Diffusive Load Balancing of Loosely-Synchronous Parallel Programs over Peer-to-Peer Networks

Scott Douglas and Aaron Harwood*
Department of Computer Science and Software Engineering
University of Melbourne
Victoria, 3010. AUSTRALIA
{scdougl,aharwood}@cs.mu.oz.au

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Abstract

The use of under-utilized Internet resources is widely recognized as a viable form of high performance computing. Sustained processing power of roughly 40T FLOPS using 4 million volunteered Internet hosts has been reported for embarrassingly parallel problems. At the same time, peer-to-peer (P2P) file sharing networks, with more than 50 million participants, have demonstrated the capacity for scale in distributed systems. This paper contributes a study of load balancing techniques for a general class of loosely-synchronous parallel algorithms when executed over a P2P network. We show that decentralized, diffusive load balancing can be effective at balancing load and is facilitated by the dynamic properties of P2P. While a moderate degree of dynamicity can benefit load balancing, significant dynamicity hinders the parallel program performance due to the need for increased load migration. To the best of our knowledge this study provides new insight into the performance of loosely-synchronous parallel programs over the Internet.

keywords: peer-to-peer computing, load balancing, loosely-synchronous

1 Introduction

As the number and performance of Internet hosts continues to increase, so does the number of under-utilized resources. These under-utilized resources are widely recognized as potential processing nodes for high performance computing (HPC) projects; Seti@Home\(^1\) reports gaining 40T FLOPS of average processing power using about 4 million hosts. This is a remarkable use of idle processing power that can’t be understated albeit that the problem is embarrassingly parallel. This paper addresses the execution of loosely-synchronous parallel programs over a similar number of resources, which poses significant additional burdens on the distributed system.

There is now a widely proliferating Grid methodology\(^2\) that is being used repeatedly to link HPC centers and other distributed resources together. The methodology is hierarchical, consisting of Grid controllers that manage a homogeneous pool of hosts, e.g. Globus\(^1\), XGrid\(^2\) and Grid brokers that coordinate jobs over a heterogeneous set of controllers. Brokers compete against or cooperate with one another in a computational market\(^2\), selling processing power to Grid clients. An essential aspect that requires significantly more research is the realization of a system architecture that facilitates the efficient coordination of these resources. The conventional Grid hierarchy is a centralized method of achieving coordination. While a tree

\(^*\)Author for correspondence.

\(^1\)http://www.setiathome.ssl.berkely.edu

\(^2\)http://www.apple.com/acg/xgrid/
does provide scalability and is suitable for some problems, e.g. Domain Name Service is quite successful, we believe that a hierarchical structure will not allow the spontaneous growth of massively parallel programming that is suitable for all kinds of parallel programs.

We propose the continued development of Peer-to-Peer (P2P) networks to construct a massively parallel programming infrastructure. P2P networks provide a completely decentralized approach that emancipates the system from a hierarchy without compromising scalability. Basically, a host in the Internet runs a peer process that uses a P2P protocol to connect to a number of existing peers. A P2P protocol provides efficient data storage and retrieval over all peers in the network without significant impact from the continual connecting and disconnecting of peers. By distributing the coordination overhead among all participating hosts, P2P networks allow greater scalability and robustness, simply stated: the failure of any given host is no more likely to disrupt the system than the failure of any other host.

In particular, we consider the coordination of resources for the purpose of maximizing the efficiency of loosely-synchronous parallel programs. Fundamental to this is the load balancer which should support the favorable characteristics of the P2P network on which it runs, namely decentralization. In addition, since P2P networks consist of hosts that participate for limited time intervals, it must be able to adapt to the changing network: in other words be dynamic.

While distributed computing on (semi) P2P networks has been shown to work for some parametric and data parallel problems such as Distributed.net\(^3\) and Seti@Home in which load balancing can be accomplished by work pooling, loosely synchronous problems have the additional challenge of accounting for inter-task communication. For example, in the simulation of fluid dynamics\(^1\)\(^8\) each task requires regular synchronization with a subset of other tasks. Consequently the overall progress of the application is restricted to the rate of the slowest task, and therefore the quality of the load distribution has a significant impact on performance. Furthermore, since communication latency is affected by the distance between coupled tasks, the load balancer should be able to account for task locality.

