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A Multi-Skilled Approach to Property Maintenance Considering Temporal, Spatial and Resource Constraints

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A Multi-Skilled Approach to Property Maintenance Considering Temporal, Spatial and Resource Constraints

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Declaration

This thesis has not been submitted in support of an application for another degree at this or any other university. It is the result of my own work and includes nothing that is the outcome of work done in collaboration with others except where specifically indicated. Many of the ideas developed in this thesis were the product of discussion with my doctoral chairs Dr. Haitao Li and Dr. Keith Womer. Select elements of this thesis have been presented in the following conference manuscripts, presentations and academic publications:

INFORMS Annual Conference, Nashville, Tennessee, Nov 16, 2016

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Abstract

With the continued increase in age of the United States housing and building stock, as well as the continued need to maintain properties across the U.S., the need for timely, cost-optimal maintenance is ever more critical. This paper proposes the application of a mathematical model to aid in the scheduling and assignment of construction and maintenance tasks, considering the multi-skilled workforce. The benefit of this approach is to take advantage of the economies of scale that can be developed using cross-functional skilled workers with varying levels of competence and efficiency. This approach schedules and assigns tasks using data from maintenance task software datasets, using the least-cost, competent worker available for the job while also considering the trade-off between skilled labor cost and travel costs, both in terms of travel wage and vehicle wear and tear. The model is enhanced to include pairing between a mentor and an apprentice, where combined efficiency and pairing costs are considered at the same time as travel costs. Due to the practical nature of this research, a case organization was used and data from that firm was analyzed so that operational insights into the necessity of such a model could be considered. The mathematical backbone of the optimization approach to multi-skilled resource allocation considers the temporal and spatial demands of a geographically dispersed property management program. Actual, as opposed to sample, data allows us to evaluate the real financial implications on the case firm, if such an approach to scheduling is used. The generalization of this data provides excellent fit for a model that can be used to assign the best capable worker to the most cost-efficient task, considering deadlines, priorities and availability. Results of this scheduling approach provide significant cost and resource reductions over the historical firm performance, though practical considerations should temper that expectation. The above approach offers exceptional scalability and adaptability with the continued advancement of algorithm approaches to network-distribution and peer-to-peer work platforms.

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Chapter 1

Introduction

1.0 Introduction

This research introduces an efficient method to manage property maintenance work and construction project resources using data analysis and mathematical modeling.

1.1 Overview

While the traditional supply chain areas of interest include manufacturing and logistics operations, project management organizations possess a unique set of business levers, operating dynamics and best practices. It is the goal of this research to aid decision-making in project management. Project Management is defined as the application of knowledge, skills, tools and techniques to project activities to meet the project requirements. A project is temporary in that it has a defined beginning and end in time, and a defined scope and resources. A project is unique in that it is not a routine operation, but a specific set of operations designed to accomplish a singular goal (PMI).

The traditional approach to organization of labor is single-trade, where an individual develops one definitive area of expertise: electrical, mechanical, or carpentry, for example. Single-trade skilled labor has been extensively developed and organized both within labor unions and through federal or municipal code compliance requirements where licensure implies single-skill specialization and often prohibits multi-skilling. Despite this existing structure for skill development, there appears to exist potential economies of scale, scope and practice in the cross-functional development of labor; in particular, in the domain of building and facilities maintenance, residential construction, and residential maintenance. This research highlights a case study of a focal firm, where multi-skilled trade labor practices exist, are evaluated, and are classified into a taxonomy of competency. This taxonomy of labor supports the data set for a mathematical modeling and the Mixed Integer Linear Programming (MILP) approach to develop a more efficient scheduling and assignment routine considering the spatial and temporal—as well as availability and priority—constraints common in this business sector.

In addition to the evaluation of worker skill, the model I develop also presents a novel method to sequencing work assignment so as to reduce the transportation cost between jobs. As with many work environments where multiple jobs must be assigned to a service technician or skilled worker, the cost of travel across a geographical area can be significant. The reduction of drive time as an opportunity cost allows more work to be assigned, resulting in a more compact schedule. In the proposed scenario, workers possess a unique level of efficiency compared to mean expected service times for completion, and therefore jobs can be scheduled back to back considering the time to perform a job and distance to travel between jobs. Jobs are also classified as high, medium or low priority, to reflect the urgency required for the job to be performed. Higher priority jobs must be completed within the short-term (for example, 24 work hours), before other priorities of lesser urgency. This temporal constraint is checked against the distance between jobs and skills required to perform a job. This paper incorporates resource constraints on individual skills to represent the real operating environment where not all workers can perform all jobs.

Possibly the most innovative component of this paper is the introduction of a model that makes a pairing and assignment decision so that a non-competent worker (named the apprentice) can work alongside a skilled worker (named the mentor). The apprentice role is a long-standing approach to skill development in the craft and trades environment. However, in the property maintenance environment, the dispersion of work makes timing the pairing of a mentor and a trainee a logistical challenge. This paper offers a method to ensure that if a solution can benefit from the pairing of workers to achieve feasibility (a possible reduction in make span or the reduction in cost, perhaps) then the mentor and apprentice are scheduled concurrently to that task. This paper also proposes a method to allow the adjustment of resonance within a pairing assignment; in this instance synergy. Preliminary results from these models are promising: significant reductions in total travel cost, total labor cost, and other “economies of schedule” occur that would benefit the firm. This research explores the potential and limitations of skill advancement, knowledge transfer, standards of practice, and work breakdown structures, and posits several ancillary areas of relevance that may be advanced in the future.

1.2 Background of the Problem

Construction Management traditionally involves the purchasing, distribution and installation of labor and materials for the manufacture of a commercial or residential structure; the project is generally of large scale and wide scope; for example, when managing a subdivision, neighborhood development, or multi-story building. The necessary material and labor components of such a project scale proportionately to the size of the construction project. In the case of remodeling and renovation, this generality does not apply. The demolition aspect of many renovation and remodeling projects requires an additional labor resource that is not easy to predict using a standards based approach. Truly, it is often impossible to know what exists behind a partition or above an interstitial space until one cuts into that wall or partition and evaluates the working conditions. Often, in the case of critical maintenance or disaster mitigation, there is not enough time to fully evaluate the work scope before beginning the labor initiative to locate and remediate the root cause and repair associated damages. After-market repairs, home improvements and additions to existing structures all require a more careful consideration of the labor and materials requirement; and at the same time lack the benefit of carefully drafted plans and specifications as new construction does. The difficulty of estimating such scopes of work with accuracy is often a process more of trial and error than of scalable rule of thumb. However, certainly such an operating environment can benefit from a more accurate scheduling, assignment and routing method considering actual performance times and historical data sources inherent in the operating environment. This paper ventures to identify such benefits.

As the scale of a maintenance project is likely to be smaller than many new construction projects, the number of projects (often referred to as work orders) required to maintain business growth is likely to be greater than typical construction. Planned margins for such smaller scopes of work are likely to be greater than that of large scale construction, with less ability to assume risk from one job to the next, a general feature of service maintenance. In larger scale construction projects, a mistake in purchasing can be offset by an engineered design change or the sheer size of a project; in the replacement of a single living room ceiling fan, the cost of fan selection—or the doubling of the time to install it—can be the difference in a profit or a loss. Furthermore, from one project to the next, the quality of the existing structure will determine the level of product or material quality for finishes; therefore it is not always feasible to standardize one product for all applications, reinforcing the problem of economies of scale. These concerns pose a real challenge; that is, to remain cost effective and to standardize the usage of materials across projects in property maintenance, renovation or home improvement.

So, “are efficiencies at such a level of operation likely to exist?” Certainly, when considering the required number of projects sustaining such a business, the advantage of an efficient routing and scheduling component can result in variable-cost efficiencies. When the work is planned so that jobs are placed in order to minimize travel costs, the non-value added activity of so-called “windshield time” can be reduced. If such routes for the performance of work are constantly being updated with feedback from the completion of jobs, then efficiencies of performance can be improved. For example, if a worker skilled with electrical competences and already possessing a toolkit for such work were to perform three electrical jobs in a route, the requirement to exchange tools may be eliminated. Or, if a maintenance technician were able to by virtue of his experience qualify to perform the same electrical work, it might make sense to route that technician to one of the electrical jobs *en route* to other work. Therefore, the ability to determine the competence level of the skilled workforce across several trades or skills sets becomes of significant benefit in the renovation, maintenance and repair environment.

Alternately, the misallocation of skilled labor to jobs can result in immediate cost overruns due to the job’s unknown scope. Therefore, such a design for work scheduling and assignment must accurately and precisely determine the level of competence of any worker assigned to any skill, to leverage the cross-functional benefit while protecting the quality and efficiency of performance. The same can be said of generally single-skilled labor. Outside of the new-construction and design-build environments, the prevalence of a multi-skilled workforce is normative, defined within the scope of general contracting services. However, the principles of planning, scheduling and assigning work using sophisticated mathematical models and cost-efficiency policies improved by optimization engines is not yet ubiquitous. This promises to be an area of competitive advantage as digital enhancement of work processes continues to advance.

However, the development of a structure for mixed-skill based work scheduling and assignment deserves attention. The existence of a hierarchy of organized multi-skill labor does not exist as a benchmark for subsequent research, so any hierarchy must be taken aside the context of standardization as it is currently understood in construction. The hierarchy of a multi-skilled labor force, if it wishes to be scalable across many work scopes, must be diverse in standardized talent, yet also standardized in those aspects of the workflow that are not directly tied to skill, such as systems of knowledge transfer, standards of performance and information collection, among many others. These “soft capabilities” must be interlocked with what are traditionally considered “hard activities” so that a recursive effect occurs that reinforces the organizational behavior while also advancing the standards of practice that are common throughout all trade practices.

Because the common practice in trade labor is to gain in-field experience as an apprentice and to accumulate skills by practical work, the ability to develop a task-level work breakdown structure is presumed. This paper attempts to explain such a process flow. The proposed hierarchy is a purely meta-informational one, utilizing the actual reporting mechanisms from a real operating environment such as work orders, job tickets and statements of work performed, expert evaluation and classification. This time-sensitive feedback from the field is the data basis of skill development where standardization from one handyman to another would take much longer to ensure than standardization from one electrician to another, due to the sheer depth and breadth of skills to learn. In fact, it may not make sense for the duplicity of skills among a cohort of multi-skilled labor; therefore, this paper considers a different model of workforce assignment to take advantage of efficiencies of competence as a basis for skill development while also considering the full operating environment.

Academic research in the areas of integer optimization, building and facilities maintenance, and construction scheduling have great potential to improve the practical body of knowledge in skilled trades if it can be tied to real operations; this research intends to develop the objectives that will join the practical and academic fields of study together. The project management body of knowledge primarily leverages scheduling and assignment without explicit consideration for skill-development; it also does not usually consider the transportation logistics of an array of projects as it deals with the activities at the jobsite, and not between sites, so this paper attends to that. The operations aspect of property management and maintenance and building and facilities maintenance takes a primarily capital-asset and expense based approach which lends itself to forecasting cost-accounting, and timely financial practice; yet it lacks any substantial developments in the areas of execution of work at the labor level which would increase the scale of performance beyond a job-shop mentality. By taking work out into the streets and considering the travel component, a dynamic paradigm-shift in the conceptualization, performance and long-term strategic objectives of a varied-skill contracting operation would be possible, if such connections between performance of skilled labor, knowledge of practice, and intelligence of schedule and assignment occurred in such a way as to reinforce skill advancement and promote operational efficiencies while also incorporating the distances and times between jobs.

1.3 Purpose of the Study

The purpose of this study is to evaluate the potential for new methods of operational efficiency in the project-oriented, maintenance environment. As an example, I evaluate, as a case study, a small-medium sized property management franchise office. The case study example firm maintains a total of 100+ portfolios and 200+ units, with the objective of optimizing the maintenance function considering the temporal and spatial constraints common in maintenance routing. I develop a system of work assignment to fully utilize the available multi-skilled worker skill sets while offering the least cost to work completion. The benefits of this research extend beyond the research domain; in fact, while this research integrates best practices for knowledge management into the property management business sector—the intersection of two research areas that has gone largely overlooked by academics—it also may offer benefits to the general construction and facilities maintenance environments.

The research period of the focal property management company consists of over 18 months of data collection and a year and a half of work within the operating environment during which I determine the practical structure of a property management business model. Scopes of work are classified using expert evaluation and a hierarchy of work assignment is optimized for both routing and assignment with respect to the critical path and priority scheduling rules. The result allows the expression of a novel mathematical approach that may be adapted to a wide range of operational environments where the geographic dispersion of work locations must be balanced against human resource competences. The work pays careful to the over-arching goal of best practice and continuous improvement. I culled the databases and gathered information regarding the phenomenon of the maintenance working environment, its actors and agents, resources and operating parameters. From individual to collective schemas of interaction, I describe the operational work flows and where necessary, work within the organization to modify the operating environment. As a result of this research, I develop a model of maintenance performance utilizing a multi-skill workforce. This approach can serve as the basis for understanding the environmental considerations of the property management field of practice as well as to identify the more specific skill development paths necessary to effectively manage human resource development in a constantly evolving work environment. The goal of this research is to promote positive continuous human resource and skill demand matching, while satisfying the financial objectives of the property owner; at the same time achieving a consistent level of quality of life for the tenant, considering the requisite safety, ordinance and legal constraints inherent in the operating environment.

1.4 Significance of the Study

The development and application of a mathematical model to optimize multi-skilled work assignment and scheduling has the potential to turn the traditional approaches to skilled labor management in a direction that allows more variety of skill development paths for the worker, and more flexibility in career development. It also would allow more opportunity for the firm where a diverse workforce truly paired to the demands of multi-skill projects can be developed. In this study, I hope to show that the development of strong multi-skilling principles in an environment of continuous skill development can result in remarkable optimization of force, resources, vehicle wear/ tear and travel costs; from a business owner’s advantage the benefit is obvious: streamlined business practice, fewer organizational complexities, fewer redundancies and easier management of resources. From the workers’ perspective, the opportunity to more fully utilize and develop individual competencies, and perhaps advance in skill to reinforce job security through acquired work routines, fosters a sense of accomplishment gained thorough on-the-job experience; this can translate into increased human resource asset value.

As computer technology continues to gain power, and as the ability to network across geographical boundaries becomes the normal work environment, the need for more flexible organized labor models which can adapt to a continually changing skill demand is at the forefront of new technology application. One does not need to go far to see how technology is continuing to be used to outsource customer service agents working at home as opposed to at a centralized call center. Crowdsourcing marketplaces like Amazon’s Mechanical Turk (MTurk), Airbnb, Uber and Lyft are now ubiquitous, and the concept of optimal human resource utilization is the basis of a robust sharing-economy. New technology-driven methods of assignment and resource utilization are being promoted by the most successful technology entrepreneurs of the age. Daily routines are consistently more affected by the technologies that make our lives easier; it makes sense that such technologies frame our desire for work-based routines.

This study endorses the use of information technology and (Big) data repositories to collect work practices to support mathematic scheduling and assignment formulations to ensure the not-tacit knowledge such as travel times, performance times and efficiency levels are tracked and monitored. The definition and development of the process for data collection allows the craftsman the ability to focus on the work at hand; the remedy, repair and renovation of equipment or structure; aspects of their work that aid in the development of potential efficiencies of scale, talent and utility. Priority principles common in most project management software platforms (for example, sequence dependencies) satisfy temporal requirements in the proposed model while allowing as much slack as possible. In the operational environment under study, various levels of priority define the level of urgency for each work order. These priorities of demand are difficult to adjust and manage in construction projects due to the resource intensive nature of the project organization and the time-sensitive nature of the project schedule. The ability to remain a lean, flexible and agile/responsive organization while improving the task-demand satisfaction requirements of this business sector offers competitive advantages that work beyond traditional project boundaries, in terms of time, space and capability/capacity.

1.5 Primary Research Questions

The interest of this research is first to determine what exists in the body of academic literature that can inform, and be practically applied to, the development of a working model for task-level construction project management. I demonstrate the savings that an optimization model founded in practical firm performance will yield. I also work to evaluate the various levers and influences on firm performance, and the limitations of the firm in adapting to such a model, so that such barriers may be removed or accommodated. I seek to evaluate the effect of such an organizational design on the adoption of best practices, and to show that the adoption of a multi-skilled labor organization model makes practical business sense. I am also interested in whether a mathematical model can produce realistic performance objectives and what the impact of such scheduling decisions would look like visually compared to the standard routines.

1.6 Hypotheses

In the process of validating the results of a longitudinal study and the accompanying data that spanned 18 months of work in this area of study, several research questions become apparent. First, the question exists as to whether or not this systematic structure, mathematical formulation, computational approach and assignment of task based work can result in a lower cost of operation. Considering tradeoffs with sequencing jobs and task competency, can reasonable assignments be made to more fully utilize the available resources? What is the potential impact to satisfying expected task deadlines and durations, given a certain level of competence and a certain number of workers? How do varying levels and classes of skill relate to solution times and cost variables? Finally, when evaluating a large number of data instances, do the findings at various levels of workers, jobs, and skill divisions display different variable characteristics? These practical questions form the basis of an algorithm to make the assignment and scheduling sequence decision. I analyze and validate a model to resolve such hypotheses.

1.7 Theoretical Framework

While the explicit description of a general framework is outside the scope of this paper, if any such theoretical framework is said to exist within the practice of trade or skill-based labor, it would be the decomposition of tasks in such a way as to reinforce the higher order skills and tasks based on the mastery of primary skills and tasks. This study devises a task-level matrix to represent the hierarchy of skills, with each trade category broken into levels of increasing competence. The required framework must represent the actual individual worker's skill set, while also allowing comparison to the available labor pool in assigning jobs to the least cost worker available. At the same time, the structure of the skill class-level decomposition approach allows for future work to be performed to tie advancement of skills to the assignment and scheduling problem.

1.8 Assumptions, Limitations, and Scope

The decomposition of labor into skill classes and levels requires some assumptions to be made regarding the level of competence necessary to perform one skill versus another. These assumptions were made using expert practitioner opinion so as to classify each task order to the most appropriate skill class-level. Because the nature of trade-based work is such that human resource efficiency can fluctuate due to unforeseen factors such as weather, health, time-constraints, competency, initiative and effort, we approach the time requirements for tasks using composite scores based on each worker's actual times of performance. This would remove the effect of averages which may dilute the impact of performance assessment at the individual worker level. At the mentor-apprentice level, we use these efficiency scores to inform the combined synergy of a paired work-team.

There may be instances where a job for evaluation took much longer or required much less time than would be expected for such as is standard practice. Because we adhere strictly to the actual time-based accounting approach for this study, there may be instances where the industry standard does not fit our results. This limitation would be primarily due to the limited size of our data set used in analysis, and a more comprehensive data set may more accurately influence composite scores. Further limitation may exist in the evaluation of classification of work into skill classes and levels, as there is much in the way of overlapping skills. For example, some furnace repair work requires both plumbing and electrical skill, so how do we decide which category of work best suits that specific type of job? To the best of my ability, these classifications have been made in collaboration with subject matter experts and it is possible that different classifications could be argued. The overlapping of skills is the basis for a subsequent decomposition that is outside the scope of this experiment and the focus of future research where skill development is represented by a chain of successive skill developments.

Finally, this work is limited to the actual human resources performing the job. That is to say, the time standards used in this study should not be assumed to reflect the standard across the industry. It may be that evaluated performance in this study is either above or below the industry standard. In part, performance may be the result of phenomenological management practice, as well as an inherent bias due to the longitudinal nature of the study and the impact of observation on behavior. The scope of this work is limited to the actual operating environment of a single property management firm and this study is limited to the Saint Louis Metropolitan Area, and all work performed or evaluated in this study over the research period occurred in the City and Counties of Saint Louis, Missouri. The labor resources evaluated for this study were from one maintenance company's data and that company's resources served one property management company's labor demands in a linked supply-demand relationship, allowing a semi-structured and semi-controlled observation environment where other contractor involvement was the exception and not the rule; this is generally the case in property management organizations of a similar size, that a single base of human resources is utilized to perform most of the work order tasks. However, the inputs of this study may be considered a phenomenon of the special relationships formed in the interdependence of the supply chain partnership that existed, and this may not be as is currently standard practice across the general property management environment. That noted, subsequent interviews with other property management companies have identified the similarity between the processes, structures and concepts in the focal firm compared to other firms of similar size and larger.

1.9 Summary

The potential for a valuable contribution to academic research in the area of optimization of maintenance tasks using a multi-skilled approach is both timely and significant as the formal bounds of skill development are dissolved and new technologies that can evaluate cost-benefit decisions continue to gain in processing power and sophistication. This does not change the practical underpinnings of the research and lends potential benefit to an area of practice that has gone largely overlooked in the supply chain research. In the process of collecting and evaluating a large data set spanning 18 months, this paper evaluates the maintenance function and decomposes the actual performance of work into skill-class-level categories and develops from this the mathematical engine to schedule and assign work on a least-total-cost basis.

The mathematical models are extensively tested using a vast array of data sets modified from the base data, so that the salient features of the data are intact, while testing the flexibility of the model under temporal, resource and other constraints. The models are very efficient in solving for a reasonable number of jobs, compared to existing models in literature. The models also provide a total cost objective that this paper evaluates for correlation against several variables in the data such as number of workers, work-load capacity, and number of skill class and level divisions. I make some decisions regarding the best ways to use this mathematical engine for making timely and accurate business decisions, and I offer several areas of future research that could benefit from such an approach.

The remainder of the dissertation is structured as follows. The next chapter offers an extensive literature review that informs the practical nature of this research and areas of theoretical foundation, extension and overlap. It is broken into topical sections including literature reviewed in property management, building and facilities maintenance and construction project management; and in optimization and mathematical approaches to scheduling and assignment. In Chapter 3, I describe the operational environment and present data analytics and statistical inferences from the focal firm's operations. I then in Chapter 4 present the optimization model and the results from preliminary application of this model. In Chapter 5, I perform case studies of the model and present solutions for single assignment, assignment with sequence dependency, and assignment considering pairing with mentor-apprentice tasks assignment. In Chapter 6, I offer areas where this work can be advanced and future development of this research, as well as offer some potential hypotheses that may be advanced using this dissertation’s data set and models. I make some summary conclusions in Chapter 7.

Chapter 2

Literature Review

2.0 Introduction to Literature Review

This literature review informs the research design of this dissertation. The structure of the research is essentially in two areas of concentration: practical insights in property management and optimization approaches in construction management.

2.1 Practical Insights in Building Maintenance and Property Management

Ottoman et al. (1999) address budget-level estimating of the cost of planned facility repair and maintenance, describing the four common bases for budgeting. One such method that is also referred in subsequent literature is the real assessment approach, where the actual physical condition of the facility is evaluated and information is reported to a database for further analysis. While an approach such as this appears practical if not convenient—as it requires a field based approach to assessment as opposed to a percentage of property value or percentage of system cost approach—it is not uncommon for such practice to be foregone. The authors cite Kahn (1966) who described the decision of many owners or investment groups to allow long-term maintenance costs to escalate and functional reliability to degrade, with every needed maintenance dollar conceded to other priorities. Among life-cycle cost, plant value and other formula based methodologies, only condition based assessment is addressed by the National Research Council's Building Research Board and the U.S. Army Construction Engineering Research Laboratory (USACERL). The condition based assessment method requires completing physical assessments followed by cost estimates to perform maintenance and repair for deficiencies noted. Other methods factor a cost of maintenance and repair ranging from 1%-4% of current property value (BRB 1990), whereas the U.S. Coast Guard allocates an annual budget of $2000 per residential unit for recurring Maintenance and Repair (M&R), based on the Building Owners and Managers international (BOMA) 1994 Standard; the range per square foot is from $1.37/S.F. in 1993 and increases about 1.1% per year. However, underfunding has been institutionalized as organizations and firms allocate M&R funding to other, more emergent needs, honoring an "out of sight, out of mind" mentality. Since incremental and other formula based approaches do not consider current and changing specific property conditions, they effectively underestimate the impact of neglect and the penalties caused by maintenance deferral. Of the condition-based assessment approaches, the BUILDER Sustainment Management System (SMS) model developed by the USA-CERL offers a comprehensive condition assessment process, "intended to collect the minimum amount of data necessary to define the condition of a building and its components, develop annual and long-range work plans and budgets, and formulate M&R budgets." Ottoman et al also point out that advanced modeling techniques, including expert systems, had not been widely adopted at the time of this work.

Sun and Che (2012) propose the integration of existing Building Information Modeling (BIM) designs into the real-time monitoring of the update of equipment information, maintenance and fault handling. As the design requirement for especially newer building stock is captured in the design/construction phase of a project, the data can be readily accessed within the BIM model including equipment schedules, location matrices and specification tables. BIM involves the digital capture of constructible information that is updated as real-time conditions on a construction project change as the project approaches the operations and maintenance phase. Therefore, the relevant information for maintenance and repair of constructed systems is captured in a 3D spatial representation of the constructed facility, in a design method that facilities staff can understand. However, BIM is not actively pursued as a decision support visual aid in facilities management departments (only 42% adoption) compared to its use in design (83%) and construction (79%) phases (Burcin Becerik-Gerber, 2011). While only 42% of respondents have adopted BIM in the O&M phase, 78% of non-BIM users agreed that BIM could be used more heavily during O&M of a facility.

