P2P-Based, Multi-Attribute Resource Discovery under Real-World Resources and Queries

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Collaborative *peer-to-peer* (P2P), grid, and cloud computing rely on *resource discovery* (RD) solutions to aggregate groups of multi-attribute, dynamic, and distributed resources. However, specific characteristics of real-world resources and queries, and their impact on P2P-based RD, are largely unknown. We analyze the characteristics of resources and queries using data from four real-world systems. These characteristics are then used to qualitatively and quantitatively evaluate the fundamental design choices for P2P-based multi-attribute RD. The datasets exhibit several noteworthy features that affect the performance. For example, compared to uniform queries, real-world queries are relatively easier to resolve using unstructured, superpeer, and single-attribute-dominated query-based structured P2P solutions, as queries mostly specify only a small subset of the available attributes and large ranges of attribute values. However, all the solutions are prone to significant load balancing issues, as the resources and queries are highly skewed and correlated. The implications of our findings for improving RD solutions are also discussed.

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1. INTRODUCTION

Collaborative *peer-to-peer* (P2P) systems, an emerging class of applications, look for diverse peers that could bring in unique resources and capabilities to a virtual community, thereby empowering it to engage in greater tasks beyond what can be accomplished by individual peers, yet are beneficial to all of them [Bandara and Jayasumana 2012b]. In contrast to conventional P2P systems that focus on pairwise interactions between similar types of resources (e.g., file sharing), future P2P applications will thrive on the interactions among groups of diverse and distributed resources. A collaborative P2P system may consist of a set of voluntary nodes, dedicated nodes from multiple grid/cloud sites, or a combination of both. These systems are expected to share a variety of *resources* such as processor cycles, storage capacity,

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network bandwidth, sensors/actuators, services, middleware, scientific algorithms, and data to not only consume a variety of contents but also to generate, modify, and manage these contents.

To consider the salient features of collaborative P2P systems, we use four representative applications. First is *collaborative adaptive sensing of the atmosphere* (CASA) [McLaughlin et al. 2009], an emerging network of weather radars that operates collaboratively to detect hazardous atmospheric conditions such as tornados and flash floods. Collaborative P2P data fusion provides an attractive implementation choice for real-time radar data fusion in CASA, wherein multiple data volumes are constantly being generated, processed, and pushed and pulled among radars, storage, and processing nodes [Lee et al. 2012]. Second, cloud computing is transforming the way we host and run applications because of its rapid scalability and pay-as-you-go economic model. Open cloud initiatives are pressing for interoperability among multiple cloud providers and sites. Alternatively, community cloud computing [Briscoe and Marinos 2009], based on underutilized computing resources in homes/businesses, targets issues such as centralized data, privacy, proprietary applications, and cascading failures in modern cloud computing systems. Certain applications also benefit from a mixture of dedicated and voluntary cloud resources [Andrzejak et al. 2010]. Collaborative P2P systems are useful for interconnecting resources, which may be dedicated or voluntary, in multisite or community cloud systems. We refer to such systems as *P2P clouds*. The third example is *global environment for network innovations* (GENI) [Elliott 2009], a collaborative and exploratory platform that allows users to aggregate diverse hardware and software resources from multiple administrative domains for a common task. A collaborative P2P system is a natural fit for GENI because of its distributed, dynamic, and collaborative nature. Fourth, the value of social networks can be enhanced by allowing users to share diverse resources available in their mobile devices. For example, a group sharing their holiday experiences in a coffee shop could use one of their members' projection phone to show pictures from others' mobiles or tablets, or stream videos from their home servers. Such applications, referred to as *mobile social networks*, also benefit from collaborative P2P technology.

CASA, GENI, P2P clouds, and mobile social networks depend on some form of collaboration among resources. Therefore, these applications need the ability to locate and aggregate groups of complex resources as and when needed to meet the performance and *quality-of-service* (QoS) requirements. P2P-based *resource discovery* (RD) is a natural fit for these distributed, collaborative applications and further enhances their scalability, load balancing, and robustness. P2P-based RD solutions have been also proposed for many conventional applications such as grid, desktop grid, and cloud computing [Cai et al. 2004; Lazaro et al. 2013; Shen and Xu 2012b], as timely aggregation of complex and distributed resources is becoming increasingly necessary due to the proliferation of parallel applications that utilize multiple and distributed resources. Yet it is nontrivial to discover and utilize heterogeneous, multi-attribute, and dynamic resources that are distributed. Nevertheless, a good RD solution should satisfy several key phases where they: (1) efficiently *advertise* all the resources and their state, (2) *query* to find resources that satisfy application requirements, (3) *match* resources according to application and resource constraints, and (4) *bind* resources and applications to ensure guaranteed service [Bandara and Jayasumana 2012b]. Moreover, solutions need to be adaptive, fault tolerant, and should satisfy multiple aspects of scalability such as query resolution latency, number of attributes, number of messages, and routing state. The focus of this article is on the first two phases, namely advertising and querying.

Significant progress has been made in multi-attribute RD in grid computing and P2P [Albrecht et al. 2008; Bharambe et al. 2004; Cai et al. 2004; Costa et al. 2009;

Lazaro et al. 2013; Shen 2009; Shen and Hwang 2012; Shen and Xu 2012]. However, compared to single-attribute P2P systems such as file sharing, formal characterization of real-world, multi-attribute resources and queries received attention only recently [Bandara and Jayasumana 2011b; Heien et al. 2012]. Characteristics of *static attributes* (i.e., attribute values are fixed, e.g., CPU speed) of nodes from a set of volunteer computing systems are presented in Heien et al. [2012]. Our preliminary work in Bandara and Jayasumana [2011b] presented both the static and *dynamic* (i.e., attribute values change with time, e.g., free CPU) resource and query characteristics of PlanetLab [Kim et al. 2011] and SETI@home [Anderson and Fedak 2006] nodes. In the absence of information, data, and understanding of real-life, multi-attribute resource and query characteristics, designs and evaluations of existing RD solutions have relied on many simplifying assumptions. For example, they assume independent and identically distributed (i.i.d.) attributes [Shen and Hwang 2012; Shen and Xu 2012], uniform, Zipf's, or Pareto distribution of all the resources/queries [Costa et al. 2009; Shen et al. 2013; Shen and Hwang 2012; Shen and Xu 2012], and queries specifying a large number of attributes and a small range of attribute values [Cai et al. 2004; Shen and Xu 2012; Shen et al. 2013]. Moreover, the cost of updating dynamic attributes is ignored in all designs. Such assumptions affect both the designs and performance analyses of RD solutions, and consequently their applicability under real workloads [Bandara and Jayasumana 2012a]. Furthermore, direct comparison of these solutions is impractical due to the diversity of designs. Therefore, a formal and detailed comparison of fundamental design choices for P2P-based RD with respect to the behavior learned from actual systems is needed. Such an analysis will not only provide a better understanding of the applicability of different design choices but also help identify best practices for resource aggregation in emerging collaborative P2P systems.

We qualitatively and quantitatively evaluate the fundamental design choices for P2P-based, multi-attribute RD using the characteristics learned from real-world systems. Qualitative evaluation considers aspects such as load balancing, support for new attributes, and freshness of query results under the learned characteristics. Quantitative evaluation uses performance bounds and simulation results (using real datasets) to evaluate aspects such as cost of RD, load distribution, routing state, and scalability. The main contributions of this article are as follows.

- We give an approximation to capture the overall cost of RD in terms of overlay messages. It helps identify important parameters that affect the cost of RD and performance bounds.
- Characteristics of multi-attribute resources from PlanetLab, SETI@home, EGI grid, and a campus network are then analyzed to determine the nature of parameters (e.g., their distributions and temporal characteristics) that affect the cost of RD in different systems. PlanetLab data are also used to analyze the multi-attribute query characteristics. Such an understanding is useful in designing and evaluating RD solutions and job schedulers.
- A representative subset of design choices, based on centralized, unstructured, superpeer, and structured P2P architectures, is then qualitatively and quantitatively evaluated using the learned characteristics. Nine design choices are evaluated based on the cost of advertising and querying resources, routing-table size, load balancing, and scalability. A simulation-based study using node and query traces from PlanetLab is used for the quantitative evaluation. These findings help identify best practices for resource aggregation.
- The implications of real-world resource and query characteristics for improving and developing new P2P-based RD solutions are discussed.

Our findings include the following.

- Attributes of most resources are highly skewed and correlated. Attribute values have different marginal distributions and most of them are too complex/skewed to be described using any of the standard probability distributions. Ones that fit a known distribution satisfy Gaussian, generalized extreme value, and generalized Pareto distributions. While resources are characterized by many attributes, most attributes have only a few distinct sets of values. Attribute values change at different rates and a few attributes change quite rapidly.
- Attribute values specified in queries are skewed; however, they do not satisfy a Zipf's-like distribution. Queries are less specific where each query tends to specify only a small subset of the available attributes and large ranges of attribute values.
- Simulation-based analysis indicates that real-world queries are relatively easier to resolve using unstructured, superpeer, and single-attribute-dominated query-based structured P2P architectures compared to uniform queries used in conventional studies. The cost of RD in ring-based structured P2P systems is effectively $O(n)$, where n is the number of nodes in the overlay, as most range queries specify large ranges of attribute values. The cost of advertising dynamic attributes is significant and increases with the number of attributes, and hence should not be ignored in performance studies. Furthermore, all the design choices are prone to significant load balancing issues where only a few nodes are mainly involved in answering the majority of queries and indexing resources. Therefore, existing design choices perform poorly under realistic workloads.

Our work differs from Heien et al. [2012] in several aspects. Heien et al. analyzed the evolution of static attributes of multiple volunteer computing systems (e.g., SETI@home, Einstein@home, and World Community Grid) over five years and developed a model to forecast how the composition of hardware resources will evolve in the future. Conversely, we analyze both the static and dynamic attributes as well as short-term (ranging from a few minutes to days) changes in dynamic attributes. We also consider four different computing environments. Multi-attribute query characteristics are also analyzed using PlanetLab data. Several other attempts to model grid computing resources are presented in Kee et al. [2004], Lu and Dinda [2003], and Sulistio et al. [2008]; however, they also do not capture the dynamic attributes. While Shen and Xu [2012] analyzed the performance of several *distributed hash-table* (DHT)-based designs, they extensively relied on conventional assumptions. Consequently, the authors concluded that the query cost increases sublinearly with the number of nodes (i.e., $\log n$) and linearly with the number of attributes. Moreover, they concluded that LORM could provide better index size distribution than other DHT-based solutions. Conversely, our analysis based on real-world resources and queries shows that query cost is $O(n)$ and reduces with the number of attributes (in certain DHT-based designs). Moreover, index size and query load cannot be balanced using conventional DHT-based techniques due to highly skewed and correlated attributes. Furthermore, our analysis also considers other fundamental design choices, including centralized, unstructured, and superpeer architectures, as well as the dynamic attributes. Our work not only demonstrates that real-world, multi-attribute resource and query characteristics diverge substantially from conventional assumptions, but also highlights the need for understanding the characteristics of different systems for the correct design, validation, and performance analysis of RD solutions and job schedulers. Our analysis of PlanetLab resources and queries is complementary to the work in Kim et al. [2011], which analyzes the behavior of workloads in PlanetLab.

Section 2 presents an approximation for the cost of RD. Four datasets are described in Section 3 and their characteristics analyzed in Section 4. Different resource

advertising and querying options are qualitatively and quantitatively evaluated in Section 5. Section 6 presents the simulation setup and performance analysis. Implications and best practices for future RD solutions are discussed in Section 7. Concluding remarks are presented in Section 8. This is an extended version of the papers in Bandara and Jayasumana [2011b, 2012a]. The major extensions include the analysis of more recent and multiple datasets, extending the RD cost equation for different design choices for P2P-based RD, extended performance analysis, and a detailed discussion on the implications of our findings for improving P2P-based RD.

