits the server allocation graph.

From Figure 4, the static server allocation performs best, in terms of response time, as its response times never

Algorithm 4 Total Cost Algorithm

Require: Switched servers s
Server Allocation S
Arrival rate λ
Completion rate μ
Switches in Progress $w_{m,n}$
Switch rate $r_{m,n}$
Queue Length q
Ensure: Total Cost, tc
if $q > 0$ **then**
  if $\lambda < S - s + w_{m,n} \times \mu_1$ **then**
    Let st be an array of size $w_{m,n} + 1$
    for i in $w_{m,n}$ **do**
      $st_i \leftarrow \frac{1}{(w_{m,n} - i) \times r_{m,n}}$
    end for
    $st_{w_{m,n}} \leftarrow \infty$
    $tc_1 = 0$
    Let vq be the virtual queue length
    $vq \leftarrow q$
    for j in $w_{m,n} + 1$ **do**
      if $vq > 0$ **then**
        Let x be the rate at which the queue drains
        $x \leftarrow vq + (\lambda - (S - s + j) \times \mu) \times st_j$
        if $x \geq 0$ **then**
          $tc \leftarrow tc + 0.5 \times (vq + x) \times st_j$
          $vq \leftarrow x$
        else
          $tc \leftarrow tc + 0.5 \times \frac{-vq}{\lambda - (S - s + j) \times \mu \times vq}$
          $vq \leftarrow 0$
        end if
      end if
    end for
  else
    $tc \leftarrow \infty$
  end if
else
  $tc \leftarrow 0$
end if
return tc

exceed four seconds. The Average Flow Policy demonstrates the best results for the results for Application 1, but this improvement comes at the expense of the response time for Application 2. The response time at 325 minutes exceeds the 60 second timeout for the requests. From Figure 7,the framework derived policy delivers the worst response time for Application 1. However, this remains below the timeout threshold for the duration of the experiment. This policy also delivered intermediate results for Application 2, but, again, the response time remained below the threshold. Table II gives details of the request failures observed by each application under each policy.

The performance of the framework policy is guided by the mechanism used to predict workload. The exponential moving average uses the values observed from the 5 previous windows. Where the workload trend changes, for example Application 1 at 300 minutes, the predication does not capture the increase and the policy migrates servers away from Application 1, which is not the desired behaviour.

The static allocation policy had a failed request rate of 7.03% for Application 1 and 1.24% for Application 2. The Average Flow Policy demonstrates a 0% failure rate for Application 1, but a large 62.73% failure rate for Application

Figure 4. Static allocation results

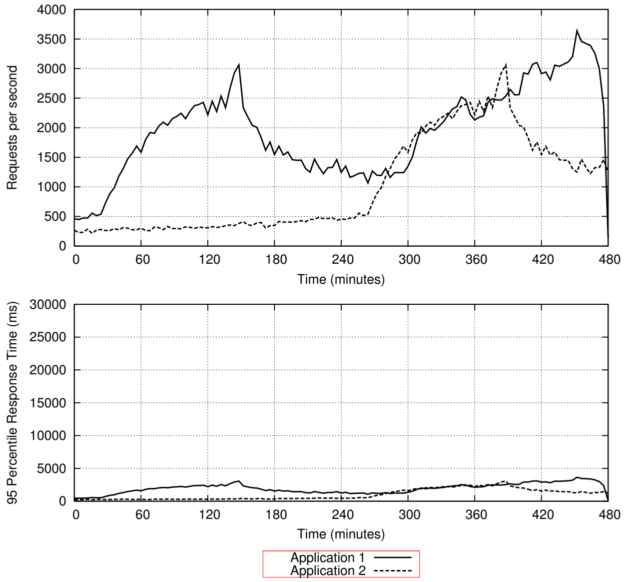
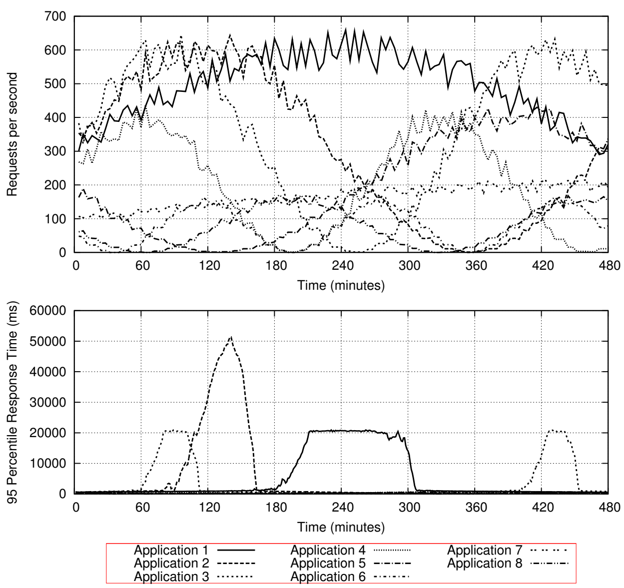


