Multi-hop Wireless Mesh Networks:
Performance Evaluation and Empirical Models

A Dissertation

Presented to the

Graduate Faculty of the

University of Louisiana at Lafayette

In Partial Fulfillment of the

Requirements for the Degree

Doctor of Philosophy

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Spring 2007

Multi-hop Wireless Mesh Networks:
Performance Evaluation and Empirical Models

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DEDICATION

This dissertation is dedicated to Phyllis, my wife, and Malorie, our daughter, both of whom have supported and encouraged me to persevere through life's challenges.

ACKNOWLEDGMENTS

I would like to thank my advisor, Dr. Dmitri Perkins. His willingness to support my work and his guidance throughout my doctoral studies have allowed me to develop my skills as a researcher within a supportive team environment. I thank him for that opportunity. Also, I would like to thank Dr. Magdy Bayoumi. His advice, support, and counsel over the years have been of equal importance. I would further like to thank the other members of my committee: Dr. Nian-Feng Tzeng and Dr. Hong-Yi Wu. I greatly appreciate their time and input to this dissertation.

Within The Center for Advanced Computer Studies, I owe many thanks to faculty, staff, and students. I thank Cathy Pomier, Nancy Franks, and Rochelle Brasseaux, who have always greeted me with a smile. To my fellow graduate students, I express my sincerest gratitude for the many conversations that have had a tremendous impact on my research and me as a person. Denvil, Ihklas, Moursy, Adam, Rajesh, and Haining, thank you so much.

To my colleagues and friends in the B. I. Moody III College of Business Administration, I owe my gratitude for their unwavering encouragement and support, as I progressed from one milestone to the next in my doctoral studies. I am particularly grateful to Dr. Zhi Wei Zhu; I appreciate the unwavering support given me throughout this process.

Where I am today is due in no small measure to my family. I am immensely grateful to my father, mother, brother, and sister, who have always been there for me. To my wife and daughter, who have given me their unwavering love and support, and have sacrificed considerable time apart from me during these past years, I dedicate this dissertation.

Finally, I must express a profound thanksgiving to Our Lord and Savior Jesus Christ, through Whom all things are possible.

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CHAPTER 1

INTRODUCTION

> "All models are wrong, but some are useful."
>
> —George E. P. Box

I shall begin by considering three hypothetical scenarios. The first scenario involves the deployment by a military peacekeeping force of multiple, possibly heterogeneous, wireless networks. Moreover, these wireless networks might collectively span a distance of several miles within the theater of operations. There is the added requirement of integrating these disparate wireless networks, such that both intra- and inter-network communications, along with backhaul access to the wired Internet, are supported. Given the presumed danger to both military and non-military personnel in such a potentially hostile environment, a network deployment such as this must be done both quickly and efficiently, and with minimal risk of serious injury to personnel or even loss of human life. Finally, the deployed network must be reliable, robust, and easy to maintain.

The second scenario centers around an ambulance company that services a large metropolitan area—Dallas, Texas, for example. Such a large-scale deployment should support reliable wide-area, high-speed, wireless voice and data communications. In an effort to maintain a fiduciary responsibility to all stakeholders, there should be relatively low deployment costs associated with this scenario. Similar to the first scenario described earlier, easy maintenance, reliability, and robustness, are all essential.

The third scenario involves the development of a wireless community network, such that residents of homes and apartments have reliable high-speed backhaul access to the

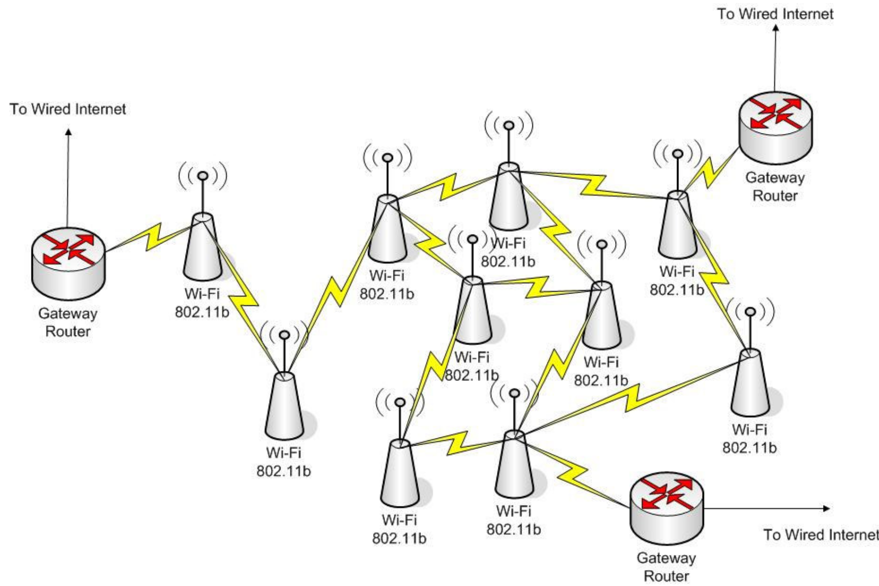

Figure 1.1: 802.11b Multi-hop Wireless Mesh Network

wired Internet. Although less serious in nature than the two preceding scenarios, subscribers to such a wireless community network would presumably expect QoS levels that are somewhat comparable to QoS levels expected of the wired Internet. Irrespective of whether a wireless community network such as I have described it is owned and operated by a for-profit organization or is operated by a governmental entity (in which case, it is owned by taxpayers), this infrastructure must be relatively inexpensive and easy to deploy, in order to be considered affordable by prospective subscribers.

The three scenarios just described differ with respect to their operating conditions, scope, and scale; however, there also are requirements common among them. These might include simple deployment at low-cost, reliability, robustness, and easy maintenance, to name a few. Current advances in the state-of-the-art in *multi-hop wireless mesh networks* (*WMNs*) suggest that such infrastructures might conceivably satisfy such requirements.

Figure 1.1 illustrates a conceptual view of a multi-hop WMN, around which my dissertation work is centered. As shown in the figure, an 802.11b multi-hop WMN is a set of topologically-static backhaul mesh routers, similar to an ad hoc network [1]. The traffic generated by each mesh router, M_i, is the aggregate traffic of j clients, $C_{i1}, C_{i2}, \ldots, C_{ij}$, that are within the *basic service set* (*BSS*) of M_i.

There is considerable research activity in the design of algorithms, protocols, techniques, and architectures for multi-hop WMNs. Such research activity is not unexpected, given the ever-increasing demand by end users for anywhere-anytime connectivity. Moreover, unlike many of the hybrid wired-wireless infrastructures already in use, multi-hop WMNs may be deployed with comparative ease.

An important objective of multi-hop WMN deployment, as suggested in the literature, is to provide for the wireless domain what has been until now a hybrid wired-wireless scheme. Achieving this is no small accomplishment, however. Unlike wired networks, the wireless channel entails an environment that may be hostile, chaotic, and unpredictable.

Multi-hop WMN research is still in its relative infancy; however, a survey of the literature suggests that much has been accomplished thus far. This is due in no small measure to continued improvements in IEEE 802.11-based wireless networks, which are considered by some researchers as a subset of multi-hop WMNs [2]. If we accept this premise, then many of the same problems, challenges, and opportunities associated with IEEE 802.11 networks might indeed apply to multi-hop WMNs.

Research Problem

Let us again consider the diverse conditions under which the three hypothetical scenarios described earlier might operate. The environment with which a military peacekeeping force must contend may be, depending upon the particular area of the world in which it occurs, a region fraught with mountains and valleys. In contrast, the metropolitan area serviced by our hypothetical ambulance company might be comprised of a variety and multitude of small, medium, and large buildings, all located in a rather large urban environment. Finally, the wireless community network scenario might possibly be developed in a rural area that is flat, topologically speaking.

The foregoing discussion of these three, very diverse, operating environments is intended to highlight the point that a "one-size-fits-all" deployment of a multi-hop wireless mesh network is not likely to work for all three scenarios. Depending upon the particular environment in which the network is to be deployed, factors such as routing protocol, traffic load, network size, number and placement of gateways, and so on, will probably differ among the different deployments. Thus, an understanding about how to evaluate the behavior and performance of multi-hop wireless mesh networks might prove useful to network system/protocol designers and developers.

Research Goals

In light of the research problem described in the previous section, I intend to accomplish the following three research goals:

1. Develop a better understanding of fundamental performance, scaling properties, and trade-offs of mesh networks;
2. Conduct a comprehensive evaluation of network performance over a large design space; and
3. Characterize the functional relationship between performance metrics and relevant factors.

My third research goal requires some elaboration. Realization of this research goal suggests three questions. First, how is system performance affected by various combinations of factor settings? Second, which combination of factor settings achieves specific performance requirements over a specified region of interest? Third, which combination of factor settings produces the optimal response or set of responses?

Motivation

My dissertation work has a threefold purpose. First, such an evaluation should facilitate an understanding about: (1) performance responses (i.e., throughput, delay, jitter, and packet delivery ratio); (2) particular system/network parameters that may affect performance responses; and (3) the degree to which performance responses are affected when varying system/network parameters. Second, results of my work should provide insight about performance issues to system and protocol architects. Third, a holistic approach such as mine expresses a chain of analyses, the result of which leads to response optimization.

I anticipate the following benefits from the results of my work:

1. The development of generalized empirical models of multi-hop wireless mesh networks;

2. Characterization of cause/effect functional relationships between performance responses and their factors and factor interactions;
3. Prediction of system performance and behavior, based upon factor variables and their levels; and
4. Optimization for four response metrics—throughput, delay, jitter, and packet delivery overhead.

Most scientific endeavors involve making observations and inductively drawing inferences about the phenomena under study. These inferences can then be generalized in such a way that predictions about the system may be deductively estimated. Characterizing the functional relationships between performance responses and their factors and factor interactions may be useful to system designers and developers when, for instance, deciding upon the routing protocol that should lead to a desired performance level, given the environment within which the wireless network will operate.

Prediction is one of the most important objectives of scientific research. In the case of multi-hop wireless mesh networks, reliable empirical models, along with particular factor levels, may lead to accurate predictions about performance of the system, even before deployment actually takes place. This predictive aspect may lead to greater efficiency and higher cost-effectiveness, since resources would not be depleted in real-time, as the network is tuned to operate at a certain level of performance.

The aforementioned benefits highlight what I believe are important strengths of empirical modeling. Basically, empirical modeling characterizes the "How" mechanism of a system, but does not offer very much about the "Why." Such "why" questions are the locus of analytical models. Even though my work does not involve such models, empirical models may offer a useful starting point from which analytical models might then be developed.

Empirical modeling

Performance of a target system is contingent upon the environment within which it operates; this operating environment is comprised of possibly numerous variables, some of which are controllable, and others over which there is little or no control. Empirical modeling provides a framework by which a functional relationship between the target system and its factors may be formed. Thus, observations of the interaction between a target system and its environmental factors are the foundation upon which empirical modeling may take place.

Derivation of viable empirical models is both interesting and challenging. It is interesting in that the researcher expands his knowledge about the world around him; and it is challenging because the process usually involves considerable experimentation and observation. The upshot, according to George E. P. Box, is that "all models are wrong, but some are useful" [3].

At first glance, Box's statement might seem to suggest that most, or perhaps all, attempts at empirical modeling are less than worthwhile. However, because empirical modeling has been used for centuries, it is difficult not to concede that there is both merit and significant utility in developing and using empirical models. The literature in general scientific principles, statistics, and philosophy of science contains significant support for the "principle of simplicity" (also labeled as the "principle of parsimony"), which posits that simpler models are preferred to more complex models, so long as they provide a reliable representation of the phenomena under study. Because this principle has been applied successfully in many different research contexts, I intend to abide by it as well.

Terms and Definitions

I shall next identify terms and their definitions I use throughout this dissertation; these are as follows.

- Empirical model — a model that is derived from observed functional relationships between a dependent variable (response) and one or more independent variables (factors).
- Multi-hop wireless mesh network — a set of topologically-static backhaul mesh routers, similar to an ad hoc network [1], such that the traffic generated by each mesh router, M_i, is the aggregate traffic of j clients, $C_{i1}, C_{i2}, \ldots, C_{ij}$, that are within the basic service set (BSS) of M_i.
- Parsimony — given two or more viable solutions or approaches to a problem, the simpler solution or approach is preferred.
- QoS — quality of service; a specification, either by a human administrator or by some predetermined classification scheme, such that one or more responses (e.g., throughput, control overhead, delay) are maintained within certain upper and lower bounds.
- Signal — a response variable whose value changes over time. There are two types of signals, complete signals and partial signals. Complete signals take on values at each time instance, whereas partial signals do not. A signal is synonymous with a response, such as throughput, delay, and so on.

Approach

As my work relies significantly upon empirical observations, the matter of whether to operate either within an experimental framework or within a simulation framework must be addressed. The literature provides substantial support for the latter; therefore, my investigation is done almost entirely by means of simulation. I shall discuss related work in this area in Chapter 2, which should make lucid my choice of a simulation environment.

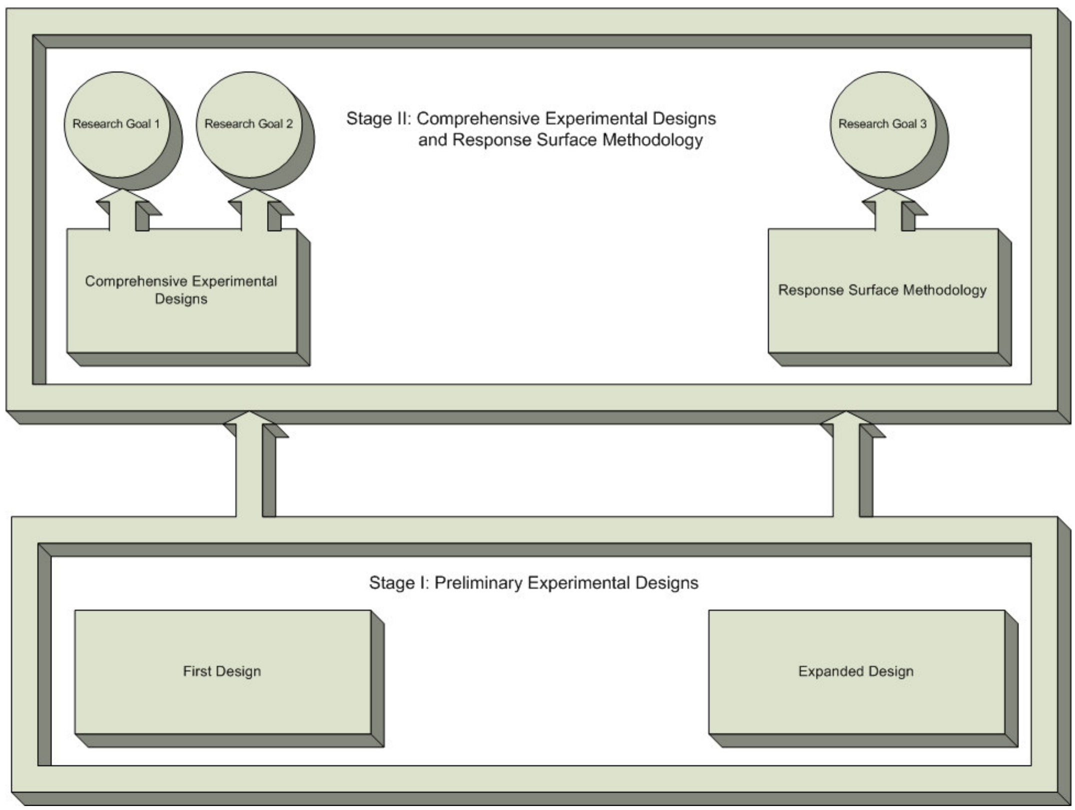

Figure 1.2: Research Approach

Figure 1.2 illustrates a conceptual view of my approach. As shown in the figure, I accomplish my work in two stages. In Stage I of my methodology, I develop preliminary experimental designs, while in Stage II, I develop comprehensive experimental designs and apply response surface methodology for factor optimization. Moreover, I attain my three research goals in Stage II.

Stage I

As shown in Figure 1.2, Stage I of my work includes both first and expanded designs, neither of which is comprehensive. The decision not to begin at the outset with a comprehensive design is warranted by the so-called “25% Rule,” which says that no more than one-quarter of an overall design effort should be expended in first designs [4]. The objective of the first design is to demonstrate how a systematic design of experiments (DOE) strategy can be used to analyze network system and protocol performance, thus leading to more objective conclusions valid over a wide range of network conditions and environments [5].

In my expanded design, I begin with a large factor space and use fractional factorial design to: (1) develop insights about the behavior and performance of multi-hop WMNs; and (2) eliminate factors that have little or no impact on responses. Unlike full factorial designs, which structure experiments such that all combinations of factors and their high and low values comprise the design matrix (discussed in greater detail in the Methodology chapter), fractional factorial designs are “abbreviated” forms that highlight main effects of factors upon responses. This makes for fairly expedient (and efficient) factor elimination, which is very important in the early part of experimental designs.

Stage II

Completed work in Stage I establishes a foundation upon which I may develop comprehensive experimental designs and apply response surface methodology; both of these comprise Stage II of my work. The objective of my comprehensive experimental designs is multifaceted: (1) Identify and list potential critical factors and parameters that might impact multi-hop WMN performance; (2) Evaluate system performance at various factor levels; (3) Quantify main effects and two-factor interaction effects; (4) Design first-order empirical models; and (5) Employ response surface methodology, in order to develop second-order models, if applicable, and to optimize one or more response metrics.

Methodology: Motivation

Statistical design of experiments (DOE) and response surface methodology (RSM) approaches have been used successfully in a variety of fields and disciplines, as both approaches are highly systematic and methodical. Application of both these approaches is intended to develop viable empirical models; there are differences between them, however. Where first-order models might be considered adequate for the system being evaluated, statistical DOE is used. In contrast, where second-order or higher-order models are needed, along with factor optimization, response surface methodology becomes necessary.

As I have already indicated, a considerable amount empirical work in science is done using the classical one-factor-at-a-time (OFAT) strategy. Unlike the OFAT approach, statistical DOE offers greater efficiency, improved reliability of measured factor interactions, and conclusions that are valid over a range of conditions. In sum, comparatively speaking, statistical DOE should lead to empirical models that are superior to those derived from OFAT approaches.

Response surface methodology (RSM) is a set of statistical techniques that may be applied when first-order models are inadequate, thus requiring higher-order empirical models. Moreover, as I have earlier stated, unlike statistical DOE, RSM may lead to models for which optimal factor values may be determined, such that a maximum (or minimum) response signal may be attained. As with statistical DOE, OFAT approaches are severely limited in not supporting such outcomes.

State-of-the-Art

A survey of the state-of-the-art in the empirical evaluation of the performance and behavior of multi-hop wireless infrastructures indicates considerable research activity. I shall now discuss work done by others that is representative of the state-of-the-art. Additionally, I describe how my dissertation work compares with these representative works.

IEEE 802.11 Mesh Network Performance

Seo *et al.* in [6] evaluate the performance of the 802.11 MAC protocol in a wireless mesh network. My work is similar to that of Seo *et al.* in that measurements are made of response variables such as throughput and delay under a variety of simulation scenarios. Moreover, factors such as number of gateway nodes, number of users generating data traffic, and ranges of transmission and carrier sensing are varied, in order to measure the impact of such changes in factor values upon response variables.

In contrast to my work, for which I employ statistical design of experiments approaches, Seo *et al.* use the traditional one-factor-at-a-time (OFAT) approach. That is, each design point of theirs varies the value of a single factor variable, while maintaining fixed values for all remaining factors. Results of the work done by Seo *et al.* in [6] correspond generally to my Stage I results; that is, network performance degrades with increasing traffic load, and improved performance may be realized by increasing the number of gateway nodes.

Unplanned 802.11b Mesh Network

Bicket *et al.* in [7] study the performance of an 802.11b wireless mesh network, deployed with minimal planning or management in an urban environment. Specifically, the target system of study is Roofnet, a community wireless network deployed in Cambridge, Massachusetts, which (at the time their paper was published) was comprised of 37 nodes located over a roughly four to six square kilometer area. An important research goal of their work in this study is to combine the best characteristics of: (1) well-planned, highly-coordinated, multi-hop networks; and (2) unplanned, loosely-connected, access point networks.

Ease-of-deployment features of Roofnet include: use of omni-directional antennas, self-configuring software, and multi-hop routing that is link-aware [7]. Results of the evaluation by Bicket *et al.* in [7] suggest that performance of an unplanned 802.11b wireless mesh network is likely acceptable to users. Specific conclusions made by Bicket *et al.* are as follows [7]:

- Throughput and delay both are comparable to end-to-end characteristics of DSL, with an average throughput between nodes of 627 kilobits/second;
- As the number of hops increases, throughput decreases; however, eight-hop routes average 160 kilobits/second;
- Performance of Roofnet is not dependent upon any particular small set of nodes; and
- Irrespective of the number of wired access points, Roofnet's multi-hop mesh enhances both connectivity and throughput.

A comparison between my work and the work done by Bicket *et al.* in [7] highlights an important similarity. That is, the configurations of the preliminary designs in Stage I of my work (see subsection 1.6.1) parallel somewhat the loosely-connected nature of Roofnet. Unlike the work done by Bicket *et al.*, however, my work includes finding the traffic load and network size at which a specific performance metric is optimized.

	CONTRIBUTION
1	Comprehensive performance evaluation of multi-hop wireless mesh networks
2	Empirical models that characterize the functional relationship between performance responses and system/network parameters (factors)
3	Determine the levels of two statistically-significant factor variables at which four performance responses are optimized

Table 1.1: List of contributions in this dissertation

Two-Tier Urban Mesh Network

Work done by Camp *et al.* in [8] offers an interesting contrast both to the work done by Bicket *et al.* in [7] and to my own work. Among several research goals, Camp *et al.* study node placement, the findings of which suggest that grid placement lead to throughput levels that are up to 50% higher than randomly placed nodes, which, as I have discussed in subsection 1.8.2, is the node placement topology used in the MIT Roofnet. This finding is a result of evaluating performance as impacted by factors such as the density of mesh nodes and random node placement [8].

In comparing my work in Stage I to the work done by Camp *et al.* in [8], I employ a loosely-connected grid node placement, with significant lack of network planning. Stage II of my work, however, involves a well-planned, highly-organized, node placement strategy.

Contributions

Table 1.1 lists my contributions to the state-of-the-art. My contributions are as follows: (1) A comprehensive performance evaluation of multi-hop wireless mesh networks; (2) Derivation of empirical models that characterize the functional relationship between performance metrics and system/network parameters; and (3) Determination of the levels of two statistically-significant factor variables at which four performance responses are optimized.

It is of special significance that my three research contributions form a "chain" of sorts, in that, with the exception of my third contribution, each is an antecedent event to subsequent contributions. Thus, my first contribution leads directly to the starting point for my second contribution, the results of which set the stage for my third research contribution. Moreover, my work involves two stages, whereby the first stage is preliminary, with the second stage leading to the realization of my three research contributions.

Dissertation Organization

The remainder of this dissertation documents the details of my development of empirical models for and performance evaluation of multi-hop wireless mesh networks. Chapter 2 presents a survey of the literature for each of my contributions and also justifies my approach. I then describe my use of statistical design of experiments and response surface methodology in Chapter 3. The results of my dissertation research are discussed in Chapter 4; these results directly address my research goals. Finally, I discuss conclusions and future work in Chapter 5.

CHAPTER 2

LITERATURE REVIEW

> "People think that computer science is the art of geniuses
> but the actual reality is the opposite, just many people doing
> things that build on each other, like a wall of mini stones."
> —Donald Knuth

In this section, I present a survey of the literature for each of my three contributions to the state-of-the-art, listed in Table 1.1 of this dissertation. Moreover, I justify my application of empirical modeling to multi-hop wireless mesh networks.

My first contribution to the state-of-the-art is motivated by the rapid growth and use of multi-hop wireless mesh networks (WMNs), where performance is expected to approximate that of wired network infrastructures. In this context, systematic and efficient approaches are crucial for evaluating behavior and performance of multi-hop WMNs. Moreover, a comprehensive evaluation—at all levels of the protocol stack—would benefit the research community.

My second contribution to the state-of-the-art is motivated by the extensive use of empirical modeling in many areas of science, engineering, and even agriculture. In addition to my discussion highlighting the use and benefits of empirical modeling in wireless networks, I call attention to the importance of having insight about the nature and form of modeling, especially limitations that are inherently a part of all modeling efforts.

My third contribution to the state-of-the-art is motivated by the heterogeneity that exists among the diverse environments within which multi-hop WMNs are deployed. The research literature suggests that, at the very least, traffic load impacts significantly network performance. A set of powerful techniques by which performance response may be optimized is response surface methodology (RSM).

Comprehensive Performance Evaluation

IEEE 802.11

Because empirical models describe the relationship between response variables and their factors, one may also glean insights about performance from such models. Fortunately, considerable work has been done in the area of IEEE 802.11 wireless network performance. My work is related to, and is an extension of, these performance investigations.

Crow *et al.* in [9] investigate IEEE 802.11 throughput performance via simulation, when all mobile stations generate asynchronous data traffic with equal intensity. Simulation results are as follows: (1) the condition of the channel may negatively impact throughput performance; (2) RTS_Threshold (a tunable parameter, used to determine when RTS/CTS should be used) may negatively impact throughput performance due to collisions; (3) Fragmentation Threshold, which, like RST_Threshold, is a tunable parameter, may be useful in terms of reducing the effects of poor channel quality; and (4) a longer MAC Service Data Unit (MSDU) may lead to a more efficient level of throughput performance.

Chhaya and Gupta in [10] evaluate the performance of the *Distributed Coordination Function* (*DCF*), which is the basic access method for the IEEE 802.11 MAC. Specifically, Chhaya and Gupta examined both the throughput and fairness properties of the DCF in IEEE 802.11 MAC. Moreover, Chhaya and Gupta compared DCF against an RTS/CTS scheme. Their simulation results showed higher throughput with the DCF scheme than was realized using the RTS/CTS scheme, if the load was small. On the other hand, at higher loads, the RTS/CTS scheme provided higher throughput than did DCF.

Shakkottai and Rappaport in [11] conclude that research strategies which have been used for wireline networks are inadequate for the unique issues found in wireless networks. Thus, they emphasize the importance of modeling network performance, particularly with the objective of understanding mixed traffic and service types over wireless networks. My use of statistical experimental design increases the likelihood of statistically valid network performance modeling within certain upper and lower bounds. Moreover, analyses of variance (ANOVA) figures of merit support my own work in allowing me to compare objectively the expected performance improvements that result from my proposed adaptive MAC protocol against the performance of comparable multi-hop WMNs that do not include my proposed adaptive MAC protocol.

As indicated by Andersen *et al.* in [12], the properties of radio propagation determine the physical layer characteristics of most wireless networks; this affects the design and performance limitations of higher level network layers, including the MAC sublayer. Their work in modeling radio propagation highlights, among other things, the importance of factoring in different physical environments (e.g., wireless networks in an urban setting as opposed to, say, a rural area).

An interesting study was done by Royer *et al.* in [13], which addressed the question of whether the choice of MAC protocol has any effect on the performance of routing protocols. Simulations were done using GloMoSim (a precursor to QualNet), whereby three routing protocols—Wireless Routing Protocol (WRP), Fisheye State Routing (FSR), and Ad hoc On-Demand Distance Vector (AODV)—and four MAC protocols—Carrier Sense

Multiple Access (CSMA), Multiple Access with Collision Avoidance (MACA), Floor Acquisition Multiple Access (FAMA), and IEEE 802.11 DCF (CSMA/CA/RTS/CTS/ACK)—are used in the simulations. Their results suggest that selection of the MAC protocol does indeed impact the performance of the routing protocol; thus, this should be considered when doing performance comparisons among different routing protocols.

Royer *et al.* in [14] attempt to find the optimum node density for ad hoc mobile networks that leads to maximal delivery of data packets. Their results suggest that such a global optimum does not exist. Instead, the node density should increase with increasing node speed.

Broch *et al.* in [15] present both detailed and summarized performance results of packet-level simulations for four different multi-hop wireless ad-hoc network routing protocols: DSDV, TORA, DSR, and AODV. Moreover, these simulations were done using the popular ns-2 simulator, to which they made "improvements." The purpose of their work in this paper was to model the behavior and performance of the aforementioned routing protocols.

Jun *et al.* in [16] develop a calculation of the theoretical maximum throughput of IEEE 802.11 networks, which considered a variety of physical layer and MAC layer variations. Moreover, Jun *et al.* apply their results by monitoring the link utilization of a particular IEEE 802.11 network. An objective of their applying these results to an actual network is to demonstrate how their calculation of the theoretical maximum throughput of IEEE 802.11 networks may be generalized to both ad hoc and infrastructure networks.

Cross-Layering Issues

Corson *et al.* in [17] make a two-fold claim concerning MANETs: (1) researchers and scientists should look to the existing fixed (wired) infrastructure as a starting point (or model) for integrating methods and approaches that actually work; and (2) developers must acknowledge that the "principle of strict protocol-layer separation" may need to be relaxed, in order to deploy a viable MANET design that overcomes extreme bandwidth limitations that are ubiquitous in the wireless medium. As per my work in multi-hop WMNs, I believe that Corson *et al.* make a compelling case for increasing the two-way vertical communication between upper-layer protocols and lower-layer protocols, so that many of the aforementioned inefficiencies (as they put it) associated with peer or horizontal requirements can be removed. While Corson *et al.* acknowledge potential risks in not following the "traditional layered design" approach, they seem to do so half-heartedly, which suggests a somewhat strong bias toward cross-layering.

Shakkottai *et al.* in [18] address issues that surround what they refer to as the "cross-layer paradigm shift," which they claim is well underway. Of relevance to my work is their acknowledgment of the importance of performance modeling and evaluation of mixed traffic and service types in wireless networks. Moreover, Shakkottai *et al.* recognize that such networks will likely be deployed in many diverse propagation environments, thereby supporting the necessity of employing viable techniques and approaches for evaluating these networks.

Similar to Shakkottai *et al.* in [18], Kawadia and Kumar in [19] warn against taking what they refer to as "unbridled cross-layer design," because the number of cross-layer factor interactions may potentially be large. Moreover, while some interactions may be intended, and therefore exploited, other interactions may be both unexpected and unintended. Therefore, cross-layer protocol architects should be cognizant of the likelihood of such interactions, and develop an understanding about their impact on system performance and behavior.

IEEE 802.11 MAC Layer

The IEEE 802.11 protocol and its related standards (e.g., *b*, *g*, *e*, etc.) dominate the wireless communications market. This is subject to change, of course, as there is considerable ongoing work in wireless communications. Still, even with new protocols, designers and architects should ensure seamless integration of their protocols with existing IEEE 802.11 wireless infrastructures.

Because a multi-hop WMN may be viewed in much the same way as a stationary ad hoc wireless network, the *Distributed Coordination Function* (*DCF*) access method is of direct relevance to my work; moreover, according to the original IEEE 802.11 standard [20], the implementation of Point Coordination Function (PCF) is optional. Hence, I shall forgo any discussion about the PCF access method. I should point out, however, that the literature has numerous sources that describe in detail the IEEE 802.11 DCF. In particular, the interested reader may wish to read more about DCF in [20], [21], [22], and [9].

The MAC sublayer is concerned with, among other things, coordination of channel access among and between multiple wireless hosts. Considerable insight about channel access methods and related challenges—particularly with respect to minimizing both the hidden terminal and exposed terminal problems—can be gleaned from Karn in [23] and Bharghavan *et al.* in [24]. Specifically, Karn in [23] describes how he extends the use of RTS and CTS packets in CSMA/CA to better handle the hidden and exposed terminal problems, which he accomplishes via his proposed Multiple Access with Collision Avoidance (MACA) channel access algorithm. Bharghavan *et al.* in [24] extend Karn's MACA RTS-CTS-DATA exchange by means of their proposed MACAW RTS-CTS-DS-DATA-ACK exchange algorithm. Unlike Karn, who merely proposed the idea of MACA, but without any sort of implementation, Bharghavan *et al.* implement both MACA and MACAW and compare the performances of the two. According to Bharghavan *et al.* in [24], even with the additional overhead in MACAW, throughput is increased by over 37% with MACAW as compared to MACA.

In my simulation work and empirical analyses, I employ an IEEE 802.11b wireless networking infrastructure. The IEEE 802.11 MAC sublayer notwithstanding, I do not discuss the IEEE 802.11 protocol in detail (e.g., IEEE 802.11 architecture and physical layer). There are many useful references concerning the IEEE 802.11 protocol; I would encourage the interested reader to consult the following, which I have found quite useful: the IEEE 802.11 Working Group website [20], Pahlavan and Krishnamurthy [25], Toh [26], and Crow *et al.* [9].

