Cloud Benchmark Testing of Cassandra on Raspberry Pi for Internet of Things Capability

THESIS

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Abstract

This paper explores distributed NoSQL database Cassandra's performance limitations in an IoT using limited hardware, namely the Raspberry Pi 2. Our aim is to use Cassandras reliable and efficient data distribution to enable distributed exploits on real-time streaming data. At the time of this writing, the proposition of Cassandra on IoT-like hardware carries some development risk for a would-be application developer. This work not only demonstrates that actual operation of Cassandra is possible on Raspberry Pi, but also varies the conditions of operation to serve the expectation management of the variations inherent in new, creative, and cutting-edge applications. This work uses the Yahoo Cloud Services Benchmark (YCSB) not only for its popularity but to catalyze infusion of this research with existing and future research that will fully characterize IoT in the realm of controlled, flexible and resilient data storage. To represent IoT, we vary the memory on a virtual machine among 1GB, 2GB, and 4GB as well as implement Cassandra on the Raspberry Pi platform. Four (4) different YCSB workloads were executed on five (5) different network types: virtual machine equipped with 1GB of RAM on an internal virtual network, virtual machine equipped with 2GB of RAM on an internal virtual network, virtual machine equipped with 4GB of RAM on an internal virtual network, Raspberry Pi's with 1GB of RAM on an Ethernet LAN, and Raspberry Pi's with 1GB of RAM on an 802.11a/b/g/n wireless LAN. Node cluster sizes ranged from 1 to 6. Between at least five (5) but no more than seven (7) effects were evaluated: (1) comparison between virtual machine equipped with 1GB of RAM on an internal virtual network and a comparable configuration in another paper, (2) comparison among the effects of varying RAM within the virtual machine environment, (3) effect of varying

cluster size given limited hardware, (4) comparison between the Raspberry Pi node and a network from another paper, (5) comparison between the limited hardware (Raspberry Pi) and the 1GB RAM virtual machine, (6) the effect of cluster size on a 802.11a/b/g/n wireless given limited hardware (Raspberry Pi) nodes, and/or (7) comparison between wireless 802.11a/b/g/n network and a similarly configured wired Ethernet network. This work demonstrates the feasibility and expected performance drops when porting a distributed database like Cassandra from powerful, stationary nodes to less powerful, but more flexible nodes.

CLOUD BENCHMARK TESTING OF CASSANDRA ON RASPBERRY PI FOR INTERNET OF THINGS CAPABILITY

I. Introduction

1.1 Background and Motivation

There is a trend that information technology and electronics generally become cheaper, powerful, and physically smaller as time progresses, which has led to the ensuing ubiquity of the IoT. Open source software and limited hardware like the Raspberry Pi embody this trend, both in terms of of lowering requisite eclectic expertise as well as price. Databases, key to IoT, are no exception, and it is of interest to explore the trade space involved in porting distributed database technology among such limited hardware. At the time of this writing, distributed databases like Cassandra are normally associated with large capacity nodes.

1.1.1 Potential Challenges.

Using Cassandra on nodes like the Raspberry Pi series in IoT is not without its challenges. First, while software developers may have the luxury of assuming increasingly powerful processing units and limitless memory, an IoT application cannot take such resources for granted. The Raspberry Pi 2 Model B, which will be used in this thesis, has 1GB of RAM available [2]. Storage for a single node depends on the SanDisk (SD) card, whose disk storage can vary from 8 GB to 256 GB and whose Input/Output (I/O) data rates can from 2 MB/s to 30 MB/s at the time of this writing. These amounts pale to the 768GB memory and 74.4 TB storage for, say, the

Lenovo Thinkserver RD650 [3] or some other server on the market. Prior to making a server purchase, it may of interest to predict the effect of varying the computing power of underlying hardware for some software of interest.

Second, using a node like the Raspberry Pi in IoT can imply a requirement for a finite (primary cell) or periodic (secondary cell) power source. Larger nodes, of course, consume their fair share of power, which comes with its own set of constraints. The prospect of deploying a node in new and unusual places is part of the motivation of porting software to low-power nodes like the Raspberry Pi series.

The prospect of nodes implying less power consumption, less weight, smaller dimensions, and/or maybe even a better price compared to an alternative all do their part to chip away barriers that creative minds would otherwise face in deploying applications for the betterment of mankind.

1.1.2 Potential Benefits.

Giving up computing power for less in power consumption, weight, dimensions, and price also has potential positive implication for innovation management.

Potential Benefits Particular to Supply Chain Management.

In supply chain management, especially in government, there is perpetual interest in items that qualify as Commercial-Off-The-Shelf (COTS). This interest, naturally, ties directly to cost and economies of scale. The more purposes something can serve, the greater demand is likely to be in the free market. This not only save on the actual unit price, but also engineering and administrative costs that may be incurred by triggering the full acquisition process of an application specific integrated circuit. The defense acquisition process is notorious for being overly burdensome, and limited hardware like the Raspberry Pi can represent the potential for rapid or general

schedule acquisition.

There is another supply chain benefit as well. Despite security measures, it can be difficult to completely conceal a supply chain from an interested and skilled third party. The more application-specific a device is, the more insight it may give an unsavory adversary knowledge of mission parameters, whether it is physically captured, or if technical requirements leave a leaky paper trail. Purchasing limited hardware rather than application specific hardware has the potential to effect diffusion of such insight.

Potential Benefits Particular to Wireless.

There is no shortage of options for networking different hosts together, but the ability to exchange a wired networking medium for a wireless networking medium enables increased mobility and flexibility in placement. Wired networking options require cables that may incur installation costs and risk damage when exposed to many environments of interest. Allowing for wireless technology may be a critical enabler for some applications that have yet to be seen. However, along with these potential benefits comes with the risk of decreased or degraded performance. It is helpful to know in advance how similar endeavors have fared.

1.2 Problem Statement

This paper seeks to gain insight into how modern distributed databases operate in an IoT environment and what actions or configurations may be required or recommended to be in place to ensure feasible operation.

1.3 Research Goals and Hypothesis

1.3.1 Characterization of IoT and the IoT device.

Echoing [4], there is no "standard identification" of IoT or an IoT device, although invoking the phrase can identify some archetypes, such as home automation systems or facilities management systems. All of these incorporate transducing some process over time, such as water pressure, steam pressure, temperature, etc, and may provide indication, such as a thermometer or dashboard, and/or actuation, such as actuation of a furnace or pump. This concept and its relationship to limited hardware is further addressed in the Chapter II.

The Raspberry Pi is able to receive digital data, audio signals, and video signals, and thus represents some of the computation and storage that could be attached or otherwise networked to one of these transducers. This question of how the Raspberry Pi fits into the IoT will be addressed in Chapter II through examination of current published work as well as commercial specifications.

The Raspberry Pi has no shortage of competitors. These will be briefly examined in Chapter II. In addition to the Raspberry Pi, Chapter III will evaluate a virtual machine set up to emulate limited hardware. Thus, both the Raspberry Pi and a virtual machine simulator will serve as representatives of IoT devices in this thesis.

Databases are key, and distributed databases offer flexibility and robustness that an alternative may not imply. Section 2.1.2 explains the current use of Cassandra and the benefits of porting distributed databases from a thinner client to a thicker client.

While IoT may imply the internet protocol (IP) at the network layer, there is no shortage of options at the data link and physical layers. Chapter II will discuss some networking considerations and explain some of the background behind varying between data link layers.

1.3.2 Feasibility of Distributed Database on Limited Hardware.

There is the question of whether a given distributed database will work on a given hardware platform or not. Any one-off results at a nonzero measure of performance indicate feasibility, but replicating operation and slightly varying the conditions gradually increases the confidence that such feasibility can be extended to yet untested environments. With the distributed database being represented by Cassandra, and limited hardware being represented by virtual machines as well as the Raspberry Pi, the experiments in this work aim toward refining the answer to this question.

Section 2.2.2 explains the reasoning behind selecting Cassandra as the representative of a distributed database. Section 2.2.3 addresses the reasoning behind the selection of YCSB.

Finally, this thesis aims to answer the following questions:

- *Does the amount of RAM affect Cassandra's performance?*

  Chapter III describes the empirical method used to determine an effect with respect to varying memory.

- *Platform Testing, Scalability Testing - What are the implications of using limited hardware?*

  Varying hardare platforms implies varying a variety of factors closely related to performance: Central Processing Unit (CPU), RAM, networking interfaces, and hard disk interfaces. Chapter III describes the empirical method used to measure the effect of porting Cassandra between a virtual machine the Raspberry Pi, as well as measuring the effect of cluster size. A common selling point for distributed databases is an ability to accept additional nodes for storage, as opposed to say, more storage in-situ.

- *Link Layer Testing - What effects on performance result from varying networking schemes?*

  Chapter III describes the empirical method used to measure the effect of switching between Ethernet links and 802.11a/b/g/n wireless links, as well as the scalability implied given 802.11a/b/g/n links.

- *Sensitivity Testing - How does variation in the configuration of a distributed database affect performance?*

  Different applications may imply different configurations associated with distributed databases, including compression strategies and replication factors. Chapter 3.1 does some investigating into how these can affect performance.

1.4 General Approach and Research Activity Overview

The general approach to this will be to implement a scientific methodology for understanding the effect of inherent aspects of IoT networks on factors that limit performance of distributed databases. Of particular interest are the effects of low memory and processor speed, limited bandwidth and scalability on IoT networked devices. In general, this study follows a template that includes varying configuration and environment settings, performing stress testing, measuring results, and interpreting the results to form a conclusion.

This paper will apply the YCSB benchmarking tool to gauge performance changes over variation in the following: keyspace configuration, network configuration, platform choice, and node scaleup.

1.5 Expected Contributions

Aggregating lower-cost, lightweight hardware spawns a lingering question of possibilities and performance due to lower barriers to proliferation. With distributed database Cassandra representative of application, and the Raspberry Pi a representative of low-cost hardware, we explore the performance of a distributed database over Raspberry Pi networked clusters. This paper asserts the following contributions:

- *Methodology*

  First, this paper develops a methodology to leverage existing tools [5] to evaluate a NoSQL distributed database in IoT. This will expand on such work as [1] and [5] developing a test methodology to explore the limits of Cassandra, and how its performance is affected by the number of nodes, nature of hardware, and links.

- *Performance Implications of Limited Hardware*

  Second, this paper reports results that suggest and characterize a differential between a simulated environment for IoT using virtual machines and an internal network and a physical one using Raspberry Pi's and an Ethernet network.

- *Performance Implications of Link Layer Variance*

  Third, this paper reports results that suggest a predictable performance cost associated with exchanging an 802.11a/b/g/n wireless links with those of a wired Ethernet network.

1.6 Organization

Chapter II paints the relevant parts of the landscape that have emerged as a result of much interest in distributed databases, limited hardware, and IoT. We also

present the gaps of the current literature to describe the technical goals for the current work. Chapter 3.1 demonstrates some sensitivity testing. Chapter III presents a methodology to examine and evaluate the performance implications of varying hardware, network, and cluster size. Chapter IV describes the results and evaluation of the methodology presented in Chapter III. In Chapter V, this study is brought to a conclusion and future work is discussed.

II. Background and Related Works

2.1 Characterization of IoT and IoT devices

This section will seek to define where in IoT distributed databases such as that which is tested here, can augment or enable applications.

2.1.1 IoT Model.

See Figure 1 for where Cassandra is often used at present in IoT, as a back-end database for time-series sensor data. Figure 1 depicts a token sensor that sends data to a router, which in turn sends the data over a connection to a back-end database. It is here, at the back-end database, where Cassandra is put to use. The data is split and replicated over several servers with plentiful memory and storage where it can be queried from afar.

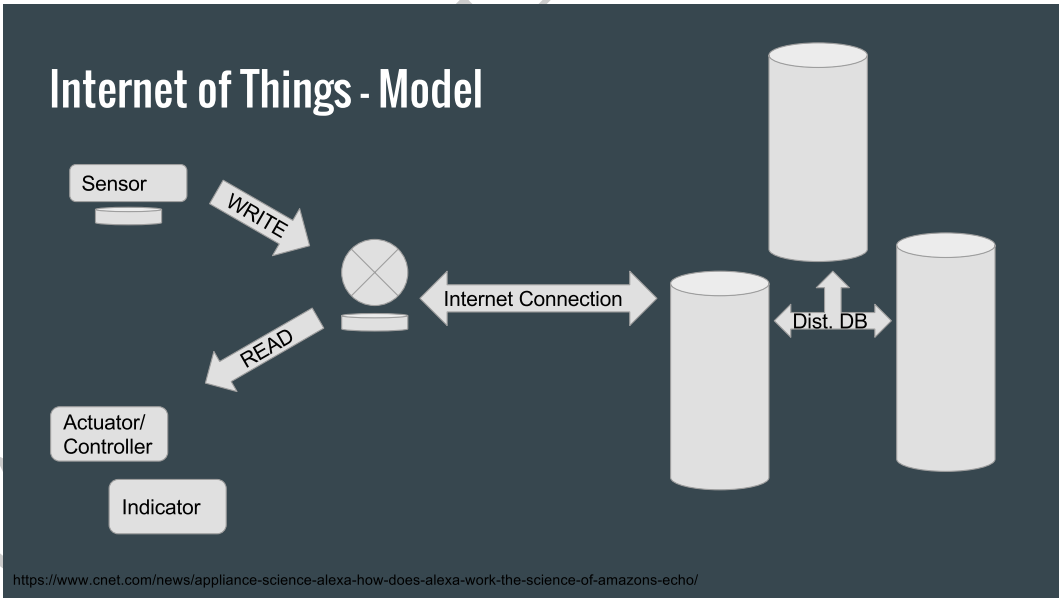

Figure 1. IoT This represents what for some might be a nominal "IoT" application. Some measurement of interest, such as temperature is sensed, that raw data is stored and sent afar, and if desired, the user may also query for some kind of feedback or indication.

2.1.2 Application Space.

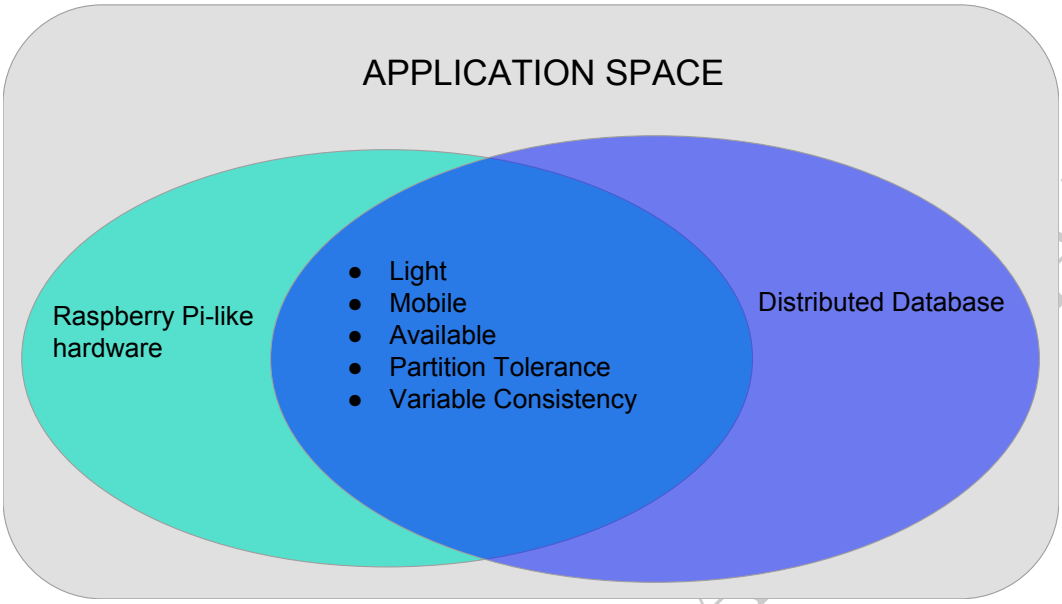

Figure 2. Venn Diagram of Application Space. The application space of interest takes advantage of some combination of lightness in weight, mobility, availability, partition tolerance, and variable consistency.

At the time of this writing, back-end database operating on powerful, but stationary nodes dominate documented use cases of Cassandra, as well as other distributed databases. This paper explores the idea of moving toward a more in-situ database, where the sensing nodes may also contain serve as mechanisms for storage and do not require a pipeline to another datacenter, a pipeline that from an operational perspective, represents a single point of failure, or from a security perspective, a threat to privacy. These ideas are depicted in Figures 2 and 3. Figure 2 paints in words what applications might seek to benefit the most from this research. Figure 3 is a modified version of Figure 1, where the connection to the back-end servers is either degraded or non-existent, and some version of in-situ storage must take its place to the best extent possible. There are obvious trade space among hardware capabilities and cluster size, but what is not obvious is how the database will actually perform.

The next few sections map this general concept to some existing applications and

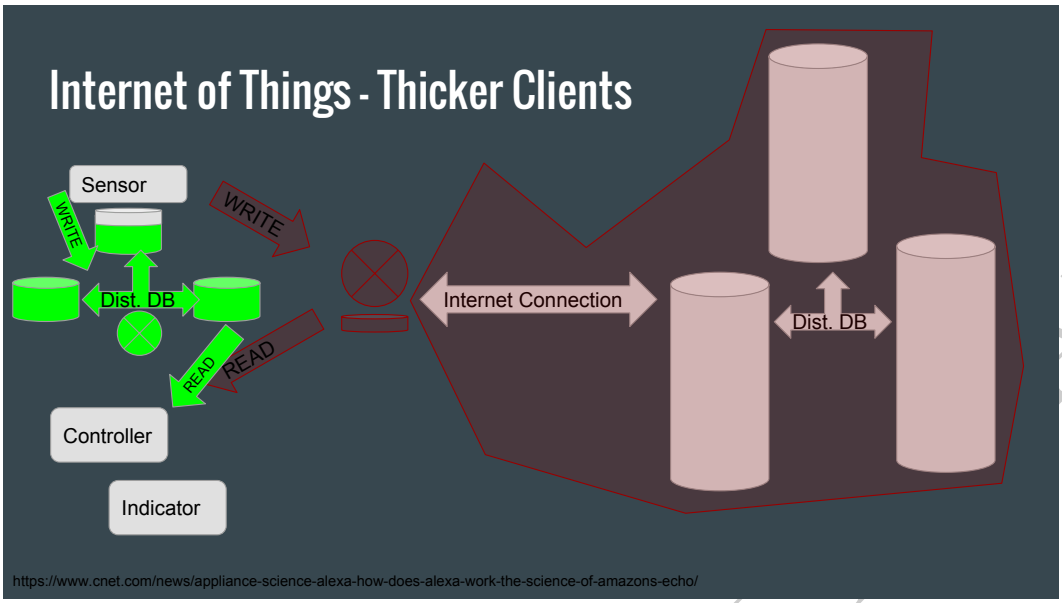

Figure 3. IoT Application with Thicker Clients...Depending on the application, using a distributed database on thicker clients in-situ may suitably replace a remote database operating in a remote location. From an operational standpoint, the pipeline may be unreliable, resulting in a loss of data. From a security standpoint, this pipeline may be subject to undesired third-party monitoring.

research that may benefit from such distributed database research.

2.1.3 WiFi Collection, Mapping and Analysis.

WiFi Sniffing, Collection.

WiFi (802.11) sniffing, or war-driving, has been explored by a number of enthusiasts, both in and out of the academic realm. These techniques for WiFi sniffing, at least on the front-end, are well-documented and thus represents a low barrier to entry for initial operations, often just requiring a specific WiFi chipset, such as the ALFA card, and open-source software. One example that has been well-documented goes by "Snoopy" [6]. Snoopy provides a framework for collecting WiFi data and observing with another handy piece of software, Maltego. Of course, a multitude of other software exists. For example, one can sniff wireless traffic by using software Aircrack-ng [7] or Airsnort [8]. However, although sensing the data is easy, the subject of stor-

age has not been fully explored with respect to the selling points mentioned above. Investigating the limits of storage operations is key to unlocking realistic aspirations and application development.

WiFi Mapping.

It may worth noting one off-shoot of the WiFi sniffing mentioned above: WiFi mapping. There is much interest in WiFi mapping: it implies extra assurance to existing technologies that may be overly taken for granted. There has been much work done with respect to WiFi mapping. Argos [9] describes a similar system of a distributed system, but there is no mention of Cassandra or any distributed database, which may serve as an improvement on such a sensor network. Wigle.net [10] is an aggregate map that distributes a smart-phone application to collect GPS coordinate-Access Point pairs, but relies on a central database, and has an unreliable user base and irregular sampling and update frequencies (Relying on the public will often do that, unfortunately.). Heat Mapper [11] is partially free and commercial software that can generate a heat map for a small room or office. Wi2Me [12] performs this mapping as well, with an emphasis on performance and data throughput. It uses an instance of SQLite to store the traces on the individual's smart-phone, but again, none of these make use of a distributed database like Cassandra as part of the sensor network. Once again, this is a realm that may benefit integration with distributed databases, expanding the range possible node types, or both. However, there are limits that have to be anticipated. This paper aims to add a piece to that expectation management.