Lind and Muyingo (2011) define the specific uncertainties attendant to building maintenance planning that make long-term planning less meaningful. Building maintenance is viewed within industry as moving from something seen as a necessary evil to something that is an integral part of this business process with a focus on reliability and cost effectiveness (Ahuja and Khamba, 2008) especially since the increase in housing stock as a result of the decades of economic growth after World War II. However, the author comments that "the research on property maintenance is underdeveloped, as argued in Wu et al (2010)." While many owners make three to five-year maintenance plans, these plans are not adhered to for more than a few months (Wu et al, 2006). In addition, property managers who were asked how much of the past year's M&R budget should carry forward to the next year, the answer was only about 50% of last years' budget, which the authors deemed as "irrational."

Industrial Standards for Operation (ISO) European Norm (EN) 13306 classifies M&R into two categories: maintenance required prior to a detected fault (preventative maintenance) and maintenance required after a detected fault (corrective maintenance). Preventative maintenance is sub-divided into condition-based maintenance (scheduled, continuous or upon request), and pre-determined maintenance (scheduled). An area of developing interest is "opportunistic maintenance"; that is, maintenance that is able to be undertaken when an opportunity to perform it coincides with other work routines, leveraging economies of scale. Genetic algorithms and robust optimization have been used to determine the appropriate timing of opportunistic maintenance (Saranga, 2004; Kuhn and Mandat, 2006). While the authors promote the concept of a maintenance strategy, they also recognize the lack of consensus on what the definition of a strategy should be, as even the industrial standards (EN 13306 and ISO 9000) disagree on the scope and scale of a strategy.

Outside the real estate sector, there is a concentration on collection of information to make failure rate prediction possible; a smaller group of people are entrusted with collecting and increasing available information, in a dynamic decision support environment. Failure rates and costs are also explicitly modeled in an optimizing framework where tradeoffs between costs versus expected revenues of a maintenance policy can be compared, with a graduation from time-based maintenance to condition-based maintenance. More dynamic systems of M&R are the natural response to inherent uncertainties in property management including uncertainty about the structure of an object, expected life times, cost of specific remedies or corrective actions, and the value of the option to wait (which is inherently appealing as its cost is zero in the current time period). Pre-conditions for good planning under uncertainty within the real estate sector, and in the development of a knowledge management system include automatic monitoring, inspection rounds with regular intervals, and feedback from the field. A division of more or less critical components, the prioritization of systems (heating system in an older home, etc.) and core versus non-core properties or systems is also suggested. Plans and projections for the short-term (one year or less) should be updated several times throughout the year, and opportunistic maintenance should be considered in parallel with preventative maintenance, though the authors do not suggest a specific method for achieving such efficiency.

Tsui and Fong (2012) specify the primary and secondary functions of a knowledge management system for knowledge workers in a property management division in Hong Kong, as document management and process management systems have rapidly developed with advances in IT applications. The use of a single gateway of stored information with a single entry point and the ability to customize content, tools and utility in line with business decision support, are the fundamental features of an Enterprise Information Portal (EIP). Such a portal developed for property managers must factor into collaboration between office and out-posted (field) staff. Of those surveyed, business intelligence ranks as the highest priority for most respondent segments (including job type, years of working experience and among workers of a property management division), followed by collaboration and communities of practice (CoP's). Expressed frustrations exist around lack of proper data management and governance, lack of user tools for the completion of reports and poor search engine and taxonomy support.

Lambie-Hanson (2015) utilized public data for the City of Boston regarding reported violations, citations and property maintenance violations and found that there is a correlation between the different stages of the foreclosure process and the level of required maintenance on a property; that bank owned properties are the likeliest violators of property maintenance; and that the "dis-amenity" of decreased maintenance on a Real Estate Owned (REO) or foreclosed property results in the reduction in property valuations within the same neighborhood. A result of the sub-prime mortgage crisis, increased foreclosures negatively impact minority-dominant communities, as Hispanics and African-Americans were 2.8 times more likely to have been granted a sub-prime mortgage. Explanations for subsequent delinquent property management include financially distressed property owners, a lower sense of community solidarity resulting from a high concentration of vacant properties which dilutes the sense of neighborhood/community, and a negative response to a decrease in adjacent property values subsequent to a foreclosure. Foreclosure most adversely affects single-family homes, which are "more than 10 times more likely to receive a complaint while bank owned as while owned by a borrower who is current on his/her mortgage." Because foreclosed properties are often in neighborhoods with decreased property values, negative equity (upside-down) mortgage holders spend 30% less than homeowners with positive equity. As foreclosed properties tend to sit for long period of dormancy, these negative effects are further confounded by continued dilapidation of housing stock, which when placed into rental, results in lack of occupant or owner initiative to maintain and improve the property. Property management is proven to add value, especially for older and more distressed properties (Li and Monkkonen, 2014). In fact, a study by Reischl et al (2016) showed that unoccupied properties were three to 11 times as likely to exhibit visible features indicating disorder (i.e., broken windows, boarded doors, discarded appliances/furniture, and graffiti) than occupied parcels.

Tan et al (2014) identify the critical success factors for building maintenance and client satisfaction and company qualifications (certification) ranked highest among Hong Kong property management clients. The top factors were Client Satisfaction (1), Certification of the Company (2) and Reliability (3) and Quality (4) of service. Cost management, work execution control, communication and responsiveness also scored in the top 10 factors, followed closely by reliability of service and quality of service. Cost management ranked 6th in the survey, while education and training (15th), risk management (16th) and innovativeness (25th) rank below the 50th percentile. The principal factor to property management success was defined as maintenance service; the authors suggest a service quality control program could be a competitive advantage. Another principal factor is organization and project management, entailing an “appropriate organization structure” to “enable a contractor to make optimum use of resources and improve quality and efficiency of communication.” This fits well with the resource based view of the firm as espoused in project management literature.

The most prevalent tool for managing a property is a property management plan, which operationalizes the immediate and long-term decisions attendant to sufficient upkeep of a property. Muczynski and Gawron (2014) propose a methodical basis for developing a property management plan as a “compact set of documents (i.e. analyses, forecasts and programs) which comprehensively characterize a property, the market surrounding it, as well as a manager’s goals and tasks in relation to the specific property… within a specified period of time.” Salient features of a property management plan as described in the literature include a clear scope of the rights and obligations of a property manager, the goals of the owner in having a property managed (as a result of legal, ethical and financial analysis), the goal of the most intensive use of the property taking overall constraints and opportunities into consideration, and a top-down approach that integrates both long-term property management requirements with more operational requirements. The plan should be a plan of “directed actions, aimed at ensuring the optimal method of property use and management” and should include a schedule of maintenance, investment and repairs, marketing and organization of management.

2.2 Optimization Approaches in Construction Management

Brusco and Johns (1998) present an integer goal-programming model to investigate cross training and multi-skilled resource policies to optimize the labor force of a large United States paper mill. The study found that the breadth of cross-training (number of skill categories) is more influential on workforce size than the depth of cross-training (productivity levels in each skill category). The study focused on 4 skill categories and only 100% or 50% competency levels in assigning the workforce to 30-minute planning intervals for an 8.5 hours shift in a continuous operation (24 hours a day). Results showed that partially skilled workers were able to match the solution cost of more than 50% of the 100% productivity assignments.

Hegazy (2000) uses the Earliest Late Start Rule (ELS) to simplify the computational effort required to model resource substitution for laborers within a Multi-skill resource scheduling algorithm to achieve a reduction in project delay of up to 80%. However, the author notes the difficulty with which such a model is accepted due to United States labor regulations and possible jurisdictional issues regarding division of labor, whereas in Canada such multi-skilled labor schemes are encouraged by the Christian Labor Association of Canada, and the use of multi-skill labor is accepted practice in other countries.

The Construction Industry Institute (Burleson et al, 1998) evaluated multi-skill craft capabilities in construction as a solution to the declining number of trade entrants into the workforce, and found that multi-skilling of trade labor resources resulted in a 5% savings in labor costs, a 35% reduction in required project workforce, and a 47% increase in average employment duration per worker. The report conducted an in depth investigation of current literature to develop a new craft strategy where overlapping areas of skill were assigned to more than one trade. A model plant that has been used in two prior benchmark productivity studies was used to evaluate the operational benefits of multi-skilling, where the application of this new approach to the division of labor with a dual skill strategy as well as a four crafts strategy of Civil/Structural, General Support, Mechanical and Electrical skill types. The study presumes that some limitations may occur using this strategy to include:

1. Infrequent use of skills makes maintaining some skills difficult.
2. Constant movement of workers on the site may become disruptive, in the case of large projects.
3. Training costs may eventually outweigh the benefits of increased flexibility provided through multi-skills.

The most common benefits reported from the proposed multi-skilling approach were increased employment duration, improved marketability and increased sense of security/satisfaction, increased flexibility in worker assignment, lower turnover, smoother workflow with less downtime between tasks, fewer workers needed to complete the project, and lower costs to the owner. The research found that users believed complex tasks were not suited well to multi-skilling, and that recruiting multi-skilled workers and validating their cross-functional skills would be difficult. Also, the question remained of how to address deteriorating skills due to lack of use.

Gomar et al (2002) expands on work by Gomar and Haas that concluded that the benefits of multi-skilling are marginal beyond 10-20% concentration of multi-skilled workers in a project workforce and that individual benefits are marginal after acquiring competency in two or three crafts. Gomar applied the multi-skilling strategy to a partially multi-skilled workforce to develop the Multiskilling Optimization Model for Allocation (MOMA) which was tested and validated using the Construction Industry Institute (CII) model plant data and pursued the objectives of:

- Minimize the number of worker days used in a project
- Minimize the number of hires and fires.
- Minimize the switching of workers from crew to crew.
- Increase the employment duration.

The model was programmed in General Algebraic Modeling System (GAMS) and a demand histogram was derived from the demand schedule, derived from a standard resource loaded Critical Path Method (CPM) schedule. An economic penalty function enforces worker hiring and firing conservation and the model emulates the superintendent decision of who to assign, hire and fire. CII model data were systematically varied to test the capabilities of the model. The findings of this study reinforce the CII findings that single skilled workers were preferred in the model only after multi-skilled workers were allocated. The study also finds that after two or three additional skills are obtained (based on the model's skill classifications) the extra benefit from additional skills is marginal. However, the authors also suggest that the model should be field tested against actual construction project plans to evaluate the model's actual potential.

Tam et al (2001) propose a Genetic Algorithm (GA) approach to modeling the effect of multi-skilling in the Hong Kong Housing Authority and public works departments. The GA begins with an initial population of random solutions and their respective fitness values for the current scenario. Solutions to the model with higher fitness values are more likely to 'reproduce' new solutions. Through a process that mirrors genetic mutation and crossover, the solutions evolve toward optimality for the model, in a process that imitates survival of the fittest. Three scenarios were pursued, first the base single-skill scenario; then a limited multiskilling scenario where the number of single-skilled laborers was limited so that additional labor would be from a multi-skilled labor pool; and finally a scenario where the volume of work was increased. In the base study, with a population size of 1000 and 150 generations of the model, the arithmetic results of the matrix assignment matched the base case. However, multiskilling resulted in a 3.7% cost increase to use other tradesmen to satisfy work demand. The study concludes that such a cost increase may be offset by the benefits gained from multi-skilling, in terms of labor retention, laborer loyalty and worker sense of well-being.

Fitzpatrick and Askin (2004) develop and test mathematical models for formation of effective human teams to ensure depth and breadth of technical skills within a cellular manufacturing environment. Each employee in the study begins with a key skill upon which a multiskilling strategy is built upon. The Kolbe Conative Index (KCI), a psychometric system that can be used to form teams, measures conation which refers to the part of the mind that controls conscious effort and strives to carry out volitional acts, and is used to predict team performance. The study constructs teams based on a balance of the psychometric traits of the laborers, based on individual capacities for four instinctive behaviors: probing, patterning, innovating and demonstrating. The study also compares the measures of synergy (distribution of team energy across operating zones) and inertia (an excess of conative energy in a combination of action mode and operating zone). A Multiple Integer Program (MIP) is utilized to sequentially build teams while maintaining a good balance of modal instincts but constraining assignments to the least flexible skill group-mode combination, and nine different problem sizes were tested, each problem consisting of four skill groups, and each group was required to consist of an equal number of individuals. Due to computational complexity, a construction heuristic was developed in CPLEX. Results found that the heuristic had both positive and negative characteristics. While the average deviation from the lower bound in the model was always less than 12%, the maximum deviations from the selected measures were higher but remain below 22%. The model found, however, that when the number of potential members is higher the results may overstate the weighted values might not be a good indicator of potential problem areas. The study concludes that future research should include study into more suitable measures of group productivity.

Bennour and Crestani (2007) formalize and generalize performance estimation by linking human capabilities and process performance within an industrial process. Human resources possess implicit cognitive and decision making capacities and represent a key factor in process performance. Most industrial engineering approaches fail to consider the effect of human resource competency, as they view human resources as material resources. In the resource based view of labor, individual competencies are attributes that define the resource capacity in terms of knowledge, know-how and behavior, observed at the individual and collective level. The research posits that it is possible to quantitatively estimate the impact of such competencies on performance (in terms of quality, cost, time, etc.). These competencies modulate the performance of the system-wide process under practical industrial engineering laws. Individual worker profiles are developed from worker evaluations and interviews. Competences in the study were technicality (ability to realize), decision making (ability to decide-supervise-manage), autonomy (ability to undertake), innovation (ability to create), management (ability to negotiate-organize-animate) and relational (ability to communicate-cooperate). A novice worker will increase process duration, whereas an expert will decrease it, and each worker is assigned a value for each trait from “inferior” to “excellent”. Intra-business and inter-business behaviors are distinguished in the formation of teams. The Model for the Organization and the Validation of Enterprise Structures (MOVES) modeling language is adapted to represent the enterprise model, and a competency-based perception of the human entity to support performance estimation. All stakeholders and technical aspects of the system were captured in a meta-model, and activities are broken down into sets of tasks, and the relationships between competence and performance is formulated. The approach allows for a connection between quantitative aspects of the system-wide performance metrics, and the qualitative aspects of the worker-performance review process. This makes it possible to simultaneously integrate aspects related to the individual as well as collective work while using a single formalization of a performance expression. However, the model is only as strong as the underlying performance modulation laws and inter-relational weights of competencies. The authors suggest future development of the model where human resource capacities and behaviors at work are formulated in more detail to more rationally link knowledge and competence.

Elfwing et al (2007) approach the Reinforcement Learning (RL) algorithms and the development of hierarchical learning structures to observe how the work breakdown structure of a project or task into subtasks can inherently speed up the cognitive capacity of an operator. The study evaluates a robot programmed with low-level motor actions that are able to combine to form higher-order modules adapted to the working environment.
The RL approach is used to optimize the meta-aspects of the learning routine including primitive behaviors and hierarchical learning structures. A search and collect program is performed by a robot within three distinct environments. When the robot (agent) successfully navigates (by virtue of adopting one or a combination of low-order functions) the search space, it also learns to adapt the lower-order functions to resolve higher-order requirements. The MAXQ framework based on Q-learning and State-Action-Reward-State-Action (SARSA) is used where hierarchical RL is defined as a semi-Markov Decision Process (semi-MDP). Depending on the task decomposition, the MAXQ framework searches for the recursively optimal policy to achieve subtask, sub-routine, and task completion with minimal cumulative penalty or maximum cumulative reward within a continuous state of information. The role of the evolutionary process is similar to the GA) approach, where already primitive behaviors evolve into more complex behaviors by mixing competing strategies according to how well they perform the task. When the program was evaluated during robotic performance of a simple “forage” program (consisting of three levels of decomposition into successively lower

order tasks), the robot continued to learn more stable routines and advance its learning policies, even when the learning structure was almost fixed. The study found that the robot pursued a minimal strategy that minimizes the number of primitive subtasks that achieve the subtasks' goals, in particular the program searches for the scenario where only one subtask is required to process a sub-goal, which removes the need to re-learn behaviors. The research shows the difficulty attendant to process and task decomposition, as well as the benefit in reduced learning time when higher-order routines are composed of simple lower-order behaviors. The main conclusion of the experiments is that Genetic Programming can find a minimal strategy to the problem at hand, i.e., a hierarchy that uses as few primitive subtasks as possible for each type of situation the agent can experience while performing the task.

Canini and Griffiths (2010) model transfer learning in a Bayesian general model—the Hierarchical Derichlet Process (HDP)—as a general characterization algorithm that exhibits when a learner must simultaneously learn about multiple categories of information to be shared between participants. The relational model categorizes 14 artificial categories containing 8 different clusters of stimuli, where the clusters induced by learning one category can be used to inform learning about another category; this type of learning is observed in human learning behavior. The HDP allows us to explore how the capacity to share clusters between categories influences category learning by comparing performance models that allow sharing to ones that do not. The research finds that human learners are able to accurately reconstruct taxonomy structures in category systems from a limited number of examples.

Janiak et al (2009) develop solutions algorithms for the make span minimization problem to include the learning effect. Whereas most research to this point in the area of operations research and computer science focus on application of Wright's learning curve, this research implements a learning function that is an S-shape curve which has been found in practice, a novel application in the scheduling domain of research. The experienced-based learning scheduling model developed by the authors instead of the time-based learning approach commonly seen in machine learning environments, is an NP-Hard, branch and bound algorithm, and job processing times are non-increasing experience based functions. The computational results of the experience-based model are compared to other heuristic algorithms and is found to perform well, solving optimally for 30 jobs on average in a few minutes with very low mean relative errors and low computational effort.

Janiak and Rudek (2010) address the project assignment make-span minimization problem with a multi-ability learning effect. Depending on a job, a worker can learn a skill faster or slower; thus reduction of processing time should result in more rapid learning. The solution algorithm for multi-ability learning (SAMALE) schedules jobs according to the non-decreasing order of the learning ratios, as well as scheduling any jobs where learning can be advanced before arbitrarily assigning those jobs where no learning will occur. An exact polynomial time algorithm was performed and found to solve optimally.

Pitio et al (2010) proposed the evolutionary algorithm oriented by knowledge (EAOK) based on the adapted evolutionary algorithm and a model of knowledge based on the Bayesian Network formalism and used to direct relevant orientations into the search process. The Bayesian network (BN) is the formalization of expert knowledge from individuals generated by the GA. Again, projects are recursively decomposed into sub-projects and a hierarchy of tasks is constructed into a project graph. Knowledge can be capitalized from previous optimizations (learning from experience) and knowledge is improved by learning from the most interesting solutions obtained during the search. This model requires a priori knowledge about the structure of the network and the learning during optimization is achieved through probability updates to make it possible to concentrate learning effort to the probabilities estimation. Prior to this study most searching and learning processes have few interactions during the algorithm execution. The model of knowledge (MOK) helps to formalize the links between the decision space, evaluation space and context space. The BN is a probabilistic model that represents a set of variables (nodes) and their conditional dependencies (edges between nodes) in a directed acyclic graph. The conditional probability of each state of a node can be inferred according to the state of other nodes. 4 node types exist in the model: objective, decision, concept and environment. A decision node can take into account all possible choices (states) for a decision; the objective node is generally to solve cost minimization or project delay minimization. Concept nodes reduce the complexity of the model and also model expert knowledge and enable the model to progressively build links between decisions and objectives. Concept nodes are the result of knowledge in the work environment that can be contextualized into concept nodes.

Two strategies can be used when executing the model: structural knowledge utilization (subsequent gene inhibition) and diploid knowledge preservation (inactive genes are repurposed in some other area of the search space). The MOK is not updated as long as the best solutions of the Pareto front are improved each cycle. Probabilities of the BN are learned from source cases using the Expectation-Maximization (EM) algorithm and the junction tree algorithm is used to exploit the learned model. The quality of available learning cases appears to be the most important characteristic in order to obtain a relevant model. Those strategies where the focus is on utilizing qualified individuals first helps to ensure learning capabilities of the MOK are not saturated among individuals with a poor fit. Stopping criterion also has significant influence on the model performance. Fast learning is good for global guidance and decision support whereas longer learning can cause over-guidance of the search resulting in over-learning or stagnation of search around already found individuals. While structural knowledge can be used to build a network model, the best strategy is reliable, actual information. However, actual benchmarks have not been explored in presenting the EAOK approach.

Wongwai and Malaikrisanachalee (2010) aim to improve the starting time of projects by resource substitution where a project’s labor resources can be fulfilled with a combination of single and multi-skilled labor if substitutions satisfy the complete requirements for that project, in an all or nothing approach. The objective is overall shorter project duration subject to project timeline and resource availability constraints. While the approach can solve for the shortest project duration it does not guarantee minimum project cost. The model does not consider overtime or temporary external workers, or lag and lead times, in its solutions.

Czyz et al (2011) works to minimize total tardiness using a parallel computation approach where an autonomous human learning system (ALS) is formalized. There is no precedent relationship among tasks, so tasks are scheduled in order to maximize autonomous learning efficiencies from task repetition. Proposed computation approaches utilize Nawaz-Enscore-Ham (NEH), tabu search and simulated annealing which show high accuracy of problem solution. Parallel computation approaches significantly reduce computation times of these methods.

Florez et al (2012) argue that the consideration for social sustainability measures has been absent from literature and can be beneficial in deriving a system-wide stability as an optimization goal. As work volume ebbs and flows, the cost to hire, train and release labor resources can cause problems with maintaining steady state efficiencies and compromise team dynamics. The lack of training and growth in trades based jobs results in high turnover rates while the opportunity for advancement of new skills is limited. Multi-skilling is presented as a suitable option for reducing negative attitude of workers, offering a chance for skill development and team cross-pollination, an increase in average employment duration and increased job continuity, and a reduction of time and cost delays due to behavioral factors. A MILP is used to solve the Multi-Skill Resource Constrained Project Scheduling Program (MRCPSP) in a fixed multi-period panning horizon and allocates resources so that drastic measures (hiring, firing, etc.) are reduced. The objective of the model is to minimize the absolute distance of the number of workers around the average resource level required.

Liu and Wang (2012) optimize the linear project schedule (as exemplified in the case as a bridge construction project) using single and multi-skilled labor resources to improve work continuity. Single skilled crews are selected for corresponding work types first, and multi-skilled contractors are used to backfill remaining crew needs and improve work productivity. However, only one multi-skilled crew can execute one task at a time before moving to the next work as scheduled. The model anticipates reducing slack time and project delays as work repetition is promoted. Constraint Programming (CP) is used to prevent limitations due to certain model formulations, while offering flexibility in modeling different constraints. Project duration is minimized for 5 types of repetitive activity including excavation, foundation, column, beam and slab work. Integrated productivity is derived by utilizing the multi-skilled crew to ensure single-skilled workers maintain task consistency required for increased efficiencies. The model is situated as either able to be interrupted or unable to allow interruption. The utility of the model is in the ability to anticipate the temporal hiring for a linear project where repetitive task efficiencies can be achieved.

Zha and Zhang (2012) consider both induced and autonomous learning to schedule projects with multi-skilled workers. The sum of processing time based learning function developed by Kuo and Yang was used to model the learning effect. A randomly generated example project was used and results show that total cost first increases due to costs incurred in the induced learning process, but as efficiencies grow though learning, the cost increases are offset and eventually total costs are decreased. The level of induced learning for a worker corresponds to the combination of project make-span and total cost.

Alikhani and Fazlollahtabar (2014) optimize a model of organizational learning capability (OLC) which consists of 10 effective factors for organizational learning in different parts of an organization. A multi-objective approach utilizing the epsilon constraint is used to validate the methodology. Such factors under consideration include risk taking, interaction with the external environment, team dialogue, participative decision making, managerial commitment and a systems perspective, among others. These factors are measured for a firm and incorporated into the optimization. The context of this model is of knowledge management in companies. Learning capacity can thusly be maximized. A conflict avoiding heuristic scheduling algorithm is implemented in Lucko et al (2014) that minimizes total project duration, in particular addressing the complexity of considering physical workflow direction within a Cartesian coordinate framework. The algorithm considers and resolves all spatial conflicts in the progress of work on site among overlapping pairs. As Geographical Positioning Systems (GPS) and Geographic Information Systems (GIS) are more fully utilized in project planning, such data can be converted to real time workflow in this three dimensional space to record work paths. Most models assume a one-directional workflow and dependencies are not structured to remedy spatial conflicts. The benefits of such an approach can be seen with the adoption of Computer Aided Design (CAD) and Building Information Modeling (BIM) which have become ubiquitous in current construction practice on linear projects while reconsidering workflow to allow least critical tasks to be pre-empted by the critical workflow path. The algorithm itself identifies the progress direction and start time of each activity and the shortest possible total duration. A greedy procedure based on predefined spatial heuristics schedules the work in chronological order to achieve the maximum time gain at each step. The approach when applied to a sample case resulted in 31.3% time savings compared to CPM when considering the task progress in the two-dimensional space.

Abotaleb (2014) applies the GA approach to assign multi-skilled workers to non-pre-emptable tasks so that lost productivity due to downtime (a by-product of a salaried worker not being considered for work which he is unqualified) is eliminated. A productivity factor matrix is used to structure the relative comparative productivity between secondary sources of skilled labor when trained primary sources are unavailable, also considering the additional cost to train or hire multi-skilled workers. Solution results find that even if the multi-skilled wage is 30% more than a single-skilled worker, the total labor costs are decreased. Total project duration was likewise decreased by over 45% using a multi-skill strategy. This approach is an alternative to crashing and overtime costs while offering more flexibility on the utilization of resources.