Slightly more than just a decade ago, Cox in [27] commented about the lack of real success (at that time) by "an IEEE standards committee, 802.11." While this sort of insight might today be considered somewhat laughable, it is not altogether unexpected, given the chaotic nature of the wireless medium. Fortunately, in the ten-plus years since the formation of the IEEE 802.11 Working Group, many challenges and obstacles have been overcome, particularly as regards the IEEE 802.11 MAC sublayer.

An excellent discussion about the IEEE 802.11 MAC sublayer is presented both by Pahlavan and Krishnamurthy in [25] and Crow *et al.* in [9]. Chandra *et al.* in [28] survey the literature for discussions about MAC protocols. In addition to describing these protocols, Chandra *et al.* compare them based upon three classifications: network architecture, performance, and support for multimedia traffic. Of particular interest to me is the inclusion and discussion of performance metrics by Chandra *et al.* in [28]; two of these are especially relevant to my work: *delay* and *throughput*.

Multi-hop Wireless Mesh Networks

Because my work focuses on the performance evaluation and empirical modeling of multi-hop WMNs, I include here a discussion about related work in performance studies of such networks. Interesting work in evaluating both the performance of wireless networks in general, and wireless mesh networks in particular, is described by Gupta and Kumar in [29] and Jun and Sichitiu in [30], respectively. The latter work done by Jun and Sichitiu in [30] is of special significance, since it addresses the problem of determining the exact capacity of a WMN. Their results show that the throughput for each mesh node decreases as $O(1/n)$, where n is the total number of nodes in the mesh network.

Solutions

I include a brief discussion about and examination of currently available (and deployed) multi-hop wireless mesh network solutions for the purpose of establishing additional context for my dissertation work. In this section, I discuss multi-hop WMN solutions by Cisco Systems, Kiyon, Nortel Networks, and Tropos Networks. Along with this, I shall, of course, describe features that are unique to each of these solution providers' approaches. A common thread among these four multi-hop WMN solutions—and one that is crucially important to their success—is that these networks are designed to integrate seamlessly with existing

802.11 wireless networks. Examples of such 802.11 wireless networks include those found in many public venues such as coffeehouses, school and university campuses, apartment complexes, and residential dwellings, to name a few.

Cisco Wireless Mesh Networking Solution

Cisco Systems is a well-known and highly-respected company that continues to provide the state-of-the-art in wired and wireless networking solutions. Consistent with its ongoing design and development of such infrastructures, Cisco Systems (http://www.cisco.com) has developed a wireless mesh networking solution that exploits the fast-growing (and relatively inexpensive) Wi-Fi client base [31]. The Cisco Systems Wireless Mesh Networking Solution purports to integrate well with existing Wi-Fi (802.11) wireless networks. My empirical work deals exclusively with 802.11b wireless networks. Unlike the dual-radio approach adopted by Cisco Systems, however, I employ a single-radio approach.

Kiyon Autonomic Network

In contrast to the solution developed by Cisco Systems, Kiyon's Autonomic Networking Technology (http://www.kiyon.com) is self-managing, which employs a cross-layer design that includes: (1) a modified MAC protocol that purportedly addresses the problem of throughput degradation, inherent in most multi-hop wireless networks; and (2) an enhanced ad hoc on-demand routing protocol that integrates a multiple-attribute metric for both topology discovery and route selection [32]. Moreover, Kiyon's cross-layer design facilitates improved TCP performance, since the modified MAC protocol informs TCP when packet loss is due to link failure, as opposed to congestion within the channel.

Kiyon's entry into the wireless mesh networking market is motivated by the increasing appeal of interconnecting existing IEEE 802.11 networks, using a wireless backhaul. It is this interconnection of IEEE 802.11 access points and routers that forms a mesh. As I have already suggested, however, forming a mesh using a wired infrastructure is both costly and resource-consuming (both in terms of time and labor requirements).

Kiyon Autonomic Networks—MAC: An unintended consequence of wireless mesh networks built upon IEEE 802.11 technology is the impact on both throughput and quality due to multiple hops. Like Cisco Systems, Kiyon exploits high-throughput, self-managing communications to circumvent throughput and quality problems. Kiyon employs a novel approach for overcoming the throughput degradation problem usually present in multi-hop wireless mesh networks. Rather than attempting to work around this problem, Kiyon exploits the use of available non-overlapped channels by employing them either simultaneously or alternatively. Specifically, Kiyon has developed a distributed TDMA MAC protocol that implements an automatic channel selection and fast switching algorithm in the MAC layer. Kiyon's multi-channel approach purportedly results in higher link throughput.

Kiyon Autonomic Networks—Routing: Kiyon Autonomic Networks mesh solution uses a novel ad hoc on demand routing protocol called *Kiyon Wireless Attribute Routing Protocol* (*WARP*), which, supported by a cross-layer design, uses attributes such as signal strength, SNR, and round-trip delay, among others, as the basis for routing decisions. Moreover, WARP works with both WARP-enabled and standard 802.11 clients, which facilitates easy deployment with existing 802.11 networks.

Kiyon Autonomic Networks—Cross-layer design: In addition to the purported benefits of Kiyon's cross-layer design, a key element is the sharing of information between the MAC and TCP layers concerning packet losses. Specifically, if packet losses are the result of channel errors or link failures, the Kiyon MAC informs TCP, in which case the standard TCP exponential backoff that accompanies congestion detection is not employed. This information-sharing should, presumably, lead to a much-improved TCP implementation, as compared to the typical TCP.

Kiyon Autonomic Networks—Architecture: The network architecture of the Kiyon Autonomic Network is very similar to the architecture illustrated in Figure 1.1 of this dissertation. The principal difference is that several Kiyon routers form a broadband backbone of the network. Additionally, each Kiyon router contains both WARP and the Kiyon MAC, along with a standard IEEE 802.11 radio. According to the available information posted on Kiyon's web site, this architecture gives clients several options by which the network may be accessed.

Nortel Wireless Mesh Network Solution

According to information by Nortel Networks in [33], its Wireless Mesh Network solution exploits the growing 802.11 wireless network consumer base, bringing existing "hot spots" together to form a *Community Area Network*, or *CAN*. A CAN is a set of wireless access points (APs) that form a mesh, which is self-organizing, auto-configuring, self-healing, and uses multi-hop, wireless backhaul from a wired broadband connection point.

Tropos Networks MetroMesh Architecture

The wireless mesh networking solutions developed by Tropos Networks each build upon the idea of combining the ubiquitousness of cellular networks with the relative simplicity and speed of Wi-Fi networks. My discussion of Tropos Networks solutions is based upon information found in [34].

Tropos Networks MetroMesh Architecture—Throughput: Tropos Networks solutions purportedly deliver consistent symmetric throughput rates that exceed 1.0 Mbps to Wi-Fi clients. Tropos Networks accomplishes this using its proprietary Predictive Wireless Routing Protocol™, or PWRP, implemented as part of its MetroMesh routers, which dynamically optimizes the data path between client and server. Specifically, PWRP adapts to changes in the wireless channel conditions, as well as new backhaul routes that come available due to the addition of MetroMesh routers. This adaptation feature is an important aspect of self-organization, inherent in the Tropos MetroMesh architecture. A further benefit from PWRP optimization of the client-server data path is that a constant routing overhead is maintained, irrespective of the whether the network scales up in size or whether it scales down in size.

Two additional features of PWRP include: (1) the use of predictive algorithms, used to select the "best" multi-hop paths available from among the myriad paths in the mesh; and (2) the virtual elimination of all single points of failure, a result of its fully-distributed architecture.

Confidence in Simulations

In chapter 1, I raised the point concerning the use of computer simulation studies instead of experimentation. The most probable reason for the wide use of simulators in multi-hop

WMN and MANET research is that deployment of actual large networks may not be realizable, particularly if hundreds of nodes are needed [35]. Researchers should not forgo the ease with which simulators support evaluation of significant changes imposed upon a network environment [36]. Additionally, I alluded to evidence from the literature which suggests that the use of simulation studies may in fact be more useful than experimentation, due mainly to the degree of control over parameters and the environment available in a simulator. According to Dodig-Crnkovic in [37], modern computing allows researchers to simulate considerable phenomena, particularly non-linear phenomena. Because my empirical work relies heavily on results from QualNet simulations, I shall discuss related work in this area.

Network simulations are often used instead of "live" experimentation, mainly because testbeds with the necessary configuration are not readily available. (Studies of wireless networks with several dozen nodes—hundreds, perhaps—come to mind.) Suppose, however, that an acceptable testbed were available, the issue of experiment repeatability remains. Unlike experimental "real world" networks, such experiment repeatability is, in theory, virtually assured in a simulation environment, since the experimenter has "absolute" control over the system being simulated. Moreover, experimentation with a "live" network is both expensive and difficult to accomplish [38].

Pawlikowski *et al.* in [39] discuss the use of simulation studies in telecommunications networks. They suggest that there is growing concern by many in the scientific community over the validity of such simulation studies. Using survey results from 2200 published scientific papers, as well as anecdotal evidence, Pawlikowski *et al.* in [39] argue that the question of credibility of simulation studies of telecommunication networks is both valid and legitimate. Thus, Pawlikowski *et al.* in [39] posit two necessary conditions for a credible telecommunication networks simulation: (1) Appropriate pseudo-random number generators of independent uniformly distributed numbers must be used; and (2) Analysis of simulation output data should be based upon an appropriate methodology, as well as identification of and discussion about the final statistical errors associated with the results.

Kurkowski *et al.* in [40] extend the work done by Pawlikowski *et al.* in [39], with a particular focus on MANET simulation. The goal of the work done by Kurkowski *et al.* is to heighten awareness of the apparent lack of credibility of MANET simulation results among the research community. In their study, Kurkowski *et al.* in [40] analyze MANET simulation studies published in the Proceedings of the ACM International Symposium on Mobile Ad Hoc Networking and Computing (*MobiHoc*) from 2000 through 2005, focusing on four areas of credibility in MANET research: (1) repeatability; (2) lack of bias; (3) rigor; and (4) statistical reliability. The results of their study suggest that significant deficiencies exist in MANET simulations for the four areas of credibility on which their work was focused. In addition to their emphasis on addressing these four areas of credibility for MANET simulation studies, Kurkowski *et al.* discuss briefly tools available to researchers that might aid in the development of credible MANET simulation studies [40].

Kotz *et al.* in [41] describe their detailed study of wireless assumptions that compared experimental against simulation results, using the same routing protocols. The purpose of this study was to show that assumptions used in most MANET simulation studies lead to results that differ substantially from reality. Moreover, similar to Pawlikowski *et al.* in [39] and Kurkowski *et al.* in [40], Kotz *et al.* in [41] surveyed articles over a multi-year period that involved simulations (*MobiCom* and *MobiHoc* proceedings, 1995 through 2003). The results of their survey showed that the number of “Simple” and “Flat Earth” models far exceed the number of “Good” models [41]. Kotz *et al.* list the following axioms that usually accompany “Simple” and “Flat Earth” models [41]:

- the world is two dimensional;
- the transmission area of a radio is roughly circular;
- all radios have equal range;
- if I can hear you, you can hear me;
- if I can hear you, then I can hear you perfectly; and
- signal strength is a simple function of distance.

In sum, results of the comparison between experimental results and simulation results offer compelling evidence against the validity these axioms [41].

A study similar to that of Kotz *et al.* in [41] is a comparative study done by Lucio *et al.* in [36], whereby outputs from two popular network simulators, OPNET Modeler and NS-2, were compared against the output for a network testbed. Their objective in doing so was to offer researchers a guide in performing packet-level network simulations [36]. If indeed simulation tools are used by such researchers, then accuracy of simulation relative to a real network is paramount. It is important to note that Lucio et al. are not comparing between the two network simulators; rather, they want to determine the accuracy of each. A summary of their results is as follows:

- Both simulators accurately modeled testbed behavior for CBR traffic;
- Neither of the simulators accurately modeled testbed behavior for FTP traffic, using default simulation parameters; and

- When simulation parameters were adjusted, OPNET Modeler seemed to be more accurate than did NS-2.

One final point emphasized by Lucio *et al.* in [36] is that configuring the network simulators and the testbed for such comparisons is indeed complicated.

The literature supports strongly the idea that researchers involved in wireless communication networks usually decide upon a particular simulator on which to do their work. That is, because of time and resource constraints, the researcher is unable to compare among the various discrete event simulation tools available. Cavin *et al.* in [35] undertake such an endeavor. They compare simulation results of a **flooding** algorithm among three simulators: OPNET Modeler, NS-2, and GloMoSim (the precursor to QualNet). Cavin *et al.* measure three performance responses [35]: (1) *time delay*, which is the average time required by a packet to reach a node *n*; (2) *success rate*, which is the measured difference between the expected and actual number of messages received at node *n*; and (3) *overhead*, which is the sum of duplicated packets received by node *n*. Moreover, the parameters were the same for all three simulation environments. The results collected from the three simulation environments differed significantly from one another. Cavin *et al.* identify possible causes of such differences; these include the following [35]:

- Differing physical layer implementations;
- Implementation of a new protocol is itself difficult to transpose from one simulator to another; and

- Given that successive releases provide bug fixes, it is reasonable to assume that MANET simulators still contain errors or incompatibilities to the IEEE 802.11 standard.

Cavin *et al.* in [35] conclude that a hybrid approach that involves simulation of only the MAC and physical layers, with the upper layers executed on, say, a cluster of machines, is preferred.

Despite problems and pitfalls usually associated with network simulations, use of such simulations is likely to continue. Heidemann *et al.* in [42] offer guidelines that may increase the validity of simulation studies. Their guidelines are the result of a workshop held in May 1999 by the National Institute of Standards and Technology (NIST) and the Defense Advance Research Projects Agency (DARPA) to discuss network simulation validation. Heidemann *et al.* in [42] emphasize the point that validation is required *both* in simulation and laboratory (that is, experimental) environments. Moreover, validation as a process is multi-level, from the standpoint that its degree is a function of the question or questions being posed by the researcher (see [42] and [43]). A summary of the recommendations made during the aforementioned workshop is as follows [42]:

- Simulation results should be compared against results from laboratory experiments, analytical models, and other, independently contrived results;
- Visual representations, usually by way of animation, may aid in the identification of erroneous behavior by the system;
- Because real systems operate in real time, asynchronization (among, say, individual wireless nodes) should be injected within the simulation runs;

- Reproducibility of simulations and their results is an imperative;
- Comparative simulation studies are easier to validate than simulation studies that emphasize absolute system behavior; and
- Introducing artificial boundaries into the model (e.g., an artificial physical topology) may introduce inaccuracies.

Interesting work has been done by Judd and Steenkiste, described in [44], in which they have developed a wireless network emulation tool that utilizes real MAC and PHY layers, while supporting real applications. They claim that their emulator allows for realistic and repeatable wireless experimentation, because their emulator provides accurate wireless signal transmission, propagation, and reception in an emulated physical space [44]. The paper by Judd and Steenkiste in [44] focuses on the purported success with which they have been able to conduct sophisticated wireless experiments that suggest considerable accuracy.

A helpful guide to designing and working with viable simulation experiments is presented by Kleijnen *et al.* in [45]. Their focus is on statistical DOE as it may be applied to simulation studies. Of particular importance is their discussion of a "toolkit" of designs for experimenters who have limited DOE expertise and experience.

A number of significant challenges remain with the use of network simulation studies. Indeed, from the foregoing discussion, one might be tempted to concede that results from network simulation studies are tenuous at best. By extension, it follows that: (1) network simulation studies should be avoided; and (2) experimentation via wireless network testbeds should be the only acceptable alternative. Such a conclusion, however, may be both problematic and incorrect. From my review of the literature, I am confident that simulation studies, if done correctly, can provide important insights from analyses of their results; hence, justification for my use of simulation studies in my own work.

Empirical Models

Scientific Investigation and Empirical Models

The main purpose of scientific investigation is to lead the researcher ever closer to truth regarding physical reality. This requires observation of the physical phenomena under investigation. Merely observing these phenomena, however, is insufficient; models—empirical models, to be more precise—must be developed.

Gauch in [46] states that models *describe* the reality being investigated; in other words, models are not the reality being investigated. This point may seem patently obvious and not worth mentioning; however, I wish to amplify Gauch's point about models and reality, as I intend not to succumb to the temptation to place too great an emphasis on the models. A supporting perspective to Gauch's assertion is taken from Giere in [47], who states that representing reality is done by the scientist, not by the model itself.

Berg in [48] claims that the scientist and researcher should remain cognizant of the inescapable subjectivity in the interpretation of empirical data. Like Giere, Berg's point gives rise to the likelihood that divergent empirical models could be developed by different researchers—even if the same empirical data are used. Thus, the models I develop through my work: (1) apply to my stated research problem; (2) are within a defined scope; and (3) are subject to my interpretation of the empirical results.

From the preceding, an important objective for me is to develop empirical models that *correspond* to reality, not copy reality—an objective supported by Meadows in [49], who says that there is a virtual nonexistence of isomorphism between models and the reality they describe. From the empirical models I develop, I seek to gain insights about the phenomena under study—in this case, multi-hop WMNs.

In my approach to empirical model development, I employ the principle of parsimony, or simplicity. The literature supports strongly such parsimonious empirical modeling. A caveat to my development and use of parsimonious empirical models hinges around a simple but compelling assertion made by George E. P. Box, the noted statistician and scientist, who claims that all models are wrong, but some may be useful [3].

George E. P. Box is considered by both statisticians and scientists alike as the intellectual progeny of Sir Ronald A. Fisher, the man credited with conceiving and developing statistical design of experiments (DOE). It is worth noting that Sir Fisher was the father-in-law of Box, who was married to Sir Fisher's daughter. I mention this point merely to suggest the very real possibility that both Box and Sir Fisher had, on more than one occasion, various discussions about empirical modeling in general and statistical DOE in particular. In any case, Box in [3] makes the point that simple but illustrative models are the signature of a capable scientist; he further amplifies this point by stating that "overelaboration" and "overparameterization" are the marks of mediocrity in scientific research. Thus, I avoid the latter category.

Gauch in [50] makes the point that most statisticians understand the increase in both accuracy and efficiency that result from parsimonious modeling; Gauch goes on to say that, unfortunately, very few scientists recognize this important opportunity. Feuer in [51] says that the greatest of scientists hold the view that the laws of nature are fundamentally simple, which is the main reason for their successful employment of the principle of simplicity (parsimony). Beck in [52] aligns himself with the idea of parsimonious modeling, but cautions against what he calls “an overly conscientious use of the principle of parsimony,” as this might lead to models that are too narrow.

Statistical Design of Experiments

Factorial design offers the researcher a mechanism by which empirical models may be developed that provide considerable information with minimal time and resource requirements. While factorial design approaches have been used for some time, and by researchers in many different fields, a review of the literature suggests that the vast majority of empirical model development is done using the “one-factor-at-a-time” approach (OFAT), which, unfortunately, is inferior to factorial design, both in terms of accuracy and efficiency. An excellent tutorial on statistical DOE for simulation is given by Kelton and Barton in [53].

Empirical models developed using factorial design techniques present the researcher with equations that describe the functional relationship between response variables and factors that affect them. It turns out that the empirical models contrived using factorial design techniques are in fact least-squares regression models. Insights gleaned from least-squares regression models are more fruitful when the researcher doing the analysis has some understanding about the process upon which least-squares regression is based.

Barrett *et al.* in [54] apply statistical design of experiments and analysis of variance (ANOVA) to ad-hoc networks, in order to characterize the interaction between routing and MAC protocols. The results of their simulation studies and statistical analyses suggest that there is no single MAC/routing protocol combination that outperforms all others. Rather, the fact that interaction exists suggests that protocol design should consider the combination of routing and MAC protocols as operating in tandem, in terms of the performance impact on the system.

It is one thing to contrive empirical models that describe the relationship between responses and the factors that affect them, and quite another thing to ascertain such attributes as validity, accuracy, and reliability of such models. Analysis of variance, or ANOVA, offers the researcher *figures of merit* (or *merit functions*, as they are sometimes called), by which the aforementioned attributes may be determined. Usually, the ANOVA is presented as an ANOVA table.

Analysis of variance was developed by Sir R. A. Fisher, whom I have previously mentioned, and who is generally considered as the "father" of modern experimental design. Most experimental results exhibit variation among the data, the sources of which come from variance between treatments and variance within treatments. Analysis of variance helps the researcher determine whether the variability is statistically significant, or, if not, then perhaps small enough such that chance is the probable explanation for variability [46].

Application of ANOVA to the study of interaction between network protocols, topology, and traffic, was done by Barrett *et al.* in [55]. Their objective was to empirically characterize the interaction effect between the routing layer and the MAC layer in wireless radio networks. The results of their statistical analysis and application of ANOVA led to their concluding that different combinations of routing and MAC protocols lead to varying performance under varying topology and traffic conditions. The significance of their work to my own work is the emphasis on identifying and measuring factor interaction.

Perkins *et al.* in [56] apply statistical DOE to the study of the behavior and performance of ad hoc networks. In their study, Perkins *et al.* evaluated the impact of five factors—node speed, pause-time, network size, number of traffic sources, and type of routing (source versus distributed)—on three performance responses—throughput, average routing overhead, and power consumption. Their study was the catalyst for my first design, the details of which are described by Totaro and Perkins in [5], and upon which my discussion about my first design is based, included in chapter 3 of this dissertation.

A similar study was done by Vadde and Syrotiuk in [57], whereby statistical DOE was used to study the impact of factors and their interactions on service delivery in mobile ad hoc networks. Their results suggest that for average delay, the MAC protocol and its interaction with the routing protocol are the most significant. Of particular relevance to my work, however, is their conclusion that statistical DOE and ANOVA offer powerful tools by which simulation results may be analyzed and evaluated, such that main effects and interaction effects may be identified.

Statistical DOE involves many different techniques; I describe my application of these tools in chapter 3 of this dissertation. I should add that four sources from the literature in statistics are especially important to my methodology and results; these sources are: Box [4], Jain [58], Law [59], and Montgomery [60].

Response Surface Methodology

Response surface methodology (RSM) has been used successfully in various domains, not the least of which includes agriculture, the chemical industry, and pharmaceutical drug development. Excellent references that describe these techniques include Myers and Montgomery in [61], and Box and Draper in [62]. For a brief overview of RSM, see Angun *et al.* in [63].

Interestingly, application of RSM to computer communications is relatively new and sparse. However, a recent paper by Vadde *et al.* in [64] demonstrates that RSM can be successfully applied to the domain of networking. Specifically, their work is applied to mobile ad hoc networks (MANETs), whereby they use RSM to optimize protocol interaction found by factor screening. Moreover, Vadde *et al.* employ RSM to optimize multiple responses, which is similar to my work, described in this dissertation.

Along with [61] and [62], helpful descriptions about RSM can be found in both [4] and [60]. Moreover, these two references present the use of RSM by way of several excellent examples. As with statistical DOE, I discuss the application of RSM in chapter 3.

CHAPTER 3

METHODOLOGY AND DATA ANALYSIS

> "For every complex question there is a simple and wrong solution."
>
> —Albert Einstein

Stage I: Preliminary Designs

In chapter 1 of this dissertation, I included a very brief conceptual description of my work in Stage I, which involves experimental designs that I view as preliminary to subsequent comprehensive designs. My decision to employ a two-stage approach is the result of Box's "25% Rule," which says that no more than one-quarter of an overall design effort should be expended in first designs [4]. Within Stage I, I employ a two-phase approach: (1) first design; and (2) expanded design.

The "first design" phase has a limited factor space. The motivation for the experimental design work done in this first phase is to whether a systematic design of experiments (DOE) strategy can be used to analyze network system and protocol performance, thereby leading to more objective conclusions valid over a wide range of network conditions and environments [5]. Results from this first design seem to support the use of statistical DOE for empirical modeling.

The "expanded design" phase involves a larger factor space than was used in the "first design." Moreover, I employ fractional factorial design to: (1) develop insights about the behavior and performance of multi-hop WMNs; and (2) eliminate factors that have little or no impact on responses. Unlike full factorial designs, which structure experiments whereby all combinations of factors and their high and low values form the design matrix, fractional factorial designs highlight main effects of factors upon response variables. This leads to fairly expedient (and efficient) factor elimination, which is very important in the use of statistical DOE.

Stage I serves as the foundation upon which Stage II shall be built. Indeed, the motivation to formulate Stage II is a direct result of the findings from Stage I work. I have completed both phases of Stage I, the results of which should prove useful as I employ comprehensive designs and response surface methodology in Stage II.

Motivation

Scientists and researchers have for years followed what is commonly referred to as the "one-factor-at-a-time" (OFAT) approach as a means for developing empirical models that show the functional relationship between a response and one or more factors that affect it. Suppose, for example, that we wish to quantify the effects of network size and traffic load upon, say, throughput. The OFAT approach would have us first vary network size, while holding traffic load constant, and measure the effect upon throughput from doing so. We would next take this measured effect and use its value for network size, then vary traffic load, with the objective of measuring its effect upon throughput.

The preceding description of the OFAT approach appears reasonable, and we might readily accept that the functional relationships indicated are accurate. Unfortunately, while the OFAT approach may explain main effects by factors upon the response, what this approach does not do is explain whether two-way factor interaction effects are present. That is, it is possible that neither factor alone has a statistically-significant impact on the response; however, varying both factors simultaneously might indeed result in a statistically-significant effect on the response, which indicates the presence of factor interactions.

In addition to completely ignoring two-way factor interaction effects, problems with the OFAT approach are further exacerbated as additional factors are included for analysis. It goes without saying, then, that applying the OFAT approach becomes increasingly more confusing as we add factors, since we must run experiments for all possible values of all factors, while at the same time holding non-varying factors at fixed levels. Today's scientists are quite fortunate in that there are a powerful set of techniques that are straightforward and offer considerable analytical power—these techniques are referred to collectively as 2^k factorial designs.

First Design

Most of the material in this subsection comes directly from Totaro and Perkins [5], of which I was co-author[1]. Subsequent references to "we" and "our" are intended to highlight the collaborative nature of our work in [5]. Moreover, our work in [5] served as a significant starting point for me in applying statistical DOE and response surface methodology to the empirical study of multi-hop wireless mesh networks. Earlier, I made the point that multi-hop wireless mesh networks may be viewed as stationary ad-hoc wireless networks. Our application of statistical DOE to mobile ad-hoc networks as discussed in [5] can be generalized for subsequent experimental design work I undertake as it relates to my prospectus.

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[1] This work is based on an earlier work: Using Statistical Design of Experiments for Analyzing Mobile Ad Hoc Networks, in Proceedings of The 8th ACM International Symposium on Modeling, Analysis and Simulation of Wireless and Mobile Systems, MSWiM '05, © ACM, 2005, http://doi.acm.org/10.1145/1089444.1089472.

Statistical DOE

To yield objective conclusions, an experimental evaluation should comprise two key and interrelated components: (1) the experimental design, which refers to the process of planning the experiment so that data can be collected in a manner feasible for statistical analysis; and (2) the actual statistical analysis of the data [4, 60]. Our aim in [5] was to provide a brief overview of statistical design of experiments (DOE), while introducing the specific experimental design and analysis techniques used.

Terminology

Before I discuss our experimental strategy in [5], it would be useful to define several standard statistical DOE terms used throughout the remainder of my prospectus [58].

- *Factors:* The variables that affect the response variable. Factors may be classified as primary, secondary, or constant, depending on their use in an experiment design.
- *Levels:* The values that a factor can assume are called its levels.
- *Response Variable:* The measured performance of the protocol or system under study.
- *Design:* The experimental design specifies the number of experiments, the factor level combinations for each experiment, and the number of replications of each experiment.
- *Replication:* This refers to the process of repeating an experiment or set of experiments.
- *Main effects:* Intuitively, the main effect of a factor refers to the average change in a response variable produced by a change in the level of the factor.

Label	Factor	Level 1 $(-)$	Level 2 $(+)$
1	Avg. neighbors	7 (strongly-connected)	3 (weakly-connected)
2	Avg. node speed	5 m/sec (1-10 m/sec range)	30 m/sec (25-35 m/sec range)
3	Traffic load	10% of no. of nodes	20% of no. of nodes
4	No. of nodes	100	500
5	MAC layer	802.11b w/ RTS	802.11b w/out RTS

Table 3.1: First Design: Experimental Factors

- *Interaction effects:* Two factors interact if the performance response due to factor *i* at level *m* depends on the level of factor *j*. In other words, the relative change in the performance response due to varying factor *i* is dependent on the level of factor *j*.

Designing the Experiment

Step l. Defining the experimental objectives. Our underlying goal of the work done in [5] was to demonstrate the effectiveness of a statistical DOE strategy when evaluating the performance of mobile ad hoc networking systems or protocols. To this end, the specific objectives of our experiments were to quantify the main and interactive effects of a subset of potentially influential factors on the performance of ad hoc networks. Using these effects, we developed empirical models, which could then be used to predict performance of the ad hoc network over the range of values examined in our experimental design.

Step 2. Selecting the factors (and their levels). The next step in the experimental design process is selecting the potentially influential factors. In practice, numerous factors may impact the performance response of an ad hoc networking system. Since our overarching goal in [5] was only to illustrate the effectiveness of the statistical DOE strategy, in our preliminary work, we analyzed only a subset of five factors, while holding all other factors constant. Table 3.1 shows the factors studied in this first design.

I next provide our justification for the factor levels (values) used in [5]. *Average number of neighbors* is the average number of single-hop nodes within transmission range of any arbitrary node in the network. This can be considered a measure of network density and is expected to influence network connectivity, routing overhead, MAC contention, and source-destination path length, thereby influencing the performance responses. For the average number of neighbors factor, we considered two levels: strongly connected (7 neighbors[2]) and weakly connected (3 neighbors). *Node mobility*, which is measured as the average node speed, will impact the frequency of topology changes. We also considered *traffic load*, which is measured as the percentage of nodes acting as source traffic generators. *Network size*[3], measured as the number of nodes in the system, will impact the path length and route discovery time, which could influence overall system performance. Finally, we considered the medium access control protocol as a primary factor. We investigated two levels: the IEEE 802.11 DCF with the optional RTS/CTS handshake and the IEEE 802.11 DCF without RTS/CTS handshake. Research results show that the RTS/CTS handshake is useful in relatively static one-hop wireless networks. However, it is not clear what effect the RTS/CTS handshake will have in a multi-hop wireless environment with frequent topology changes where nodes move in and out of contention areas arbitrarily.

Step 3: Selecting the response variables. We considered two performance responses, each of which relates directly to the ability of the system to meet specific quality of service requirements. The *packet delivery ratio* is defined as the number of packets delivered to a destination divided by the number of packets actually transmitted. *End-to-end delay* is the

[2] It has been suggested by Takagi and Kleinrock in [65] and Royer [66] that throughput performance is optimal when the average number of neighbors is between six and eight neighbors.
[3] The terrain size was adjusted appropriately to maintain the required network density or average neightbors.

