

# Analytical Model for Mobile P2P Data Management Systems

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*Abstract*— The need for efficient and scalable data management has increased in the contemporary distributed mobile and fixed networks. Sharing growing amounts of multimedia data stored in autonomous, heterogeneous and distributed equipment such as mobile devices, personal computers, enterprise servers etc. is a trend, especially considering peer-to-peer networking scenarios. In this paper we describe a simple yet extendable analytical model to enable comparison of various aspects of the existing and emerging distributed data management systems. We introduce an abstract model for analyzing service enabler efficiency indicating operational costs for system external and internal parameters. Model is applied to benchmark distributed data management techniques to support optimal design choices, especially considering the design guidelines for data management in mobile P2P environments.

*Keywords*— peer-to-peer, mobile, data management.

## I. INTRODUCTION

Peer-to-peer (P2P) networks have been used widely for file and resource sharing and real-time session management, mostly for free-time activity. The emerging professional usage, due to remote work and remotely collaborating working teams, will also generate new requirements for data management in P2P networking, concerning especially the data consistency, integrity, security and availability. The data needs to be systematically and logically organized for fulfilling these requirements. However, the data management in today's mainstream P2P solutions is still underdeveloped or there is no organized data management at all.

In P2P systems, database management needs special algorithms to be able to reliably store and distribute the data in dynamic peer networks. The mobile environment brings more challenges to the data management in P2P networks. The transient mobile nodes make the network even more dynamic, while the limited physical capabilities of the devices and the networks bring their own challenges. In this paper, we focus on the before-mentioned problem areas from the viewpoint of true-P2P mobile business applications and the needs of remotely working teams.

We make a comparative analysis of the existing systems and bring out the gaps between the technologies, and furthermore provide the guidelines for filling the gaps found. We utilize an

abstract model for service enabler efficiency, which is applied to benchmark the selected data management techniques to find the optimal design choices for the future distributed mobile data management system.

## II. DATA MANAGEMENT SYSTEMS EVOLUTION

Data management consists of the rules and functions for managing data as a valuable resource, regarding adding, storing, modifying and retrieving data. The data management architectures have evolved through the time from the first client-server based architectures [1] to distributed data management [2] and to the currently investigated peer-to-peer and grid-based architectures [3].

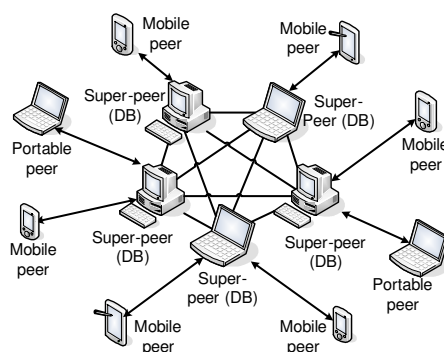


Figure 1: Peer-to-peer data management architecture.

Instead of storing the data into distributed database servers, the storage space of all the nodes in the P2P network, or super-nodes in the case of hierarchical P2P network, can be utilized using P2P type networking. The fundamental difference between the P2P and Client-Server architectures is that whereas in Client-Server architectures one or more nodes assume the role of a service provider and the others assume the role of service consumers, P2P systems are peer-oriented and thus interacting nodes assume the role of both, clients and servers, at the same time. Figure 1 illustrates the architecture of third generation data management system in a hierarchical super-peer P2P network.

The potential advantages of P2P systems are the node autonomy, scalability, high availability through replication and performance through parallelism [4]. There are already some experimental systems that utilize some data management algorithm, but there are no commercial third generation data management solutions on the markets yet. Some example P2P data management systems include APPA [4], PeerDB [5], GridVine [6] and AmbientDB [7].

The typical use of mobile devices differs fundamentally from the typical use of fixed devices. Due to the power saving requirements, the network connectivities cannot be open continuously. This makes the mobile device transient in the sense of network visibility. This makes especially the data management very demanding task, as it has to frequently adapt to changed situation. On this account, the operational requirements are very different for the mobile P2P systems.

The developing technology of mobile devices and networks brings some relief for some of the hardware requirements. The processing- and memory capacity is growing fast, whereas the new network enablers strengthen the communication capabilities. However, the need for power saving management seems to remain, as the more powerful components require more power and in the other hand there are strict requirements for the physical battery size. This means that the transient nature of mobile devices will remain.

A mobile P2P data management system has been analyzed and measured in [8]. We use its results later in this paper as a part of our analysis for the requirements of mobile P2P data management.