2. COST OF ADVERTISING AND QUERYING RESOURCES

We consider those resources that are characterized by multiple attributes, for example, a computing node is characterized by its CPU speed, memory, operating system, etc. Similar to advertising file names in file sharing, these attributes are advertised to a central database, neighboring nodes, or nodes implementing DHTs. All the attributes of a resource may be advertised together as a vector, or separately as a set of scalar values. We analyze the cost of RD in terms of the number of overlay messages involved in advertising such resources and querying them. Our objective is to derive a first-order approximation to capture the cost of RD. This serves two purposes. First, it helps to identify a set of key parameters and their relationship to the cost of advertising and querying (in Section 4, we identify how these parameters behave in real-world systems). Second, it helps to identify the performance bounds of RD solutions under real-world resources and queries. This is presented in Section 5, where the analysis is extended to represent the cost of RD in centralized, unstructured, and structured P2P-based architectures using the real-world resource and query characteristics learned in Section 4. These performance bounds are then validated in Section 6 using a set of simulations.

Consider a P2P overlay used to index (i.e., keep track of) resources, where resources are advertised to a distributed set of nodes, and queries are resolved by contacting these nodes. Let $\mathbf{R}$ be the set of resources in the system and $\mathbf{A}$ the set of attributes used to describe those resources. We use boldface symbols to refer to a set and the corresponding italic symbol refers to its cardinality, for instance, $R = |\mathbf{R}|$. A list of symbols is given in Table I. Each resource $r \in \mathbf{R}$ is defined as follows [Bandara and Jayasumana 2012b]:

$$r = (a_1 = v_1, a_2 = v_2, \dots, a_i = v_i). \quad (1)$$

Each attribute $a_i \in \mathbf{A}$ has a corresponding value $v_i \in \mathbf{D}_i$ that belongs to a given domain $\mathbf{D}_i$. The $\mathbf{D}_i$'s are typically bounded, may be continuous or discrete, or correspond to a set of categories/names. For example, free CPU is continuous, number of CPU cores is discrete (integer), operating system is a category, and a file is represented by a name. A multi-attribute Resource Specification (RS) with such a set of attributes may look like the following:

$$RS = \left(\begin{array}{l} CPUSpeed = 2.4\text{GHz}, NumCores = 2, CPUFree = 53\%, \\ MemoryFree = 1071\text{MB}, OS = \text{"Linux 2.6.31"} \end{array} \right).$$

Attribute values are classified as *static* (e.g., CPU speed, total memory, and operating system) or *dynamic* (e.g., free CPU, memory, and bandwidth). Let $\mathbf{a}_r \subseteq \mathbf{A}$ be the collection of a_i 's that is used to describe r . Let $\mathbf{A}^s$ and $\mathbf{A}^d$ be the set of static and dynamic attributes in the system, respectively. $\mathbf{A} = \mathbf{A}^s \cup \mathbf{A}^d$. Similarly, let $\mathbf{a}_r^s$ and $\mathbf{a}_r^d$ be the subsets of static and dynamic attributes of $\mathbf{a}_r$. Dynamic attributes need to be re-advertised whenever their values/states change. Let λ_r^i be the rate at which the change in i -th attribute of $\mathbf{a}_r$ occurs. The cost of advertising a dynamic attribute is proportional to

Table I. List of Symbols

Symbol	Name
$\mathbf{a}_r$	Attribute set of resource r
$\mathbf{a}_r^s / \mathbf{a}_r^d$	Set of static/dynamic attributes of resource r
$\mathbf{a}_q$	Attribute set of query q
$\mathbf{A}/A$	Set/number of distinct attributes in system
$\mathbf{A}^s / \mathbf{A}^d$	Set of static/dynamic attributes in system
c_r^i	Number of copies of i -th attribute of resource r
$\mathbf{D}_i$	Domain of i -th attribute
$h_{Advertise}^i / h_{Query}^i$	Hops to advertise/query i -th attribute
h_{TTL}	Time to live value used by random walks
l_i	Lower bound of i -th attribute
m_q	Desired number of resources in query q
n	Number of nodes in system
$Q(t)$	Set of queries issued in time interval t
$\mathbf{R}/R$	Set/number of resources in system
t	Time
u_i	Upper bound of i -th attribute
v_i	Value of i -th attribute
λ_r^i	Rate of change of i -th attribute of resource r

its rate of change. However, in practice, λ_r^i is bounded by the sampling rate. For example, though *CPUFree* changes frequently, the applications sample them infrequently (every few seconds or minutes). In some cases, multiple copies of a_i are placed in different databases, neighboring nodes, or DHTs. Let c_r^i be the number of copies of the i -th attribute of $\mathbf{a}_r$.

We are interested in the number of messages that are either sent or forwarded within the overlay to advertise and query resources. Cost of acknowledgement messages is ignored. Typically, the time required to resolve a query within a node is lower than the inter-node communication time. Therefore, if each overlay link is assumed to have approximately the same latency, then the query resolution latency can be also represented using the number of overlay hops. Assuming each attribute a_i is advertised separately, the total cost of advertising r is

$$C_{Advertise}^r = \sum_{i \in \mathbf{a}_r} c_r^i h_{Advertise}^i + \sum_{j \in \mathbf{a}_r} c_r^j h_{Advertise}^j \lambda_r^j t = \sum_{i \in \mathbf{a}_r} c_r^i h_{Advertise}^i (1 + \lambda_r^i t), \quad (2)$$

where $h_{Advertise}^i$ is the number of overlay hops that the advertising message corresponding to the i -th attribute travels. First summation captures the initial cost of advertising all the attributes. Second summation captures the recurrent cost of advertising dynamic attributes within time t . Resources need to re-enter the system after churn or failure. Moreover, resources indexed in unstructured P2P systems and DHTs typically expire after a predefined timeout. In either case, resource attributes need to be re-advertised. Therefore, even the static attributes can be interpreted as behaving like dynamic attributes, but with much lower turnover. Hence, λ_r^i should be defined considering the rate of change of attributes, sampling rate, and both the available and unavailable time of r . λ_r^i is lower for static attributes compared to that for dynamic attributes.

Let $\mathbf{Q}(t)$ be the set of all queries issued within the time interval t . A multi-attribute range query $q \in \mathbf{Q}(t)$ is defined as follows [Bandara and Jayasumana 2012b]:

$$q = (m_q, a_1 \in [l_1, u_1], a_2 \in [l_2, u_2], \dots, a_i \in [l_i, u_i]), \quad (3)$$

where, $m_q \in \mathbf{Z}^+$ specifies the required number of resources and $a_i \in [l_i, u_i]$ specifies the desired range of attribute values (l_i and u_i are lower and upper bounds, respectively). A query that requests for five computing nodes with a given CPU speed, free memory, and operating system may look like the following:

$$q = \left(m_q = 5, \text{CPUSpeed} \in [2.0 \text{ GHz}, \text{MAX}], \right. \\ \left. \text{MemoryFree} \in [256 \text{ MB}, 512 \text{ MB}], \text{OS} = \text{"Linux 2.6.32"} \right),$$

where MAX_i is the upper bound of the domain $\mathbf{D}_i$. The set of attributes specified in a query ($\mathbf{a}_q$) may contain only a subset of the attributes that are used to describe resources (i.e., $\mathbf{a}_q \subseteq \mathbf{A}$). When $l_i = u_i$, $a_i \in \mathbf{a}_q$, q is referred to as a *point query*. In practice, attributes in a query may specify a mixture of point and range values. Unspecified attributes are considered as “don’t care”. Query q is referred to as a *single-attribute query* when $a_q = 1$ and a *multi-attribute query* when $a_q > 1$. In practice, it may be necessary to find/discover more than m_q resources, as some of the selected resources may not be available by the time they are required for use, due to resource churn/failure. Moreover, RD systems may not index all the attributes used to describe a resource, for example, only the static attributes are indexed in Costa et al. [2009]. In such cases, unadvertised attributes have to be validated by directly contacting the resources. Contacting the resource is also important when a binding has to be established between the resource and the application planning to use it [Bandara and Jayasumana 2012b]. Let $f(m_q, \mathbf{R}, \mathbf{A}_{\text{Index}})$ indicate the cost associated with these complex scenarios. $\mathbf{A}_{\text{Index}} \subseteq \mathbf{A}$ is the subset of attributes indexed in the P2P overlay. Then the cost of a point query can be given as

$$C_{\text{Query-Point}}^q = \sum_{i \in \mathbf{a}_q} h_{\text{Query}}^i + f(m_q, \mathbf{R}, \mathbf{A}_{\text{Index}}), \quad (4)$$

where h_{Query}^i is the number of overlay hops required to reach the node that indexes the value of the i -th attribute defined in q , and $f(\cdot)$ captures the cost of directly contacting resources to either validate those attributes that are not advertised or to establish a binding between a resource and the application. After reaching the first node, queries that specify a range of attribute values need to be forwarded further. As in Albrecht et al. [2008], Cai et al. [2004], and Shen and Xu [2012], we initially assume the range of attribute values $[l_i, u_i]$ to be uniformly distributed within the overlay. As the domain of attribute i (D_i) is mapped to n nodes, each node is responsible for indexing D_i/n fraction of the attribute space. Therefore, a range query that searches for $[l_i, u_i]$ has to go through $(u_i - l_i)n/D_i$ nodes (i.e., range to search divided by range per node). Then (4) can be extended to indicate the overall cost of a range query as follows:

$$C_{\text{Query}}^q = \sum_{i \in \mathbf{a}_q} \left(h_{\text{Query}}^i + \left\lceil \frac{(u_i - l_i)}{D_i} n \right\rceil - 1 \right) + f(m_q, \mathbf{R}, \mathbf{A}_{\text{Index}}). \quad (5)$$

Then the overall cost of RD is

$$C_{\text{Total}} = \sum_{r \in \mathbf{R}} C_{\text{Advertise}}^r + \sum_{q \in \mathbf{Q}(\mathbf{t})} C_{\text{Query}}^q. \quad (6)$$

3. RESOURCE AND QUERY DATASETS

We use four datasets from PlanetLab, SETI@home, EGI grid, and our campus to identify the nature of parameters that affect the cost of RD. The set of resource attributes that are used in the analysis are described first. Then details on traces used in this study are presented.

3.1. Node Model

Though resources are characterized by many static, dynamic, and categorical attributes, only a subset of them are useful in RD. Even among these attributes, some are more important than others. Therefore, we consider 11 representative attributes that are essential to characterize a typical node useful for collaborative P2P, grid, and cloud computing systems.

- (1) *CPU Speed*. This is the processor clock speed in GHz. It provides insight on the relative computing power of a node.
- (2) *CPU Archi*. This is the CPU architecture, such as x86 and SPARC.
- (3) *NumCores*. It is the number of processor cores of a node and indicates how much parallelism in processing is possible. Some processors may count hardware-level threads as separate cores.
- (4) *CPU Free*. (100 – percentage *CPU utilization*). This indicates to what extent the CPU(s) is available for processing. When multiple cores are available, the average value is given.
- (5) *CPU Load*. It is the number of active processes competing or waiting for the CPU. It is typically represented as one min (*1MinLoad*), five min (*5MinLoad*), and 15 min (*15MinLoad*) exponentially weighted moving averages of the number of competing processes. *CPU Load* indicates how long a user process has to wait for the CPU. Both *CPU Free* and *CPU Load* are complementary to each other, as a large *CPU Load* does not necessarily mean high CPU utilization (e.g., processes could be blocked for I/O).
- (6) *Mem Size*. This is the size of volatile memory in GB.
- (7) *Mem Free*. It is free user-level memory as a percentage or in GB and indicates how much memory is available for user processes.
- (8) *Disk Free*. This is the free disk space in GB.
- (9) *Tx Rate*. This indicates the average transmission rate in Kbps. In conjunction with the bandwidth limit specified by most nodes, it provides insight on available bandwidth. It may also give insight on how much bandwidth will be available if an application uses the node exclusively.
- (10) *Rx Rate*. This denotes the average receive rate in Kbps.
- (11) *OS*. It is the type of operating system and version.