Figure 5. Static allocation at scale results



2. The framework policy delivers a failure rate of 2.93% for Application 1 and 5.28% for Application 2. The framework derived policy delivers the lowest overall failure rates from all three of the policies.

In Section V it was stated that the priority of Application 1 was double that of Application 2. We use this to infer a cost for each allocation policy by considering request failures for Applications 1 and 2 to have an associated cost of 2 and 1 units respectively. We may then use this metric as a basis for comparison. The static allocation incurs a cost of 8,321,175, the cost of the Average Flow Policy is 18,321,675 and the cost of the framework derived policy is 4,861,395. Hence, the framework policy shows significant cost advantages.

Figure 6. Average flow policy results

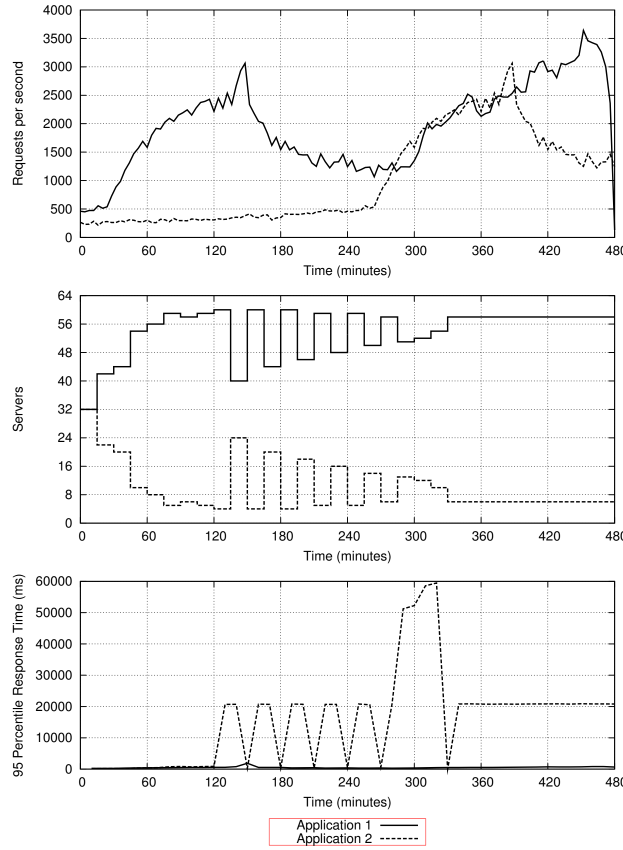


Table II
REQUEST FAILURE PERCENTAGES UNDER PERFORMANCE EXPERIMENTS

	Requests	Static Alloc.	Average Flow	Framework
App.1	56582546	7.03	0	2.93
App.2	29208765	1.24	62.73	5.28
Total	85791311	5.06	21.36	3.73

B. Scalability Results

We now present a larger scale deployment of applications than the performance study. Table III shows the time taken for the Average Flow Policy and the Framework Policy to perform a switching decision. The times for the Average Flow Policy are derived from combining the size of the state space with a timed value for Algorithm 4.