### III. ANALYTICAL MODEL

#### A. Evaluation Framework

In the following, we discuss our analytical model for evaluation of data management and related implementation strategies from the viewpoint of mobile environment. Figure 2 illustrates the logical entities of the framework.

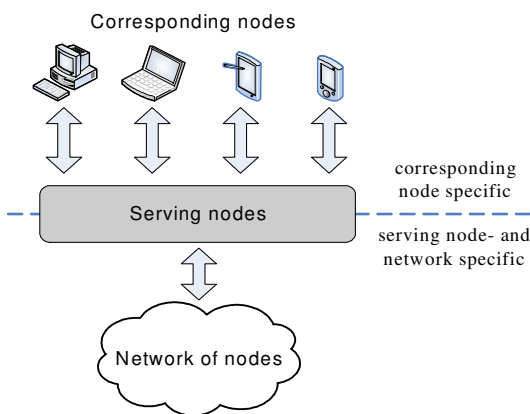


Figure 2: Logical entities.

Service enabler (indexed with  $i$ ) can be e.g. a protocol or network architecture that can be measured or otherwise quantified within the data management implementation. In this case, the service enablers represent the data management models. These models are 1) client/server model, 2) distributed client/server model, 3) fully decentralized (flat) P2P model, and 4) hierarchical P2P model. Each service enabler is characterized by different operational costs that are seen in the usage of the node- or network specific resources.

$\tau_n$  represents data management related operational costs that are explicit variables, indexed with  $n$ . In this case, the operational costs are categorized into two groups: corresponding node specific costs (e.g. memory and processor usage), and network/serving node specific costs (e.g. administration expenses or serving node's processor usage), implicating temporal and spatial performance and efficiency.

Numerical value of the operational cost of a service enabler can be formulated as:

$$\tau_{n(i)} \quad (1)$$

where

$i$  = service enabler instance index number  
(e.g. 1. generation, 2. generation ...)

$\tau_{n(i)}$  =  $n$ th operational cost with service enabler  $i$   
 $n$  = operational cost index number

For practical implementation, one may want to set different priorities for different service enablers. One service enabler operational cost may have more emphasis in the data management (e.g., from the user or service provider perspective) than the other. For these reasons we introduce weight factors  $a$  for varying operational costs.

The developed algorithm manages the evaluation of the suitability of available service enablers. It can compare two or more service enablers simultaneously. At first, 1) all measured values  $\tau_{n(i)}$  of an operational cost  $n$ , from alternative service enablers  $i$ , are compared with each other and arranged into an order. 2) All the values  $\tau_{n(i)}$  are then divided by the best value determined. This is done to normalize the values so that a set of generalized polynomial functions or interpolation neural networks, in more complex cases, could be utilized in grading the different service enablers.

3) For every operational cost  $n$ , all service enablers  $i$  are given a grading  $g$  (e.g. ranging from 0 to 5) calculated using the above-mentioned polynomial functions. A set of polynomial functions can be created using Matlab and designed to manage different kinds of sets of  $\tau_{n(i)}$ , where the range of values can be very dissimilar. To illustrate this, all the values might be concentrated in a very small range, when e.g. a linear grading function would perform very poorly giving all the service enablers almost maximum points. However, with this particular operational cost  $n$ , every service enabler  $i$  might actually perform well, but on the other hand, the scale with some

operational costs is just regularly narrower, requiring stricter grading and the use of a steeper polynomial function.

4) Every grading  $g$  is then multiplied by a corresponding weight factor  $a$ . In this paper, we use the Analytical Hierarchy Process (AHP) [9] for determining the normalized weight factors. AHP is based on pairwise comparison between each of the evaluated values that are checked for internal consistency and then combined. There are also other alternatives for weighting the grades, as discussed in [9], but the further definition of the used method is out of the scope of this paper. 5) Finally, all grading-weight factor products are summed up as:

$$\delta_i = \sum_{n=1}^k g_{n(i)} a_n \quad (2)$$

where

$\delta_i$  = the operational suitability of the service enabler  $i$

$g_{n(i)}$  = grading of the operational cost  $n$  for the service enabler  $i$

$a_n$  = weight factor for operational cost  $n$

$k$  = total number of evaluated operational costs

6) Operational suitability is compared between all the service enablers and the one with the highest score is then selected. Practically, the operational suitability is an outcome of two factors: the choice of service enablers and their weight factors. We use this algorithm in evaluation of varying data management architectures in order to find the most suitable one for the restricted mobile environment.

Determined cost values  $\tau_{n(i)}$  for varying operational costs are presented in Table 1. Presented numerical values are based on estimates using realistic values from current solutions.