CPU Speed, *NumCores*, and *Mem Size* are static, *CPU Archi* and *OS* are categorical, and the rest of the attributes are dynamic. RD solutions and job scheduling algorithms for latency-sensitive applications are typically interested only in short-term trends. Therefore, we capture statistical characteristics that are valid for several minutes to a few weeks.

3.2. PlanetLab

PlanetLab [Kim et al. 2011; Park and Pai 2006] is a global research network that supports the development of new network services. It provides a versatile platform for testing distributed applications and protocols by aggregating a globally distributed set of nodes. PlanetLab reflects many characteristics of Internet-based distributed systems such as heterogeneity, multiple end-users, dynamic nodes, and global presence. Hence, it is being used to evaluate many preliminary P2P protocols and applications. Typical P2P applications include file sharing, streaming, resource sharing, publisher-subscriber, and security. We analyzed data from two PlanetLab tools, CoMon [Kim et al. 2011; Park and Pai 2006] and SWORD [Albrecht et al. 2008], to determine multi-attribute resource and query characteristics. CoMon is a node and slice monitoring system that provides a snapshot of static and dynamic attributes of all the nodes

Table II. Summary of Traces

	CoMon	SWORD	SETI@home	GCO	CSU
Applications	Experiments on protocols & applications, e.g., P2P file & resource sharing, streaming, & security		Volunteer computing, e.g., astronomy research	Grid computing, e.g., high-energy physics	Campus computing, e.g., teaching & research
Resource/query representation	As Eq. (1)	As Eq. (3)	As Eq. (1)	As Eq. (1)	As Eq. (1)
No of nodes/queries	~650	915	234,421	205	387
No of attributes	64	49	34	87	27
Attributes useful in RD	46	49	25	17	17
Static attributes	12	8	21	6	8
Dynamic attributes	34	41	4	11	9
Sampling interval	5 min	Not tracked	Hours to days	1 min	1 min
Date(s)	2011/2/1 - 14	2010/3/12 - 7/20 & 2010/10/2 - 2012/6/5	Active as of 2012/4/30	2012/4/23 - 5/6	2011/12/1 - 14

every five minutes. Table II summarizes the traces used in this study. Further details on specific attributes of all four systems are given in Bandara [2012]. SWORD is a multi-attribute RD tool for PlanetLab. It enables users to query for multiple groups of nodes while specifying inter- and intra-group latency and bandwidth constraints. Though initially designed as a P2P solution, its current deployment is centralized and does not support latency and bandwidth constraints due lack of such data from PlanetLab. This dataset provides a unique insight into real-world, multi-attribute, and multiresource queries that are unknown, albeit the analysis is based on 915 queries (due to light usage).

3.3. SETI@home

BOINC [Anderson and Reed 2009] is a volunteer computing platform (a.k.a. desktop grid) that is used to remotely execute jobs using idle computing resources. SETI@home is one of the largest BOINC deployments and utilizes a much larger and diverse set of nodes compared to other datasets. Detailed representation of attribute values of SETI nodes is presented in Anderson and Fedak [2006] and Heien et al. [2012] but their characteristics are not analyzed in the context of RD systems. Therefore, we briefly analyze the distribution of resource attributes collected from SETI@home [Anderson and Reed 2009]. Except for *DiskFree*, BOINC collects only the static attributes of a node. Attribute values are collected only when a node contacts a BOINC server, therefore the time between two samples varies from several hours to a few days. Hence, *DiskFree* is not sampled periodically. BOINC also collects CPU performance in terms of Dhrystone (integer) and Whetstone (floating-point) benchmarks. BOINC is a pull-based system where nodes request jobs based on their hardware resources and hence do not support a resource query mechanism.

3.4. EGI Grid

European grid infrastructure (EGI) aggregates multiple grid computing sites across Europe [Newhouse 2011]. Data related to job submission, workloads, and computing and storage nodes from EGI sites are collected and published through the Grid Observatory [Germain-Renaud et al. 2011a]. We use node traces from *green computing*

Fig. 1. Distribution of *CPUSpeed*: (a) PlanetLab; (b) SETI@home.

observatory (GCO) [Germain-Renaud et al. 2011b], a recently launched subproject within the Grid Observatory, that currently collects static and dynamic attributes of ~ 200 computing nodes every minute. Though the number of nodes in the dataset is much smaller than the size of the EGI grid, GCO dataset provides a unique view of grid computing resources due to its high-resolution sampling in both time and number of attributes, which are useful in multi-attribute RD. The specific queries that may have been used to select those nodes for processing are not available.

3.5. Campus Dataset

We also collected a dataset within our campus, Colorado State University (CSU). A set of PCs and servers within the Department of Computer Science and another set on the College of Engineering network were sampled every one minute. The dataset includes both Linux and Windows nodes and reflects an enterprise computing environment. Resource characteristics of such environments are becoming important as we are seeing the emergence of applications such as P2P clouds that aggregate residual computing resources from enterprise environments and homes [Briscoe and Marinos 2009]. No explicit query mechanism is provided and users are free to use any unoccupied PC in a lab. Server *CPULoads* are published in real time on the web, enabling students and researchers to pick unloaded servers manually.

4. RESOURCE AND QUERY CHARACTERISTICS

We now describe the characteristics of resources and queries, and the observed behavior of parameters identified in Section 2. The discussion that follows is primarily based on the characteristics of PlanetLab, as we have both the resource and query datasets. Specific characteristics of other datasets are presented to illustrate the commonalities and differences across different systems. A detailed discussion on these datasets and characteristics is available in Bandara [2012].

4.1. Resource Characteristics

Figure 1 shows the distribution of *CPUSpeed* of PlanetLab and SETI@home nodes. Both distributions can be approximated using Gaussian distributions. Due to many identical nodes, *CPUSpeed* of GCO and CSU datasets were highly skewed and did not fit a standard distribution. Specifically, 11% of the PlanetLab nodes had identical static attributes such as *CPUSpeed*, *NumCores*, *MemSize*, and *DiskSize*. This may have been caused by a donation of a set of similar machines to multiple sites. Most sites also had few identical hosts. This is the case even in grid, cloud, and enterprise computing environments where sites may simultaneously deploy or upgrade to a

Fig. 2. Distribution of dynamic attributes during peak times: (a) *CPUFree*; (b) *MemFree*.

similar set of machines. For example, the largest set of identical nodes in CSU and GCO datasets corresponded to 14% and 95% of the nodes, respectively. Nodes in student labs are typically homogeneous; hence, the four largest sets of identical nodes corresponded to 45% of the nodes in the CSU dataset. Due to such large sets of homogeneous nodes and the discrete nature of attribute values, *NumCores* and *MemSize* of nodes in all the systems do not fit standard distributions. One may argue that we can still attempt to fit data to a set of well-known distributions by applying more complex subsampling techniques, rounding attribute values (e.g., rounding *MemSize* to the nearest power of two), or discarding some values (e.g., discarding *NumCores* values that are not powers of two). While we do discard outliers, other techniques are of little value as our objective is to understand the true distributions and behavior of attributes but not to generate synthetic data using them. Such techniques are applied in Heien et al. [2012] for SETI nodes, which are more heterogeneous, as the authors' objective was to generate synthetic data. However, these techniques do not apply well to PlanetLab, GCO, and CSU datasets, as they consist of multiple sets of homogeneous nodes. If the objective is to generate synthetic data, in Bandara and Jayasumana [2011a] we demonstrate that it is more accurate to summarize the data using tables of *empirical cumulative distributions* (ECDF) and then use empirical copulas to generate synthetic data, as copulas preserve the complex multivariate distributions and correlations among attributes.

Table III. Distribution of Attribute Values

Distribution of Attribute Values	PlanetLab*	SETI@home*
<i>CPU</i> Speed (GHz)	$N(2.63, 0.43)$	$N(2.53, 0.51)$
<i>Disk</i> Free (GB)	No fit	$GPD(0, 104.9, 0.51)$
<i>1Min</i> Load	$GPD(0, 6.82, 0.38)$	N/A
<i>Tx</i> Rate (Kbps)	$GEV(0.51, 0.57, 0.54)$	$GEV(12.9, 9.8, 0.34)$
<i>Rx</i> Rate (Kbps)	$GEV(0.49, 0.54, 0.54)$	$GEV(111.4, 122.8, 0.84)$
Integer performance (MIPS)	N/A	$Weibull(6,498, 2.2)$
Floating-point performance (MIPS)	N/A	$Weibull(2,507, 3.4)$

* $GEV(\mu, \sigma, k)$, $GPD(\mu, \sigma, k)$, $N(\mu, \sigma^2)$, $Weibull(\lambda, k)$, N/A – Not applicable

Fig. 3. Distribution of *TxRate*: (a) PlanetLab; (b) SETI@home. For fitting the curve for SETI@home, only those nodes with bandwidth utilization up to 1Mbps are considered.

It was observed that both PlanetLab and GCO (as a system) experience idle and busy periods. Average resource utilization of GCO nodes was higher (lower average *CPUFree* and *MemFree*) than the other two systems. For example, Figure 2 illustrates the distribution of *CPUFree* and *MemFree* during the peak time, of each system. Large fractions of PlanetLab and CSU nodes were idle (high *CPUFree*) even during the peak time, whereas GCO nodes were heavily utilized throughout the day. For example, 37% and 71% of the PlanetLab nodes had over 95% of *CPUFree* and 2GB of *MemFree*, respectively. Similarly, 92% and 97% of the CSU nodes had the same amounts of *CPUFree* and *MemFree*. Even though students used the nodes during peak hours, their workloads do not fully utilize the capabilities of the nodes. However, only 0.5% and 46% of the GCO nodes had similar amounts of *CPUFree* and *MemFree*. Due to the highly skewed distributions, instantaneous values (at a given time t) of dynamic attributes do not fit standard distributions. Except for SETI nodes, *DiskFree* also had a similar behavior in the other three datasets. SETI nodes had a skewed but monotonically decreasing distribution that fit the *generalized Pareto distribution* (GPD). Attributes that satisfy known probability distributions are listed in Table III.

Figure 3 shows the distribution of *TxRate* of PlanetLab and SETI nodes which can be approximated using the *generalized extreme value* (GEV) distribution. The *RxRate* of these nodes can be also approximated using the GEV distribution. The average *TxRate* of SETI nodes is an order of magnitude lower than the average *RxRate* (see Table III). This may be a consequence of the asymmetric bandwidth availability in volunteer nodes. The *TxRate* and *RxRate* of GCO nodes were skewed and did not fit standard distributions. While it was possible to approximate the distribution of *1MinLoad* using GPD, other datasets and *5MinLoad* and *15MinLoad* did not fit standard distributions.

Fig. 4. Cumulative distribution of number of attribute value changes within 24 hours: (a) PlanetLab; (b) GCO; (c) CSU. Thresholds: $CPUFree = \pm 10\%$, $MemFree = \pm 100MB$, $DiskFree = \pm 5GB$, $1MinLoad = 15MinLoad = \pm 2$, $TxRate = RxRate = \pm 10Kbps$.