While some work considers execution of load balancing over unreliable networks\(^2\) and the execution of parallel applications, in particular with MPI\(^3\), the use of P2P for loosely synchronous programs is not well studied. This paper investigates the issues involved with the execution of loosely synchronous programs over unreliable P2P networks, in particular, we focus on the applicability of Diffusive load balancers.

Diffusive load balancers achieve a global balance by continuously arranging load within a subset (or domain) of the network. We consider their use for P2P networks because they are: decentralized, using only locally available information; dynamic, since static techniques can not accommodate the dynamic behavior of P2P networks; applicable to any network; and they are simple to implement.

The remainder of the introduction gives a background on previous approaches to load balancing. Section \(^4\) describes the model, strategies and evaluation metrics used in the simulation, the results of which are discussed in Section \(^4\).

## 2 Decentralized load balancing techniques

We model loosely synchronous applications as a graph called the guest graph $G$. Each node in $G$ represents a job and an edge exist between two nodes if synchronization is required between them. The network is also modeled as a graph, called the host graph $H$. Nodes and edges in $H$ represent hosts and communication channels between them respectively.

Load balancing is the process of allocating or mapping each host in $H$ an amount of work that maximizes the overall application performance. Typically this involves the collection of system information, calculation

\(^3\)http://www.distributed.net
of the optimal arrangement, and the \textit{migration} of work units or \textit{jobs} between hosts. We discuss here only load balancing strategies that are relevant to distributed applications, a broader introduction can be found in [13] and [7].

Throughout this paper we refer to \textit{quality} and \textit{stability}. We use the term quality to indicate the effectiveness of a mapping with regard to the progress of a parallel program, a good quality mapping leads to a faster progression of the program. Quality is a function of processor load and communication delays. Stability is the property of a load balancing which indicates whether it reaches a point where no further migration is performed.

\section{2.1 Random load balancing}

Two common methods for random load balancing are random pushing and random pulling. For random pushing, an over-loaded host migrates load from itself to another host chosen at random. For random pulling, an under-loaded host migrates load from another host chosen at random. Both methods have been shown to be effective in [24]. Commonly, a host is deemed either under-loaded or over-loaded depending on whether its’ load is respectively greater than or less than, a threshold. In this way the quality of the balance is sensitive to the chosen threshold. An adaptation to this method is discussed in [1] where a collection of hosts are polled in order to choose the most appropriate migration destination.

The simplest randomized load balancers do not require any system wide information, avoiding the overhead associated with collecting it. Consequently, the method scales well and is thus applicable to P2P networks. In addition, since exiting hosts (those leaving the P2P network) perform pushing, the method suits dynamic networks. However, the approach can suffer from excessive communication when the system is under-loaded. Random pulling suffers when there are not many hosts with load since a randomly chosen host will likely not have any load to share. Random pushing suffers when there are many hosts with load since a randomly chosen host will likely already have sufficient load. Furthermore, the distribution of load occurs without regard to the locality of the application, in other words, closely coupled jobs may be placed on distant hosts thereby causing increased latency.

\section{2.2 Clustering methods}

Assigning an administrative host to a subset of the system allows each cluster to be balanced by centralized methods. Administrative hosts negotiate load migration between clusters thus globally balancing the load. Scalability is achieved by using scalable protocols for inter-cluster balancing.

This approach suits systems that have a hierarchical structure such as grids [26] and wide area networks of work stations [4]. Grid architectures for example, often have different communication capabilities between hierarchies making inter-cluster migration unfavorable. Several “cluster-aware” approaches based on random pulling and pushing that take this into account are proposed in [26].

Many favorable characteristic of P2P such as scalability and anonymity, stem from the absence of hierarchy. Consequently, while clustering strategies are sensitive to the locality of jobs, hierarchical load balancing approaches should be avoided.