Malachowski and Korytowski (2015) marry hierarchical competences modeled as a weighted diagraph and learning curves to model individual learning rates when multi-skilled workers perform repetitive operations. As worker performance changes with experience (the number of repetitions) this research also considers the interrelation between competences; that is, advancement of one competence loads positively on other competences when the interrelation of those competences is quantified. The objective is minimizing the cost of expanding a workers' competence in order to meet some given requirement. Competence construction follows the hierarchical structure where elementary competence cannot be divided into more precise competences. A competence analysis phase is conducted to assess individual competence bases. Advanced competence is composed of elementary competences; thus, simple competence builds and combines to create complex competence, mimicking the natural hierarchical learning process. Compound competence is where a synergy effect occurs due to the combination of sub-level competences; this can be different than advanced level competence. Competence relation force tells how much a higher-order competence relies on component competences; whereas relation forces factor the interrelation of competences; for every competence, a learning curve is assigned. Consideration for minimum thresholds is enforced so that prerequisite competences are satisfied in order to be considered for a working post (active competence). The proposed approach is shown to more precisely estimate performance of a worker, individually and as a work cell.

However, the research assumes a manufacturing assembly line application as opposed to the domain of scheduling and staff assignment in construction.

2.3 Summary of Literature Review

In the existing academic literature, models show the potential for efficiency gains when utilizing a multi-skilled approach to labor allocation. Other studies offer mixed results when considering the integration of multi-skilling into a single-skilled environment. Authors also suggest that a model should be field tested against actual construction project plans to evaluate the model's actual potential. Multi-skill resource assignment in prior literature did not take into consideration multiple locations or competence. Optimization approaches such as genetic algorithms and strict integer linear optimization have been used with noted success when evaluating existing data sets. The research shows the complexity of process and task decomposition, as well as the benefit in reduced learning time when higher-order routines are composed of simple lower-order behaviors. The authors point out the obvious limitation; that is, how do you maintain levels of reinforced learning in a human system?

This research supports the advantages of a team-oriented approach to training and skill development; however, most of this research is grounded in theory. Developments in software technology facilitate the development of mechanisms of knowledge transfer within a construction organization; however, dynamic visualizations tend to create an extraneous cognitive load as working memory attends to the complex presentation of information as opposed to the actual content of the work in practice. Project-based learning mechanisms and practices are often not adequately supported by management since they involve returns from intangible assets that are not directly visible or measurable. Future research should delve into more suitable measures of group productivity and where human resource capacities and behaviors at work are formulated in more detail to more rationally link knowledge and competence. More personal and social approaches to the flow of knowledge is needed to enhance knowledge creation and knowledge sharing practices. Organizational learning structures should be “firmly embedded within the existing short supply-chain structures and beyond.” This presents “one of the greatest challenges to the creation of commercially viable and socially enduring supply-chain management practice in construction”.

Despite the incorporation of sophisticated mathematical modeling approaches, the more advanced modeling techniques, including expert systems, had not been widely adopted at the time of this work. Property management literature conveys a lack of consensus on what the definition of a strategy should be, disagreement on scope and scale or such a strategy, ambiguity of industrial standards as applied to the growing field, lack of proper data management and governance, lack of user tools for the completion of reports and poor search engine and taxonomy support to support a plan of directed actions, aimed at ensuring the optimal method of property use and management.

Authors (Year)	Decisions	Constraints	Methodologies	Multi-Skilled Personnel	Time Window of Tasks	Precedence	Assignment	Sequencing	Routing	Travel Distance	Pairing	Priority	Interruption	Competence	Training /Learning	Breaks	Overtime	Materials	Condition	Constraint Programming	Integer Programmin	Simulation
Brusco and Johns (1998)	Minimize Staffing Costs	Minimum labor requirements	Mathematical Programming	X	X		X									X					X	
Burleson et al (1998)	Optimal Labor Allocation	Skill mix	Economic Model	X																		
Fitzpatrick and Askin (2000, 2005)	Worker Assignment	Kolbe Index Scores	Mathematical Programming	X			X													X	X	
Hegazy (2000)	Substitution	Resource scarcity	Mathematical Programming, Sensitivity Analysis				X														X	
Tam et al (2001)	Minimize Total Cost	Productivity Rates, Daily Wage	Genetic Algorithm	X																		
Gomar et al (2002)	Minimize weighted sum of switching crews, hiring/firing costs and number of workers.	Demand	Mathematical Programming	X	X		X														X	
Saranga (2004)	Minimize cost of lost revenue	Cost of risk, Cost of remaining life, cost of downtime	Genetic Algorithm																X			
Kuhn and Madanat (2006)	Optimal management Policy and future management costs	Facility condition states	Robust Optimization																X			
Madanat et al (2006)	Optimal cost of maintenance policy	Long term model: budgets, limits on volume of faciities in each condition state. Short term model: near-term costs are time dependent.	LP Optimization																	X	X	
Bennour and Crestani (2007)	Performance Estimation	Human resource skills	Mathematical Programming	X			X							X						X		
Elfwing et al (2007)	A Recursive Optimal Policy	Value of subtasks, pseudo-reward	Genetic Algorithm, Markov Decision Processes												X							X
Janiak et al (2009)	Minimize Makespan	Process times	Branch and Bound					X							X							
Canini et al (2010)	Level of Transfer Learning	Distribution of stimulus	Rational Models and HDP												X							
Janiak and Rudek (2010)	Minimize Makespan	Process time	Polynomial Time Algorithm		X			X							X							
Pitiot et al (2010	Knowledge development	Knowledge utilization and preservation	Bayesian Network, Evolutionary Algorithm																			
Wongwai and Malaikrisanachalee (2010)	Project Duration	Resource substitution	Resource Substitution	X	X		X	X												X		
Czyz et al (2011)	Minimize Total Tardiness	Process time of sequential tasks	Simulated Annealing, Tabu Search, NEH					X							X							
Florez et al (2012)	Minimize Total Execution Time of Schedule, Maximize Labor Stability	Number of available machines. Can only use one skill at a time. Hiring and firing	RCPSP	X			X														X	
Liu and Wang (2012)	Minimize Project Duration	Number of multi-skilled workers to complement a single-skilled crew. Various costs.	Constraint Programming	X									X							X		
Chunfeng Liu (2013)	Minimize Total Tardiness	1 job Per machine	Hybrid Genetic Algorithm			X	X	X				X									X	
Abotaleb (2014)	Project Duration	Skill mix	Genetic Algorithm	X			X								X							
Alikhani and Fazlollahtabar (2014)	Maximize Learning Capability, Minimize Cost	Implementation value of various dimensions of learning capability	Epsilon Constraint				X								X					X		
Kuo et al (2014)	Minimize weighted sum of shortfalls in total staff assignment	Operational tasks and language needs.	Mathematical Programming	X	X		X									X					X	
Lucko (2014)	Sequencing of Tasks in 2D and 3D space.	Work space, Time	Singularity functions, Buffers		X	X		X	X	X												
Zha and Zhang (2014)	Minimize Project Makespan	Cumulative skill, levels of learning, fitness	Genetic Algorithm	X		X	X								X					X		
Chen et al (2016)	Minimize Policy to assign all jobs to technicians over planning horizon.	Experience level, level of learning	Markov Decision Process		X		X	X							X					X	X	
Małachowski, B., & Korytkowski, P. (2016)	Scheduling	Levels of competence	Mathematical Programming	X										X								X
Mathlouti et al (2016)	Maximize gain minus distance and overtime	Breaks	Optimization				X	X	X	X		X				X	X	X			X	
Mehrgani et al (2016)	Minimize production Cost	Machine maintenance and inventory management	Sensitivity Analysis															X		X		
Chen et al (2017)	Minimize Risk	Travel and service times	Bebo hyperheuristic						X			X										X
De Jonge et al (2017)	Level of deterioration	Time	Simulation																X			X
Vatterott (2018)	Minimize Total Cost	Deadlines, experience, wage	Mathematical Programming, Expert Classification, Efficiency Scores	X	X	X	X	X	X	X	X	X		X	X					X	X	

Table 2.1 Summary of Mathematical Models in Literature Review Compared to this Work.

Authors (Year)	Industry Focus	Application/Approach	Results
Army Corps of Engineers Construction Engineering Research Laboratory (1990)	Building and Facilities Maintenance	Conception of the BUILDER Engineered Management System (EMS)	Assesment of the various other Operation Related Software systems in use at State and Federal Institutions. Provides a framework for advancement of the ARMY property maintenance program. Because building components use different technology disciplines, the BUILDER EMS l must be multi-displined. The system must be created in steps or modules.
Carley (1999)	Construction	Site Visits and Interviews	70% of workers have skills in other trades; 79% of these workers are interested in more primary trade training; 57% would pursue training in another trade.
Haas (1999)	Construction	Site Visits and Interviews	Multi-Skilling depends on Superintendent ability to assign appropriate tasks to workers and build effective work crews; 20% productivity gain found among 6 companies surveyed. Multi-Skilling Benefits marginal after 10-20% multi-skill workforce composition; benefits marginal after 2-3 craft competency.
Ottoman, G. R., Nixon, W. B., & Lofgren, S. T. (1999)	Building & Facilities Maintenance	Literature Review: Life-Cycle Costing and Property Valuation Approaches	Maintenance costs are primarily overlooked; Annual budgeting can conflict with short-term maintenance requirements. 18 estimating approaches are presented. Sophisticated data-modeling appraoches are uncommon in practical use. Analysis relies more on professional evaluation and proportional Maintenance and Repair (M&R) value, life-cycle expected cost or condition-based assessment.
Wu and Clements-Groome (2006)	UK Construction Industry	Modified version of Pride's Scheduled Maintenance Logic Tree	The term "failure-based maintenance" may be misunderstood. Only 23% of firms apply corrective maintenance whereas 45% of firms apply preventative maintenance, which may be more costly. Data analysis should be applied in maintenance strategy development.
Biskup (2007)	Manufacturing Scheduling	Literature Review on Learning Curve Literature	The well known sum of processing time sequence yields strong results for competition time goals.
Ahuja and Khamba (2008)	Total Productive Maintenance (TPM)	Literature Review	TPM might be considered one of the best proactive strategic initiatives that can lead the organization to success over failure. TPM must be regarded as a "change process."
Wu, Neale, Williamson, Hornby (2010)	Industrial Maintenance	Workshop-based review of practitioner's insights on maintenance policy.	Practioners want simple tools to aid in Maintenance Planning; Acadmic research aims to be published and may not be suitable for practical use. The gap between practical and academic application needs to be narrowed. Case study is one suggestion for bridging this gap.
Burcin-Becerik Gerber et al (2012)	Facilities Management	Building Information Modeling (BIM)	BIM adoption rate has increased and its vizualization of facilities management goals and controls holds undeveloped possibilities. Facilities Management Oragnizations have already stared incorporating BIM or plan to implement BIM in the immediate future.
Lind and Muyingo (2012)	Review of Swedish studies on building maintenance strategies.	Alternative Model of Maintenance Strategy	Identifies a "before-fault" and "after-fault" classification of most commonly applied mainteance strategies.
Tsui and Fong (2012)	Hong Kong Housing Organization (Property Management Division)	Combined Qualitative and Quantitative Approach Using Survey instrument and Follow-Up Discussion	Business Information was largely the preferred collaboration tool for Property Management Division (PMD) knowledge management. Suggests a two-phase adoption plan with regard to Knowledge Management (KI) and Business Information (BI) Tools
Han et al (2014)	Construction management; Property Maintenance	Evaluation of Building Information Technology	Introduction of technical capabilities of BIM as applied in construction and property management. Technology is expected to be adopted more widely in the future.
Li and Monkkonen (2014)	Property Management	Experimental Survey Methodology of 150 experts in Hong Kong Property Management Market.	Moderate increases in appreciation of value of property management among respondents over 34 years in age.
Muczynski and Gawron (2014)	Property Management	Elicitation of a Property Management Plan	A methodology for planning property management with emphasis on immediate and long term objectives shouldensure the optimal method of property usage and management.
Tan et al (2014)	Building and Facilities Maintenance	Critical Success Factor Analysis Using Varimax , Oblimin, Quartimax and Equimax Rotation Methods	Concentration of 28 factors into 8 distinct principal factors. The top factors were Client Satisfaction (1), Certification of the Company (2) and Reliability (3) and Quality (4) of service. Cost management, Work execution control, communication and responsiveness also scored in the top 10 factors.
Lambie-Hanson (2015)	Property Maintenance	Statistical Analysis including Multi-Level, Longitudinal Regression Model estimated as a logit model.	Magnitude of code violation is increased as property falls into foreclosure. Indicates benefit of maintaining occupied properties.
Reischl et al (2015)	Neighborhood Development, Property Maintenance	Parcel Maintenance Observation Tool (PMOT)	Unsecured and secured windows and doors are a main observation of unoccupied properties, and also contribute to 19.9% of occupied property observations reported.
Sheng and Baharum (2015)	Property Management	Survey Rank of 20 Criteria each for both Client (40 of 59 respondents) and Service Provider (19 of 59 respondents).	Quality (best possible affordable and sustainable level) and Flexibility (meet changes with existing resource base)are the two most important criteria by both clients and service providers.
De Breucker (2015)	Workforce Planning	Literature Review of Workforce Planning Considering Multiskilling.	It is almost impossible to solve problems of realistic complexity to optimality. Often, management of a company will sacrifice optimality for feasibility. Suggests using assumptions based on sound empirical evidence and with consideration for uncertainty, for a balance of both fast and good solutions.
Keizer et al (2017)	Equipment Maintenance	Literature review of Condition-Based Maintenance (CBM)	Resource-dependence is still ill-researched. Most pooled resource research considers constant availability over time.
Pun et al (2017)	Facility Management	Fuzzy Analytics Hierarchy Process Decision Support System	There is a lack of a systematic approach to determine how maintenance strategies are recorded in most companies. The suggested approach uses cloud based data management to provide clear direction in formulating various maintenance plans.

Table 2.2 Summary of Qualitative Research from the Literature Review

Chapter 3

Problem and Data Description

3.0 Introduction to Data Analysis

The data analysis on property management took considerable time and effort to prepare. The focal firm allowed complete access to data repositories from which relevant insights were collected. I explain the subject of analysis and offer more detail into the operating environment through the exploration of this data, which sets up subsequent model design.

3.1 Problem Setting

The problem I explore is how maintenance tasks are assigned and scheduled to maintenance technicians in the course of property management and how to reduce, to the maximum extent possible, all costs associated with the assignment of labor to tasks of various urgencies, locations and skill requirements. The nature of the operating environment plays a significant factor in these decisions. Jobs are geographically dispersed; each maintenance requirement has a priority independent of other jobs; and the rapid pace of work requests increase the likelihood that assignment fails to enforce cost minimization while considering competence, distance of jobs or completion times.

Pen/pencil and paper methods can solve the scheduling problem for a handful of jobs assigned to a few workers; it becomes significantly more complicated to simultaneously consider dozens of jobs with their required priorities, deadlines, and skill requirements. In the focal firm's standard of practice, jobs were assigned daily. Enough work was assigned to an available competent worker so that each worker was given a day of work. If a job was assigned and a worker felt they could not complete the work, it was subsequently reassigned until it was performed. Routing was not considered in work assignment. A general rule was, "if a worker was on one side of town, he should stay near that area." Jobs were assigned based on a squeaky-wheel approach, responding to the most demanding tenant or owner regardless of cost or seriousness, indicating a motivation caused by urgency so that work deemed of highest priority by the tenant or the owner was always assigned first, indicating an emotional decision making policy as opposed to an economic decision, which could lead to instability in work assignment and worker-job mismatch.

Property management requires that both routine and non-routine maintenance tasks are performed on time, and by a qualified maintenance technician who is competent to perform that task. The conditions of work in property management do not always allow such single-skill focus. The use of single-skilled labor can be expensive if the worker is not fully utilized. Single–skill labor also requires such a volume of single skill work that is not always feasible in the working environment of property management I studied where a single-skill approach would not be optimal for property management organizations twice the size (greater than 300 properties) where a workforce may be required to alternate skills and adapt to fluctuating skill demands.

The result of the ad hoc assignment using only management discretion is capable of keeping workers busy; it is not necessarily capable of making the best assignment decisions, defined as the decision of assigning a worker to a job that s/he is qualified to perform. That worker is also the least-cost, qualified person available from a pool of labor, when also considering every other job available for assignment. At the same time, the assignment decision also considers the deadline of each job, in terms of how many days are allowed before the job must be completed, and I make this decision based on the urgency level of the work. Priority rules consider all scenarios where a task assignment deemed “more necessary, now” is presented. Furthermore, while I introduce a model that assigns work based on competence, it also allows for the assignment of an unskilled worker to a job when assigned to a mentor, at the trade-off of paired labor cost. Finally, the model I introduce optimizes the distance between jobs for each worker’s assigned route.

3.2 Assumptions

In the addressed problem, the following assumptions are made:

1. All jobs require a specific single skill to be completed. Those skills in this model include the most prevalent skills retrieved from an evaluation of 431 jobs performed in a 6-month period between September 2015 and February 2016. All work orders were categorized using the experience of a senior technician who possesses over 10 years of property management and maintenance experience with the guidance of a business owner with a background in general construction and a degree in mechanical engineering with 50+ years combined experience in manufacturing, engineering, design, construction and maintenance.

2. It is assumed that both the skill classes and skill levels derived from available data are adequate for this evaluation. These skill classes include Heating, Ventilation and Air Conditioning (HVAC), Electrical, Plumbing, Security and Other. In some cases, HVAC, Electrical and Plumbing have been combined as Mechanical, Electrical and Plumbing (MEP), and Security has been classified into the Other Category, and in a separate case all jobs are classified into one category called Other. The skill levels have been divided up into 4 Grades of skill: A, B, C, D. In some cases, the skill levels A and B have been combined into a single level A, and skills C and D have been combined into a single level of skill B. In another instance, all jobs are considered to be the same skill level.

3. It is assumed that all work completion times are real and accurate. Work completion times are defined here as the time required to perform a job as reported on job tickets collected from the field. The work completion times used are real times of performance.

4. It is assumed that priority can be generalized to 24, 72 and 120 day working time-deadlines, and that work once assigned is not pre-empted. It is assumed that the information as entered into the database from which historical work orders were retrieved, are entered as true and accurate as is able to be performed, and the classification of said work is as true and accurate as is capable of being evaluated.

5. The scheduling function in property maintenance is such that it is typical to perform several tasks at different properties which often are not co-located. The required travel from one task to another becomes a source of waste (measured in time and cost of travel). Because of the great number of locations in the property portfolio, the minimization of such costs may offer significant value. In addition, because tasks that

are co-located are often skill or task-dependent, the decision of whom to assign which job at which location becomes a challenge for pen and paper scheduling when cost-minimization is considered. The cost to the transition from one task to another is based on estimated distances and times traveled. With regard to the transportation and distance costs:

a.) An assumed standard mileage cost of $.565 as allowed in a prior tax year (2013) by the IRS, though the cost has fluctuated in recent years. For the sake of computational elegance, I also generalize location of jobs to the relevant zip code, as opposed to the actual address of the building or unit. In the routing analysis, I then place specific addresses on route, to determine the routes more specifically.

b.) An assumed average travel time combines the shortest and fastest route options in terms of mileage and time. For jobs that require travel within a zip code, I assume a .17-hour travel time and a 10-mile travel distance, based on the sum-average time to travel between the extents of all zip codes within the Saint Louis Metropolitan Area under evaluation, which when evaluating subsequent computations falls in line with actual results.

6. It is assumed that once a job is started, it can be completed, or that the general practice of a commute to and from work offsets the time and travel cost to and from a job that carries over from one day to the next, as is standard practice.

3.3 Decisions

When we consider the structure of this problem, we observe a workforce network where assignment and schedule is paired with competence so as to maximize utility of skill. The objective function consists of a transportation cost, a labor cost, indicators of competency and efficiency, and the necessary temporal constraints and spatial parameters based on the data set. We decide the best cost assignment of a sequence of work orders for property maintenance to an available pool of skilled workers. Those workers have been evaluated for competency in 5 classes of skill, and at 4 levels of competence within each class. We decide to assign work to competent workers based on the total cost of assignment. Variable travel costs between jobs can be a significant contributor to cost minimization and therefore directly influence work assignment. I make this decision considering limitations on labor availability, the requirement of timely performance due to priority rules, and the competency of each worker.

3.4 Data Description and General Statistics

The data set was exported from the software as a service (SaaS) platform in use by the focal property management company. That data set consisted of over 18 months of collected input. Input for 2,598 work orders was generated between Monday, September 1, 2014 through Monday, April 11, 2016; or 584 days. This equates to more than 1 year, 7 months—more than 84 weeks—of data. 25 data field entries were acquired through four primary reports: Work Order, Property Profile, Job Ticket and Invoice Calculation.

3.4.1 Descriptive Statistics

From a population of 2,597 work orders, the year each property was built is documented in the property profile. For all work orders in the data set, the mean year built for a property on a work order is 1931.8.

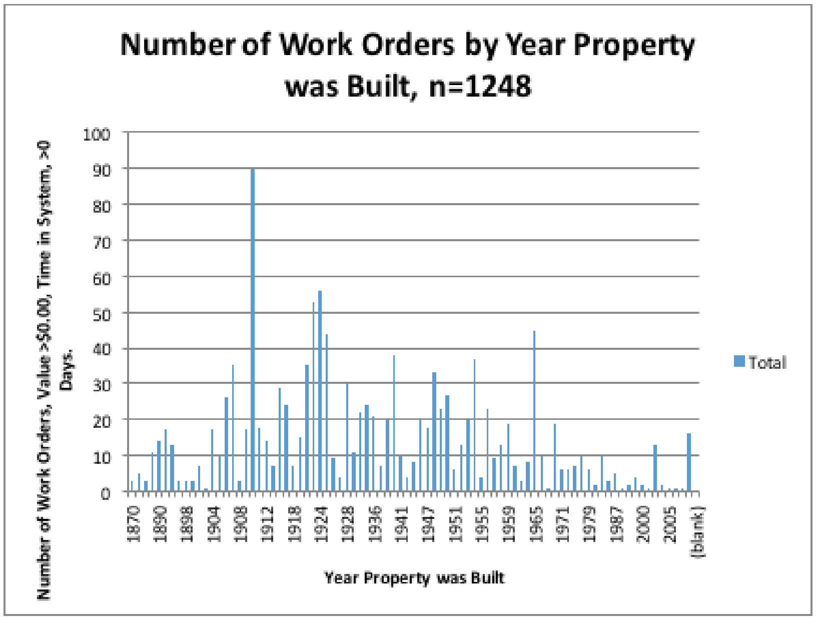


Figure 3.1 Number of Work Orders by Year.

When comparing this to the mean age of properties (each physical building only counted once) we find that the mean age of construction is 1939, indicating that older properties may have more work orders performed as a proportion of the total population. For all work orders where the cost to the owner was greater than $0.00, and where the time in the system was documented as greater than 0 days, the distribution of work orders by age of property is approximately symmetrical and a satisfactory kurtosis for normal distribution. The frequency of work orders with a cost greater than $0.00, where the work order spent more than 0 days in the system—indicating that the work order was posted for assignment and not just billed out in the system—is shown below. We find that 885 of 1248 work orders (70.91% of the sample) were for properties constructed prior to 1950 (at least 68 years old).

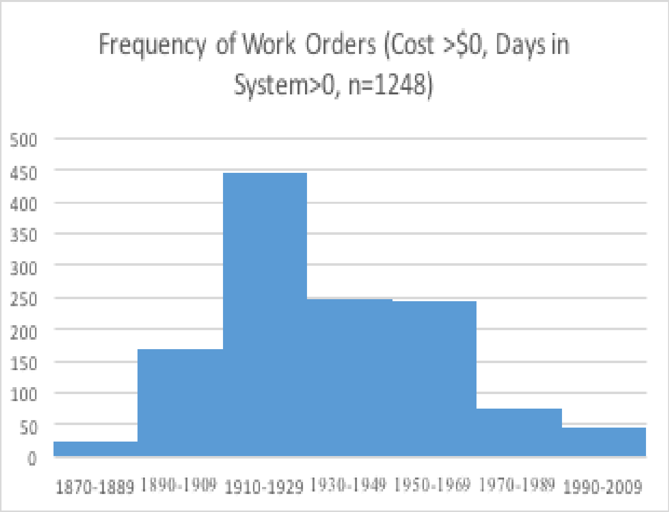


Figure 3.2 Frequency of Work Orders by Year.

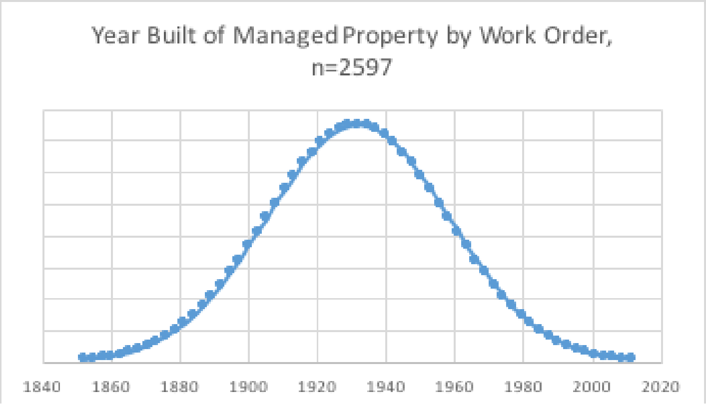


Figure 3.3 Summary Statistics on Year Built by Work Order.

Descriptive Statistics for Year Built by Work Order	
Mean	1931.83558
Standard Error	0.520322061
Median	1925
Mode	1910
Standard Deviation	26.51601249
Sample Variance	703.0989185
Kurtosis	0.205397273
Skew	0.603393661
Range	148
Minimum	1860
Maximum	2008
Sum	5016977
Count	2597
Confidence Level(95.0%)	1.020288198

Table 3.1 Data for Figure 3.3.