It was also observed that integer and floating-point performance of SETI nodes could be approximated by a Weibull distribution. We further observed a few SETI nodes with very large *NumCores*, *MemSize*, *DiskSize*, *TxRate*, and *RxRate*. However, these nodes were active only for a few weeks. These could be high-performance machines that utilize SETI as a workload to test and measure their performance. Nevertheless, these nodes provide a significant amount of computing, storage, and networking resources for a short time span.

Distributions of categorical attributes were extremely skewed and had only a few distinct attribute values. For example, *CPUArch* of all the PlanetLab, GCO, and CSU nodes and 99% of the SETI nodes were $\times 86$. All PlanetLab and GCO nodes were Linux but nodes had several different kernel versions. Specifically, 76% of the CSU nodes ran a Linux variant with different kernel versions, and 82.2% of the SETI nodes had a Windows variant (44% of them were Windows 7), and 10.6% and 7% of the nodes had variants of MacOS and Linux, respectively. The remaining 0.2% correspond to BSD, SunOS, OS/2, AIX, HP-UX, and IRIX. Therefore, categorical attributes are highly skewed and their domains have only a few valid attribute values.

We further analyze the rate of change of attribute values, as it affects the resource advertising cost (Eq. (2)). There is a wide variation in how frequently the attribute values change. The number of changes in dynamic attributes over a 24-hour period is observed for two weeks. Figure 4 shows the CDF of number of significant changes in several selected attribute values. A fixed threshold is applied to ignore minor variations. *MemFree* of PlanetLab and GCO nodes changed frequently. For example, 54% of the PlanetLab nodes changed *MemFree* by at least 100MB in every sample taken at

Table IV. Distribution of Number of Significant Changes in Attribute Values within 24 Hours

No of Changes in Attribute Values	PlanetLab*	GCO
<i>CPUFree</i>	No fit	$GPD(0, 34.4, -0.45)$
<i>MemFree</i>	No fit	$TLS(124, 23, 2.7)$
<i>DiskFree</i>	No fit	$TLS(14.2, 6.86, 3.84)$
<i>1MinLoad</i>	No fit	$GEV(11.2, 7.99, 0.06)$
<i>15MinLoad</i>	No fit	$GEV(2.57, 2.93, 0.31)$
<i>TxRate</i>	$NB(0.08, 0.19)$	$TLS(79.7, 22.9, 4.18)$
<i>RxRate</i>	$NB(0.09, 0.19)$	$TLS(142.9, 51.6, 13.7)$

* $GEV(\mu, \sigma, k)$, $GPD(\mu, \sigma, k)$, $NB(r, p)$, $TLS(\mu, \sigma, \nu)$

5-minute intervals, and 50% of the GCO nodes changed *MemFree* at least 123 times within 24 hours (out of 288 samples taken at 5-minute intervals). While the number of changes in *DiskFree* was insignificant in PlanetLab and CSU datasets, it moderately changed in the GCO dataset. This may be due to the data incentive, high-energy physics applications that frequently run on these nodes [Germain-Renaud 2011b]. A relatively high rate of change was observed for *1MinLoad* in PlanetLab and CSU datasets and *TxRate* and *RxRate* in the GCO dataset. These rates indicate that the number of processes running on PlanetLab nodes shows a rapid variation with time, which could be either due to the variability in applications' resource usage or the execution of small jobs. The number of changes in *1MinLoad* of CSU nodes was moderate; however, *15MinLoad* changed infrequently, indicating most processes are short lived. Surprisingly, *TxRate* and *RxRate* do not change rapidly in PlanetLab; however, average bandwidth consumption of nodes remained relatively high. *CPUFree* moderately changed in the GCO dataset, as nodes were mostly busy. The number of processes running on nodes was stable with time, hence *CPUFree* changed infrequently. It was observed that the rate of change of some of the attributes could be approximated by probability distributions such as GPD, GEV, *negative binomial* (NB), and *T location-scale* (TLS) as listed in Table IV. In summary, rate of change λ_r^i depends on the attribute and system.

Next, we analyze the linear and ranked correlation among attributes. Table V(a) lists the linear (Pearson's) correlation among PlanetLab nodes. For the dynamic attributes, we first calculated the correlation among all nodes in a given sample (taken at a given time instance) and then calculated their average across all the samples (taken at every 5 minutes over two weeks). Correlation values of most of the attribute pairs in different samples had a standard deviation of ≤ 0.1 , confirming that correlation does not significantly change with time. It can be seen that (*15MinLoad*, *1MinLoad*), (*DiskFree*, *NumCores*), (*DiskFree*, *MemSize*), and (*RxRate*, *TxRate*) are positively correlated. *1MinLoad* and *15MinLoad* are correlated because they are the one-min and 15-min averages of *CPUFree*. Nodes with a large disk space also tend to have a large number of CPU cores and memory (correlation between *NumCores* and *MemSize* is 0.43). Time series of *TxRate* and *RxRate* are highly correlated as PlanetLab nodes tend to simultaneously transmit and receive data. Spearman's ranked correlation ρ among attributes is listed in Table V(b). Spearman's ρ measures how well the correlation between two attributes can be described using a monotonic function. The correlation between (*CPUFree*, *NumCores*), (*MemFree*, *NumCores*), and (*MemFree*, *MemSize*) have increased. This indicates that when a node has a large *NumCores*, *CPUFree* tends to increase, as it is the average of all the CPUs and some of them may be idle. It is also apparent that, when nodes have more CPU cores, their memory capacity also tends to increase. (*1MinLoad*, *CPUFree*) and (*15MinLoad*, *CPUFree*) are negatively correlated as *CPUFree* reduces when the number of processes using the CPU increases.

Table V. Correlation among Attributes of PlanetLab Nodes (Values with Relatively High Correlation are Highlighted)

(a) Pearson's Correlation Coefficient

Index*	1	2	3	4	5	6	7	8	9
2	-0.10								
3	-0.01	0.46							
4	-0.03	-0.03	-0.16						
5	-0.03	-0.02	-0.15	0.98					
6	0.02	0.43	0.30	-0.03	-0.03				
7	0.06	0.25	0.35	-0.12	0.10	0.36			
8	-0.11	0.56	0.41	-0.09	-0.09	0.58	0.30		
9	0.06	-0.06	-0.12	-0.04	-0.04	0.00	0.01	-0.03	
10	0.05	-0.05	-0.11	-0.03	-0.03	0.00	0.01	-0.03	0.87

(b) Spearman's Ranked Correlation Coefficient

Index*	1	2	3	4	5	6	7	8	9
2	0.06								
3	-0.09	0.68							
4	0.08	-0.20	-0.62						
5	0.08	-0.18	-0.62	0.94					
6	-0.01	0.45	0.35	-0.34	-0.35				
7	0.20	0.61	0.51	-0.03	-0.03	0.69			
8	-0.21	0.66	0.56	-0.42	-0.42	0.44	0.60		
9	0.03	0.00	-0.21	0.10	0.10	0.10	0.28	-0.09	
10	0.02	0.02	-0.21	0.11	0.11	0.11	0.29	-0.07	0.95

* 1 – *CPU*Speed, 2 – *NumCores*, 3 – *CPU*Free, 4 – *1MmLoad*, 5 – *15MmLoad*, 6 – *MemSize*, 7 – *MemFree*, 8 – *DiskFree*, 9 – *TxRate*, 10 – *RxRate*

Table VI. Pearson's Correlation Coefficient among Attributes of GCO Nodes

Index*	1	2	3	4	5	6	7	8	9
2	1.00								
3	0.26	0.26							
4	0.40	0.40	-0.68						
5	0.42	0.42	-0.67	0.96					
6	1.00	1.00	0.26	0.40	0.42				
7	0.42	0.42	0.61	-0.31	-0.30	0.42			
8	0.96	0.96	0.29	0.34	0.35	0.95	0.48		
9	0.03	0.03	0.01	0.04	0.04	0.03	-0.01	0.03	
10	0.12	0.12	0.03	0.08	0.07	0.12	-0.06	0.10	0.25

* 1 – *CPU*Speed, 2 – *NumCores*, 3 – *CPU*Free, 4 – *1MmLoad*, 5 – *15MmLoad*, 6 – *MemSize*, 7 – *MemFree*, 8 – *DiskFree*, 9 – *TxRate*, 10 – *RxRate*

Increased Spearman's ρ values show that complex correlation patterns exist among attributes that are not necessarily linear. Similar behavior is also observed for SETI, GCO, and CSU nodes. Linear correlation of GCO nodes is listed in Table VI, where many attributes were correlated due to homogeneous nodes and heavy utilization of nodes (when a node is heavily utilized, *CPU*Free and *MemFree* reduce while *CPU*Load increases). Analysis of Spearman's ρ also indicates *TxRate* and *RxRate* are positively correlated with a coefficient of 0.82.

Table VII. Composition of PlanetLab Queries

	Attributes (a_q)	Resources (m_q)	Groups
Average	2.13	63.66	1.09
Minimum	0	1	1
Maximum	10	All	3
Median	2	65	1
Mode	1	All	1
Standard deviation	1.62	380	0.3

Fig. 5. Distribution of number of distinct attributes specified in a query.

Fig. 6. Popularity of attributes specified in queries. Only the first 20 shown.

Fig. 7. Popularity distribution of queries and attributes specified in queries.

Fig. 8. Range of *CPUFree* values specified in queries.

4.2. Query Characteristics

Table VII summarizes the number of attributes (a_q), resources (m_q), and groups of resources specified in PlanetLab queries. Figure 5 shows the distribution of the number of attributes specified in a query. Specifically 2% of the queries requested a certain number of resources without specifying any attribute, while 78% of queries specified at most two attributes. Only 0.4% of queries specified 10 attributes. Thus, queries tend to specify a lower number of attribute values (i.e., $a_q \ll A$). There is also a tendency to request a large number of resources (i.e., large m_q), where 30% of queries requested ten resources while 52% requested 50 or more resources and 19% of queries requested all the resources in the system. Figure 6 shows the popularity of attributes specified in the queries. Dynamic attributes are the most popular. Specifically, 26 attributes (out of 49) were never queried. Many queries requested both *CPUFree* and *CPUSpeed*

Table VIII. Summary of Resource and Query Characteristics

Characteristics	PlanetLab	SETI@Home	GCO	CSU
Application behavior	Many small jobs, variable CPU and memory usage, high bandwidth utilization	Long running jobs	Long running jobs, high CPU, memory, and bandwidth utilization	Short lived jobs, low CPU and memory utilization
Resource attributes	Correlated, some identical resources	Correlated, heterogeneous	Correlated, many identical resources	Correlated, many identical resources
a_r	Large, many dynamic attributes	Moderate, no dynamic attributes	Large, many dynamic attributes	Moderate, many dynamic attributes
D_i	Non-uniform, several highly skewed attributes, categorical attributes with few values	-Do-	-Do-	-Do-
λ_r^i	Very high for several attributes	Moderate due to churn	Very high for several attributes	Moderate for several attributes
a_q	Small, dynamic attributes are more popular	N/A	Small, mostly static attributes	Small, mostly dynamic attributes
$[l_i, u_i]$	Large, skewed	N/A	N/A	N/A
m_q	Large	N/A	Large	N/A

(or *MemFree* and *MemSize*). This may be because the percentage values (PlanetLab represents both *CPUFree* and *MemFree* as percentages) are inadequate to represent the actual availability of resources. We observed the query popularity by clustering identical queries together. Similarly, we clustered attributes with the same range of values. We found 24% of the queries and 13% of the attributes specified in queries appeared only once. The number of identical queries in the largest query cluster was 31 and the largest attribute cluster had 117 queries. Figure 7 shows the distribution of the cluster size. Though the popularity distribution is skewed, it does not satisfy a Pareto (or Zipf's-like) distribution as some of the queries are equally popular (curves do not approximate straight lines). It was further observed that the ranges of attribute values $[l_i, u_i]$ specified in queries are somewhat large. As seen in Figure 8, 89% of the queries that specified *CPUFree* requested values of 40–100%. Similarly, 86% of queries requested *DiskFree* values of 5–1000GB. Therefore, most queries are less specific as they specify a lower a_q and large $[l_i, u_i]$. This could be due to several reasons: (1) the experimental applications (Table II) that run on PlanetLab may not require fine-grained resource selection, (2) users might have had an inability to identify detailed resource requirements, or (3) there may have been a principle of least effort [Brophy and Bawden 2005] where users are willing to specify only the simplest queries that satisfy their resource requirements.