\section{2.3 Diffusive methods}

Diffusive load balancing, first proposed by [10] and [5], allows hosts to be members of several overlapping domains. In this approach the intersecting host of two domains perform the task of inter-domain balancing. In other words, by locally balancing overlapping domains a global balanced is achieved.

Corradi, Leonardi and Zambonelli give a useful definition of diffusive load balancers in [8]. A load balancing strategy can be said to be diffusive when: \( (i) \) it consists of identically distributed components acting autonomously and asynchronously, and \( (ii) \) it balances the load within its domain as if it were a separate system and based only on information from this domain, and \( (iii) \) each local domain partially overlaps with other domains so that their unification gives full coverage of the network.
In sender-initiated diffusion (SID) [9] an over-loaded host migrates load to an under-loaded neighbor. Each domain consists of two hosts. For example, if hosts $i$ and $j$ have loads of $w_i$ and $w_j$ respectively, where $w_i > w_j$, then $\frac{w_i - w_j}{2}$ load can be migrated to $j$ to balance the load. Since the domains overlap, this method performs an optimal mapping, however, it is based on an unreasonable assumption that the load is continuous.

The model can be adapted to handle discrete load by migrating $\lfloor \frac{w_i - w_j}{2} \rfloor$ load to $j$ if $w_i > w_j$, assuming 1 to be the unit load. However, if $w_j < w_i \leq w_i + 1$, migrating a unit of load to $w_j$ results in $w_i < w_j \leq w_i + 1$. Since an imbalance remains, the next balancing step may return the load to $w_i$, we call this condition over-migration. Essentially the load continues to migrate between the two hosts until it is consumed, consequently the strategy is unstable.

To avoid this, often strategies only migrate load between two neighbors $i$ and $j$ if $w_i - w_j > 1$, however, this leaves the hosts in an imbalance. While each domain has an imbalance of at most 1 every domain may have such an imbalance resulting in a global load gradient. In general if such a gradient exists, the maximum imbalance is $\frac{D_H}{D_d}$, where $D_H$ is the diameter of the network and $D_d$ is the diameter of the domains, i.e. the larger the domain size, the lower the global gradient and imbalance.

Extensions to this model have been proposed in [15] to accommodate heterogeneous networks and in [21] [12] which uses a limited memory of previous migrations to avoid over-migration. In [11] it is suggested that diffusive methods should be used as a preprocessing step to avoid needless migrations.

### 2.4 Load balancing on P2P

Distributed hash tables (DHT) such as Chord [25] do intrinsically support a kind of load balancing since the hash function, when applied to a job’s unique identifier, will distribute jobs over the P2P network at random with approximate uniform distribution. While the allocation itself requires little overhead, it can result in a poor quality mapping, since when $|G| = |H|$, there is a high probability that some hosts don’t receive any jobs [26]. Stoica, Morris et al. (in more detail [23]) address this by proposing a set of virtual hosts, $V$, that map to hosts, such that $|V| > |H|$. By moving virtual hosts between hosts the load is adjusted accordingly, increasing the quality. This approach cannot take into account the heterogeneous nature of the network since jobs are mapped to a hash space and not to appropriate hosts. There is also no real mechanism to account for locality, although caching has been suggested to provide locality of data access.

An adaption of this method is discussed by Byers, Considine and Mitzenmacher [6] who avoid the use of virtual hosts, arguing that it gives an unnecessary increase in the communication overhead, since hosts need to monitor a greater number of connections. Alternatively, they use a set of hash functions that associates each resource to a number of hosts. Each host is polled prior to allocation to choose the most appropriate. This approach does not consider the locality of communicating jobs either.

An interesting approach to load balancing is discussed by Montrosor, Meling and Babaoglu in [20]. It uses an ant analogy to find unbalanced pairs of nodes. The authors claim this approach to be relevant to P2P networks since it exhibits both; reliability, the loss of ants or peers does not greatly the system and scalability, since more peers can be easily handled by more ants.