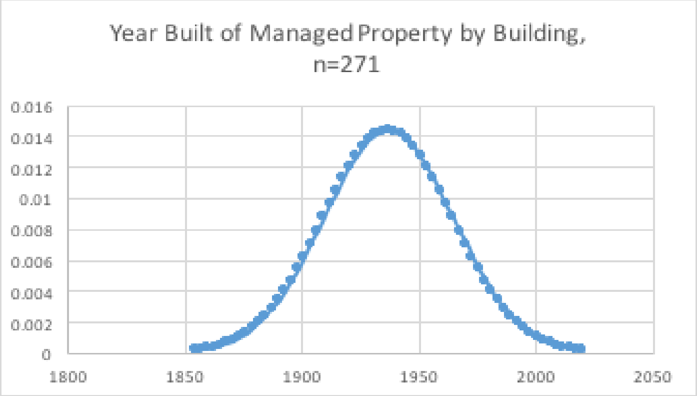


Figure 3.4 Summary Statistics on Year Built by Building.

Descriptive Statistics for Year Built By Property	
Mean	1936.900369
Standard Error	1.6806641
Median	1939
Mode	1965
Standard Deviation	27.66722288
Sample Variance	765.4752221
Kurtosis	-0.36215025
Skew-ness	0.288847413
Range	138
Minimum	1870
Maximum	2008
Sum	524900
Count	271
Confidence Level(95.0%)	3.308873029

Table 3.2 Data for Figure 3.4.

More than half of the sample (51.04%) were work orders on properties older than 88 years (built 1929 or earlier). Only 9.5% of the work orders were on properties built in 1970 or later (48 years old or newer). Again the normal probability plot of the population indicates excellent distribution characteristics.

Correlations for Age and Cost		Built	Cost	Age
Built	Pearson Correlation	1	.016	-.041
	Sig. (2-tailed)		.583	.145
	Sum of Squares and Cross-products	859389.576	641356.813	-53807.287
	Covariance	689.166	514.320	-43.149
	N	1248	1248	1248
Cost	Pearson Correlation	.016	1	.263**
	Sig. (2-tailed)	.583		.000
	Sum of Squares and Cross-products	641356.813	1973523993.908	16407793.355
	Covariance	514.320	1582617.477	13157.813
	N	1248	1248	1248
Age	Pearson Correlation	-.041	.263**	1
	Sig. (2-tailed)	.145	.000	
	Sum of Squares and Cross-products	-53807.287	16407793.355	1979614.997
	Covariance	-43.149	13157.813	1587.502
	N	1248	1248	1248

Table 3.3 Correlations for Age and Total Cost for Year Built.

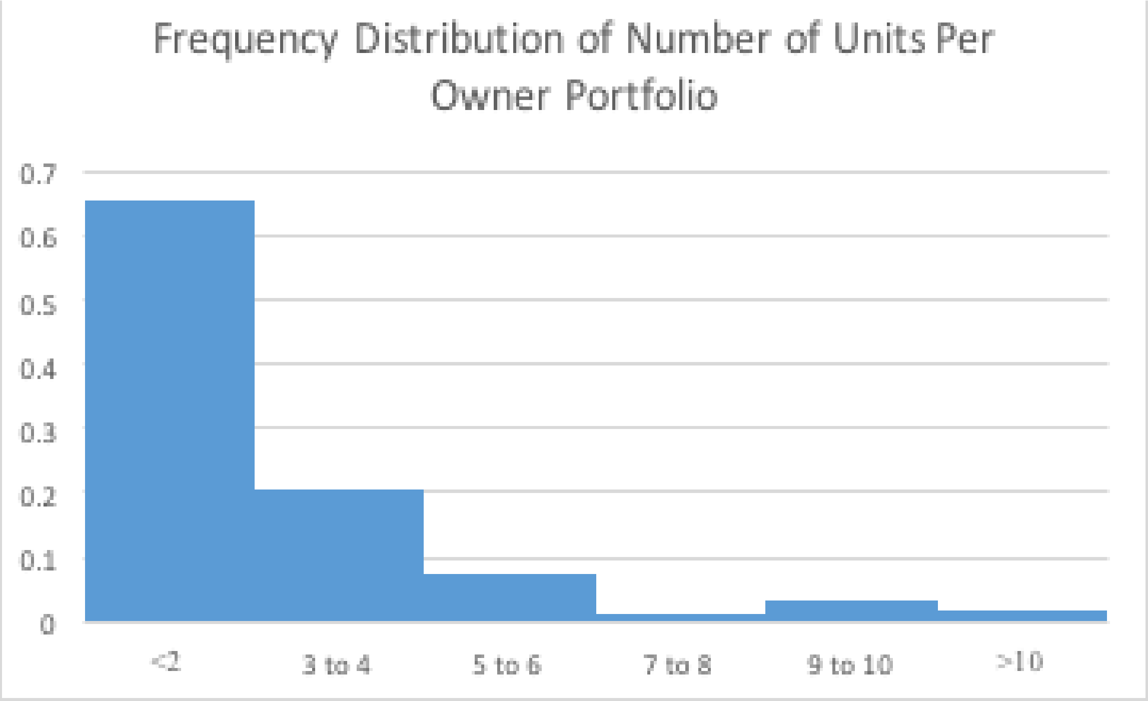


Figure 3.5 Frequency of Units Per Portfolio.

In the case studies, we evaluate a set of 39 sequential jobs. These jobs are evaluated in batches of assignment of 13, 26 and 39 work orders. Among the samples for each batch, the age of the properties are likewise similarly distributed, normally with little skewness and kurtosis. While the average age of the 13 instance set has a mean age of construction of 1925, the set of 39 jobs indicates an average date of construction of 1932. The mean distribution between the 26 and 39 instance set is very similar. Compared to the overall sample and the reduced samples, the dataset indicates a high level of normality for age of property.

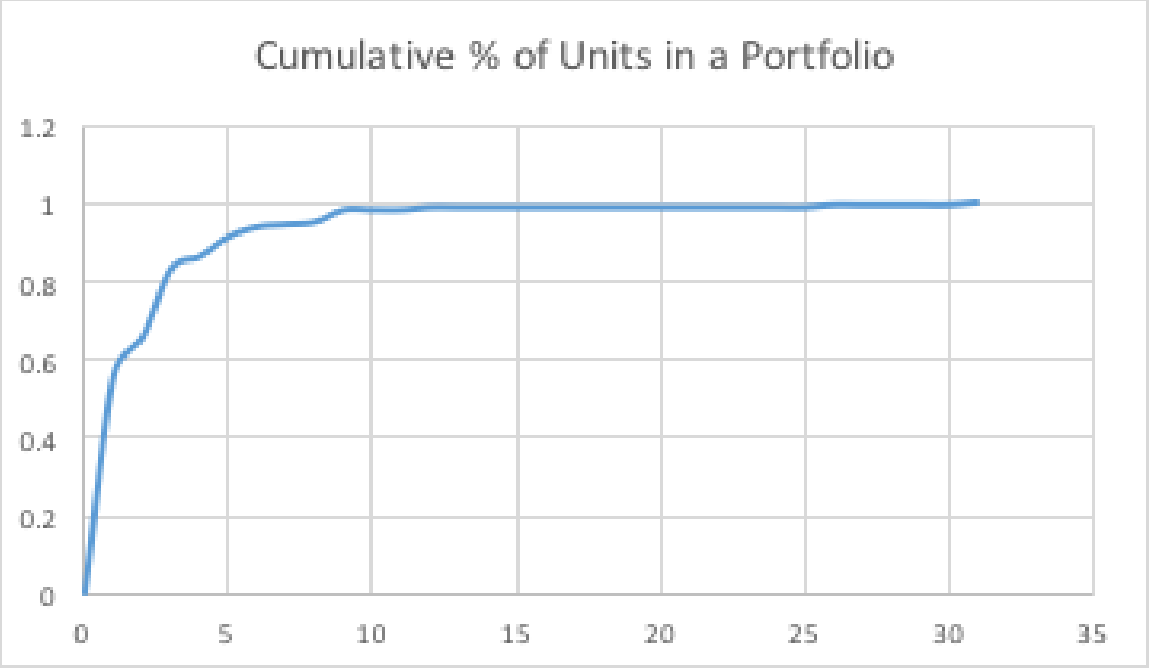


Figure 3.6 Cumulative % of Units Per Portfolio.

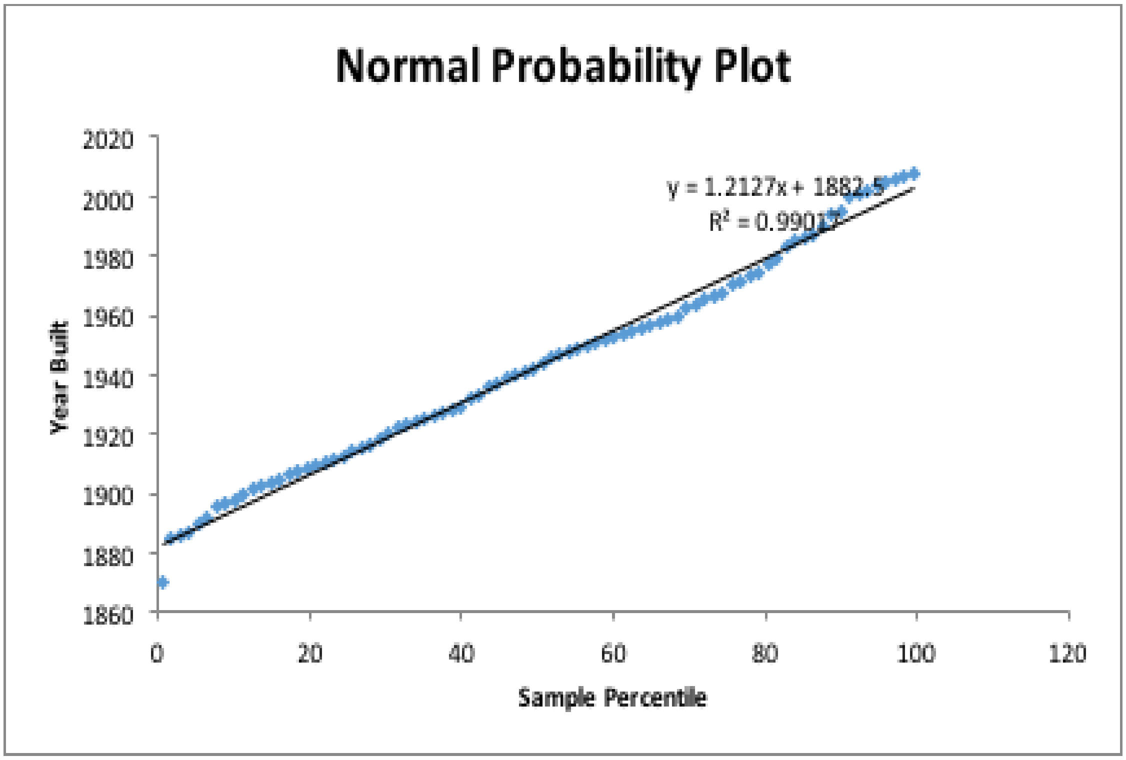


Figure 3.7 Linear Estimation for Year Built.

When considering the age of the year built of the property and the age of a property, the length of time a work order is in the system before completion, and the cost of a work order, we find that there is no statistically significant correlation between the age of property and the cost of a work order. The managerial implications of this finding are that work costs scale approximately normally based on something *other* than age of a building. We also find that there is a significant relationship ($p<.01$) between the time a work order remains in the system before completion, and the cost of a work order. This may indicate that more expensive work takes longer time of performance.

Year Built (39 Jobs)			Year Built (26 Jobs)			Year Built (13 Jobs)	
Mean	1932.410256		Mean	1929.846154		Mean	1925.076923
Standard Error	4.228895835		Standard Error	4.79123954		Standard Error	7.103142622
Median	1932		Median	1927		Median	1923
Mode	1923		Mode	1923		Mode	1923
Standard Deviation	26.40944603		Standard Deviation	24.43062391		Standard Deviation	25.61074494
Sample Variance	697.4588394		Sample Variance	596.8553846		Sample Variance	655.9102564
Kurtosis	0.344899725		Kurtosis	-0.799845849		Kurtosis	0.024690472
Skew	0.413452421		Skew	-0.029204135		Skew	0.63041551
Range	122		Range	91		Range	85
Minimum	1886		Minimum	1886		Minimum	1892
Maximum	2008		Maximum	1977		Maximum	1977
Sum	75364		Sum	50176		Sum	25026
Count	39		Count	26		Count	13
Confidence Level(95.0%)	8.560952049		Confidence Level(95.0%)	9.867742548		Confidence Level(95.0%)	15.47641828

Table 3.4 Descriptive Statistics for Year Built, 39, 26 and 13 Jobs.

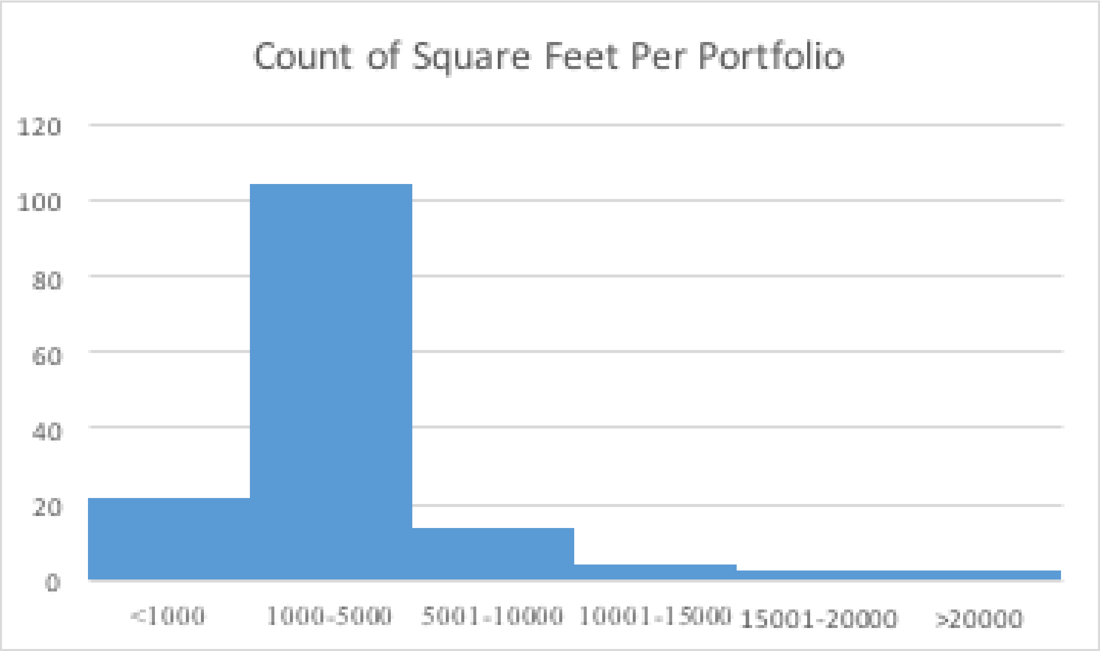


Figure 3.8 Frequency of Portfolio Square Feet.

It may also indicate that more costly work orders consist of more task complexity. However, it is not to say that labor costs, materials costs, or a combination of labor, material and travel are the significant contributors to this cost. We intend to explore this aspect later in this work.

When evaluating the size of an owner’s portfolio, approximately 65% consist of less than 2 properties, with 20.7% of owners possessing 2-4 properties. Less than 2% of portfolios consist of more than 10 properties. 93% own less than 6 properties. The 95% confidence interval estimate of the sample mean number of properties in a portfolio is 2 to 3.17 units per owner. A cumulative 95% of owners own less than 8 properties.

104 portfolios, or 65% of portfolios, consist of between 1000-5000 square feet of leasable space. 88% of portfolios consist of less than 10,000 square feet. Only three portfolios consist of more than 20,000 square feet. The mean square feet per portfolio is 3,468.98 with a 95% confidence interval estimate of the mean of 2,768.75 and 4,169.21. The data is moderately skewed to the right, and indicates a high level of aggregation about the mean, with a kurtosis of 13.96.

Descriptive Statistics for Size of Portfolio in Square Feet	
Mean	3468.986667
Standard Error	354.3692499
Median	1824.5
Mode	3600
Standard Deviation	4340.119214
Sample Variance	18836634.79
Kurtosis	13.95833579
Skew	3.396060097
Range	28111
Minimum	795
Maximum	28906
Sum	520348
Count	150
Confidence Level(95.0%)	700.2383076

Table 3.5 Statistics for Size of Portfolio.

Descriptive Statistics on Number of Units in Portfolio	
Mean	2.616352201
Standard Error	0.28465502
Median	1
Mode	1
Standard Deviation	3.589363228
Sample Variance	12.88352838
Kurtosis	35.22990996
Skewness	5.255852301
Range	30
Minimum	1
Maximum	31
Sum	416
Count	159
Confidence Level(95.0%)	0.562219873

Table 3.6 Statistics for Units in Portfolio.

Descriptive Statistics of Owner Cost per Work Order	
Mean	336.26737
Standard Error	18.45406243
Median	120
Mode	45
Standard Deviation	940.4332167
Sample Variance	884414.6351
Kurtosis	113.0630658
Skew	8.80016015
Range	19493.75
Minimum	0
Maximum	19493.75
Sum	873286.36
Count	2597
Confidence Level(95.0%)	36.18616911

Table 3.7 Statistics Cost Per Work Order.

Owner Cost/SQFT	
Mean	0.498253795
Standard Error	0.095094047
Median	0.19837814
Mode	#N/A
Standard Deviation	0.855846419
Sample Variance	0.732473092
Kurtosis	14.38545827
Skew	3.567448865
Range	5.086584375
Minimum	0
Maximum	5.086584375
Sum	40.35855738
Count	81
Confidence Level(95.0%)	0.189243184

Table 3.8 Statistics Cost Per Square Feet.

The mean owner cost for a work order for all jobs in the data set was $336.26. with an interval (95%) of between $300.08 and $372.45. Some jobs in the data set were performed for no cost, whereas the most costly work order was at $19,493.75. The data is skewed toward higher price and is highly aggregated about the mean. The total billed cost to the owner of the data time range for work orders was $873,286.36. The mean cost per square foot for all portfolios where such information was available, was $.498/square foot of leasable space. This indicates that on average, an owner would pay approximately 50 cents per square foot per work order, with a 95% confidence interval of $.31 and $.69 per square foot per work order. A plot of expected versus observed costs per square foot indicates that data points drift to the higher end of cost for a handful of portfolios. Managerial insight would indicate we evaluate the specific phenomenon of these portfolios and determine what single large projects—possibly gut-rehab or large ticket item work orders—are included in the portfolio.

There is a significant correlation between the sum of square feet in a port- folio, the sum of owner cost, and the count of unit. This is expected, that the total cost for an owner

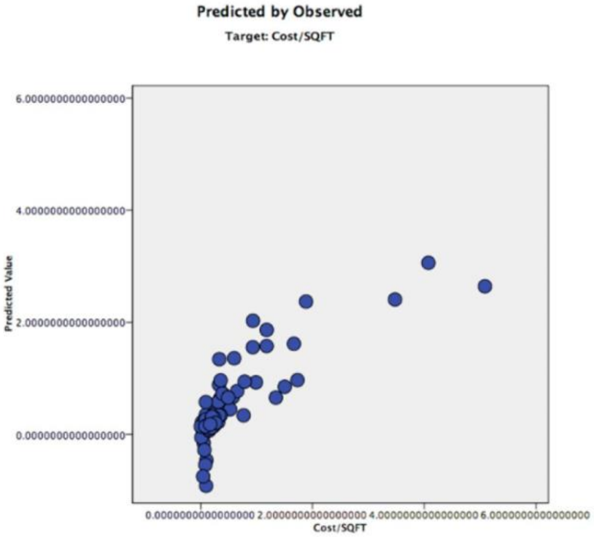


Figure 3.9 Target Cost per Square Feet, Predicted vs. Observed.

to maintain his portfolio should increase as more units or larger units are included in a property portfolio. However, what is interesting is the relative cost per square foot and the correlation with the total owner cost over the data time period of 18 months. There appears to be a statistically significant relationship between the total cost for an owner to maintain his property and the total number of square feet in the port- folio. However, this is not the case for the number of units in a portfolio and the cost per square foot. This may indicate that non-property factors, such as labor cost, travel cost, or other costs that are not due to the physical age of the property contribute to a higher cost per square foot for maintenance. The relationship between cost per square foot and the sum of owner cost by portfolio, is significant at the p<.01 level (two-tailed, .003) and explains .326 of the variance.

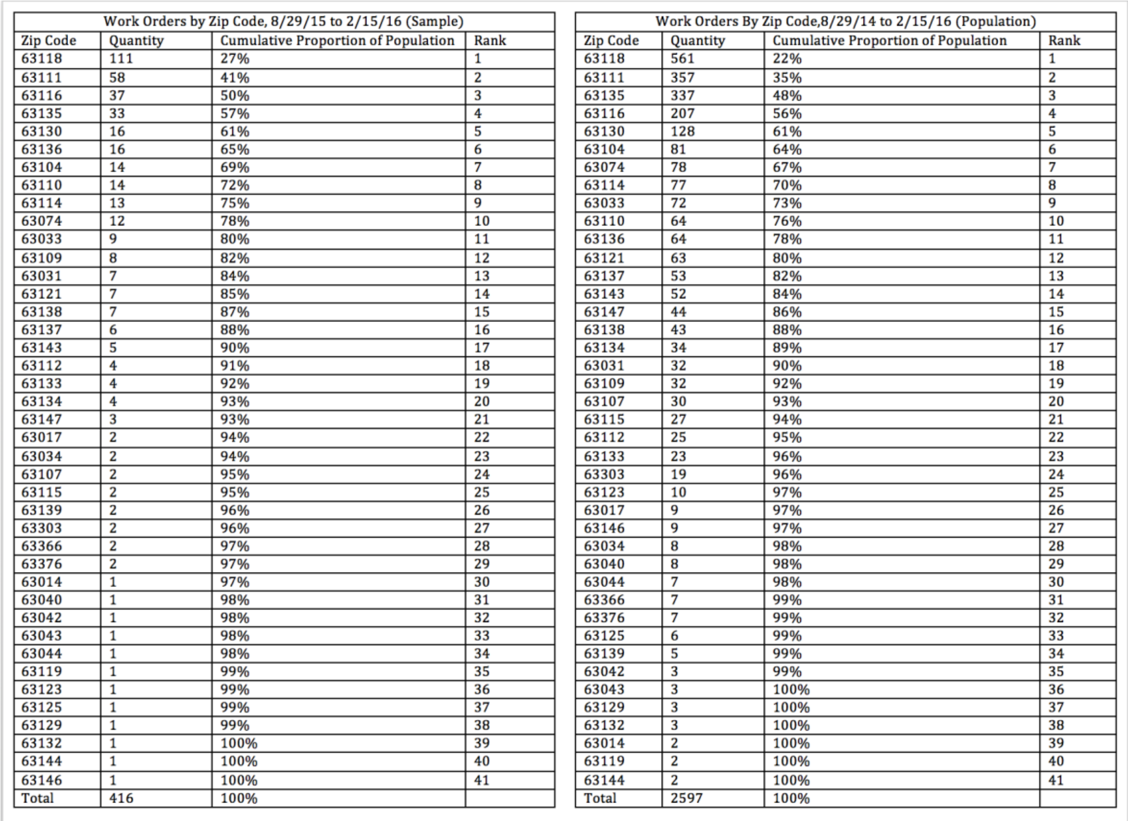
Correlations for Portfolio Total Square Feet, Total Owner Maintenance Cost, Maintenance Cost per Square Foot and Number of Units Per Owner

		Sum of Square ft.	Total Owner Cost	Cost/SQFT	Count of Unit
Sum of Square ft.	Pearson Correlation	1	.604**	-.057	.696**
	Sig. (2-tailed)		.000	.617	.000
	Sum of Squares and Cross-products	33097320748.988	21505935447.082	-78856.422	5337335.288
	Covariance	418953427.202	272227030.976	-998.183	67561.206
	N	80	80	80	80
Sum of Owner Cost	Pearson Correlation	.604**	1	.326**	.721**
	Sig. (2-tailed)	.000		.003	.000
	Sum of Squares and Cross-products	21505935447.082	38333814593.745	487504.086	5949893.734
	Covariance	272227030.976	485238159.414	6170.938	75315.111
	N	80	80	80	80
Cost/SQFT	Pearson Correlation	-.057	.326**	1	.184
	Sig. (2-tailed)	.617	.003		.103
	Sum of Squares and Cross-products	-78856.422	487504.086	58.477	59.196
	Covariance	-998.183	6170.938	.740	.749
	N	80	80	80	80
Count of Unit	Pearson Correlation	.696**	.721**	.184	1
	Sig. (2-tailed)	.000	.000	.103	
	Sum of Squares and Cross-products	5337335.288	5949893.734	59.196	1778.388
	Covariance	67561.206	75315.111	.749	22.511
	N	80	80	80	80

**. Correlation is significant at the 0.01 level (2-tailed).

Table 3.9 Correlations for Portfolio Size and Maintenance Cost.