WiFi/Wireless Crowd Detection.

There is also considerable interest in crowd detection and related data gathering. Privacy implications notwithstanding, this kind of data can give a marketing-type a

sense if certain areas are popular or versus other areas, or if certain paths are well-traveled or not. The way WiFi broadcasts Service Set Identifier (SSID)s in plain text, crowds can even be characterized as to whether individuals connect to similar access points or not. The data can indicate whether you have a crowd of people from a certain country, a crowd of people who know each other or maybe just a crowd of strangers. It can add assurance to more primitive forms of tracking, such as person-by-person registration. Informally, some have even reported to make art exploiting this mechanism [13], and not surprisingly, there are numerous claims that members of the public are routinely tracked via commercial entities via WiFi [14]. There have been more academic efforts to track crowds as well, notably a university campus and a music festival in [15] and an airport in [16]. In [15], data travels through Global System for Mobile Communications / Groupe SpecialMobile (GSM) to a central node, but does not use any kind of distributed database, like Cassandra. There are commercial entities that claim to track crowds and report data, namely "Bluemark" [17]. Here as well, a central server is utilized to collect the data. Users then reportedly log into the web to view the metrics. According to their marketing literature, they do use Raspberry Pi, but not for data storage. Paper [18] used this product line for their tests. Although WiFi utilizes Media Access Control (MAC) addresses supposedly unique to each device, research has found that this leaves more to be desired for many applications, namely crowd-tracking. For instance, some devices have been reported to change their MAC addresses [18]. There exist a number of papers that explore characterizing mobile devices and their users at the individual level [19, 20, 21, 22, 23, 24, 25] and propose techniques to better prepare data for analysis [18]. What is clear in the subtext of all these papers, is that these types of application research can only benefit from a wider choice in nodes, and a wider choice storage options as well as a reasonable amount of foresight into their performance.

In all of these, however, distributing the stored data among the nodes, like with Cassandra is either not used or not mentioned. Many utilize a central server that represents a single point of vulnerability.

2.1.4 CBIR and others and summary statement on application space.

The motivation for WiFi mapping can also be extended to other types of mapping, such as Content-based image retrieval (CBIR). Paving the way for feasible, desirable in-situ data storage increases the portability and development of these and many more applications.

The experiments that follow read and write random data in the context of a generic schema, but the experiments were done with the following in mind: A schema supporting any of these applications could be substituted in instead, and ideally with predictable results.

2.1.5 IoT Devices and Raspberry Pi.

The Raspberry Pi 2 (Model B) [2] is a low-cost computer designed sold from the United Kingdom. It can be described as a motherboard about the size of a 3x5 index card and has been available since February 2015. This experiment is interested in the Raspberry Pi 2 as a representative of the low-cost hardware domain, which implies low cost, low power consumption, and low in terms of size and weight.

This author's interest in the Raspberry Pi 2 is that its ARM Cortex-A7 processor and 1GB RAM [2] makes it a key representative of the low-cost hardware domain and IoT. The Raspberry Pi 2 has cost as low as 35 USD [26]. It is lightweight and has limited power consumption [2]. Constraints on size, weight, power, and cost can all be barriers to entry for applications seeking computing nodes.

Expanding this experiment, to say the BeagleBone black [27], is in touch with the

spirit of this experiment but outside the scope of this paper and is reserved for future work. Various analogues and/or competitors to the Raspberry Pi are enumerated in Table 1.

Restricting the database schema to time series data, [31] claims to have achieved about 4 million inserts on a relational database on a Raspberry Pi 2 B+, one of the same models used in this work. However, the database in [31] lacked the capability and flexibility as Cassandra, and due to its custom nature could not be tested by the YCSB to be as robustly studied against other databases.

2.2 Benchmarking Distributed Databases for IoT

2.2.1 Small Cluster Computing on Raspberry Pi.

Considering the educational purpose of Raspberry Pis, it is no surprise to find academic interest in Raspberry Pi clusters. For instance, [32] evaluates a cluster of 8 Raspberry Pi nodes using SysBench.

Existing Raspberry Pi clusters, built to serve as a "practical balance" [33], such as in [34] and [33], suggest the value of Raspberry Pi nodes compared to large, traditional servers both in terms of power construction and actual purchasing price. In [35], Cassandra is used to store videos for a video streaming application on after a "a lot of configuration", albeit the configuration parameters were unspecified. However, [35] shows a high index of suspicion that Cassandra can be used in a small cluster environment.

2.2.2 Cassandra.

A distributed database offers a trade space among consistency, availability, and partition tolerance. Mostly this means that a system of nodes can still operate as expected even if there is a loss of one or two nodes. There is no shortage of distributed

Name	CPU	RAM	DISK	Price
Banana Pi M3 [28]	Octa-core 1.8GHz CPU	2 GB RAM	8 GB eMMC flash storage	73.00
CHIP [29]	R8 1GHz	512 MB	4 GB	9.00
VoCore	360 MHz MIPS CPU	32 MB	8 MB Flash	20.00
Arduino INDUSTRIAL 101 []	Atheros AR9331 Processor	64 MB	16 MB Flash	40.00
NanoPi 2 Fire []	Samsung S5P4418 quad-core ARM Cortex-A9, 1.4 GHz	unk	1 GB MicroSD card	22.99
NanoPC-T3 []	Samsung S5P6818 octa-core ARM Cortex-A53 up to 1.4 GHz	1-2GB of RAM	8GB of flash storage	60.00
Intel Edison with Kit for Arduino	Dual-core, dual-threaded Intel Atom CPU with a 32-bit Intel Quark microcontroller	1GB of RAM	4GB of flash storage	92.00
cloudBit []	Freescale i.MX23 ARM926EJ-S processor	64MB of RAM	4GB SD Card	59.95
Parallella [30]	16-core Epiphany RISC SOC	unk	unk	unk
Zynq SOC	(FPGA + ARM A9)	1GB SDRAM	Micro-SD storage	99
PixiePro	Freescale i.MX6Q Soc Quad Core ARM Cortex-A9 up to 1GHz	2GB of RAM	SD Card	129.95
Raspberry Pi	900 MHz quad-core ARM Cortex-A7 CPU	1GB RAM	MicroSD Card	35.90

Table 1. Raspberry Pi Alternatives, Depending on Application

databases to choose from, but Cassandra is widely used and is known to have a high write throughput [36]. Cassandra specifies the latest versions of both Java 8 and Python 2.7. In turn, Java can run on Windows, Mac OS X, Linux, and Solaris [37].

Cassandra is a widely used distributed Not Only Structured Query Language (NoSQL) database with many use cases [38] and boasts a high write throughput. Not only has Cassandra been reportedly been used in practice [39], but has been, using the Yahoo Cloud Services Benchmark [5], formally evaluated in scholarly literature against other databases such as MongoDB and proposed as the NoSQL database of choice in the Internet of Things and distributed sensor networks [40].

If possible, it is important to get realistic expectation from available specifications whether or not the database of interest, Cassandra, would be supported by the node of interest, in this case Raspberry Pi. At the time of this writing, Cassandra specifies it is supported by the latest versions of both Java 8 and Python 2.7 [37]. In turn, Java can run on Windows, Mac OS X, Linux, and Solaris. Raspbian, a Linux-based operating system, can be run on Raspberry Pi. In addition, there have been credible claims of Cassandra being used on Raspberry Pi [41, 42], but to the author's knowledge, no white paper with the details exists.

This author's interest in Cassandra lies in the fact that Cassandra is a distributed database used in practice for cloud computing. Although it describes itself as a NoSQL database, the interface allows for Structured Query Language (SQL) commands and has a Python Application Program Interface (API). Cassandra allows for configuration of distributed systems parameters, such as replication factor, but detailed knowledge of distributed systems protocols is not critical for operation.

The aim of this paper is to examine Cassandra's performance coupled with a simplified Wi-Fi collection and analysis application, where the nature of link nodes may be less reliable than wired Ethernet.

From an experimental standpoint, the distributed nature of a Cassandra "keyspace" lies in four parameters [43]: cluster size (the number of nodes), replication factor (configured in software), write level (configured in software), and read level (configured in software). As alluded to in the Methodology section, these factors will be held constant for this experiment.

2.2.3 Benchmarking Distributed Databases.

Benchmarks are the common parlance for a way to test a computing system's capabilities. There has been a lot of interest in testing distributed databases, databases that cover multiple nodes.

The "cassandra-stress" [44] tool is used to initially probe for sensitivity to configuration changes. Documented use includes [42], which, could be used as an anchor for methodology if desired. This tool is developed along with, and is optimized for Cassandra. However, it falls short if one desires to compare two different databases for the same task.

Instead, we explore a benchmark in this thesis that has been used to characterize scaling of Cassandra in other computing environments. Paper [36] presents the YCSB, highlighting "scaleup" and "elastic speedup" as parameters for benchmarking. It provides a survey of five databases: PNUTS, BigTable, HBase, Cassandra, and Sharded MySQL. As might be expected, Cassandra has the ability to be tuned based on the application, data distribution, and workload type. In [36], they claimed to "[tune] each system as best [they] know how." In contrast to boasting optimized performance, this paper, in the interest in repeatability and expectation management, will rely on default parameters and makes it a point to identify any tuning parameters that have been modified from the default. It is also worth noting that the version of Cassandra has evolved from year 2010, the time [36] was published.

The YCSB provides six pre-defined workloads and also allows one to determine a custom workload.

Cassandra was shown in [40] to be favorable to write-heavy workloads compared to another database in the domain. Notable about this paper is that the paper scales the node's RAM down to 2GB, compared to higher powered machines in other papers such as the Cooper paper [36] or as specified on the website [37]. Although it is not explicitly mentioned as an interest in the paper, this shows a transition of using Cassandra for lower powered machines. One thing that is not clear in [1] is how cache effects are accounted for. If unaccounted for, a cache effect may result in the initial run resulting in longer execution times than subsequent runs, all other factors being constant. The key cache is set at 100 MB and the row cache at 0. In contrast, this paper clears the data from (or truncates) the table of interest. [1] mention that each 7200 rpm with no stated limits on hard drive space. Moving into the realm of in-situ storage, this paper takes a significant deviation in limiting the hard disk space to 8 or 16 GB.

2.3 Networking Considerations

Although this paper takes an empirical, top-down approach to evaluation, some networking concepts may be useful to parse out, and predict what they mean to this

Workload	Description	Breakdown
A	Update heavy workload	50/50 reads and writes
B	Read mostly workload	95/5 reads/write
C	Read only	100% read
D	Read latest workload	95/5 reads/writes
E	Short ranges	95 scans / 5 inserts
F	Read-modify-write	50 read / 50 read-modify-write

Table 2. This table describes the predefined workloads available from the YCSB

work. This work only varies parameters at the link level. All terminology follows from [45].

This section will address delay in a local area network implied by the physical layer. Explanations are paraphrased from [45]. Variation in the physical layer may imply variation in end-to-end delay of a message composed of the following: Queuing Delay, Propogation Delay, Transmission Delay, and Processing Delay. Propogation delay is the most predictable, and reflects on the physical properties of the transmission medium. Transmission delay is dependent upon the message length and the transmission rate. In these experiments, the Maximum Transmission Unit (MTU) is set to 1500 on the router, so the message length would not change between Ethernet and 802.11a/b/g/n. However, the transmission rates do differ between Ethernet and 802.11a/b/g/n. Queuing delay, the outgoing delay, and processing delay, the incoming delay are not as predictable.

Ethernet is the dominant technology in modern wired LANs. Ethernet uses carrer sense multiple access with collision detection (CSMA/CD) and often uses switches.

The 802.11 protocol avoids collisions one of two ways. For shorter data frames, after sensing a channel idle for a specified interval called the Distributed Inter-frame Space (DIFS), the source sends the data frame. Then, it waits for an Acknowledge (ACK). For longer data frames, instead of sending the data frame right away, the source might send an Request-To-Send (RTS). This threshold can be set on the router, and in the case of these experiments it is set high, such that the RTS is never employed.

A key difference between the 802.11 protocol, or really any wireless protocol, is can be referred to as the 'hidden terminal problem' [45]. If nodes are spread out, it is possible for one node to miss interference caused by another node. A transmission source waits for an acknowledgement or retransmits. Contrasted with CSMA/CD, which does not require an acknowledgement from the receiver, this has the potential

to cause greater latency.

III. Methodology

3.1 Cassandra Pilot Tests

This section will demonstrate some of the variance that is possible by varying configuration of a cassandra keyspace itself. These configurations may differ from application to application.

Cassandra comes with its own stress-testing tool, denoted 'cassandra-stress' [44] in the tarball installation. By all appearances, it is designed to give an operator an idea of how Cassandra performs over time on a given hardware setup. But, it also allows an operator to vary a limited set of configuration parameters with each command line execution. Naturally, this stress testing tool does not allow one to compare Cassandra to a competitor, hence the YCSB in the main section of this paper, but in theory Cassandra-stress may also serve as a check on the YCSB.

3.1.1 Experimental Setup.

The set-up follows the guidelines established in the main methodology. The set of experiments described in this section explored how Cassandra performs. Here a cluster of 3 Raspberry Pi 2 nodes was used. The tarball version of Cassandra version 3.9 was downloaded and installed. The stressor application cassandra-stress was executed from a laptop also connected to the LAN.

3.1.2 Variance in Nature of the Links with Compression Algorithms.

The plot in Figure 5 shows the effect of varying compression strategies for a given configuration on a pure write load as load-tested through the cassandra-stress module. In the left, wireless 802.11 links were used. On the right, wired Ethernet links were used. A one-way analysis-of-variance (ANOVA) may be able to test whether there is a

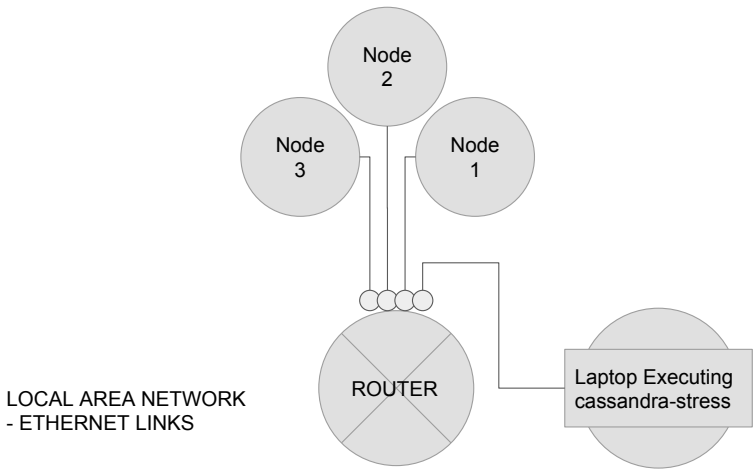

Figure 4. Experimental Setup for cassandra-stress Tests

significant differential between either of these two means, but from visual inspection, one could say that for a given configuration and a write-heavy load, varying the compression strategy does not have a large effect on performance as far as writes per second.

3.2 Overview of Similar Experiment

Although this work has a slightly different aim than [1]'s stated purpose, this paper aims to follow [1]'s methodology closely enough as to anchor its results to a cross-section of similar work that has been done. This work assumes that an in-situ storage application in the realm of IoT implies a small database, in this case represented by 1 million records, as opposed to 10 million or 100 million or more. Although [1] seems to imply there is feasibility for large database with many, many nodes given the right balance, this work focuses more on the initial impact to performance of introducing limited hardware in order to lighten costs or actual physical weight for an application that would see this as a benefit.

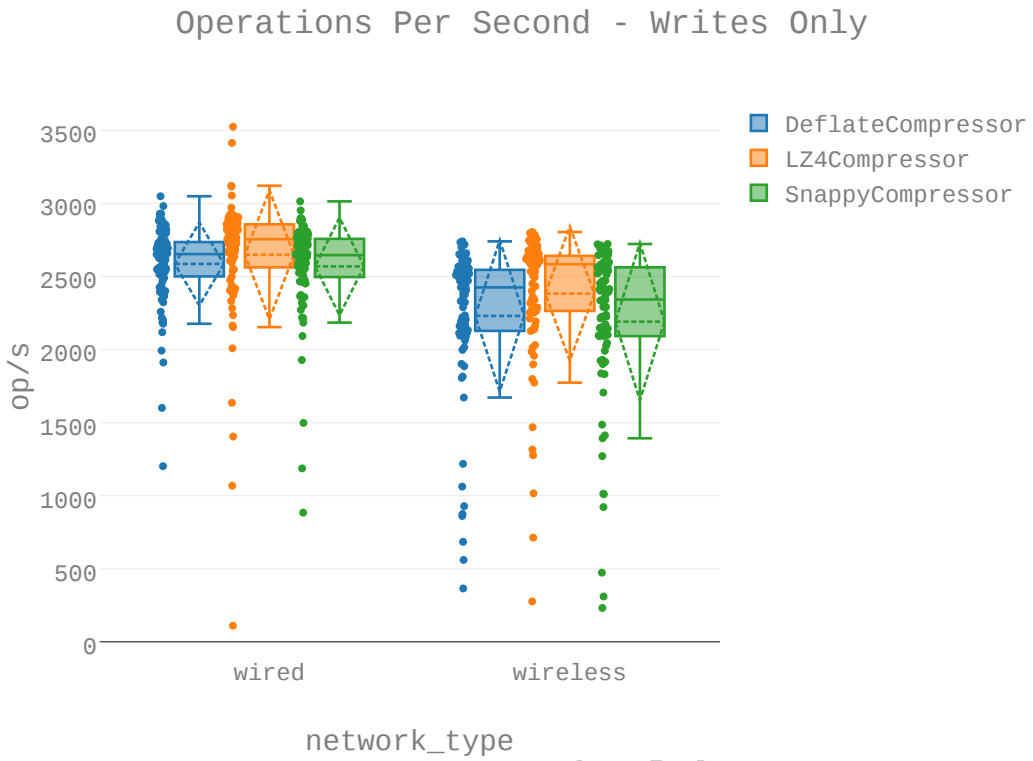

Figure 5. Varying Compression Methods: Writes ... Results are grouped by wired and wireless LAN configurations. From top to bottom, the solid horizontal lines of each box represent the maximum, 75 percentile, median, 25 percentile, and minimum. The dashed horizontal line represents the mean. The oblique dashed lines represent the standard deviation. The plotted points to the left of each box represent the actual data points.

Using standard workloads A, C, and E from the popular YCSB, the authors of [1] examined and evaluated Cassandras scalability over database [sizes] and cluster sizes [1]. The authors found that this trend, depicted in Figures 7, 8, and 9 did not necessarily hold true across database sizes, that in fact for larger database sizes of 10 million and 100 million records, 3 node clusters performed better than both a single node cluster and a 6-node cluster. The authors concluded that for sufficiently small databases, which is the likely case for IoT, more nodes imply more time to execute, which overwhelms any advantageous parallelism that may ensue with increasing nodes.

Because there are so many variables that can be at work, this work aims to anchor

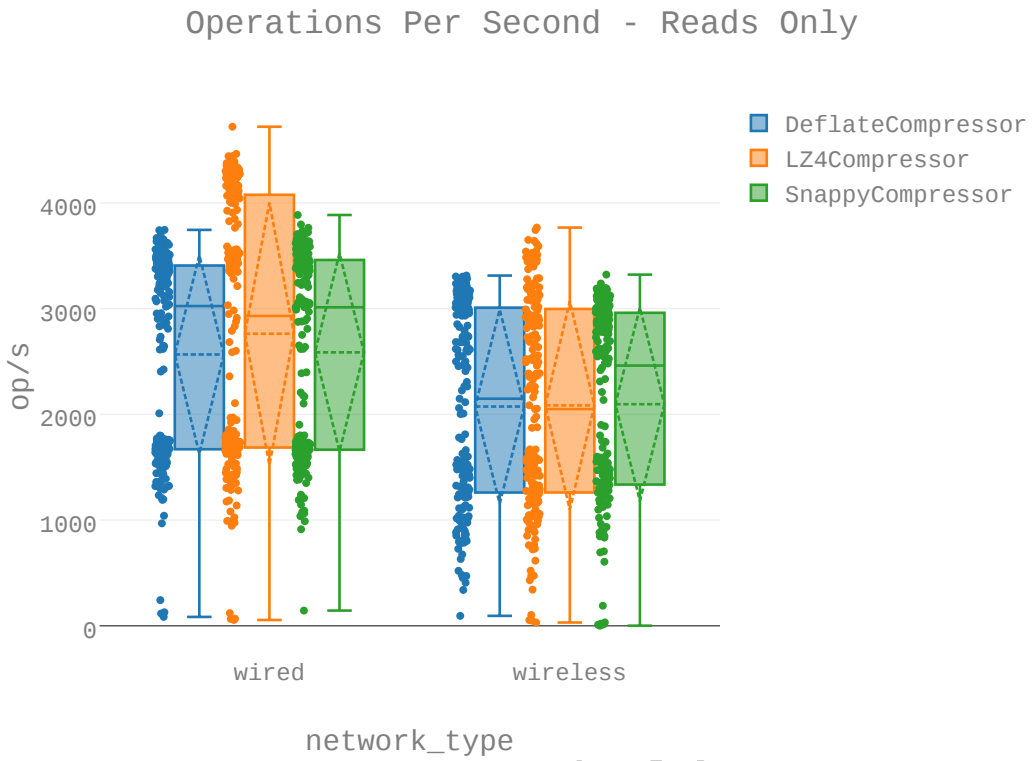

Figure 6. Varying Compression Methods: Reads ... Results are grouped by wired and wireless LAN configurations. From top to bottom, the solid horizontal lines of each box represent the maximum, 75 percentile, median, 25 percentile, and minimum. The dashed horizontal line represents the mean. The oblique dashed lines represent the standard deviation. The plotted points to the left of each box represent the actual data points.

its results by replicating part of Abramovas study. The extent of the details of the network in [1] is detailed below:

"The characteristics of nodes used are, as follows: Node 1 Dual Core (3.4 GHz), 2GB RAM and disk with 7200 rpm; Node 2 Dual Core (3.4 GHz), 2GB RAM and disk with 7200 rpm; Node 3 Dual Core (3.4 GHz), 2GB RAM and disk with 7200 rpm; Node 4 Dual Core (3.0 GHz), 2GB RAM and disk with 7200 rpm; Node 5 Dual Core (3.0 GHz), 2GB RAM and disk with 7200 rpm; Node 6 Virtual Machine with one Core (3.4 GHz), 2GB RAM and disk with 7200 rpm." [1]

The results of Workloads A, C, and E in [1] are depicted in Figures 7, 8, and 9 respectively, all depicting a positive correlation between execution time and the

number of nodes. The actual values are depicted in Table 3.