### 3 P2P parallel processing model

This section describes our model for parallel processing on P2P. Section 3.1 describes the host network model and its dynamic behavior. Section 3.2 describes the loosely synchronous application model and section 3.3 describes the metrics used to evaluate the load balancing strategies. We then describe the three diffusive load balancing policies considered for detailed analysis in this paper.

#### 3.1 The P2P network model

Two events affect the topology of the host network ($H$). A host $v$ may enter the network, $V(H) = V(H) \cup \{v\}$, or a host $u \in H$ may leave the network, $V(H) = V(H) - \{u\}$. Typically an entering host, $u$, immediately
connects with a subset of other hosts which become its neighbors, denoted \( N(u) \). We assume these connections remain until either \( u \) or \( v \in N(v) \) leave. The rate at which network events occur is called the \textit{dynamicity} of the network, measured by \textit{half-life}.

Let \( H_t \) denote the host network at time \( t \). A network is said to have a half-life of \( \tau_\epsilon \) for a positive constant \( \epsilon \geq 0 \) if there is a constant \( t_0 \) and \( t' \) such that for all \( t > t_0 \) with \( \tau_\epsilon = t' - t \) the following holds:

\[
\left| H_{t'} \cap H_t \right| - \left| H_{t'} \right| \leq \epsilon.
\]

In the instance of an unexpected disconnection, all data on the offending host is lost, disrupting the application performance. We consider this a distinct problem and assume that upon departure each host passes all necessary data and processed work to its neighbors. Likewise, the model assumes that partitions in the network do not occur.

P2P networks that connect peers according to some strategy, and do not use ad-hoc connections, are termed \textit{structured}. Chord is an example of a structured P2P network which has been shown to have a distance between hosts of \( O(\log |H|) \). Our model is intended to represent a structured P2P network, it is therefore assumed the organization strategy can produce a structure that has a similar topological properties. However we did not want to choose a particular protocol, such as Chord, so as to avoid anomalies that may arise that are artifacts of the protocol. Therefore we use a simple, favorable and realistic strategy: when a host enters the network it connects to \( \log |H| \) other hosts at random.

In order to isolate the effect of dynamicity the size of the host network is kept constant. This is achieved in simulation by forcing \( \epsilon \to 0 \) such that a host can only enter the network when another host leaves and vice versa. While this is unlikely to occur in practice, we believe that it does not detract from the generality of the experiment. As discussed in [19], two topological characteristics that affect load balancing are the average degree and average distance. While the topology continues to change for dynamic networks using the above strategy, the degree and average distance are bounded since the probability that a node survives \( k \) half-lives is \( \frac{1}{2^k} \). They form the initial network graph in each of our experiments.

### 3.2 The application model

An application is classed as loosely synchronous if its jobs require regular communication with other jobs. For example, finite element methods divide a large space into smaller, connected, parts. Each part needs only to synchronize with its neighbors. Loosely synchronous applications account for a wide variety of useful computations that can significantly benefit from parallelization. We model a loosely synchronous application by a graph \( G \), called the guest graph. Each node in the graph represents a job (for example an element) and an edge exists between two nodes if they require synchronization.

There are four actions that a guest host may perform: \textit{run}, \textit{synchronize}, \textit{block} and \textit{end}. A running job \( A \) continues to run until it reaches a synchronization point, upon which it begins communicating with its neighbors in the guest graph. If any of \( A \)'s neighbors are not ready to synchronize, job \( A \) enters the blocking state in which it remains until it has synchronized with each of its neighbors. After synchronization it changes to the running state. Upon completion of an application, all jobs simultaneously end.

The granularity size of a loosely-synchronous application is determined by the ratio of time spent communicating to time spent running (large grained applications spend more time running). Smaller grained loosely-synchronous applications are less applicable to distributed networks since they are restricted by communication latency. However, continued improvements to communication technology does broaden the class of applications that are suited to distributed networks.

### 3.3 Evaluation metrics

We define and use two different evaluation metrics: the \textit{standard deviation in load} and \textit{application progress}.