		Factors					Performance Metrics	
		1	2	3	4	5		
Design Points	Factor Level	Avg. No. of Neighbors	Avg. Node Speed (m/s)	Traffic Load	Number of Nodes	MAC Layer	Packet Delivery Ratio	End-to-End Delay (secs)
	(−)	7	5	10% of Number of Nodes	100	802.11b w/ RTS		
	(+)	3	30	20% of Number of Nodes	500	802.11b w/out RTS		
1		(−) 7	(−) 5	(−) 10	(−) 100	(−) 802.11 b w/RTS	0.71568	0.86571101
2		(+) 3	(−) 5	(−) 10	(−) 100	(−) 802.11 b w/RTS	0.11592	1.27659734
3		(−) 7	(+) 30	(−) 10	(−) 100	(−) 802.11 b w/RTS	0.58568	0.9923993
4		(+) 3	(+) 30	(−) 10	(−) 100	(−) 802.11 b w/RTS	0.25776	2.13651797
5		(−) 7	(−) 5	(+) 20	(−) 100	(−) 802.11 b w/RTS	0.72484	0.76839629
6		(+) 3	(−) 5	(+) 20	(−) 100	(−) 802.11 b w/RTS	0.17076	1.41365995
7		(−) 7	(+) 30	(+) 20	(−) 100	(−) 802.11 b w/RTS	0.563	0.96332324
8		(+) 3	(+) 30	(+) 20	(−) 100	(−) 802.11 b w/RTS	0.24584	2.19733746
9		(−) 7	(−) 5	(−) 50	(+) 500	(−) 802.11 b w/RTS	0.395968	1.49277102
10		(+) 3	(−) 5	(−) 50	(+) 500	(−) 802.11 b w/RTS	0.092656	0.78984261
11		(−) 7	(+) 30	(−) 50	(+) 500	(−) 802.11 b w/RTS	0.271504	2.07584805
12		(+) 3	(+) 30	(−) 50	(+) 500	(−) 802.11 b w/RTS	0.08344	3.28247314
13		(−) 7	(−) 5	(+) 100	(+) 500	(−) 802.11 b w/RTS	0.330824	5.25921359
14		(+) 3	(−) 5	(+) 100	(+) 500	(−) 802.11 b w/RTS	0.099736	1.04019082
15		(−) 7	(+) 30	(+) 100	(+) 500	(−) 802.11 b w/RTS	0.16395	3.11871308
16		(+) 3	(+) 30	(+) 100	(+) 500	(−) 802.11 b w/RTS	0.07568	4.98781013
17		(−) 7	(−) 5	(−) 10	(−) 100	(+) 802.11 b w/out RTS	0.71568	0.865711017
18		(+) 3	(−) 5	(−) 10	(−) 100	(+) 802.11 b w/out RTS	0.11592	1.27659734
19		(−) 7	(+) 30	(−) 10	(−) 100	(+) 802.11 b w/out RTS	0.58568	0.9923993
20		(+) 3	(+) 30	(−) 10	(−) 100	(+) 802.11 b w/out RTS	0.25776	2.13651797
21		(−) 7	(−) 5	(+) 20	(−) 100	(+) 802.11 b w/out RTS	0.72484	0.76839629
22		(+) 3	(−) 5	(+) 20	(−) 100	(+) 802.11 b w/out RTS	0.17076	1.41365995
23		(−) 7	(+) 30	(+) 20	(−) 100	(+) 802.11 b w/out RTS	0.563	0.96332324
24		(+) 3	(+) 30	(+) 20	(−) 100	(+) 802.11 b w/out RTS	0.24584	2.19733746
25		(−) 7	(−) 5	(−) 50	(+) 500	(+) 802.11 b w/out RTS	0.395968	1.49277102
26		(+) 3	(−) 5	(−) 50	(+) 500	(+) 802.11 b w/out RTS	0.092656	0.78984261
27		(−) 7	(+) 30	(−) 50	(+) 500	(+) 802.11 b w/out RTS	0.271504	2.07584805
28		(+) 3	(+) 30	(−) 50	(+) 500	(+) 802.11 b w/out RTS	0.08344	3.28247314
29		(−) 7	(−) 5	(+) 100	(+) 500	(+) 802.11 b w/out RTS	0.330824	5.25921359
30		(+) 3	(−) 5	(+) 100	(+) 500	(+) 802.11 b w/out RTS	0.099736	1.04019082
31		(−) 7	(+) 30	(+) 100	(+) 500	(+) 802.11 b w/out RTS	0.16952	3.11871308
32		(+) 3	(+) 30	(+) 100	(+) 500	(+) 802.11 b w/out RTS	0.07568	4.98781013

Table 3.2: Design Matrix for 2^5 Factorial Design

application layer end-to-end delay, which includes all processing, queuing, and transmission delays at each node along the path.

Step 4. Selecting the appropriate design. We used a $2^k\ r$ factorial design. The $2^k\ r$ factorial design technique considers k factors, where each factor has two distinct levels (or values). For simplicity and computational purposes, it is often useful to code the factor levels as a + or – level, as shown in the design matrix in Table 3.2. The design matrix shows all possible combinations of factor levels (called design points). Each design point corresponds to a simulation scenario, which is replicated $r = 5$ times, in our experiments.

The response values for the performance metrics (i.e., *packet delivery ratio* and *end-to-end delay*) are also included in Table 3.2.

Step 5. Simulation and data collection. Our simulations were carried out using QualNet, a network modeling tool developed by Scalable Network Technologies. In order to obtain results that approximate an actual MANET, we ran each of the 32 simulations five times, after which we computed the average of the five runs for each design point. This results in a total of 160 simulation runs (32 design points × 5 runs each). Each simulation experiment was executed for 320 seconds. Formally speaking, our approach is a $2^5 5$ factorial design, which implies there are five factors, each at two levels, and the experiment is repeated five times. In addition to the five aforementioned factors that were measured in this study, several other potentially influential factors were held constant. All nodes have a transmission range of 250 meters. The traffic sources were all constant-bit-traffic generators transmitting 512-byte UDP packets at a rate of 2 packets/second. The Location-Aided Routing (LAR) protocol was used as the routing protocol. The channel propagation model is based on the free-space model with a channel capacity of 2Mbps. The random waypoint mobility model is used to model mobility, with a pause-time of 25 seconds.

Step 6: Computing the main and interactive effects. Recall that we are interested in analyzing the main and interactive effects that factors have on specific response metrics. For clarity, we illustrate a simple approach for estimating main and two-factor interaction effects [58]. Let us consider the 2^2 factorial design shown in Table 3.3, with factors x_1 and x_2 for which we are interested in quantifying their effect on the response metric y. Notice in experiments 1 and 2 we vary x_1 from its − level to its + level while holding x_2 at its − level. In both cases, we obtain values for the response metric y. Similarly, in experiments 3 and 4

Experiment	x_1	x_2	y
1	$(-)$ 5	$(-)$ 10	0.75
2	$(+)$ 25	$(-)$ 10	0.25
3	$(-)$ 5	$(+)$ 100	0.40
4	$(+)$ 25	$(+)$ 100	0.15

Table 3.3: Example Experimental Data

we vary x_1 from its $-$ level to its + level while holding x_2 at its + level. As before, we obtain values for the response metric y. We can express the functional relationship $y(x_1, x_2)$ using the following effects model:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{12} x_1 x_2 \tag{3.1}$$

where β_0 is the average response over all simulation runs, β_1 and β_2 represent the main effects of x_1 and x_2, respectively, and β_{12} represents the interactive effect of factors x_1 and x_2, respectively

Substituting the four response observations y_1, y_2, y_3, and y_4 (one for each design point in a 2^2 design matrix) and the coded values for each factor in Equation 3.1, we have

$$y_1 = \beta_0 - \beta_A - \beta_B + \beta_{AB}, \tag{3.2}$$

$$y_2 = \beta_0 + \beta_A - \beta_B - \beta_{AB}, \tag{3.3}$$

$$y_3 = \beta_0 - \beta_A + \beta_B - \beta_{AB}, \tag{3.4}$$

and

$$y_4 = \beta_0 + \beta_A + \beta_B + \beta_{AB}. \tag{3.5}$$

Solving Equations 3.2, 3.3, 3.4, and 3.5 for β_i's, we have

$$\beta_0 = 1/4(y_1 + y_2 + y_3 + y_4), \tag{3.6}$$

$$\beta_1 = 1/4(-y_1 + y_2 - y_3 + y_4), \tag{3.7}$$

$$\beta_2 = 1/4(-y_1 - y_2 + y_3 + y_4), \tag{3.8}$$

and

$$\beta_{12} = 1/4(y_1 - y_2 - y_3 + y_4). \tag{3.9}$$

From these results, we see that the main effect of each factor is actually the difference between two averages:

$$\boldsymbol{E} = \bar{y}_+ - \bar{y}_- \tag{3.10}$$

where $\bar{y}_+$ is the average response when the factor is at its *high* level and $\bar{y}_-$ is the average response when the variable is at its *low* level. Furthermore, the interactive effect is the average change in the response metric when the two factors are at the same level (+ or −) and when they are at different levels. It is important to note that all responses for each experimental design point is used to determine all main and joint effects [4].

Data Analysis

I shall discuss the results of our statistical DOE, along with an analysis of these results. Specifically, I shall first provide an intuitive and visual illustration regarding the impact of the factors on performance. I then quantify this intuition by way of statistical analysis. For the discussion which follows, the reader may find it helpful to refer to the design matrix shown in Table 3.2.

Preliminary Insights. A scatterplot can be used to visualize performance changes as the factor levels are changed. Each value along the *x*-axis corresponds to a design point (or simulation scenario) as shown in Table 3.2. The *y*-axis is the performance metric under consideration, and each point on the graph is the average of $r = 5$ simulations for that particular design point.

Upon inspection of the scatterplots in Figures 3.1 and 3.2, it is important to note that the individual points in each of the scatterplots reflect a change in the *average number of neighbors* factor from its – to its + level (that is, from 7, or strongly-connected, to 3, or weakly-connected). Similarly, point-pairs 1-2/3-4, 5-6/7-8, and so on, reflect a change in the *average node speed* from its – to its + level (i.e., from 5 m/sec to 30 m/sec). This observable pattern can help the researcher determine whether or not particular effects are present between factors and performance metrics.

Before we examine the two scatterplots in detail, it is useful to first glean some preliminary insights into what these graphs tell the researcher. The most apparent element when contrasting the two scatterplots is that when end-to-end delay is small, the packet delivery ratio is large (see run numbers 1 through 9 and run numbers 17 through 25 in Figures 3.1 and 3.2). Conversely, we observe that the packet delivery ratio is small when end-to-end delay is large (see run numbers 10 through 16 and run numbers 26 through 32 in the same two graphs). These observations are reasonable because a smaller end-to-end delay implies that: (1) a greater number of packets are being received by the receiver per unit time

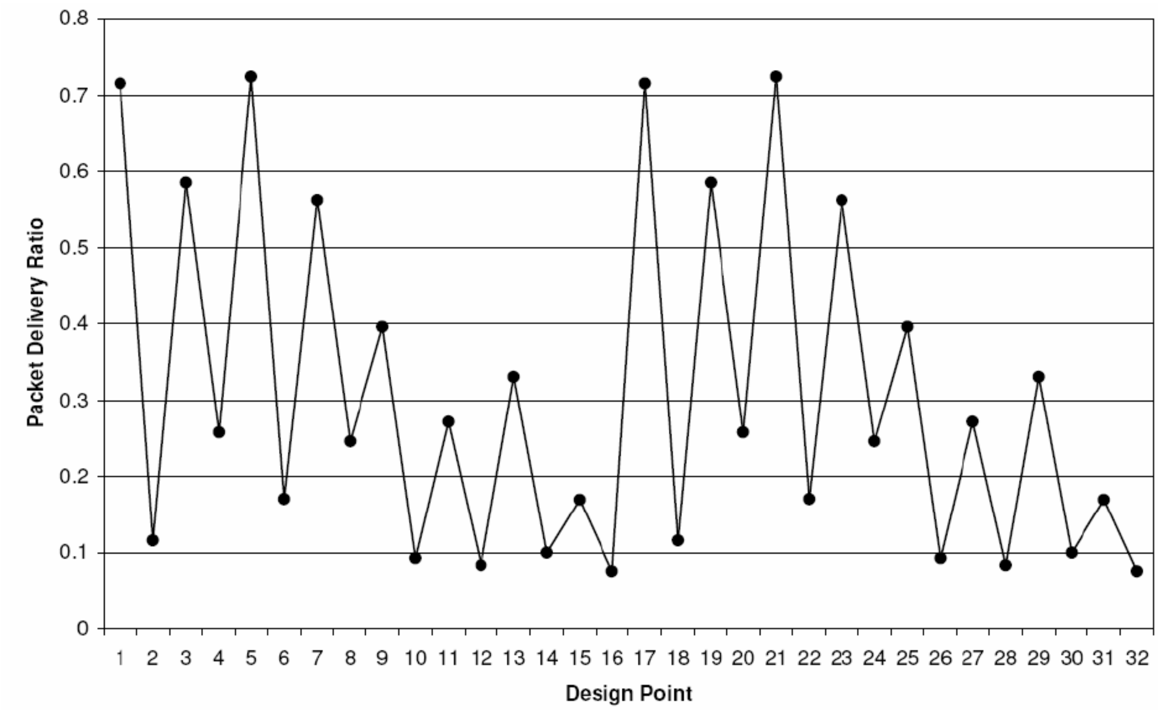

Figure 3.1: Scatterplot—Packet Delivery Ratio

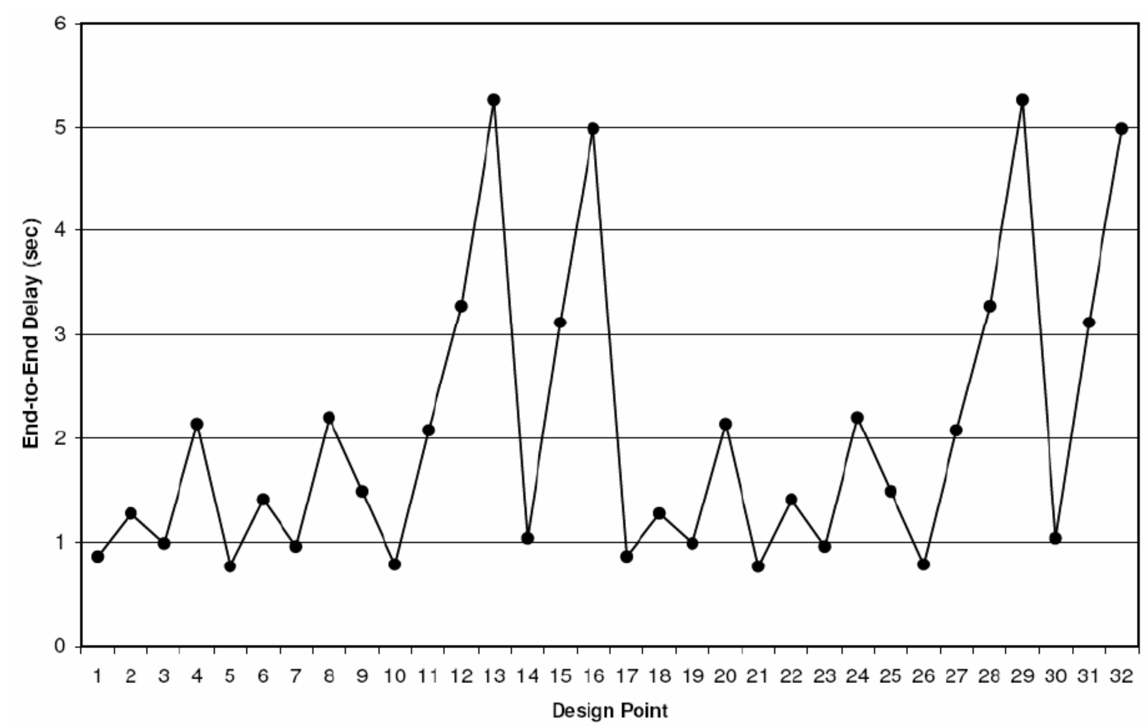

Figure 3.2: Scatterplot—End-to-End Delay

when there is very little end-to-end delay; and (2) a smaller number of packets are being received by the receiver per unit time when the end-to-end delay is large.

Packet Delivery Ratio. Figure 3.1 illustrates the average packet delivery ratio for the experimental runs. Observe that the same pattern occurs twice. Specifically, experimental run numbers 17 through 32 exhibit the same general behavior as that of experimental run numbers 1 through 16. The “shift” at run 17 reflects the change in the MAC layer protocol from 802.11b with RTS (– level) to 802.11b without RTS (+ level). By inspection, we may infer that, regarding packet delivery ratio at least, the presence of RTS–or lack thereof–seems to have little or no effect. Next, we observe how the behavior of the packet delivery ratio changes, beginning at the 9th and 25th experimental runs. These are the run numbers at which the number of nodes switches from 100 to 500. Of course, the number of nodes switches from 500 to 100 at run number 17. As can be seen from Figure 3.1, there is a decrease in the variation of average packet delivery ratio as the number of nodes increases. Continuing with our analysis, it appears that varying the traffic load from 10% to 20% has no effect on average packet delivery ratio, relative to the overall number of nodes. A similar observation is made regarding node speed, where there seems to be minimal change in behavior. Finally, when varying the number of neighbors from 7 to 3, the impact on packet delivery ratio is somewhat striking.

End-to-end Delay. Figure 3.2 illustrates the average end-to-end delay for the 32 experimental runs. Here we see a pattern of repetition that resembles that which was discussed for Figure 3.1. As before, experimental run numbers 17 through 32 exhibit the same general behavior as that of experimental run numbers 1 through 16. Again, the “shift” at run 17 reflects the change in the MAC layer protocol from 802.11b with RTS (– level) to

802.11b without RTS (+ level). As with packet delivery ratio, we may infer that, regarding end-to-end delay, the presence of RTS versus its non-presence appears to have little effect. Next, we observe that the behavior of end-to-end delay changes, beginning at the 10th and 26th experimental runs. Given that the number of nodes switches from 100 to 500 at experimental run numbers 9 and 25, there seems to be a slight delay before the effect of this change actually impacts average end-to-end delay. As before, the number of nodes switches from 500 to 100 at run number 17. As can be seen in the figure, there is a substantial "spike" in the variation of average end-to-end delay as the number of nodes increases. Continuing with our analysis, it seems that varying the traffic load from 10% to 20% has minimal impact on average end-to-end delay, relative to the overall number of nodes. The impact on end-to-end delay from varying the node speed between 5 meters/sec and 30 meters/sec appears to be rather substantial, especially as the speed is increased. Finally, as with the packet delivery ratio, the impact on end-to-end delay appears to be very prominent when varying the number of neighbors from 7 to 3.

Main and Interaction Effects. A main effects plot can be used to visualize performance changes as each individual factor level is changed. Each value along the x-axis corresponds to a – or + level for a particular factor as shown in Table 3.2. The *y*-axis is the performance metric under consideration, and the line shifts connecting the two points illustrate the average main effect on the performance metric when varying a factor from its – level to its + level. The slope of the line shift for a performance metric by varying a particular factor from its – level to its + level indicates the degree to which the particular factor has a main effect on the performance metric. In short, the greater the slope of a line shift, the greater the average main effect upon the performance metric by the particular factor. If a line shift exhibits a

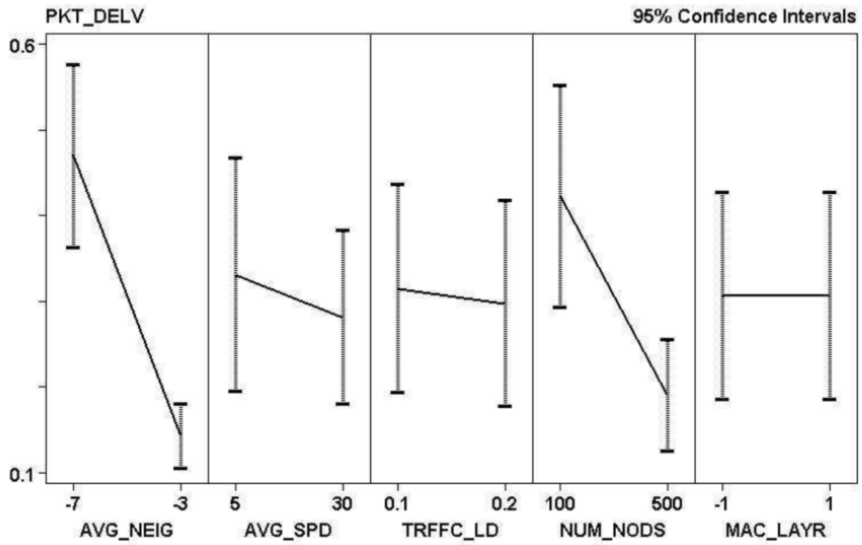

Figure 3.3: Main Effects—Packet Delivery Ratio

small slope (or, for that matter, no slope), then the average main effect upon the performance metric by the particular factor is negligible (or, in the case of no slope, is nonexistent). It is important to keep in mind that the insights gleaned from main effects plots are only for the range of values used for the – and + levels of the factors under consideration.

As can be seen in Figure 3.3, the main effect on *packet delivery ratio* by varying *average number of neighbors*, *average speed*, *traffic load*, and *number of nodes* from their – levels to their + levels is apparent. Moreover,it appears from Figure 3.3 that both *average number of neighbors* and *number of nodes* markedly impact the packet delivery ratio, whereas the *MAC layer* has a negligible impact on packet delivery ratio. For example, we see that the packet delivery ratio decreases from roughly 0.4 to roughly 0.2 when the number of nodes is varied from 100 (its – level) to 500 (its + level). In contrast, the packet delivery ratio remains at around 0.3 when varying the MAC layer protocol from 802.11b w/RTS (its – level) to 802.11b w/out RTS (its + level).

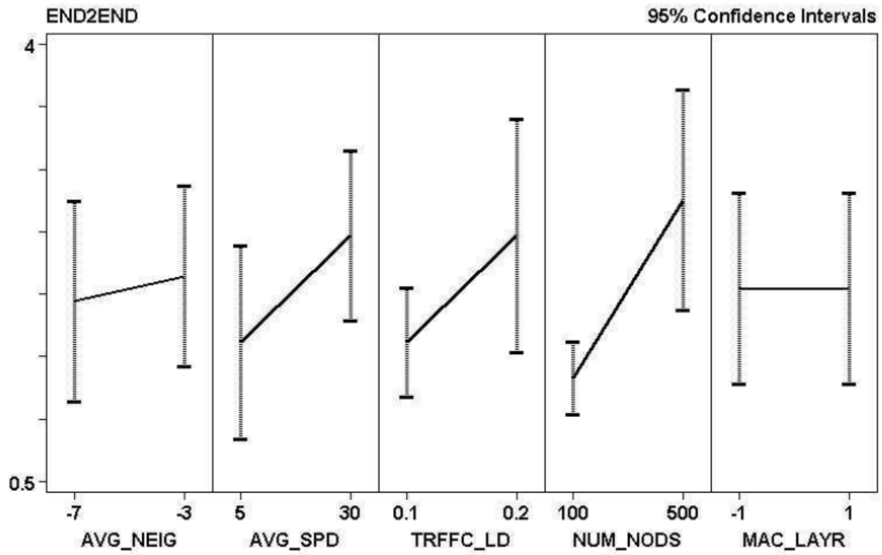

Figure 3.4: Main Effects—End-to-End Delay

Figure 3.4 suggests that the main effects of all factors, except for the *MAC layer*, impact the *end-to-end delay*. For example, we see that the end-to-end delay increases from roughly 1.5 seconds to roughly 2.5 seconds when the average node speed is varied from 5 meters/second (its $-$ level) to 30 meters/second (its $+$ level). In contrast, the end-to-end delay remains at around 2 seconds when varying the MAC layer protocol from 802.11b w/RTS (its $-$ level) to 802.11b w/out RTS (its $+$ level).

Comparing Figures 3.3 and 3.4, we observe that as the average neighbors is varied from "strongly-connected" to "weakly-connected" (that is, when the number of neighbor nodes changes from 7 to 3), the main effect upon packet delivery ratio is such that it is dramatically decreased, with a corresponding slight increase in end-to-end delay. This is likely due to the reduction in the availability of links, since there are fewer neighbor nodes. We observe similar main effects phenomena when varying the average speed, traffic load, and number of node factors from their "–" levels to their respective "+" levels. A particularly significant main effect results from varying the number of nodes from

100 to 500, whereby the packet delivery ratio is drastically reduced *and* end-to-end delay increases substantially. A probable explanation is that the greater number of nodes also leads to increased network traffic, which results in much greater contention of the channel among the nodes in the network. A final point of interest is the fact that the MAC layer protocol has virtually no effect on either performance metric.

Having examined the apparent main effects of each of the factors on the response metrics, we next turn our attention to interaction effects, which are those combinational effects that two factors have on the two response metrics. Thus, two-way factor interaction effects plots can be used to visualize the performance changes that result from the combined varying of two factors from their – levels to their + levels. This is particularly important, since such two-way factor interactions are not apparent when using the traditional OFAT approach. Note that parallel lines suggest a lack of factor interaction, whereas non-parallel lines suggest the presence of two-way factor interactions.

Figure 3.5 shows the two-way factor interactions on the average *packet delivery ratio* metric by varying from low to high levels for each factor. From Figure 3.5, we see that the following two-way factor interactions have a notable impact on the *packet delivery ratio*: (1) average number of neighbors and average node speed; (2) average number of neighbors and number of nodes; (3) average node speed and traffic load; and (4) number of nodes and average node speed.

Figure 3.6 shows the two-way factor interactions on the *end-to-end delay* response metric by varying from low to high levels for each of the five factors. The following two-way factor interactions appear to have notable impact on the *end-to-end delay*: (1) average number of neighbors and average node speed; (2) average number of neighbors and traffic

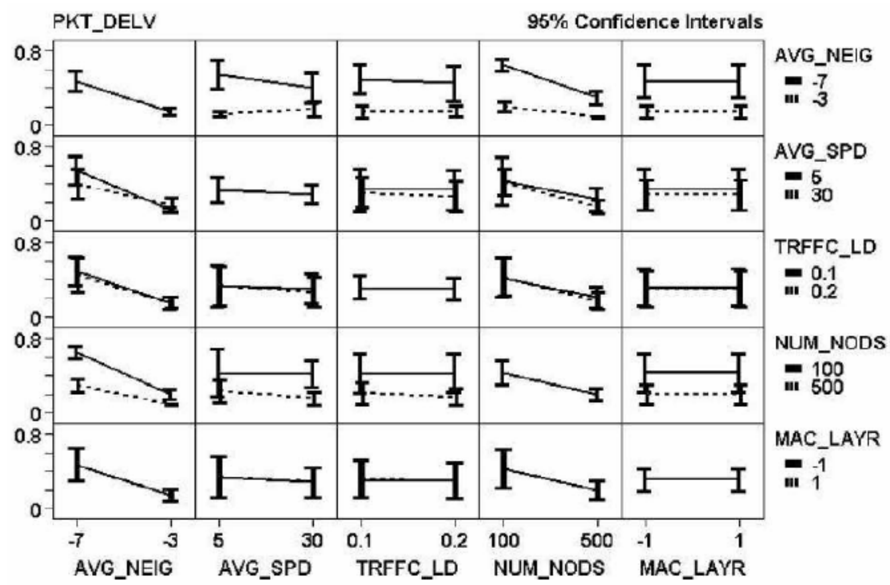

Figure 3.5: Two-Way Interaction Effects—Packet Delivery Ratio

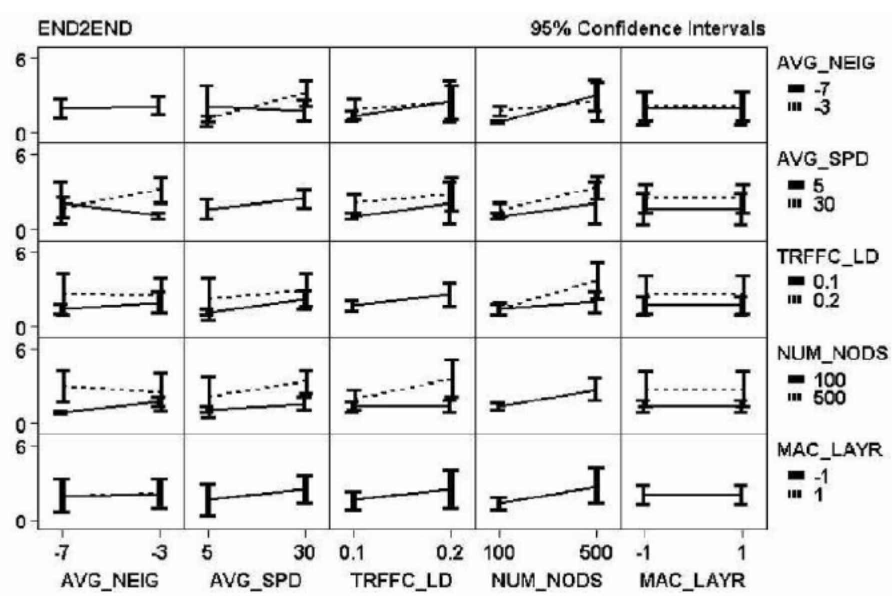

Figure 3.6: Two-Way Interaction Effects—End-to-End Delay

load; (3) average number of neighbors and number of nodes; (4) average node speed and traffic load; (5) average node speed and number of nodes; and (6) average traffic load and number of nodes.

These visual observations of two-way factor interactions intuitively correspond with the aforementioned main effects. Similar to what we observed in the main effects graphs, the MAC layer protocol appears to have no apparent two-way factor interaction effects. These observed results are important for researchers when considering new protocol designs, since it is obvious that varying single factors may lead to undesirable performance results. However, an awareness of and knowledge about two-way factor interactions may allow researchers to exploit these interactions in such a way that desirable performance results may be realized.

Quantifying the Main and Joint Effects. Scatter plots and effects plots offer a graphical and intuitive way of inferring whether main and interactive effects exists. Such "evidence" is not sufficient to draw definitive conclusions regarding factors and their impact on the response metrics. We must go one step further and quantify these effects using statistical analysis. Using a simplified method called the "sign-table" method, which is based on the mathematical properties discussed in Subsection 3.1.2, we compute the main and two-way interaction effects for each factor. Performing an analysis of variance (ANOVA) allows us to determine the statistical significance of the main and two-way interaction effects.

Table 3.4 shows the effect estimate and the allocation of variation for each factor and two-way interaction. The allocation of variation indicates the percentage of response variation contributed to a specific factor or two-way interaction. We see that certain factors account for a large percentage of the performance change. For example, we see in Table 3.4

	Packet Delivery Ratio		E2E Delay	
Effect	**Estimate**	**Allocation of Variation**	**Estimate**	**Allocation of Variation**
AVG_NEIG	−0.3269	55.727	−0.12728	3.031
AVG_SPD	−0.049245	1.265	−0.34479	22.171
TRFFC_LD	−0.017301	0.156	−0.12024	2.696
NUM_NODS	−0.23252	28.193	-0.31514	18.522
MAC_LAYR	5.20417E−18	0.000	−6.245E−17	0.000
AVG_NEIG × AVG_SPD	0.095157	4.722	−0.22768	9.668
AVG_NEIG × TRFFC_LD	0.027861	0.401	−0.0042055	0.00329
AVG_NEIG × NUM_NODS	0.12283	7.867	0.39482	29.072
AVG_NEIG × MAC_LAYR	6.07153E−18	0.000	0	0.000
AVG_SPD × TRFFC_LD	−0.018785	0.184	0.058292	0.634
AVG_SPD × NUM_NODS	−0.030515	0.486	−0.1002	1.872
AVG_SPD × MAC_LAYR	5.20417E−18	0.000	-1.3878E−17	0.000
TRFFC_LD × NUM_NODS	−0.024651	0.317	−0.14219	3.771
TRFFC_LD × MAC_LAYR	−8.6736E−18	0.000	6.93889E−18	0.000
NUM_NODS × MAC_LAYR	5.20417E−18	0.000	4.85723E−17	0.000

Table 3.4: Effects Table

that average neighbors and number of nodes together account for almost 85% of the performance change in packet delivery ratio. A similar observation may be made for end-to-end delay, where the average speed and number of nodes factors, as well as the average neighbors and number of nodes two-way interaction, together account for approximately 70% of the performance change.

As shown in Table 3.4, each factor and two-way interaction has an “estimate” associated with it. This estimate quantifies the change in the performance metric when varying the factor (or two-way interaction) from its “–” level to its “+” level. For example, we see that the estimate for average neighbors is –0.3269 with respect to *packet delivery ratio*. Since varying the average neighbors factor from its “–” level to its “+” level is a two-unit change (that is, moving from –1 to +1), we take one-half the value of its estimate, –0.3269, which is –0.163452, and say this is the expected change in packet delivery ratio when average neighbors changes by one unit. Table 3.4 also highlights those factors, as well as the two-way factor interactions, that are statistically significant for the prediction of end-to-end delay. Here we see the following individual factors that are statistically significant per their impact on *end-to-end delay*: average number of neighbors, average node speed, traffic load, and number of nodes. The two-way factor interactions that are statistically significant include: average number of neighbors and average node speed; average number of neighbors and number of nodes; and traffic load and number of nodes.

Expanded Design

This expanded experimental design involve three responses and an initial factor space of size $F_s = 10$. The purpose of this initial experimental design is twofold. First, I wish to gain preliminary insights into the behavior and performance of a multi-hop WMN; these insights should prove useful throughout the various stages of my empirical modeling. Second, in order to reduce the size of F_s, I shall employ a *fractional* factorial design, a technique by which such factor space size reduction may be expedited both efficiently and reliably.

An important point to keep in mind is that experimental design methods are by their very nature iterative. As I shall later show, results from this initial experimental design are dubious at best. Thus, successive experimental designs usually are required, which involve not only a smaller factor space, but also high and low factor values that are "fine-tuned" relative to earlier experimental designs.