### B. Grading the architecture costs

For calculating the total suitability of service enablers, in our case the data management network models, we need to grade their operational costs. For transforming the operational costs to grades, we use a simple function (3). According to our evaluation framework, operational costs should be standardized by dividing them by the best value determined. In our case, however, numerical values of operational costs are estimates

(not measured values) and their mutual relations have already been determined in the estimation.

$$g_{n(i)} = -n(i) + 5 \quad (3)$$

where

$g_{n(i)}$  = grading of the operational cost  $n$  for the service enabler  $i$

$n(i)$  = operational cost of the service enabler  $i$

### C. Weight Factors

When determining weight factors for the operational costs, it is crucial to find the very essential ones, affecting most the data management suitability for the mobile environment. Especially these operational costs need to be optimal for the system to be feasible.

In the corresponding node side, the network interface load is the most important operational cost, as it increases the battery consumption. Other reasons are low transfer rates in many cases and relatively high data service tariffs. Computational load is also very important operational cost, since processing capabilities are still relatively low in average mobile smartphones. As new small-sized memory cards and microdrives with the capacity of gigabytes have started to emerge at decent prices, the storage utilization will not be a major problem in the future. Thus, the weight factor of the storage utilization is not as high as the two before mentioned. The need for configuration, however, plays only a minor role in the total feasibility of data management solution, since it consumes time only at introduction phase.

From the perspective of the serving node and the overall communication system, the network utilization, serving node load, equipment costs and data integrity are the most crucial operational costs. Inefficient signaling, especially in the networks of large node population, and especially in flat-P2P systems, brings a lot of overhead to the overall traffic, increasing the need for upgrading the network infrastructure. The load of the serving nodes raises the resource and maintenance requirements as the network size grows

Requirements for mobile and fixed data management systems differ from each other. Thus, we have used separate weight factors for fixed systems. The main differences between the environments are concerning the balance of the weight factors of node load, network utilization and storage utilization

Table 1: Operational costs with weight factors and the total operational suitability.

Network architecture	Corresponding node specific operational cost (smaller=better)				Serving node and network specific operational costs (smaller=better)						Operational suitability mobile/fixed
	Corresponding node load	Storage utilization	Network interface load	Configuration need	Network utilization	Serving node load	Equipment cost	Administration cost	Failure tolerance and scalability	Data integrity	
<b>Weight factor (mobile/fixed)</b>	0.15325 / 0.1784	0.08325 / 0.0892	0.2101 / 0.1432	0.0534 / 0.0892	0.0769 / 0.09375	0.0769 / 0.09375	0.0769 / 0.09375	0.0385 / 0.03125	0.1154 / 0.09375	0.1154 / 0.09375	1/1
Client-server	1	1	1	2	1	5	4	3	5	1	2.87 / 2.82
Distributed client-server	1	1	1	2	2	3	5	5	3	2	2.91 / 2.85
P2P -flat	3	3	5	1	5	3	0	0	1	5	1.88 / 2.08
P2P -hierarchical	2	2	1	1	4	3	1	1	2	3	3.03 / 2.98
P2P -optimized for mobile	<b>1</b>	<b>2</b>	<b>1</b>	<b>1</b>	<b>4</b>	<b>4</b>	<b>1</b>	<b>1</b>	<b>2</b>	<b>2</b>	3.22 / 3.16

between the corresponding node side and serving node- and system side. In fixed systems, the serving node has a more central role than in mobile architectures, where, in turn, the requirements for corresponding nodes are emphasized. The weight factors are determined separately for corresponding-node specific and serving node/network specific operational cost categories. Furthermore, these categories have been weighted equally (50%) for both mobile and fixed weight factors. The resulting weight factors are marked in Table 1, and their effect to the total suitability is illustrated in Figure 3.

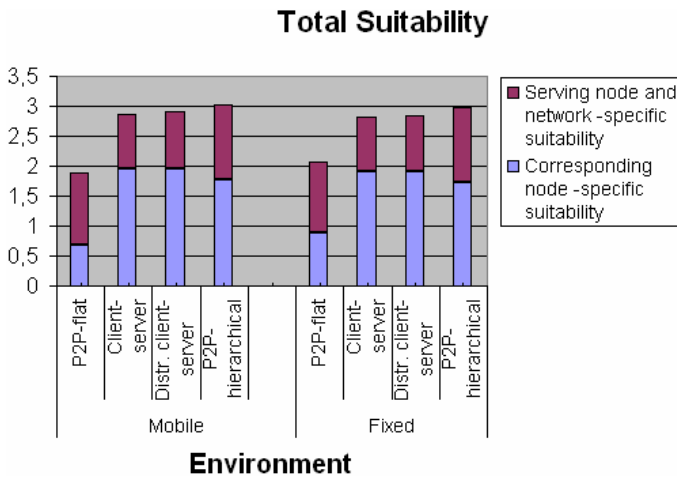


Figure 3: Total suitability.