4Throughout the paper log is used to mean \( \log_2 \)
The standard deviation, $\sigma$, is used to measure the load imbalance. If $w_i(t)$ is the load of the $i^{th}$ host at time $t$ and $\bar{W}(t)$ is the average load at time $t$, then $\sigma$ is given by:

$$\sigma(t) = \sqrt{\frac{1}{|H| - 1} \sum_{i=0}^{H} (w_i(t) - \bar{W}(t))^2}$$

A standard deviation of zero represents an optimal mapping where each host has exactly the same load. The rate of convergence of the standard deviation effects the application performance, since the faster the optimal arrangement is reached, the more work is performed. In dynamic networks where network events may increase the standard deviation at indeterminate intervals, if the load balancer is incapable of repairing the imbalance (reducing the standard deviation) fast enough, the optimal arrangement may never be reached.

For diffusive strategies the greatest rate of reduction in the standard deviation is when the local imbalance is high, as at the beginning of an application when jobs enter the network on a single host. Therefore the rate of change of $\sigma$ decreases as the network becomes more balanced, resulting in near\(^5\) asymptotic behavior.

The progress of loosely synchronous applications is limited to the slowest job, thus it may be more applicable to measure this progress as opposed to the fairness of the load mapping. If $I_j(t)$ is the number of times job $j$ has entered the synchronizations state at time $t$ then the average progress, $\bar{P}$, is given by:

$$\bar{P}(t) = \frac{1}{|G| - 1} \sum_{j \in G} I_j(t)$$

Unlike standard deviation the progress at one time is indicative of the performance of the application until that time. Consequently, after a set time period the progress of an application using two different load balancers can be compared to indicate their respective performance.

The number of migrations, $M$, made by a load balancing strategy is important because excessive migration inhibits the application performance. If $M_u(t)$ is the number of jobs that have been migrated from host $u$ at time $t$ then the number of migrations is:

$$M(t) = \sum_{u \in H} M_u(t)$$

In the following sections we describe the load balancing policies used in this paper.

### 3.4 Extended Neighbor

The Extended Neighbor (EN) strategy is discussed by Corradi, Leonardi and Zambonelli in [8]. It is an extension of the sender-initiated strategy and is parameterized by the size of the domain. EN $x$ represents the EN strategy where each domain consists of all hosts a distance of $x$ from the central host. In other words, if $|Path_{ij}|$ denotes the length of a path between hosts $i$ and $j$ then the domain of a central host $i$ is given by:

$$D_i = \{ j \mid j \in V(H), x \geq |Path_{ij}| \}$$

If $i$ is the central host and $j$ is the least loaded host then the EN strategy migrates $\lfloor \frac{L_i - L_j}{2} \rfloor$ load $j$. If the central host is the least loaded host in the domain then a proportional amount of load is migrated from the most loaded host in the domain. Since load is migrated only if doing so reduces the imbalance, a gradient may occur in the domain.

Note that when simulating this algorithm any domain value of $x$ may be used, however, in practice the communication overhead involved with larger values becomes prohibitive. With values of $x$ that are greater than the diameter of the graph the strategy behaves like a centralized method and because it produces an optimal load mapping it is useful for purposes of comparison.

\(^5\)The optimal will eventually be reached.
3.5 Diffusion Algorithm Searching Unbalanced Domains

The DASUD strategy proposed by Cortés, Ripoll, Senar and Luque in [9] differs from the EN strategy in that the minimum and maximum hosts in the domain are used to move load regardless of whether the central host is one of them. The DASUD strategy uses only the direct neighbors of the central host as the domain. This permits a maximum difference between hosts in the domain of 1 unit of load, which means that the local gradient is half as steep as the EN 1 strategy.

The main difference between the DASUD and EN strategies is the amount of overhead incurred in coordinating the domain since the DASUD algorithm can effectively achieve the same quality mapping of the EN 2 strategy with significantly less communication.