3.3 Objective of This Set of Experiments

The objective of this experiment is to characterize varying configurations for Cassandra. This characterization will be in service of assessing the utility of Cassandra on the Raspberry Pi 2, which will in turn be an indicator toward the greater population of both distributed databases, archetype Cassandra, and hardware of archetype Raspberry Pi.

We aim to recreate results in [1] and then extend these experiments for a better characterization for IoT. In doing so, we answer the following research questions:

- Research Question 1: How much is the execution time for a given number of operations extended in the system under test using workload A (reads/updates)?
- Research Question 2: How much is the execution time for a given number of operations extended in the system under test using workload C (reads)?
- Research Question 3: How much is the execution time for a given number of operations extended in the system under test using workload E (insert/scans)?

Nodes	Workload	[OVERALL] RunTime(ms)
1	A	58430
3	A	65650
6	A	87310
1	C	88000
3	C	90210
6	C	118090
1	E	223180
3	E	330820
6	E	404660

Table 3. Results from [1] for 1 million record size database

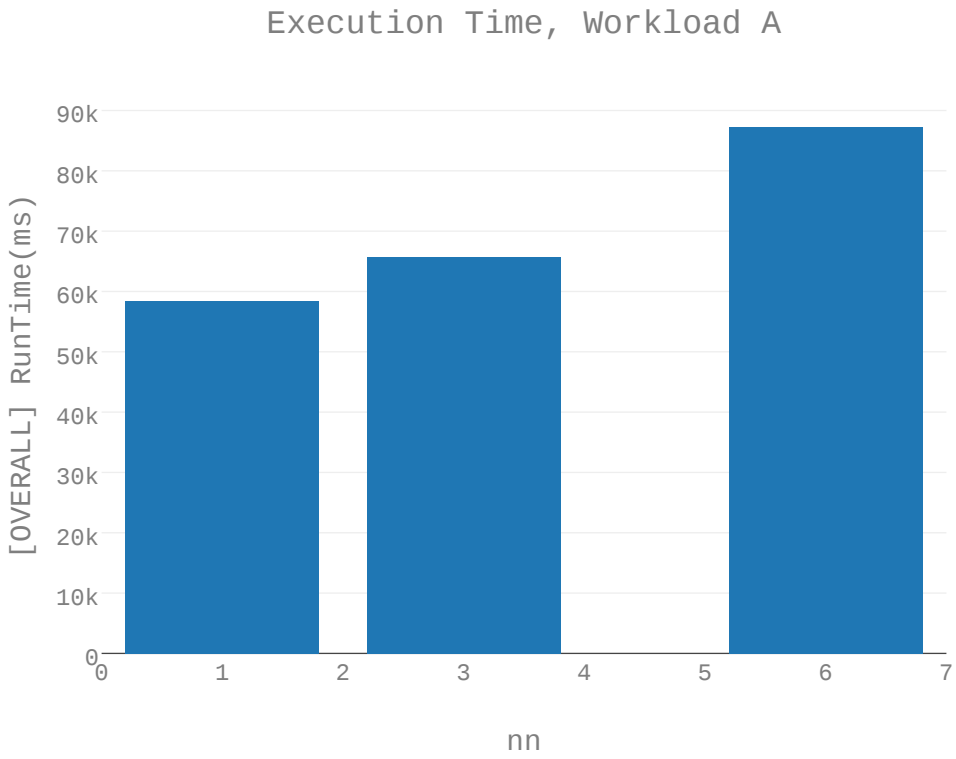

Figure 7. Cross Section of Results Imported from [1]. This figure shows the execution time reported for 10,000 operations of Workload A over three given configurations: a network with only one (1) node, a network with 3 nodes, and a network with 6 nodes.

- Research Question 4: And finally, how much is the execution time for a given number of operations extended in the system under test using custom workload I, the anticipated representative of in-situ distributed database IoT application?

To answer each of these questions, we pose the following questions:

- How do the results from virtual machine compare to the corresponding values from [1]?
- How do the results compare among the various RAM levels assigned to virtual machines?
- How do the results from the limited hardware on an Ethernet LAN scale as the cluster size increases?

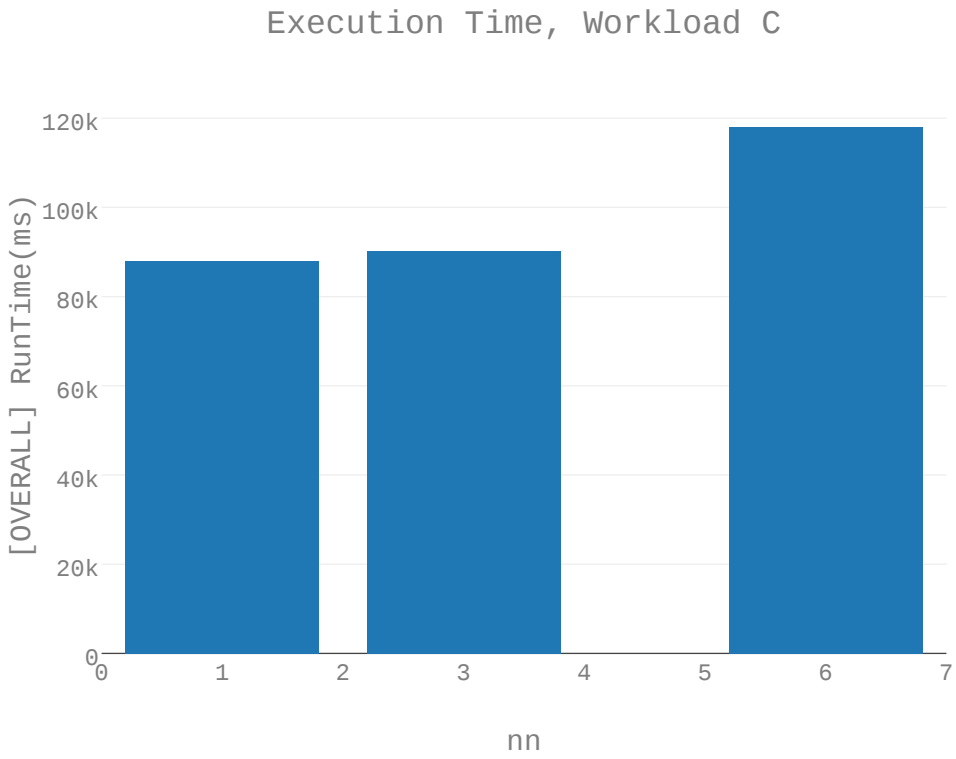

Figure 8. Cross Section of Results Imported from [1]. This figure shows the execution time reported for 10,000 operations of Workload C over three given configurations: a network with only one (1) node, a network with 3 nodes, and a network with 6 nodes.

- How do the results from the limited hardware on an Ethernet LAN compare to the corresponding values from [1]?
- How do the results from the limited hardware on an Ethernet LAN compare to the corresponding virtual machine results?
- How do the results from the limited hardware on a wireless LAN scale as the cluster size increases?
- How do the results from the limited hardware on an Ethernet LAN compare to that of the limited hardware on a wireless LAN?

The results of these experiments are anticipated to be within reasonable bounds of previous work [1]. Increasing the cluster size will result in an increase in execution

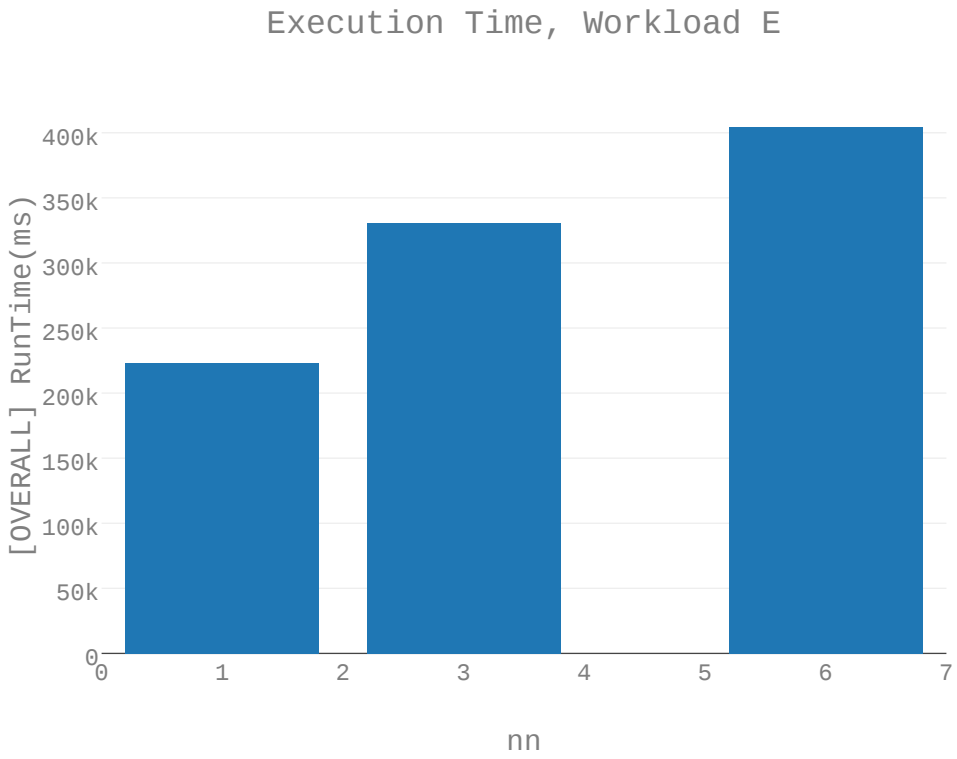

Figure 9. Cross Section of Results Imported from [1]. This figure shows the execution time reported for 10,000 operations of Workload E over three given configurations: a network with only one (1) node, a network with 3 nodes, and a network with 6 nodes.

time. Wireless links will cost significantly in performance compared to their wired counterparts.

3.4 Testbed Environment

3.4.1 System Boundaries.

Virtual machine nodes were contained in a single laptop. The wired LAN experiments were performed with all nodes and the associated router within about 3 meters of one another on a dedicated LAN. Likewise, the wireless LAN experiments were performed with all nodes and the router within a radius of 3 meters on a dedicated and secured LAN. The experiments were done in a residential, suburban area. The network was periodically monitored for unexpected hosts.

3.4.2 Experimental Limitations, Nuisance Factors, Known/Suspected Interactions.

The amount of interference on the industrial, scientific, and medical (ISM) band could not be controlled. It is left to the assumptions that any variation in interference was negligible between any two trials.

The laptop running the YCSB may have been running other minor programs or other processes to a limited extent. No experiments were done to determine if this would have a significant effect, and this was not strictly controlled.

3.4.3 Coordination and Networking.

On an Ethernet LAN, no coordination was needed. This network was physically isolated and no additional traffic was expected to interfere with it. On a wireless LAN, because the scale and timing of this experiment was limited, there was no formal coordination needed. However, because a larger experiment could possibly fill up one (or more) frequency channels, one must be courteous of the environment. An extended test would not be appropriate in an uncontrolled environment.

Ethernet LAN Setup.

The wiring of the Ethernet LAN is depicted in Figure 10. Note that for the Ethernet set up, the wireless capability for the home router was switched OFF.

All nodes, including the laptop used to execute the YCSB, were on the same network. Their IP addresses are listed in Table 4.

802.11 LAN Setup.

Table 6 describes the local area network as the wireless the. Note that for this setup, the Ethernet cables were physically unplugged.

Node	Host Name	IP Address	Model
Node 1	raspberrypi0	192.168.1.100	2B
Node 2	raspberrypi1	192.168.1.101	2B
Node 3	raspberrypi2	192.168.1.102	2B
Node 4	raspberrypi3	192.168.1.103	2B
Node 5	raspberrypi4	192.168.1.104	2B
Node 6	raspberrypi9	192.168.1.109	3
Laptop	daniel-ThinkPad-W541	192.168.1.200	-

Table 4. This table describes the IP addresses in order to paint a further detailed understanding of network set up. The netmask is 255.255.255.0

Node	Host Name	IP Address
Node 1	c0	192.168.56.100
Node 2	c1	192.168.56.101
Node 3	c2	192.168.56.102
Node 4	c3	192.168.56.103
Node 5	c4	192.168.56.104
Node 6	c5	192.168.56.105
Laptop	daniel-ThinkPad-W541	192.168.56.200

Table 5. This table describes the IP addresses in order to paint a further detailed understanding of network set up. The netmask is 255.255.255.0

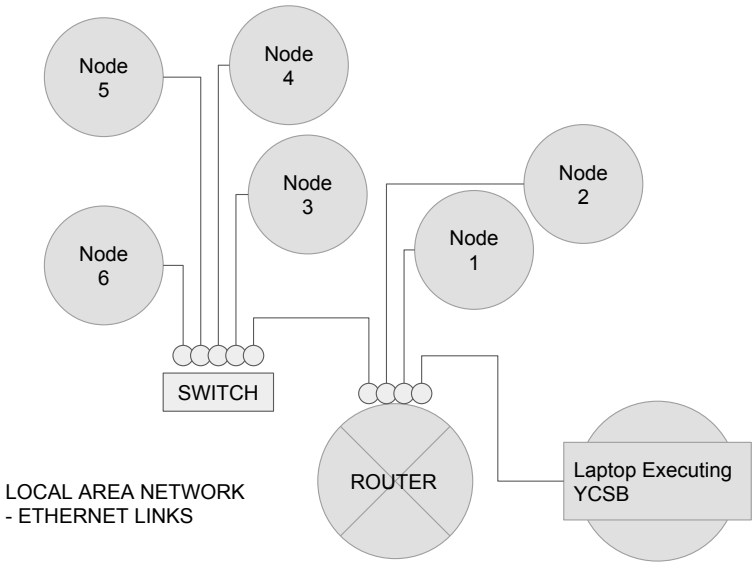

Figure 10. Topology and Wiring for Ethernet Setup

To enable wireless links on the Raspberry Pi 2's, the Wi-Pi Universal Serial Bus (USB) module was utilized, with transmission speed capabilities listed at "11b 1/2/5.5/11Mbps, 11g 6/9/12/18/24/36/48/54Mbps, 11n up to 150Mbps". The Raspberry Pi 3 model comes with its own built-in WiFi capabilities.

Node	Host Name	IP Address
Node 1	raspberrypi0	192.168.1.130
Node 2	raspberrypi1	192.168.1.131
Node 3	raspberrypi2	192.168.1.132
Node 4	raspberrypi3	192.168.1.133
Node 5	raspberrypi4	192.168.1.134
Node 6	raspberrypi9	192.168.1.139
Laptop	daniel-ThinkPad-W541	192.168.1.200

Table 6. This table describes the IP addresses in order to paint a further detailed understanding of network set up. The netmask is 255.255.255.0

3.4.4 Treatments, Independent Variables.

The independent variables of interest are the node type and link type. Node type is characterized by memory, or RAM, processor speed, and I/O rates, and are represented by virtual nodes and the Raspberry Pi.

The link types are the internal nodes on the virtual machine network, Ethernet links, and wireless 802.11 links.

There are many other factors at work, but other factors, like workload, are only varied to give appropriate context to the variance in node type and link type.

3.4.5 Configuration of Cassandra.

Unless otherwise specified, the configuration of Cassandra, the keyspace, and the table within the keyspace are all held constant to their default values. All three of these things can be configured hierarchically, and their configuration can affect the performance of Cassandra on a given load. A skillful adjustment of these parameters can result in an optimized performance of Cassandra.

This paper aims to highlight the differences in varying hardware, and thus the exact configuration, despite that it might raise the absolute level of performance, is not expected to elevate the relative level of performance one would see shifting between, say a virtual node on a laptop and a Raspberry Pi module.

There are a few settings that had to be taken into account. Denoted *commitlog_total_space_in_mb*, this will accumulate to an undesired level. This was set to 512 MB in the Cassandra configuration file, cassandra.yaml. (Changing this to 256 MB for the 512 RAM case did not correct the error mentioned above.) Also, to prevent the accumulation of space, the setting *auto_snapshot* to false in configuration file cassandra.yaml. Having *auto_snapshot* set to true automatically backs up, or saves a snapshot of, the data on Cassandra. For a limited-capacity node, this would quickly lead to a crash.

The configuration files can be found among the appendices.

3.5 Experimental Setup

In this experiment, we measure the total run time of a fixed number of operations of Workload A for various memory sizes. The choice of memory size is due to the expectations of IoT devices. The Raspberry Pi 2 and 3 have 1GB of memory and is our representative technology for IoT. The 4GB configuration can be considered be more representative of a low-end desktop, laptops, or virtual machine. The 2GB configuration is an intermediate stage that show an intermediate performance level and naturally, may represent the aim of future of IoT nodes. In addition, [1] used 2GB machines, which may help this work to be compared against existing work.

The experiments performed can be summarized in Table 7.

3.5.1 Virtual Node Setup.

For this work, virtual nodes were created to match these characteristics to a reasonable extent. Facing minimal propagation delay due to being connected on a nodal network, experiments with the virtual machines seek to place an upper limit on potential IoT performance expectations. Replicating the exact network in [1] is not absolutely necessarily, notwithstanding the details and materials available to do

Communication (nm)	Platform (nt)	Assigned RAM
Nodal	Virtual Machine	1 GB
Nodal	Virtual Machine	2 GB
Nodal	Virtual Machine	4 GB
Ethernet LAN	Raspberry Pi	1 GB
802.11 LAN	Raspberry Pi	1 GB

Table 7. This table summarizes each network topology that was explored in each research question. The RAM was varied on the Virtual Machines.

so are unavailable.

On a 64-bit 31.1GiB RAM laptop with Intel Core i7-4910MQ 2.90GHz 8-core central processing unit, six (6) identical virtual machines were created in software VirtualBox. Each machine consisted of Ubuntu 64 bit machine was was allocated 8 GB of hard drive disk space. The full details for these machines, reported by means of the lshw Linux command, are located among the appendices. Also in VirtualBox, a host-only network entitled vboxnet0 was instantiated, to which all six machines were connected.

The YCSB was installed and run on the host laptop. PyCharm drove a terminal process, which in turn drove the YCSB software.

To further paint the picture of the network setup, the IP addresses are included in Table 5.

3.5.2 Other Factors.

The manufacturer and model for each SD card was kept constant for each node. The details can be found in Table 8.

This work assumes that an in-situ storage application in the realm of IoT implies a small database, in this case represented by 1 million records, as opposed to 10 million or 100 million or more. Although Abramovas paper seems to imply there is feasibility for large database with many, many nodes given the right balance, this work focuses

Specification	Value
Capacity	16 GB
Read Speed	up to 90 MB/s
Write Speed	up to 40 MB/s
Video Speed	C10 U3

Table 8. Specifications for SD Cards

more on the initial impact to performance of introducing less-capable hardware in order to lighten costs or actual physical weight for an application that would see this as a benefit.

3.5.3 Number of Operations Per Trial.

The results in [1] report an execution time after 10,000 operations, and the decision was made to keep this constant rather than vary the representative number of operations. No explicit justification is given in [1] for the number 10,000, but it can be inferred that is a compromise between under-sampling and an undue burden in time spent sampling.