1/64 fractional factorial design

I begin with a relatively large factor space, an objective of which, as earlier stated, is to expedite factor elimination. At this point, only main effects are indicated; that is, because of the inherent limitations normally found in fractional factorial experimental designs, interaction effects are not indicated. Subsequent to factor space reduction, I shall apply a

Response	Label	Units
THROUGHP	Average Throughput	bits/second
END2END	Average End-to-End Delay	seconds
JITTER	Delay Jitter	seconds

Table 3.5: 1/64 Fractional Factorial Design: Responses

Factor	Label	Low	High
RTS_THRS	MAC 802.11 RTS Threshold	0	512
SHR_TRNS	MAC 802.11 Short Pkt Trans Limit	3	11
LNG_TRNS	MAC 802.11 Long Pkt Trans Limit	2	6
TERRAIN	Terrain Size (Network Density)	1279	2216
TRAFF_LD	Traffic Load (Mesh Routers)	10	25
GW_ROUTR	Gateway Routers	5	20
IP_FRAG	IP Fragmentation	256	2048
PHY_RATE	PHY 802.11 Data Rate (Mbps)	1.0	5.5
AODV_BUF	AODV Buffer Max Packets	50	150
ITEM_SIZ	Application (FTP) Item Size (bytes)	256	1024

Table 3.6: 1/64 Fractional Factorial Design: Factors and Levels

full-factorial design, the results of which should offer information both about main and interaction effects.

Table 3.5 shows three responses of interest and their units of measure. Selection of these responses was based on their significance to QoS in both wired and wireless networks. It is important to note that no single response is considered as the most important; rather, QoS levels for one or more of these responses usually are indicated.

Table 3.6 lists ten factors with their low and high levels. With ten factors, a two-level full-factorial design would require 2^{10} = 1024 design points. Moreover, with three replicates, this would involve 1024 × 3 = 3072 experimental runs. Clearly, this would require considerable computing time and real time.

Since we are here concerned mainly with factor elimination, only main effects are relevant; hence, we use a 1/64 fractional factorial design, which, with three replicates, requires 48 total experimental runs. Moreover, because we are concerned mainly with factor elimination, examination of two-factor interactions at this point, is both unreliable and unnecessary. This particular type of factorial design enables us to expedite that which we hope to gain from the initial factor set, which is factor elimination.

As shown in Table 3.6, most of the factors I have included for this initial experimental design are representative of the various layers of the protocol stack. Specifically, AODV_BUF and ITEM_SIZ belong to the application layer; IP_FRAG is a factor that resides in the network layer; RTS_THRS, SHR_TRNS, and LNG_TRNS all are part of the MAC layer; and PHY_RATE is at the physical layer. The remaining three factors—TERRAIN, TRAFF_LD, and GW_ROUTR—are not directly tied to any particular layer of the protocol stack, but are nonetheless adjustable in a simulation environment.

Experiment Setup. For this Stage I simulation, and all subsequent simulations, I use the QualNet [67] discrete-event simulator developed by Scalable Network Technologies, Inc. The communications structure I define for my simulations is a wireless-to-wired mixed network that includes a wireless subnet with 100 mesh routers, with one or more of these configured as wireless/wired gateway routers. Node placement of mesh routers in the wireless subnet is uniform with no mobility, and the MAC protocol used for all simulation experimental runs is 802.11b. Finally, the simulation time for each experiment is set at 900 seconds (i.e., 15 minutes).

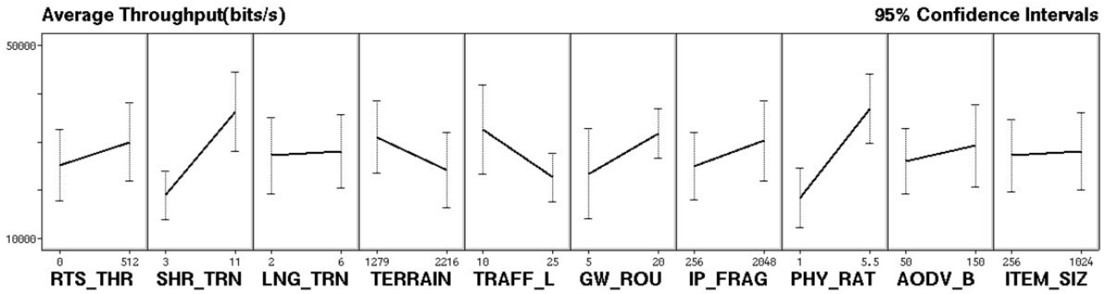

Figure 3.7: 1/64 Fractional Factorial—Main Effects (Throughput)

Throughput—Main Effects. Figure 3.7 illustrates the main effects for throughput. As shown in the figure, varying factors in the factor space seems to have some impact on the throughput response. Still, varying both LNG_TRN and ITEM_SIZ appears to have minimal impact on the average throughput. Assessments about the significance of these main effects should be viewed with some skepticism. As Figure 3.7 shows, most of the 95% confidence intervals are unacceptably large. This should not be cause for discouragement, however, as these results reflect a 1/64 fractional factorial design, and are not intended to lead to definitive empirical conclusions.

Throughput—ANOVA. Table 3.7 is an ANOVA (analysis of variance) for throughput. ANOVA is a useful tool for identifying factors whose main effects upon a response are statistically significant. The degrees of freedom (DF) is equal to 1 for each factor; the sum of squares (SS) is the variation; the mean-square (MS) is the variance, or *SS/DF* ; and *F* is the *F*-ratio, which is *MS/Error*. The *P*-value is of particular interest, since it serves as a measure of "statistical significance," which indicates the degree to which the value of a factor is "true." Factors for which the *P*-value is small ($P < 0.05$) are considered significant and should therefore be included in the prediction, or *regression*, model. From the ANOVA in Table 3.7 we observe that RTS_THRS, LNG_TRNS, IP_FRAG, AODV_BUF, and

	Master Model					Predictive Model				
Source	DF	SS	MS	F	Pr > *F*	DF	SS	MS	F	Pr > *F*
RTS_THRS	1	2153.712	2153.712	2.119357	0.153881					
SHR_TRNS	1	34542.39	34542.39	33.99138	0.0001	1	34542.39	34542.39	34.33863	0.0001
LNG_TRNS	1	80.79003	80.79003	0.079501	0.779546					
TERRAIN	1	6538.76	6538.76	6.434457	0.015543	1	6538.76	6538.76	6.50019	0.014526
TRAFF_LD	1	5540.739	5540.739	5.452355	0.025075	1	5540.739	5540.739	5.508055	0.023719
GW_ROUTR	1	16451.15	16451.15	16.18872	0.000272	1	16451.15	16451.15	16.3541	0.00022
IP_FRAG	1	1814.964	1814.964	1.786012	0.189574					
PHY_RATE	1	44931.5	44931.5	44.21478	0.0001	1	44931.5	44931.5	44.66646	0.0001
AODV_BUF	1	445.1305	445.1305	0.43803	0.512176					
ITEM_SIZ	1	154.8475	154.8475	0.152377	0.698512					
Model	10	112654	11265.4	11.0857	0.0001	5	108004.5	21600.91	21.47349	0.0001
Error	37	37599.77	1016.21			42	42249.22	1005.934		
(Lack of fit)	5	18517.1	3703.42	6.210317	0.000395	10	23166.55	2316.655	3.88483	0.001607
(Pure Error)	32	19082.67	596.3335			32	19082.67	596.3335		
Total	47	150253				47	150253.8			

Table 3.7: 1/64 Fractional Factorial Design: ANOVA for THROUGHP

	Master Model	Predictive Model
Mean	156.3921	156.3921
R-square	74.98%	71.88%
Adj. R-square	68.21%	68.53%
RMSE	31.87805	31.71646
CV	20.38342	20.2801

Table 3.8: 1/64 Fractional Factorial Design: Fit Statistics for THROUGHP

ITEM_SIZ are not statistically significant, and should therefore not be included as part of the regression model.

Throughput—Fit Statistics. Fit statistics for throughput are indicated in Table 3.8, the predictive model of which may be interpreted as follows. The *mean* is the intercept, which, as shown in Table 3.8, is 156.3921. The quantity *R-square* is 74.98%, which is the proportion of total variability explained by the model, where $0 \leq R2 \leq 1$, with larger values being more desirable. A related quantity, *Adj. R-square*, is a variation of the *R-square* statistic, whose value decreases as more factors are included within the model. The *RMSE*, or *root mean square error*, is determined by calculating the deviations of points from their true position, summing up the measurements, and then taking the square root of the sum,

	Master Model					Predictive Model			
Term	Estimate	Std Err	t	Pr > $\|t\|$		Estimate	Std Err	t	Pr > $\|t\|$
RTS_THRS	13.39866	9.202401	1.455801	0.153881					
SHR_TRNS	53.651954	9.202401	5.830213	0.0001	<**	53.651954	9.155753	5.859917	0.0001
LNG_TRNS	2.5947067	9.202401	0.28196	0.779546					
TERRAIN	-23.34302	9.202401	-2.53662	0.015543	<**	-23.34302	9.155753	-2.54955	0.014526
TRAFF_LD	-21.48786	9.202401	-2.33503	0.025075	<**	-21.48786	9.155753	-2.34692	0.023719
GW_ROUTR	37.026056	9.202401	4.023521	0.000272	<**	37.026056	9.155753	4.044021	0.00022
IP_FRAG	12.298251	9.202401	1.336418	0.189574					
PHY_RATE	61.190619	9.202401	6.649419	0.0001	<**	61.190619	9.155753	6.683297	0.0001
AODV_BUF	6.0905014	9.202401	0.661838	0.512176					
ITEM_SIZ	3.5922084	9.202401	0.390356	0.698512					

<** Significant at P < 0.05

Table 3.9: 1/64 Fractional Factorial Design: Effect Estimates for THROUGHP

with smaller values being more desirable. Finally, the *CV*, or *coefficient of variation*, a measure of the precision or relative dispersion, is 20.2801. The *CV* is calculated as the standard deviation divided by the mean, and is used to compare variation among multiple data series that have significantly different means.

Throughput—Effect Estimates. The predictive model estimates shown in Table 3.9, along with the mean for the predictive model indicated in Table 3.8, provide the data needed to develop a preliminary empirical model for throughput.

Throughput—Preliminary Empirical Model. The SAS application applies automatically a Box-Cox transformation on the dependent variable—that is, $SQRT(Y_{throughp})$—because the initial empirical model (not shown here) exhibits heterogeneous, or non-Gaussian, errors. The transformed preliminary empirical model for throughput is shown in Equation (3.11).

$$\begin{aligned} Y_{throughp} = \; & 156.3921 + 26.82598x_2 - 11.67151x_4 - \\ & - 10.74393x_5 + 18.51303x_6 + 30.59531x_8 \end{aligned} \tag{3.11}$$

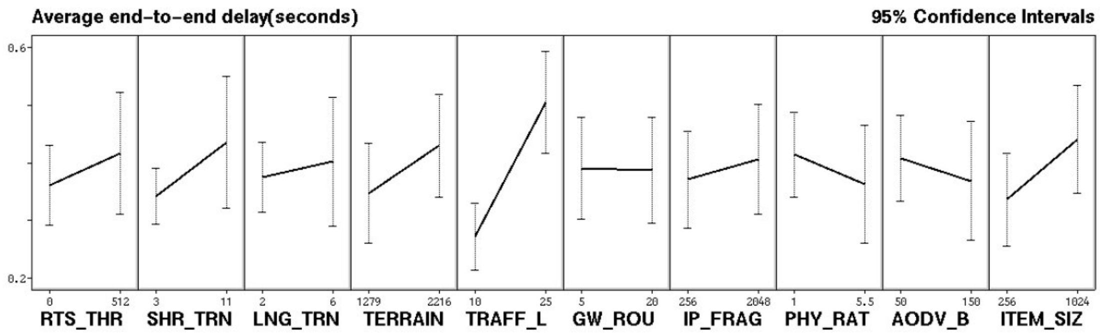

Figure 3.8: 1/64 Fractional Factorial—Main Effects (End-to-End Delay).

where x_1 = RTS_THRS, x_2 = SHR_TRNS, x_3 = LNG_TRNS, x_4 = TERRAIN, x_5 = TRAFF_LD, x_6 = GW_ROUTR, x_7 = IP_FRAG, x_8 = PHY_RATE, x_9 = AODV_BUF, and x_{10} = ITEM_SIZ.

The equation for $Y_{throughp}$ is a function that describes the empirical relationship between the response $Y_{throughp}$ and its corresponding factors. In fact, Equation (3.11) is called a *regression* equation. The general *multiple linear regression model* with *k* regressor variables is of the form

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + \varepsilon. \tag{3.12}$$

The parameters β_j, $j = 0, 1, \ldots, k$, are called the *regression coefficients*. The model shown in Equation (3.12) describes a hyperplane in the *k*-dimensional space of the regressor variables $\{x_j\}$. The parameter β_j represents the expected change in response y per unit change in x_j when all the remaining independent variables x_j $(x \neq j)$ are held constant.

End-to-End Delay—Main Effects. Figure 3.8 shows the main effects for end-to-end delay. Similar to our observations of throughput main effects, we see that main effects upon end-to-end delay result from varying nearly all variables in the factor space, except for the

	Master Model					Predictive Model				
Source	**DF**	**SS**	**MS**	**F**	**Pr > *F***	**DF**	**SS**	**MS**	**F**	**Pr > *F***
RTS_THRS	1	0.036996	0.036996	1.346971	0.253242					
SHR_TRNS	1	0.102959	0.102959	3.748584	0.06052					
LNG_TRNS	1	0.008898	0.008898	0.323974	0.572669					
TERRAIN	1	0.081945	0.081945	2.983497	0.092458					
TRAFF_LD	1	0.648783	0.648783	23.62131	0.0001	1	0.648783	0.648783	22.24548	0.0001
GW_ROUTR	1	0.000079	0.000079	0.002861	0.957632					
IP_FRAG	1	0.015274	0.015274	0.556123	0.460538					
PHY_RATE	1	0.031289	0.031289	1.139203	0.292736					
AODV_BUF	1	0.01873	0.01873	0.681945	0.414211					
ITEM_SIZ	1	0.131255	0.131255	4.77883	0.035214	1	0.131255	0.131255	4.500484	0.039427
Model	10	1.076208	0.107621	3.91833	0.001086	2	0.780038	0.390019	13.37298	0.0001
Error	37	1.016242	0.027466			45	1.312412	0.029165		
(Lack of fit)	5	0.776677	0.155335	20.74901	0.0001	1	0.008898	0.008898	0.30036	0.586426
(Pure Error)	32	0.239565	0.007486			44	1.303514	0.029625		
Total	47	2.09245				47	2.09245			

Table 3.10: 1/64 Fractional Factorial Design: ANOVA for END2END

	Master Model	**Predictive Model**
Mean	0.388402	0.388402
R-square	51.43%	37.28%
Adj. R-square	38.31%	34.49%
RMSE	0.165729	0.170777
CV	42.66932	43.96903

Table 3.11: 1/64 Fractional Factorial Design: Fit Statistics for END2END

GW_ROUTR factor, where there seems to be virtually no effect on average end-to-end delay. Since we are concerned mainly with factor elimination at this preliminary stage, we should not be overly concerned with the significant span of the 95% confidence intervals.

End-to-End Delay—ANOVA. Table 3.10 is an ANOVA table for end-to-end delay. Recall from our previous discussion, ANOVA is a useful tool for identifying factors whose main effects upon a response are statistically significant.

End-to-End Delay—Fit Statistics. Fit statistics for end-to-end delay are indicated in Table 3.11, the predictive model of which may be interpreted as follows. The *mean* is the intercept, which, as shown in Table 3.11, is 0.388402. The quantity *R-square* is 37.27%, which is the proportion of total variability explained by the model, where $0 \leq R2 \leq 1$, with larger values being more desirable. A related quantity, *Adj. R-square*, is a variation of the *R-square* statistic, whose value decreases as more factors are included within the model. The *RMSE*, or *root mean square error*, is determined by calculating the deviations of points from their true position, summing up the measurements, and then taking the square root of the sum, with smaller values being more desirable. Finally, the *CV*, or *coefficient of variation*, a measure of the precision or relative dispersion, is 43.96903. The CV is calculated as the standard deviation divided by the mean.

Unlike the previous predictive model for THROUGHP, the predictive model for END2END does not explain sufficiently the variability exhibited by the model. Of particular significance in this case is the very low R-square value for the predictive model. As I have indicated earlier, an R-square value that is less than 65.00% generally is unacceptable. I should here again emphasize, however, that my goal at this point is not to derive viable emprical models; rather, the purpose for a 1/64 fractional factorial design is to expedite factor elimination.

End-to-End Delay—Preliminary Empirical Model. The predictive model estimates shown in Table 3.12, along with the mean for the predictive model indicated in Table 3.11, provide the data needed to develop a preliminary empirical model for end-to-end delay. The preliminary empirical model for end-to-end delay is shown in Equation (3.13).

$$Y_{end2end} = 0.388402 + 0.11626x_5 - 0.052292x_{10} \qquad (3.13)$$

where x_1 = RTS_THRS, x_2 = SHR_TRNS, x_3 = LNG_TRNS, x_4 = TERRAIN,

	Master Model					Predictive Model			
Term	Estimate	Std Err	t	Pr > |t|		Estimate	Std Err	t	Pr > |t|
RTS_THRS	0.0555247	0.047842	1.160591	0.253242					
SHR_TRNS	0.0926277	0.047842	1.936126	0.06052					
LNG_TRNS	0.0272309	0.047842	0.569187	0.572669					
TERRAIN	0.0826361	0.047842	1.72728	0.092458					
TRAFF_LD	0.2325193	0.047842	4.860176	0.0001	<**	0.2325193	0.049299	4.716511	0.0001
GW_ROUTR	-0.002559	0.047842	-0.05349	0.957632					
IP_FRAG	0.0356774	0.047842	0.745737	0.460538					
PHY_RATE	-0.051063	0.047842	-1.06733	0.292736					
AODV_BUF	-0.039508	0.047842	-0.8258	0.414211					
ITEM_SIZ	0.1045846	0.047842	2.186054	0.035214	<**	0.1045846	0.049299	2.121435	0.039427

<** Significant at $P < 0.05$

Table 3.12: 1/64 Fractional Factorial: Effect Estimates for END2END

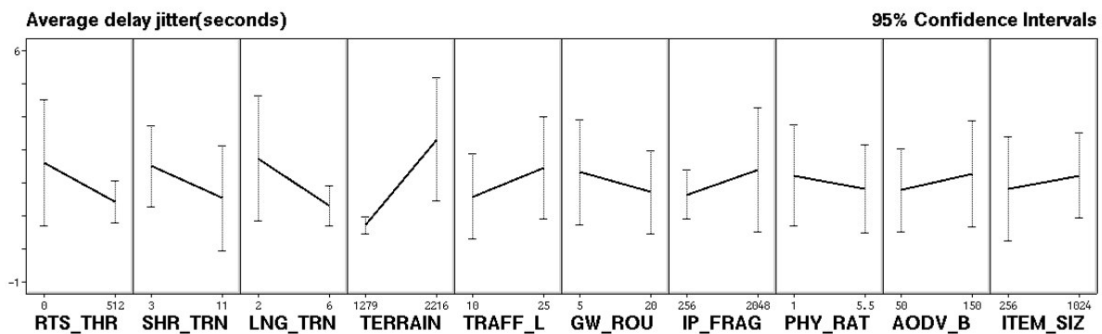

Figure 3.9: 1/64 Fractional Factorial—Main Effects (Jitter)

x_5 = TRAFF_LD, x_6 = GW_ROUTR, x_7 = IP_FRAG, x_8 = PHY_RATE, x_9 = AODV_BUF, and x_{10} = ITEM_SIZ.

The equation for $Y_{end2end}$ is a function that describes the empirical relationship between the response $Y_{end2end}$ and its corresponding factors.

Jitter—Main Effects. Much of what we have discussed thus far concerning main effects by the factor space upon both throughput and end-to-end delay may be similarly applied to jitter, as shown in Figure 3.9. We observe, as before, what appear to be significant main effects by factors upon jitter; however, notice, too, the, by now, all too familiar 95% confidence intervals that are of significant length.

Source	DF	SS	MS	F	Pr > F	DF	SS	MS	F	Pr > F
	Master Model					Predictive Model				
RTS_THRS	1	16.66946	16.66946	1.648821	0.207103					
SHR_TRNS	1	11.25789	11.25789	1.113548	0.298154					
LNG_TRNS	1	24.40002	24.40002	2.413472	0.128808					
TERRAIN	1	80.9735	80.9735	8.009308	0.007478	1	80.9735	80.9735	8.216915	0.00624
TRAFF_LD	1	9.08244	9.08244	0.898369	0.349369					
GW_ROUTR	1	4.42965	4.42965	0.438149	0.512119					
IP_FRAG	1	6.498847	6.498847	0.642819	0.427811					
PHY_RATE	1	1.920771	1.920771	0.189989	0.665459					
AODV_BUF	1	2.897682	2.897682	0.286618	0.5956					
ITEM_SIZ	1	2.082569	2.082569	0.205993	0.652578					
Model	10	160.2128	160.2128	1.584709	0.149807	1	80.9735	80.9735	8.216915	0.00624
Error	37	374.0672	10.10992			46	453.3065	9.85449		
(Lack of fit)	5	49.58319	9.916638	0.97796	0.446195					
(Pure Error)	32	324.484	10.14013							
Total	47	435.28				47	534.28			

Table 3.13: 1/64 Fractional Factorial Design: ANOVA for JITTER

	Master Model	Predictive Model
Mean	2.018852	2.018852
R-square	29.99%	15.16%
Adj. R-square	11.06%	13.31%
RMSE	3.179611	3.139186
CV	157.496	155.4936

Table 3.14: 1/64 Fractional Factorial Design: Fit Statistics for JITTER

Jitter—ANOVA. Table 3.13 is an ANOVA table for jitter. Recall from our previous discussion, ANOVA is a useful tool for identifying factors whose main effects upon a response are statistically significant.

Jitter—Fit Statistics. Fit statistics for jitter are indicated in Table 3.14, the predictive model of which may be interpreted as follows. The *mean* is the intercept, which, as shown in Table 3.14, is 2.018852. The quantity *R-square* is 15.16%, which is the proportion of total variability explained by the model, where $0 \leq R2 \leq 1$, with larger values being more desirable. A related quantity, *Adj. R-square*, is a variation of the R-square statistic, whose value decreases as more factors are included within the model. The *RMSE*, or *root mean square error*, is determined by calculating the deviations of points from their true position,

	Master Model					Predictive Model			
Term	**Estimate**	**Std Err**	**t**	**Pr** $> \lvert t \rvert$		**Estimate**	**Std Err**	**t**	**Pr** $> \lvert t \rvert$
RTS_THRS	-1.17861	0.917875	-1.28406	0.253242					
SHR_TRNS	-0.968585	0.917875	-1.05525	0.06052					
LNG_TRNS	-1.425951	0.917875	-1.55354	0.572669					
TERRAIN	2.5976512	0.917875	2.83002	0.007478	$<$**	2.5976512	0.906205	2.866516	0.00624
TRAFF_LD	0.8699828	0.917875	0.947823	0.349369					
GW_ROUTR	-0.607567	0.917875	-0.66193	0.512119					
IP_FRAG	0.7359148	0.917875	0.80176	0.427811					
PHY_RATE	-0.40008	0.917875	-0.43588	0.665459					
AODV_BUF	0.4913996	0.917875	0.535367	0.5956					
ITEM_SIZ	0.4165902	0.917875	0.453864	0.652578					

** Significant at $P < 0.05$

Table 3.15: 1/64 Fractional Factorial Design: Effect Estimates for JITTER

summing up the measurements, and then taking the square root of the sum, with smaller values being more desirable. Finally, the *CV*, or *coefficient of variation*, a measure of the precision or relative dispersion, is 155.4936. The CV is calculated as the standard deviation divided by the mean; thus, a smaller CV is more desirable.

Of the three predictive models we analyze, the predictive model for JITTER explains very little, if any, of the variability exhibited by the model. Of particular importance in this case is the exceptionally low R-square value of 15.16% for the predictive model. As I have indicated earlier, an R-square value less than 65.00% generally is considered poor. Thus, for all intents and purposes, this model does not explain variability. Still, this is not cause for significant concern, since my goal at this early stage is not to derive viable emprical models, but to expedite factor elimination.

Jitter—Effect Estimates. The predictive model estimates shown in Table 3.15, along with the mean for the predictive model indicated in Table 3.14, provide the data needed to develop a preliminary empirical model for jitter.

Jitter—Preliminary Empirical Model. The preliminary empirical model for jitter is shown in Equation (3.14).

$$Y_{jitter} = 2.018852 + 1.298826x_4 \qquad (3.14)$$

where, for consistency, x_1 = RTS_THRS, x_2 = SHR_TRNS, x_3 = LNG_TRNS, x_4 = TERRAIN, x_5 = TRAFF_LD, x_6 = GW_ROUTR, x_7 = IP_FRAG, x_8 = PHY_RATE, x_9 = AODV_BUF,and x_{10} = ITEM_SIZ.

The equation for Y_{jitter} is a function that describes the empirical relationship between the response Y_{jitter} and its corresponding factors.

Full factorial design

Having gleaned some insights into the behavior of our responses of interest, I have eliminated factors that appear not to have any effect on these responses. Recall that the 1/64 fractional factorial design has allowed for an examination of main effects, using a relatively small number of design points, although we began with a significant number of factors. Because we have reduced the number of factors from ten to three, a 2^3 factorial design contains only eight design points, which is manageable in most cases, including my current work. A full factorial design should lead to an analysis both of main effects and two-factor interaction effects. Moreover, in the case of a full factorial design, I shall "trim" the value range within which the factors are varied, which should permit formulation of empirical models that exhibit a reliable fit. The resultant empirical models should lead us directly into a more penetrating analysis using least-squares regression.

Table 3.16 shows the four responses for a full factorial design—three of the four responses carry-over from my previous 1/64 fractional factorial design. My inclusion of

Response	Label	Units
THROUGHP	Average Throughput	bits/second
END2END	Average End-to-End Delay	seconds
JITTER	Delay Jitter	seconds
PDRATIO	Packet Delivery Ratio	percentage

Table 3.16: Full Factorial Design: Responses

Factor	Label	Low	High
SHR_TRNS	MAC 802.11 Short Pkt Trans Limit	3	14
LNG_TRNS	MAC 802.11 Long Pkt Trans Limit	2	8
TRAFF_LD	Traffic Load (Mesh Routers	10	30

Table 3.17: Full Factorial Design: Factors and Levels

Run	SHR_TRNS	LNG_TRNS	TRAFF_LD
1	3	2	10
2	3	2	10
3	3	2	10
4	14	2	10
5	14	2	10
6	14	2	10
7	3	8	10
8	3	8	10
9	3	8	10
10	14	8	10
11	14	8	10
12	14	8	10
13	3	2	30
14	3	2	30
15	3	2	30
16	14	2	30
17	14	2	30
18	14	2	30
19	3	8	30
20	3	8	30
21	3	8	30
22	14	2	30
23	14	2	30
24	14	2	30

Table 3.18: Full Factorial Design Matrix

packet delivery ratio (PDRATIO) in the response set should provide some context within which my analysis of throughput (THROUGHP) is made. As important as throughput is, the ratio of the number of packets sent to the number of packets received is equally important.

My reduced factor space F_s, shown in Table 3.17, is now of size 3. Notice also that I have revised the low and high values for the factors. Since this is a full factorial design, and because there are three factors, this design contains $2^3 = 8$ design points. Moreover, my design involves point replication; that is, each design point is replicated three times. Thus, this design is called a $2^3\ 3$ factorial design, which requires 24 experimental runs ($2^3 \times 3 = 24$)

Employment of these preliminary factorial designs has led to a far simpler design, from which a set of simulations that test the full-factorial design may be devised. This completes Stage I work, whereby the principle objective was to gain familiarity with the process of first-design, fractional factorial design, and full factorial design. In Stage II, I move forward with a more comprehensive approach, in that I begin with a large factor space, the size of which I reduce by way of fractional factorial designs.

Stage II: Models and Response Surfaces

My principle objective in Stage I was to gain preliminary insights about the use of statistical DOE, as well as understand better the behavior and performance of multi-hop WMNs. Following Box's recommendation that the resources spent on preliminary designs should not exceed 25% of the overall design, analysis, and modeling effort, I shall next discuss Stage II of my methodology. Specifically, I employ statistical DOE to develop viable empirical models for multi-hop wireless mesh networks. Additionally, I apply response surface methodology (RSM) to find the levels of traffic load and network size that optimize a single response metric.

Statistical Design of Experiments

I begin Stage II of my work by employing fractional factorial design approaches, similar to my work in Stage I. Recall that fractional factorial design permits fairly expedient identification of factors in the factor space that do not exhibit statistically-significant effects on response metrics of interest. Such factors may then be removed from the factor space, after which subsequent full-factorial designs may be applied. An added benefit is that results of fractional factorial designs may offer some insight into the behavior of the target system under study.

As indicated earlier, I used the QualNet Version 3.8 simulator by Scalable Networks for all Stage I simulation studies. Scalable Networks has since released QualNet Version 4.0. I use this most recent version of the QualNet simulator for all Stage II simulation studies.

Fractional Factorial Design: Simulation Setup

Figure 3.10 illustrates the terrain within which the wireless mesh routers operate. As shown in the figure, the terrain size is 3000 meters by 3000 meters for all fractional factorial simulation experiments. The wireless mesh router nodes form a grid, such that nodes are spaced 270 meters apart, irrespective of the network size. Propagation pathloss model is two-ray, which, in the QualNet simulator, translates to free space path loss for near sight and plane earth path loss for far sight. Moreover, the antenna height is fixed, using this pathloss model. Simulation time for all experimental runs is 15 minutes.

Each simulation run results in the generation of output files by QualNet, each of which is named <run#>.stat. Because each of these files tends to be somewhat large, I have developed several Perl scripts that parse .stat files, calculates average values for response

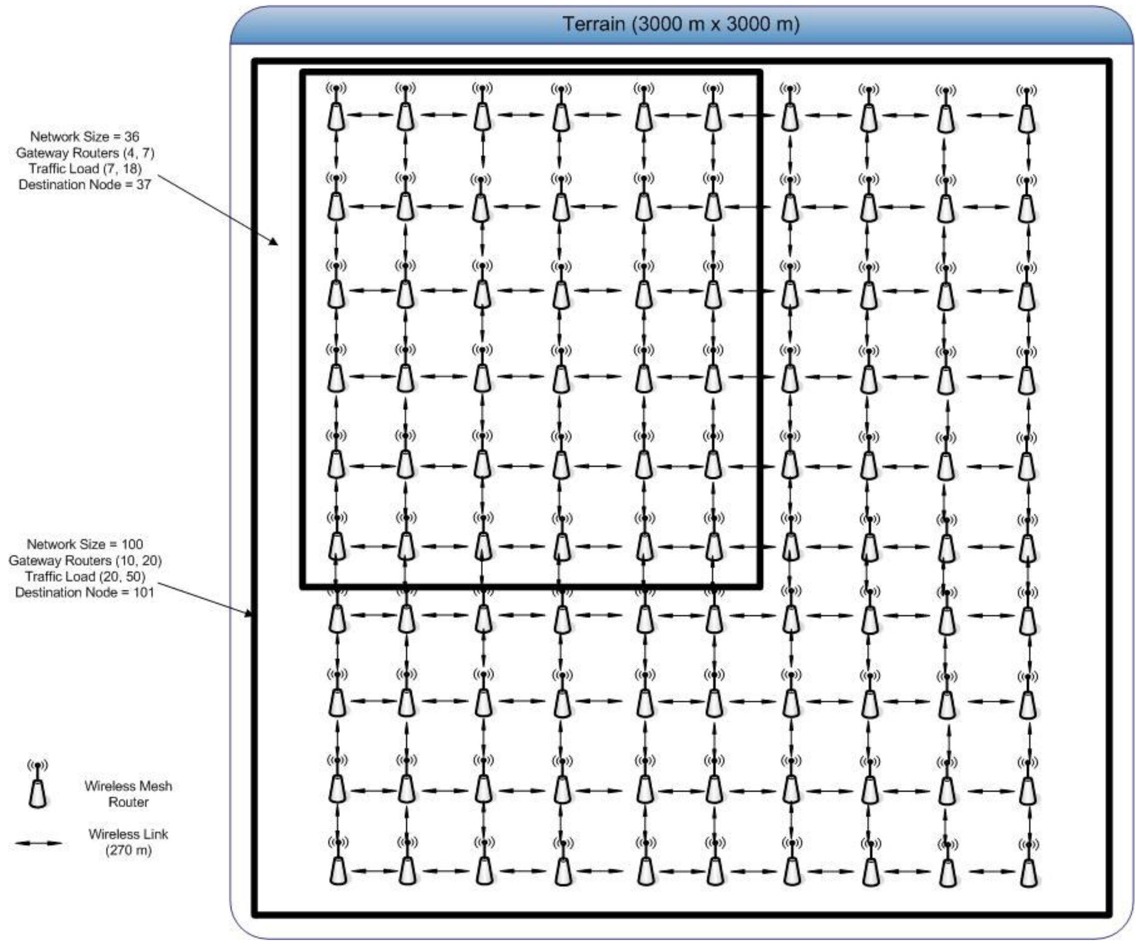

Figure 3.10: Multi-hop WMN Terrain

Factor	Label	Low	High
GATEWAYN	Gateway Nodes (% of total nodes)	0.10	0.20
TRAFFLD	Traffic Load (% of total nodes)	0.20	0.50
ITEMSIZE	Item Size (bytes)	512	1500
BITRATE	Bit Rate (Mbps)	1279	2216
ROUTINGP	Routing (AODV, OLSR-Inria)	−1	1
NETWRKSZ	Network Size (mesh routers)	36	100
TRANSPRT	Transport (UDP, TCP-Lite)	−1	1

Table 3.19: Two-Level 1/16 Fractional Design

variables, and writes these values to .csv (comma separated values) files. I import the .csv data into SAS, which is the statistics tool I use for data analyses.