3.6 Probabilistic migration

Both the EN and DASUD strategies migrate load only if doing so reduces the imbalance between the two hosts. Doing this makes them stable and results in a global gradient limiting the quality of the mapping. The PM \(x\) (probabilistic migration) strategy allows load to be migrated even if it doesn’t reduce the imbalance according to the probability \(x\). In other words, load is migrated between hosts \(i\) and \(j\) when \(|w_i - w_j| \leq 1\) with a probability of \(x\). By occasionally over-migrating load the global gradient can be reduced because it allows highly loaded domains to diffuse their load to less loaded neighboring domains.

A tradeoff between stability and quality exists since allowing a gradient reduces the quality of the strategy, while reducing the gradient results in greater stabilization time. The PM strategy parameterizes this tradeoff by assigning a probability to the likelihood of migrating load when it does not reduce the imbalance.

4 Simulation and analysis

This section details the simulation experiments. Section 4.1 explores the effect of various PM parameters on the standard deviation and application progress. In Section 4.2 the number and effect of migrations is looked at, in particular in regard to the progress. The effect of the size of the application in relation the size of the network is discussed in 4.3. Section 4.4 explores the effect dynamic networks have on the three diffusive strategies and section 4.5 explores the benefit on progress of job selection. All results are averaged over 50 trials.

4.1 Probabilistic Migration

Fig. 1 shows the standard deviation and progress for various PM parameters. It uses a static graph, with an equal number of jobs to hosts.

The PM 0 strategy migrates jobs from a host only when it does not leave the host with less work than its neighbor thus allowing a gradient. It is stable and behaves exactly the same as the EN 1 strategy. The standard deviation in Fig. 1(a) levels off at close to one for the PM 0 strategy, consequently the progress is significantly less than the optimal (Fig. 1(b)).

The PM 1 strategy always migrates jobs to under-loaded neighbors even if it does not reduce the gradient. This effectively shuffles the jobs around the network at random until all hosts have an equal amount of work. If the number of jobs and hosts is the same (as is in Fig. 1) then the optimal arrangement is eventually found and therefore the strategy is stable. Otherwise, the remaining jobs are passed around the network indefinitely and the strategy is unstable.

By only over-migrating with a probability of 0.5 the PM 0.5 strategy becomes a hybrid of the previous two. This means that in general it won’t find the optimum arrangement as quickly as the PM 1 balancer, however it does find it eventually and makes approximately half as many migrations when the number of jobs and hosts is unequal.
Figure 1: A comparison of the PM parameters using the standard deviation (a) and average progress (b).

Figure 2: The number of migrations for the DASUD, PM 1, PM 0.5 and EN 1 strategies. Using a static graph.

4.2 Migration cost

The disparity in the number of migrations between the load balancing strategies is made clear by Fig. 2. The number of migrations made by the stable DASUD and EN 1 strategies does not increase after time $t = 25$, while, the PM strategies clearly continue to make migrations.

Migration cost is the time taken for a job to migrate from one machine to another, during which no work can be performed on that job. The tradeoff between stability and quality represented by the PM parameter provides a means of measuring the relationships between migration cost and progress. Fig. 2 is a graph of PM probability vs. migration cost in terms of application progress at time $t = 500$. It shows that migration cost has a greater effect on the progress for high probabilities. The most robust performance over a variation in the migration cost occurs at a value of approximately 0.35.

4.3 Application coverage

Stability is particularly important when the number of jobs does not equally divide into the number of hosts which means there are always some edges over which an imbalance exists. When a mapping is stable, jobs remain on a host regardless of whether their neighbors are under-loaded, otherwise, load may be migrated across these edges even though this cannot remove the gradient over all edges, consequently the migration
Figure 3: The number of migrations vs. the probability of migration in relation to the progress at $t = 500$.

does not improve the mapping quality and thus disrupts the application performance.

Figure 4: A comparison of the DASUD and PM 0.35 strategies in relation to the progress at $t = 500$. With a migration cost of 5, $|H| = 31$.