As a brief exploration into the possbility of under-sampling, one can take a look at what it might look like to vary the sample size in a given trial, and how the execution time would vary over the sequence of trials. The graph above shows this for two different configurations: 1GB and 4GB RAM on a virtual machine. As expected, the execution time does reflect initial cache warm-up time, but then, more or less, reflects some sort of steady state, albeit oscillating performance. It was also not made explicit whether or not the 10,000 operations represented one of many trials of 10,000 or represented a single and only trial. For the purposes of exploring the data, this author chose to run 30 trials of 10,000 operations each.

The oscillating behavior seen in trials 5 through 120 of Figure 11 is distracting and risks inaccurate comparisons among configurations. Although it is beyond the scope of this paper to determine the exact cause of this oscillation, one might consider that activities required for the operation of the database, such as compaction, the gossip protocol, and other operations compete with the reads and will contribute to continuous variation over time, and may affect performance measurements. The reason for choosing 10,000 operations is not explicitly reported in [1], but one may

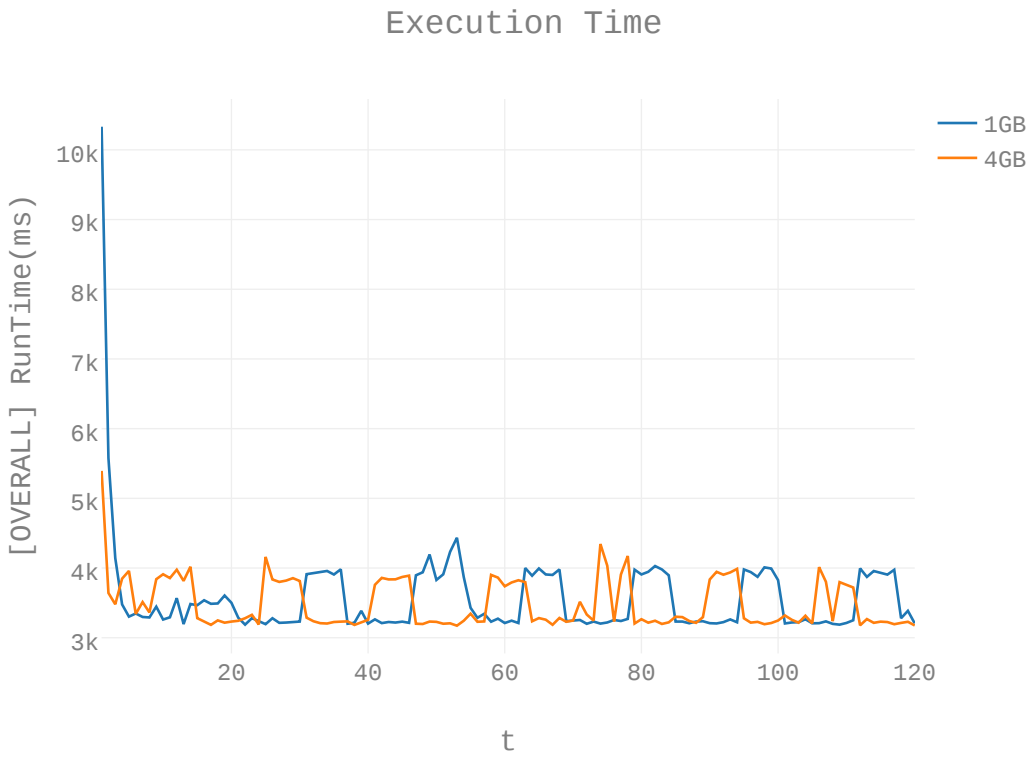

Figure 11. Two sample runs, adjusting the trials such that only 1000 operations of Workload A to a given trial. Once the cache is warmed up, it can be seen that for both series, there is a periodicity present with respect to the progress of trials. In an experiment concerned with steady state performance and overall trends, such oscillation may be an undue distraction.

infer the reason is to integrate this variation to make better comparisons among configurations.

Contrast the 1k operation trials with the 10k operation trials depicted in Figure 12. Here, at least with the naked eye, there is no oscillation, and most certainly not to the extent seen in the 1k trial case. Whatever effected the oscillating behavior in the previous graph is integrated into the 10k trial case and is no longer a distraction to steady-state analysis, as each 10k operation trial soaks up, or rather integrates, the performance of quantity 10 1k operation trials. Of course, more operations take longer to run, and thus the cost in testing time starts to curtail the value of integrating more trials.

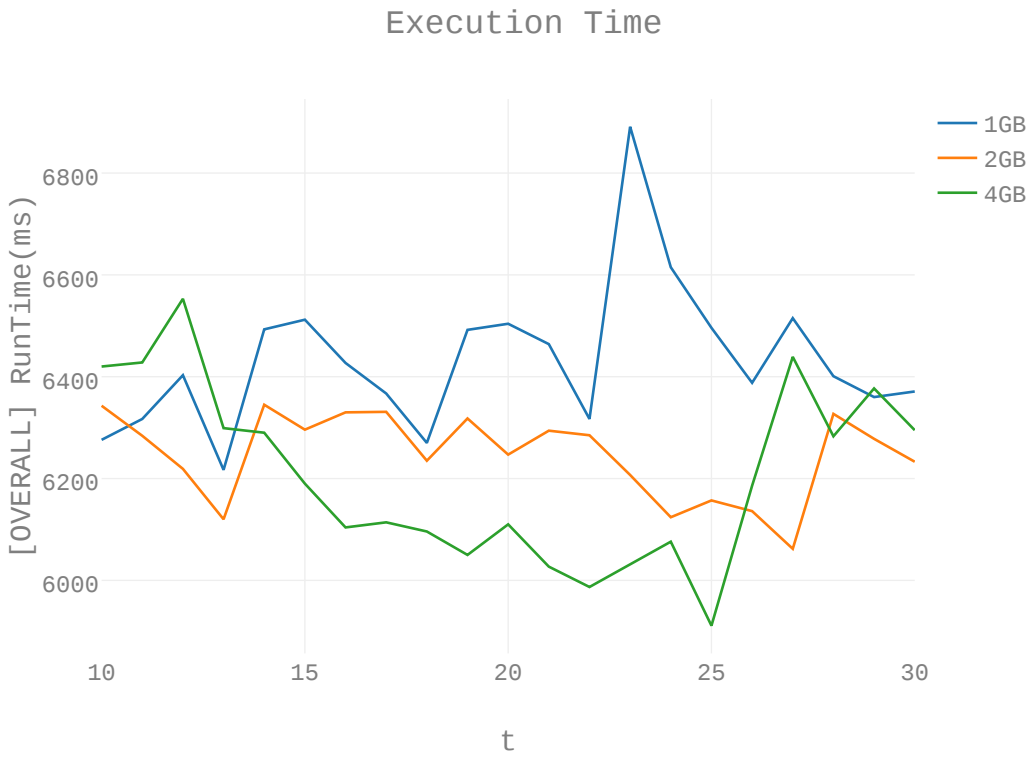

Figure 12. A series of trials for 1GB, 2GB, and 4GB RAM virtual machines. The inset demonstrates that any pattern that could significantly distinguish one trial from another, such as the oscillation seen in Figure 11 is integrated such that, after the cache warm-up period, the relative position of the trial does not predict the relative outcome.

3.5.4 Workloads.

Just as in [1], standard workloads A, C, and E were put to the test, while B, D, and F are de-prioritized. In addition, this paper introduces a custom workload, denoted I, to represent an IoT application, many inserts and few reads, a 99 percent to 1 percent ratio.

Standard workloads A, C, and E, from the YCSB are summarized in Table 9.

3.5.5 Threads in the YCSB.

The number of threads was kept constant at 1, although by increasing the number of threads one could achieve greater throughput. However, since it was desired to

Workload	Read	Update	Scan
A	0.5	0.5	0.0
C	1.0	0.0	0.0
E	0.0	0.0	0.95

Table 9. Standard YCSB workloads used in this methodology. Workload A consists of 50 percent reads and 50 percent updates. Workload C consists of 100 percent reads. Workload E consists of 100 percent scans.

Workload	Read	Update	Scan	Insert
A	0.50	0.50	0.00	0.00
C	1.00	0.00	0.00	0.00
E	0.00	0.00	0.95	0.05
I	0.01	0.00	0.00	0.99

Table 10. Standard YCSB workloads used in this methodology. Workload A consists of 50 percent reads and 50 percent updates. Workload C consists of 100 percent reads. Workload E consists of 100 percent scans. In addition, a custom workload I is summarized, which consists of 99 percent writes and 1 percent reads to represent IoT.

compare different calculations, the default was retained for all configurations.

It may be worth noting that for loads, this number was increased for practical reasons. However, these preparatory loads were not measured in these experiments, only the defined workloads A, C, E, and custom workload I.

3.5.6 Assumptions.

Naturally, in order to perform the experiment and evaluate the results, some assumptions had to be made. Investigation into any of these assumptions may be an avenue for future work.

1. The benchmark represents the application, which assumes a simple schema. In other words, Cassandra's performance is not particularly sensitive to the schema.

2. There is no active attacker or intrusion into the local area networks. Both the

local area networks are isolated.

3. There are no errors with the custom benchmark that would skew the results. Any error is due to the fact that the system's limits have been reached.

4. There are no bugs in the benchmark that would skew the results.

5. Effects on the network due to distance are negligible.

6. This experiment assumes that nodes are homogeneous. The basis for this assumption is that all nodes have been specified to the same model of Raspberry Pi 2. The same make and model for the SD Cards have been used. The image upon the SD Cards has been copied and only adjusted to account for specific, differentiated IP addresses.

7. This experiment assumes an uninterrupted power supply. Power is not measured nor accounted for in the model. As long as the power has been turned on, it stays on, and fluctuations in voltage or any kind of imperfections in the power supply are negligible with respect to Cassandra's performance.

8. Although the ISM band is unregulated, this experiment assumes invariant interference from other emitters. The experiment assumes an urban to suburban environment. In other words, congestion that overwhelms Cassandra's performance can be assumed to be rare with respect to the population, and is ignored for the purposes of the experiment.

3.6 Execution and Analysis

The YCSB, installed on the host laptop, is also run from the host laptop. The YCSB can be run from the terminal, but for convenience, a Python script was developed to drive a series terminal processes.

For each experiment, the trials for each configuration will be reported as a summary of execution times for 10,000 operations. All execution times will be reported in milliseconds.

The YCSB reports a number of measured values, including operations per second and latency distribution (minimum, mean, 50 percentile or median, 75 percentile, 99 percentile, maximum). The total execution time in milliseconds was chosen in order to keep the measured values true to the limits of the experiment. Although this paper aims to analyze results to reflect the steady state, this paper does not deny the possibility that variance in operations per second or variance in latency may result from variance in the number of operations per trial.

Also, one can note in both Figure 11 and Figure 12, that in the first five trials or so, one can observe the cache warm-up period. This steep decline is expected due to the effect of the key cache, which is at its default setting: Cassandra sets the key cache to the either 5% of the heap, or 100 MB, whichever is less. In [1], the key cache is reported to be at 100 MB. The steady state operation is dependent on the keys requested, so for a workload like the YCSB, one would not expect a lot of variation.

Truncating the head of the trials, trials 1 though 9, the cache effect is no longer depicted, rendering an expectation of steady-state performance after cache warm-up. This is necessary to meet the assumptions of any ANOVA test.

Taking the issues of oscillating behavior and cache warm-up period into account, we can remove them to find a stable viewing window into the behavior of the Cassandra database, as depicted in Figure 12. Figure 12 shows the desired observation of the behavior in question for 1GB, 2GB ad 4GB memory sizes. We use this data to recreate Abramovas work and extend it for other memory sizes.

This is also the logic behind using the median to summarize the execution times, which should not differ significantly whether the cache warm-up trials are included

or not.

Another important observation here, is that once the cache effect is cropped out, there is no obvious correlation between trials and the performance measurement. This further supports that 10,000 operations, minus cache effect, does represent a steady state that is likely to extend beyond 10,000 operations.

IV. Results and Evaluation

4.1 Introduction and Overview

This section will report and display the results from the resulting experiments described in III For standard workloads A, C, an E, as well as custom workload I, the results will be displayed in both graph and table format. First, the results of the virtual machine will be compared to its analogy in [1]. Second, the results among the varying RAM will be compared. Third, the results of implementing the workload on the Raspberry Pi will be reported. Fourth, the Raspberry Pi results will be compared against the system in [1]. Fifth, the Raspberry Pi results will be compared against the corresponding virtual machine. Sixth, the results from the wireless network, using the Raspberry Pi nodes, will be explored. Finally, seventh, the wired and wireless results will be compared.

4.2 Results for Workload A

4.2.1 Comparing Existing Work: Virtual Machine vs the Reference Value.

It is of interest to compare the performance of the virtual machine to that of the reported value. The results are depicted in Figure 14. For a node cluster size of 1, the experimental values fell within 52368.0 milliseconds, or about 52 second(s), of the value reported, which was 58430 milliseconds, or about 58 second(s). For a node cluster size of 3, the experimental values fell within 55415.0 milliseconds, or about 55 second(s), of the value reported, which was 65650 milliseconds, or about 1 minute(s). For a node cluster size of 6, the experimental values fell within 73280.0 milliseconds, or about 1.2 minute(s), of the value reported, which was 87310 milliseconds, or about 1 minute(s). Overall, the experimental values fell within 73280.0 milliseconds, or

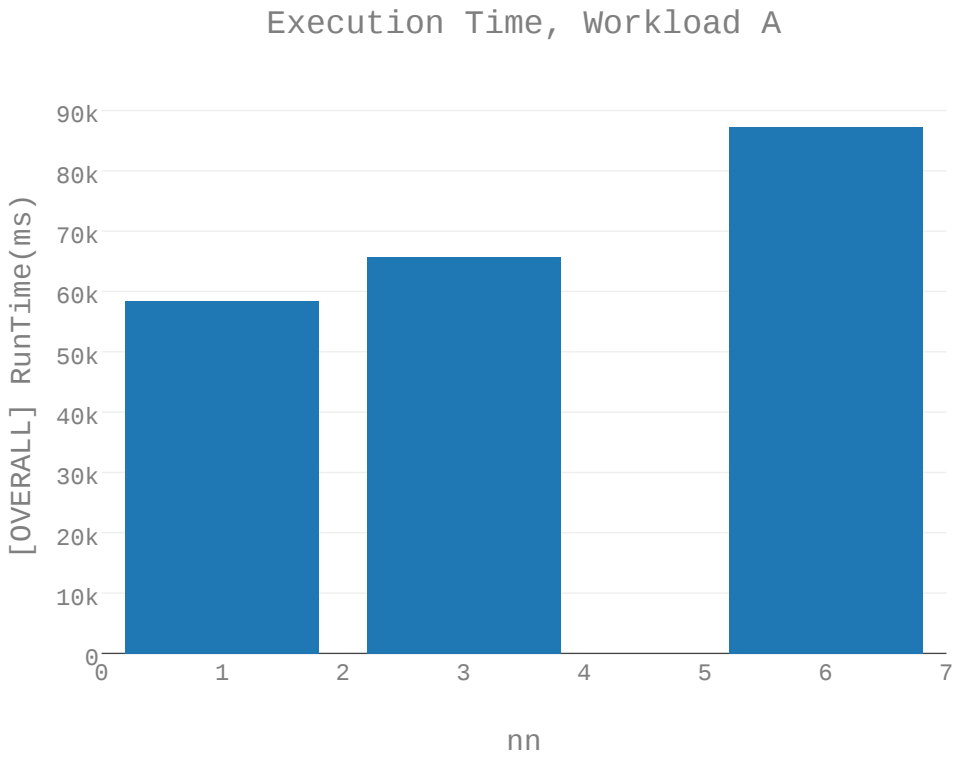

Figure 13. This plot shows the execution times imported from [1].

about 1.2 minute(s), of the corresponding reference value. The full summary of the

nn	1	3	6	OVERALL
count	21	21	21	63
mean	5.2e+04	5.5e+04	7.3e+04	6e+04
std	84	2.2e+02	1.7e+02	9.3e+03
min	5.2e+04	5.5e+04	7.3e+04	5.2e+04
25%	5.2e+04	5.5e+04	7.3e+04	5.2e+04
50%	5.2e+04	5.5e+04	7.3e+04	5.5e+04
75%	5.2e+04	5.5e+04	7.3e+04	7.3e+04
max	5.2e+04	5.5e+04	7.3e+04	7.3e+04

Table 11. Summary of the absolute value of the differences between the empirical execution time on the Virtual Machine clusters and the corresponding execution time reported in [1]

differences are reported in Table 11.

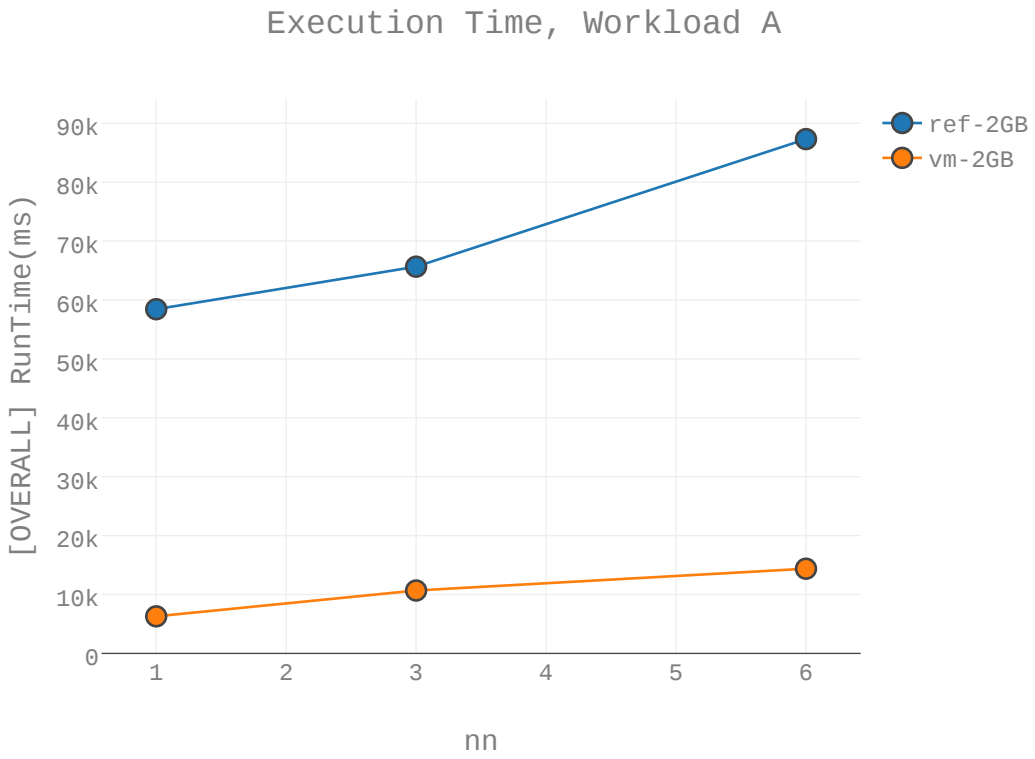

Figure 14. This compares the 2GB virtual machine with the corresponding value from [1].

4.2.2 1GB RAM vs 2GB RAM vs 4GB RAM.

The results are depicted in Figure 15.