Fractional Factorial Designs

I begin with a two-level, 1/16 fractional factorial design, which consists of seven factors (shown in Table 3.19) and a single response, **Throughput** (measured in bps). A full factorial design with seven factors would require $2^7 = 128$ design points, each of which requires a simulation run. In contrast, a 1/16 fractional design with seven factors requires only eight design points, a considerable reduction in the number of simulation runs. Each design point is replicated three times, in order to reduce (and better explain) variability.

With this 1/16 fractional design, main effects by factors are calculable; however, two-way factor interactions are not. However, at this point, we are interested only in identifying factors that should be eliminated from the factor space; thus, two-way factor interactions are of minimal relevance. The expected reduction of the factor space should allow for subsequent full-factorial designs.

The design matrix (uncoded) is shown in Table 3.20, along with the average values for the throughput response in each simulation run. The seed value for each simulation is equal to its run number (e.g., the seed value for the fifteenth simulation run is 15).

1/16 Fractional—Graphical Analysis. Figure 3.11 illustrates main effects on throughput by varying factors from their −1 levels to their +1 levels. By inspection, it appears that varying all factors from their −1 levels to their +1 levels has an impact on throughput. Recall from previous main effects charts that 95% confidence intervals are indicated by vertical bars, with smaller vertical bars being more desirable. In other words, there is a 95% likelihood that the

Run	GATEWAYN	TRAFFLD	ITEMSIZE	BITRATE	ROUTINGP	NETWRKSZ	TRANSPRT	THROUGHP
1	10	20	512	11	OLSR-Inria	100	UDP (CBR)	4095.15
2	10	20	512	11	OLSR-Inria	100	UDP (CBR)	4095.65
3	10	20	512	11	OLSR-Inria	100	UDP (CBR)	4094.05
4	20	20	512	2	AODV	100	TCP-Lite	42981.05
5	20	20	512	2	AODV	100	TCP-Lite	42557.40
6	20	20	512	2	AODV	100	TCP-Lite	42512.65
7	4	18	512	2	OLSR-Inria	36	TCP-Lite	20609.11
8	4	18	512	2	OLSR-Inria	36	TCP-Lite	20732.94
9	4	18	512	2	OLSR-Inria	36	TCP-Lite	20793.56
10	7	18	512	11	AODV	36	UDP (CBR)	4097.00
11	7	18	512	11	AODV	36	UDP (CBR)	4096.67
12	7	18	512	11	AODV	36	UDP (CBR)	4097.33
13	4	7	1500	11	AODV	36	TCP-Lite	56480.57
14	4	7	1500	11	AODV	36	TCP-Lite	56484.57
15	4	7	1500	11	AODV	36	TCP-Lite	56480.00
16	7	7	1500	2	OLSR-Inria	36	UDP (CBR)	7429.86
17	7	7	1500	2	OLSR-Inria	36	UDP (CBR)	7381.57
18	7	7	1500	2	OLSR-Inria	36	UDP (CBR)	7179.29
19	10	50	1500	2	AODV	100	UDP (CBR)	5900.28
20	10	50	1500	2	AODV	100	UDP (CBR)	5794.54
21	10	50	1500	2	AODV	100	UDP (CBR)	5792.88
22	20	50	1500	11	OLSR-Inria	100	TCP-Lite	27970.50
23	20	50	1500	11	OLSR-Inria	100	TCP-Lite	28022.52
24	20	50	1500	11	OLSR-Inria	100	TCP-Lite	27965.22

Table 3.20: 1/16 Fractional Design Matrix

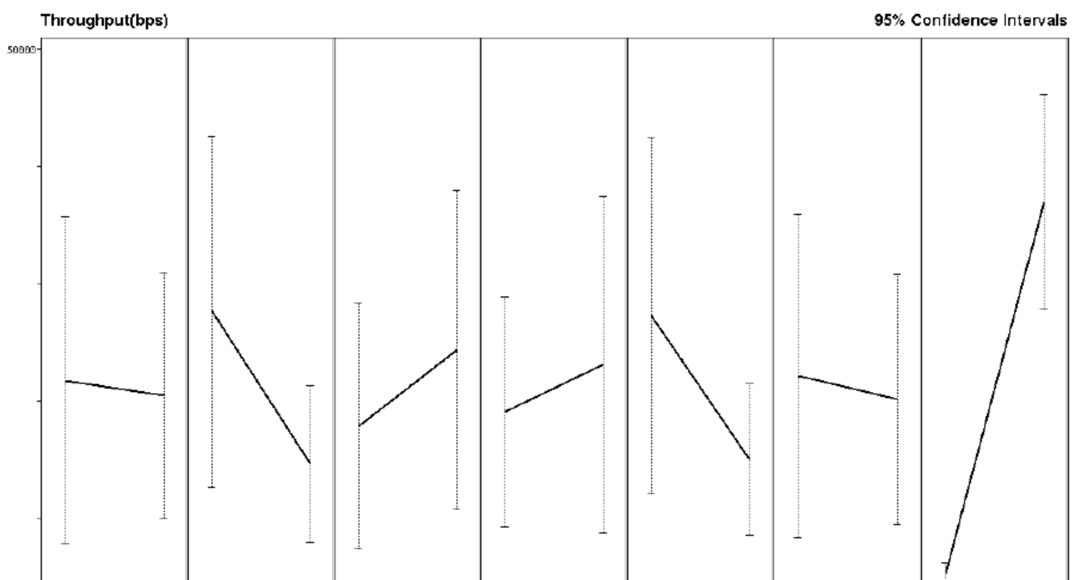

Figure 3.11: 1/16 Fractional Factorial Design—Main Effects (Throughput)

average measured response (throughput, in this case) will fall somewhere within the indicated confidence interval.

From Figure 3.11, we can gain some insight about the behavior of the target system, as well as begin the process of determining which factors to eliminate for subsequent full-factorial experimental designs. A reminder that the results of this 1/16 fractional design provide main effects only, and do not include two-way factor interactions. In the paragraphs that follow, I shall discuss my visual analysis of Figure 3.11, beginning with the factor that appears to have the greatest main effect on throughput, and concluding with the factor that appears to have the least main effect on throughput.

Varying the the traffic type from UDP (CBR traffic) to TCP-Lite appears to have a significant effect on average throughput, in that average throughput seems to be substantially higher with TCP-Lite than with UDP. Notice, however, that the confidence interval is considerably smaller with UDP than with TCP-Lite. Nonetheless, even with the confidence intervals shown, it is clear that throughput is higher when using TCP-Lite when compared to using UDP.

Varying the routing protocol from AODV to OLSR-Inria seems to have the next highest level of main effect on throughput, with the greater level of throughput realized when using AODV. The 95% confidence intervals associated with varying the routing protocol suggest, however, that favoring AODV over OLSR-Inria may not always necessarily hold. As seen in the figure, the 95% confidence interval for AODV spans (vertically) a significant portion of the measured throughput range.

Varying traffic load from 20% of wireless mesh routers to 50% of wireless mesh routers suggests measured average throughput similar to what we see when varying the routing protocol. What is suggested by the figure is that increasing the traffic load leads to a reduction in average measured throughput. Similar to what we observed with the routing protocol, the 95% confidence interval for the lower traffic load spans a substantial segment of the measured throughput range.

An increase in average measured throughput is indicated by an increase in item size from 512 bytes to 1500 bytes. This seems hardly surprising, since items of ITEMSIZE are generated once every second. Thus, in the case of the larger item size, more data is transmitted per unit time than with the smaller item size. However, there seems to be considerable overlap in the confidence intervals for the low and high factor values, which suggests that conclusions about the main effect from varying this factor may be doubtful.

Varying the bit rate from 2 Mbps to 11 Mbps seems to have a relatively small main effect on throughput. This effect may be further mitigated by the somewhat large 95% confidence intervals for both the low and high factor values. Indeed, the graphical evidence here suggests that BITRATE may be a candidate factor for elimination from the factor space.

Both the NETWRKSZ and GATEWAYN factors exhibit highly similar main effects, when varying their values. In addition to the seemingly small main effect upon throughput from varying their values, the confidence intervals in both are rather substantial. As with BITRATE, these factors may also be candidate factors for elimination from the factor space.

The insights gleaned thus far result from graphical inspection; however, this is just one perspective. I introduced analysis of variance (ANOVA) as a useful analytical tool for Stage I work. Because we wish to identify factors that may be eliminated from the factor space, ANOVA offers an additional perspective to my simulation studies by which such identification might occur.

Source	Master Model DF	SS	MS	F	Pr > F	Predictive Model DF	SS	MS	F	Pr > F
GATEWAYN	1	9452974	9452974	770.7233	0.0001	1	9452974	9452974	770.7233	0.0001
TRAFFLD	1	1.0127E9	1.0127E9	82567.07	0.0001	1	1.0127E9	1.0127E9	82567.07	0.0001
ITEMSIZE	1	2.5428E8	2.5428E8	20731.69	0.0001	1	2.5428E8	2.5428E8	20731.69	0.0001
BITRATE	1	97260541	97260541	7929.882	0.0001	1	97260541	97260541	7929.882	0.0001
ROUTINGP	1	8.9922E8	8.9922E8	73315.37	0.0001	1	8.9922E8	8.9922E8	73315.37	0.0001
NETWRKSZ	1	24161427	24161427	1969.938	0.0001	1	24161427	24161427	1969.938	0.0001
TRANSPRT	1	6.002E9	6.002E9	489355.4	0.0001	1	6.002E9	6.002E9	489355.4	0.0001
Model	7	8.299E9	1.1856E9	96662.86	0.0001	7	8.299E9	1.1856E9	96662.86	0.0001
Error	16	196241.1	12265.07			16	196241.1	12265.07		
Total	23	8.2992E9				23	8.2992E9			

Table 3.21: 1/16 Fractional: ANOVA for THROUGHP

	Master Model	Predictive Model
Mean	21151.85	21151.85
R-square	100.0%	100.0%
Adj. R-square	100.0%	100.0%
RMSE	110.7478	110.7478
CV	0.523584	0.523584

Table 3.22: 1/16 Fractional: Fit Statistics for THROUGHP

1/16 Fractional—Analysis of Variance. Table 3.21 is an ANOVA (analysis of variance) for throughput. Recall from Stage I that ANOVA is a useful tool for identifying factors whose main effects upon a response are statistically significant. The *degrees of freedom* (*DF*) is equal to 1 for each factor; the *sum of squares* (*SS*) is the variation; the *mean-square* (*MS*) is the variance, or *SS/DF* ; and *F* is the *F*-ratio, which is *MS/Error*. The *P*-value is of particular interest, since it serves as a measure of "statistical significance," which indicates the degree to which the value of a factor is "true." Factors for which the *P*-value is small ($P < 0.05$) are considered significant and should therefore be included in the prediction, or regression, model. From the ANOVA in Table 3.21 we observe that all factors in the factor space—that is, *GATEWAYN*, *TRAFFLD*, *ITEMSIZE*, *BITRATE*, *ROUTINGP*, *NETWRKSZ*,

Term	Master Model Estimate	Std Err	t	Pr > |t|		Predictive Model Estimate	Std Err	t	Pr > |t|
GATEWAYN	-1255.187	45.21259	-277619	0.0001	<**	-1255.187	45.21259	-277619	0.0001
TRAFFLD	-12991.6	45.21259	-287.345	0.0001	<**	-12991.6	45.21259	-287.345	0.0001
ITEMSIZE	6509.9363	45.21259	143.985	0.0001	<**	6509.9363	45.21259	143.985	0.0001
BITRATE	4026.1756	45.21259	89.04988	0.0001	<**	4026.1756	45.21259	89.04988	0.0001
ROUTINGP	-12242.13	45.21259	-270.768	0.0001	<**	-12242.13	45.21259	-270.768	0.0001
NETWRKSZ	-2006.715	45.21259	-44.384	0.0001	<**	-2006.715	45.21259	-44.384	0.0001
TRANSPRT	31627	45.21259	699.5394	0.0001	<**	31627	45.21259	699.5394	0.0001

<** Significant at P < 0.05

Table 3.23: 1/16 Fractional Factorial: Effect Estimates for THROUGHP

and *TRANSPRT*—are statistically significant, and should therefore be included as part of the regression model.

1/16 Fractional: Throughput—Fit Statistics. Fit statistics for throughput are indicated in Table 3.22, the predictive model of which may be interpreted as follows. The *mean* is the intercept, which, as shown in Table 3.22, is 21151.85. The quantity *R-square* is 100.0%, which is the proportion of total variability explained by the model, where $0 \leq R2 \leq 1$, with larger values being more desirable. A related quantity, *Adj. R-square*, is a variation of the *R-square* statistic, whose value decreases as more factors are included within the model. The *RMSE*, or *root mean square error*, is determined by calculating the deviations of points from their true position, summing up the measurements, and then taking the square root of the sum, with smaller values being more desirable. Finally, the *CV*, or *coefficient of variation*, a measure of the precision or relative dispersion, is 0.523584. The CV is calculated as the standard deviation divided by the mean, and is used to compare variation among multiple data series that have significantly different means.

Throughput—Effect Estimates. The predictive model estimates shown in Table 3.23, along with the mean for the predictive model indicated in Table 3.22, provide the data needed to develop a preliminary empirical model for throughput.

Throughput—Preliminary Empirical Model. The preliminary empirical model for throughput (coded levels) is shown in Equation (3.15).

$$\begin{aligned} Y_{throughp} = \; & 21151.85 - 627.5937x_1 - 6495.802x_2 + 3254.958x_3 + \\ & + 2013.088x_4 - 6121.064x_5 - 1003.357x_6 + 15813.99x_7 \end{aligned} \tag{3.15}$$

where x_1 = GATEWAYN, x_2 = TRAFFLD, x_3 = ITEMSIZE, x_4 = BITRATE, x_5 = ROUTINGP, x_6 = NETWRKSZ, and x_7 = TRANSPRT

Recall from Stage I that the equation for $Y_{throughp}$ is a function that describes the empirical relationship between the response $Y_{throughp}$ and its corresponding factors. In fact, Equation (3.15) is called a *regression* equation. The general multiple linear regression model with k regressor variables is of the form

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + \varepsilon. \tag{3.16}$$

The parameters β_j, $j = 0, 1, \ldots, k$, are called the *regression coefficients*. The model shown in Equation (3.16) describes a hyperplane in the k-dimensional space of the regressor variables $\{x_j\}$. The parameter β_j represents the expected change in response y per unit change in x_j when all the remaining independent variables x_j $(x \neq j)$ are held constant. The effect estimates shown in Table 3.23 reflect a *two-unit* change in the value of its associated regressor variable. Thus, the regression coefficients are computed as ½ the effect estimates.

1/16 Fractional—Preliminary Factor Eliminations. Drawing preliminary conclusions about factor elimination is difficult at this point, for two reasons. First, although the information provided in the ANOVA table suggests strongly that all factors in the factor space are significant at the 0.05 level, the main effects chart seems to indicate otherwise. Second, this 1/16 fractional factorial design highlights a single response variable, throughput. As a response, throughput, although very important for any network, should be viewed along with other related responses, such as end-to-end delay, jitter, and packet delivery ratio. Therefore, before deciding upon specific factor eliminations from the factor space, it may be useful to work through an additional set of simulation studies, which consists of many of the same factors in the current 1/16 fractional factor space, as well as the responses, throughput, end-to-end delay, jitter, and packet delivery ratio.

1/8 Fractional Design. The design matrix for a 1/8 fractional factorial design is shown in Table 3.24. Unlike the previous fractional design, which had a factor space of size 7, this new fractional design has a factor space of size 6. The principal difference between this new fractional design and the previous one is the fact that only CBR traffic is involved. Moreover, I measure four average responses, instead of just a single response; these include: throughput, end-to-end delay, jitter, and packet delivery ratio. The simulation setup for this fractional factorial design is exactly the same as the setup I used for the 1/16 fractional design.

Table 3.25 shows the average response values for throughput, end-to-end delay, jitter, and packet delivery ratio. Recall, however, that we are interested mainly in factor elimination; that is, we seek to efficiently identify factors whose main effects are not statistically-significant. Thus, we shall exploit both graphical and ANOVA support, in order

Run	GATEWAYN	TRAFFLD	ITEMSIZE	BITRATE	ROUTINGP	NETWRKSZ
1	10	20	512	11	OLSR-Inria	100
2	10	20	512	11	OLSR-Inria	100
3	10	20	512	11	OLSR-Inria	100
4	20	20	512	2	AODV	100
5	20	20	512	2	AODV	100
6	20	20	512	2	AODV	100
7	4	18	512	2	OLSR-Inria	36
8	4	18	512	2	OLSR-Inria	36
9	4	18	512	2	OLSR-Inria	36
10	7	18	512	11	AODV	36
11	7	18	512	11	AODV	36
12	7	18	512	11	AODV	36
13	4	7	1500	11	AODV	36
14	4	7	1500	11	AODV	36
15	4	7	1500	11	AODV	36
16	7	7	1500	2	OLSR-Inria	36
17	7	7	1500	2	OLSR-Inria	36
18	7	7	1500	2	OLSR-Inria	36
19	10	50	1500	2	AODV	100
20	10	50	1500	2	AODV	100
21	10	50	1500	2	AODV	100
22	20	50	1500	11	OLSR-Inria	100
23	20	50	1500	11	OLSR-Inria	100
24	20	50	1500	11	OLSR-Inria	100

Table 3.24: 1/8 Fractional Factorial Design Matrix

Run	THROUGHP	E2EDELAY	JITTER	PDRATIO
1	4095.15	0.1719954945	0.152275329	0.9930555556
2	3918.1	0.1420281565	0.1356318355	0.9562222222
3	2961.1111111	0.1984861615	0.7774051557	0.7175925926
4	3589.9	0.1897799233	0.3378855327	0.876
5	3557.4	0.192768984	0.3506078444	0.8681111111
6	3579.5	0.1827 23769	0.3359911407	0.8735
7	2955.7777778	0.1981747149	0.7808030867	0.7166666667
8	2923.3333333	0.1976961781	0.7890497982	0.7080864198
9	2996.6111111	0.1973932589	0.7141870077	0.7243209877
10	4096.8333333	0.1446673851	0.0582909321	0.9997530864
11	4097.1666667	0.1378414826	0.0479471099	0.9998765432
12	4096.6666667	0.1332025989	0.040418526	0.9997530864
13	12002.142857	0.2319893111	0.0586002406	0.9996825397
14	11997.571429	0.2324964386	0.0620709621	0.9993650794
15	11996.285714	0.2564051329	0.106439943	0.9992063492
16	7414.1428571	0.2416283279	1.5167644083	0.6138095238
17	7173.1428571	0.2422923157	1.5291807876	0.5941269841
18	7053.1428571	0.2395999631	1.5386357164	0.5841269841
19	5839.36	0.5467579643	1.8609375357	0.4858444444
20	5765.94	0.5525030559	1.8853952856	0.4799111111
21	5795.58	0.5450052118	1.8706480637	0.4823333333
22	11878.42	0.4646265624	0.4553749912	0.9837333333
23	11882.44	0.4625282062	0.4538679087	0.9838222222
24	11880.96	0.4660171771	0.4579143124	0.9838

Table 3.25: 1/8 Fractional Factorial Design Responses

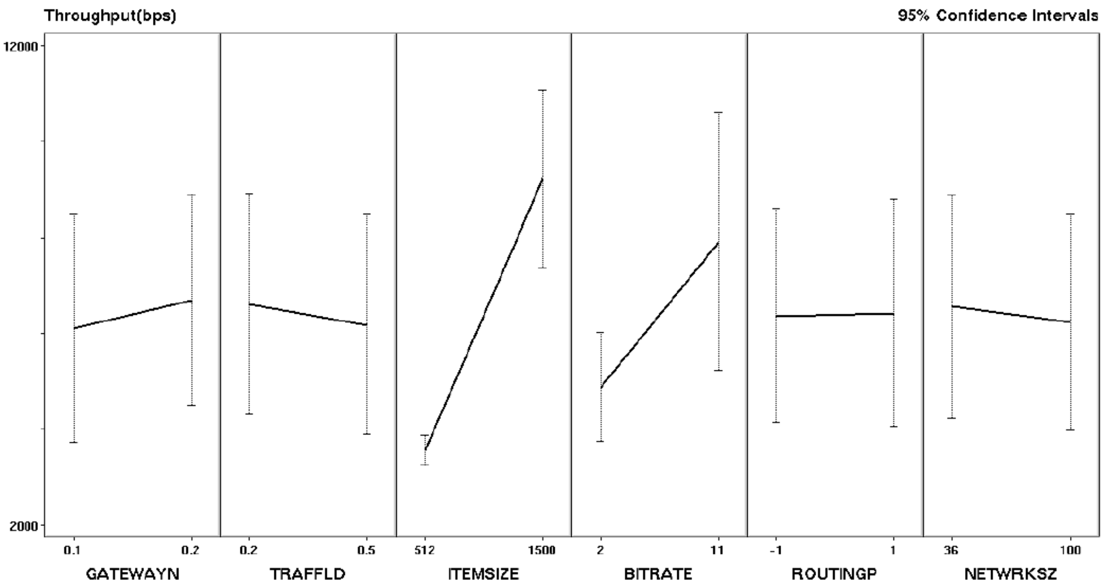

Figure 3.12: 1/8 Fractional Factorial Design—Main Effects (Throughput)

to make reasonable decisions about which factors should not be included in our first-order empirical models.

Figure 3.12 illustrates the main effects for the throughput response. Upon examination, it appears that varying both ITEMSIZE and BITRATE have significant main effects upon the throughput response. Moreover, the slopes of the other factors (i.e., GATEWAYN, TRAFFLD, etc.) seem rather insubstantial, and the 95% confidence intervals for these have considerable overlap.

Figure 3.13 illustrates the main effects for the end-to-end delay response. In contrast to the main effects for the throughput response, we observe that TRAFFLD, ITEMSIZE, and NETWRKSZ appear to be significant.

Figure 3.14 illustrates the main effects for the delay jitter response. As with the main effects on throughput, it seems from this figure that both ITEMSIZE and BITRATE have substantial main effects on jitter, with far lesser effects by the other factors.

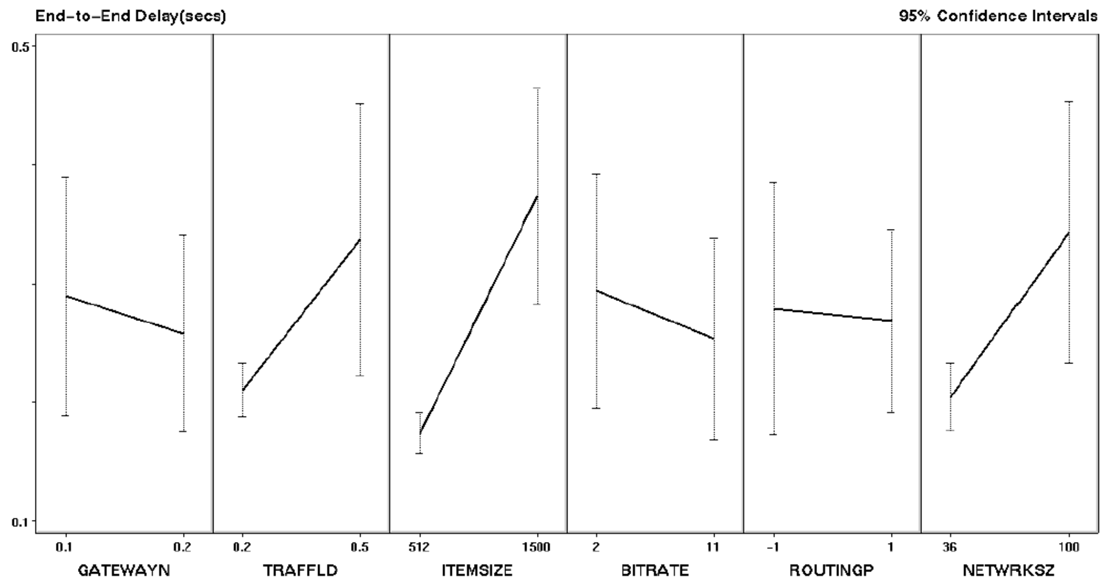

Figure 3.13: 1/8 Fractional Factorial Design—Main Effects (End-to-End Delay)

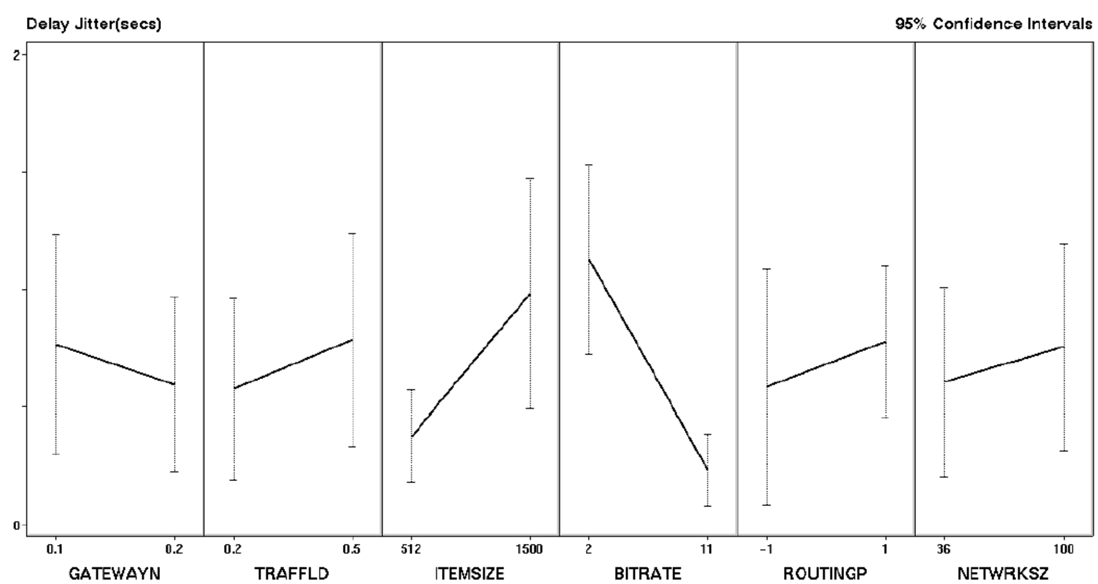

Figure 3.14: 1/8 Fractional Factorial Design—Main Effects (Jitter)

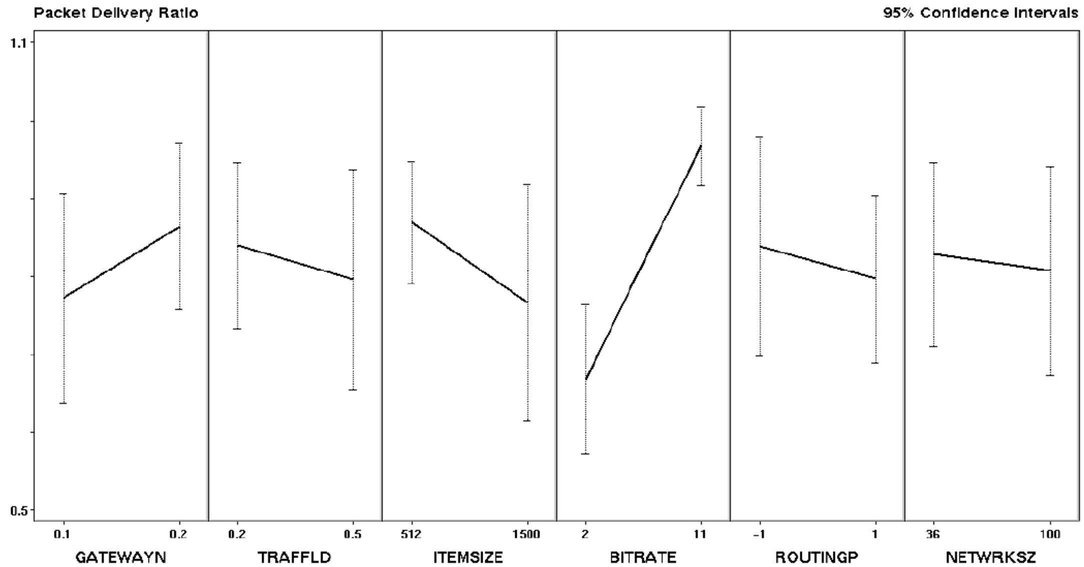

Figure 3.15: 1/8 Fractional Factorial Design—Main Effects (Packet Delivery Ratio)

Figure 3.15 illustrates the main effects for the packet delivery ratio response. Examination of this figure again suggests significant main effects by both ITEMSIZE and BITRATE, with far fewer main effects on packet delivery ratio by varying the remaining factors.

2^k Full Factorial Design

The results of both the 1/16 and 1/8 fractional factorial simulation studies provide important insight into the behavior and performance of the multi-hop WMN. Moreover, an important methodological objective was met, which was to retain those factors in the factor space for which their main effects are statistically-significant. The next step in Stage II is to develop a full factorial design, from which further simulation experiments may be contrived. Unlike the two previous fractional factorial design studies, which measured main effects on responses, full factorial designs measure main effects *and* two-way factor interaction.

Factor	Label	Low	Center	High
NETWRKSZ	Network Size (mesh routers)	36	68	100
TRAFFLD	Traffic Load (% of total nodes)	0.20	0.35	0.50
ITEMSIZE	Item Size (bytes)	512	1006	1500

Table 3.26: Two-Level Full-Factorial Design

Design Structure

The factor space for my full factorial design is rather small—three, to be exact. From the two preceding fractional design results, we shall include only NETWRKSZ, TRAFFLD, and ITEMSIZE factors. The factors and their levels are shown in Table 3.26. A factor space of size 3 requires $2^3 = 8$ design points in a 2^k factorial design. Additionally, there are four response variables of interest, which include: THROUGHP, E2EDELAY, JITTER, and PDRATIO.

We have already seen that variability may be reduced through the use of replicates. Thus, for this particular statistical DOE, I define five point-replicates. As a result, the total number of simulation runs is 40.

As with the two fractional factorial simulation studies, I used the QualNet 4.0 simulator, where the number of gateway nodes is set at 15% of the network size (a variable that is itself part of the factor space). The terrain size is 3000 *meters2,* with a grid node placement and 270 meter wireless mesh node separation. The bit rate is 11 Mbps. The pathloss model is two-ray, and traffic is CBR (UDP), generating one packet per second. The routing protocol used in the simulation experiments is AODV, with each experiment running 15 minutes in time length.

The design matrix for a 2^k factorial design is shown in Table 3.27. With five replicates per design point, runs 1 through 5 reflect design point 1, runs 6 through 10 reflect

Run	NETWRKSZ	TRAFFLD	ITEMSIZE
1	36	7	512
2	36	7	512
3	36	7	512
4	36	7	512
5	36	7	512
6	100	20	512
7	100	20	512
8	100	20	512
9	100	20	512
10	100	20	512
11	36	18	512
12	36	18	512
13	36	18	512
14	36	18	512
15	36	18	512
16	100	50	512
17	100	50	512
18	100	50	512
19	100	50	512
20	100	50	512
21	36	7	1500
22	36	7	1500
23	36	7	1500
24	36	7	1500
25	36	7	1500
26	100	20	1500
27	100	20	1500
28	100	20	1500
29	100	20	1500
30	100	20	1500
31	36	18	1500
32	36	18	1500
33	36	18	1500
34	36	18	1500
35	36	18	1500
36	100	50	1500
37	100	50	1500
38	100	50	1500
39	100	50	1500
40	100	50	1500

Table 3.27: 2^k Factorial Design Matrix

design point 2, and so on. Also, the number of gateway nodes is 15% of the network size; thus, when the network size is 36, the number of gateway nodes is 5, and when the network size is 100, the number of gateway nodes is 15.