In the Figures 4 and 5, the effect of weight factors to the overall relational suitability of varying data management architectures is shown. In mentioned Figures, all other weight factors are locked to neutral value (0.125 in corresponding node specific operational costs and 0.8333 for serving node/network specific operational costs), except one adjusting the importance of a particular operational cost. This unlocked weight factor is then run from 0 to 0,3.

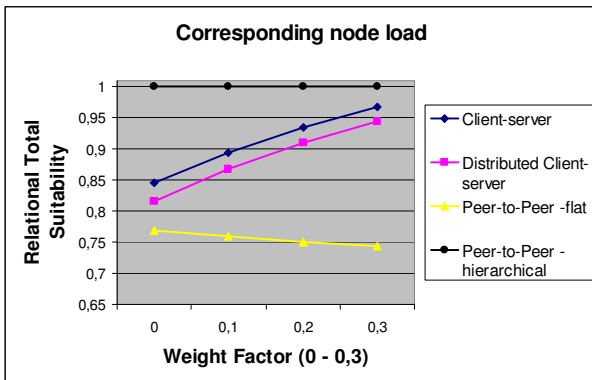


Figure 4: Corresponding node load.

Figure 4 illustrates the case the hierarchical P2P would be the most suitable architecture with all weight factors, but the difference to client-server models gets smaller when the corresponding node load's weight factor grows. The total suitability of P2P-flat model gets slightly worse. Similarly, Figure 5 illustrates that the basic client-server model's suitability in this case gets worse very fast, when the serving node load's weight factor is growing. Distributed client/server model's and P2P-flat model's scores are affected only slightly.

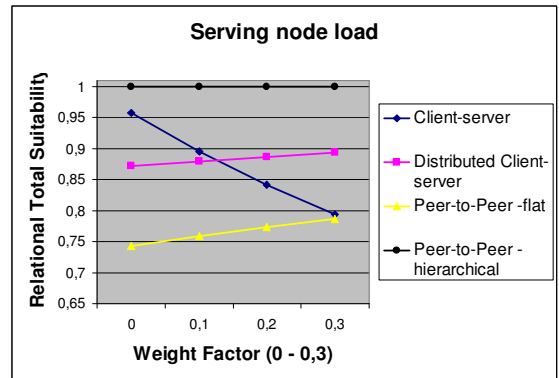


Figure 5: Serving node load.

#### IV. DESIGN GUIDELINES FOR MOBILE P2P DATA MANAGEMENT

As Table 1 shows, the operational suitability of hierarchical P2P model for the data management is highest among the measured models. This result applies to both mobile and fixed environments. However, when weighting the factors important to mobile environment, the difference is even bigger to hierarchical P2P model's credit. The flat-P2P model does not perform well in either case, mainly because of its high network costs in both corresponding node- and serving node end and high corresponding node load. Client-server based systems, especially in the case of distributed client-server systems, are also rather good options in the mobile environment.

As the most suitable model is the hierarchical P2P model, we base our guidelines on it. The most significant operational costs from the viewpoint of mobile environment are the corresponding node load, network interface load, failure tolerance, scalability and data integrity. As some of these functionalities are already quite well managed in current systems, we focus on the operational costs, where we can still make significant improvements. These areas are corresponding node load, failure tolerance, scalability and data integrity.

The corresponding node computational load can still be decreased by leaving more functionality to be taken care by super-peers on behalf of them. This makes the model closer to client-server model, so that correspondent node's role gets closer to a client in the client-server model. The drawback of this is that serving nodes' computational load increases. However, the weight factor for the serving node's load is lower

in the mobile environment, meaning that the total operational suitability increases.

Failure tolerance can be increased by developing the underlying P2P protocols and their algorithms in this sense. For example, using the structured P2P protocols that implement reliable and efficient DHT algorithm and semantic routing for overlay management, can lead to better failure tolerance and efficiency. The research on these areas is very active at the moment. Chord [10] is a good example of simple but efficient and reliable DHT algorithm. One example of semantic routing algorithm is Neurogrid [11].