When evaluating both the complete sample set, and a selection of 416 work orders from the last 6 months of the data set, we find that the majority of work orders (greater than 80%) are derived from the top 12 zip codes. The top two zip codes (63118 and 63111) both increased in relative proportion of total work orders for the sample versus the population. The proportion of work orders that were performed in zip code 63135 increased, and switched places with 63116 at the third rank, in more recent work orders. 63116 fell to rank 4. The proportion of work orders in zip code 63130 remained approximately the same. It is from the top 15 zip codes in the population that 10 popular work zones were selected for further evaluation in a computer optimization later in this work. As noted, while the top 5 zip codes remain the same, there is considerable movement in rank for the remaining 5 zip codes.



Work Orders by Zip Code, 8/29/15 to 2/15/16 (Sample)			
Zip Code	Quantity	Cumulative Proportion of Population	Rank
63118	111	27%	1
63111	58	41%	2
63116	37	50%	3
63135	33	57%	4
63130	16	61%	5
63136	16	65%	6
63104	14	69%	7
63110	14	72%	8
63114	13	75%	9
63074	12	78%	10
63033	9	80%	11
63109	8	82%	12
63031	7	84%	13
63121	7	85%	14
63138	7	87%	15
63137	6	88%	16
63143	5	90%	17
63112	4	91%	18
63133	4	92%	19
63134	4	93%	20
63147	3	93%	21
63017	2	94%	22
63034	2	94%	23
63107	2	95%	24
63115	2	95%	25
63139	2	96%	26
63303	2	96%	27
63366	2	97%	28
63376	2	97%	29
63014	1	97%	30
63040	1	98%	31
63042	1	98%	32
63043	1	98%	33
63044	1	98%	34
63119	1	99%	35
63123	1	99%	36
63125	1	99%	37
63129	1	99%	38
63132	1	100%	39
63144	1	100%	40
63146	1	100%	41
Total	416	100%	

Work Orders By Zip Code,8/29/14 to 2/15/16 (Population)			
Zip Code	Quantity	Cumulative Proportion of Population	Rank
63118	561	22%	1
63111	357	35%	2
63135	337	48%	3
63116	207	56%	4
63130	128	61%	5
63104	81	64%	6
63074	78	67%	7
63114	77	70%	8
63033	72	73%	9
63110	64	76%	10
63136	64	78%	11
63121	63	80%	12
63137	53	82%	13
63143	52	84%	14
63147	44	86%	15
63138	43	88%	16
63134	34	89%	17
63031	32	90%	18
63109	32	92%	19
63107	30	93%	20
63115	27	94%	21
63112	25	95%	22
63133	23	96%	23
63303	19	96%	24
63123	10	97%	25
63017	9	97%	26
63146	9	97%	27
63034	8	98%	28
63040	8	98%	29
63044	7	98%	30
63366	7	99%	31
63376	7	99%	32
63125	6	99%	33
63139	5	99%	34
63042	3	99%	35
63043	3	100%	36
63129	3	100%	37
63132	3	100%	38
63014	2	100%	39
63119	2	100%	40
63144	2	100%	41
Total	2597	100%	

Table 3.10 Number of Work Orders by Zip Code, Sample.

Table 3.11 Number of Work Orders by Zip Code, Population.

Descriptive Statistics for Property Features Within 10 Select Zip Codes									
Row Labels	Average of Beds	Std. Dev of Beds	Var. of Beds	Average of Baths	Std. Dev of Baths	Var. of Baths	Average of Sq. ft.	Std. Dev of Sq. ft.	Var. of Sq. ft.
63033	3.00	0.50	0.25	2.00	0.50	0.25	1204.11	540.26	291881.86
63074	2.75	0.75	0.57	1.17	0.25	0.06	982.17	613.74	376680.15
63104	2.21	1.12	1.26	1.54	0.84	0.71	1246.50	759.72	577167.35
63110	2.29	0.47	0.22	1.18	0.37	0.14	1322.29	243.81	59445.45
63111	2.67	1.26	1.59	1.89	0.98	0.97	1388.38	1008.74	1017563.89
63114	2.31	0.85	0.73	1.23	0.44	0.19	498.77	506.57	256617.03
63116	1.78	0.89	0.79	1.38	0.75	0.56	995.76	952.26	906806.86
63118	2.28	0.90	0.80	1.37	0.59	0.35	1549.65	874.25	764315.14
63130	2.69	0.48	0.23	1.25	0.41	0.17	1211.25	446.18	199079.53
63135	2.70	0.77	0.59	1.15	0.34	0.12	937.18	347.24	120575.72
Measure Mean	2.39	0.97	0.94	1.44	0.70	0.50	1276.84	842.28	709439.42
n=317									

Table 3.12 Properties Features of Zip Codes Selected in this Study.

For the zip codes being used in this research, those properties were collected (n=317). The summary statistics are collected for each zip code. Overall, the mean number of bedrooms is 2.39 and the mean number of bathrooms is 1.44. Average square feet is 1276.84.

Work Order by Request Type		
Row Labels	Count of Type	Proportion of Population
Emergency Service Request	49	2%
Estimate	3	0%
General	6	0%
Inspection	719	28%
Service Request	1760	68%
Turnover	1	0%
Violation	27	1%
Winterize	32	1%
Grand Total	2597	100%

Table 3.13 Work Order by Request Type.

The operational nature of the type of work order is also interesting. Emergency Service calls only comprise 2% of total service requests (population); however they require immediate attention (no greater than 24 hours). Inspections are scheduled quarterly for each property, generally around higher priority work orders, and while they contribute to 28% of the work orders, they contribute only 3.7% of total costs. Service Requests (68% of all work orders) contribute 81.5% of owner maintenance costs. Generally, these tasks must be performed in a reasonable time, subject to customer satisfaction (both owner and tenant).

One category of work that results from Inspection, Service Request, Violation or an Emergency, is a Make Ready. Make Ready is where a more complete scope of work is required in order to make a rental property marketable or in compliance with local regulations. These 123 of 2597 Work Orders (4.7% of work assigned) contribute 22% of all owner costs. 55% of all work orders were performed by a single vendor, contributing to 78.33% of costs. Of these 1428 work orders, they include 69% of all Emergency Service Requests, 81% of Violations, and 68% of Service Requests. 87.8% of the Make Ready Projects (108/123) were performed by a single vendor, contributing 88.4% of all make ready costs.

Work Order Type For A Single Vendor		
Type of Work order	Count of Type	Percentage
Emergency Service Request	30	16%
Inspection	12	6%
Service Request	122	65%
Violation	21	11%
Winterize	3	2%
Grand Total	188	100%

Table 3.14 Work Order Frequency for A Prime Vendor.

Work Order Category For a Single Vendor		
Category of Work Order	Count of Category	Percentage
Planned Maintenance	15	8%
Unplanned Maintenance	173	92%
Grand Total	188	100%

Table 3.15 Frequency of Work Order by Category.

From a sample of 2,598 work orders, 1555 were entered with data specifying the time required to close the work order. The time to close a work order was on average, 32.95 days, with a standard deviation of 62.34 days.

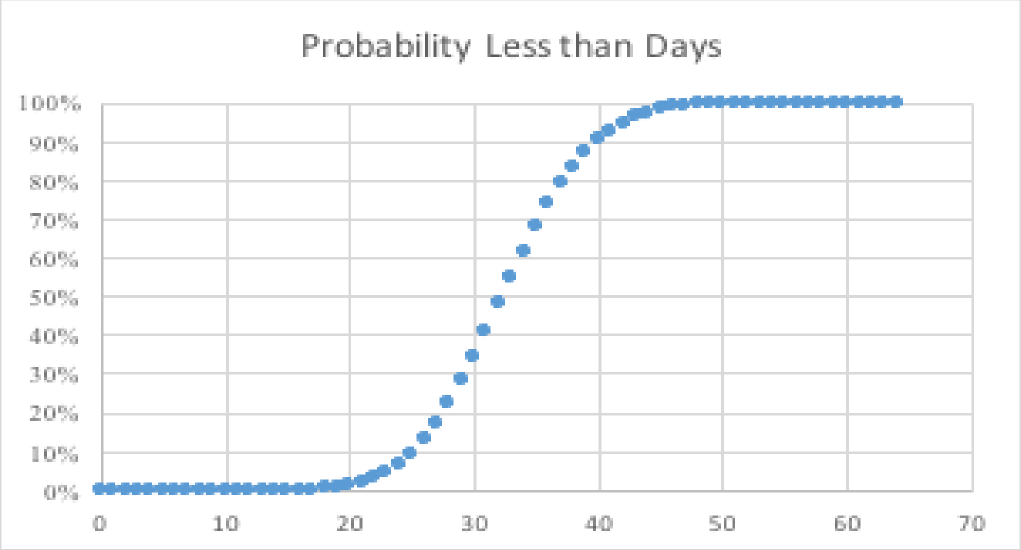
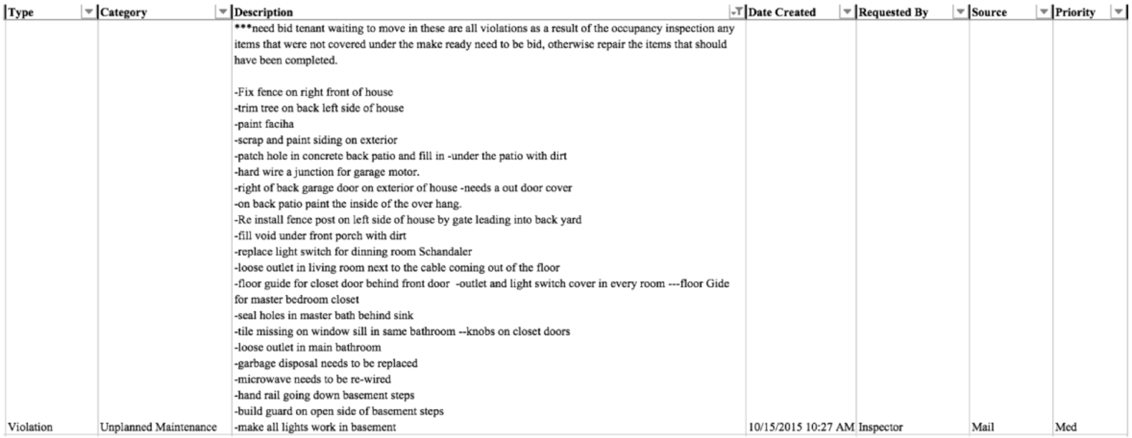


Figure 3.10 Probability of a Work Order Taking Less than a Certain Number of Days.

When parsing the date of completion for work orders into time windows of 0 to 30 days, 31 to 60 days, and 61to 90 days, we observe a general positive linear trend for the periods from 0-30 days and from 31-60 days, indicating that cost of work increases over time to perform the work. However, after 61 days, the costs begin to decrease, indicating a potential over-run of work time, delay, scope creep, or some other non-value added delay not tied to cost of performance.



Type	Category	Description	Date Created	Requested By	Source	Priority
Violation	Unplanned Maintenance	***need bid tenant waiting to move in these are all violations as a result of the occupancy inspection any items that were not covered under the make ready need to be bid, otherwise repair the items that should have been completed. -Fix fence on right front of house -trim tree on back left side of house -paint faciha -scrap and paint siding on exterior -patch hole in concrete back patio and fill in -under the patio with dirt -hard wire a junction for garage motor. -right of back garage door on exterior of house -needs a out door cover -on back patio paint the inside of the over hang. -Re install fence post on left side of house by gate leading into back yard -fill void under front porch with dirt -replace light switch for dinning room Schandaler -loose outlet in living room next to the cable coming out of the floor -floor guide for closet door behind front door -outlet and light switch cover in every room ---floor Gide for master bedroom closet -seal holes in master bath behind sink -tile missing on window sill in same bathroom --knobs on closet doors -loose outlet in main bathroom -garbage disposal needs to be replaced -microwave needs to be re-wired -hand rail going down basement steps -build guard on open side of basement steps -make all lights work in basement	10/15/2015 10:27 AM	Inspector	Mail	Med

Table 3.16 Sample Raw Data for a Work Order.

These may be jobs that are considered low priority and are therefore assigned last—especially if labor resources is needed elsewhere; whereas the objective is to ensure low value jobs are performed quicker as opposed to later in order to capture value from the work as early as possible in a revenue cycle.

For work orders ranging from 90-120 days to complete, the cost for these jobs remains flat at just under $1000 per job. A few points of data in this range are apparent make ready projects, potentially of low priority. It is also possible that funding delay, budgetary constraints and progress payment may cause delay in project closeout. However, most of the data in this time range show lower value work; if a convenient way to schedule these jobs earlier is possible—considering an average cost per job of less than $400—these jobs should be performed much earlier in the schedule and motivates the need for short term scheduling.

For work orders that range 120-150 days in age, these jobs appear to be of two types: large make ready projects and very low cost work orders (make-good work, remedy-to-cure work, or re-work). From a quality perspective the low value work should be scheduled quickly and performed with competence to reduce re-work. The large value projects, whenever possible, need to maintain their integrity as a project as opposed to a task. However, this is difficult in the maintenance and repair operational environment where temporal pressures drive scheduling and assignment. The ability to manage larger scopes in line with tasks becomes an arduous undertaking for a single manager. Overall the summary of age data on work orders shows that there is relatively good cost benefit for jobs of increasing age up to no greater than 60 days, at which point the return value of work orders drops off.

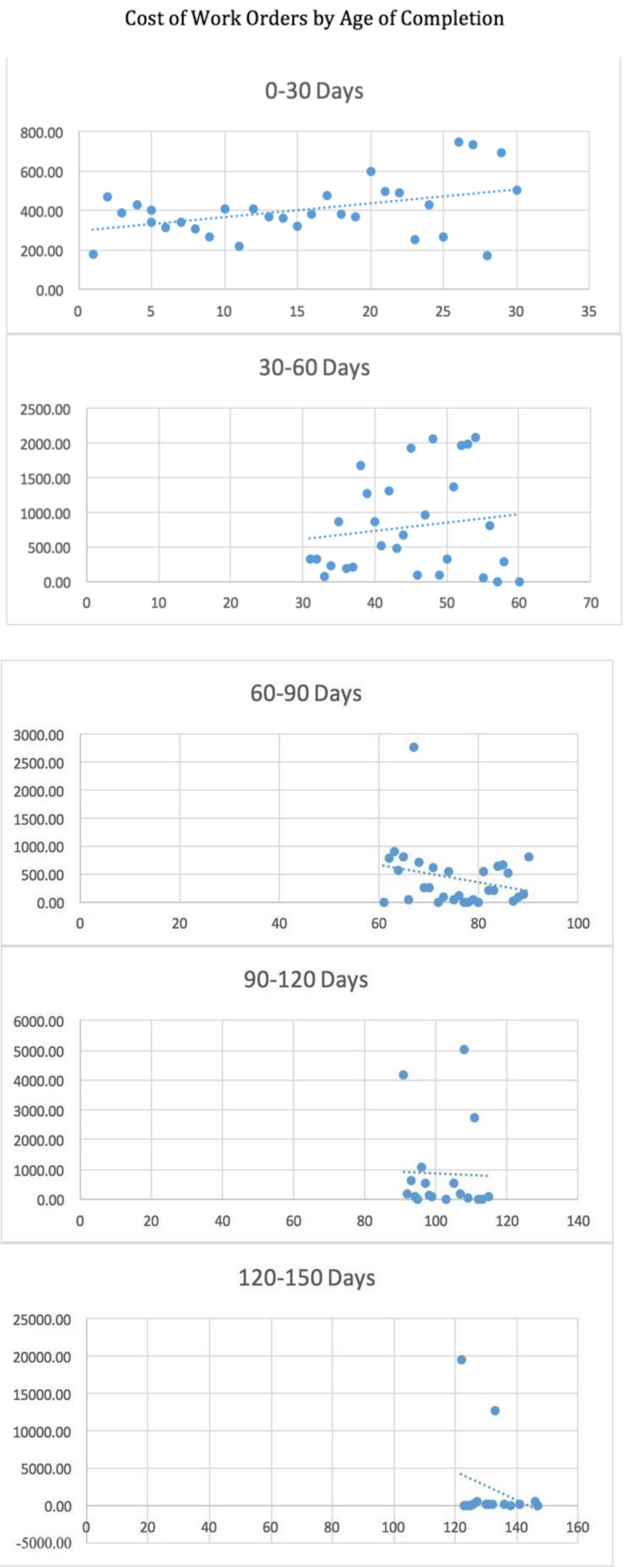
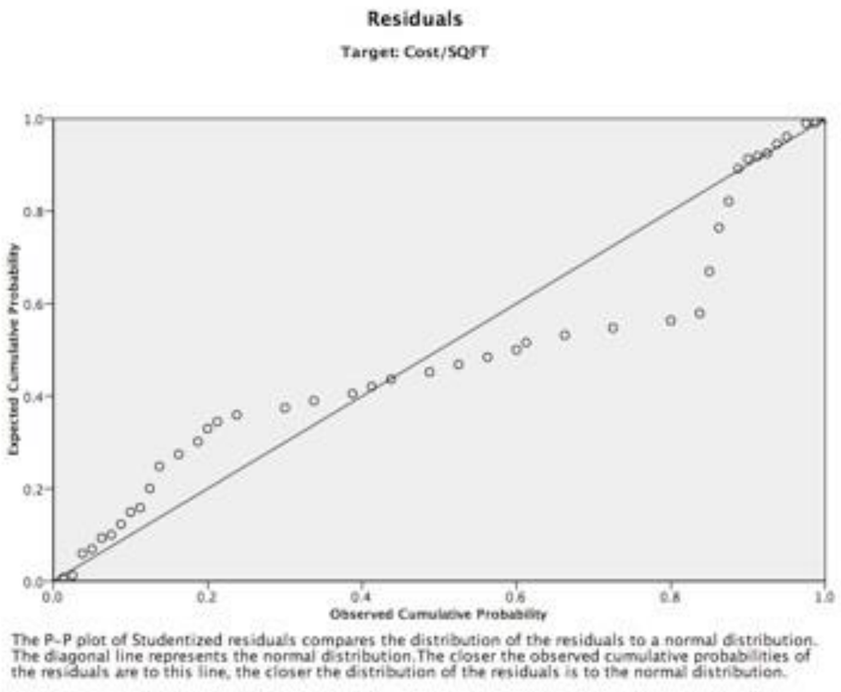


Figure 3.11 Work Order Cost by Time to Complete



The P-P plot of Studentized residuals compares the distribution of the residuals to a normal distribution. The diagonal line represents the normal distribution.The closer the observed cumulative probabilities of the residuals are to this line, the closer the distribution of the residuals is to the normal distribution.

Figure 3.12 Studentized Residuals of the Observed Cumulative Probability of the TargetCost per Square Foot.

When running the total cost per square foot cumulative probability in SPSS, we find that the residuals for the data set compared to the linear trend line indicate deviation in the residual of cost per square foot. Cost appears to be disproportionately greater up to 40% cumulative probability, and then indicates a more gradual increase in cost/square foot until around 80% cumulative probability.

Finally, when evaluating the type of work order when evaluated for skill level and worker assigned to perform the job, we find that there is a need for workers who have a higher level of skill. On average the number of jobs per worker requiring a level of low skill (D) is 2.6, compared to an average demand per worker for jobs requiring high skill (A) is 11.1. Jobs that require a moderate level of skill (B, C) are in the range of on average, 5-7 jobs per worker, supporting a need for appropriate assignment of job of skill level to worker with that skill, to reduce process time mismatch.

Distribution of Number of Jobs per Worker by Skill Level, N=350

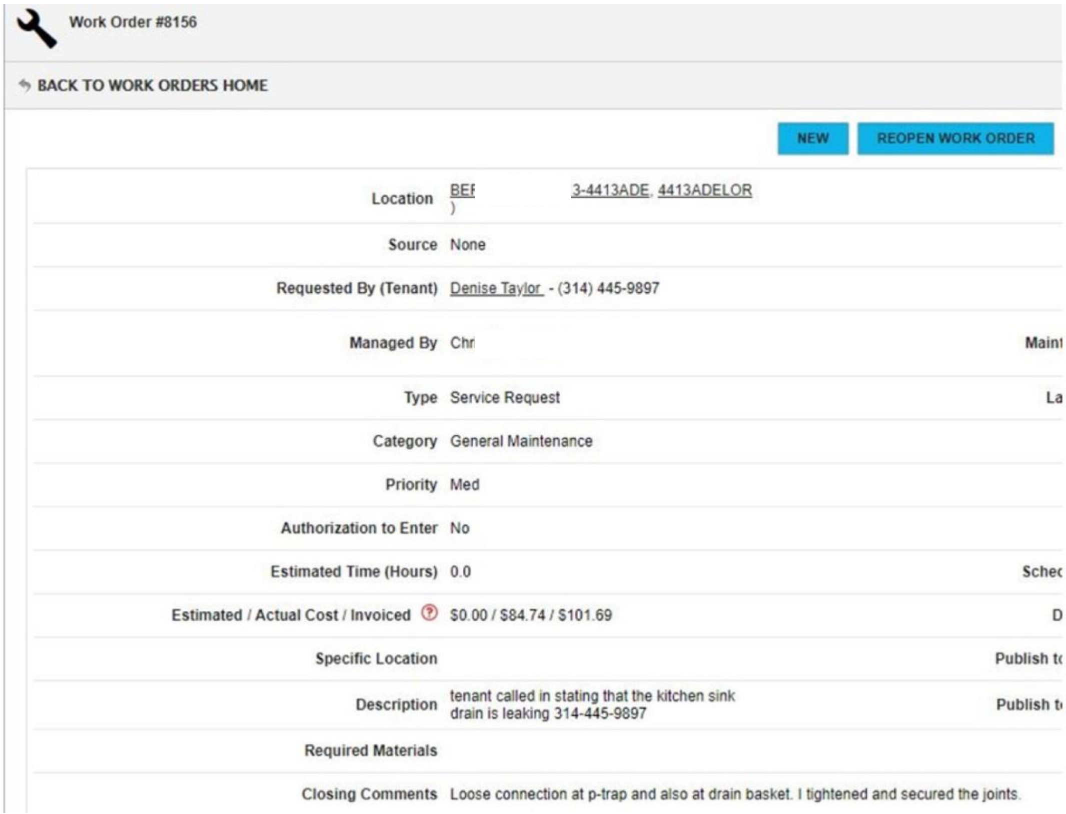
Level A Jobs		Level B Jobs		Level C Jobs		Level C Jobs		Level D Jobs	
				Without Inspections		With Inspections			
Mean	11.1	Mean	5.428571	Mean	6.666667	Mean	19.44444	Mean	2.6
Standard Error	5.075978	Standard Error	1.875368	Standard Error	2.619372	Standard Error	9.922073	Standard Error	0.635959
Median	2.5	Median	3	Median	3	Median	4	Median	2
Mode	1	Mode	1	Mode	3	Mode	3	Mode	1
Standard Deviation	16.05165	Standard Deviation	4.961759	Standard Deviation	7.858117	Standard Deviation	29.76622	Standard Deviation	2.01108
Sample Variance	257.6556	Sample Variance	24.61905	Sample Variance	61.75	Sample Variance	886.0278	Sample Variance	4.044444
Kurtosis	2.161988	Kurtosis	-1.39762	Kurtosis	1.436163	Kurtosis	5.576788	Kurtosis	1.458287
Skew	1.665785	Skew	0.730695	Skew	1.615405	Skew	2.30063	Skew	1.405674
Range	47	Range	12	Range	22	Range	92	Range	6
Minimum	1	Minimum	1	Minimum	1	Minimum	1	Minimum	1
Maximum	48	Maximum	13	Maximum	23	Maximum	93	Maximum	7
Sum	111	Sum	38	Sum	60	Sum	175	Sum	26
Count	10	Count	7	Count	9	Count	9	Count	10
Confidence Level(95.0%)	11.48266	Confidence Level(95.0%)	4.588861	Confidence Level(95.0%)	6.040283	Confidence Level(95.0%)	22.88034	Confidence Level(95.0%)	1.43864

Table 3.17 Distribution of Jobs by Skill Level Per Worker.