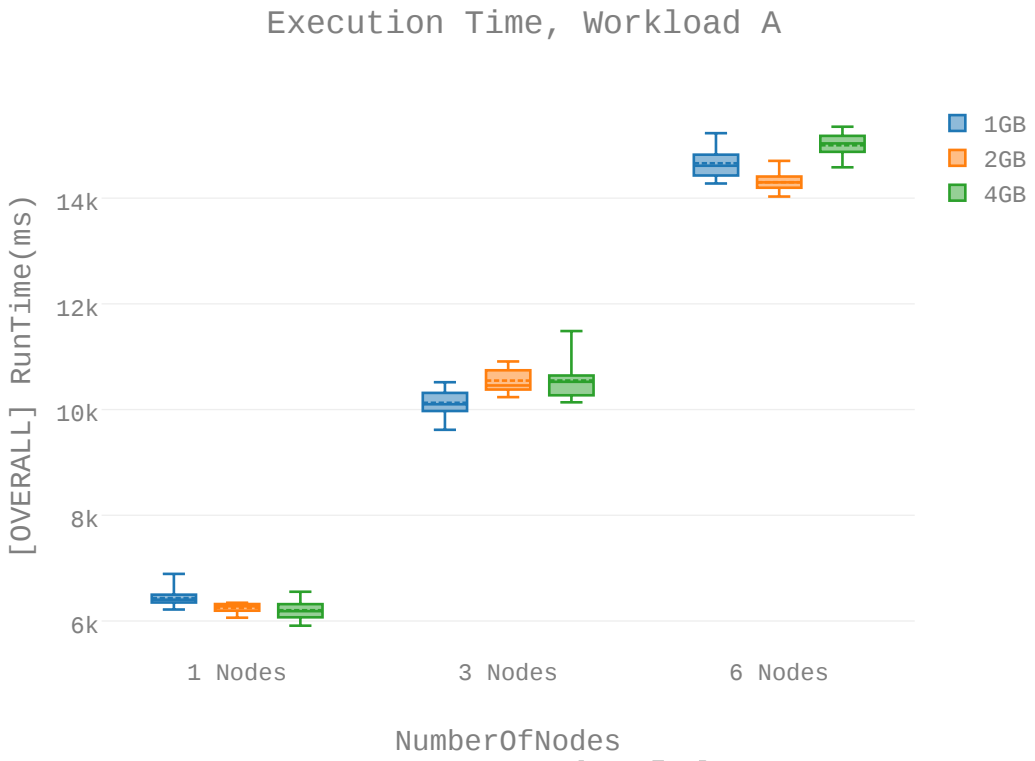

Figure 15. Execution time for virtual machines with 1GB, 2GB, and 4GB of RAM. The first 9 trials have been removed in order to filter out the trials representing cache effect and thus represents the steady state.

index	ram1GB	ram2GB	ram4GB
count	21	21	21
mean	6433.14	6246.24	6203.14
std	144.084	84.0255	174.375
min	6217	6062	5911
25%	6360	6207	6076
50%	6403	6278	6186
75%	6496	6318	6299
max	6891	6345	6553
range	674	283	642

Table 12. Summary Statistics for 1-Node Configuration. All values represented fall between 5911.0 ms and 6891.0 ms, or rather within a span of 980.0 ms.

index	ram1GB	ram2GB	ram4GB
count	21	21	21
mean	10127.9	10548.1	10549.1
std	229.485	221.21	336.981
min	9617	10235	10137
25%	9973	10382	10275
50%	10100	10456	10525
75%	10302	10735	10640
max	10517	10910	11485
range	900	675	1348

Table 13. Summary Statistics for 3-Node Configuration. All values represented fall between 9617.0 ms and 11485.0 ms, or rather within a span of 1868.0 ms.

index	ram1GB	ram2GB	ram4GB
count	21	21	21
mean	14659.3	14300.5	15000
std	266.999	166.709	216.828
min	14277	14030	14583
25%	14432	14200	14876
50%	14613	14298	15035
75%	14802	14407	15177
max	15229	14705	15351
range	952	675	768

Table 14. Summary Statistics for 6-Node Configuration. All values represented fall between 14030.0 ms and 15351.0 ms, or rather within a span of 1321.0 ms.

The results are summarized in Tables 12, 13, and 14.

4.2.3 Implementation on Raspberry Pi.

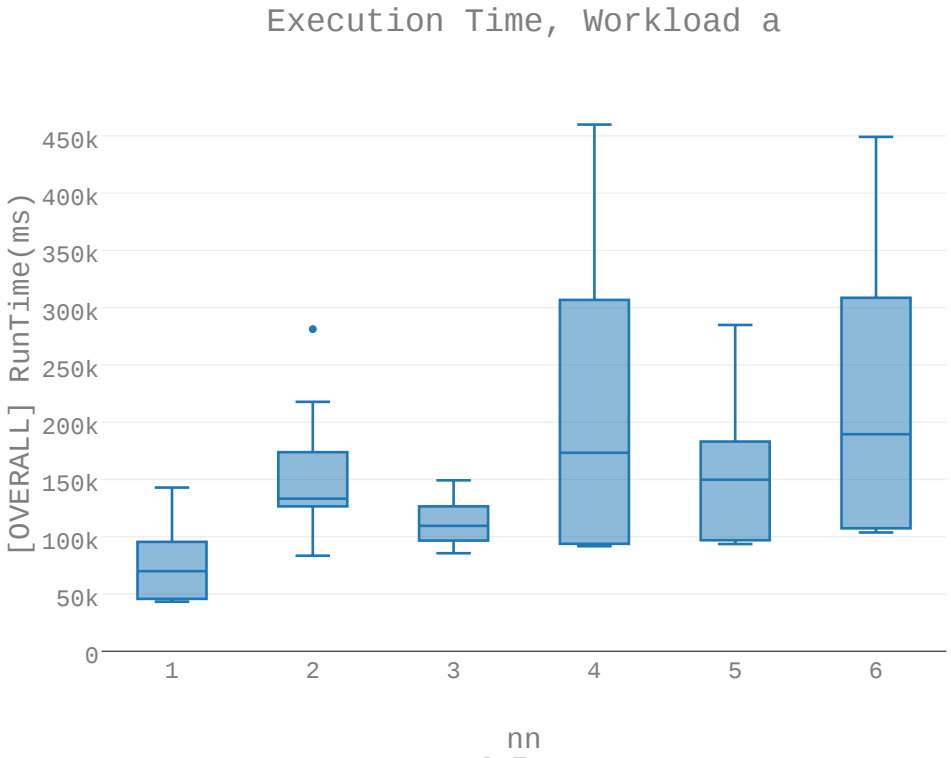

Figure 16. Results of limited hardware, the Raspberry Pi, on an Ethernet LAN. Execution time is plotted over cluster size.

This section summarizes the results from running Workload a on Raspberry Pi clusters networked via an Ethernet LAN. The results are depicted in Figure 16. For a node cluster size of 1, the median execution time was 45619.0 milliseconds, or about 46 second(s), and all execution times fell within 43260.0 milliseconds, or about 43 second(s), and 48123.0 milliseconds, or about 48 second(s), inclusive. For a node cluster size of 2, the median execution time was 127945.0 milliseconds, or about 2.1 minute(s), and all execution times fell within 117205.0 milliseconds, or about 2 minute(s), and 131722.0 milliseconds, or about 2.2 minute(s), inclusive. For a node cluster size of 3, the median execution time was 97096.0 milliseconds, or about 1.6 minute(s), and all execution times fell within 93702.0 milliseconds, or about 1.6 minute(s), and 100501.0

milliseconds, or about 1.7 minute(s), inclusive. For a node cluster size of 4, the median execution time was 94190.0 milliseconds, or about 1.6 minute(s), and all execution times fell within 92620.0 milliseconds, or about 1.5 minute(s), and 96195.0 milliseconds, or about 1.6 minute(s), inclusive. For a node cluster size of 5, the median execution time was 96377.0 milliseconds, or about 1.6 minute(s), and all execution times fell within 93668.0 milliseconds, or about 1.6 minute(s), and 98582.0 milliseconds, or about 1.6 minute(s), inclusive. For a node cluster size of 6, the median execution time was 106718.0 milliseconds, or about 1.8 minute(s), and all execution times fell within 103728.0 milliseconds, or about 1.7 minute(s), and 111002.0 milliseconds, or about 1.9 minute(s), inclusive. Overall, the median execution time was 96827.5 milliseconds, or about 1.6 minute(s), and all execution times fell within 43260.0 milliseconds, or about 43 second(s), and 131722.0 milliseconds, or about 2.2 minute(s). The full summary

nn	1	2	3	4	5	6	OVERALL
count	21	21	21	21	21	21	126
mean	45595.2	127110	97220.9	94247.2	96367.8	106816	94559.4
std	1121.24	3504.88	1647.78	915.051	1486.71	1784.93	24725.9
min	43260	117205	93702	92620	93668	103728	43260
25%	44922	126363	96382	93593	95656	105630	93904.2
50%	45619	127945	97096	94190	96377	106718	96827.5
75%	46091	129008	97886	94585	97585	107473	106635
max	48123	131722	100501	96195	98582	111002	131722

Table 15. Summary of Workload a executed on Raspberry Pi clusters on an Ethernet LAN

of the differences are reported in Table 15.

4.2.4 Raspberry Pi vs Reference Value.

It is of interest to compare the performance of the Raspberry Pi to that of the reported value. The results are depicted in Figure 17. For a node cluster size of 1, the experimental values fell within 15170.0 milliseconds, or about 15 second(s), of

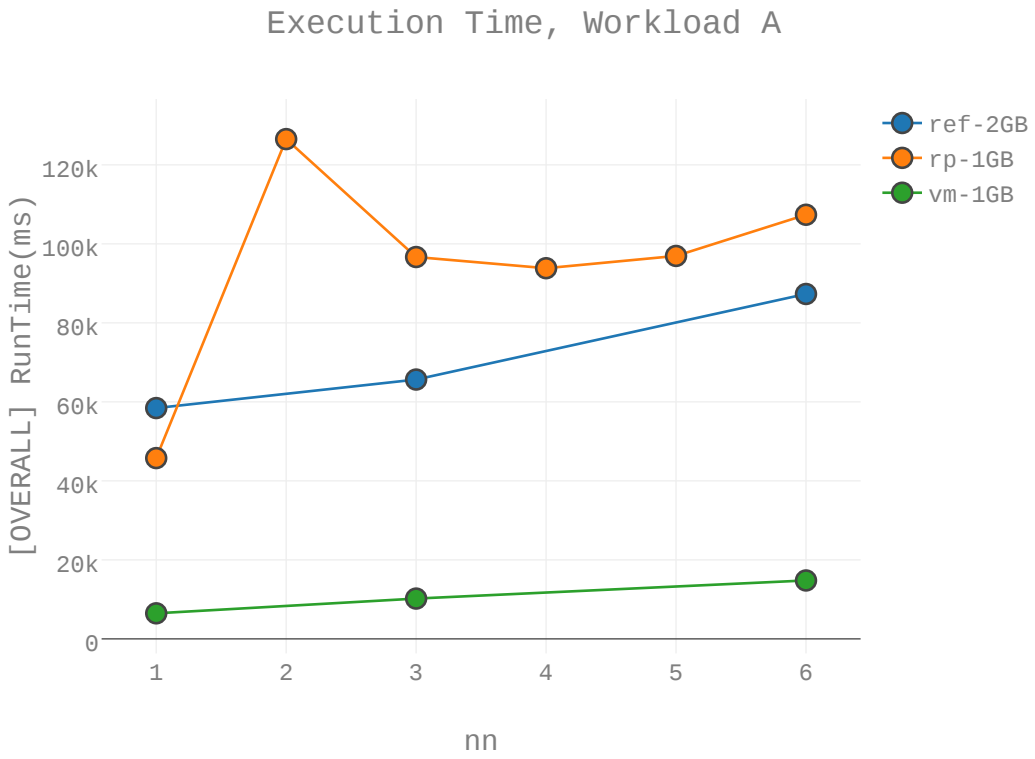

Figure 17. Comparison among the Raspberry Pi nodes (rp-1GB), the results reported in [1], and the virtual nodes with 1GB of RAM.

the value reported, which was 58430 milliseconds, or about 58 second(s). For a node cluster size of 3, the experimental values fell within 34851.0 milliseconds, or about 35 second(s), of the value reported, which was 65650 milliseconds, or about 1 minute(s). For a node cluster size of 6, the experimental values fell within 23692.0 milliseconds, or about 24 second(s), of the value reported, which was 87310 milliseconds, or about 1 minute(s). Overall, the experimental values fell within 34851.0 milliseconds, or about 35 second(s), of the corresponding reference value. The full summary of the differences are reported in Table 16.

nn	1	3	6	OVERALL
count	21	21	21	63
mean	12834.8	31570.9	19505.7	21303.8
std	1121.24	1647.78	1784.93	7962.56
min	10307	28052	16418	10307
25%	12339	30732	18320	13522
50%	12811	31446	19408	19408
75%	13508	32236	20163	30627.5
max	15170	34851	23692	34851

Table 16. Summary of the absolute value of the differences between the empirical execution time on the Raspberry Pi clusters and the corresponding execution time reported in [1]

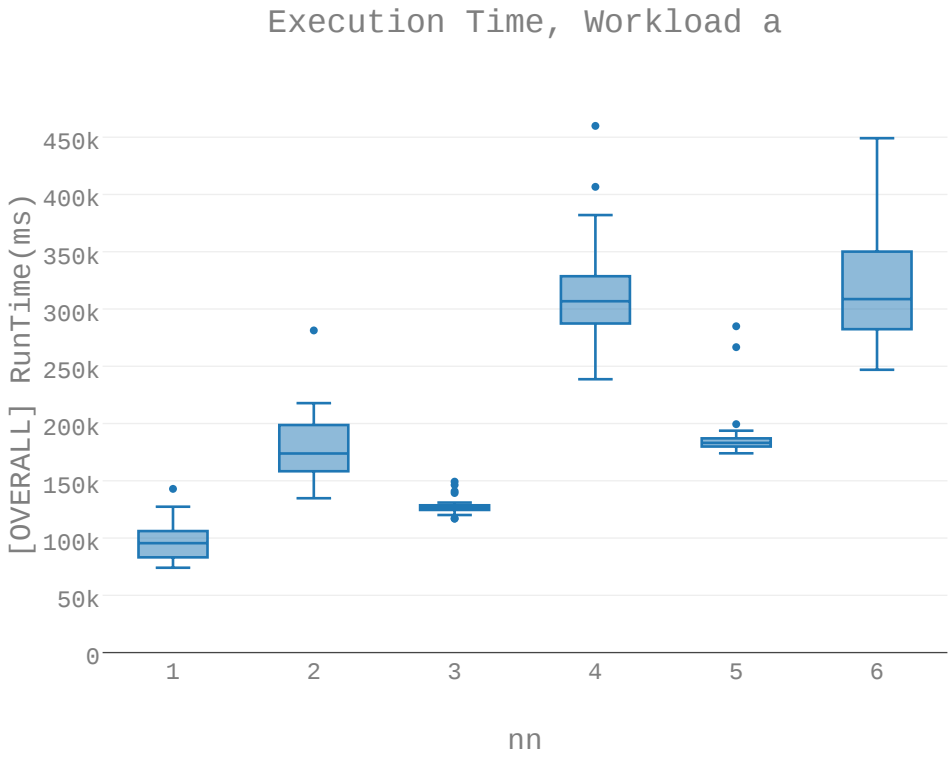

Figure 18. Results of wireless testing. There seems to be a steady climb in execution time as the cluster size increases. Any oscillation cannot be explained with current analysis and would require additional experimentation.

4.2.5 Raspberry Pi vs Virtual Machine.

4.2.6 Wireless Links Only.

This section summarizes the results from running Workload a on Raspberry Pi clusters networked via an Wireless LAN. The results are depicted in Figure 18. For a node cluster size of 1, the median execution time was 89885.0 milliseconds, or about 1.5 minute(s), and all execution times fell within 74072.0 milliseconds, or about 1.2 minute(s), and 119580.0 milliseconds, or about 2 minute(s), inclusive. For a node cluster size of 2, the median execution time was 178471.0 milliseconds, or about 3 minute(s), and all execution times fell within 151046.0 milliseconds, or about 2.5 minute(s), and 281282.0 milliseconds, or about 4.7 minute(s), inclusive. For a node cluster size of 3, the median execution time was 127303.0 milliseconds, or about 2.1 minute(s), and all execution times fell within 123064.0 milliseconds, or about 2.1 minute(s), and 149252.0 milliseconds, or about 2.5 minute(s), inclusive. For a node cluster size of 4, the median execution time was 316364.0 milliseconds, or about 5.3 minute(s), and all execution times fell within 264920.0 milliseconds, or about 4.4 minute(s), and 459882.0 milliseconds, or about 7.7 minute(s), inclusive. For a node cluster size of 5, the median execution time was 181345.0 milliseconds, or about 3 minute(s), and all execution times fell within 173990.0 milliseconds, or about 2.9 minute(s), and 284925.0 milliseconds, or about 4.7 minute(s), inclusive. For a node cluster size of 6, the median execution time was 302271.0 milliseconds, or about 5 minute(s), and all execution times fell within 246945.0 milliseconds, or about 4.1 minute(s), and 355538.0 milliseconds, or about 5.9 minute(s), inclusive. Overall, the median execution time was 181190.5 milliseconds, or about 3 minute(s), and all execution times fell within 74072.0 milliseconds, or about 1.2 minute(s), and 459882.0 milliseconds, or about 7.7 minute(s). The full summary of the differences are reported in Table 17.

nn	1	2	3	4	5	6	OVERALL
count	21	21	21	21	21	21	126
mean	91275	188383	129902	321025	190768	296618	202995
std	12903.4	28519.5	7389.64	44948.4	28706.3	31586.1	87456.6
min	74072	151046	123064	264920	173990	246945	74072
25%	81708	172256	125843	295183	179619	273738	127402
50%	89885	178471	127303	316364	181345	302271	181190
75%	99647	200156	128869	333497	184424	313764	284287
max	119580	281282	149252	459882	284925	355538	459882

Table 17. Summary of Workload A executed on Raspberry Pi clusters on an Wireless LAN

4.2.7 Wireless Links vs Wired Links.

In this section, the median value of the corresponding wired experiment will serve as the reference for the purposes of evaluating the wireless links. Figure 38 depicts the two experiments using Raspberry Pis: a wireless LAN (wlan) and an Ethernet LAN (eth). In Figure 38, as well as previous graphs, one can observe that the Ethernet LAN effects about 50 seconds of execution time for 10,000 operations.

4.3 Results for Workload C

4.3.1 Comparing Existing Work: Virtual Machine vs the Reference Value.

It is of interest to compare the performance of the virtual machine to that of the reported value. The results are depicted in Figure 20. For a node cluster size of 1, the experimental values fell within 82034.0 milliseconds, or about 1.4 minute(s), of the value reported, which was 88000 milliseconds, or about 1 minute(s). For a node cluster size of 3, the experimental values fell within 80361.0 milliseconds, or about 1.3 minute(s), of the value reported, which was 90210 milliseconds, or about 1 minute(s). For a node cluster size of 6, the experimental values fell within 104599.0 milliseconds,

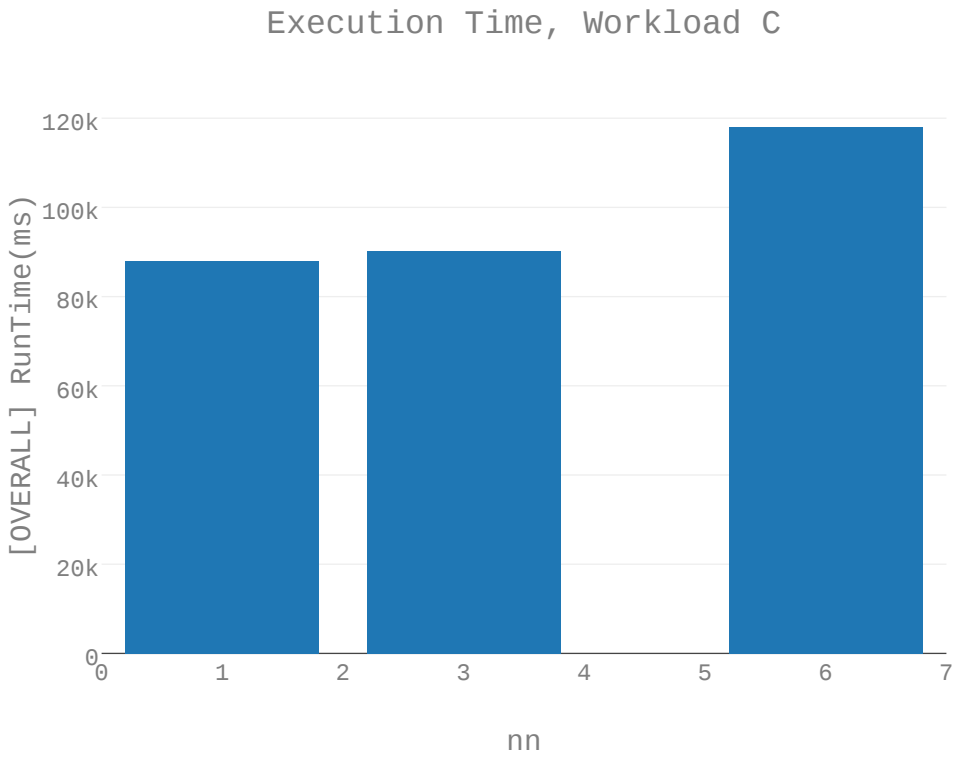

Figure 19. This plot shows the execution times imported from [1].

or about 1.7 minute(s), of the value reported, which was 118090 milliseconds, or about 1 minute(s). Overall, the experimental values fell within 104599.0 milliseconds, or about 1.7 minute(s), of the corresponding reference value. The full summary of the

nn	1	3	6	OVERALL
count	21	21	21	63
mean	81736.3	80070.4	104180	88662.1
std	221.031	180.863	263.331	11084.1
min	81054	79765	103622	79765
25%	81694	79903	104070	80211
50%	81770	80161	104282	81770
75%	81848	80201	104327	103993
max	82034	80361	104599	104599

Table 18. Summary of the absolute value of the differences between the empirical execution time on the Virtual Machine clusters and the corresponding execution time reported in [1]

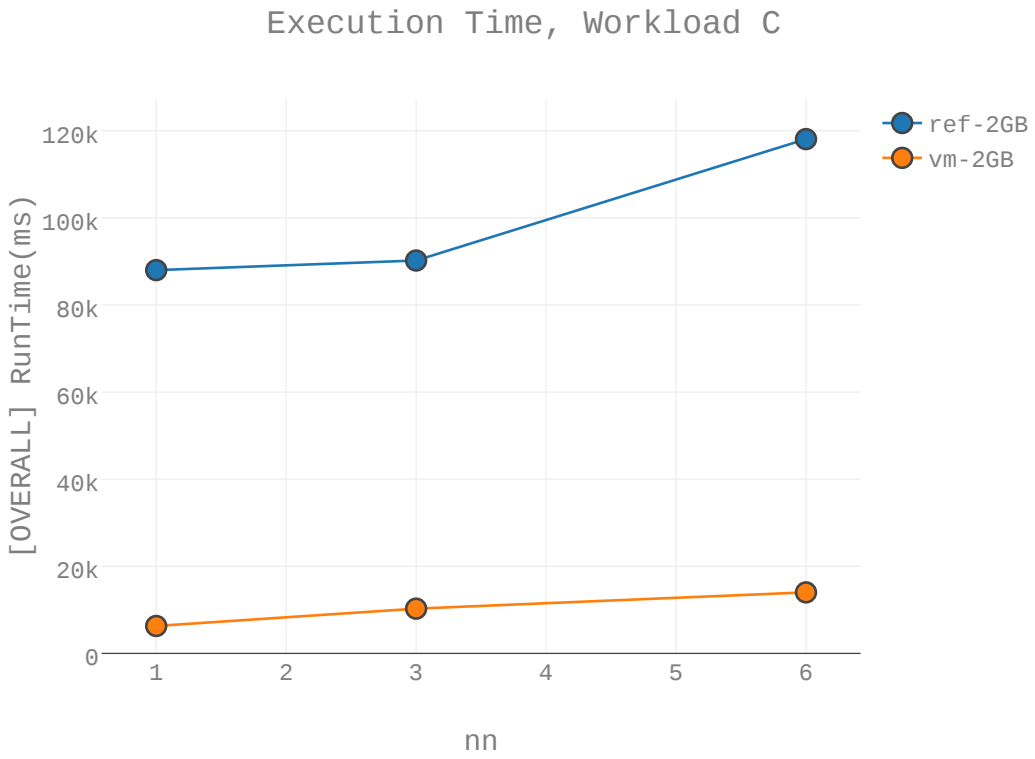

Figure 20. This compares the 2GB virtual machine with the corresponding value from [1].

differences are reported in Table 18.