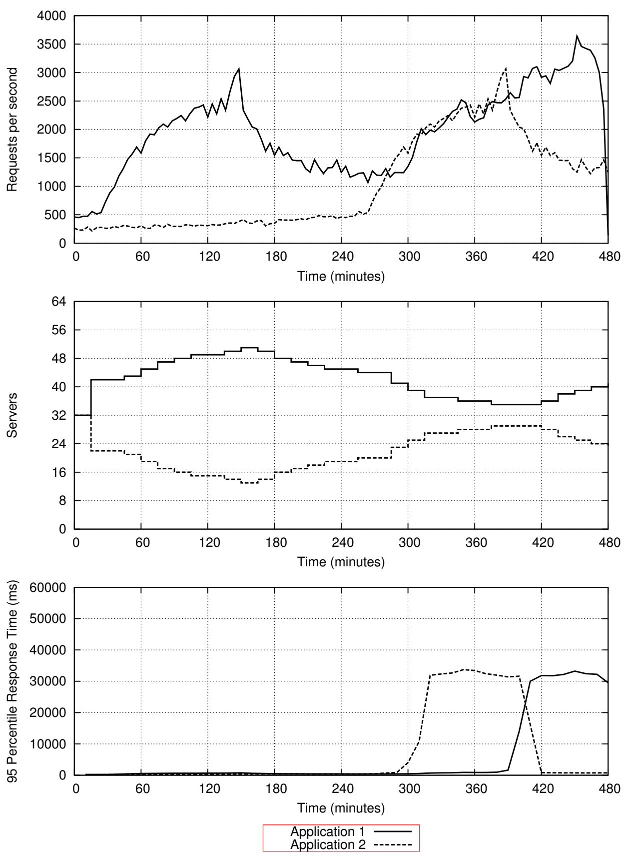
The Average Flow Policy is currently designed for allocation of servers between two applications. To avoid modification of the original algorithm we shall not consider it under the scaling experiment parameters of 8 application across 64 servers. Table III shows that under these circumstances the policy would take 22 minutes to develop a new allocation. This exceeds the periodic allocation interval of 15 minutes. Thus the lowest possible bound for server reallocations is the decision time of the algorithm. We will exclude the Average Flow Policy from the evaluation of the Framework policy.

The results for the scaling experiment are shown in Figures 5 and 8. Figure 5 shows the performance obtained

Table III
APPROXIMATE DECISION MAKING TIME PRIOR TO REALLOCATION

	Average Flow Policy							Framework Policy						
Servers	8	16	32	64	128	256	512	8	16	32	64	128	256	512
2 Apps.	<1s	<1s	<1s	<1s	<1s	<1s	<1s	<1s	<1s	<1s	<1s	<1s	<1s	<1s
4 Apps.	<1s	<1s	<1s	<1s	<1s	3s	22s	<1s	<1s	<1s	<1s	<1s	<1s	<1s
6 Apps.	<1s	<1s	<1s	11s	5 mins	3 hours	4 days	<1s	<1s	<1s	<1s	<1s	<1s	<1s
8 Apps.	<1s	<1s	15s	22 mins	38 hours	184 days	61 years	<1s	<1s	<1s	<1s	<1s	<1s	<1s
10 Apps.	<1s	2s	6 mins	1 Day	1 Year	490 years	2.3e5 years	<1s	<1s	<1s	<1s	<1s	<1s	<1s

Figure 7. Framework policy results



from a static allocation. The static allocation exhibits more variation in response time than the dynamic policy. The performance of the framework policy is shown in Figure 8. It is clear that the dynamic resource allocation is beneficial to the response time of the applications, as the highest 95th percentile result is 20 seconds.

The failures delivered by the system with a large number of applications is reduced by 21% over the static allocation by the derived policy. However, the distribution of failures is also significant. The failure results for both allocation schemes can be seen in Table IV. The static server allocation delivers a zero failure rate for Applications 4-8. The failure rate for Application 8 under the Framework Policy is 1.99% which is due to migration of servers from this application to applications with higher priorities. In this case the static allocation outperforms the policy as the application is over provisioned for the duration of the experiment. A statically allocated Application 1 is under provisioned at points in the experiment which causes request failures that do not occur when the policy is used. If we consider the cost of failed requests to be inversely proportional to the ranking of the application, then the static allocation costs 440,128 while the policy results cost only 59,181. The policy yields a 7-fold reduction in the the cost of failed requests.