The best application performance is achieved when $|G| \leq |H|$, using a stable strategy. In this case each host gets an equivalent amount of CPU time from each host. When $|G| + 1 = |H|$ one host has twice as many jobs and so the application progresses at half the average rate as when each host has exactly one job. This means that as the number of jobs increases the application performance degrades in a stepped fashion which can be seen in Fig. 4. The line labeled theoretical optimal is the performance expected if load were continuous and is defined as 50 if $|G| < |H|$ and otherwise as $\frac{|G|}{|H|}$. With no migration cost the PM 0.35 strategy has a closer fit to the theoretical optimum than the DASUD strategy, however, when a migration cost of 5 is used as in Fig. 4, it performs better than the DASUD strategy only when $|G|$ is close to but not more than $|H|$. 

4.4 Network dynamicity

A host graph becomes dynamic when hosts enter and exit the network. Such network events alter the load distribution and the effect this has on the application is determined by the rate at which the load balancer can repair these imbalances.

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6By comparison, on a dedicated host, each iteration takes 10 time units.
Figure 5: The affect of network events on the standard deviation (a) and progress (b) using the EN 5, DASUD and PM 0.35 strategies.

Fig. 5 shows the standard deviation (a) and the progress (b) for a network in which a host exits at time $t = 200$ and another enters at time $t = 300$. For the EN 5 strategy which implements an optimal mapping, an exiting host causes an increase in the standard deviation since where before each host had the same number of jobs, now at least one has more than the others. The standard deviation is also increased in the PM 0.35 strategy, however, the DASUD strategy results in an improved mapping.

On static networks the DASUD strategy has a local gradient of $\frac{1}{2}$ but when the load of an exiting host is pushed into the network it is altered. If a job is migrated to a domain with such a gradient, the DASUD strategy will re-map the local domain, resulting in a reduced gradient and thus a reduced standard deviation. In other words, exiting hosts randomize the local load distribution allowing the balancer to reduce the gradient.

An entering host connects to $\log|H|$ neighbors at random and creates a new domain. The connection of two hosts to the new host reduces the distance between them to at most the diameter of the domain. When this occurs to two hosts with an imbalance the result is a better mapping and hence a reduction in the standard deviation.

While the standard deviation improves with network events for the DASUD strategy little difference is made to the progress, as shown by Fig. 5(b), since a gradient still exists. The progress, when balanced by the PM 0.35 strategy, is effected by the events but less obviously than for the optimal EN 5 strategy. When a host exits at least one host has more work than others which reduces the progress. When a host enters, the optimal mapping is restored and the progress rate returns to its value before the exit event.

A similarity exists between dynamic networks and the PM strategy since both network events and over-migration result in a greater number of migrations but also a better quality mapping. In other words, increased instability in the load balancing strategy and increased dynamicity in the host network have a similar effect on the applications performance.

Networks with a low half-life (highly dynamic) suffer from a greater number of migrations. In addition, if the balancing strategy is unable to re-map the load between network events fast enough longer periods will be spent in an imbalance, resulting in less productive applications. The graph in Fig. 5 shows the load balancing performance of the EN 5, DASUD and PM 1 strategies in terms of standard deviation and progress for a network with $\tau = 1000$. The dynamicity has a positive effect on the DASUD strategy which is evident by the consistent reduction in the standard deviation throughout the experiment. The PM 1 strategy does not reach an optimum balance as it would on a static network indicating that it is unable to repair imbalances between network events. This is a consequence of its near asymptotic rate of convergence.

The fact that the DASUD strategy has a lower standard deviation on dynamic networks is a result of
the randomizing behavior of network events. Entering and exiting hosts re-distribute the local load which alters the load gradient, positively effecting the global balance. However, too much dynamicity impairs the application performance due to a greater time spent imbalance and an increase in the number of migrations. Fig. 7 shows the effect of host dynamicity on the application progress at $t = 500$ for the DASUD and PM 0.35 strategies. The DASUD strategy has the best performance when $\tau$ is approximately 50 re-affirming that dynamicity can have a positive effect. Networks with more dynamicity than this have a detrimental effect implying that this level of dynamicity has an average network interval roughly equivalent to the stabilization time of the strategy. The effect of highly dynamic networks on the PM 0.35 strategy is more dramatic since its instability incurs more migrations. For less dynamic networks however the performance is better on average than the DASUD strategy.