The data integrity is another important aspect when talking about distributed data management. This is an important factor in both mobile and fixed environments. For optimizing the data management integrity in the mobile environment, the data management algorithms should take into account the transient nature of mobile devices, e.g. leaving most of the functionalities to more reliable super-peers. The efficiency and reliability of replica management is in very important role in this sense. There is a lot of work to do in optimizing the algorithms for mobile environment. The last line of Table 1 shows our estimation of how much could the total suitability value be increased with the before-mentioned improvements.

## V. DISCUSSION AND FUTURE WORK

In this work, we introduced a simple method for defining the operational suitability for different service enablers, based on the weighted operational costs. In this paper, the operational cost grades were based on estimates. The future work includes using improved methods for defining the operational costs and grading them.

The operational costs in this work were defined using the analytical estimation. In future, we need to provide measured results for defining more realistic and accurate grading for operational costs. These measurements should include several protocols from each model to provide enough accurate results.

More sophisticated approach to manage the grading of the operational costs instead of using predefined polynomial functions would be to utilize neural networks that can be taught dynamically according to varying criteria. Neural networks can handle more complex grading situations. When interpolating or approximating neural networks, the mutual relations of operational costs with different service enablers and the knowledge of their nature can be exploited.

Future work includes also developing practical, real-life application scenarios that could be used in both defining the operational costs and their weight factors.

## VI. CONCLUSIONS

There exist many different data management solutions ranging from first generation centralized client-server systems and second generation distributed client-server systems to P2P-

based distributed data management systems. In this paper, we analyzed the existing systems and their features from the viewpoint of mobile environments. We introduced our novel evaluation framework, which can be used to evaluate the efficiency of varying service enablers. The evaluation framework was applied for comparative analysis of various aspects of different distributed data management systems. From the results of the analysis, we introduced some important design guidelines for implementing data management systems especially considering mobile environments. Future work includes developing the evaluation framework further and applying it for grading measured results in empirical settings. This work forms the basis for further investigating of mobile data management using real-life application scenarios and prototypes.

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## REFERENCES

- [1] N. Roussopoulos, A. Delis, "Modern client-server DBMS architectures", ACM SIGMOD Record archive, Vol. 20, Issue 3, September 1991, pp. 52-61.
- [2] M.T. Özsu, P. Valduriez, "Principles of distributed database systems (2nd ed.)", Prentice-Hall, Inc., Upper Saddle River, NJ, 1999.
- [3] L.G.A. Sung, N. Ahmed, R. Blanco, H. Li, M.A. Soliman, D. Hadaller, "A Survey of Data Management in Peer-to-Peer Systems", CS856 - Web Data Management, Winter 2005, pp. 1-50.
- [4] R. Akbarinia, V. Martins, "Data Management in the APPA P2P System", International Workshop on High-Performance Data Management in Grid Environments (HPDGrid), Rio de Janeiro, Brazil, 2006.
- [5] W. Siong, B. Chin, K-L. Tan, A. Zhou, "PeerDB: A P2P-based System for Distributed Data Sharing", The 19th International Conference on Data Engineering (ICDE), Bangalore, India, 2003, pp. 633-644.
- [6] K. Aberer, P. Cudr'e-Mauroux, M. Hauswirth1, T. Van Pelt, "GridVine: Building Internet-Scale Semantic Overlay Networks", International Semantic Web Conference, (ISWC), Hiroshima, Japan, 2004, pp. 107-121.
- [7] W. Fontijn, P. Boncz, "AmbientDB: P2P Data Management Middleware for Ambient Intelligence", 2nd IEEE Annual Conference on Pervasive Computing and Communications Workshops (PERCOM), Orlando FL, USA, 2004, pp. 203-207.
- [8] M. Kan, "Data Management in Mobile P2P Systems", Technical Report, University of Stanford, September 2005.
- [9] F. Akhavi, C. Hayes, "A comparison of two multi-criteria decision-making techniques", IEEE International Conference on Systems, Man and Cybernetics, Washington DC, USA, 2003, Vol. 1, pp. 956 - 961.
- [10] I. Stoica, R. Morris, D. Liben-Nowell, D.R. Karger, M.F. Kaashoek, F. Dabek, H. Balakrishnan (2003) "Chord: A Scalable Peer-to-Peer Lookup Protocol for Internet Applications", IEEE/ACM Transactions on Networking (TON), Vol. 11, Issue 1, pp. 17- 32.
- [11] S. Joseph, "Neurogrid: Semantically routing queries in peer-to-peer networks", The 1st International Workshop on Peer-toPeer Computing (IPTPS), Pisa, Italy, 2002, pp. 202-214.