3.4.2 Data Acquired from the Work Order

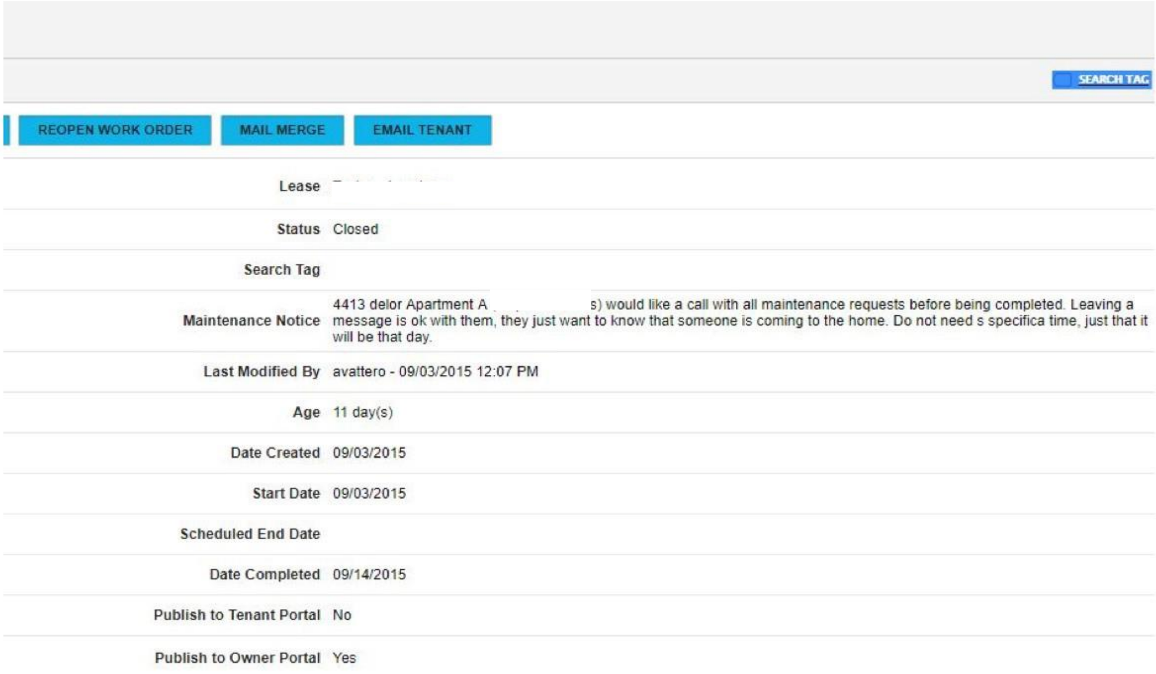
The Work Order is developed by the property manager to capture the salient features of a maintenance task, and includes the following information:

- WO#: Each worker was assigned a tracking number, in chronological order.
- Type: The category of work to be performed (service request, emergency service, inspection, violation).
- (Derived) Category: Whether the work to be performed is unplanned or planned.
- Description: A narrative description of the work order to be performed and any pertinent detail necessary to plan the work.
- Date Created: The date the work order was entered into the system by a staff member, tenant, or other agent.
- Requested By: The classification of individual who requested the work to be performed (i.e. owner, tenant, inspector).
- Source: How the work request is reported (i.e. email, tenant portal, phone, in person).
- Priority: The level of urgency for the work to be performed (i.e. high, medium, low).
- Approved date: The date the work order was approved by an authorized staff member.
- Start Date: The date work was to be started.
- Date Completed: The date work was closed in the system.
- Age from Creation (Days): The number of days since the work order was created.
- Age from Start (Days): The number of days since the work order was started.
- Vendors: The vendor is the company hired to perform the work. In our example, all workers are of the same vendor.
- Status: current state of the work (i.e. open, closed).
- Closing Comments: a narrative statement of work that was performed and remedy to initial cause for work order request.
- Owner Cost: The final cost to the owner.



Location	BEF [redacted] 3-4413ADE, 4413ADELOR)	
Source	None	
Requested By (Tenant)	Denise Taylor - (314) 445-9897	
Managed By	Chr [redacted]	Maint
Type	Service Request	La
Category	General Maintenance	
Priority	Med	
Authorization to Enter	No	
Estimated Time (Hours)	0.0	Schec
Estimated / Actual Cost / Invoiced ?	$0.00 / $84.74 / $101.69	D
Specific Location		Publish t
Description	tenant called in stating that the kitchen sink drain is leaking 314-445-9897	Publish t
Required Materials		
Closing Comments	Loose connection at p-trap and also at drain basket. I tightened and secured the joints.	

Figure 3.13a Sample of Work Order Entry Field in Management Software.



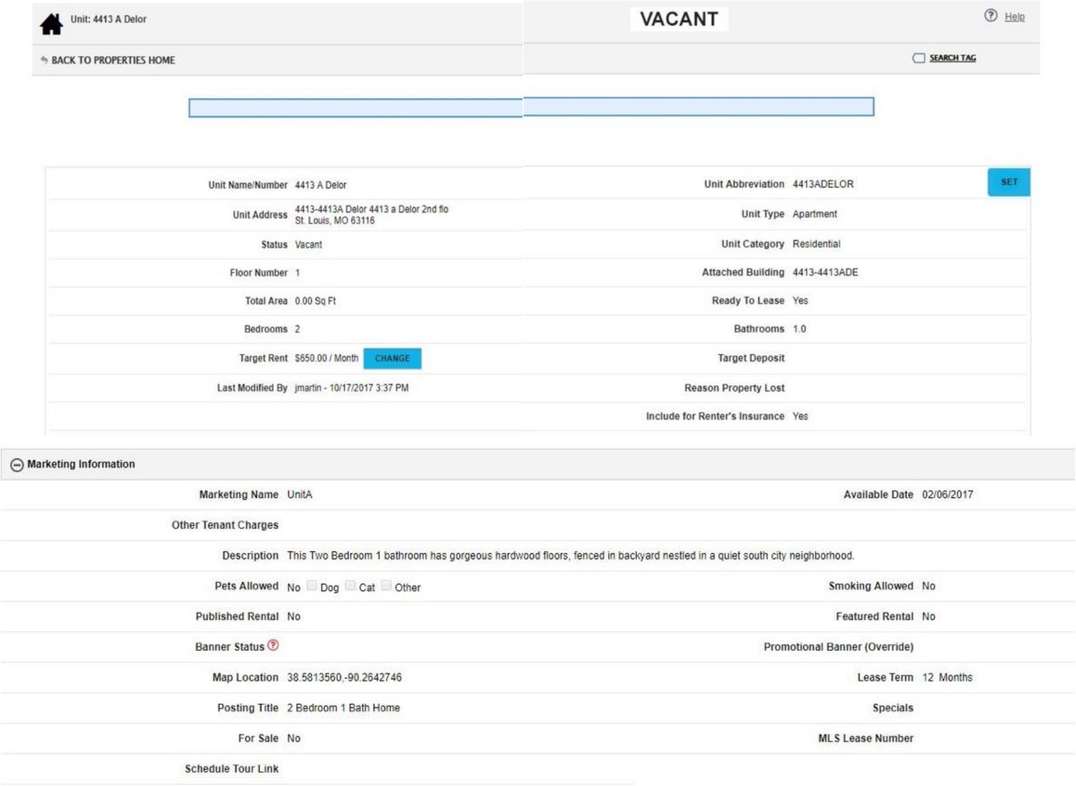
Lease	[redacted]
Status	Closed
Search Tag	
Maintenance Notice	4413 delor Apartment A [redacted] s) would like a call with all maintenance requests before being completed. Leaving a message is ok with them, they just want to know that someone is coming to the home. Do not need s specifica time, just that it will be that day.
Last Modified By	avattero - 09/03/2015 12:07 PM
Age	11 day(s)
Date Created	09/03/2015
Start Date	09/03/2015
Scheduled End Date	
Date Completed	09/14/2015
Publish to Tenant Portal	No
Publish to Owner Portal	Yes

Figure 3.13b Sample of Work Order Entry Field in Management Software.

3.4.3 Data Acquired from Property or Portfolio Profile

A Portfolio consists of a collection of properties owned by the same individual, company or investment group. The following information describes the physical dimension, location and age of a given property:

- Portfolio: Each work order is assigned to a portfolio consisting of a group of properties owned by the same business entity.



Unit Name/Number	4413 A Delor	Unit Abbreviation	4413ADELOR
Unit Address	4413-4413A Delor 4413 a Delor 2nd flo St. Louis, MO 63116	Unit Type	Apartment
Status	Vacant	Unit Category	Residential
Floor Number	1	Attached Building	4413-4413ADE
Total Area	0.00 Sq Ft	Ready To Lease	Yes
Bedrooms	2	Bathrooms	1.0
Target Rent	$650.00 / Month	Target Deposit	
Last Modified By	jmartin - 10/17/2017 3:37 PM	Reason Property Lost	
		Include for Renter's Insurance	Yes

Marketing Name	UnitA	Available Date	02/06/2017
Other Tenant Charges			
Description	This Two Bedroom 1 bathroom has gorgeous hardwood floors, fenced in backyard nestled in a quiet south city neighborhood.		
Pets Allowed	No ☐ Dog ☐ Cat ☐ Other	Smoking Allowed	No
Published Rental	No	Featured Rental	No
Banner Status		Promotional Banner (Override)	
Map Location	38.5813560,-90.2642746	Lease Term	12 Months
Posting Title	2 Bedroom 1 Bath Home	Specials	
For Sale	No	MLS Lease Number	
Schedule Tour Link			

Figure 3.14 Example of Data Entry Field for Unit in Management Software.

- Building: The building being managed, consisting of a physical street address.
- Unit: The specific dwelling unit within a multi-family dwelling.
- Zip: Postal Zip Code.
- Beds: The number of beds in the dwelling.
- Baths: The number of bathrooms in the dwelling.
- Sqft: The total square feet of livable space within the dwelling.
- Year Built: The year the dwelling was built.

3.4.4 Data Acquired from the Worker's Job Ticket

Other data were acquired through the more precise evaluation of individual work order job tickets used by workers in the performance of the work. These job tickets were carbon-duplicate paper copies and were meticulously transcribed into digital, working data during the cost-accounting and invoicing function by the vendor performing the work:

- Work Order Number: As reference din the Property Management System
- Job Ticket Number: Serial Number of the Job Ticket used for that Work Order.
- Date: Date of Work Order being performed.
- Address of Work Order: Location of Work Order
- Details: Diagnostic, Prescriptive Description of Work Performed, stated as a fix implemented and any follow up work (corrective or preventative maintenance) required.
- (Derived)Job Class: The type of skilled class that work order is classified to (i.e. mechanical, electrical, plumbing, security, miscellaneous).
- (Derived)Job Level: The level of skill required to complete that job (i.e. A, B, C, D).
- Laborer 1 ID: First Name of the primary worker assigned to a work order.
- Laborer 1 Time: The number of hours worked by Worker 1.
- Laborer 1 Cost: The hourly rate of worker 1.
- Laborer 2 ID: First Name of the second worker assigned to a work order.
- Laborer 2 Time: The number of hours worked by Worker 2.
- Laborer 2 Cost: The hourly rate of worker 2.
- Laborer 3 ID: First Name of the third worker assigned to a work order.
- Laborer 3 Time: The number of hours worked by Worker 3.
- Laborer 3 Cost: the hourly rate of worker 3.
- Materials Cost: the cost of all materials required to complete that work order.

3.4.5 Data Acquired from Invoice Calculation

Information from the field tickets were used to prepare the invoice. In this step, costs were calculated and totaled, and profit added to an invoice, along with closing comments to describe the extent of repair or remedy:

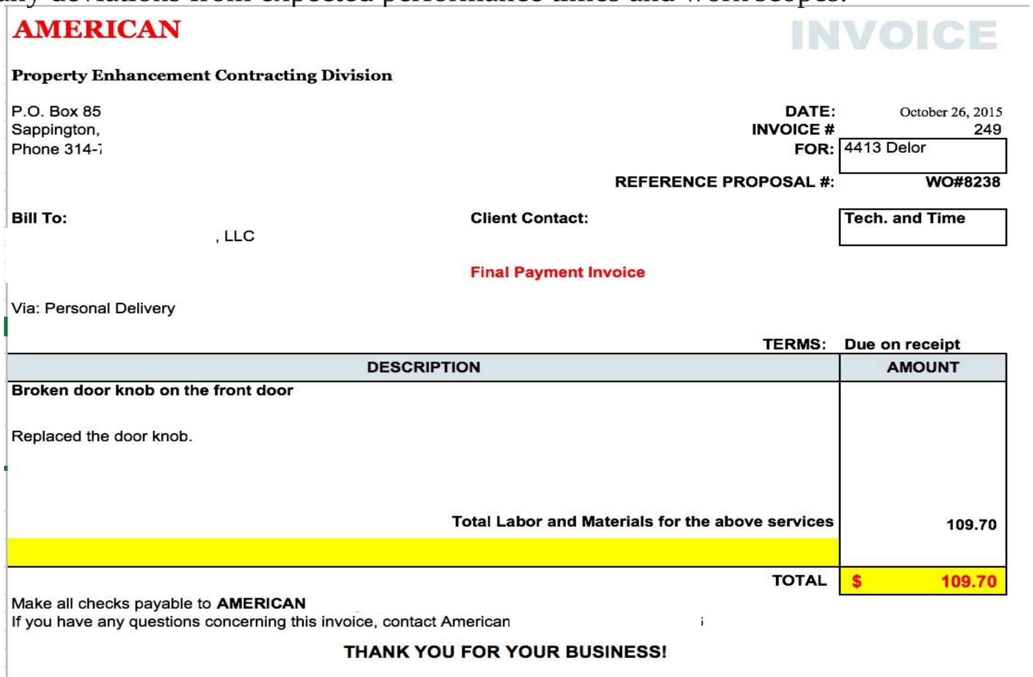
- Total Labor Time: The total number of hours worked to complete that work order.
- Total Labor Cost: The total labor cost to complete that work order.
- Total Cost: The total labor and material cost to complete the work order.
- Bill Amount: the amount billed to the property management company.
- Profit %: The gross margin of profit at the subcontractor level.

WO#	Laborer 1 ID	Laborer 1 Time	Laborer 2 ID	Laborer 2 Time	Laborer 3 ID	Laborer 3 Time	Total Labor Time
Work Order #8156	PD	1.00					1.00
Work Order #8182	PD	2.50					2.50
Work Order #8197	PD	4.50					4.50
Work Order #8214	PD	3.00					3.00
Work Order #8237	PD	7.00	JS	2.00			9.00
Work Order #8238	JT	1.50					1.50
Work Order #8251	PD	3.00					3.00
Work Order #8265	GD	3.00					3.00
Work Order #8286	JT	4.00	PD	8.00			12.00
Work Order #8294	JT	3.00	PD	3.00			6.00
Work Order #8368	PD	6.00					6.00
Work Order #8396	PD	6.00					6.00
Work Order #8400	JT	2.25					2.25
Work Order #8422	GD	5.00					5.00
Work Order #8476	PD	3.50					3.50
Work Order #8532	GD	1.50	JA	1.50			3.00
Work Order #8534	GD	2.00					2.00
Work Order #8625	PD	3.00					3.00
Work Order #8644	JT	2.00					2.00
Work Order #8661	JT	4.50	NC	3.00			7.50
Work Order #8671	NC	1.00					1.00
Work Order #8679	CW	1.00					1.00
Work Order #8708	NC	1.50					1.50
Work Order #8714	JT	4.50					4.50
Work Order #8732	JT	8.50	KS	2.50	RV	3.00	14.00
Work Order #8735	GD	2.00					2.00
Work Order #8737	GD	3.00					3.00
Work Order #8744	JT	1.50					1.50
Work Order #8749	PD	3.50					3.50
Work Order #8750	PD	2.00					2.00
Work Order #8751	JT	2.00					2.00
Work Order #8753	JT	3.00					3.00
Work Order #8769	CW	1.00					1.00
Work Order #8775	PD	4.00					4.00
Work Order #8797	JT	1.75					1.75
Work Order #8803	JT	1.00	CW	1.00			2.00
Work Order #8838	CW	2.50					2.50
Work Order #8839	JT	1.25					1.25
Work Order #8842	GD	3.00					3.00

Table 3.18 Work Order Data Collected from the Job Ticket.

3.4.6 Use of Data

Each work order ticket is returned to the office with completion notes that detail the resolution to a work order request. The Field Manager can identify if the solution to a work order request is commensurate with the time reported on the job ticket, as well as any deviations from expected performance times and work scopes.



AMERICAN

INVOICE

Property Enhancement Contracting Division

P.O. Box 85
Sappington,
Phone 314-

DATE:	October 26, 2015
INVOICE #	249
FOR:	4413 Delor
REFERENCE PROPOSAL #:	**WO#8238**

Bill To:
, LLC

Client Contact: **Tech. and Time**

Final Payment Invoice

Via: Personal Delivery

TERMS: **Due on receipt**

DESCRIPTION	AMOUNT
Broken door knob on the front door Replaced the door knob.	
Total Labor and Materials for the above services	**109.70**
TOTAL	**$ 109.70**

Make all checks payable to **AMERICAN**
If you have any questions concerning this invoice, contact American

THANK YOU FOR YOUR BUSINESS!

Figure 3.15 Invoice for a Work Order.

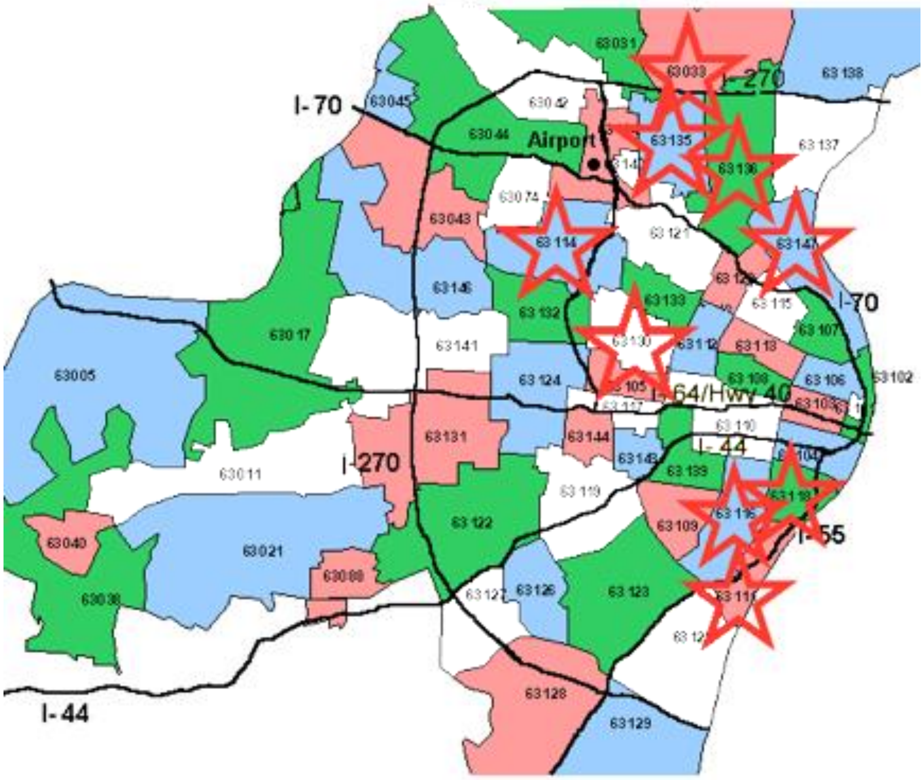


Figure 3.16 Map of Saint Louis Metro Area and Zip Codes of Research Focus.

These inputs comprise the basis for average work completion times and the parsimony of work into classes and levels. The zip code is used for each work order to determine the appropriate travel time and distance tables. Sample data is limited to only the top ten zip codes by number of properties.

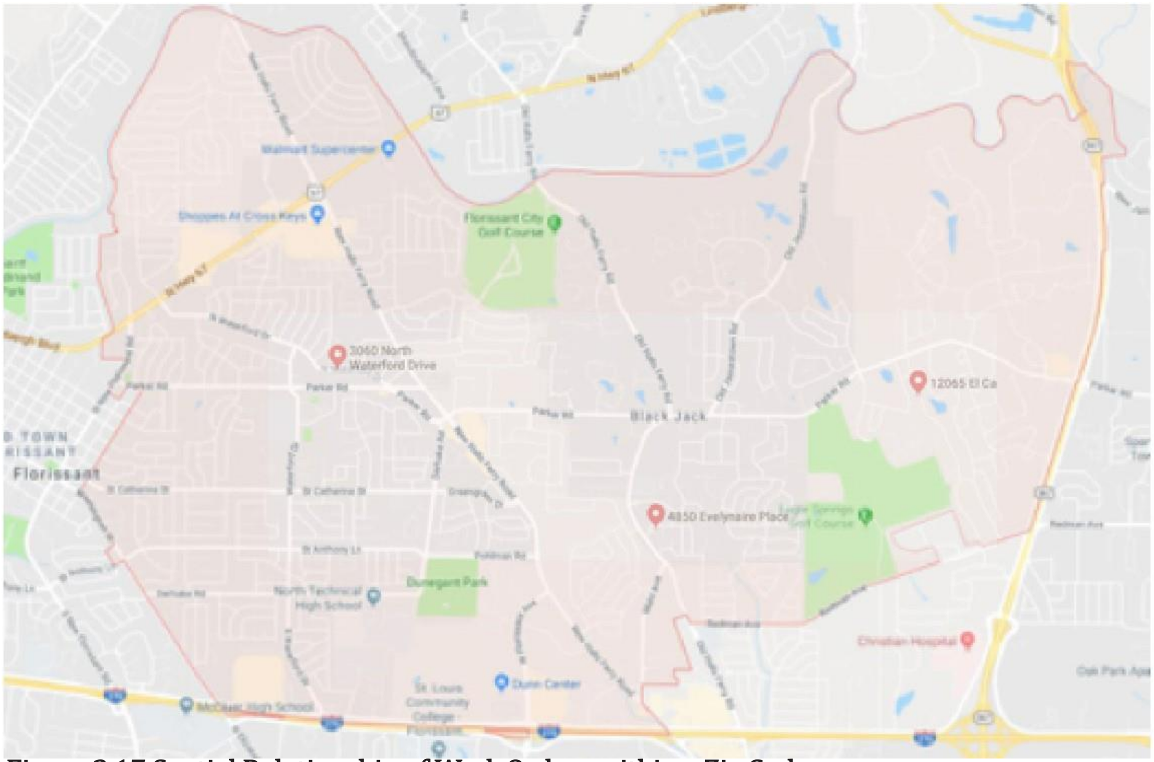
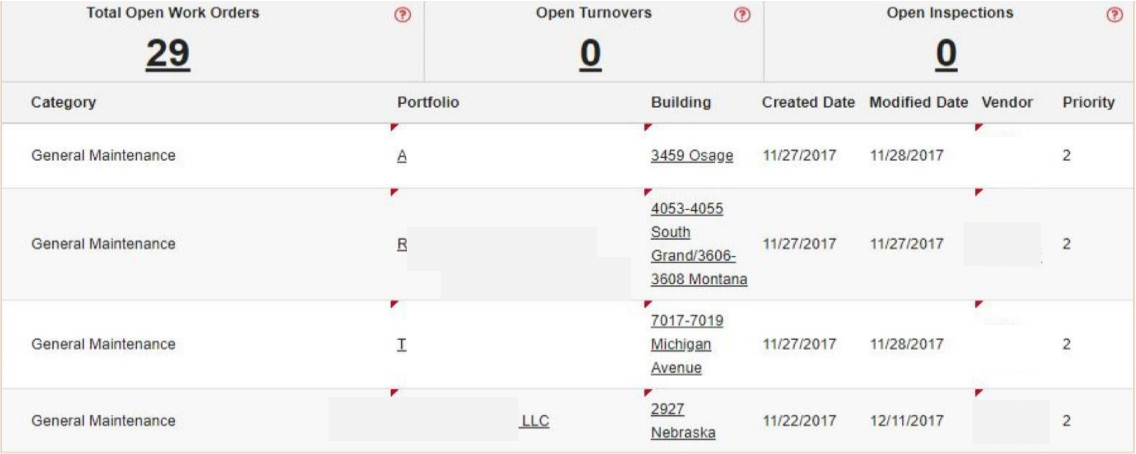


Figure 3.17 Spatial Relationship of Work Orders within a Zip Code.



Total Open Work Orders **29** | Open Turnovers **0** | Open Inspections **0**

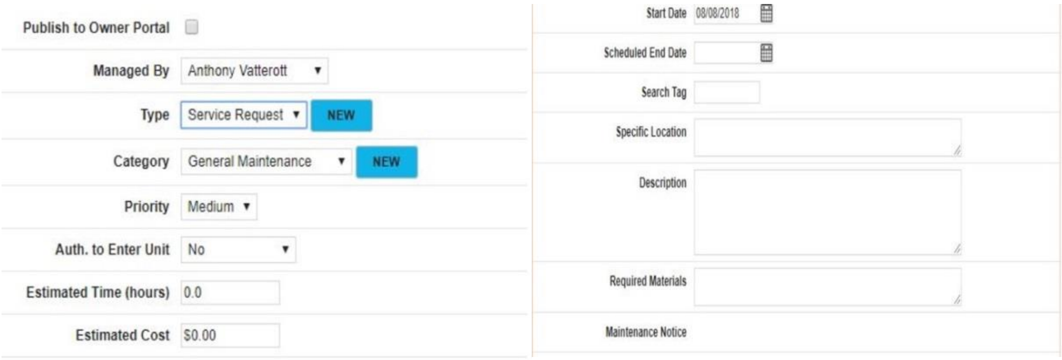
Category	Portfolio	Building	Created Date	Modified Date	Vendor	Priority
General Maintenance	A	3459 Osage	11/27/2017	11/28/2017		2
General Maintenance	R [redacted]	4053-4055 South Grand/3606-3608 Montana	11/27/2017	11/27/2017	[redacted]	2
General Maintenance	T	7017-7019 Michigan Avenue	11/27/2017	11/28/2017		2
General Maintenance	[redacted] LLC	2927 Nebraska	11/22/2017	12/11/2017	[redacted]	2

Figure 3.18 Maintenance Module in Management Software.

In constructing a mathematical model, I generalize specific property addresses to the relevant zip code, and then use specific addresses to determine the cost savings of optimization. In this particular case, the difference in cost of optimization using zip codes versus specific addresses indicates that using zip codes instead of specific addresses provides very good fit with the benefit of reduced set-up times for the model.