4.3. Summary of Resource and Query Characteristics

Observed resource and query characteristics are summarized in Table VIII. Analysis of four datasets confirms that the different attribute values are correlated, marginal distributions of attributes are often quite different from one another, and in most cases are highly skewed and too complex to be represented using well-known probability distributions. Queries are skewed and less specific, as they specify small a_q , large $[l_i, u_i]$, and large m_q . These trends are likely to remain valid even in collaborative applications where users may not be informed enough to issue very specific queries, or due to the principle of least effort. Iosup and Epema [2010] also observed that, while most of the

jobs in grids use a single CPU, a few tend to use a large number of CPUs (128 CPUs or more), and hence m_q tends to be large even in grids. These findings invalidate the commonly used assumptions such as i.i.d. attributes, uniform/Zipf's distribution of all the attributes [Bharambe et al. 2004; Cai et al. 2004; Shen and Xu 2012], and queries specifying a large number of attributes and small ranges of attribute values [Cai et al. 2004; Shen and Xu 2012]. The correlation between attribute pairs indicates that resources are not uniformly distributed throughout the multi-attribute space (domain of all $\mathbf{D}_i$ s). Domain $\mathbf{D}_i$'s of categorical attributes such as *CPUArch* and *OS* are small, as they have only a few distinct attribute values. Various hardware constraints favor having *NumCores* and *MemSizes* that are powers of two. Therefore, these attributes occupy only a small fraction of their $\mathbf{D}_i$ s. Moreover, large numbers of identical resources in PlanetLab, grid, cloud, and enterprise computing environments appear as sets of clusters within the multi-attribute space.

Both a_r and A are large as the resources are described using tens of attributes (see Table II). Dynamic attributes change at different rates and some frequently (high λ_r^i). A user can decide when to run a BOINC client. Hence, overall availability of SETI nodes is 68% and nodes were reachable through the network 67% of the time [Anderson and Fedak 2006]. Alternatively, most nodes in PlanetLab, GCO, and CSU datasets were available throughout the two-week period. Thus, the availability of nodes in volunteer computing environments is significantly lower compared to more stable environments like PlanetLab, grids, and clouds. Consequently, λ_r^i increases further due to frequent arrival and departure of nodes. It is also observed that grids tend to experience sudden arrivals of sets of jobs (a.k.a. a bag of tasks) [Iosup and Epema 2010]. Such arrivals suddenly change the dynamic attributes of many resources.

As the real-world resources and queries diverge substantially from the conventional assumptions, it is imperative to understand how existing P2P-based RD solutions will perform in real systems. Based on our findings from this section, next we evaluate a representative subset of design choices for P2P-based RD. In Section 5, we evaluate the asymptotic behavior of RD solutions based on real-world parameters. In the subsequent section, we also empirically evaluate RD solutions using resource and query traces from PlanetLab.

5. DESIGN CHOICES IN P2P-BASED RESOURCE DISCOVERY

To ease the RD, resources are typically advertised and indexed at specific or random locations within the RD system. Resources are then located using various querying mechanisms. Resource advertising and querying options of centralized, unstructured P2P, and structured P2P solutions are analyzed next using the characteristics learned in the previous section. Eq. (6) is also extended to reflect the specific behavior of each solution.

5.1. Centralized Designs

Resources can be advertised and indexed at a well-known central location. Centralized indexes are utilized in PlanetLab, GENI, and grid and cloud computing. Latency and cost of resource advertising and querying are minimum, as nodes can directly communicate with the central node. Hence, the cost per message is $O(1)$. Resolving queries with large $[l_i, u_i]$ and m_q does not introduce additional routing overhead. Thus, the RD cost depends on the initial advertisement cost, recurrent cost of advertising static/dynamic attributes, and query cost. Then (6) can be modified as

$$C_{Total} = \sum_{r \in \mathbf{R}} \left(1 + \sum_{j \in \mathbf{a}_r} \lambda_{rt}^j \right) + Q(t), \quad (7)$$

where $c_r^i = 1$, as resources are advertised only to the central location. If the query arrival rate is constant, the total cost of RD is bounded by $O(RA\lambda_r^i)$. In the worst case, all the resources may have all the attributes. Therefore, the cost of indexing resources at a central node is $O(RA)$. This approach is not scalable (in terms of both the number of messages and index size) as A , R , and λ_r^i are typically large in production systems. It also leads to a single point of failure.

Hierarchical indexes are proposed to overcome these limitations where separate indexing nodes are assigned to different geographic regions, sites, or organizations [Elliott 2009]. Then a higher-level node(s) is assigned to keep track of aggregated resources from these nodes. However, aggregation along the hierarchy reduces the resolution at which resources are advertised. Therefore, such hierarchies are not desirable for indexing highly dynamic attributes such as *MemFree* and bandwidth. This approach could also lead to conflicts while querying and binding resources. Partial failures in subregions of the system are also problematic.

5.2. Unstructured P2P-Based Designs

Unstructured P2P systems [Lua et al. 2004] are attractive as they distribute the resource information across many nodes in the system while providing resilience and load balancing. They are utilized in file sharing, mobile social networks, and adhoc networks. These systems use either flooding or random walks [Tan et al. 2008] to disseminate information about resources and/or resolve queries. Though resources are guaranteed to be found with flooding, it is extremely costly. Random-walk-based solutions use agents for advertising and/or querying. Agent lifetime is controlled using a time-to-live (h_{TTL}) value that tries to balance the cost of advertising/querying and query success rate. As queries are forwarded to individual nodes, their availability is known. Hence, no additional overhead is introduced. Assuming a new agent is generated for each change in attribute value or query, the RD cost is

$$C_{TOTAL} = \sum_{r \in \mathbf{R}} \left(\sum_{i \in \mathbf{a}_r} h_{TTL} + \sum_{j \in \mathbf{a}_r} \lambda_r^j h_{TTL} \right) + \sum_{q \in \mathbf{Q}(t)} h_{Query}^q, \quad (8)$$

where h_{Query}^q is typically $O(h_{TTL})$. Therefore, the total cost is bounded by $O(RA\lambda_r^i h_{TTL})$. However, random walks are not guaranteed to find resources, and this will become even harder if one reduces h_{TTL} with the intention of reducing the cost of RD. It has been shown that the hitting time (i.e., expected number of hops to reach any node starting at any given node) of a random walk on an arbitrary finite graph is $O(n^3)$ [Ikeda et al. 2009]. Hence, h_{TTL} has to scale with n^3 to increase the success rate of queries. Therefore, unstructured P2P systems are suitable only for moderate-scale, best-effort, and highly dynamic environments that can tolerate large delays. Resource indexing cost per node is $O(RA)$. Though advertising resources to other nodes speeds up the query resolution, the state of the selected resources may be stale.

A more scalable version of this approach uses a two-layer overlay where resource rich nodes, namely *superpeers*, form a separate overlay while acting as proxies for the rest of the nodes. Similar to hierarchical solutions, superpeers manage multiple resources. Resources can communicate with their superpeers using one overlap hop. When local resources are insufficient to resolve a query, superpeers query other superpeers using flooding or random walks. Therefore $h_{Query}^q = O(n_{Superpeer})$ or

Fig. 9. Ring-based address spaces: (a) Separate address space for each attribute and single-attribute-dominated query resolution; (b) address space partitioned across multiple attributes and query resolution with multiple subqueries; (c) overlapped address space and single-attribute-dominated query resolution.

$h_{Query}^q = O(h_{TTL})$, where $n_{Superpeer}$ is the number of superpeers in the system. The cost of RD is

$$C_{TOTAL} = \sum_{r \in \mathbf{R}} \left(1 + \sum_{i \in \mathbf{a}_r} \lambda_{r,t}^i \right) + \sum_{q \in \mathbf{Q}(t)} h_{Query}^q. \quad (9)$$

As $n_{Superpeer} \ll n$, h_{TTL} can be set to a relatively lower value than in unstructured P2P systems. However, superpeers are also not guaranteed to find resources with random walks. Indexing load on a superpeer is proportional to A and the number of resources to which it connects. If resources are uniformly assigned to superpeers, the index size is $O(RA/n_{Superpeer})$.

5.3. Structured P2P-Based Designs

Structured P2P systems are appropriate for large-scale implementations due to their high scalability and their ability to provide some guarantees on performance [Lua et al. 2004]. These systems use a DHT to index resources. Each DHT node or resource has a unique identifier called a *key*. Each resource's contact information is indexed (i.e., stored) at a node having a closeby *key* in the key space. Resources are advertised and queried using messages that are forwarded to appropriate nodes using a deterministic overlay network. Chord, Kademlia, CAN, and Pastry are some of the well-known solutions that are used to build such an overlay [Lua et al. 2004]. These solutions typically keep pointers to nodes that are spaced at exponentially increasing gaps in the key space, enabling messages to be routed with a bounded path length of $O(\log n)$. DHTs are designed to index resources characterized by a single attribute. As such, they are not efficient for simultaneous selection of multiple and multi-attribute resources. Four solutions representative of methods that extend DHTs to support multi-attribute RD are discussed next.

Multiple Address Spaces. As seen in Figure 9, ring-based DHTs can be extended to support multiple attributes. One of the simplest solutions is to maintain a separate DHT for each attribute in A [Bharambe et al. 2004]. Figure 9(a) illustrates a design based on three DHTs with a circular address space, also referred to as a *ring*. Each resource r advertises either each attribute value to the corresponding ring or all the attribute values to all the rings responsible for $\mathbf{a}_r$. In the former case, a multi-attribute query q is first split into a set of *subqueries* where each subquery searches for one of the

attributes in $\mathbf{a}_q$. Subqueries are then simultaneously forwarded to appropriate rings. Query results have to be then combined at the application using a join operation like that in databases. A range query is resolved by forwarding each subquery to a series of nodes responsible for indexing attribute values in the range $[l_i, u_i]$. Thus, the RD cost is

$$C_{TOTAL} = \sum_{r \in \mathbf{R}} \left(\sum_{i \in \mathbf{a}_r} h_{Advertise}^i + \sum_{j \in \mathbf{a}_r} h_{Advertise}^j \lambda_{rt}^j \right) + \sum_{q \in \mathbf{Q}(\mathbf{t})} \left\{ \sum_{i \in \mathbf{a}_q} \left(h_{Query}^i + \left\lceil \frac{(u_i - l_i)}{D_i} n \right\rceil - 1 \right) \right\}. \quad (10)$$