4.5 Job Selection

In the previous experiments the time required to synchronize jobs is constant, regardless of the distance between them. This is unrealistic since latency increases with the distance between hosts. While it is also dependent on a number of other factors, not least of which is the network traffic, for the purposes of simulation we introduced a synchronization latency that is dependent on the number of hops it makes. In this way the synchronization time of a job is proportional to the maximum distance between the hosts of neighboring jobs. In other words, if $u \in H$ is the host of job $i \in G$ and $V$ is the set of hosts of each of $i$'s neighbors, then the synchronization time of $i$ is $S_i = \gamma \max \{|PATH_{uv}| \mid v \in V\}$, where $\gamma$ is a constant.
representing the cost per hop.

Previously jobs were selected for migration at random. However, when using the latency model above, by taking into account the locality of neighboring jobs, an increase in the application progress can be made, evident by Fig. 8.

Three selection methods are considered: minimum total distance, minimum edge cut and none. Minimum distance selects the job that will reduce the maximum total distance when migrated to a neighboring host. It represents the best possibly reduction in latency for migration between two hosts, however, in practice the overhead required in measuring this value could be very large, since it involves measuring the distance between each neighboring pair of jobs on both the current host and the proposed host. To avoid this overhead the minimum edge cut selects the job with the smallest edge cut on the proposed host. The edge cut is defined as follows: If $u, v \in H$ are the hosts of jobs $i, j \in G$ respectively then the edge cut of a job $i$ is given by $C_i = |\{j \mid u \neq v, j \in N(i)\}|$. As expected this approach does not perform as well as the minimum total distance, however, it does give a marked improvement over no job selection without excessive overhead.

![Figure 8: The effect of job selection on progress using minimum total distance, minimum edge cut and none. With the PM 0.35 strategy and $\gamma = 3$.](image)

5 Conclusion

This paper contributed a parallel processing model for loosely-synchronous parallel programs executing over a P2P network. The network was modeled as a host graph and the program was modeled as a guest graph. We compared the quality of a number of relevant load balancing strategies, where good quality leads to a faster rate of progression.

We have shown that for loosely synchronous applications the quality of the mapping is important, since the average progress of the application is limited to the rate of the slowest job. Stable diffusive strategies lead to an undesirable global load gradient and hence are a poor quality mapping. With unstable strategies, migrations may continue indefinitely and the relative improvement in quality is no longer significantly proportional to the number of migrations. Consequently, the performance of the application deteriorates as the migration cost increases, especially for applications that do not cover the network.

The PM strategy parameterizes the tradeoff between quality and stability. The result of varying PM parameter shows that the most robust value is around 0.35 indicating that a little over-migration improves performance.

For stable strategies with a local gradient, network dynamicity can result is an improvement in the quality. This is a consequence of exiting hosts temporarily disrupting the local gradient, effectively randomizing the local load in a similar manner to the PM strategy. Entering hosts facilitate the load balancing by joining randomly selected hosts which in turn can reduce the distance between host pairs that are in an imbalance.

If the stabilization time of the load balancer is less than the average period between network events then the mapping will never stabilize. Therefore, strategies with fast stabilization times perform better for
highly dynamic networks even if the quality is less than optimal. The PM strategy has better application performance than the DASUD strategy only for static or slightly dynamic networks and when the number of jobs divides equally into the number of hosts.

Diffusive load balancing strategies have been shown to be applicable to P2P networks, with the dynamic behavior of the network having a positive effect on the quality of the mapping. For loosely synchronous applications, however, the inherent gradient involved with the stable diffusive strategies results in poor application performance.

We plan to extend our simulations to realistic internets using a more detailed simulation package and to make use of real P2P protocols. This will allow the study of heterogeneous networks, with greater analysis on the affect of job communication and host capacity. Since P2P networks may consists of non-dedicated hosts this capacity may change over time. In other words, not all load is migratable.

Further theoretical analysis is also needed in order to determine the most appropriate organizational strategy to form efficient structures and to better understand the limit to which network dynamicity has an beneficial affect on the quality of diffuse load balancing.

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