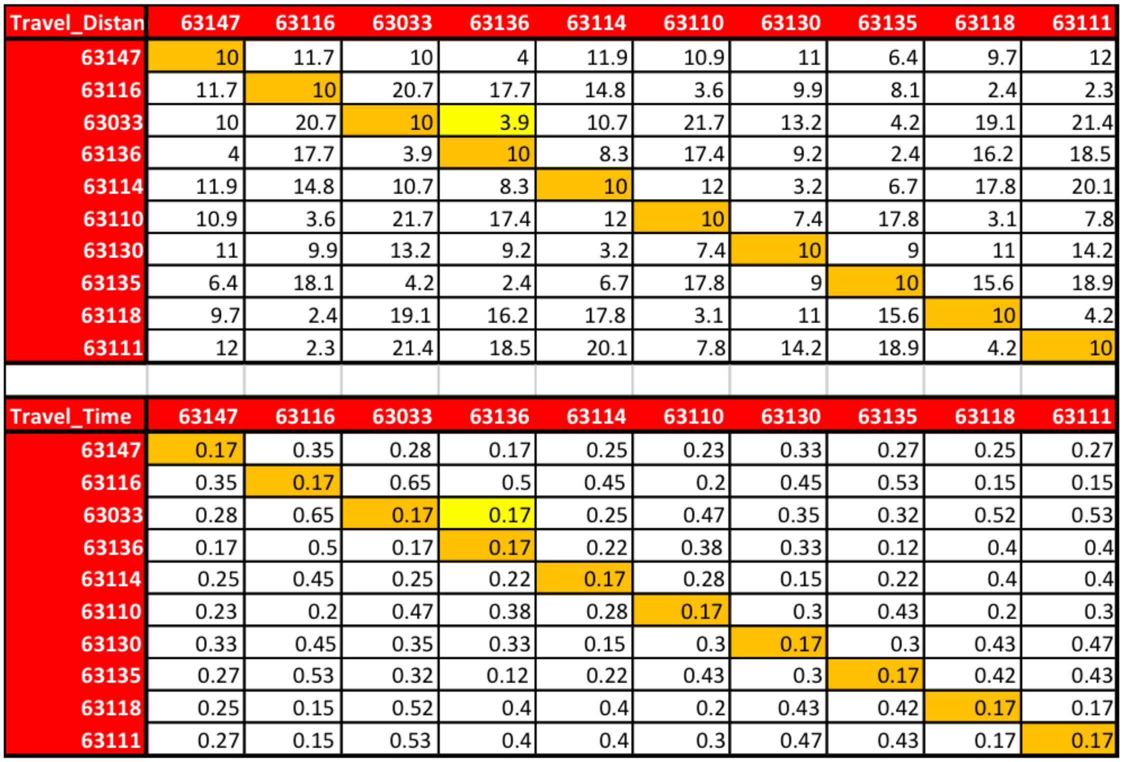
I use the Laborer ID data to collect the performance times for individual workers which are then utilized in the development of the process times and efficiency ratings of each worker for each skill class and level. I use the Total Labor Time to determine the process time for each job, whereas the Labor Costs were fixed to each Laborer ID. These inputs comprise the basis for average work completion times and the parsimony of work into classes and levels.

The zip code is used for each work order to determine the appropriate travel time and distance tables. Sample data is limited to only the top ten zip codes by number of properties. In constructing a mathematical model, I generalize specific property addresses to the relevant zip code, and then use specific addresses to determine the cost savings of optimization. In this particular case, the difference in cost of optimization using zip codes versus specific addresses indicates that using zip codes instead of specific addresses provides very good fit with the benefit of reduced set-up times for the model.



Publish to Owner Portal ☐
Managed By: Anthony Vatterott ▾
Type: Service Request ▾ NEW
Category: General Maintenance ▾ NEW
Priority: Medium ▾
Auth. to Enter Unit: No ▾
Estimated Time (hours): 0.0
Estimated Cost: $0.00
Start Date: 08/08/2018
Scheduled End Date:
Search Tag:
Specific Location:
Description:
Required Materials:
Maintenance Notice

Figure 3.19 Maintenance Request Entry Screen in Management Software.



Travel_Distan	63147	63116	63033	63136	63114	63110	63130	63135	63118	63111
63147	10	11.7	10	4	11.9	10.9	11	6.4	9.7	12
63116	11.7	10	20.7	17.7	14.8	3.6	9.9	8.1	2.4	2.3
63033	10	20.7	10	3.9	10.7	21.7	13.2	4.2	19.1	21.4
63136	4	17.7	3.9	10	8.3	17.4	9.2	2.4	16.2	18.5
63114	11.9	14.8	10.7	8.3	10	12	3.2	6.7	17.8	20.1
63110	10.9	3.6	21.7	17.4	12	10	7.4	17.8	3.1	7.8
63130	11	9.9	13.2	9.2	3.2	7.4	10	9	11	14.2
63135	6.4	18.1	4.2	2.4	6.7	17.8	9	10	15.6	18.9
63118	9.7	2.4	19.1	16.2	17.8	3.1	11	15.6	10	4.2
63111	12	2.3	21.4	18.5	20.1	7.8	14.2	18.9	4.2	10

Travel_Time	63147	63116	63033	63136	63114	63110	63130	63135	63118	63111
63147	0.17	0.35	0.28	0.17	0.25	0.23	0.33	0.27	0.25	0.27
63116	0.35	0.17	0.65	0.5	0.45	0.2	0.45	0.53	0.15	0.15
63033	0.28	0.65	0.17	0.17	0.25	0.47	0.35	0.32	0.52	0.53
63136	0.17	0.5	0.17	0.17	0.22	0.38	0.33	0.12	0.4	0.4
63114	0.25	0.45	0.25	0.22	0.17	0.28	0.15	0.22	0.4	0.4
63110	0.23	0.2	0.47	0.38	0.28	0.17	0.3	0.43	0.2	0.3
63130	0.33	0.45	0.35	0.33	0.15	0.3	0.17	0.3	0.43	0.47
63135	0.27	0.53	0.32	0.12	0.22	0.43	0.3	0.17	0.42	0.43
63118	0.25	0.15	0.52	0.4	0.4	0.2	0.43	0.42	0.17	0.17
63111	0.27	0.15	0.53	0.4	0.4	0.3	0.47	0.43	0.17	0.17

Table 3.19 Matrices of Travel Time Distance between Zip Codes of Research Interest.

The Work Order number is used as a reference number for the purpose of tracking and scheduling assignments to human resources. The priority of a job is set by the Property Manager and is High Priority (performed in less than 24 hours), Medium Priority (performed in less than 72 hours) or Low Priority (performed in less than 120 hours). If a work order was an emergency service request, it was given a value of highest urgency and needs completion within 24 hours. Field Managers evaluate the narrative description of each job to determine the accuracy of completion times for each assigned worker. The Field Manager also accessed the job narrative to classify a work order into the best available class of work. Each work order ticket is returned to the office with completion notes that detail the resolution to a work order request. The Field Manager can identify if the solution to a work order request is commensurate with the time reported on the job ticket, as well as any deviations from expected performance times and work scopes. These inputs comprise the basis for average work completion times and the parsimony of work into classes and levels.

I use the Laborer ID data to collect the performance times for individual workers which are then utilized in the development of the process times and efficiency ratings for each worker for each skill class and level. I use the Total Labor Time to determine the process time for each job, whereas the Labor Costs were fixed to each Laborer ID. The distance to travel between any two jobs assigned to the same worker is calculated as the distance travelled at the travelling cost per mile. (in this study, $.565; the Federal Standard rate for deduction or reimbursement purposes). The time to travel between two successive jobs assigned to the same worker is calculated as the travel time, and charged at the standard hourly rate for that worker.

Travel times and distances were collected from Google Maps using the routing function. Times for travel were determined as the average travel time considering periods of peak travel during regular business hours; the mean travel time and travel distance between the fastest and shortest route was always obtained. Travel was measured from the center of the zip code where the work takes place, to the center of the zip code of the next job. In testing the differences between the actual distances from address to address, it was found that this approximation scales accurately to the actual address data; in fact, it was found that using the actual addresses to finalize the routing for jobs after using the method developed in this work added an additional 1.4% of potential costs in this example; travel time was decreased marginally while miles driven increased slightly. If two jobs are within the same zip code, they are treated as having some distance between them. We use a standard time and distance allowance of .17 hours and 10 miles to represent the sum-average travel time and distance between all zip codes. Travel between two units in the same building, or two buildings on the same lot, as well as two units at different locations within the same zip code, use this time and distance rate.

64 sample work orders were measured for the time required to perform each assigned task. Work Orders are classified by the skills required to perform the work to satisfaction. Each work order is given a classification of one skill in this study:

- **Electrical:** includes, wiring, lighting fixtures, receptacles, circuit breakers, panel service, cabling, data, installation of fans, outlets and switches, etc.
- **HVAC:** includes heating systems and cooling systems; cooling and air conditioning both central and window; condensers, evaporation coils, refrigerant charging, hot water heaters, boilers, furnaces, ducting, ventilation, etc.
- **Plumbing:** includes for example, copper water lines and braising, Schedule 40 and 80 PVC piping; drains, sinks, toilets, shower diverters and hoses, cleanouts, stacks, wyes, mains and laterals, and faucets, for conveyance of water.
- **Security:** door and window locks, access control systems and installation, window, door, and security system repair, and any emergency calls due to theft, vandalism, squatters, trespassing, fire damage and police-related reporting.
- **Other:** any task that does not sufficiently qualify for one other category, such as gutter cleaning, yard cleaning, winterizing, occupancy violations and code compliance issues.

All tasks were classified into the selected skill groups by a consensus of workers in the focal firm and are as true to a representation of how tasks would be classified into trades as could be reinforced from expert opinion. Further, these tasks were graded for the level of skill required to accomplish a satisfactory outcome:

- **A:** Expert skill level, considered the level of mastery.
- **B:** Advanced skill level.
- **C:** Intermediate skill level
- **D:** Novice skill level; the entry level of skill in any skill category.

WO#	Zip	Type	Priority	Job Class	Job Level
Work Order #8476	63116	Service Request	High	Electrical	C
Work Order #8182	63111	Service Request	High	Miscellaneous	A
Work Order #8368	63033	Service Request	Med	Miscellaneous	A
Work Order #8197	63033	Service Request	Low	Security	B
Work Order #8214	63130	Service Request	Med	Security	B
Work Order #8238	63116	Service Request	Med	Security	B
Work Order #8265	63118	Inspection	Low	Miscellaneous	C
Work Order #8661	63135	Emergency Service Request	High	Security	A
Work Order #8735	63147	Service Request	Low	Plumbing	B
Work Order #8732	63111	Emergency Service Request	High	HVAC	A
Work Order #8396	63118	Service Request	Med	Miscellaneous	A
Work Order #8400	63114	Service Request	Low	HVAC	B
Work Order #8532	63136	Service Request	Med	Plumbing	B
Work Order #8422	63111	Service Request	High	Plumbing	A
Work Order #8714	63111	Service Request	High	HVAC	B
Work Order #8294	63114	Service Request	Med	Security	A
Work Order #8286	63118	Service Request	Low	Security	A
Work Order #8803	63118	Service Request	Med	HVAC	D
Work Order #8534	63114	Service Request	Med	Plumbing	C
Work Order #8237	63118	Service Request	High	Miscellaneous	A
Work Order #8625	63033	Service Request	Low	Electrical	B
Work Order #8644	63111	Service Request	Med	HVAC	A
Work Order #8671	63111	Service Request	High	Security	A
Work Order #8679	63136	Service Request	Med	HVAC	D
Work Order #8156	63116	Service Request	Med	Plumbing	C
Work Order #8708	63135	Emergency Service Request	High	Plumbing	C
Work Order #8737	63136	Service Request	Med	Plumbing	D
Work Order #8744	63135	Emergency Service Request	High	HVAC	A
Work Order #8749	63111	Service Request	Low	Security	D
Work Order #8750	63118	Service Request	Med	Plumbing	A
Work Order #8751	63135	Service Request	Med	Plumbing	B
Work Order #8753	63130	Emergency Service Request	High	Plumbing	B
Work Order #8769	63111	Service Request	Low	Security	D
Work Order #8775	63135	Emergency Service Request	High	Electrical	A
Work Order #8797	63135	Emergency Service Request	High	Plumbing	A
Work Order #8838	63111	Emergency Service Request	High	Plumbing	A
Work Order #8839	63118	Emergency Service Request	High	HVAC	B
Work Order #8251	63111	Service Request	Med	Miscellaneous	C
Work Order #8842	63118	Service Request	Med	Miscellaneous	A

Table 3.20 Work Order Data Classified Based on Managerial Insight and Expert Opinion.

If a worker belongs to the set of workers who possess a specific skill, then the normal processing time of a job by the average worker for any task is derived from the historical performance for that data set, and used as a benchmark for individual performance. However, each individual worker is given a weighted competence to reflect that individual's actual performance historically; we call this their efficiency rating: efficiency of a worker s for skill k with respect to the average process time for skill k. This approach incorporates actual performance times relative to mean performance. If a worker is not competent to perform a task at any skill class and level, that worker is exempt from consideration. It is possible to require a severe penalty to assign the job to an underqualified worker) to complete a job on time. A performance time score of .01, equal to a job taking 100 times longer than average, is used to consider a worker who is not competent to perform a job. The decision to assign a job to a less-than skilled worker with such a penalty proves to be cost prohibitive. If a worker is considered inexperienced and capable, then an efficiency of either .300 or .500 is used to indicate that jobs at the lowest levels of performance, Level C or D, may be completed by a worker at a completion time well below the mean performance time, for planning purposes, subject to managerial discretion.

The capacity limit for assignment of work to worker s in hours (40, 60 or 80), is used to prevent more assigned hours than is allowable for an individual worker.

Worker Skills

	HVAC				Electrical				Plumbing				Security				Other			
Row Labels	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D
CW	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0
GD	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	1	0	1	0
JT	1	1	0	1	0	0	0	0	1	1	0	0	1	1	0	0	0	0	0	0
NC	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0
PD	0	0	0	0	1	1	1	0	1	0	1	0	0	1	0	1	1	0	1	0
JS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
RV	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
JA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
KS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Individual Process Times

	HVAC				Electrical				Plumbing				Security				Other			
Row Labels	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D
CW	-	-	-	1.00	-	-	-	-	2.50	-	-	-	-	-	-	1.00	-	-	-	-
GD	-	-	-	-	-	-	-	-	5.00	2.50	2.00	3.00	-	-	-	-	3.00	-	3.00	-
JT	5.83	2.67	-	2.00	-	-	-	-	1.75	2.50	-	-	8.50	1.50	-	-	-	-	-	-
NC	-	-	-	-	-	-	-	-	-	-	1.50	-	1.00	-	-	-	-	-	-	-
PD	-	-	-	-	4.00	3.00	3.50	-	2.00	-	1.00	-	-	3.75	-	3.50	5.88	-	3.00	-
JS	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
RV	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
JA	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
KS	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

Mean Process Times

	5.83	2.67	0.00	1.50	4.00	3.00	3.50	0.00	2.81	2.50	1.50	3.00	4.75	2.63	0.00	2.25	4.44	0.00	3.00	0.00

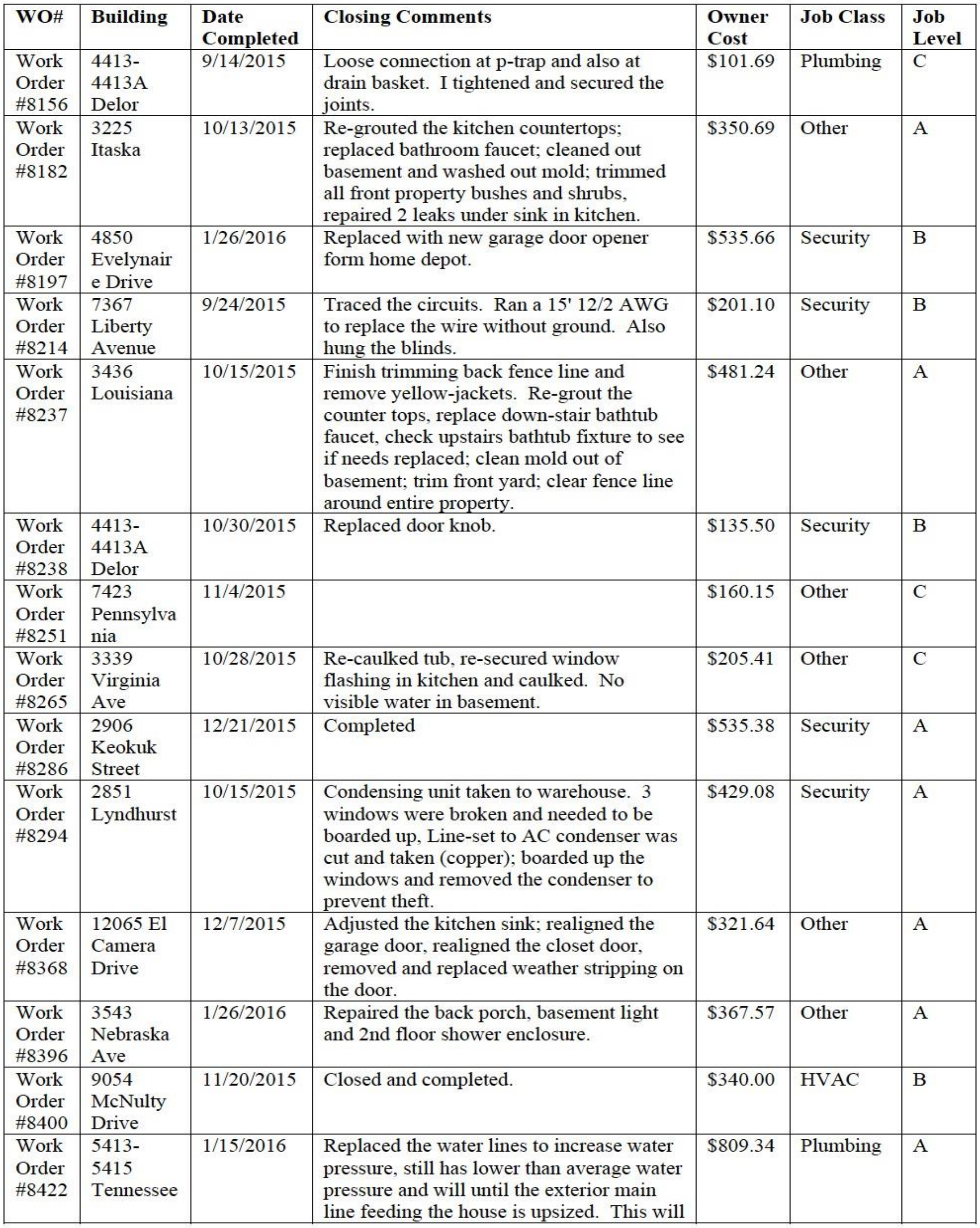
Worker Efficiency Scores

	HVAC				Electrical				Plumbing				Security				Other			
Row Labels	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D
CW	0.01	0.01	0.01	1.50	0.01	0.01	0.01	0.01	1.13	0.01	0.01	0.01	0.01	0.01	0.01	2.25	0.01	0.01	0.01	0.01
GD	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.56	1.00	0.75	1.00	0.01	0.01	0.01	0.01	1.48	0.00	1.00	0.01
JT	1.00	1.00	0.01	0.75	0.01	0.01	0.01	0.01	1.61	1.00	0.01	0.01	0.56	1.75	0.01	0.01	0.01	0.01	0.01	0.01
NC	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	1.00	0.01	4.75	0.01	0.01	0.01	0.01	0.01	0.01	0.01
PD	0.01	0.01	0.01	0.01	1.00	1.00	1.00	0.01	1.41	0.01	1.50	0.01	0.01	0.70	0.00	0.64	0.76	0.00	1.00	0.01
JS	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
RV	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10
JA	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
KS	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

Table 3.21 Worker Competence, Process Times and Efficiency Scores By Skill Class and Level.

Using 64 chronological work orders, the process times and individual performance weights (efficiency ratings) for a sample computational experiment are shown. For example, the mean process time for a Security Job Level B is 2.625 hours. Since Worker "JT" can perform this job with an efficiency of 1.75 it would take him 1.5 hours to complete the job. Compare this to the completion time of Worker "PD" for the same job at a total time of 3.75 hours. Alternately, if you notice jobs where workers are not competent, they are given a significantly penalized efficiency rating (in this chart, .01). Since worker "JT" does not have the competency to perform the job, HVAC Level C, his completion time would be penalized severely, if he were assigned to such a task. Given the limited number of work hours, the penalty function results in an infeasible solution. I evaluate a step-wise procedure for improving upon this penalty value (as a representation for improved competency) later on in this paper.

Whereas the larger data set consists of more workers, we look to solve the problem utilizing as few workers as is possible while satisfying all constraints. From 14 potential workers, we consider 9 workers to which all the work must be assigned.



WO#	Building	Date Completed	Closing Comments	Owner Cost	Job Class	Job Level
Work Order #8156	4413-4413A Delor	9/14/2015	Loose connection at p-trap and also at drain basket. I tightened and secured the joints.	$101.69	Plumbing	C
Work Order #8182	3225 Itaska	10/13/2015	Re-grouted the kitchen countertops; replaced bathroom faucet; cleaned out basement and washed out mold; trimmed all front property bushes and shrubs, repaired 2 leaks under sink in kitchen.	$350.69	Other	A
Work Order #8197	4850 Evelynaire Drive	1/26/2016	Replaced with new garage door opener form home depot.	$535.66	Security	B
Work Order #8214	7367 Liberty Avenue	9/24/2015	Traced the circuits. Ran a 15' 12/2 AWG to replace the wire without ground. Also hung the blinds.	$201.10	Security	B
Work Order #8237	3436 Louisiana	10/15/2015	Finish trimming back fence line and remove yellow-jackets. Re-grout the counter tops, replace down-stair bathtub faucet, check upstairs bathtub fixture to see if needs replaced; clean mold out of basement; trim front yard; clear fence line around entire property.	$481.24	Other	A
Work Order #8238	4413-4413A Delor	10/30/2015	Replaced door knob.	$135.50	Security	B
Work Order #8251	7423 Pennsylvania	11/4/2015		$160.15	Other	C
Work Order #8265	3339 Virginia Ave	10/28/2015	Re-caulked tub, re-secured window flashing in kitchen and caulked. No visible water in basement.	$205.41	Other	C
Work Order #8286	2906 Keokuk Street	12/21/2015	Completed	$535.38	Security	A
Work Order #8294	2851 Lyndhurst	10/15/2015	Condensing unit taken to warehouse. 3 windows were broken and needed to be boarded up, Line-set to AC condenser was cut and taken (copper); boarded up the windows and removed the condenser to prevent theft.	$429.08	Security	A
Work Order #8368	12065 El Camera Drive	12/7/2015	Adjusted the kitchen sink; realigned the garage door, realigned the closet door, removed and replaced weather stripping on the door.	$321.64	Other	A
Work Order #8396	3543 Nebraska Ave	1/26/2016	Repaired the back porch, basement light and 2nd floor shower enclosure.	$367.57	Other	A
Work Order #8400	9054 McNulty Drive	11/20/2015	Closed and completed.	$340.00	HVAC	B
Work Order #8422	5413-5415 Tennessee	1/15/2016	Replaced the water lines to increase water pressure, still has lower than average water pressure and will until the exterior main line feeding the house is upsized. This will	$809.34	Plumbing	A

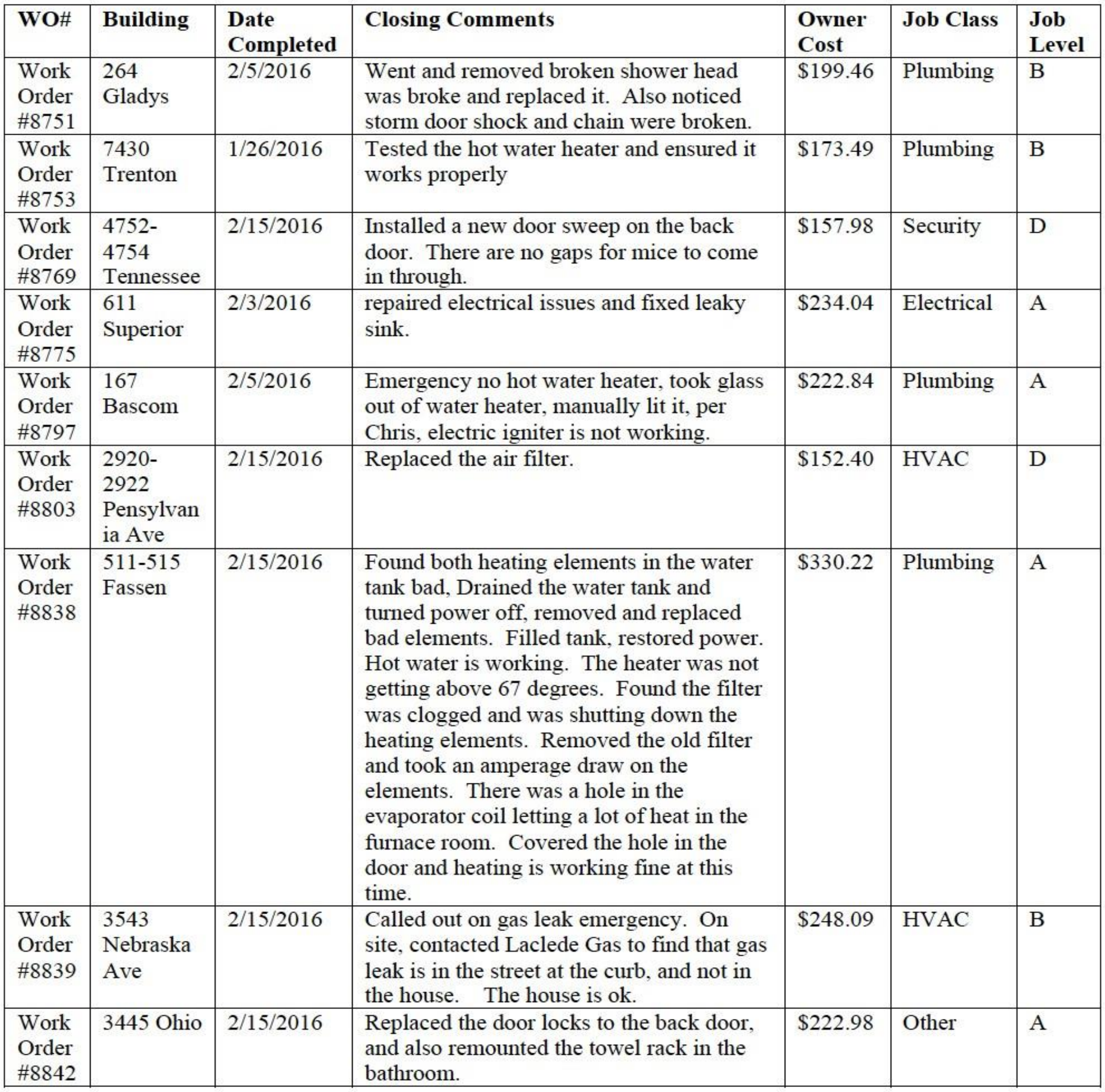
Table 3.22 Details of Work Scope, Location and Cost for Work Orders Used in Case Studies.