4.3.2 1GB RAM vs 2GB RAM vs 4GB RAM.

The results are depicted in Figure 21.

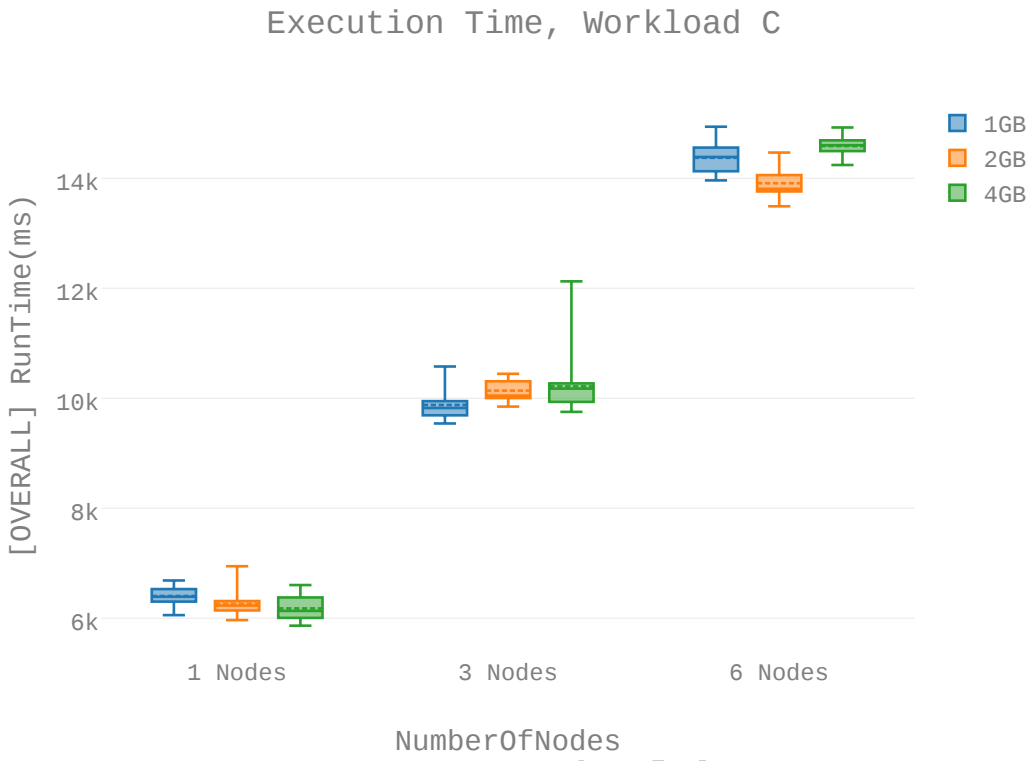

Figure 21. Execution time for virtual machines with 1GB, 2GB, and 4GB of RAM. The first 9 trials have been removed in order to filter out the trials representing cache effect and thus represents the steady state.

index	ram1GB	ram2GB	ram4GB
count	21	21	21
mean	6404.62	6263.71	6179
std	165.241	221.031	231.934
min	6057	5966	5865
25%	6304	6152	6017
50%	6391	6230	6134
75%	6526	6306	6377
max	6687	6946	6604
range	630	980	739

Table 19. Summary Statistics for 1-Node Configuration. All values represented fall between 5865.0 ms and 6946.0 ms, or rather within a span of 1081.0 ms.

index	ram1GB	ram2GB	ram4GB
count	21	21	21
mean	9878.24	10139.6	10215.5
std	255.122	180.863	495.567
min	9542	9849	9753
25%	9695	10009	9935
50%	9823	10049	10176
75%	9929	10307	10263
max	10578	10445	12126
range	1036	596	2373

Table 20. Summary Statistics for 3-Node Configuration. All values represented fall between 9542.0 ms and 12126.0 ms, or rather within a span of 2584.0 ms.

index	ram1GB	ram2GB	ram4GB
count	21	21	21
mean	14373.4	13910.4	14586.3
std	302.838	263.331	180.081
min	13962	13491	14242
25%	14137	13763	14496
50%	14388	13808	14601
75%	14551	14020	14690
max	14938	14468	14924
range	976	977	682

Table 21. Summary Statistics for 6-Node Configuration. All values represented fall between 13491.0 ms and 14938.0 ms, or rather within a span of 1447.0 ms.

The results are summarized in Tables 19, 20, and 21.

4.3.3 Implementation on Raspberry Pi.

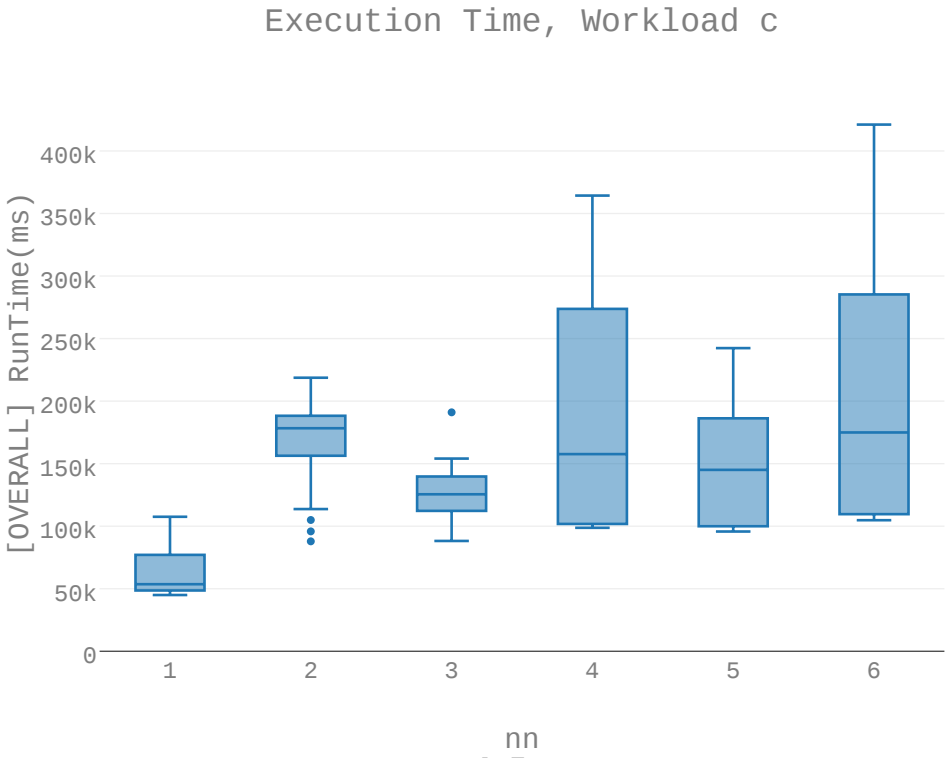

Figure 22. Results of limited hardware, the Raspberry Pi, on an Ethernet LAN. Execution time is plotted over cluster size.

This section summarizes the results from running Workload c on Raspberry Pi clusters networked via an Ethernet LAN. The results are depicted in Figure 22. For a node cluster size of 1, the median execution time was 48509.0 milliseconds, or about 49 second(s), and all execution times fell within 44975.0 milliseconds, or about 45 second(s), and 50422.0 milliseconds, or about 50 second(s), inclusive. For a node cluster size of 2, the median execution time was 181060.0 milliseconds, or about 3 minute(s), and all execution times fell within 159291.0 milliseconds, or about 2.7 minute(s), and 190954.0 milliseconds, or about 3.2 minute(s), inclusive. For a node cluster size of 3, the median execution time was 113228.0 milliseconds, or about 1.9 minute(s), and all execution times fell within 108872.0 milliseconds, or about 1.8

minute(s), and 125420.0 milliseconds, or about 2.1 minute(s), inclusive. For a node cluster size of 4, the median execution time was 102067.0 milliseconds, or about 1.7 minute(s), and all execution times fell within 100805.0 milliseconds, or about 1.7 minute(s), and 104762.0 milliseconds, or about 1.7 minute(s), inclusive. For a node cluster size of 5, the median execution time was 98057.0 milliseconds, or about 1.6 minute(s), and all execution times fell within 95741.0 milliseconds, or about 1.6 minute(s), and 102772.0 milliseconds, or about 1.7 minute(s), inclusive. For a node cluster size of 6, the median execution time was 107970.0 milliseconds, or about 1.8 minute(s), and all execution times fell within 104791.0 milliseconds, or about 1.7 minute(s), and 112869.0 milliseconds, or about 1.9 minute(s), inclusive. Overall, the median execution time was 104776.5 milliseconds, or about 1.7 minute(s), and all execution times fell within 44975.0 milliseconds, or about 45 second(s), and 190954.0 milliseconds, or about 3.2 minute(s). The full summary of the differences are reported

nn	1	2	3	4	5	6	OVERALL
count	21	21	21	21	21	21	126
mean	48259	180014	113605	102490	98716.2	108789	108646
std	1796.74	6660.89	3214.38	1174.42	1954.42	2140.98	38810.2
min	44975	159291	108872	100805	95741	104791	44975
25%	47111	178315	112239	101662	97339	107773	98172.2
50%	48509	181060	113228	102067	98057	107970	104776
75%	49966	183460	114262	103268	100028	109824	113200
max	50422	190954	125420	104762	102772	112869	190954

Table 22. Summary of Workload c executed on Raspberry Pi clusters on an Ethernet LAN

in Table 22.

4.3.4 Raspberry Pi vs Reference Value.

It is of interest to compare the performance of the Raspberry Pi to that of the reported value. The results are depicted in Figure 23. For a node cluster size of 1,

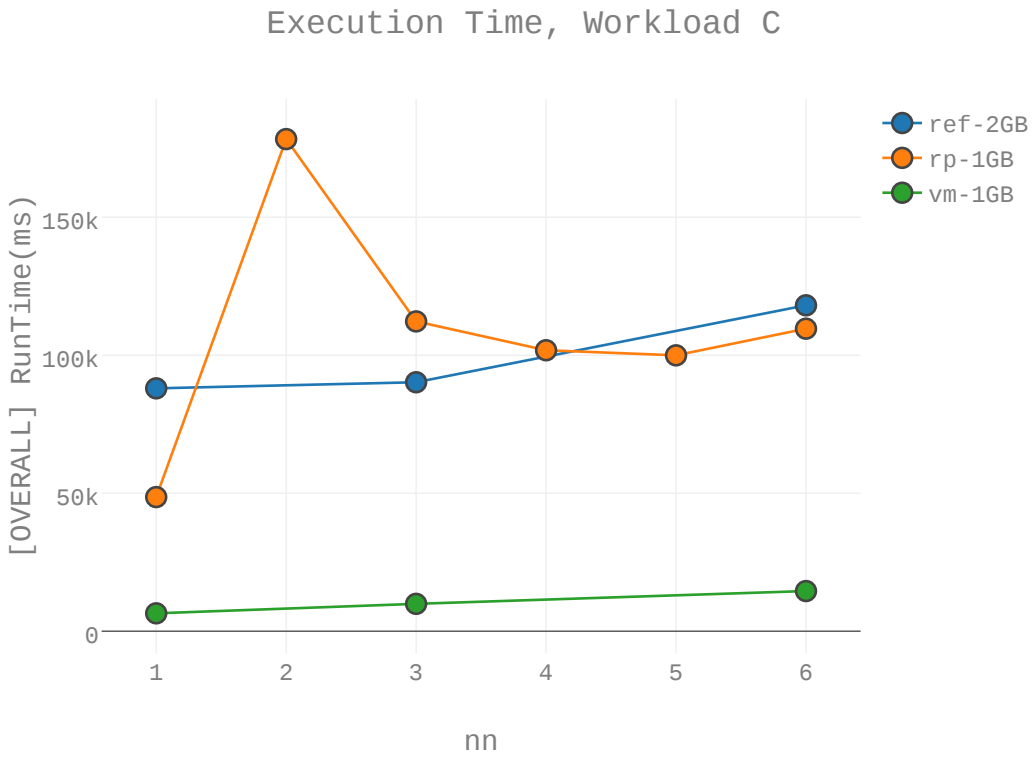

Figure 23. Comparison among the Raspberry Pi nodes (rp-1GB), the results reported in [1], and the virtual nodes with 1GB of RAM.

the experimental values fell within 43025.0 milliseconds, or about 43 second(s), of the value reported, which was 88000 milliseconds, or about 1 minute(s). For a node cluster size of 3, the experimental values fell within 35210.0 milliseconds, or about 35 second(s), of the value reported, which was 90210 milliseconds, or about 1 minute(s). For a node cluster size of 6, the experimental values fell within 13299.0 milliseconds, or about 13 second(s), of the value reported, which was 118090 milliseconds, or about 1 minute(s). Overall, the experimental values fell within 43025.0 milliseconds, or about 43 second(s), of the corresponding reference value. The full summary of the differences are reported in Table 23.

nn	1	3	6	OVERALL
count	21	21	21	63
mean	39741	23395.2	9300.71	24145.6
std	1796.74	3214.38	2140.98	12769.7
min	37578	18662	5221	5221
25%	38034	22029	8266	10358
50%	39491	23018	10120	23018
75%	40889	24052	10317	38005.5
max	43025	35210	13299	43025

Table 23. Summary of the absolute value of the differences between the empirical execution time on the Raspberry Pi clusters and the corresponding execution time reported in [1]

4.3.5 Raspberry Pi vs Virtual Machine.

4.3.6 Wireless Links Only.

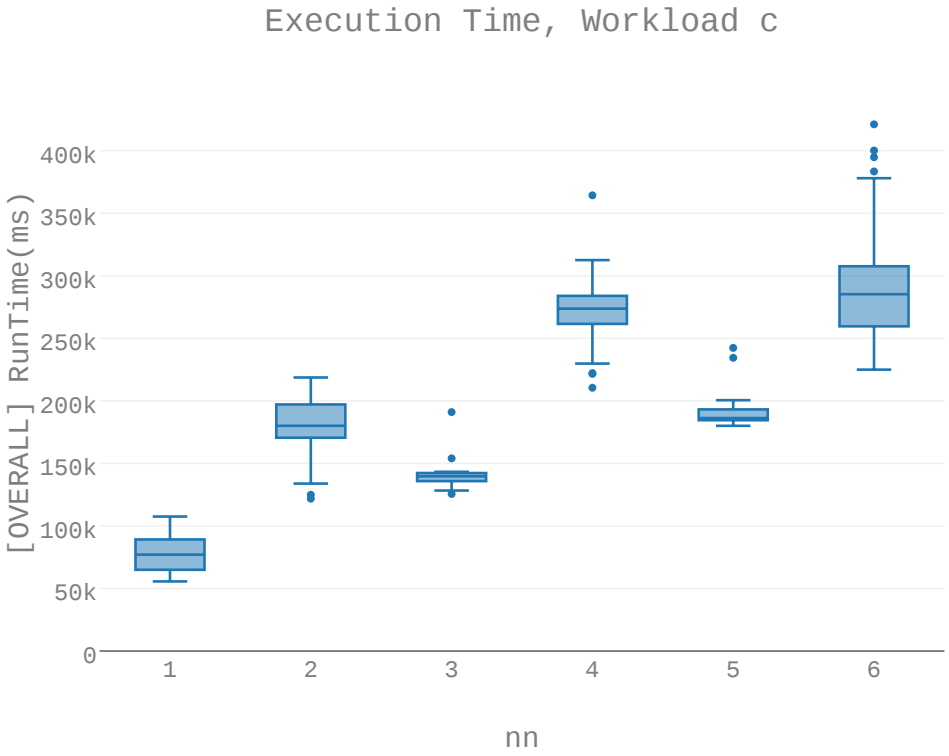

Figure 24. Results of wireless testing. There seems to be a steady climb in execution time as the cluster size increases. Any oscillation cannot be explained with current analysis and would require additional experimentation.

This section summarizes the results from running Workload c on Raspberry Pi clusters networked via an Wireless LAN. The results are depicted in Figure 24. For a node cluster size of 1, the median execution time was 70234.0 milliseconds, or about 1.2 minute(s), and all execution times fell within 55663.0 milliseconds, or about 56 second(s), and 94077.0 milliseconds, or about 1.6 minute(s), inclusive. For a node cluster size of 2, the median execution time was 191787.0 milliseconds, or about 3.2 minute(s), and all execution times fell within 170562.0 milliseconds, or about 2.8 minute(s), and 218706.0 milliseconds, or about 3.6 minute(s), inclusive. For a node cluster size of 3, the median execution time was 140868.0 milliseconds, or about 2.3 minute(s), and all execution times fell within 135953.0 milliseconds, or about 2.3 minute(s), and 191029.0 milliseconds, or about 3.2 minute(s), inclusive. For a node cluster size of 4, the median execution time was 270256.0 milliseconds, or about 4.5 minute(s), and all execution times fell within 229821.0 milliseconds, or about 3.8 minute(s), and 312564.0 milliseconds, or about 5.2 minute(s), inclusive. For a node cluster size of 5, the median execution time was 185406.0 milliseconds, or about 3.1 minute(s), and all execution times fell within 180069.0 milliseconds, or about 3 minute(s), and 242376.0 milliseconds, or about 4 minute(s), inclusive. For a node cluster size of 6, the median execution time was 268290.0 milliseconds, or about 4.5 minute(s), and all execution times fell within 224984.0 milliseconds, or about 3.7 minute(s), and 307635.0 milliseconds, or about 5.1 minute(s), inclusive. Overall, the median execution time was 185933.0 milliseconds, or about 3.1 minute(s), and all execution times fell within 55663.0 milliseconds, or about 56 second(s), and 312564.0 milliseconds, or about 5.2 minute(s). The full summary of the differences are reported in Table 24.

nn	1	2	3	4	5	6	OVERALL
count	21	21	21	21	21	21	126
mean	72893.6	190956	143635	275247	190753	266724	190035
std	11926.5	15481	11403.9	19238.6	16490.1	27441.9	71974.1
min	55663	170562	135953	229821	180069	224984	55663
25%	64473	176817	139612	265486	183611	249677	140904
50%	70234	191787	140868	270256	185406	268290	185933
75%	82901	199042	142603	283769	187049	291820	259480
max	94077	218706	191029	312564	242376	307635	312564

Table 24. Summary of Workload C executed on Raspberry Pi clusters on an Wireless LAN

4.3.7 Wireless Links vs Wired Links.

In this section, the median value of the corresponding wired experiment will serve as the reference for the purposes of evaluating the wireless links. Figure 38 depicts the two experiments using Raspberry Pis: a wireless LAN (wlan) and an Ethernet LAN (eth). In Figure 38, as well as previous graphs, one can observe that the Ethernet LAN effects about 50 seconds of execution time for 10,000 operations.