Each advertising message can be sent in $O(\log n)$ hops, and thus the advertising cost is $O(RA\lambda_r^i \log n)$. Worst-case query cost is $O(n)$ as $h_{Query}^i = O(\log n)$. Even the average cost is large, as queries tend to specify large $[l_i, u_i]$. The indexing cost of all the rings is $O(RA)$ or $O(R)$ per ring. In the latter case, q can be resolved using one of the rings, as each ring is aware of all the attribute values of a resource. This also enables queries to be terminated as soon as the desired number of resources is found. Query resolution cost can be further reduced by forwarding q to the ring corresponding to the most selective attribute (i.e., attribute with the lowest $(u_i - l_i)/D_i$). For example, as seen in Figure 9(a), the query travels 3 hops in *CPUSpeed* and *bandwidth* rings, while only 2 hops in the *MemSize* ring. Thus, q is issued only to the *MemSize* ring. This approach is called *single-attribute-dominated querying* (SADQ) and used in Albrecht et al. [2008], Bharambe et al. [2004], and Cai et al. [2004]. Total RD cost in this case is

$$C_{TOTAL} = \sum_{r \in \mathbf{R}} \left(\sum_{i \in \mathbf{a}_r} h_{Advertise}^i + \sum_{j \in \mathbf{a}_r} h_{Advertise}^j \lambda_{rt}^j a_{rt} \right) + \sum_{q \in \mathbf{Q}(\mathbf{t})} \left(h_{Query}^k + \left\lceil \frac{(u_k - l_k)}{D_k} n \right\rceil - 1 \right), \quad (11)$$

where $k \in \mathbf{a}_q$ is the most selective attribute. In the worst case, each change in attribute values has to be advertised to all the rings, resulting in an advertising cost of $O(RA^2\lambda_r^i \log n)$. Worst-case query cost is still $O(n)$. Real-world queries specify only a few attributes, and hence not many options are available while choosing the most selective attribute. Therefore, even the average query cost is relatively high. Indexing cost of all the rings is $O(RA^2)$, or $O(RA)$ per ring. It has a lower query cost than using multiple subqueries. However, it has a higher advertising cost due to the presence of multiple copies where $c_r^i = a_r$ (recall that a_r tends to be large). Therefore, it is suitable only if the query rate is higher than λ_r^i . New rings can be added to support additional attributes. However, excessive routing entries associated with multiple rings (typically $O(A \log n)$) make it less scalable. Some rings experience higher load due to skewed distribution of resources and queries. This is particularly a problem in SADQ where highly selective and skewed attributes such as *CPUArch*, *NumCores*, and *OS* may get a large number of queries overloading the nodes that index them. Moreover, domain $\mathbf{D}_i$ of these attributes is small and hence may not be suitable to be placed on a separate ring/overlay.

Partitioned Address Space. Figure 9(b) shows a ring partitioned into several segments where each segment corresponds to a separate range of attribute values. Prefix bits of the overlay *key* are used to represent the attribute type and suffix bits represent the attribute value. A *locality-preserving hash* (LPH) function [Albrecht et al. 2008; Shen and Xu 2012] is used to assign the suffix bits, which preserves the locality of attribute values. Advertising and querying schemes are similar to the case of multiple address spaces. However, each partition has approximately n/A nodes,

Fig. 10. 2D torus partitioned into a set of virtual cells with respect to a given node x . A query is routed to all nodes within the query hyperbox. Here l is the level, and d the dimension [Costa et al. 2009].

therefore worst-case query cost is $O(n/A)$. Moreover, these solutions maintain a much lower number of routing entries, typically $O(\log n)$. Some partitions experience higher load due to skewed distribution of resources and queries while most of the remaining partitions are rarely utilized.

Overlapped Address Space. Another alternative is to map all the attribute values to the same ring (see Figure 9(c)) using a separate LPH function for each attribute type [Cai et al. 2004]. The cost of RD and indexing is the same as that with multiple address spaces because the same advertising and querying mechanisms are applicable here. Some nodes experience higher loads due to skewness in resources and queries. However, the routing state is $O(\log n)$ as only a single ring is used.

d-Torus. Figure 10 illustrates an alternative design where each dimension of a d -torus represents an attribute (i.e., $d = A$). Resources are mapped to the torus according to their attribute values. A multi-attribute range query q encloses a hyperbox on the torus. This approach is used in Costa et al. [2009], where dimensions of the torus reflect only the static attributes (i.e., $d = A^s$). To facilitate routing, the d -torus is partitioned into an increasing set of *levels*, each further partitioned along each dimension d , forming a set of *cells*. Each node keeps a set of pointers to all the other nodes in the same cell and to a node in each partition at level l and dimension d . In contrast to prior architectures, resources are not explicitly advertised. Instead, a gossip scheme is used to identify a random node in each (l, d) pair. These pointers are used to route q to the desired query region on the torus using depth-first search (see Figure 10). Then neighboring nodes are used to traverse from one node to another, during which dynamic attributes in q may be evaluated. The RD cost for d -torus is therefore

$$C_{TOTAL} = \sum_{q \in \mathbf{Q}(\mathbf{t})} h_{Query}^q + m_q - 1. \quad (12)$$

It can be shown that h_{Query}^q is $O(\ln 2^d / \ln d)$. After reaching the first node that satisfies q , the remaining $m_q - 1$ resources need to be found. Hence, the worst-case query cost is $O(\ln 2^d / \ln d + m_q - 1)$, ignoring the overlay maintenance cost. As the propagation of q is based on depth-first search and the query visits individual nodes (one at a time), query resolution latency is much higher. This routing scheme is inefficient when

Table IX. Summary of Resource Discovery Architectures

Architecture	Routing Mechanism	Advertising		Querying		Indexing	
		Mechanism	Cost	Mechanism	Cost	Mechanism	Cost
<i>Centralized</i>	Direct	To central node	$O(1)$	Query central node	$O(1)$	At central node	$O(RA)$
<i>Unstructured</i> – Random overlay	Random walk	Optional	$O(hTTL)$	Query random nodes	$O(hTTL)$	Index locally	$O(A)$ or $O(RA)$ if advertised
<i>Superpeer</i> – Random overlay among superpeers	Random walk among superpeers	To superpeer	$O(1)$	Query superpeers	$O(hTTL)$	At superpeer	$O(RA/n_{Superpeer})$
<i>Multi-ring</i> – Separate ring-like overlay for each attribute type	Chord	To relevant ring(s) based on attributes	$O(\log n)$	1. Multiple sub-queries 2. Single attribute dominated query	$O(n)$	1. At relevant rings 2. At all rings	1. $O(RA)$ 2. $O(RA^2)$
<i>Partitioned-ring</i> – Each attribute type is assigned a different segment of overlay ring	Chord or Cycloid	To relevant partition(s) based on attributes	$O(\log n)$	1. Multiple sub-queries 2. Single attribute dominated query	$O(n A)$	1. At relevant partitions 2. At all partitions	1. $O(RA)$ 2. $O(RA^2)$
<i>Overlapped-ring</i> – All attribute types are mapped to same ring-like overlay	Chord	To relevant nodes in the ring	$O(\log n)$	Single attribute dominated query	$O(n)$	At relevant nodes	$O(RA^2)$
<i>d-Torus</i> – <i>d</i> -torus partitioned into set of cells	Depth-first search	Not required	–	Visit cells that overlap with query hyper-box	$O\left(\frac{\ln 2^d}{\ln d}\right)$	Index locally	$O(A)$

queries are less specific, which significantly increases the volume of the hyperbox to search. Moreover, it cannot route queries with only the dynamic attributes, which accounts for a large fraction of queries in real-world systems (Figure 6). A comparative summary of all the RD solutions is provided in Table IX. In the next section, we verify the asymptotic behavior by empirically evaluating these RD solutions using the resource and query traces from PlanetLab.

6. PERFORMANCE ANALYSIS

Next, we quantitatively evaluate the fundamental design choices for P2P-based RD. We simulated seven representative architectures for RD (listed in Table IX) against the same set of resources and queries derived from PlanetLab (see Bandara [2012] for source code). The use of realistic data preserves the complex distribution of attributes, dynamic and correlated changes in attribute values, and users' interest in resources. To simplify the performance analysis and eliminate any bias due to node failure, we replayed a trace with only those PlanetLab nodes that were continuously available for three days starting 2010/11/08. There were 527 such nodes. As our query dataset was small, a large number of synthetic queries were generated using the empirical distributions of a_q , popularity of attributes, $[l_i, u_i]$, and m_q [Bandara 2012]. To capture the correlation among attributes and attribute value ranges, conditional probabilities of attribute occurrences were also taken into account. Queries were issued only after the network was stabilized.

Both the unstructured and superpeer-based networks were generated using the B-A scale-free network generator [George 2006] with a minimum node degree of two. Advertising dynamic attributes is not that useful in unstructured P2P architectures and

Fig. 11. Total cost of advertising and querying static attributes ($n = 527$).

among superpeers in superpeer architectures. As random walks are not guaranteed to follow the same path, a new advertising agent may not be able to overwrite the resource states advertised by previous agents. Hence, nodes may not reflect the current status of resources by the time they are queried. Therefore, only the query agents were used in these two solutions. The number of superpeers is set to 20. The maximum number of hops to forward a random walk (i.e., h_{TTL}) was set to 100 and 10 hops in unstructured and superpeer architectures, respectively. These values were sufficient to achieve $\sim 70\%$ query hit rate with different numbers of attributes. Multiring, partitioned ring, and overlapped ring architectures were based on the Chord overlay [Stoica et al. 2003]. According to Costa et al. [2009], the number of cell levels of the d -torus was set to three. Performance of ring-based structured P2P solutions was also evaluated under a different number of nodes ranging from 250 to 1000. Resource attributes for 750- and 1000-node networks were generated using our correlation-persevering, multi-attribute resource generation tool [Bandara and Jayasumana 2011a]. The tool uses the statistical properties of 527 PlanetLab nodes to generate large synthetic datasets. The minimum update interval for resource attributes is 5 min, which is the sampling interval of PlanetLab traces. Fixed thresholds given in Figure 4 were applied to ignore minor variations. Each node issued queries based on a Poisson distribution with a mean inter-arrival time of 2.5 min (i.e., two queries per sampling interval per node). Though we consider a modest number of nodes for the simulations, we analyze them in much more detail by considering many different attributes, their dynamic behavior over three days, and many queries. Networks with 100000 nodes, under a more constrained set of attributes, are analyzed in Bandara and Jayasumana [2012c] and Bandara [2012]. Results are based on eight sample runs with eight different random seeds.

Figure 11 shows the total cost of advertising and querying resources using only the 12 static attributes of PlanetLab nodes (see Bandara [2012] for details). This enables to validate the performance of different architectures against their prior performance studies (when such a study exists) which did not consider the cost of advertising dynamic attributes. As expected, a centralized architecture has the lowest overall cost while the unstructured P2P architecture has the highest. The superpeer-based architecture has the second-lowest cost. Less specific queries (large $[l_i, u_i]$ and small a_q) make it easier to find required resources by visiting a few superpeers that index

Fig. 12. Advertising cost of ring-based architectures ($n = 527$).

multiple resources. For example, though random walks are not granted to find all the resources, the superpeer architecture was able to resolve 96% of the queries. Therefore, most of the random walks were able to terminate within a few hops while reducing the overall cost. However, the unstructured P2P solution was able to resolve only 73% of the queries, as they visit one node at a time. The partitioned ring-based architecture has the third-lowest cost, as query cost is $O(n/A)$. Costs of multiring and overlapped ring-based architectures are higher compared to the partitioned ring, as their query cost is $O(n)$. And d -torus has the second-largest overall cost due to less-specific queries that dramatically increase the volume of the query hyperbox. It is not considered for rest of the discussion, as it cannot route those queries with only dynamic attributes, which are the most popular types of attributes defined in real-world, multi-attribute queries.