Table 3.28 shows the average response values for throughput, end-to-end delay, jitter, and packet delivery ratio. I shall rely upon both graphical and quantitative data, in order to draw inferences about main and interaction effects on the four response variables. From

Run	THROUGHP	E2EDELAY	JITTER	PDRATIO
1	4097.00	0.10592	0.00710	1.00000
2	4097.00	0.10673	0.01433	1.00000
3	4097.00	0.10652	0.01452	1.00000
4	4096.43	0.10881	0.00635	0.99984
5	4096.29	0.10630	0.01212	0.99984
6	4097.05	0.11528	0.02239	1.00000
7	4097.00	0.11155	0.01453	1.00000
8	4097.00	0.11344	0.01371	1.00000
9	4096.95	0.10791	0.00935	1.00000
10	4097.05	0.10973	0.00985	1.00000
11	4094.33	0.18515	0.07075	0.99929
12	4095.33	0.16478	0.07184	0.99920
13	4096.17	0.16542	0.06847	0.99957
14	4097.28	0.16713	0.06707	0.99981
15	4094.61	0.17857	0.08236	0.99920
16	4094.60	0.17761	0.05673	0.99918
17	4096.17	0.16012	0.05346	0.99967
18	4096.22	0.15907	0.05759	0.99953
19	4096.28	0.15805	0.05590	0.99960
20	4096.80	0.16080	0.05378	0.99969
21	11997.29	0.20000	0.03275	0.99937
22	11991.57	0.19991	0.03401	0.99889
23	11993.29	0.19979	0.03681	0.99905
24	11999.14	0.19961	0.02902	0.99952
25	11993.29	0.19982	0.02987	0.99905
26	12005.25	0.22064	0.04940	1.00000
27	12003.75	0.21525	0.03757	0.99989
28	12001.80	0.22697	0.06109	0.99967
29	12004.60	0.21027	0.03747	0.99994
30	12004.80	0.22590	0.05702	0.99994
31	11895.33	0.54754	0.21326	0.99056
32	11960.78	0.37912	0.16632	0.99605
33	11938.39	0.36754	0.18646	0.99414
34	11958.89	0.38879	0.18898	0.99574
35	11989.28	0.38650	0.17523	0.99833
36	11989.28	0.35829	0.15329	0.99764
37	11976.96	0.35483	0.14440	0.99740
38	11924.58	0.40581	0.16726	0.99307
39	11952.76	0.38680	0.15736	0.99536
40	11959.60	0.38965	0.16167	0.99596

Table 3.28: 2^k Factorial Design Responses

these results, I develop first-order empirical models that characterize the relationship between each of the four responses and the factors and their interactions.

Graphical Analysis

Figure 3.16 illustrates a scatterplot for the throughput response. Clearly, some factor change at run 21 results in a significant increase in throughput. A reexamination of Table 3.27 shows that the item size goes from 512 bytes to 1500 bytes. Because the two other factors

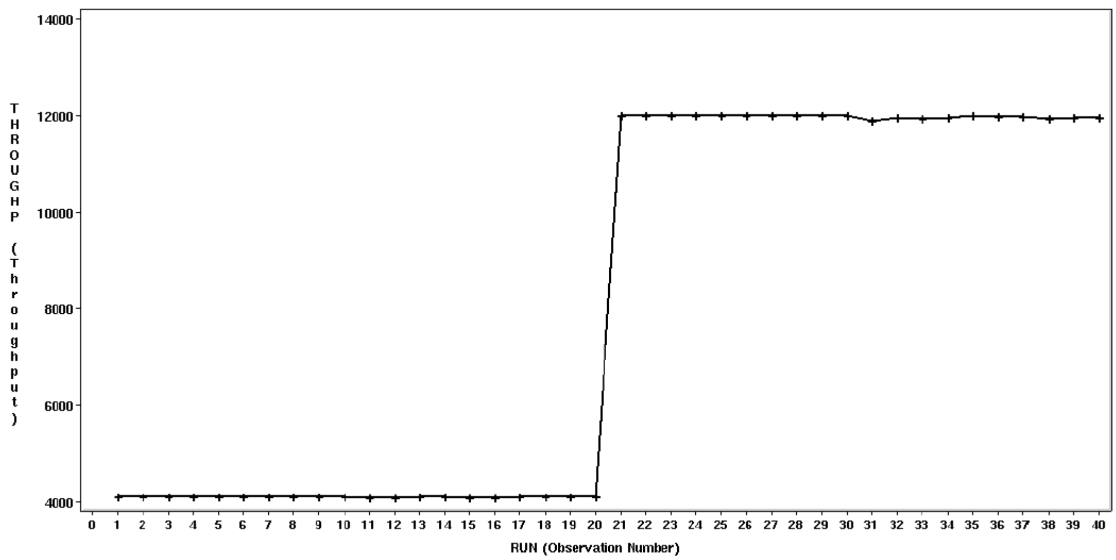

Figure 3.16: *$2^3 5$* Full Factorial—Scatterplot (Throughput)

(that is, network size and traffic load) are varied several times between runs 1 and 20 inclusive, with no discernible change in the throughput response. Thus, from the scatterplot, we may conclude that varying items size from 512 bytes to 1500 bytes has a significant effect on the throughput response.

Figure 3.17 illustrates the main effects for the throughput response. From the figure we see that throughput appears to be mostly unaffected by varying either network size or traffic load. Varying the item size, however, appears to have a substantial impact on throughput. This latter observation seems reasonable, considering that increasing the number of bytes per item at the application layer would indeed result in greater throughput.

Figure 3.18 illustrates two-way factor interaction effects for the throughput response. Two-way factor interaction is indicated by the presence of non-parallel lines. From this figure, it appears that two-way factor interaction is not present for throughput, at least not with the current factor space and the range of low/high values.

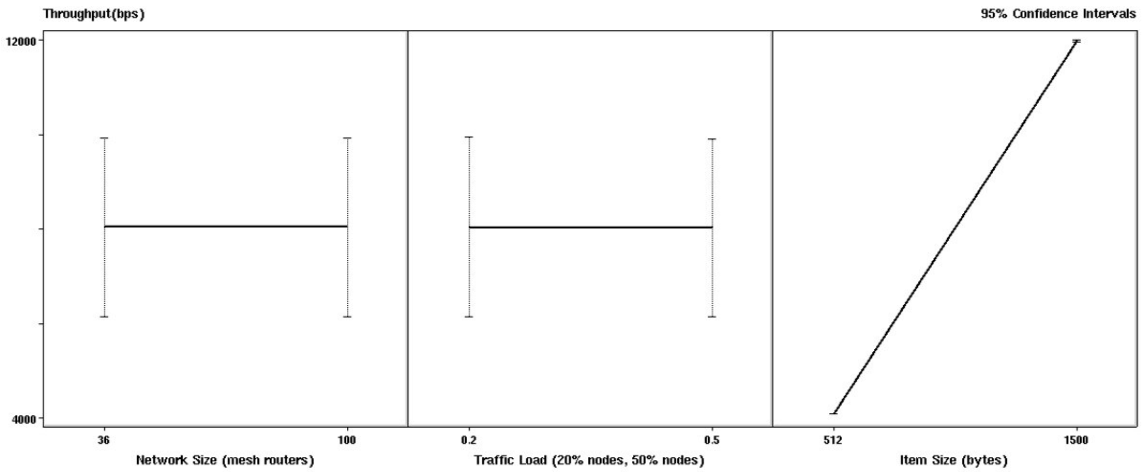

Figure 3.17: $2^3 5$ Full Factorial—Main Effects (Throughput)

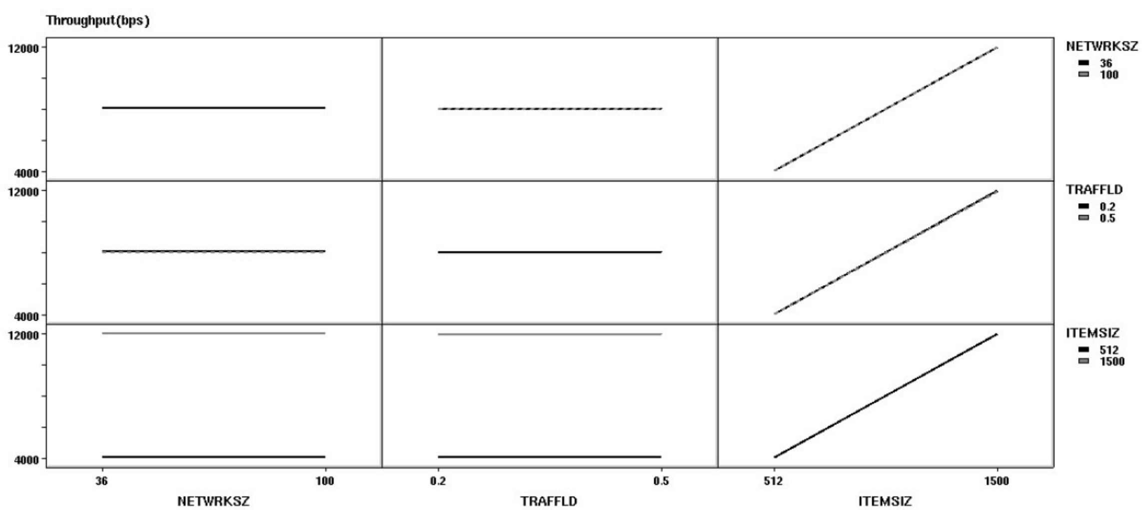

Figure 3.18: $2^3 5$ Full Factorial—Interaction Effects (Throughput)

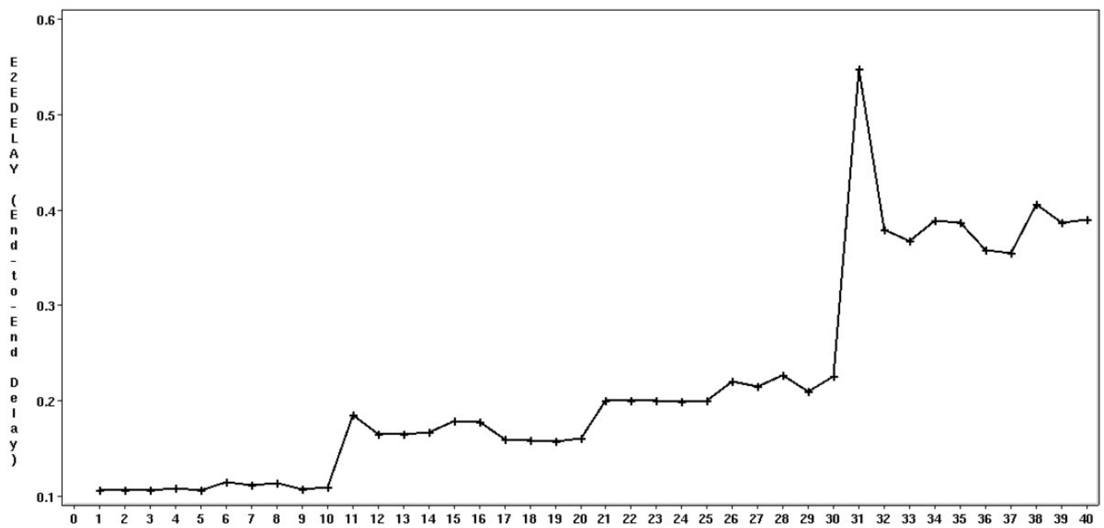

Figure 3.19: $2^3 5$ Full Factorial—Scatterplot (End-to-End Delay)

Figure 3.19 illustrates a scatterplot for the end-to-end delay response. Runs 1 through 10 suggest response signals that are seemingly homogeneous, with a noticeable change indicated at run 11 and continuing through run 30. This change reflects the shift in traffic load from 20% of total nodes (as indicated by network size) to 50% of total nodes; thus, in such a case, increases in both end-to-end delay and jitter are expected. Substantial increases both in end-to-end delay and jitter occur at runs 31 through 40, due likely to the concurrent levels of traffic load (50%) and 1500 byte itemsize.

Figure 3.20 illustrates the main effects for the end-to-end delay response. As with throughput, varying network size seems to have negligible effect on end-to-end delay; however, varying either traffic load or item size or both leads to a rather significant increase in end-to-end delay. We observe, too, the somewhat smaller 95% confidence intervals, which suggests a reliable characterization between end-to-end delay and these two factors. The observed main effect upon end-to-end delay by (independently) varying these two factors is not altogether surprising.

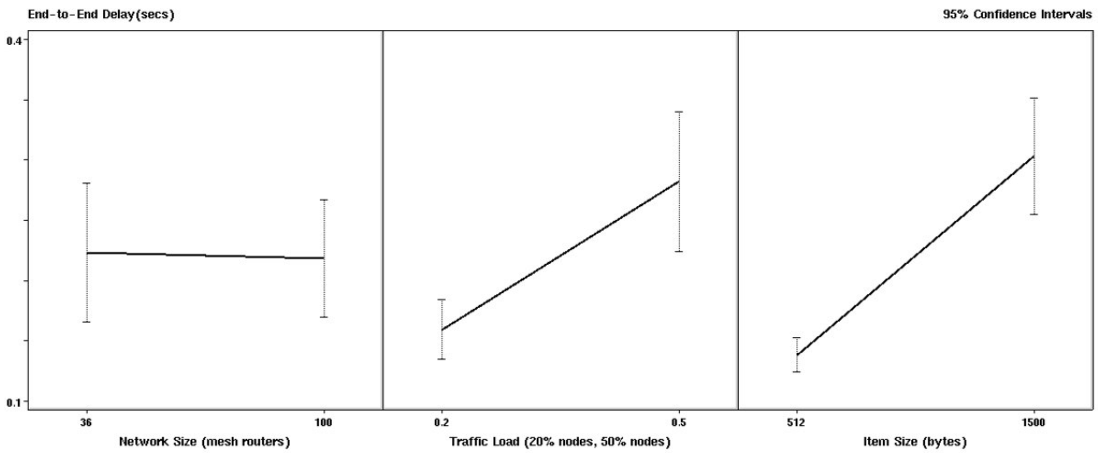

Figure 3.20: *$2^3 5$* Full Factorial—Main Effects (End-to-End Delay)

Figure 3.21 illustrates two-way factor interaction effects for the end-to-end delay response. Examination of this figure suggests two-way factor interaction between traffic load and item size. Such two-way factor interaction is indicated by the non-parallel lines shown in the intersection cells for TRAFFLD and ITEMSIZ. Moreover, some two-way factor interaction is indicated between traffic load and network size, although to a lesser degree than the two-way factor interaction indicated for traffic load and item size.

Figure 3.22, which illustrates a scatterplot for the delay jitter response. Runs 1 through 10 suggest response signals that are seemingly homogeneous, with a notable change indicated at run 11 and continuing through run 30. This notable change reflects the shift in traffic load from 20% of total nodes (as indicated by network size) to 50% of total nodes; thus, in such a case, increases in both end-to-end delay and jitter are expected. Substantial increases both in end-to-end delay and jitter occur at runs 31 through 40, due likely to the concurrent levels of traffic load (50%) and 1500 byte itemsize.

Figure 3.23 illustrates the main effects for the delay jitter response. The main effects applied to end-to-end delay may be similarly applied to the main effect for jitter. Again, we

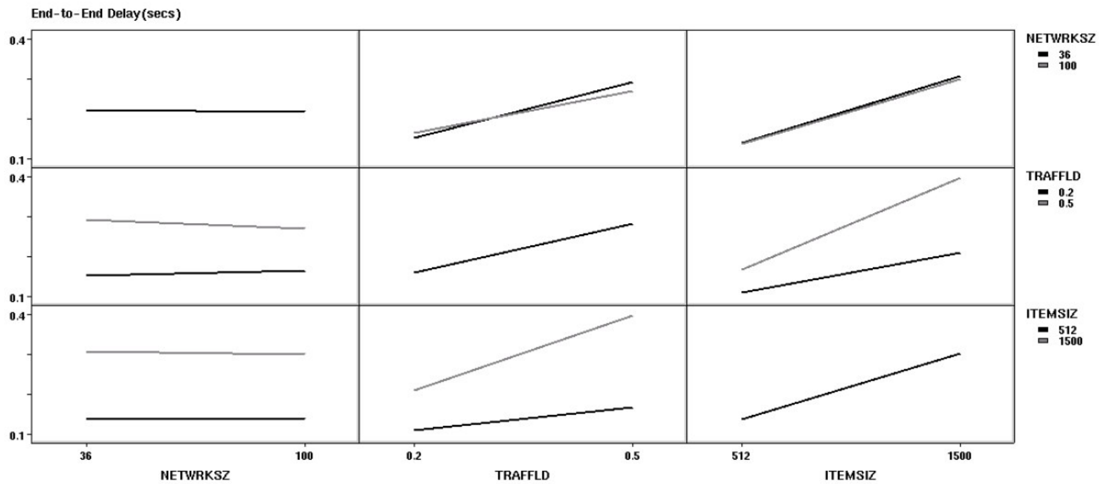

Figure 3.21: $2^3 5$ Full Factorial—Interaction Effects (End-to-End Delay)

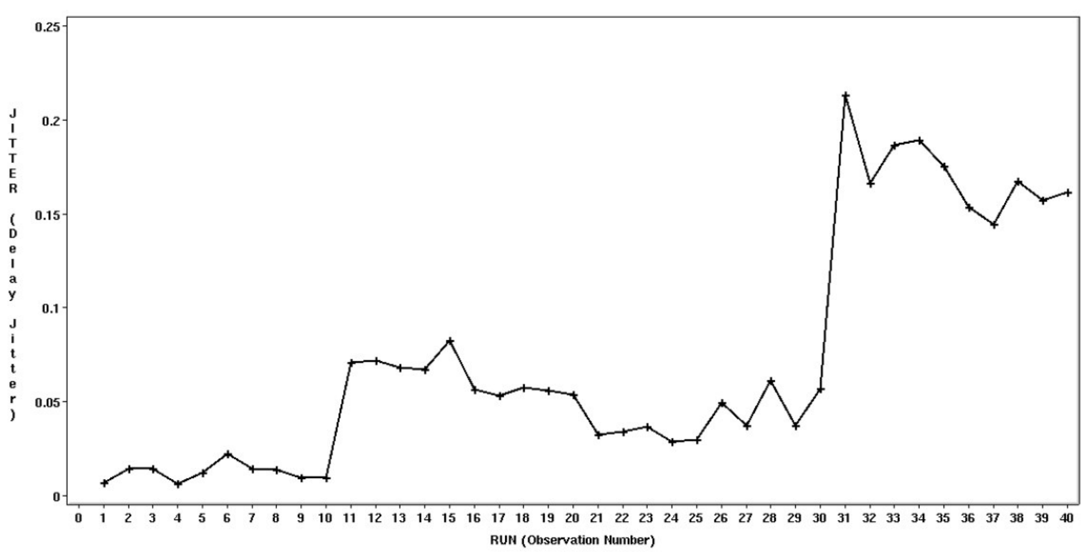

Figure 3.22: $2^3 5$ Full Factorial—Scatterplot (Jitter)

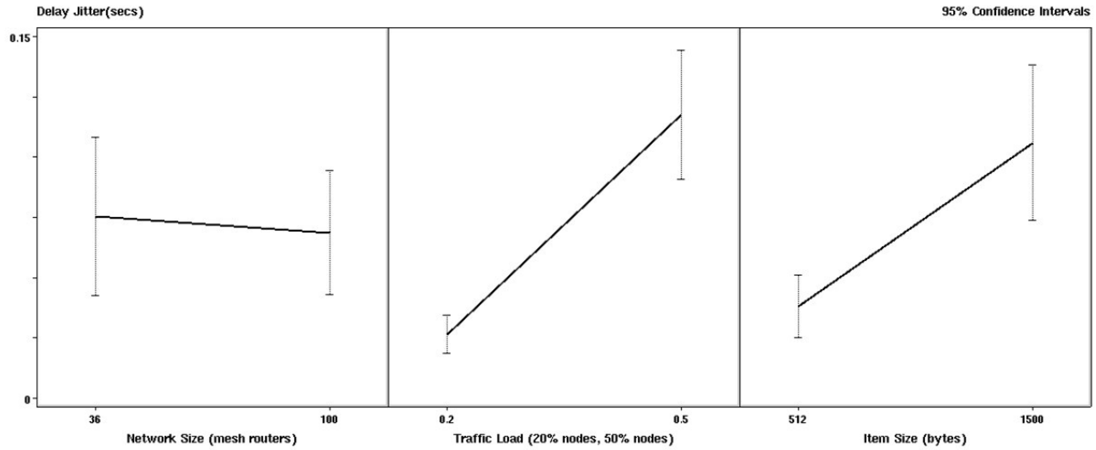

Figure 3.23: $2^3 5$ Full Factorial—Main Effects (Jitter)

see that varying both traffic load and item size seems to have significant impact on the response, which, in this case, is jitter.

Figure 3.24 illustrates two-way factor interaction effects for the delay jitter response. Similar to the two-way factor interaction we described for end-to-end delay, there seems to be two-way factor interaction between traffic load and item size for jitter. Moreover, two-way factor interaction between traffic load and network size is suggested by the figure as well.

Figure 3.25 illustrates a scatterplot for the packet delivery ratio response. As indicated in the figure, the packet delivery ratio is at acceptable levels (that is, between 0.99 and 1.00) for the entire run set. A somewhat interesting phenomenon seems to occur between runs 31 through 35. Specifically, runs 31 through 35 exhibit an erratic packet delivery ratio. This, in spite of the fact that the factor levels remain unchanged within this run set. A similar scenario is indicated for runs 36 through 40. A plausible explanation for this seemingly erratic behavior is that the network is likely reaching saturation point, beginning with run 31 and continuing through run 40.

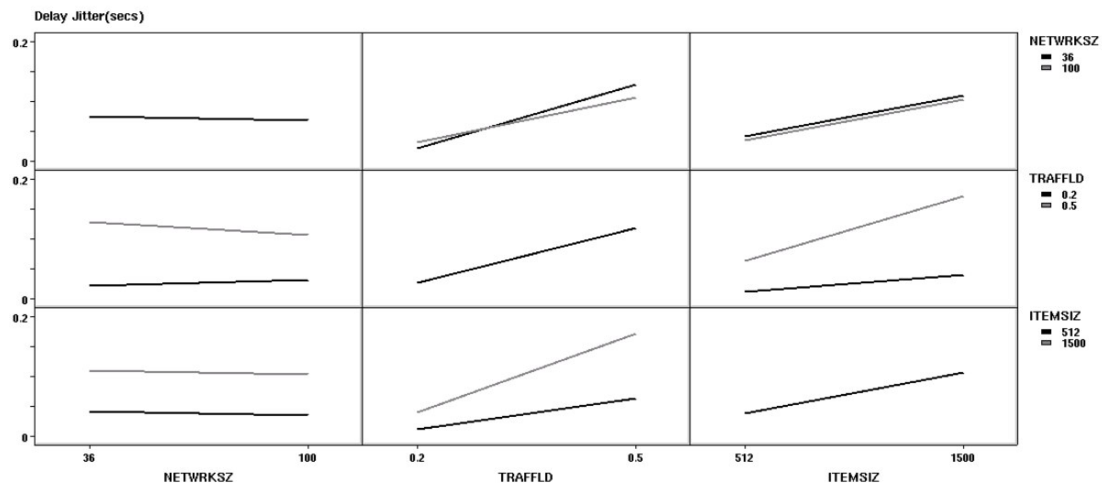

Figure 3.24: $2^3 5$ Full Factorial—Interaction Effects (Jitter)

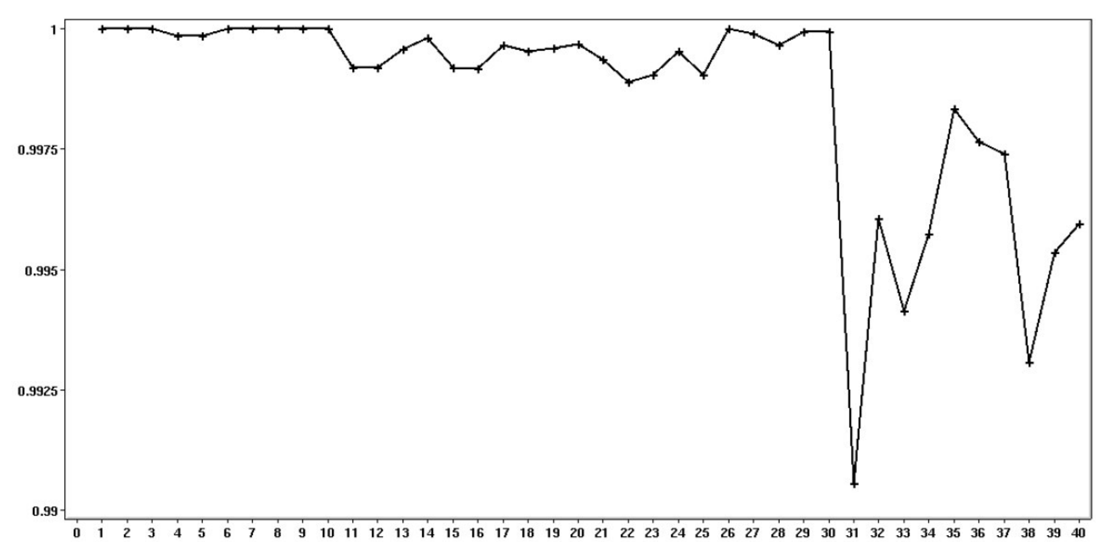

Figure 3.25: $2^3 5$ Full Factorial—Scatterplot (Packet Delivery Ratio)

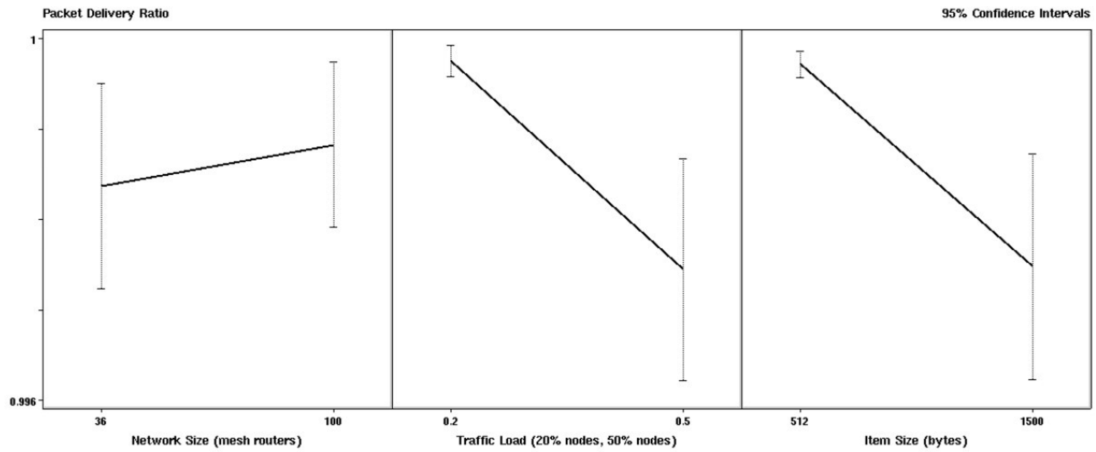

Figure 3.26: $2^3 5$ Full Factorial—Main Effects (Packet Delivery Ratio)

Figure 3.26 illustrates the main effects for the packet delivery ratio response. Interesting observations may be gleaned from the main effects for packet delivery ratio, as illustrated in the figure. At first glance, varying network size seems to have an impact on packet delivery ratio; however, we must be careful not to overlook the important consideration of the 95% confidence intervals. In the case of varying network size, the overlap between the two confidence intervals seems rather substantial. We shall need to investigate the implications of this—if indeed any such implications really are present. Varying traffic load or varying item size or varying both seems to lead to a virtually identical impact on packet delivery ratio. An interesting observation is the fact that the confidence intervals of both are exceptionally small when the factor values are at their low level; however, when the factor values are at their high levels, the confidence intervals for both are substantial.

Figure 3.27 illustrates two-way factor interaction effects for the packet delivery ratio response. The figure suggests a higher degree of two-way factor interaction between traffic

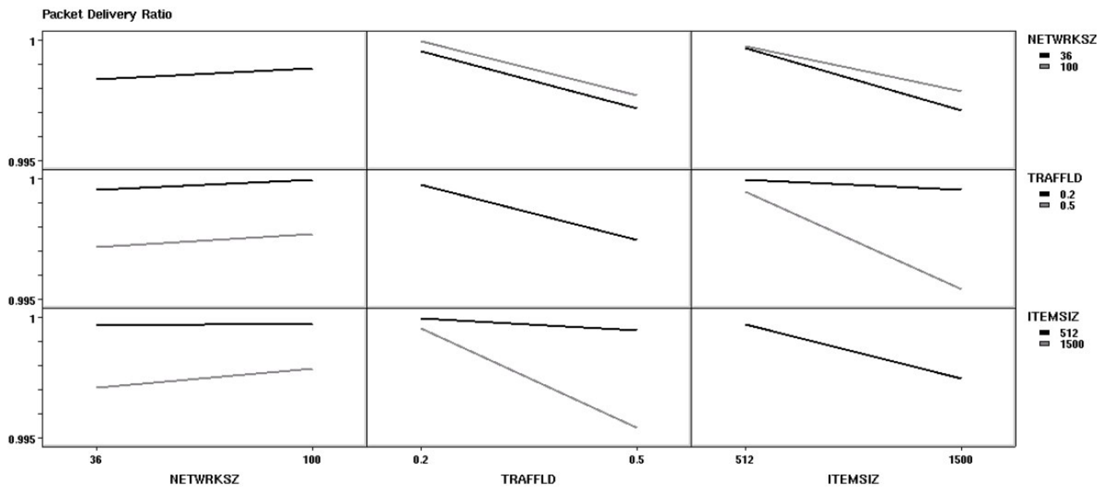

Figure 3.27: $2^3 5$ Full Factorial—Interaction Effects (Jitter)

load and item size than we have seen in previous two-way factor interaction figures. Moreover, the figure seems to indicate two-way factor interaction between item size and network size.

Empirical Models

The graphical evidence analyzed and discussed thus far offers important insight into the performance and behavior of the four response metrics upon which my analyses are focused. As beneficial as the preceding figures seem to be in my analyses, however, they are insufficient in terms of developing and measuring first-order empirical models. I shall next use three analytical tools by which such first-order empirical models may be derived; these analytical tools include: *ANOVA* (*analysis of variance*), *fit statistics*, and *effect estimates*.

***$2^3 5$* Full Factorial: Analysis of Variance—THROUGHP.** Table 3.29 is an ANOVA (analysis of variance) for throughput. Recall from my previous discussion that ANOVA is a useful tool for identifying factors whose main effects upon a response are statistically

	Master Model					Predictive Model				
Source	**DF**	**SS**	**MS**	**F**	**Pr > *F***	**DF**	**SS**	**MS**	**F**	**Pr > *F***
NETWRKSZ	1	257.4314	257.4314	1.229011	0.275614					
TRAFFLD	1	5481.377	1.0127E9	26.16882	0.0001	1	5481.377	5481.377	26.71107	0.0001
ITEMSIZ	1	6.2098E8	6.2098E8	2964643	0.0001	1	6.2098E8	6.2098E8	3026075	0.0001
NETWRKSZ*TRAFFLD	1	1.423864	1.423864	0.006798	0.934788					
NETWRKSZ*ITEMSIZ	1	216.4502	216.4502	1.033362	0.316766					
TRAFFLD*ITEMSIZ	1	5003.335	5003.335	23.88658	0.0001	1	5003.335	5003.335	24.38154	0.0001
Model	6	6.2099E8	1.035E8	494116	0.0001	3	6.2099E8	207E8	1008709	0.0001
Error	33	6912.252	209.4622			36	7387.557	205.2099		
(Lack of fit)	1	0.497891	0.497891	0.002305	0.962005					
(Pure Error)	32	6911.754	215.9923							
Total	39	6.21E8				39	6.21E8			

Table 3.29: $2^3 5$ Full Factorial: ANOVA for THROUGHP

	Master Model	Predictive Model
Mean	8036.471	8036.471
R-square	100.0%	100.0%
Adj. R-square	100.0%	100.0%
RMSE	14.47281	14.32515
CV	0.180089	0.178252

Table 3.30: $2^3 5$ Full Factorial: Fit Statistics for THROUGHP

significant. The degrees of freedom (DF) is equal to 1 for each factor; the sum of squares (SS) is the variation; the mean-square (MS) is the variance, or *SS/DF*; and *F* is the *F*-ratio, which is M S/Error. The *P*-value is of particular interest, since it serves as a measure of "statistical significance," which indicates the degree to which the value of a factor is "true." Factors for which the *P*-value is small ($P < 0.05$) are considered significant and should therefore be included in the prediction, or *regression*, model. From the ANOVA in Table 3.29 we observe that *TRAFFLD* and *ITEMSIZE* are statistically significant, and should therefore be included as part of the regression model. Moreover, the two-way factor interaction between *TRAFFLD* and *ITEMSIZE* is statistically significant, and should also be included as part of the regression model.