4.4 Results for Workload E

4.4.1 Comparing Existing Work: Virtual Machine vs the Reference Value.

It is of interest to compare the performance of the virtual machine to that of the reported value. The results are depicted in Figure 26. For a node cluster size of 1, the experimental values fell within 202016.0 milliseconds, or about 3.4 minute(s), of the value reported, which was 223180 milliseconds, or about 3 minute(s). For a node cluster size of 3, the experimental values fell within 307390.0 milliseconds, or about 5.1 minute(s), of the value reported, which was 330820 milliseconds, or about 5 minute(s). For a node cluster size of 6, the experimental values fell within 374109.0 milliseconds,

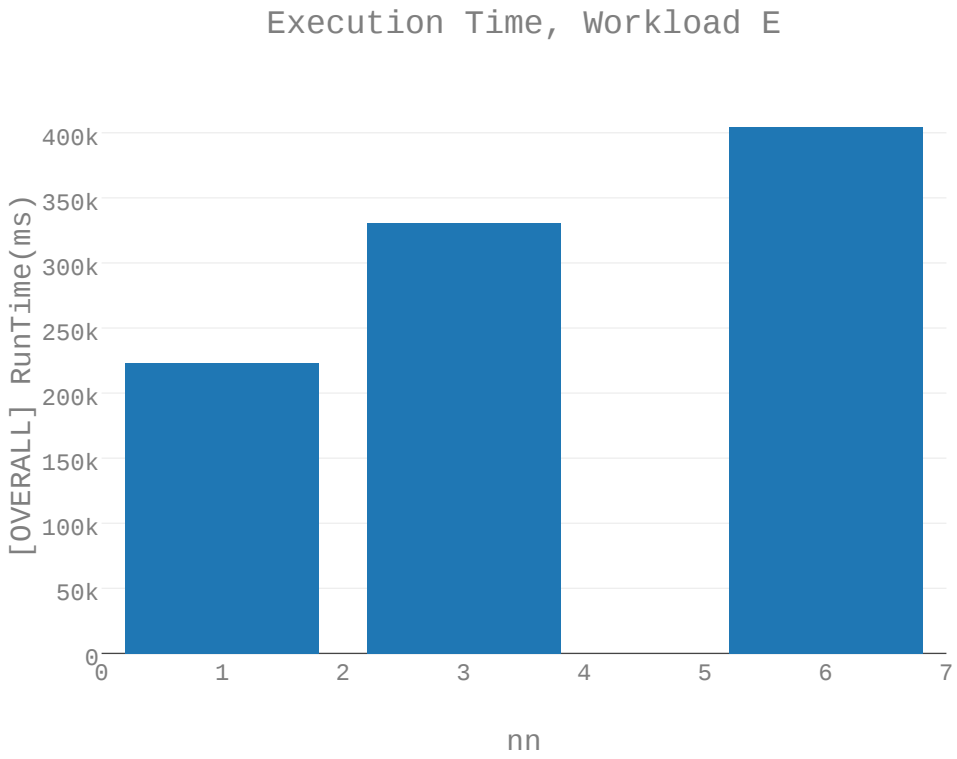

Figure 25. This plot shows the execution times imported from [1].

or about 6.2 minute(s), of the value reported, which was 404660 milliseconds, or about 6 minute(s). Overall, the experimental values fell within 374109.0 milliseconds, or about 6.2 minute(s), of the corresponding reference value. The full summary of the

nn	1	3	6	OVERALL
count	21	21	21	63
mean	198190	306276	373164	292544
std	2157.15	747.466	533.638	72681
min	194014	304424	372138	194014
25%	197035	306158	372764	199988
50%	198021	306421	373194	306421
75%	199926	306651	373579	372733
max	202016	307390	374109	374109

Table 25. Summary of the absolute value of the differences between the empirical execution time on the Virtual Machine clusters and the corresponding execution time reported in [1]

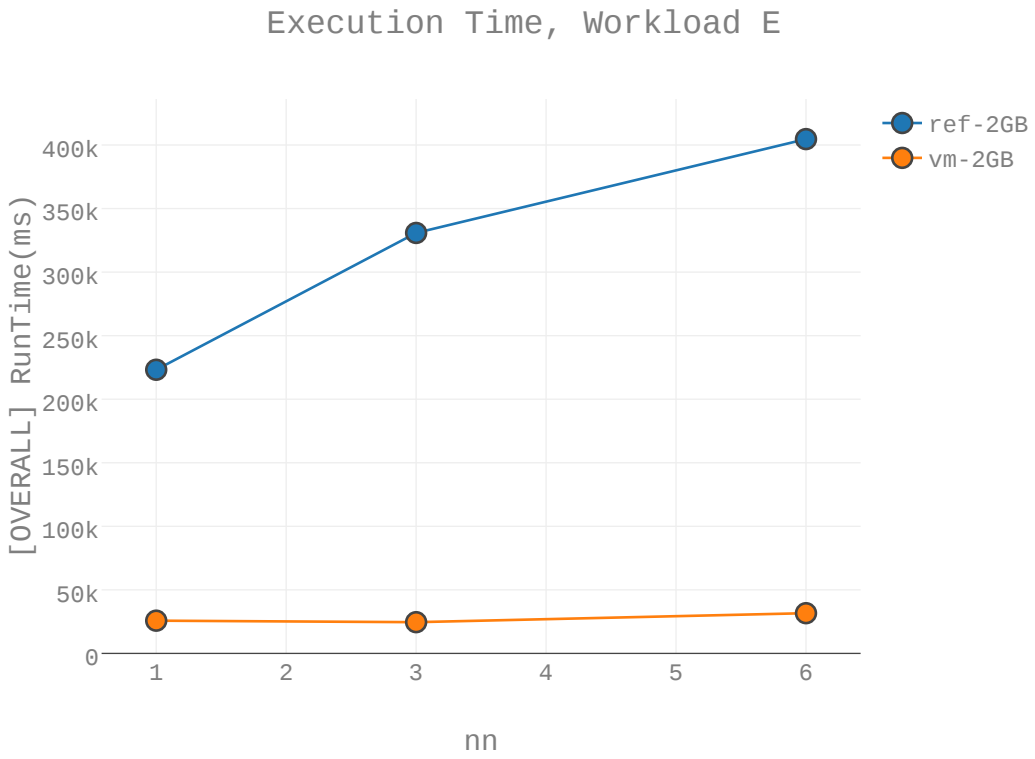

Figure 26. This compares the 2GB virtual machine with the corresponding value from [1].

differences are reported in Table 25.

4.4.2 1GB RAM vs 2GB RAM vs 4GB RAM.

The results are depicted in Figure 27.

Figure 27. Execution time for virtual machines with 1GB, 2GB, and 4GB of RAM. The first 9 trials have been removed in order to filter out the trials representing cache effect and thus represents the steady state.

index	ram1GB	ram2GB	ram4GB
count	42	21	21
mean	340151	24989.5	25145.5
std	17523.8	2157.15	2121.9
min	312012	21164	19476
25%	322860	23254	24341
50%	345396	25159	25195
75%	354768	26145	26772
max	371161	29166	27919
range	59149	8002	8443

Table 26. Summary Statistics for 1-Node Configuration. All values represented fall between 19476.0 ms and 371161.0 ms, or rather within a span of 351685.0 ms.

index	ram1GB	ram2GB	ram4GB
count	21	21	21
mean	23444	24544.1	23753.2
std	1016.02	747.466	1152.61
min	22411	23430	22828
25%	22813	24169	23292
50%	23221	24399	23572
75%	23658	24662	23892
max	26488	26396	28465
range	4077	2966	5637

Table 27. Summary Statistics for 3-Node Configuration. All values represented fall between 22411.0 ms and 28465.0 ms, or rather within a span of 6054.0 ms.

index	ram1GB	ram2GB	ram4GB
count	21	21	21
mean	32493.2	31495.7	33605.4
std	610.462	533.638	608.798
min	31508	30551	32649
25%	32108	31081	33199
50%	32448	31466	33665
75%	32899	31896	34105
max	34101	32522	34524
range	2593	1971	1875

Table 28. Summary Statistics for 6-Node Configuration. All values represented fall between 30551.0 ms and 34524.0 ms, or rather within a span of 3973.0 ms.

The results are summarized in Tables 26, 27, and 28.

4.4.3 Implementation on Raspberry Pi.

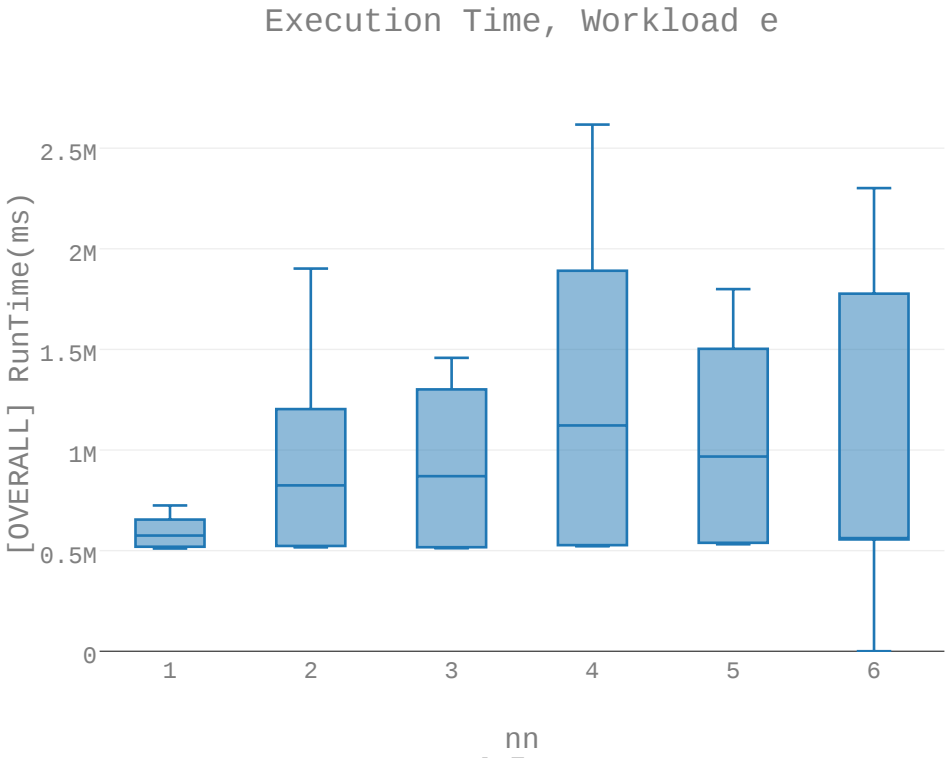

Figure 28. Results of limited hardware, the Raspberry Pi, on an Ethernet LAN. Execution time is plotted over cluster size.

This section summarizes the results from running Workload e on Raspberry Pi clusters networked via an Ethernet LAN. The results are depicted in Figure 28. For a node cluster size of 1, the median execution time was 519749.0 milliseconds, or about 8.7 minute(s), and all execution times fell within 515941.0 milliseconds, or about 8.6 minute(s), and 524199.0 milliseconds, or about 8.7 minute(s), inclusive. For a node cluster size of 2, the median execution time was 523597.0 milliseconds, or about 8.7 minute(s), and all execution times fell within 518821.0 milliseconds, or about 8.6 minute(s), and 532146.0 milliseconds, or about 8.9 minute(s), inclusive. For a node cluster size of 3, the median execution time was 516593.0 milliseconds, or about 8.6 minute(s), and all execution times fell within 511997.0 milliseconds, or

about 8.5 minute(s), and 532260.0 milliseconds, or about 8.9 minute(s), inclusive. For a node cluster size of 4, the median execution time was 526611.0 milliseconds, or about 8.8 minute(s), and all execution times fell within 521856.0 milliseconds, or about 8.7 minute(s), and 539625.0 milliseconds, or about 9 minute(s), inclusive. For a node cluster size of 5, the median execution time was 539051.0 milliseconds, or about 9 minute(s), and all execution times fell within 534059.0 milliseconds, or about 8.9 minute(s), and 543965.0 milliseconds, or about 9.1 minute(s), inclusive. For a node cluster size of 6, the median execution time was 558483.0 milliseconds, or about 9.3 minute(s), and all execution times fell within 555007.0 milliseconds, or about 9.3 minute(s), and 565388.0 milliseconds, or about 9.4 minute(s), inclusive. Overall, the median execution time was 525888.5 milliseconds, or about 8.8 minute(s), and all execution times fell within 511997.0 milliseconds, or about 8.5 minute(s), and 565388.0 milliseconds, or about 9.4 minute(s). The full summary of the differences

nn	1	2	3	4	5	6	OVERALL
count	21	21	21	21	21	21	126
mean	519824	524193	518827	529355	538985	559276	531744
std	2081.15	3454.02	5549.42	5981.47	2752.36	2975.11	14645.1
min	515941	518821	511997	521856	534059	555007	511997
25%	518543	521670	514662	525187	536993	556845	520832
50%	519749	523597	516593	526611	539051	558483	525888
75%	521294	525708	522601	535534	540580	561005	539373
max	524199	532146	532260	539625	543965	565388	565388

Table 29. Summary of Workload e executed on Raspberry Pi clusters on an Ethernet LAN

are reported in Table 29.

4.4.4 Raspberry Pi vs Reference Value.

It is of interest to compare the performance of the Raspberry Pi to that of the reported value. The results are depicted in Figure 29. For a node cluster size of 1,

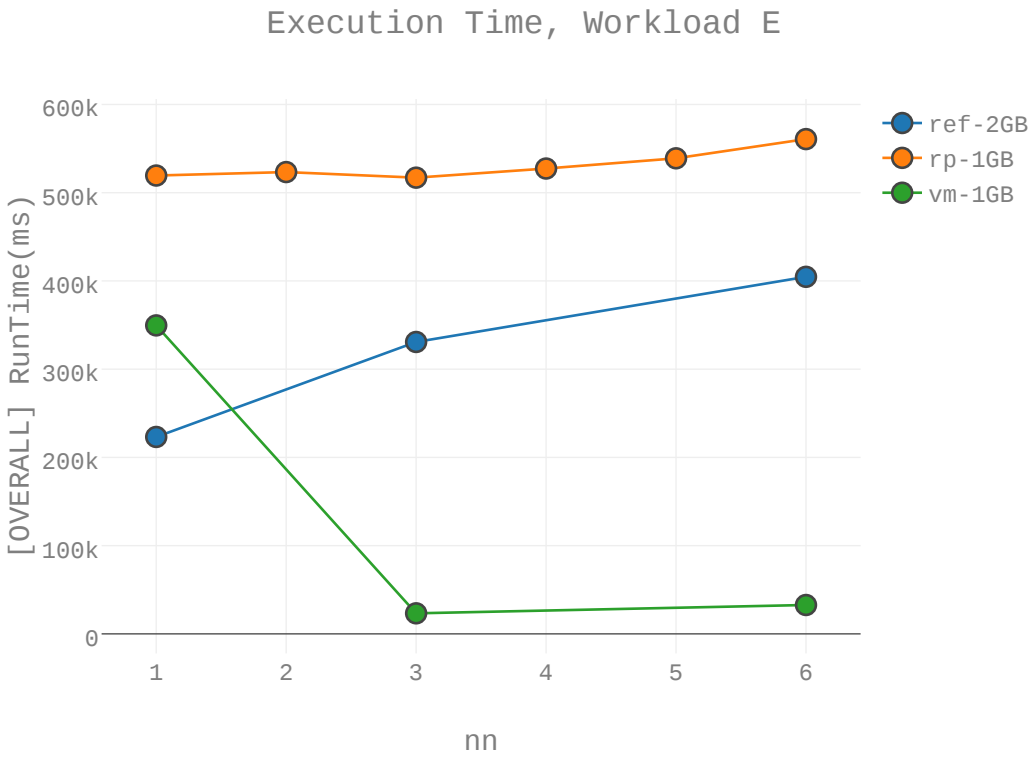

Figure 29. Comparison among the Raspberry Pi nodes (rp-1GB), the results reported in [1], and the virtual nodes with 1GB of RAM.

the experimental values fell within 301019.0 milliseconds, or about 5 minute(s), of the value reported, which was 223180 milliseconds, or about 3 minute(s). For a node cluster size of 3, the experimental values fell within 201440.0 milliseconds, or about 3.4 minute(s), of the value reported, which was 330820 milliseconds, or about 5 minute(s). For a node cluster size of 6, the experimental values fell within 160728.0 milliseconds, or about 2.7 minute(s), of the value reported, which was 404660 milliseconds, or about 6 minute(s). Overall, the experimental values fell within 301019.0 milliseconds, or about 5 minute(s), of the corresponding reference value. The full summary of the differences are reported in Table 30.

nn	1	3	6	OVERALL
count	21	21	21	63
mean	296644	188007	154616	213089
std	2081.15	5549.42	2975.11	61237.6
min	292761	181177	150347	150347
25%	295363	183842	152185	156376
50%	296569	185773	153823	185773
75%	298114	191781	156345	295306
max	301019	201440	160728	301019

Table 30. Summary of the absolute value of the differences between the empirical execution time on the Raspberry Pi clusters and the corresponding execution time reported in [1]

4.4.5 Raspberry Pi vs Virtual Machine.

4.4.6 Wireless Links Only.

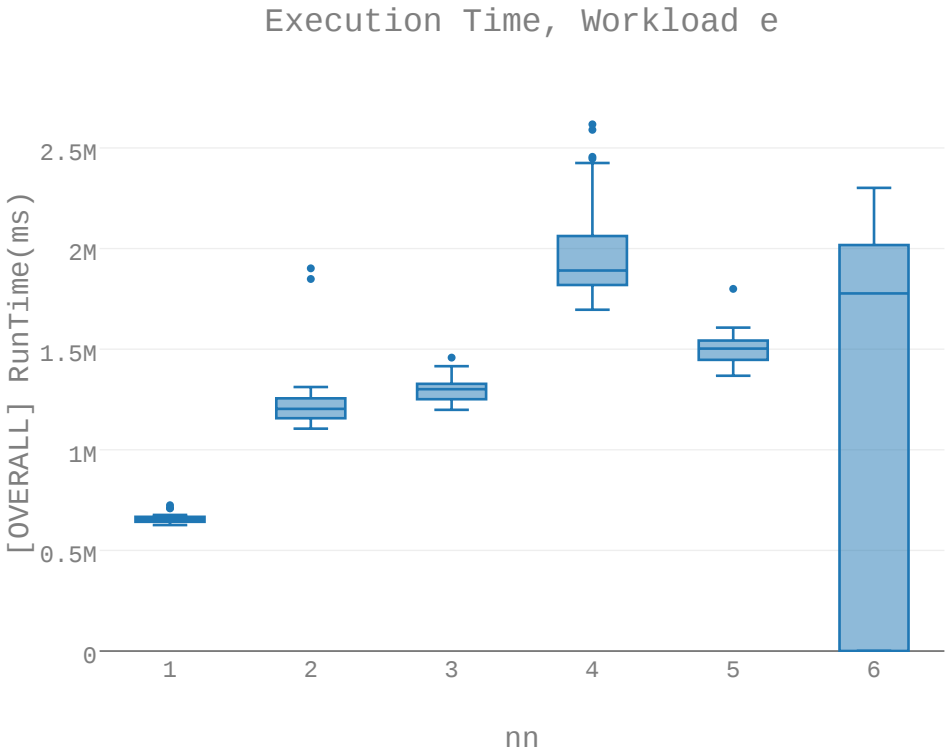

Figure 30. Results of wireless testing. There seems to be a steady climb in execution time as the cluster size increases. Any oscillation cannot be explained with current analysis and would require additional experimentation.

This section summarizes the results from running Workload e on Raspberry Pi clusters networked via an Wireless LAN. The results are depicted in Figure 30. For a node cluster size of 1, the median execution time was 647241.0 milliseconds, or about 11 minute(s), and all execution times fell within 625938.0 milliseconds, or about 10 minute(s), and 724603.0 milliseconds, or about 12 minute(s), inclusive. For a node cluster size of 2, the median execution time was 1221463.0 milliseconds, or about 20 minute(s), and all execution times fell within 1105078.0 milliseconds, or about 18 minute(s), and 1901694.0 milliseconds, or about 32 minute(s), inclusive. For a node cluster size of 3, the median execution time was 1299169.0 milliseconds, or about 22 minute(s), and all execution times fell within 1198600.0 milliseconds, or about 20 minute(s), and 1458086.0 milliseconds, or about 24 minute(s), inclusive. For a node cluster size of 4, the median execution time was 1847604.0 milliseconds, or about 31 minute(s), and all execution times fell within 1696013.0 milliseconds, or about 28 minute(s), and 2455797.0 milliseconds, or about 41 minute(s), inclusive. For a node cluster size of 5, the median execution time was 1492075.0 milliseconds, or about 25 minute(s), and all execution times fell within 1367959.0 milliseconds, or about 23 minute(s), and 1607138.0 milliseconds, or about 27 minute(s), inclusive. For a node cluster size of 6, the median execution time was 279.0 milliseconds, and all execution times fell within 260.0 milliseconds and 2018342.0 milliseconds, or about 34 minute(s), inclusive. Overall, the median execution time was 1301279.5 milliseconds, or about 22 minute(s), and all execution times fell within 260.0 milliseconds and 2455797.0 milliseconds, or about 41 minute(s). The full summary of the differences are reported in Table 31.

nn	1	2	3	4	5	6	OVERA
count	21	21	21	21	21	21	
mean	653699	1.27134e+06	1.30005e+06	1.89362e+06	1.48774e+06	689806	1.21604e
std	24457.8	207239	63996	174953	67505.1	904272	578
min	625938	1.10508e+06	1.1986e+06	1.69601e+06	1.36796e+06	260	
25%	641738	1.17563e+06	1.25383e+06	1.79477e+06	1.42959e+06	265	678
50%	647241	1.22146e+06	1.29917e+06	1.8476e+06	1.49208e+06	279	1.30128e
75%	659436	1.25662e+06	1.32132e+06	1.93214e+06	1.53608e+06	1.80377e+06	1.57608e
max	724603	1.90169e+06	1.45809e+06	2.4558e+06	1.60714e+06	2.01834e+06	2.4558e

Table 31. Summary of Workload E executed on Raspberry Pi clusters on an Wireless LAN

4.4.7 Wireless Links vs Wired Links.

In this section, the median value of the corresponding wired experiment will serve as the reference for the purposes of evaluating the wireless links. Figure 38 depicts the two experiments using Raspberry Pis: a wireless LAN (wlan) and an Ethernet LAN (eth). In Figure 38, as well as previous graphs, one can observe that the Ethernet LAN effects about 50 seconds of execution time for 10,000 operations.