We analyze ring-based architectures in detail, as they are considered applicable in large-scale applications due to scalability and some guarantees on performance. Figure 12 shows the per-node advertising cost of ring-based architectures under a varying number of attributes. Advertising cost increases as the dynamic attributes are introduced (the first 12 attributes are static). Resources need to be re-advertised whenever their attribute values change significantly. It is typically assumed that DHT entries will expire after a predefined timeout. However, our analysis shows that it is nontrivial to determine an appropriate timeout given the diversity of attributes and their rate of change λ_r^i . Therefore, the old attribute values need to be explicitly removed from the DHT to maintain a consistent resource index. We considered the cost of removing these old indexes as part of the advertising cost. Both advertise and remove messages can be delivered within $O(\log n)$ as they are sent to specific nodes. SADQ requires all the attributes of a resource to be advertised to each ring/partition corresponding to each attribute $a \in \mathbf{a}_r$. Therefore, resources need to be re-advertised to all the rings/partitions even when a single attribute is changed. Figure 12 confirms this behavior where the advertising cost of architectures that utilize SADQ is significantly higher and increases somewhat linearly with the number of attributes. We introduced dynamic attributes according to their popularity, where attribute 13 is the most popular, 14 is the second most popular, and so on. Attributes 13–15 that correspond to the response time of a node (*RespTime*), *1MinLoad*, and *MemFree* are updated frequently. This is the reason for the significant increase in advertising cost between attributes 12 and 15. The λ_r^i of the rest of the dynamic attributes was relatively lower.

Fig. 13. Query cost of ring-based architectures ($n = 527$).

Fig. 14. Total cost (advertising + querying) vs. number of attributes ($n = 527$).

Figure 13 shows the cost per query. Architectures based on SADQ have much lower query cost, as they use only the most selective attribute and queries are terminated as soon as m_q resources are found. However, overall cost (advertising and querying) of SADQ-based architectures will be acceptable only if queries are more frequent than advertisements. Alternatively, subqueries need to search in multiple rings/partitions and have to search the entire range of attribute values specified in each subquery, hence have higher cost. Queries that specified attributes 13 and 14 (*RespTime* and *1MinLoad*) tend to be relatively more specific (i.e., small $(u_i - l_i)/D_i$) therefore can be resolved by forwarding to a lesser number of nodes. Furthermore, these were the two most popular attributes, hence appeared in many queries and consequently reducing the overall query cost. Therefore, query cost drops when the number of attributes is 15. Query distribution and range of attribute values get balanced as the rest of the dynamic attributes are introduced. Consequently, query cost tends to stabilize. Though new attributes were introduced, PlanetLab queries specified only 1–10 attributes and one or two attributes were specified 78% of the time. This explains why query cost seems independent of the number of attributes in the system.

Table X. Query Cost of Ring-Based Designs under Varying Number of Nodes ($A = 24$)

n	Multi-Ring + SADQ			Partitioned-Ring + SADQ			Overlapped-Ring + SADQ		
	Min	Ave	Max	Min	Ave	Max	Min	Ave	Max
250	0	9.2	239.1	0	3.7	19.4	0	9.1	238.4
527	0	13.7	509.0	0	4.6	27.6	0	13.5	506.0
750	0	16.2	719.1	0	4.9	36.6	0	16.5	719.9
1000	0	19.8	975.5	0	5.3	45.3	0	20.4	963.8

Table XI. Query Cost, Query Load, and Index Size ($n = 527, A = 24$)

Architecture	Total Cost per Query		Query Load				Index Size	
			Min		Max		Min	Max
	SWORD	Uniform	SWORD	Uniform	SWORD	Uniform		
Centralized	2.03	2.03	950,000	950,000	950,000	950,000	527	527
Unstructured	69.5	94.8	4,859	1,272	268,497	37,824	1	1
Superpeer	6.5	9.5	81,021	22,390	289,626	87,209	17	36
Multi-ring + SADQ	48.3	69.0	0	0	178,492	22,943	0	527
Multi-ring + Sub-queries	398.8	120.8	0	0	624,837	57,518	0	230
Partitioned-ring + SADQ	36.6	37.0	0	0	185,972	15,840	0	527
Partitioned-ring + Sub-queries	40.7	16.4	0	0	432,859	46,946	0	527
Overlapped-ring + SADQ	46.0	67.2	0	0	391,738	57,524	0	527

The best design choice from each of the architectures is compared in Figure 14. The unstructured P2P-based architecture, which has the highest cost per query, is not shown to simplify the graph. The increase in advertising cost of centralized and super-peer architectures due to dynamic attributes is insignificant, as it is $O(1)$. Moreover, their query cost is independent of a_q , $[l_i, u_i]$, and m_q . Therefore, they have the lowest cost per query. Cost of ring-based architectures tends to increase linearly. In Table X, we compare the three best ring-based designs with varying numbers of nodes n . Both the average cost per query and maximum query cost tend to increase linearly with n , confirming the analysis in Section 5.3. Therefore, query cost is bounded by $O(n)$. The cost of a partitioned ring-based architecture is lower as it is bounded by $O(n/A)$.

Table XI presents the query cost as well as per-node query load and index size. For comparison, according to Cai et al. [2004], we also generated range queries based on the uniform distribution of attributes and attribute values, where each attribute in a query specified 10% of the possible range of attribute values (i.e., $(u_i - l_i) = 0.1D_i$). Resource attributes were not changed. The performance of RD architectures is different when queries are formulated by selecting attributes and ranges of attribute values uniformly at random (irrespective of the actual resources). Not all random queries match resources in the system. Therefore, both the unstructured and superpeer architectures have to keep forwarding the queries until the h_{TTL} expires. Consequently, the overall cost of RD increases. Furthermore, uniform queries cannot significantly benefit from SADQ, as the minimum range of any attribute is always 10% of the domain, whereas in real queries (collected from SWORD), at least a few attributes tend to be somewhat specific (e.g., *RespTime*, *1MinLoad*, and *NumCores*). Therefore, real-world queries can be resolved more efficiently using SADQ. Alternatively, given that the range of most of

Fig. 15. Distribution of load: (a) Query load; (b) index size ($n = 527$).

the attribute values in real-world queries tend to be large, the aggregated query cost significantly increases when multiple subqueries are used.

The centralized solution had to index all the resources and answer all the queries issued within the system (950000 queries were issued during the simulation). Unstructured and superpeer architectures have a small index size, as either resources index themselves or superpeers index only a subset of the resources in the system. Furthermore, their query load is relatively balanced due to the use of random walks. Uniform queries are issued to different overlay rings/partitions with the same probability, hence distribute the query load among many nodes. Alternatively, due to the skewed distribution of attributes and attribute values in PlanetLab queries, a few rings/partitions and subset of the nodes within these rings/partitions are used to answer the majority of queries. This is the reason that the maximum number of SWORD queries answered by a node is $3.3\text{--}11.7\times$ higher than when answering uniform queries. The query load on a node that supports SADQ is relatively lower, as queries are resolved using the most selective attribute. Moreover, queries also terminate as soon as the desired number of resources is found. Hence, each node has to handle a relatively smaller number of queries. Figures 12 through 14 confirm that a partitioned ring with SADQ outperforms all other design choices. Figure 15(a) illustrates the query load distribution of architectures supporting SADQ. It can be seen that load distribution is skewed and a few nodes had to answer the majority of queries. It is particularly poor in the partitioned ring, where 74% of the nodes did not answer any query and one of the nodes answered $\sim 20\%$ of all the queries. Such an imbalanced load distribution is not acceptable when the query rate is higher.

Because of the correlation and skewed distribution of attributes and attribute values, resources are not uniformly spread across the attribute space. Therefore, resources are indexed in only a small subset of the nodes in the ring. Multiple indexing used with SADQ and overlapped ring also force nodes to index many resources corresponding to different attributes. Moreover, some of the attributes have only a few valid attribute values and they are highly skewed, such as *CPUArch* and *NumCores*. Such attribute values are indexed in few nodes and some of these nodes have to index a large fraction of the resources with the same attribute value. The index size distribution of solutions supporting SADQ is shown in Figure 15(b). In the partitioned ring, nodes that were mapped to less popular or unused partitions were never utilized. Therefore, it suffers significant load balancing issues, though it has the lowest RD cost among the structured P2P architectures. In conclusion, load balancing is a critical issue in all the designs (except in unstructured and superpeer designs), as the popularity of resources and queries is skewed and queries are less specific.

Table XII. Design Space of Existing Solutions

Architecture	Advertising Cost	Query Cost	Query Load Balanced	Index Load Balanced	Many Resources	Many Attribute	Routing State
<i>Centralized</i>	Low	Low	No	No	No	Yes	Low
<i>Unstructured</i>	None	High	Moderate	Yes	No	Yes	Low
<i>Superpeers</i>	Low	Low	Moderate	Yes	Yes	Yes	Low
<i>Multi-ring – sub-queries</i>	Moderate	High	No	No	No	No	High
<i>Multi-ring – SADQ</i>	High	Moderate	Moderate	No	No	No	High
<i>Partitioned-ring – sub-queries</i>	Moderate	High	No	No	Moderate	Moderate	Low
<i>Partitioned-ring – SADQ</i>	High	Moderate	Moderate	No	Moderate	Moderate	Low
<i>Overlapped-ring – SADQ</i>	High	Moderate	No	No	Moderate	Moderate	Low
<i>d-Torus</i>	None	High	No	Yes	Moderate	Moderate	Low

In summary, simulation-based analysis shows that real-world queries are relatively easier to resolve using unstructured, superpeer, and SADQ-based structured P2P architectures compared to uniform queries used in conventional studies. The cost of advertising dynamic attributes is significant and increases with a_q . While the query cost of ring-based DHTs is effectively $O(n)$, it does not increase with a_q . Moreover, except for unstructured and superpeer designs, all design choices are prone to significant load balancing issues where only a few nodes are involved in answering the majority of queries and indexing resources. Among the evaluated designs, the superpeer architecture has a good balance between the ability to find resources, overall cost of RD, and load balancing. These findings differ from Shen and Xu's [2012] analysis, which is based on conventional assumptions. For example, the authors concluded that the query cost is $O(\log n)$ and increases linearly with a_q . Moreover, they concluded that LORM could provide a superior index size distribution to other DHT-based solutions. Furthermore, the authors do not analyze the impact of dynamic attributes. Therefore, our analysis shows that existing design choices are unable to provide guaranteed RD while maintaining lower overhead and balanced load.

7. IMPLICATIONS AND BEST PRACTICES FOR ENHANCING RESOURCE DISCOVERY

The design space of existing RD solutions is summarized in Table XII. From Tables IX and XII, it is apparent that none of the current design choices for RD simultaneously provides guaranteed RD, efficiency, scalability, and load balancing under real workloads. The centralized architecture has the lowest cost per advertisement and query cost. A single message can be used to either advertise or query for a resource(s) irrespective of a_r , a_q , $[l_i, u_i]$, and m_q . Lower advertising costs enables dynamic attributes to be advertised whenever their attribute values change while increasing the accuracy of indexed resources. As the central node is aware of all the resources in the system, it is also suitable for complex tasks such as matching multiple resources (for inter-resource bandwidth and latency), establishing a binding between a resource and an application that is interested in using it, and enforcing various incentives, trust, and security policies. However, a single node may not be able to handle all these messages. It further leads to a single point of failure and to privacy issues, as the central node can monitor usage patterns of resources. Nevertheless, centralized solutions are becoming more feasible, affordable, and reliable due to the recent advancements in distributed

datacenter technologies. Therefore, when applicable, a centralized solution is still a desirable option.

The superpeer architecture is relatively efficient in resolving real-world queries that are less specific. Moreover, both the query load and index size are well balanced and independent of a_r , a_q , and $[l_i, u_i]$. Resources can afford to advertise dynamic attributes whenever they change, as the superpeer can be reached within one overlap hop. However, it does not provide a best-fit-type solution, where selected resources fit the minimum requirements of a query. Hence, applications that actually require a large number of high-capacity resources may not be able to find them, as they have been already allocated to applications with much lower resource demand. Trying to enforce best-fit-type matching will increase the query cost. Therefore, a superpeer architecture is more suitable for dynamic, best-effort environments such as mobile social and ad hoc networks. Due to high query cost and relatively low query hit rate, the unstructured P2P architecture is not suitable for most applications. However, its high resilience to random node failures makes it suitable for highly dynamic environments such as small mobile social networks. Advertising agents are of little use as some dynamic attributes change very frequently, making the indexed resources stale. While it has been proposed to use aggressive timeouts to invalidate resources after a while, given the diversity in attributes and their rate of change, it is nontrivial to set a timeout.