$2^3 5$ Full Factorial: Throughput—Fit Statistics. Fit statistics for throughput are indicated in Table 3.30, the predictive model of which may be interpreted as follows. The *mean* is the

Term	Master Model Estimate	Master Model Std Err	Master Model t	Master Model Pr > |t|		Predictive Model Estimate	Predictive Model Std Err	Predictive Model t	Predictive Model Pr > |t|
NETWRKSZ	5.0737698	4.576704	1.108608	0.275614					
TRAFFLD	-23.41234	4.576704	-5.11555	0.0001	<**	-23.41234	4.530001	-5.16828	0.0001
ITEMSIZE	7880.2326	4.576704	1721.814	0.0001	<**	7880.2326	4.53001	1739.562	0.0001
NETWRKSZ*TRAFFLD	0.3773413	4.576704	0.082448	0.934788					
NETWRKSZ*ITEMSIZ	4.6524206	4.576704	1.016544	0.316766					
TRAFFLD*ITEMSIZ	-22.36813	4.576704	-4.88739	0.0001	<**	-22.36813	4.53001	-4.93777	0.0001

<** Significant at P < 0.05

Table 3.31: $2^3 5$ Full Factorial: Effect Estimates for THROUGHP

intercept, which, as shown in Table 3.30, is 8036.471. The quantity *R-square* is 100.0%, which is the proportion of total variability explained by the model, where $0 \leq R2 \leq 1$, with larger values being more desirable. A related quantity, *Adj. R-square*, is a variation of the R-square statistic, whose value decreases as more factors are included within the model. The *RMSE*, or *root mean square error*, is determined by calculating the deviations of points from their true position, summing up the measurements, and then taking the square root of the sum, with smaller values being more desirable. Finally, the *CV*, or *coefficient of variation*, a measure of the precision or relative dispersion, is 0.180089. The CV is calculated as the standard deviation divided by the mean, and is used to compare variation among multiple data series that have significantly different means.

Throughput—Effect Estimates. The predictive model estimates shown in Table 3.31, along with the mean for the predictive model indicated in Table 3.30, provide the data needed to develop an empirical model for throughput.

Throughput—Empirical Model. The empirical model for throughput (coded levels) is shown in Equation (3.17).

$$Y_{throughp} = 8036.471 - 11.70617x_2 + 3940.116x_3 - - 11.18407x_2x_3 \quad (3.17)$$

where x_1 = NETWRKSZ, x_2 = TRAFFLD, and x_3 = ITEMSIZE.

Recall from my earlier discussion that the equation for $Y_{throughp}$ is a function that describes the empirical relationship between the response $Y_{throughp}$ and its corresponding factors. Each of the effect estimates shown in Table 3.31 reflects a two-unit change in the value of its associated regressor variable. Thus, the regression coefficients are computed as ½ the effect estimates. Observe, also, the fact that NETWRKSZ is not part of the model. From the ANOVA in Table 3.29, we see that NETWRKSZ is not significant at $P < 0.05$, and should therefore be excluded from the model.

***$2^3 5$* Full Factorial: Analysis of Variance—E2EDELAY.** Table 3.32 is an ANOVA (analysis of variance) for end-to-end delay. From the ANOVA in Table 3.32 we observe that TRAFFLD and ITEMSIZE are statistically significant, and should therefore be included as part of the regression model. Moreover, the two-way factor interaction between TRAFFLD and ITEMSIZE is statistically significant, and should also be included as part of the regression model.

***$2^3 5$* Full Factorial: End-to-End Delay—Fit Statistics.** Fit statistics for end-to-end delay are indicated in Table 3.33, the predictive model of which may be interpreted as follows. The mean is 0.220798. The quantity R-square is 93.98%. the CV, or coefficient of variation, a measure of the precision or relative dispersion, is 12.9949.

	Master Model					Predictive Model				
Source	**DF**	**SS**	**MS**	**F**	**Pr > *F***	**DF**	**SS**	**MS**	**F**	**Pr > *F***
NETWRKSZ	1	0.00023	0.00023	0.287909	0.595163					
TRAFFLD	1	0.150212	0.150212	187.7892	0.0001	1	0.150212	0.150212	182.4606	0.0001
ITEMSIZ	1	0.271279	0.271279	339.1428	0.0001	1	0.271279	0.271279	329.5194	0.0001
NETWRKSZ*TRAFFLD	1	0.002942	0.002942	3.677542	0.063839					
NETWRKSZ*ITEMSIZ	1	0.000069	0.000069	0.085901	0.771289					
TRAFFLD*ITEMSIZ	1	0.041101	0.041101	51.38269	0.0001	1	0.041101	0.041101	49.92468	0.0001
Model	6	0.465833	0.077639	97.061	0.0001	3	0.462592	0.154197	187.3016	0.0001
Error	33	0.026397	0.0008			36	0.029637	0.000823		
(Lack of fit)	1	0.00105	0.00105	1.326189	0.258016					
(Pure Error)	32	0.025346	0.000792							
Total	39	0.492229				39	0.492229			

Table 3.32: *2³5* Full Factorial: ANOVA for E2EDELAY

	Master Model	**Predictive Model**
Mean	0.220798	0.220798
R-square	94.64%	93.98%
Adj. R-square	93.66%	93.48%
RMSE	0.028282	0.028692
CV	12.8092	12.9949

Table 3.33: *2³5* Full Factorial: Fit Statistics for E2EDELAY

***2³5* Full Factorial: End-to-End Delay—Effect Estimates.** The predictive model estimates shown in Table 3.34, along with the mean for the predictive model indicated in Table 3.33, provide the data needed to develop an empirical model for end-to-end delay.

***2³5* Full Factorial: End-to-End Delay—Empirical Model.** The empirical model for end-to-end delay (coded levels) is shown in Equation (3.18).

$$Y_{e2edelay} = 0.220798 + 0.06128x_2 + 0.082353x_3 + \\ + 0.032055x_2x_3 \tag{3.18}$$

where x_1 = NETWRKSZ, x_2 = TRAFFLD, and x_3 = ITEMSIZE.

Recall from my earlier discussion that the equation for $Y_{e2edelay}$ is a function that describes the empirical relationship between the response $Y_{e2edelay}$ and its corresponding factors. Each of the effect estimates shown in Table 3.34 reflects a two-unit change in the

Term	Master Model Estimate	Master Model Std Err	Master Model t	Master Model Pr > |t|	Predictive Model Estimate	Predictive Model Std Err	Predictive Model t	Predictive Model Pr > |t|
NETWRKSZ	-0.004799	0.008944	-0.53657	0.595163				
TRAFFLD	0.122561	0.008944	13.70362	0.0001**	0.122561	0.009073	13.5078	0.0001
ITEMSIZE	0.1647056	0.008944	18.41583	0.0001**	0.1647056	0.009073	18.15267	0.0001
NETWRKSZ*TRAFFLD	-0.017151	0.008944	-1.91769	0.063839				
NETWRKSZ*ITEMSIZ	-0.002621	0.008944	-0.29309	0.771289				
TRAFFLD*ITEMSIZ	0.0641099	0.008944	7.168172	0.0001**	0.0641099	0.009073	7.06574	0.0001

** Significant at $P < 0.05$

Table 3.34: *$2^3 5$* Full Factorial: Effect Estimates for E2EDELAY

value of its associated regressor variable. Thus, the regression coefficients are computed as ½ the effect estimates.

***$2^3 5$* Full Factorial: Analysis of Variance—JITTER.** Table 3.35 is an ANOVA (analysis of variance) for jitter. From the ANOVA in Table 3.32 we observe that *NETWRKSZ*, *TRAFFLD*, and *ITEMSIZE* all are statistically significant, and should therefore be included as part of the regression model. Moreover, the two-way factor interactions between NETWRKSZ and TRAFFLD, as well as TRAFFLD and ITEMSIZE, are statistically significant, and should also be included as part of the regression model.

***$2^3 5$* Full Factorial: Jitter—Fit Statistics.** Fit statistics for jitter are indicated in Table 3.36, the predictive model of which may be interpreted as follows. The mean is 0.072036. The quantity *R*-square is 98.14%, which is the proportion of total variability explained by the model, where $0 \leq R2 \leq 1$, with larger values being more desirable. The CV, or coefficient of variation, a measure of the precision or relative dispersion, is 12.61512.

Jitter—Effect Estimates. The predictive model estimates shown in Table 3.37, along with the mean for the predictive model indicated in Table 3.36, provide the data needed to develop an empirical model for jitter.

	Master Model					Predictive Model				
Source	DF	SS	MS	F	Pr > F	DF	SS	MS	F	Pr > F
NETWRKSZ	1	0.000448	0.000448	5.261476	0.028305	1	0.000448	0.000448	5.420811	0.025982
TRAFFLD	1	0.083075	0.083075	976.4081	0.0001	1	0.083075	0.083075	1005.977	0.0001
ITEMSIZ	1	0.046041	0.046041	541.1306	0.0001	1	0.046041	0.046041	557.5179	0.0001
NETWRKSZ*TRAFFLD	1	0.002637	0.002637	30.99343	0.0001	1	0.002637	0.002637	31.93202	0.0001
NETWRKSZ*ITEMSIZ	1	5.362E-8	5.362E-8	0.00063	0.980123					
TRAFFLD*ITEMSIZ	1	0.015821	0.015821	185.9488	0.0001	1	0.015821	0.015821	191.58	0.0001
Model	6	0.148021	0.02467	289.9572	0.0001	5	0.148021	0.029604	358.4855	0.0001
Error	33	0.002808	0.000085			34	0.002808	0.000083		
(Lack of fit)	1	0.000409	0.000409	5.460614	0.025871	2	000409	0.000205	2.730665	0.080365
(Pure Error)	32	0.002398	0.000075			32	0.002398	0.000075		
Total	39	0.150829				39	0.150829			

Table 3.35: $2^3 5$ Full Factorial: ANOVA for JITTER

	Master Model	Predictive Model
Mean	0.072036	0.072036
R-square	98.14%	98.14%
Adj. R-square	97.80%	97.86%
RMSE	0.009224	0.009087
CV	12.80471	12.61512

Table 3.36: $2^3 5$ Full Factorial: Fit Statistics for JITTER

	Master Model					Predictive Model			
Term	Estimate	Std Err	t	Pr > $\lvert t \rvert$		Estimate	Std Err	t	Pr > $\lvert t \rvert$
NETWRKSZ	-0.006691	0.002917	-2.29379	0.028305		-0.006691	0.002874	-2.32826	0.025982
TRAFFLD	0.0911455	0.002917	31.24753	0.0001	<**	0.0911455	0.002874	31.71714	0.0001
ITEMSIZE	0.0678532	0.002917	23.26221	0.0001	<**	0.0678532	0.002874	23.61182	0.0001
NETWRKSZ*TRAFFLD	-0.016239	0.002917	-5.56717	0.0001	<**	-0.016239	0.002874	-5.65084	0.0001
NETWRKSZ*ITEMSIZ	0.0000732	0.002917	0.025104	0.980123					
TRAFFLD*ITEMSIZ	0.0397756	0.002917	13.63631	0.0001	<**	0.0397756	0.002874	13.84124	0.0001

<** Significant at P < 0.05

Table 3.37: $2^3 5$ Full Factorial: Effect Estimates for JITTER

Jitter—Empirical Model. The empirical model for jitter (coded levels) is shown in Equation (3.19).

$$Y_{jitter} = 0.072036 - 0.003345x_1 + 0.045573x_2 + 0.0033927x_3 + \\ + 0.008119x_1x_2. + 0.019888x_2x_3 \qquad (3.19)$$

where x_1 = NETWRKSZ, x_2 = TRAFFLD, and x_3 = ITEMSIZE.

	Master Model					Predictive Model				
Source	DF	SS	MS	F	Pr > *F*	DF	SS	MS	F	Pr > *F*
NETWRKSZ	1	2.11E-6	2.11E-6	1.458432	0.235764					
TRAFFLD	1	0.000053	0.000053	36.75142	0.0001	1	0.000053	0.000053	37.39441	0.0001
ITEMSIZ	1	0.00005	0.00005	34.62992	0.0001	1	0.00005	0.00005	35.23579	0.0001
NETWRKSZ*TRAFFLD	1	4.969E-8	4.969E-8	0.034343	0.854113					
NETWRKSZ*ITEMSIZ	1	1.285E-6	1.285E-6	0.888213	0.352811					
TRAFFLD*ITEMSIZ	1	0.000032	0.000032	22.44105	0.0001	1	0.000032	0.000032	22.83366	0.0001
Model	6	0.000139	0.000023	16.0339	0.0001	3	0.000136	0.000045	31.82129	0.0001
Error	33	0.000048	1.447E-6			36	0.000051	1.447E-6		
(Lack of fit)	1	1.096E-8	1.096E-8	0.007346	0.932233					
(Pure Error)	32	0.000048	1.492E-6							
Total	39	0.000187				39	0.000187			

Table 3.38: $2^3 5$ Full Factorial: ANOVA for PDRATIO

Recall from my earlier discussion that the equation for Y_{jitter} is a function that describes the empirical relationship between the response Y_{jitter} and its corresponding factors. The effect estimates shown in Table 3.37 reflect a *two-unit* change in the value of its associated regressor variable. Thus, the regression coefficients are computed as ½ the effect estimates.

$2^3 5$ Full Factorial: Analysis of Variance—PDRATIO. Table 3.38 is an ANOVA (analysis of variance) for packet delivery ratio. From the ANOVA in Table 3.38 we observe that *TRAFFLD* and *ITEMSIZE* are statistically significant, and should therefore be included as part of the regression model. Moreover, the two-way factor interaction between *TRAFFLD* and *ITEMSIZE* is statistically significant, and should also be included as part of the regression model.

$2^3 5$ Full Factorial: Packet Delivery Ratio—Fit Statistics. Fit statistics for packet delivery ratio are indicated in Table 3.39, the predictive model of which may be interpreted as follows. The *mean* is the intercept, which, as shown in Table 3.39, is 0.998597. The quantity *R-square* is 72.62%, which is the proportion of total variability explained by the

	Master Model	Predictive Model
Mean	0.998597	0.998597
R-square	74.46%	72.62%
Adj. R-square	69.82%	70.33%
RMSE	0.001203	0.001193
CV	0.12046	0.119419

Table 3.39: $2^3 5$ Full Factorial: Fit Statistics for PDRATIO

model, where $0 \le R2 \le 1$, with larger values being more desirable. The *CV*, or coefficient of variation, a measure of the precision or relative dispersion, is 0.119419.

Packet Delivery Ratio—Effect Estimates. The predictive model estimates shown in Table 3.40, along with the mean for the predictive model indicated in Table 3.39, provide the data needed to develop an empirical model for packet delivery ratio.

Packet Delivery Ratio—Empirical Model. The empirical model for packet delivery ratio (coded levels) is shown in Equation (3.20).

$$\begin{aligned} Y_{pdratio} = {} & 0.998597 - 0.001153x_2 - 0.001119x_3 - \\ & - 0.000901x_2x_3 \end{aligned} \tag{3.20}$$

where x_1 = NETWRKSZ, x_2 = TRAFFLD, and x_3 = ITEMSIZE.

Recall from my earlier discussion that the equation for $Y_{pdratio}$ is a function that describes the empirical relationship between the response $Y_{pdratio}$ and its corresponding factors. Each of the effect estimates shown in Table 3.40 reflects a *two-unit* change in the value of its associated regressor variable. Thus, the regression coefficients are computed as ½ the effect estimates.

	Master Model					Predictive Model			
Term	Estimate	Std Err	t	Pr > |t|		Estimate	Std Err	t	Pr > |t|
NETWRKSZ	0.0004594	0.00038	1.207656	0.235764					
TRAFFLD	-0.002306	0.00038	-6.06229	0.0001	<**	-0.002306	0.00037	-6.1151	0.0001
ITEMSIZE	-0.002239	0.00038	-5.88472	0.0001	<**	-0.002239	0.00038	-5.93597	0.0001
NETWRKSZ*TRAFFLD	0.0000705	0.00038	0.185319	0.854113					
NETWRKSZ*ITEMSIZ	0.0003585	0.00038	0.942451	0.352811					
TRAFFLD*ITEMSIZ	-0.001802	0.00038	-4.7372	0.0001	<**	-0.001802	0.000377	-4.77846	0.0001

<** Significant at $P < 0.05$

Table 3.40: *$2^3$5* Full Factorial: Effect Estimates for PDRATIO

Response Surface Methodology

Results from the *$2^3$5* full-factorial simulation studies suggest that first-order models may be inadequate; thus, the development of second-order models should be considered. If such models could be shown to adequately characterize the relationship between the responses of interest and their factors, an extension to this would also include numerical optimization of responses. Response surface designs are intended to identify and develop both second-order models and numerical optimization of responses.

Response Surface Design Setup. The response surface design setup involves a *central composite, uniform precision design*, which includes *axial scaling, center blocking*. A factor space of size 2 involves $2^2 = 4$ design points; however, a central composite, uniform precision design also includes 9 center points. This type of design lends itself to the identification of both factor interaction (which we have observed previously) and quadratic effects (which usually indicate curvature of the response surface).

The simulation environment involves a 64 wireless mesh node subnet, with a grid node placement scheme (8x8 matrix) and a 270 meter node separation factor. The terrain size is 2500 x 2500 meters. Ten of the 64 mesh nodes serve as gateway nodes to a wired subnet. The bit rate is 11 Mbps, with CBR traffic at one packet per second. As before, along with AODV routing, a two-ray pathloss model is employed. All traffic generated is sent to the same destination node, thereby exploiting the routing protocol, since multiple paths are possible.

The response surface design involves the four response metrics of interest, used in the previous fractional and full-factorial experimental designs: THROUGHP, E2EDELAY, JITTER, and PDRATIO. Results of the full-factorial design experiments suggest two factors in particular: TRAFFLD and ITEMSIZE. The design points for a response surface design is shown in Table3.41. With five replicates, runs 1 through 13 reflect the first replicate, runs 14 through 26 reflect the second replicate, and so on

The average response values for throughput, end-to-end delay, jitter, and packet delivery ratio, are shown in Table 3.42, with ANOVA (analysis of variance) for throughput shown in Table 3.43. Recall from my previous discussion that ANOVA is a useful tool for identifying factors whose main effects upon a response are statistically significant. The degrees of freedom (DF) is equal to 1 for each factor; the sum of squares (SS) is the variation; the mean-square (MS) is the variance, or *SS/DF* ; and *F* is the *F*-ratio, which is *MS/Error*. The *P*-value is of particular interest, since it serves as a measure of "statistical significance," which indicates the degree to which the value of a factor is "true." Factors for which the *P*-value is small ($P < 0.05$) are considered significant and should therefore be included in the prediction, or *regression*, model. From the ANOVA in Table 3.43 we observe that *TRAFFLD* and *ITEMSIZE* are statistically significant, and should therefore be included as part of the second-order model. Additionally, quadratic effects (which suggest curvature) are indicated (by way of *TRAFFLD**TRAFFLD* and *ITEMSIZE**ITEMSIZE*).

Moreover, the two-way factor interaction between *TRAFFLD* and *ITEMSIZE* is statistically significant, and should also be included as part of the second-order model.

Response Surfaces: Throughput—Fit Statistics. Fit statistics for throughput are indicated in Table 3.44, the predictive model of which may be interpreted as follows. The *mean* is the intercept, which, as shown in Table 3.44, is 8044.128. The quantity *R-square* is 100.0%, which is the proportion of total variability explained by the model, where $0 \leq R2 \leq 1$, with larger values being more desirable. A related quantity, *Adj. R-square*, is a variation of the *R-square* statistic, whose value decreases as more factors are included within the model. The *RMSE*, or *root mean square error*, is determined by calculating the deviations of points from their true position, summing up the measurements, and then taking the square root of the sum, with smaller values being more desirable. Finally, the *CV*, or *coefficient of variation*, a measure of the precision or relative dispersion, is 0.064022. The *CV* is calculated as the standard deviation divided by the mean and is used to compare variation among multiple data series that have significantly different means.

Throughput—Effect Estimates. The predictive model estimates shown in Table 3.45, along with the mean for the predictive model indicated in Table 3.44, provide the data needed to develop a second-order model for throughput.

Throughput—Second-Order Model. The second-order empirical model for throughput (coded levels) is shown in Equation (3.21).

$$
\begin{aligned}
Y_{throughp} = {} & 8047.929 - 13.14258x_1 + 3938.635x_2 - \\
& - 12.35312(x_1)^2 - 13.14648x_1x_2
\end{aligned}
\tag{3.21}
$$

where x_1= TRAFFLD, and x_2= ITEMSIZE.

Recall from my earlier discussion that the equation for $Y_{throughp}$ is a function that describes the empirical relationship between the response $Y_{throughp}$ and its corresponding factors. The effect estimates shown in Table 3.45 reflect a *one-unit* change in the value of its associated regressor variable.

Response Surfaces: Analysis of Variance—E2EDELAY. Table 3.46 is an ANOVA (analysis of variance) for end-to-end delay. Recall from my previous discussion that ANOVA is a useful tool for identifying factors whose main effects upon a response are statistically significant. The degrees of freedom (DF) is equal to 1 for each factor; the sum of squares (SS) is the variation; the mean-square (MS) is the variance, or *SS/DF* ; and *F* is the *F* -ratio, which is *MS/Error*. The *P*-value is of particular interest, since it serves as a measure of "statistical significance," which indicates the degree to which the value of a factor is "true." Factors for which the *P*-value is small ($P < 0.05$) are considered significant and should therefore be included in the prediction, or regression, model. From the ANOVA in Table 3.46 we observe that *TRAFFLD* and *ITEMSIZE* are statistically significant, and should therefore be included as part of the second-order model. Additionally, quadratic effects (which suggest curvature) are indicated (by way of *TRAFFLD*TRAFFLD* and *ITEMSIZE*ITEMSIZE*). Moreover, the two-way factor interaction between TRAFFLD and ITEMSIZE is statistically significant and should also be included as part of the second-order model.

Response Surfaces: End-to-End Delay—Fit Statistics. Fit statistics for end-to-end delay are indicated in Table 3.47, the predictive model of which may be interpreted as follows.

The *mean* is the intercept, which, as shown in Table 3.47, is 0.209038. The quantity *R-square* is 93.98%, which is the proportion of total variability explained by the model, where $0 \leq R2 \leq 1$, with larger values being more desirable. A related quantity, *Adj. R-square*, is a variation of the *R-square* statistic, whose value decreases as more factors are included within the model. The *RMSE*, or *root mean square error*, is determined by calculating the deviations of points from their true position, summing up the measurements, and then taking the square root of the sum, with smaller values being more desirable. Finally, the *CV*, or *coefficient of variation*, a measure of the precision or relative dispersion, is 8.099644. The CV is calculated as the standard deviation divided by the mean, and is used to compare variation among multiple data series that have significantly different means.

End-to-End Delay—Effect Estimates. The predictive model estimates shown in Table 3.48, along with the mean for the predictive model indicated in Table 3.47, provide the data needed to develop a second-order model for end-to-end delay.

End-to-End Delay—Second-Order Model. The second-order model for end-to-end delay (coded levels) is shown in Equation (3.22).

$$
\begin{aligned}
Y_{e2edelay} &= 0.206855 + 0.060222x_1 + 0.08479x_2 - \\
&\quad + 0.007095(x_1)^2 + 0.039888x_1x_2 \qquad (3.22)
\end{aligned}
$$

where x_1= TRAFFLD, and x_2= ITEMSIZE.

Recall from my earlier discussion that the equation for $Y_{e2edelay}$ is a function that describes the empirical relationship between the response $Y_{e2edelay}$ and its corresponding factors. Each of the effect estimates shown in Table 3.51 reflects a *one-unit* change in the value of its associated regressor variable.

Response Surfaces: Analysis of Variance—JITTER. Table 3.49 is an ANOVA (analysis of variance) for JITTER. Recall from my previous discussion that ANOVA is a useful tool for identifying factors whose main effects upon a response are statistically significant. The degrees of freedom (DF) is equal to 1 for each factor; the sum of squares (SS) is the variation; the mean-square (MS) is the variance, or *SS/DF* ; and *F* is the *F*-ratio, which is *MS/Error*. The *P*-value is of particular interest, since it serves as a measure of "statistical significance," which indicates the degree to which the value of a factor is "true." Factors for which the *P*-value is small ($P < 0.05$) are considered significant and should therefore be included in the prediction, or second-order, model. From the ANOVA in Table 3.49 we observe that *TRAFFLD* and *ITEMSIZE* are statistically significant, and should therefore be included as part of the second-order model. Additionally, quadratic effects (which suggest curvature) are indicated (by way of *TRAFFLD*TRAFFLD* and *ITEMSIZE*ITEMSIZE*). Moreover, the two-way factor interaction between *TRAFFLD* and *ITEMSIZE* is statistically significant, and should also be included as part of the second-order model.

Response Surfaces: Jitter—Fit Statistics. Fit statistics for jitter are indicated in Table 3.50, the predictive model of which may be interpreted as follows. The *mean* is the intercept, which, as shown in Table 3.50, is 0.05398. The quantity *R-square* is 86.49%, which is the proportion of total variability explained by the model, where $0 \leq R2 \leq 1$, with larger values being more desirable. A related quantity, *Adj. R-square*, is a variation of the *R-square* statistic, whose value decreases as more factors are included within the model. The *RMSE*, or *root mean square error*, is determined by calculating the deviations of points from their true position, summing up the measurements, and then taking the square root of the sum, with smaller values being more desirable. Finally, the *CV*, or *coefficient of variation*, a measure of the precision or relative dispersion, is 21.27506. The CV is calculated as the standard deviation divided by the mean, and is used to compare variation among multiple data series that have significantly different means.

Jitter—Effect Estimates. The predictive model estimates shown in Table 3.51, along with the mean for the predictive model indicated in Table 3.50, provide the data needed to develop a second-order model for jitter.

Jitter—Empirical Model. The second-order model for jitter (coded levels) is shown in Equation (3.23).

$$\begin{aligned} Y_{jitter} &= 0.055197 + 0.038355x_1 + 0.025064x_2 - \\ &\quad - 0.003957(x_1)^2 + 0.019237x_1x_2 \end{aligned} \tag{3.23}$$

where x_1= TRAFFLD, and x_2= ITEMSIZE.

Recall from my earlier discussion that the equation for Y_{jitter} is a function that describes the empirical relationship between the response Y_{jitter} and its corresponding factors. The effect estimates shown in Table 3.51 reflect a *one-unit* change in the value of its associated regressor variable.

Response Surfaces: Analysis of Variance—PDRATIO. Table 3.52 is an ANOVA (analysis of variance) for packet delivery ratio. Recall from my previous discussion that ANOVA is a useful tool for identifying factors whose main effects upon a response are statistically significant. The degrees of freedom (DF) is equal to 1 for each factor; the sum of squares (SS) is the variation; the mean-square (MS) is the variance, or *SS/DF* ; and *F* is the *F*-ratio, which is *MS/Error*. The *P*-value is of particular interest, since it serves as a measure of "statistical significance," which indicates the degree to which the value of a factor is "true." Factors for which the *P*-value is small ($P < 0.05$) are considered significant and should therefore be included in the prediction, or *regression*, model. From the ANOVA in Table 3.52 we observe that *TRAFFLD* and *ITEMSIZE* are statistically significant, and should therefore be included as part of the second-order model. Moreover, the two-way factor interaction between *TRAFFLD* and *ITEMSIZE* is statistically significant, and should also be included as part of the second-order model.

Response Surfaces: Packet Delivery Ratio—Fit Statistics. Fit statistics for packet delivery ratio are indicated in Table 3.53, the predictive model of which may be interpreted as follows. The *mean* is the intercept, which, as shown in Table 3.53, is 0.999201. The quantity *R-square* is 88.14%, which is the proportion of total variability explained by the model, where $0 \leq R2 \leq 1$, with larger values being more desirable. A related quantity, *Adj. R-square*, is a variation of the *R-square* statistic, whose value decreases as more factors are included within the model. The *RMSE*, or *root mean square error*, is determined by calculating the deviations of points from their true position, summing up the measurements, and then taking the square root of the sum, with smaller values being more desirable. Finally, the *CV*, or *coefficient of variation*, a measure of the precision or relative dispersion, is 0.046874. The CV is calculated as the standard deviation divided by the mean, and is used to compare variation among multiple data series that have significantly different means.

Packet Delivery Ratio—Effect Estimates. The predictive model estimates shown in Table 3.54, along with the mean for the predictive model indicated in Table 3.53, provide the data needed to develop an second-order model for packet delivery ratio.

Packet Delivery Ratio—Empirical Model. The second-order model for packet delivery ratio (coded levels) is shown in Equation (3.24).

$$Y_{pdratio} = 0.999482 - 0.001189x_1 - 0.00124x_2 - \\ - 0.000915(x_1)^2 - 0.001117x_1x_2 \qquad (3.23)$$

where x_1= TRAFFLD, and x_2= ITEMSIZE

Recall from my earlier discussion that the equation for $Y_{pdratio}$ is a function that describes the empirical relationship between the response $Y_{pdratio}$ and its corresponding factors. The effect estimates shown in Table 3.54 reflect a *one-unit* change in the value of its associated regressor variable.