VII. CONCLUSION AND FUTURE WORK

In this paper, we have shown that the DRA problem is NP-hard, and demonstrated that the scalability of a general class of resource allocation algorithms is unsuitable for use in a modern data center. In response to this we have proposed a framework for the development of DRAs with improved scalability. Further, we also developed an instance of the framework and compared its performance against that of the general class for a real-world workload to demonstrate the scalability of the proposed resource allocation framework.

The work presented in this paper focuses on homogenous systems. In future work we will extend this to incorporate heterogeneous environments, which will require consideration of asymmetric migration costs and variations in application performance across resources. Further, in order to develop an improved understanding of the DRA algorithm scalability, the notion of switching cost will be explored in greater depth than was permissable in this paper.

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Figure 8. Results for framework derived policy at large-scale

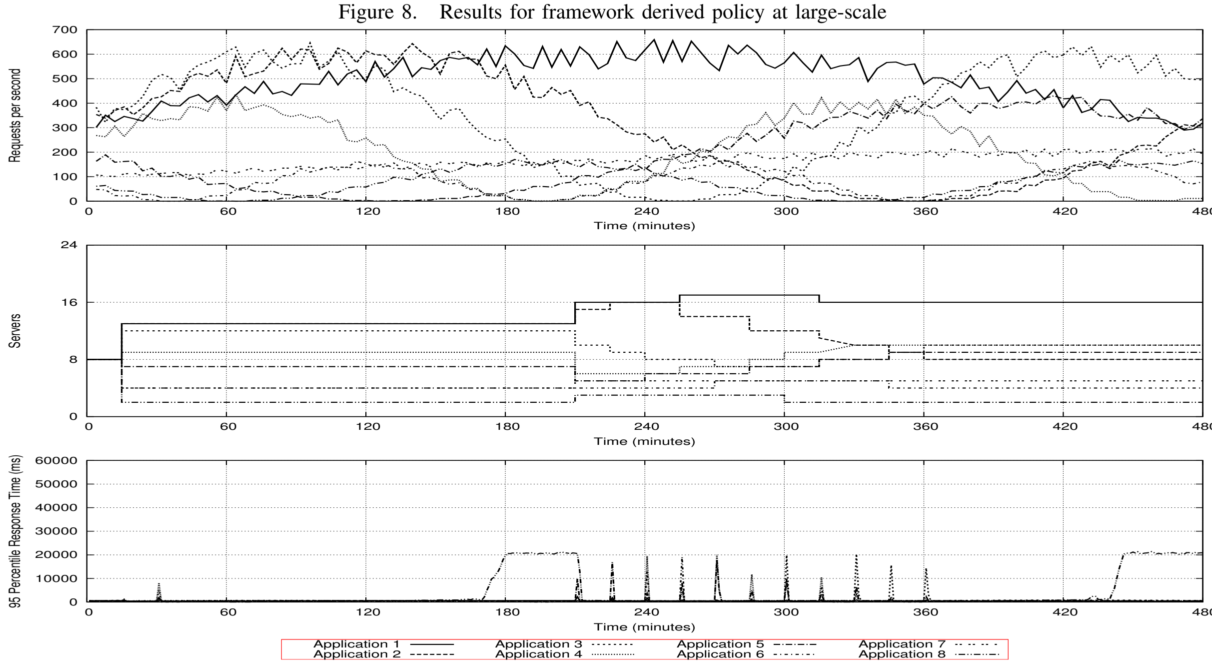

Table IV

REQUEST FAILURES UNDER SCALABILITY EXPERIMENTS

		Static Policy			Framework Policy		
	Requests	Successful	Failed	Failures (%)	Successful	Failed	Failure Rate (%)
App.1	14168988	14127937	41051	0.29	14168988	0	0
App.2	8672845	8669653	3192	0.04	8672845	0	0
App.3	10490296	10475400	14896	0.14	10488530	1766	0.02
App.4	6082631	6082631	0	0	6081776	855	0.01
App.5	5629034	5629034	0	0	5629034	0	0
App.6	2159599	2159599	0	0	2159340	259	0.01
App.7	4744868	4744868	0	0	4744868	0	0
App.8	2186604	2186604	0	0	2143071	43533	1.99
Total	54134865	54075726	59139	0.11	54088452	46413	0.09

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