4.5 Results for Workload I

4.5.1 1GB RAM vs 2GB RAM vs 4GB RAM.

The results are depicted in Figure 31.

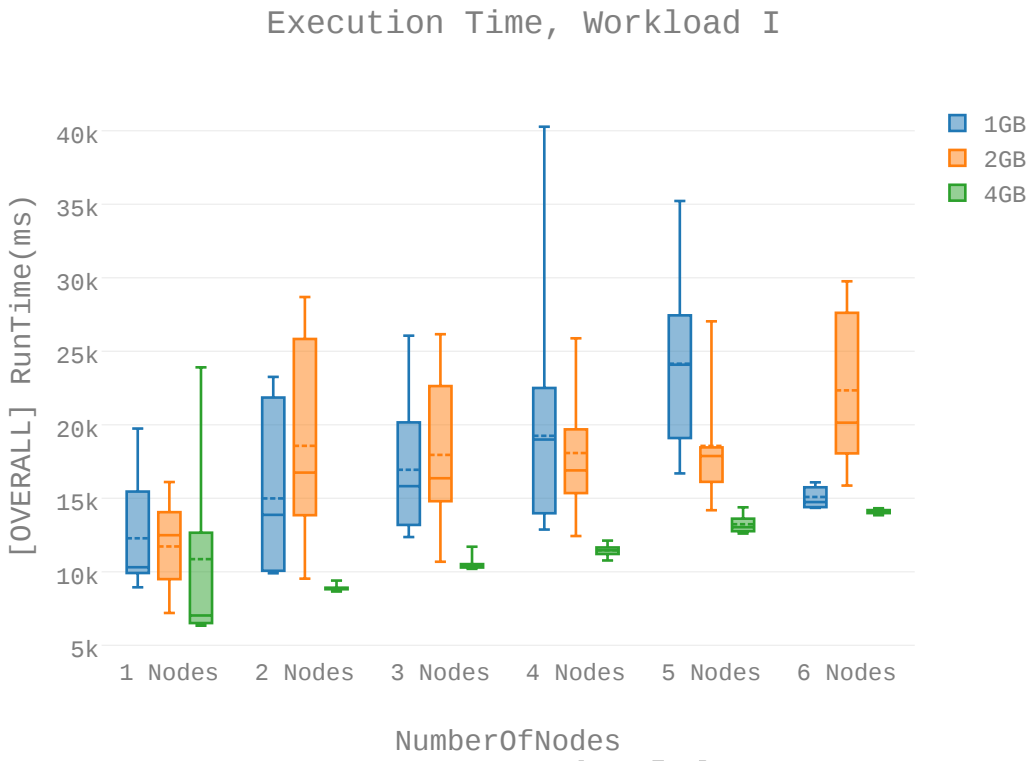

Figure 31. Execution time for virtual machines with 1GB, 2GB, and 4GB of RAM. The first 9 trials have been removed in order to filter out the trials representing cache effect and thus represents the steady state.

index	ram1GB	ram2GB	ram4GB
count	21	21	21
mean	12279.5	11724.2	10860.9
std	3701.07	2754.46	5699.56
min	8946	7200	6335
25%	9933	9777	6524
50%	10311	12490	7029
75%	14932	14045	12565
max	19744	16106	23908
range	10798	8906	17573

Table 32. Summary Statistics for 1-Node Configuration. All values represented fall between 6335.0 ms and 23908.0 ms, or rather within a span of 17573.0 ms.

index	ram1GB	ram2GB	ram4GB
count	21	21	21
mean	16939.7	17951.7	10496
std	4365.78	4858.15	362.355
min	12364	10684	10201
25%	13245	14823	10292
50%	15825	16364	10353
75%	20131	22460	10506
max	26062	26161	11707
range	13698	15477	1506

Table 33. Summary Statistics for 3-Node Configuration. All values represented fall between 10201.0 ms and 26161.0 ms, or rather within a span of 15960.0 ms.

index	ram1GB	ram2GB	ram4GB
count	21	21	21
mean	15091	22341.1	14085.2
std	683.141	4929.85	139.173
min	14349	15865	13849
25%	14402	18094	13992
50%	14743	20145	14063
75%	15728	27289	14184
max	16086	29760	14322
range	1737	13895	473

Table 34. Summary Statistics for 6-Node Configuration. All values represented fall between 13849.0 ms and 29760.0 ms, or rather within a span of 15911.0 ms.

The results are summarized in Tables 32, 33, and 34.

4.5.2 Implementation on Raspberry Pi.

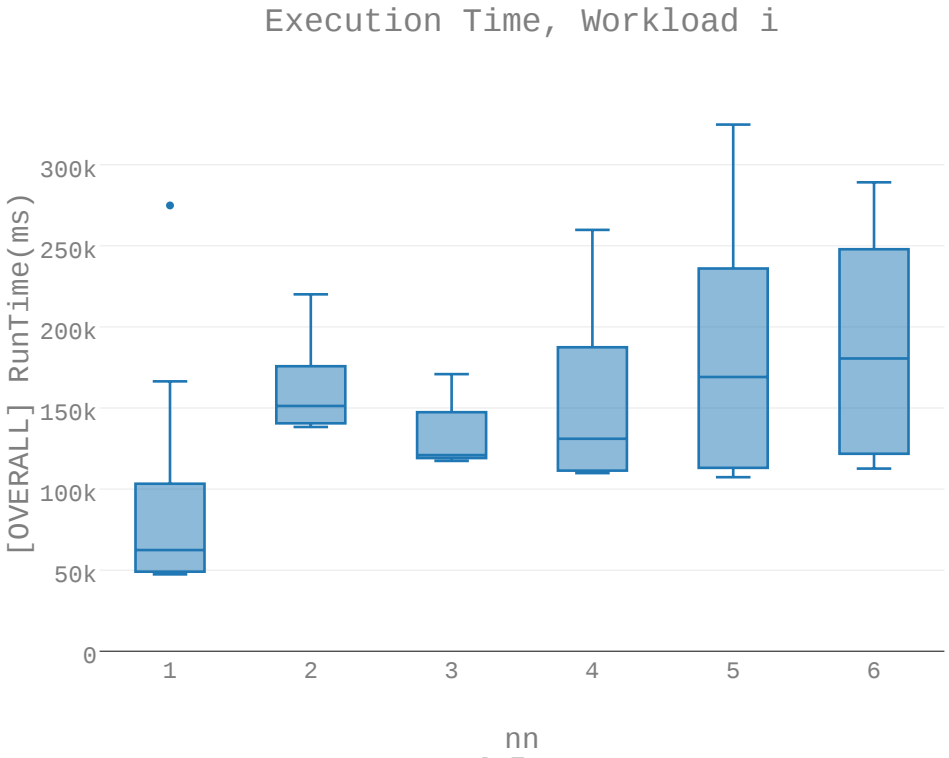

Figure 32. Results of limited hardware, the Raspberry Pi, on an Ethernet LAN. Execution time is plotted over cluster size.

This section summarizes the results from running Workload i on Raspberry Pi clusters networked via an Ethernet LAN. The results are depicted in Figure 32. For a node cluster size of 1, the median execution time was 49060.0 milliseconds, or about 49 second(s), and all execution times fell within 47424.0 milliseconds, or about 47 second(s), and 52247.0 milliseconds, or about 52 second(s), inclusive. For a node cluster size of 2, the median execution time was 140455.0 milliseconds, or about 2.3 minute(s), and all execution times fell within 138300.0 milliseconds, or about 2.3 minute(s), and 143138.0 milliseconds, or about 2.4 minute(s), inclusive. For a node cluster size of 3, the median execution time was 119189.0 milliseconds, or about 2 minute(s), and all execution times fell within 117374.0 milliseconds, or about 2

minute(s), and 120780.0 milliseconds, or about 2 minute(s), inclusive. For a node cluster size of 4, the median execution time was 111570.0 milliseconds, or about 1.9 minute(s), and all execution times fell within 110052.0 milliseconds, or about 1.8 minute(s), and 113125.0 milliseconds, or about 1.9 minute(s), inclusive. For a node cluster size of 5, the median execution time was 113136.0 milliseconds, or about 1.9 minute(s), and all execution times fell within 109666.0 milliseconds, or about 1.8 minute(s), and 117476.0 milliseconds, or about 2 minute(s), inclusive. For a node cluster size of 6, the median execution time was 121520.0 milliseconds, or about 2 minute(s), and all execution times fell within 117844.0 milliseconds, or about 2 minute(s), and 125806.0 milliseconds, or about 2.1 minute(s), inclusive. Overall, the median execution time was 117425.0 milliseconds, or about 2 minute(s), and all execution times fell within 47424.0 milliseconds, or about 47 second(s), and 143138.0 milliseconds, or about 2.4 minute(s). The full summary of the differences are reported

nn	1	2	3	4	5	6	OVERALL
count	21	21	21	21	21	21	126
mean	49330.3	140458	119087	111482	113247	121861	109244
std	923.235	1148.34	985.345	772.744	2223.7	2149.7	28555.8
min	47424	138300	117374	110052	109666	117844	47424
25%	48977	139849	118321	110927	111455	120080	111139
50%	49060	140455	119189	111570	113136	121520	117425
75%	49683	141392	119663	111986	115250	123474	121513
max	52247	143138	120780	113125	117476	125806	143138

Table 35. Summary of Workload i executed on Raspberry Pi clusters on an Ethernet LAN

in Table 35.

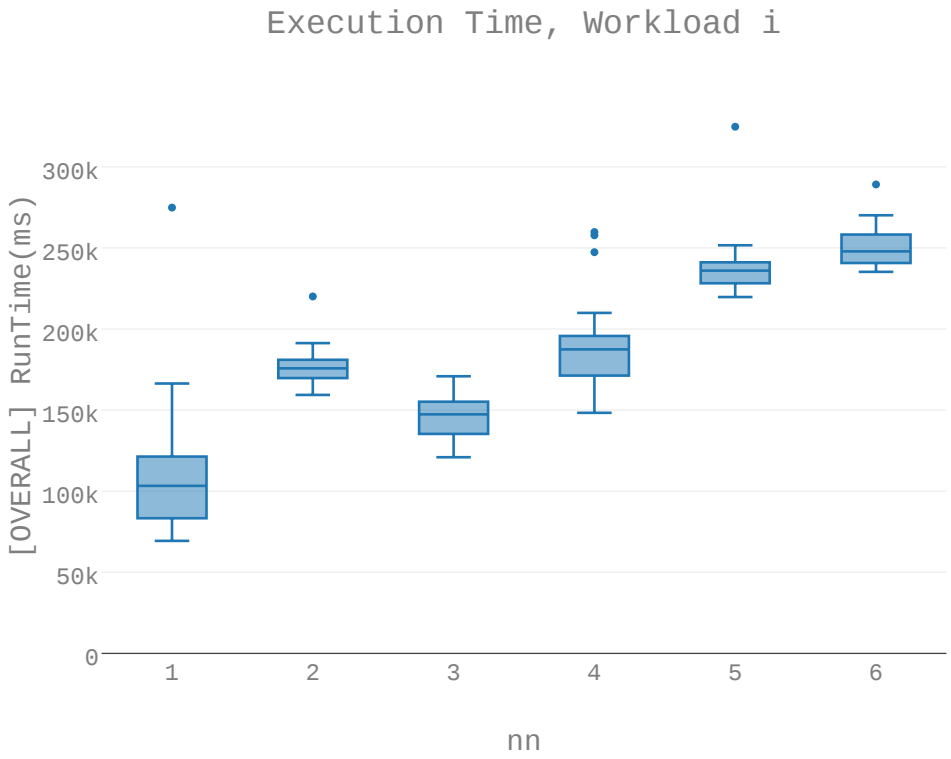

Figure 33. Results of wireless testing. There seems to be a steady climb in execution time as the cluster size increases. Any oscillation cannot be explained with current analysis and would require additional experimentation.

4.5.3 Raspberry Pi vs Virtual Machine.

4.5.4 Wireless Links Only.

This section summarizes the results from running Workload i on Raspberry Pi clusters networked via an Wireless LAN. The results are depicted in Figure 33. For a node cluster size of 1, the median execution time was 87873.0 milliseconds, or about 1.5 minute(s), and all execution times fell within 69387.0 milliseconds, or about 1.2 minute(s), and 274883.0 milliseconds, or about 4.6 minute(s), inclusive. For a node cluster size of 2, the median execution time was 176748.0 milliseconds, or about 2.9 minute(s), and all execution times fell within 167673.0 milliseconds, or about 2.8 minute(s), and 191322.0 milliseconds, or about 3.2 minute(s), inclusive. For a node cluster size of 3, the median execution time was 141594.0 milliseconds, or about

2.4 minute(s), and all execution times fell within 120958.0 milliseconds, or about 2 minute(s), and 163489.0 milliseconds, or about 2.7 minute(s), inclusive. For a node cluster size of 4, the median execution time was 186474.0 milliseconds, or about 3.1 minute(s), and all execution times fell within 148342.0 milliseconds, or about 2.5 minute(s), and 257809.0 milliseconds, or about 4.3 minute(s), inclusive. For a node cluster size of 5, the median execution time was 235977.0 milliseconds, or about 3.9 minute(s), and all execution times fell within 224335.0 milliseconds, or about 3.7 minute(s), and 324742.0 milliseconds, or about 5.4 minute(s), inclusive. For a node cluster size of 6, the median execution time was 246736.0 milliseconds, or about 4.1 minute(s), and all execution times fell within 235256.0 milliseconds, or about 3.9 minute(s), and 289145.0 milliseconds, or about 4.8 minute(s), inclusive. Overall, the median execution time was 178236.5 milliseconds, or about 3 minute(s), and all execution times fell within 69387.0 milliseconds, or about 1.2 minute(s), and 324742.0 milliseconds, or about 5.4 minute(s). The full summary of the differences are reported

nn	1	2	3	4	5	6	OVERALL
count	21	21	21	21	21	21	126
mean	105677	177172	140303	185770	238210	251376	183085
std	47129.1	6071.32	13845.3	23130.9	21249.9	13307.2	56510.2
min	69387	167673	120958	148342	224335	235256	69387
25%	75781	173138	125375	171014	227217	241456	146274
50%	87873	176748	141594	186474	235977	246736	178236
75%	115248	181665	148020	194518	239196	257248	236018
max	274883	191322	163489	257809	324742	289145	324742

Table 36. Summary of Workload I executed on Raspberry Pi clusters on an Wireless LAN

in Table 36.

4.5.5 Wireless Links vs Wired Links.

In this section, the median value of the corresponding wired experiment will serve as the reference for the purposes of evaluating the wireless links. Figure 38 depicts the two experiments using Raspberry Pis: a wireless LAN (wlan) and an Ethernet LAN (eth). In Figure 38, as well as previous graphs, one can observe that the Ethernet LAN effects about 50 seconds of execution time for 10,000 operations.

V. Conclusion and Future Work

5.1 Conclusion

One of the selling points of a distributed system, and thus a distributed database, is the option to increase the likelihood of survival of data by spreading nodes geographically. While servers can and are distributed geographically as well, the light weight of the Raspberry Pi and like devices represents a mobility and flexibility that, in certain contexts, gives these nodes potential competitive advantage over a heavy server-type node. An open question for an application considering the variance in potential nodes is how the less capable CPU may affect performance.

This work imported some results from [1] to form a set of reference points, reference points that for all practical purposes represent a likely candidate platform and network upon which one would nominally use Cassandra. The fact that the machines in [1] were restricted to 2GB was a bonus for this work, as these nodes hinted at getting slightly closer to the lucrative domain of interest: in-situ IoT storage. Using these references and some controlled variation within this work, the tests done here can start to paint a picture of what one can expect porting a distributed database like Cassandra to a platform like the Raspberry Pi 2 or 3. To summarize some of the data collected, this work was able to make the following determinations with respect to the research questions 1 through 4 posed earlier:

5.1.1 Finding 1.

For 21 trials, each consisting of 10,000 operations of workload A (50 percent reads and 50 percent updates) and performed over 1, 3, and 6-node configurations, the greatest absolute deviation from the reference to the Raspberry Pi configuration was found to be 34851.0 milliseconds, or about 35 second(s). Second, for 10,000 operations

of this workload and over 1, 2, 3, 4, 5, and 6-node configurations, the greatest absolute deviation from any given trial in the wired configuration to an analogous trial using wireless configuration was found to be 367262.0 milliseconds, or about 6.1 minute(s).

5.1.2 Finding 2.

For 21 trials, each consisting of 10,000 operations of workload C (100 percent reads) and performed over 1, 3, and 6-node configurations, the greatest absolute deviation from the reference to the Raspberry Pi configuration was found to be 43025.0 milliseconds, or about 43 second(s). Second, for 10,000 operations of this workload and over 1, 2, 3, 4, 5, and 6-node configurations, the greatest absolute deviation from any given trial in the wired configuration to an analogous trial using wireless configuration was found to be 211759.0 milliseconds, or about 3.5 minute(s).

5.1.3 Finding 3.

For 21 trials, each consisting of 10,000 operations of workload E (100 percent scans) and performed over 1, 3, and 6-node configurations, the greatest absolute deviation from the reference to the Raspberry Pi configuration was found to be 301019.0 milliseconds, or about 5 minute(s). Second, for 10,000 operations of this workload and over 1, 2, 3, 4, 5, and 6-node configurations, the greatest absolute deviation from any given trial in the wired configuration to an analogous trial using wireless configuration was found to be 1933941.0 milliseconds, or about 32 minute(s).

5.1.4 Finding 4.

For 21 trials, each consisting of 10,000 operations of workload I (99 percent inserts, 1 percent reads) and performed over 1, 3, and 6-node configurations, the greatest absolute deviation from the virtual machine at 1GB to the Raspberry Pi configuration

was found to be nan milliseconds, or about nan week(s). Second, for 10,000 operations of this workload and over 1, 2, 3, 4, 5, and 6-node configurations, the greatest absolute deviation from any given trial in the wired configuration to an analogous trial using wireless configuration was found to be nan milliseconds, or about nan week(s).

5.2 Future Work

As was alluded to in the introduction, this research seeks to support a number of possible future endeavors.

5.2.1 Generalized Model.

Overview.

Despite the complexities of hardware, a generalized model may assert that a node can be abstracted to RAM, rated I/O speeds, and the processor speed. The experiments done in this report do not vary these parameters sufficiently to characterize an empirical model, but they provide a data point as well as a framework for developing other experiments to further refine this model. This work has already suggested that the amount of memory may not be critical or useful in predicting hardware performance, leaving I/O speeds and processor speed. This work grouped them all as one.

There has been a lot of work in trying to characterize networks, but really for a model like this, this proposition suggests the network can be characterized by the mean ping team between nodes.

Experiments that would Refine This Model.

Naturally, trying other databases, like MongoDB, in Cassandra's place is one way to achieve further confidence. In part, the motivation behind using the YCSB was

its portability for testing a multitude of distributed database applications. Although the workloads for Cassandra were varied, and different databases are typically optimized and designed for particular workloads, a different database or databases would increase qualitative confidence that the model can be extended to a database not explicitly tested.

In addition, the absolute values in the results of this work do not necessarily represent Cassandra at its best. In the interest of replication, default values were used much more often than not. Cassandra boasts a multitude of parameters with which one can vary in attempt to optimize performance, almost to the point where you are almost guaranteed to be running it sub-optimally without employing a Cassandra expert.

5.2.2 Wifi Collection, Mapping and Crowd Detection.

Naturally, another step forward is developing or adapting an application that puts the system to the test. The application could be compared to the various workloads that were executed to verify if one of the workloads accurately represents an IoT application.

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