Run	TRAFFLD	ITEMSIZE
1	12	512
2	12	1500
3	32	512
4	12	1500
5	22	1006
6	22	1006
7	22	1006
8	22	1006
9	22	1006
10	22	1006
11	22	1006
12	22	1006
13	22	1006
14	12	512
15	12	1500
16	32	512
17	12	1500
18	22	1006
19	22	1006
20	22	1006
21	22	1006
22	22	1006
23	22	1006
24	22	1006
25	22	1006
26	22	1006
27	12	512
28	12	1500
29	32	512
30	12	1500
31	22	1006
32	22	1006
33	22	1006
34	22	1006
35	22	1006
36	22	1006
37	22	1006
38	22	1006
39	22	1006
40	12	512
41	12	1500
42	32	512
43	12	1500
44	22	1006
45	22	1006
46	22	1006
47	22	1006
48	22	1006
49	22	1006
50	22	1006
51	22	1006
52	22	1006

Table 3.41: Response Surface Design Points

Run	THROUGHP	E2EDELAY	JITTER	PDRATIO
1	4096.83	0.11207	0.00979	0.99981
2	12000.17	0.20446	0.03519	0.99963
3	4096.91	0.14935	0.05093	0.99969
4	11973.63	0.33166	0.12178	0.99719
5	8045.50	0.20622	0.06287	0.99924
6	8044.18	0.20821	0.04403	0.99899
7	8050.32	0.19131	0.03194	0.99980
8	8047.82	0.20342	0.05107	0.99944
9	8049.73	0.20035	0.04686	0.99970
10	8050.68	0.20689	0.05963	0.99980
11	8049.27	0.20924	0.06327	0.99975
12	8046.59	0.21775	0.08101	0.99924
13	8049.64	0.19575	0.02924	0.99965
14	4096.92	0.10846	0.00387	0.99991
15	12002.42	0.19607	0.00648	0.99981
16	4097.13	0.14927	0.04673	0.99979
17	11928.19	0.44745	0.11972	0.99333
18	8049.59	0.20703	0.06732	0.99970
19	8048.64	0.20537	0.05664	0.99960
20	8045.55	0.22249	0.07284	0.99919
21	8049.00	0.18757	0.03855	0.99965
22	8045.82	0.24810	0.07415	0.99919
23	8044.36	0.20013	0.05446	0.99909
24	8048.86	0.25205	0.06856	0.99965
25	8042.36	0.21174	0.06828	0.99869
26	8046.95	0.19793	0.05129	0.99939
27	4097.08	0.10599	0.01002	1.00000
28	12000.25	0.19707	0.02391	0.99963
29	4096.81	0.14960	0.03708	0.99972
30	11941.72	0.41366	0.14758	0.99448
31	8049.55	0.20701	0.06171	0.99960
32	8046.36	0.20569	0.05696	0.99929
33	8047.32	0.20662	0.05929	0.99939
34	8046.91	0.20183	0.04630	0.99939
35	8048.95	0.19167	0.04819	0.99965
36	8049.41	0.21032	0.05723	0.99960
37	8045.68	0.21020	0.05916	0.99929
38	8049.91	0.20788	0.06499	0.99975
39	8050.82	0.19396	0.04091	0.99980
40	4096.92	0.10877	0.00456	0.99981
41	11999.17	0.19693	0.00927	0.99944
42	4096.94	0.14974	0.04643	0.99976
43	11948.16	0.40264	0.14651	0.99507
44	8049.82	0.19130	0.04086	0.99960
45	8048.32	0.21176	0.06247	0.99949
46	8049.41	0.20896	0.05497	0.99960
47	8049.59	0.19133	0.04367	0.99975
48	8045.55	0.20105	0.06055	0.99924
49	8048.59	0.22148	0.06287	0.99949
50	8046.00	0.20579	0.04705	0.99929
51	8048.77	0.20100	0.04861	0.99965
52	8049.64	0.20738	0.04932	0.99975

Table 3.42: Response Surface Design Responses Values

	Master Model					Predictive Model				
Source	DF	SS	MS	F	Pr > F	DF	SS	MS	F	Pr > F
TRAFFLD	1	2763.638	2763.638	104.1999	0.0001	1	2763.638	2763.6388	104.1999	0.0001
ITEMSIZ	1	2.4821E8	2.4821E8	9358310	0.0001	1	2.4821E8	2.4821E8	9358310	0.0001
TRAFFLD*TRAFFLD	0	0			0.0001	1	1690.334	1690.334	63.73215	0.0001
TRAFFLD*ITEMSIZ	1	2765.281	2765.281	104.2618	0.0001	1	2765.281	2765.281	104.2618	0.0001
ITEMSIZ*ITEMSIZ	0	0			0.0001					
Model	4	2.4821E8	62053180	2339646	0.0001	4	2.4821E8	62053180	2339646	0.0001
(Linear)	2	2.4821E8	1.241E8	4679207	0.0001					
(Quadratic)	1	1690.334	1690.334	63.73215	0.0001					
(Cross Product)	1	2765.281	2765.281	104.2618	0.0001					
Error	47	1246.556	26.52247			47	1246.556	26.52247		
Total	51	2.4821E8				51	2.4821E8			

Table 3.43: Response Surfaces: ANOVA for THROUGHP

	Master Model	**Predictive Model**
Mean	8044.128	8044.128
R-square	100.0%	100.0%
Adj. R-square	100.0%	100.0%
RMSE	5.149997	5.149997
CV	0.064022	0.064022

Table 3.44: Response Surfaces: Fit Statistics for THROUGHP

	Master Model					Predictive Model			
Term	Estimate	Std Err	t	Pr > $\|t\|$		Estimate	Std Err	t	Pr > $\|t\|$
TRAFFLD	-13.14258	1.287499	-10.2078	0.0001	<**	-13.14258	1.287499	-10.2078	0.0001
ITEMSIZE	3938.6348	1.287499	3059.136	0.0001	<**	3938.6348	1.287499	3059.136	0.0001
TRAFFLD*TRAFFLD	-12.35312	1.547382	-7.98324	0.0001					
TRAFFLD*ITEMSIZ	-13.14648	1.287499	-10.2109	0.0001	<**	-13.14648	1.287499	-10.2109	0.0001

<** Significant at P $<$ 0.05

Table 3.45: Response Surfaces: Effect Estimates for THROUGHP

	Master Model					Predictive Model				
Source	DF	SS	MS	F	Pr > F	DF	SS	MS	F	Pr > F
TRAFFLD	1	0.058027	0.058027	202.4191	0.0001	1	0.058027	0.058027	202.4191	0.0001
ITEMSIZ	1	0.11504	0.11504	401.2984	0.0001	1	0.11504	0.11504	401.2984	0.0001
TRAFFLD*TRAFFLD	0	0			0.0001	1	0			0.0001
TRAFFLD*ITEMSIZ	1	0.025457	0.025457	88.80203	0.0001	1	0.025457	0.025457	88.80203	0.0001
ITEMSIZ*ITEMSIZ	0	0			0.0001					
Model	4	0.199082	0.049771	173.6162	0.0001	4	0.199082	0.049771	173.6162	0.0001
(Linear)	2	0.173068	0.086534	301.8588	0.0001	2	0.173068	0.086534	301.8588	0.0001
(Quadratic)	1	0.000558	0.000558	1.945074	0.169676	1	0.000558	0.000558	1.945074	0.169676
(Cross Product)	1	0.025457	0.025457	88.80203	0.0001	1	0.025457	0.025457	88.80203	
Error	47	0.013473	0.000287			47	0.013473	0.000287		
Total	51	0.212556				51	0.212556			

Table 3.46: Response Surfaces: ANOVA for E2EDELAY

	Master Model	Predictive Model
Mean	0.209038	0.209038
R-square	93.66%	93.66%
Adj. R-square	93.12%	93.12%
RMSE	0.016931	0.016931
CV	8.099644	8.099644

Table 3.47: Response Surfaces: Fit Statistics for E2EDELAY

	Master Model					Predictive Model			
Term	Estimate	Std Err	t	Pr > |t|		Estimate	Std Err	t	Pr > |t|
TRAFFLD	0.0602222	0.004233	14.22741	0.0001	<**	0.0602222	0.004233	14.22741	0.0001
ITEMSIZE	0.0847939	0.004233	20.03243	0.0001	<**	0.0847939	0.004233	20.03243	0.0001
TRAFFLD*TRAFFLD	0.007095	0.005087	1.394659	0.169676		0.007095	0.005087	1.394659	0.169676
TRAFFLD*ITEMSIZE	0.039888	0.004233	9.423483	0.0001	<**	0.039888	0.004233	9.423483	0.0001

<** Significant at P < 0.05

Table 3.48: Response Surfaces: Effect Estimates for E2EDELAY

	Master Model					Predictive Model				
Source	DF	SS	MS	F	Pr > F	DF	SS	MS	F	Pr > F
TRAFFLD	1	0.023538	0.023538	178.4671	0.0001	1	0.023538	0.023538	178.4671	0.0001
ITEMSIZ	1	0.010051	0.010051	76.20957	0.0001	1	0.010051	0.010051	76.20957	0.0001
TRAFFLD*TRAFFLD	0	0			0.0001	1	0			0.0001
TRAFFLD*ITEMSIZ	1	0.005921	0.005921	44.89511	0.0001	1	0.005921	0.005921	44.89511	0.0001
ITEMSIZ*ITEMSIZ	0	0			0.0001					
Model	4	0.039683	0.009921	75.22167	0.0001	4	0.039683	0.009921	75.22167	0.0001
(Linear)	2	0.033589	0.016794	127.3383	0.0001	2	0.033589	0.016794	127.3383	0.0001
(Quadratic)	1	0.000173	0.000173	1.314858	0.257321	1	0.000173	0.000173	1.314858	0.257321
(Cross Product)	1	0.005921	0.005921	44.89511	0.0001	1	0.005921	0.005921	44.89511	0.0001
Error	47	0.006199	0.000132			47	0.006199	0.000132		
Total	51	0.045882				51	0.045882			

Table 3.49: Response Surfaces: ANOVA for JITTER

	Master Model	Predictive Model
Mean	0.05398	0.05398
R-square	86.49%	86.49%
Adj. R-square	85.34%	85.34%
RMSE	0.011484	0.011484
CV	21.27506	21.27506

Table 3.50: Response Surfaces: Fit Statistics for JITTER

	Master Model					Predictive Model			
Term	Estimate	Std Err	t	Pr > $\|t\|$		Estimate	Std Err	t	Pr > $\|t\|$
TRAFFLD	0.038355	0.002871	13.35916	0.0001	<**	0.038355	0.002871	13.35916	0.0001
ITEMSIZE	0.0250638	0.002871	8.729809	0.0001	<**	0.0250638	0.002871	8.729809	0.0001
TRAFFLD*TRAFFLD	-0.003957	0.003451	-1.14667	0.257321		-0.003957	0.003451	-1.14667	0.257321
TRAFFLD*ITEMSIZE	0.0192372	0.002871	6.600381	0.0001	<**	0.0192372	0.002871	6.600381	0.0001

<** Significant at P < 0.05

Table 3.51: Response Surfaces: Effect Estimates for JITTER

	Master Model					Predictive Model				
Source	DF	SS	MS	F	Pr > F	DF	SS	MS	F	Pr > F
TRAFFLD	1	0.000023	0.000023	103.1549	0.0001	1	0.000023	0.000023	103.1549	0.0001
ITEMSIZ	1	0.000025	0.000025	112.9128	0.0001	1	0.000025	0.000025	112.9128	0.0001
TRAFFLD*TRAFFLD	0	0			0.0001	1	0			0.0001
TRAFFLD*ITEMSIZ	1	0.00002	0.00002	90.98731	0.0001	1	0.00002	0.00002	90.98731	0.0001
ITEMSIZ*ITEMSIZ	0	0			0.0001					
Model	4	0.000077	0.000019	87.32388	0.0001	4	0.000077	0.000019	87.32388	0.0001
(Linear)	2	0.000047	0.000024	108.0338	0.0001	2	0.000047	0.000024	108.0338	0.0001
(Quadratic)	1	9.266E-6	9.266E-6	42.24053	0.0001	1	9.266E-6	9.266E-6	42.24053	0.0001
(Cross Product)	1	0.00002	0.00002	90.98731	0.0001	1	0.00002	0.00002	90.98731	0.0001
Error	47	0.00001	2.194E-7			47	2.194E-7			
Total	51	0.000087				51	0.000087			

Table 3.52: Response Surfaces: ANOVA for PDRATIO

	Master Model	Predictive Model
Mean	0.999201	0.999201
R-square	88.14%	88.14%
Adj. R-square	87.13%	87.13%
RMSE	0.000468	0.000468
CV	0.046874	0.046874

Table 3.53: Response Surfaces: Fit Statistics for PDRATIO

	Master Model					Predictive Model			
Term	Estimate	Std Err	t	Pr > $\|t\|$		Estimate	Std Err	t	Pr > $\|t\|$
TRAFFLD	-0.001189	0.000117	-10.1565	0.0001	<**	-0.001189	0.000117	-10.1565	0.0001
ITEMSIZE	-0.001244	0.000117	-10.626	0.0001	<**	-0.001244	0.000117	-10.626	0.0001
TRAFFLD*TRAFFLD	-0.000915	0.000141	-6.49927	0.0001	<**	-0.000915	0.000141	-6.49927	0.0001
TRAFFLD*ITEMSIZE	-0.000117	0.000117	-9.53873	0.0001	<**	-0.000117	0.000117	-9.53873	0.0001

<** Significant at P < 0.05

Table 3.54: Response Surfaces: Effect Estimates for PDRATIO

CHAPTER 4

RESULTS

> "There is no better high than discovery."
>
> —E. O. Wilson

Figure 4.1 shows the response surface of THROUGHP for the local region, with optimization results for the maximization of THROUGHP for the local response region indicated in Table 4.1. The data in Table 4.1 are shown in decreasing order of THROUGHP. From the table we see that 12 generating mesh routers with an item size of 1500 bytes should lead to an average throughput of 12000.5 bps. At the other extreme, we see that 12 generating mesh routers with an item size of 512 bytes results in an expected THROUGHP of 4096.9 bps.

These optimization results for the maximization of THROUGHP are shown graphically in Figure 4.2. Observe that the levels of traffic load are indicated on the x axis, with a similar representation of item size indicated on the y axis. The overlays reflect the expected values for the THROUGHP response for each factor combination traffic load–item size.

Figure 4.3 shows the response surface of E2EDELAY for the local region, with optimization results for the minimization of E2EDELAY for the local response region indicated in Table 4.2. The data in Table 4.2 are shown in decreasing order of E2EDELAY. From the table we see that 12 generating mesh routers with an item size of 512 bytes should lead to an average end-to-end delay of roughly 0.104 seconds, or 104 milliseconds. At the

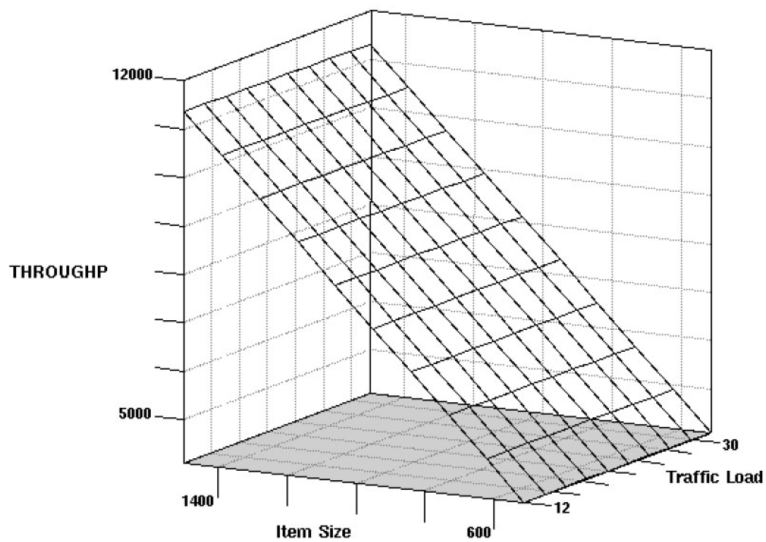

Figure 4.1: Response Surface: THROUGHP

THROUGHP (bits/sec)	Traffic Load (generating mesh routers)	Item Size (bytes)
12000.5	12	1500
11996.6	17	1500
11986.6	22	1500
11970.3	27	1500
11947.9	32	1500
10024.6	12	1253
10024.0	17	1253
10017.2	22	1253
10004.2	27	1253
9985.2	32	1253
8051.4	17	1006
8058.7	12	1006
8047.9	22	1006
8038.3	27	1006
8022.4	32	1006
6078.8	17	759
6078.6	22	759
6072.8	12	759
6072.2	27	759
6059.7	32	759
4109.3	22	512
4106.2	27	512
4106.2	17	512
4096.9	32	512
4096.9	12	512

Table 4.1: Optimization Results: (THROUGHP is Maximized)

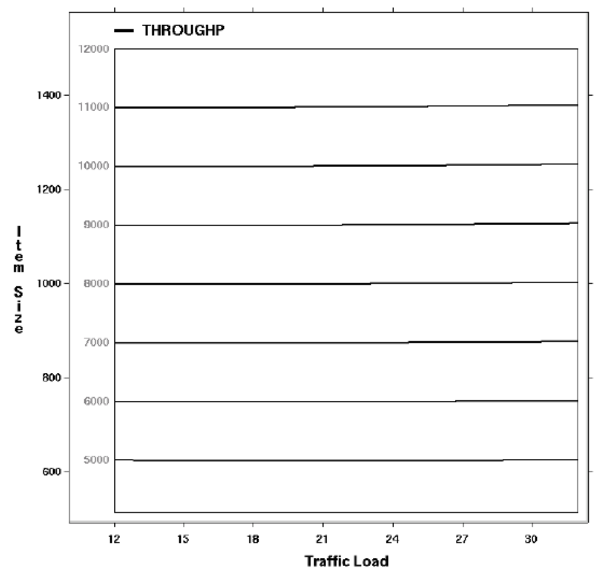

Figure 4.2: Contour Chart: THROUGHP

other extreme, we see that 32 generating mesh routers with an item size of 1500 bytes results in an expected E2EDELAY of about 0.394 seconds, or 394 milliseconds.

These optimization results for the minimization of E2EDELAY are shown graphically in Figure 4.4. Observe again that the levels of traffic load are indicated on the *x* axis, with a similar representation of item size indicated on the *y* axis. The overlays reflect the expected values for the E2EDELAY response for each factor combination traffic load–item size.

Figure 4.5 shows the response surface of JITTER for the local region, with optimization results for the minimization of JITTER for the local response region indicated in Table 4.3. The data in Table 4.3 are shown in decreasing order of JITTER. From the table we see that 12 generating mesh routers with an item size of 512 bytes should lead to an

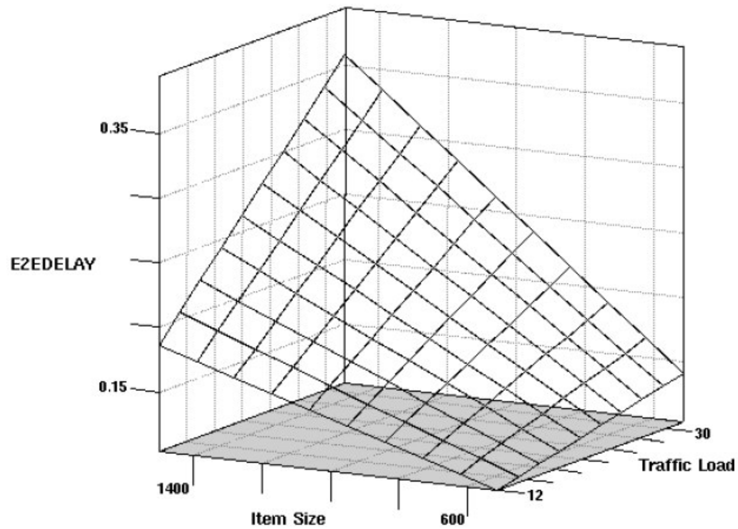

Figure 4.3: Response Surface: E2EDELAY

E2EDELAY (seconds)	Traffic Load (generating mesh routers)	Item Size (bytes)
0.1039	12	512
0.1141	17	512
0.1242	22	512
0.1264	12	759
0.1344	27	512
0.1446	32	512
0.1465	17	759
0.1488	12	1006
0.1666	22	759
0.1713	12	1253
0.1789	17	1006
0.1668	27	759
0.1937	12	1500
0.2069	32	759
0.2090	22	1006
0.2114	17	1253
0.2391	27	1006
0.2438	17	1500
0.2514	22	1253
0.2693	32	1006
0.2915	27	1253
0.2938	22	1500
0.3316	32	1253
0.3439	27	1500
0.3939	32	1500

Table 4.2: Optimization Results: (E2EDELAY is Minimized)

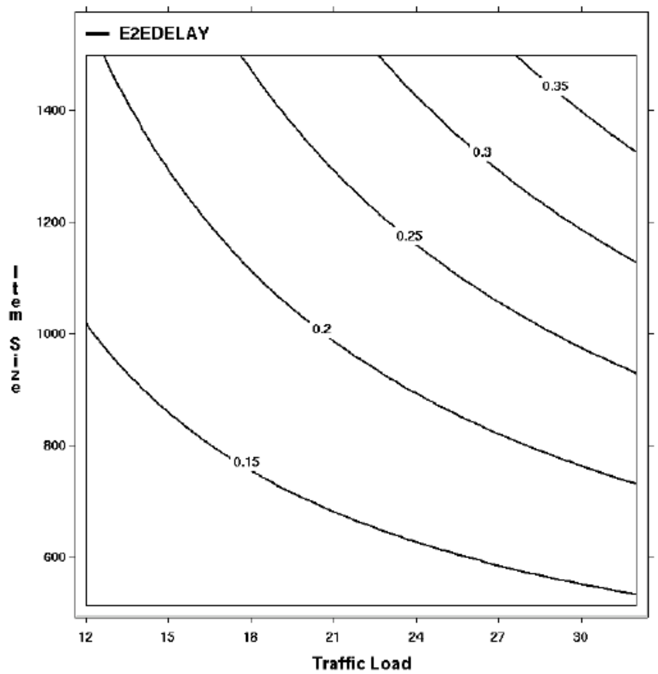

Figure 4.4: Contour Chart: E2EDELAY

average jitter of roughly 0.010 seconds, or 110 milliseconds. At the other extreme, we see that 32 generating mesh routers with an item size of 1500 bytes results in an expected JITTER of about 0.137 seconds, or 137 milliseconds.

These optimization results for the minimization of JITTER are shown graphically in Figure 4.6. Observe again that the levels of traffic load are indicated on the *x* axis, with a similar representation of item size indicated on the *y* axis. The overlays reflect the expected values for the JITTER response for each factor combination traffic load–item size.

Figure 4.7 shows the response surface of PDRATIO for the local region, with optimization results for the maximization of PDRATIO for the local response region indicated in Table 4.4. The data in Table 4.4 are shown in decreasing order of PDRATIO. From the table we see that 22 generating mesh routers with an item size of 512 bytes should lead to an average packet delivery ratio of roughly 1.0007. At the other extreme, we see that

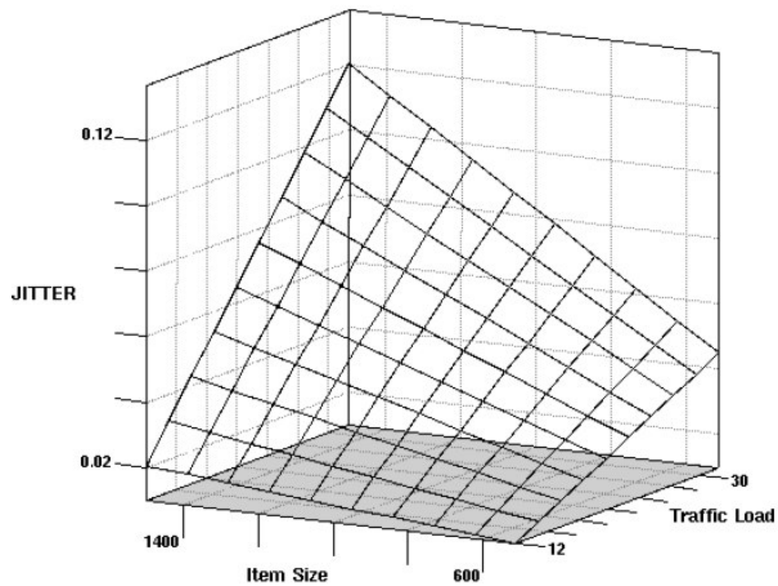

Figure 4.5: Response Surface: JITTER

32 generating mesh routers with an item size of 1500 bytes results in an expected PDRATIO of approximately 0.9950.

These optimization results for the maximization of PDRATIO are shown graphically in Figure 4.8. Observe that the levels of traffic load are indicated on the *x* axis, with a similar representation of item size indicated on the *y* axis. The overlays reflect the expected values for the PDRATIO response for each factor combination traffic load–item size.

JITTER (seconds)	Traffic Load (generating mesh routers)	Item Size (bytes)
0.0098	12	512
0.0127	12	759
0.0156	12	1006
0.0185	12	1253
0.0194	17	512
0.0215	12	1500
0.0271	17	759
0.0289	12	512
0.0348	17	1006
0.0385	27	512
0.0414	22	759
0.0425	17	1253
0.0460	32	512
0.0502	17	1500
0.0540	22	1006
0.0558	27	759
0.0665	22	1253
0.0702	32	759
0.0732	27	1006
0.0790	22	1500
0.0905	27	1253
0.0923	32	1006
0.1078	27	1500
0.1145	32	1253
0.1366	32	1500

Table 4.3: Optimization Results: (JITTER is Minimized)

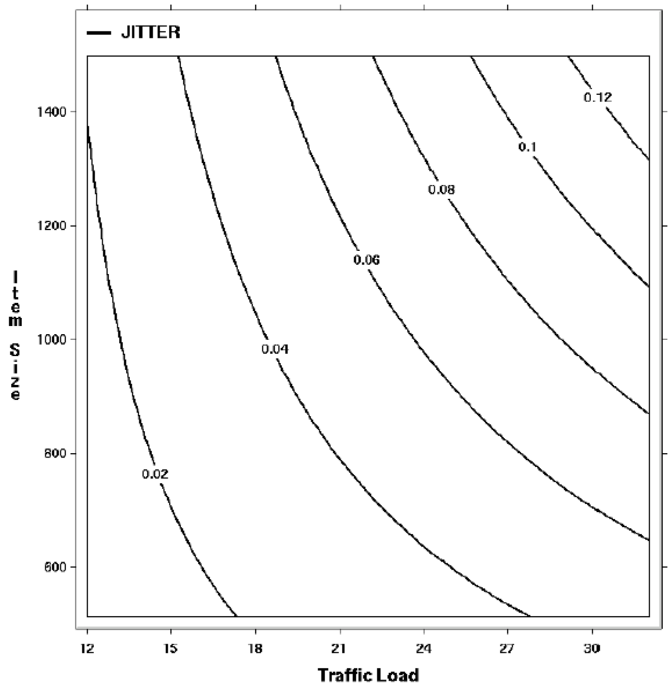

Figure 4.6: Contour Chart: JITTER

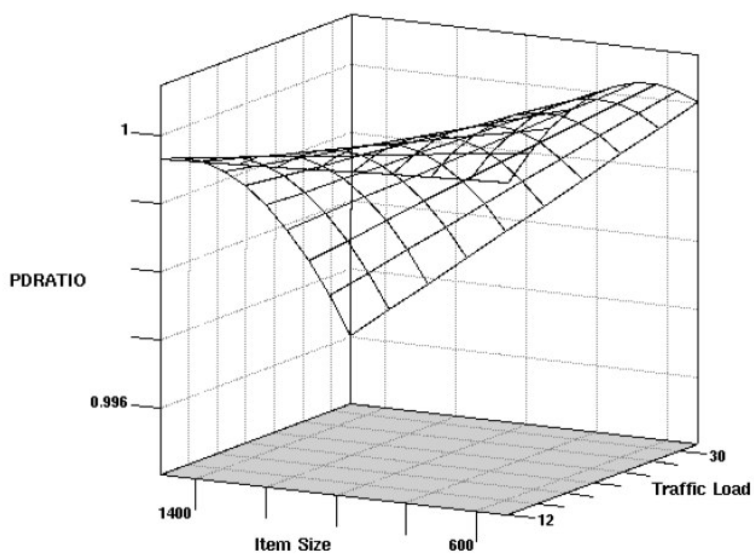

Figure 4.7: Response Surface: PDRATIO

PDRATIO	Traffic Load (generating mesh routers)	Item Size (bytes)
1.0007	22	512
1.0005	17	512
1.0005	27	512
1.0002	17	759
1.0001	22	759
0.9999	12	512
0.9998	17	1006
0.9998	12	759
0.9998	12	1006
0.9997	32	512
0.9996	12	1500
0.9996	27	759
0.9995	17	1253
0.9995	22	1006
0.9992	17	1500
0.9989	22	1253
0.9987	27	1006
0.9986	32	759
0.9982	22	1500
0.9978	27	1253
0.9974	32	1006
0.9969	27	1500
0.9962	32	1253
0.9950	32	1500

Table 4.4: Optimization Results: (PDRATIO is Maximized)

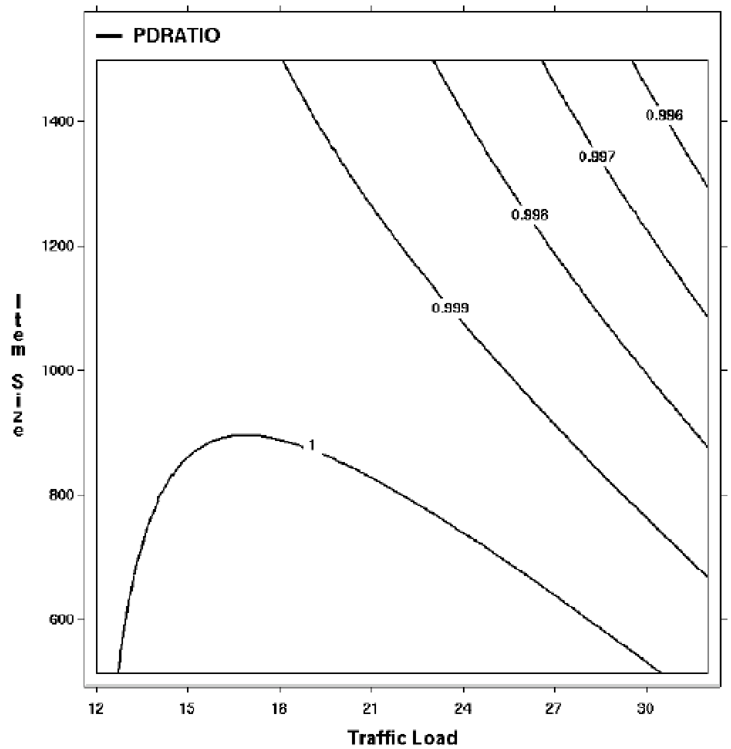

Figure 4.8: Contour Chart: PDRATIO

CHAPTER 5

CONCLUSIONS AND FUTURE WORK

> "A journey of a thousand miles begins with a single step."
>
> —Confucius

Statistical design of experiments (DOE) and response surface methodology (RSM) may be useful to researchers and scientists for evaluating the performance of existing and future multi-hop wireless mesh networks. The stepwise use of fractional and full factorial designs should lead to viable first-order empirical models. Where first-order empirical models are deemed inadequate, response surface methodology may lead the researcher to develop viable second-order empirical models. Moreover, RSM facilitates response optimization for a local region of interest.

Future work might include application of statistical DOE and RSM for a small-scale multi-hop WMN testbed, where the results of such an experimental environment may be compared against comparable simulation studies. Reconciling differences in results of the two might offer a useful starting point for developing viable first-order and second-order models, as well as the use of response optimization, for deployed multi-hop WMNs. Assuming that the preceding is done successfully, first-order and second-order models could conceivably be developed for small-scale, medium-scale, and large-scale multi-hop WMNs. The end result of such work might be the development of a vast "library" of pre-determined first-order, second-order, and optimization models, which should be of interest to protocol and network architects. Additionally, such a "library" would mitigate the need to employ time-consuming and expensive simulation studies, since the appropriate factor levels for a particular response are predetermined.

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Dissertation Director: Dr. Dmitri D. Perkins
Pages in Dissertation: 157; Words in Abstract: 346

ABSTRACT

The number of multi-hop wireless mesh networks is expected to grow dramatically during the coming years. This is due mainly to the need for wireless connection to the Internet that meets the following requirements: low cost; fast and flexible deployment; and extension to areas where wireline deployment is economically infeasible. In order to accommodate such deployments, however, research challenges such as security, QoS support for video and VoIP, and performance and scalability must be addressed. The work described in this dissertation addresses performance evaluation and empirical modeling of multi-hop wireless mesh networks. Specifically, three research goals are met. The first is the development of a better understanding of fundamental performance, scaling properties, and tradeoffs of multi-hop wireless mesh networks. The second is the comprehensive evaluation of network performance over a large design space. And the third is the characterization of the functional relationship between performance metrics and relevant factors. Statistical design of experiments and response surface methodology are used to meet these three research goals. Results of the work described in this dissertation suggest that: (1) statistical design of experiments and response surface methodology may be useful to researchers and scientists for evaluating the performance of existing and future multi-hop wireless mesh networks; (2) the stepwise use of fractional and full factorial designs should lead to viable first-order

empirical models; (3) response surface methodology may lead the researcher to viable second-order empirical models where first-order empirical models are deemed inadequate; and (4) response optimization for a local region may be attained through the use of response surface methodology. Implications of these results are as follows: (1) application of statistical design of experiments and response surface methodology for a small-scale multi-hop wireless mesh network testbed, along with comparable simulation studies, might offer a starting point for reconciling expected differences in outcomes between the two; (2) first-order and second-order empirical models could conceivably be developed for small-scale, medium-scale, and large-scale multi-hop wireless mesh networks; and (3) a “library” of first-order and second-order models, along with optimized results for responses, may eventually prove useful to protocol and network architects.

BIOGRAPHICAL SKETCH

Michael Wayne Totaro was born in New Orleans, Louisiana, on September 3, 1959, the son of Peter Salvador Totaro, Jr. and Gloria Ann Guidroz Totaro. After graduating in 1977 from Carencro High School, Lafayette, Louisiana, he attended The University of Southwestern Louisiana (now The University of Louisiana at Lafayette) in Lafayette where he received a Bachelor of Science in Computer Science in 1982, a Master of Business Administration (MBA) in 1988, and a Master of Science in 1999 in Telecommunications from the Electrical Engineering department. In addition to his extensive experience working in industry, he has worked in academia as an instructor and visiting lecturer in the B. I. Moody III College of Business Administration. During his tenure as a doctoral student, he was a member of both the Wireless Research Laboratory and Ubiquitous Computing and Monitoring Laboratory, where he completed his Doctor of Philosophy degree in 2007.

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Title:	Michael Totaro
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Comments:	
Creation Date:	4/20/2007 12:37:00 PM
Change Number:	71
Last Saved On:	4/28/2007 3:47:00 PM
Last Saved By:	Michael Wayne Totaro
Total Editing Time:	658 Minutes
Last Printed On:	4/28/2007 3:48:00 PM

As of Last Complete Printing

Number of Pages: 157

Number of Words: 29,020 (approx.)

Number of Characters: 165,419 (approx.)