While less specific queries do not affect the centralized architecture and increase the hit rate of the superpeer architecture, they increase the overhead of structured P2P architectures. Though SADQ reduces the query cost, it significantly increases the advertising cost. Advertising cost is effectively doubled as old attribute values need to be removed from the rings to maintain consistency, as it is nontrivial to set a timeout. All the structured P2P architectures are prone to significant load balancing issues due to the small number of valid attribute values and their skewed distributions. Dynamic attributes are more important while predicting the performance of latency-sensitive applications (e.g., CASA and mobile social networks) and when resources are shared across multiple applications (CASA, GENI, grids, and clouds). Therefore, the applicability of d -torus is limited, as it cannot resolve those queries with only dynamic attributes. Though it seems most of the benefits of DHTs are lost under real workloads, they can still provide guaranteed RD, bounded performance, and are distributed. Moreover, as the locality of attribute values is preserved, they can also find those resources that fit the minimum requirements of a query. Hence, it becomes even more important to overcome their deficiencies to gain their benefits.

DHT designs typically assume that the domain of attributes is much larger than the number of nodes in the DHT (i.e., $D_i \gg n$) and that resources are uniformly spread within D_i . Therefore, it is preferable to add all the nodes to the DHT(s) expecting each node to index $\sim R/n$ resources. However, attributes such as *CPUArch*, *OS*, and *NumCores* are not only skewed but also their domain sizes (i.e., number of distinct values in the domain) are much smaller (i.e., $D_i \ll n$). Even though the domain size of attributes such as *CPUFree*, *1MinLoad*, *DiskFree*, and *TxRate* can be made arbitrarily large depending on the resolution, it is not useful to advertise them at a very high resolution, as users are not interested in finding very specific values. For example, advertising *DiskFree* at the granularity of a few megabytes is not suitable as 86% of the queries requested *DiskFree* values of 5–1000GB. Similarly, advertising *TxRate* at bps resolution is not useful as users are likely to query attribute ranges in tens to thousands of Kbps. Specifying attributes at a relatively low resolution is desirable (as far as it satisfies a query with the lowest $(u_i - l_i)$), as advertising cost can be reduced by ignoring minor changes in attribute values. It was observed that highly dynamic attributes that are queried using moderate to large ranges of attribute values contributed to more than 90% of the advertising cost in SADQ-based designs. Therefore, it is desirable to

advertise attributes at a lower resolution (by applying a fixed or dynamic threshold) while reducing the effective domain sizes (i.e., $D_i \ll n$). Consequently, many nodes in the ring will not be able to index resources or answer queries. Moreover, adding all the nodes to a ring will unnecessarily increase the query cost, as both the average and worst-case query costs are proportional to n . Instead, in Bandara and Jayasumana [2012c], we show it is desirable to prune nodes that do not index any resources or answer any queries from a ring. However, this does not solve the problem of a few nodes having to index a large number of resources due to skewed distributions (e.g., when *CPUArchi* of 99% of the nodes are $\times 86$). One alternative is to append few random bits to a *key* (i.e., hash of an attribute value) such that identical resources will be mapped to different but adjacent nodes in the ring [Albrecht et al. 2008]. While this helps to distribute the index size better, it increases the query cost and does not balance the query load, as queries have to always start from the node corresponding to l_i . Bandara and Jayasumana [2012c] also present an alternative design where large index sets are split across multiple nodes that are added orthogonal to the ring. Adding nodes orthogonal to the rings does not increase the average and worst-case path length along the ring, hence the query cost is also reduced. We also used the same concept to balance the query load distribution. Another alternative is to explore hybrid designs where desirable properties such as lower advertising cost and load distribution in centralized and superpeer architectures are coupled with rings, for example, a ring of superpeers.

Performance of ring-based architectures can be approximated to $O(\log n)$ by using queries that are more specific. However, in practice, it is hard to determine specific resource requirements of an application. By specifying very specific queries, users also run the risk of not finding any useful resource. For example, a user may need only 500MB of disk space. If his/her query specified *DiskFree* $\in$ [500 MB, 1000 MB], the query is likely to fail as modern nodes have much greater free disk space. Therefore, users are compelled to specify a large range of attribute values.

The traces indicate that users tend to reissue queries with relaxed constraints once a query is unable to find the desired resources. For example, once a query for *DiskFree* $\in$ [500 MB, 1000 MB] fails, a user may try *DiskFree* $\in$ [500 MB, 10 GB]. While this user-driven iterative querying approach leads to the discovery of needed resources, it increases the overhead both for the user and the system. Alternatively, a user may know only the total amount of required resources and not how they should be divided. For example, a user interested in getting (*CPU*Cores = 4 and *MemSize* = 4GB) may not care whether he/she receives two nodes, each with (*CPU*Cores = 2 and *MemSize* = 2GB), or four nodes, each with (*CPU*Cores = 1 and *MemSize* = 1GB). Hence some queries may not specify m_q . An alternative solution for both these cases would be to allow for composite resources, where the system combines fine-grained resources into coarse-grained ones to meet the user requirements, such as by adapting approaches used within utility environments [Sahai et al. 2004]. While such optimizations usually belong to the resource matching phase [Bandara and Jayasumana 2012b], it is also possible to support identification or formation of such composite resources during the RD phase, for instance, by allowing a query (as it traverses the overlay) to keep track of potential resources that may be combined to meet the request. By exploring such optimizations, it may be possible to achieve better performance (e.g., $O(\log n)$ for a ring) and query success rate, if such complexities are incorporated into the RD solution, while enabling users to provide only the abstract details about their application requirements. Formation of composite resources by combining fine-grain resources in a flexible and efficient way within P2P environments remains an open area to be investigated.

As the number of attributes increases, the performance of all the solutions degrades due to additional memory/storage requirements and increase in advertising cost. This

is a concern in heterogeneous systems like CASA and GENI, both of which aggregate a multitude of diverse resources. One alternative is to represent multi-attribute resources using a few composite attributes. For example, BOINC uses a microbenchmark to rate nodes based on their integer and floating-point performance [Anderson and Reed 2009]. Cloud computing nodes are typically rated as high-memory, high-CPU, and cluster instances. A few attributes are attractive as they simplify and reduce the cost of RD. However, this method is not good at predicting the performance of arbitrary applications and is too abstract to be used in latency-sensitive applications such as CASA. Alternatively, applications that depend on more than one attribute cloud pick a minimum set of primary attributes that can accurately represent a resource. Dimension reduction techniques are also of interest. However, it would be challenging to resolve real-world queries that specify only a few attributes, as dimension reduction techniques are typically designed for those queries that specify all the attributes. Depending on the application(s) requirements, less informative attributes such as percentage of *CPUFree* and *MemFree* may be avoided.

Though many diverse applications run on the PlanetLab overlay, the structure of queries looked similar and requested only the computing resources. Hence, it was reasonable to use a representative mix of the queries together while conducting the performance analysis. However, vastly different applications with diverse resource requirements may run on systems like CASA and GENI. As discussed earlier, these systems combine significantly different resources such as radars and computing nodes. In such systems, the performance seen by different classes of applications could be significantly different due to the differences in query characteristics. Optimization of performance for a given mix of queries thus may not be effective, and evaluation of the system under such a mix may not be sufficient to understand its performance. More effective would be schemes that adapt to requirements of different classes of applications. A straightforward approach would be to have separate overlays for different types of resources with different parameters (e.g., with different resolutions and rate of advertising). However, this is not effective for collaborative P2P applications that rely on the ability to aggregate diverse resources. Such separation will increase their query cost while reducing the potential to aggregate the best set of resources. Therefore, it is important to develop better solutions that allow all the resources to be indexed in the same overlay but treated differently while resolving queries from different types of applications. In Bandara and Jayasumana [2013] we developed such a solution for single-attribute resources that allowed multiple communities of users with diverse interests to coexist in the same overlay but gain better query performance based on their specific interests. We wish to extend this solution to multiple attributes in the future. Generalized solutions need to be developed for handling different classes of applications in multi-attribute P2P systems for a wide range of parameters and application classes.

As the existing solutions are applicable only under very specific scenarios, novel RD solutions are needed to overcome the performance and QoS issues posed by real workloads. Based on our findings, we recommend the following guidelines for designing novel RD solutions.

- Pick an architecture based on the requirements. A centralized architecture is for stable systems requiring high performance (independent of a_r , a_q , $[l_i, u_i]$, m_q , and λ_r^i), low overhead, resource matching, resource binding, and policy enforcement. A superpeer architecture is for dynamic/distributed systems requiring good performance (independent of a_r , a_q , $[l_i, u_i]$, m_q , and λ_r^i), moderate overhead, scalability, resource matching, and privacy. A single DHT with SADQ is recommended for

distributed systems requiring guaranteed performance, moderate overhead, scalability, resource matching, and privacy.

- Support large a_r , few a_q , and large $[l_i, u_i]$. In most cases, allow users to specify simple queries with abstract details about application requirements, and let the RD system figure out which resources are a better fit. Use resource composition, key attributes, and/or dimension reduction to simplify advertising and querying. Support a diverse mix of applications and their requirements.
- Support dynamic attributes as they are popular and users are concerned about what resources are free. Consider the cost of advertising dynamic attributes and apply thresholds (static or dynamic) to reduce the advertising cost. If accurate representation of resources is required, explicitly remove previously advertised attribute values while advertising new ones.
- Balance the index size and query load distribution. Skewed distribution of resources and queries is common. Moreover, having highly skewed categorical attributes (e.g., *CPUArch*) and applying thresholds to dynamic attributes reduce D_i . Therefore, the resources will be indexed in only a subset of the DHT nodes. Use small D_i 's to improve query performance, such as in SADQ. Distribute large indexes and query loads to multiple nodes, for example, to multiple superpeers or by adding nodes orthogonal to a DHT ring. Therefore, based on the load, dynamically add/remove nodes to/from the DHT. Avoid adding random values to resource attributes in order to distribute the load, as this increases query resolution cost.
- The ability to support other key phases of resource discovery, such as resource matching, binding, and composition, as well as security and privacy, is desirable.
- Hybrid approaches that combine the desirable features of centralized, superpeer, and ring-based architectures while taking into account the complex resource and query characteristics have the potential to provide better solutions.
- Evaluate the performance using real or synthetic traces that are derived using real-world resources and queries.

8. CONCLUSIONS AND FUTURE WORK

Fundamental design choices for P2P-based resource discovery were evaluated using the characteristics learned from four different real-world systems. Results presented demonstrated that real-world, multi-attribute resource and query characteristics diverge substantially from conventional assumptions. For example, while real-world, less specific queries are relatively easier to resolve than uniform queries, they introduce significant load balancing issues due to skewed resources and queries. Dynamic attributes contribute to high resource advertising cost, and their behavior is attribute-type- and system specific, hence should not be ignored in performance studies. These findings indicate the need for more efficient, scalable, and robust resource discovery solutions as well as the importance of taking into account the specific characteristics of real-world resources and queries while designing and analyzing such solutions. Hybrid approaches that combine the desirable features of centralized, superpeer, and ring-based architectures have the potential to provide better solutions. We are working on a resource aggregation solution that can overcome current limitations while supporting resource matching, binding, and compensation.

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