Selection of these 9 workers was arbitrary though it does reflect a mix of competence both within and across skills. The labor rates, denoted as the hourly wage of workers for the selected 9 workers, includes the base rate and the calculation for added overhead costs including insurance, licensing and other costs of operation or fringe benefits. These rates are not subject to the prevailing wage rules of publicly funded construction projects, so any comparison to the Department of Labor prevailing wage rates should not be made in this case study. However, if such a project of this scope and scale were to be performed by an organization in receipt of public funding, then the commensurate prevailing wage rates would apply.

WO#	Building	Date Completed	Closing Comments	Owner Cost	Job Class	Job Level
			be a considerable expense, so it is as good as it gets without excessive cost.			
Work Order #8476	3706 Hydraulic	12/18/2015	Repaired switched and re-wired light.	$195.54	Electrical	C
Work Order #8532	2028 Jannete Drive	12/18/2015	Replaced the toilet and base components.	$296.15	Plumbing	B
Work Order #8534	2324 Wismer Avenue	12/21/2015	Replaced the toilet and mounting hardware.	$414.16	Plumbing	C
Work Order #8625	3060 North Waterford Drive	1/15/2016	Repaired the light fixture.	$215.45	Electrical	B
Work Order #8644	511-515 Fassen	1/15/2016	Repaired seals in the duct lines where leaks were happening.	$315.68	HVAC	A
Work Order #8661	427 Georgia	2/5/2016	After break-in, repair back door window and storm door. Repaired the broken windows in the 3-pane back door as well.	$900.58	Security	A
Work Order #8671	7017-7019 Michigan Avenue	1/20/2016	Replaced the door locksets for deadbolt and handle locks for the unit.	$435.38	Security	A
Work Order #8679	2340 Berwyn Drive	1/20/2016	Work has been completed per estimate.	$2,125.00	HVAC	D
Work Order #8708	263 Sadonia	1/20/2016	Adjusted the gas lines and relit the pilot light on the hot water heater.	$193.72	Plumbing	C
Work Order #8714	2834 Mount Pleasant	2/15/2016	Met the Laclede Gas technician to restore gas service. There was a shorted wire in the thermostat and it was replaced.	$265.71	HVAC	B
Work Order #8732	4752-4754 Tennessee	1/26/2016	Diagnosed HVAC system, replaced the burner assembly, diagnosed IFC Board and gas valve; found pressure switch is broken off and needed to be replaced.	$1,167.90	HVAC	A
Work Order #8735	1600 Veronica	1/27/2016	Low water pressure, inspected pipes and waster system; opened main valve and cleared lines for pressure	$240.35	Plumbing	B
Work Order #8737	2259 Ainsworth	1/27/2016	Replaced washer and dryer hookups and cleared the lines for pressure.	$204.16	Plumbing	D
Work Order #8744	37 Lee	1/25/2016	Thermostat shorted out. Replaced and heat is operational.	$248.32	HVAC	A
Work Order #8749	511-515 Fassen	2/5/2016	weather seal all doors	$245.80	Security	D
Work Order #8750	2729-2731 Miami	2/5/2016	repaired the valves on the leaking hot water heater.	$155.73	Plumbing	A

Table 3.22 (Continued)

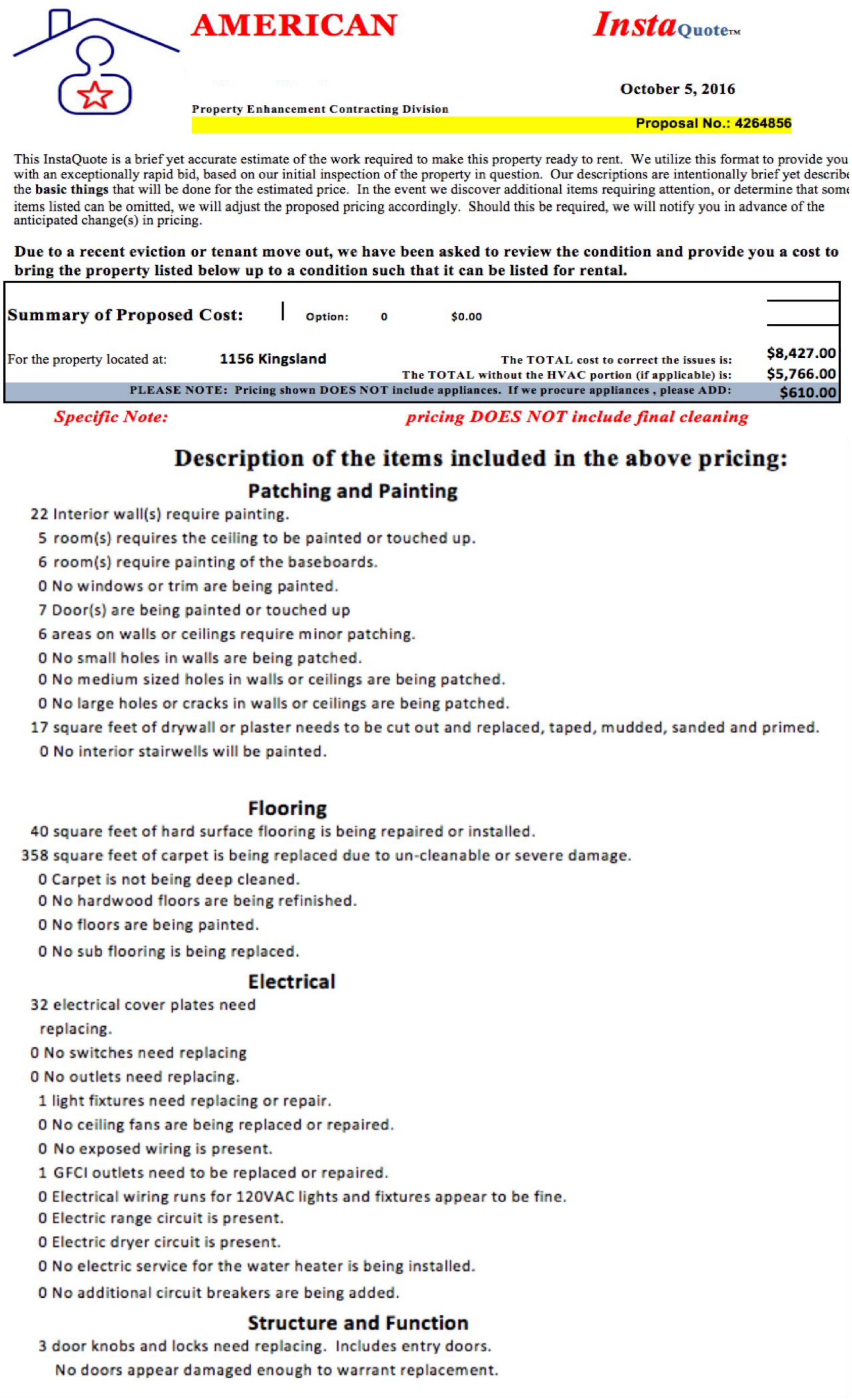
For the purpose of this study, those rates are not applicable, as all work is performed on properties privately owned and for which no generally acceptable standard of organized or prevailing labor category has been developed. The development of such a labor rate or the adoption of a method for the organization of labor within this operating environment would be a potential source of benefit for organized labor, labor standards and skilled labor development, though that is outside the scope of this research.



WO#	Building	Date Completed	Closing Comments	Owner Cost	Job Class	Job Level
Work Order #8751	264 Gladys	2/5/2016	Went and removed broken shower head was broke and replaced it. Also noticed storm door shock and chain were broken.	$199.46	Plumbing	B
Work Order #8753	7430 Trenton	1/26/2016	Tested the hot water heater and ensured it works properly	$173.49	Plumbing	B
Work Order #8769	4752-4754 Tennessee	2/15/2016	Installed a new door sweep on the back door. There are no gaps for mice to come in through.	$157.98	Security	D
Work Order #8775	611 Superior	2/3/2016	repaired electrical issues and fixed leaky sink.	$234.04	Electrical	A
Work Order #8797	167 Bascom	2/5/2016	Emergency no hot water heater, took glass out of water heater, manually lit it, per Chris, electric igniter is not working.	$222.84	Plumbing	A
Work Order #8803	2920-2922 Pensylvania Ave	2/15/2016	Replaced the air filter.	$152.40	HVAC	D
Work Order #8838	511-515 Fassen	2/15/2016	Found both heating elements in the water tank bad, Drained the water tank and turned power off, removed and replaced bad elements. Filled tank, restored power. Hot water is working. The heater was not getting above 67 degrees. Found the filter was clogged and was shutting down the heating elements. Removed the old filter and took an amperage draw on the elements. There was a hole in the evaporator coil letting a lot of heat in the furnace room. Covered the hole in the door and heating is working fine at this time.	$330.22	Plumbing	A
Work Order #8839	3543 Nebraska Ave	2/15/2016	Called out on gas leak emergency. On site, contacted Laclede Gas to find that gas leak is in the street at the curb, and not in the house. The house is ok.	$248.09	HVAC	B
Work Order #8842	3445 Ohio	2/15/2016	Replaced the door locks to the back door, and also remounted the towel rack in the bathroom.	$222.98	Other	A

Table 3.22 (Continued)

In summary, 9 workers (CW, GD, JT, NC, PD, JS, RV, JA, KS) were selected for assignment. 5 classes of skill (HVAC, Electrical, Plumbing, Security, Other) are considered, each consisting of 4 levels of skill (A, B, C, D). 3 Priorities (Hi, Medium, Low) are considered. High priority is an assignment made within the first 24 hours planning horizon; Medium priority work is assigned within the next first 72 hours planning horizon; and Low priority is work that must be assigned within the first 120 hours planning horizon, defined as working hours (a later suggestion is to incorporate shifts). The available time per employee is set to a maximum of 80 hours.



AMERICAN **Insta**Quote™

Property Enhancement Contracting Division

October 5, 2016

Proposal No.: 4264856

This InstaQuote is a brief yet accurate estimate of the work required to make this property ready to rent. We utilize this format to provide you with an exceptionally rapid bid, based on our initial inspection of the property in question. Our descriptions are intentionally brief yet describe the **basic things** that will be done for the estimated price. In the event we discover additional items requiring attention, or determine that some items listed can be omitted, we will adjust the proposed pricing accordingly. Should this be required, we will notify you in advance of the anticipated change(s) in pricing.

Due to a recent eviction or tenant move out, we have been asked to review the condition and provide you a cost to bring the property listed below up to a condition such that it can be listed for rental.

Summary of Proposed Cost:	Option: 0	$0.00	
For the property located at:	**1156 Kingsland**	The TOTAL cost to correct the issues is:	**$8,427.00**
		The TOTAL without the HVAC portion (if applicable) is:	**$5,766.00**
		PLEASE NOTE: Pricing shown DOES NOT include appliances. If we procure appliances , please ADD:	**$610.00**

Specific Note: ***pricing DOES NOT include final cleaning***

Description of the items included in the above pricing:

Patching and Painting

22 Interior wall(s) require painting.
5 room(s) requires the ceiling to be painted or touched up.
6 room(s) require painting of the baseboards.
0 No windows or trim are being painted.
7 Door(s) are being painted or touched up
6 areas on walls or ceilings require minor patching.
0 No small holes in walls are being patched.
0 No medium sized holes in walls or ceilings are being patched.
0 No large holes or cracks in walls or ceilings are being patched.
17 square feet of drywall or plaster needs to be cut out and replaced, taped, mudded, sanded and primed.
0 No interior stairwells will be painted.

Flooring

40 square feet of hard surface flooring is being repaired or installed.
358 square feet of carpet is being replaced due to un-cleanable or severe damage.
0 Carpet is not being deep cleaned.
0 No hardwood floors are being refinished.
0 No floors are being painted.
0 No sub flooring is being replaced.

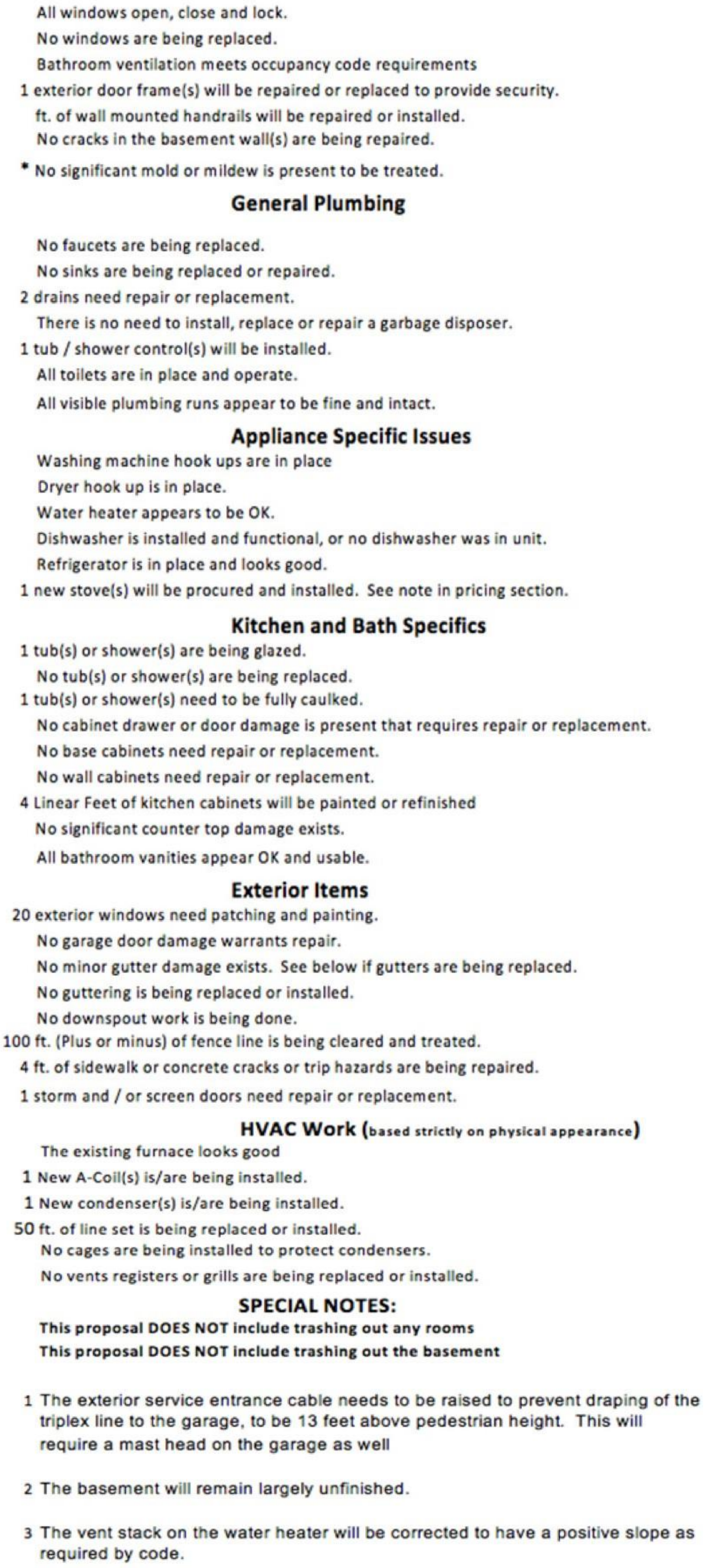
Electrical

32 electrical cover plates need replacing.
0 No switches need replacing
0 No outlets need replacing.
1 light fixtures need replacing or repair.
0 No ceiling fans are being replaced or repaired.
0 No exposed wiring is present.
1 GFCI outlets need to be replaced or repaired.
0 Electrical wiring runs for 120VAC lights and fixtures appear to be fine.
0 Electric range circuit is present.
0 Electric dryer circuit is present.
0 No electric service for the water heater is being installed.
0 No additional circuit breakers are being added.

Structure and Function

3 door knobs and locks need replacing. Includes entry doors.
No doors appear damaged enough to warrant replacement.

Figure 3.20 A Make Ready Proposal Used in the Case Study.



All windows open, close and lock.
No windows are being replaced.
Bathroom ventilation meets occupancy code requirements
1 exterior door frame(s) will be repaired or replaced to provide security.
ft. of wall mounted handrails will be repaired or installed.
No cracks in the basement wall(s) are being repaired.
* No significant mold or mildew is present to be treated.

General Plumbing

No faucets are being replaced.
No sinks are being replaced or repaired.
2 drains need repair or replacement.
There is no need to install, replace or repair a garbage disposer.
1 tub / shower control(s) will be installed.
All toilets are in place and operate.
All visible plumbing runs appear to be fine and intact.

Appliance Specific Issues

Washing machine hook ups are in place
Dryer hook up is in place.
Water heater appears to be OK.
Dishwasher is installed and functional, or no dishwasher was in unit.
Refrigerator is in place and looks good.
1 new stove(s) will be procured and installed. See note in pricing section.

Kitchen and Bath Specifics

1 tub(s) or shower(s) are being glazed.
No tub(s) or shower(s) are being replaced.
1 tub(s) or shower(s) need to be fully caulked.
No cabinet drawer or door damage is present that requires repair or replacement.
No base cabinets need repair or replacement.
No wall cabinets need repair or replacement.
4 Linear Feet of kitchen cabinets will be painted or refinished
No significant counter top damage exists.
All bathroom vanities appear OK and usable.

Exterior Items

20 exterior windows need patching and painting.
No garage door damage warrants repair.
No minor gutter damage exists. See below if gutters are being replaced.
No guttering is being replaced or installed.
No downspout work is being done.
100 ft. (Plus or minus) of fence line is being cleared and treated.
4 ft. of sidewalk or concrete cracks or trip hazards are being repaired.
1 storm and / or screen doors need repair or replacement.

HVAC Work (based strictly on physical appearance)

The existing furnace looks good
1 New A-Coil(s) is/are being installed.
1 New condenser(s) is/are being installed.
50 ft. of line set is being replaced or installed.
No cages are being installed to protect condensers.
No vents registers or grills are being replaced or installed.

SPECIAL NOTES:

This proposal DOES NOT include trashing out any rooms
This proposal DOES NOT include trashing out the basement

1 The exterior service entrance cable needs to be raised to prevent draping of the triplex line to the garage, to be 13 feet above pedestrian height. This will require a mast head on the garage as well

2 The basement will remain largely unfinished.

3 The vent stack on the water heater will be corrected to have a positive slope as required by code.

Chapter 4

Optimization Models and Preliminary Results

4.0 Introduction to Optimization Models

This section presents the mathematical models and their solutions as compared to each other and compared to the cost of actual performance in the focal firm's data set. The goal of a mathematical model is to assign the available skilled worker to the job for which he is competent to perform. However, I want to assign all the workers in such a way that minimizes total cost to route them to necessary tasks while satisfying several constraints on resource utility. First, I limit the number of hours a worker can be assigned to work. Next, I consider the constraint on a job's priority objective, which sets the deadline to complete each task. Finally, I limit the sequence of tasks so that no two jobs can be assigned to the same worker at the same time. I then consider the precedence relationship among tasks, and incorporate a larger project that is decomposed into smaller tasks, so that I can assign those tasks with precedence and those tasks without precedence at the same time. Then, I introduce a method for a pairing decision. The pairing decision is determined by evaluating the combined performance of both two competent workers, as well as a non-competent worker paired with a mentor who is competent, for a specific task to be assigned. I introduce a measure of pairing effectiveness, ρ, to evaluate the change in solution cost when varying levels of paired efficiency are considered.

4.1 Single Assignment Model Formulation

In order to develop a mixed-integer linear programming (MILP) model to represent the integrated project assignment, scheduling and routing problem with multi-skilled personnel, the following mathematical notations are introduced:

Sets:

I: $set\ of\ jobs$, indexed by i.

K: $set\ of\ skills$, indexed by k.

S: $set\ of\ workers$, indexed by s.

L: $set\ of\ locations$, indexed by l.

H: *set of precedence relationships. For* $(i,j)\epsilon$H, job i must precede job j.

Parameters:

p_i: $normal\ processing\ time\ of\ job\ i$ by the best performed worker.

k^i: $skill\ k\ required\ by\ job\ i$.

S^k: $set\ of\ workers\ who\ possess\ skill\ k$.

δ_{ks}: $efficiency\ of\ a\ worker\ s\ for\ skill\ k$ with respect to the mean performance time for skill k (e.g. Table 3.2.1). When $\delta_{ks} = 1$, s is equivalent to the performance of the benchmark; when $\delta_{ks} < 1$, s is less efficient than the benchmark; when $\delta_{ks} > 1$, s is more efficient than the benchmark.

v_{ij}: *distance to travel between job i and j.*

τ_{ij}: *time to travel to job i from job j.*

W_s: $weekly\ limit\ for\ worker\ s\ in\ hours\ (e.g. 50)$.

c_s: *hourly wage of worker s.*

b: travelling cost per mile.

d_i: due date of job i, based on the job's priority. Specifically, a job with high priority must be completed within 24 hours, a job with medium priority must be completed within 72 hours, and a job with high priority must be completed within 120 hours.

Decision Variables:

$$x_{is} = \begin{cases} 1\ if\ worker\ s\ is\ assigned\ to\ job\ i \\ \qquad 0\ otherwise \end{cases}$$

$$y_{sij} = \begin{cases} 1,\ if\ worker\ s\ travels\ from\ job\ i\ to\ job\ j \\ \qquad 0\ otherwise \end{cases}$$

$t_i \geq 0$: $start\ time\ of\ job\ i$

Objective function:

$$Min\ \sum_{i\in I}\sum_{s\in S} c_s x_{is} p_i/\delta_{k^i s} + \sum_{s\in S}\sum_{i\in I}\sum_{j\in J} y_{sij} v_{ij} b + \sum_{s\in S}\sum_{i\in I}\sum_{j\in J} y_{sij}\tau_{ij}\, c_s \quad (1)$$

Constraints:

$$\sum_{s\in S^{k^i}} x_{is} = 1, \qquad \forall i \in I \qquad (2)$$

$$\sum_{i\in I} x_{is} p_i/\delta_{k^i s} \leq W_s, \qquad \forall s \in S \qquad (3)$$

$$t_i + \sum_{s\in S} x_{is} p_i/\delta_{k^i s} \leq min\{d_i, \bar{T}\} \qquad \forall i \in I \qquad (4)$$

$$t_j - t_i \geq \sum_{s\in S} x_{is} p_i/\delta_{k^i s} \qquad \forall (i,j) \in \mathrm{H} \qquad (5)$$

$$\sum_{j\in I} y_{sij} \leq x_{is} \qquad \forall s \in S, i \in I \qquad (6)$$

$$\sum_{i\in I} y_{sij} \leq x_{js} \qquad \forall s \in S, j \in I \qquad (7)$$

$$\sum_{i\in I}\sum_{j\in I} y_{sij} \geq \sum_{i\in I} x_{is} - 1 \qquad \forall s \in S \qquad (8)$$

$$t_j \geq t_i + \sum_{s\in S} x_{is} p_i/\delta_{k^i s} + \tau_{ij} \cdot \sum_{s\in S} y_{sij} - M(1 - \sum_{s\in S} y_{sij}), \quad \forall (i,j) \in I \times I \quad (9)$$

$$x_{is}, y_{sij} \in \{0, 1\}, t_i \geq 0 \qquad (10)$$

Objective function (1) minimizes the total project delivery cost and includes three terms. The first term is the direct labor cost of working on all the jobs in the project, with the efficiency of the assigned worker factored in. The second term computes the total travel cost of moving between jobs as a function of travelled distance. The third term computes the labor cost of travel as a function of time to drive between jobs.

Constraint (2) assigns a job to one worker who possesses the skill required by the job.

Constraint (3) ensures the total working hours of a worker does not exceed capacity.

Constraint (4) enforces that for every job assigned to a skilled worker, the job is completed prior to the deadline for that job, and earlier than the total make span of completing all the jobs.

Constraint (5) satisfies the precedence relationships between a pair of jobs $(i, j) \in H$, i.e. the start time of job j must be no less than the completion time of job i plus the travel time between job i and j.

Constraints (6) through (8) together guarantee the correct configuration of each route (path) assigned to a worker. Constraint (6) states that a worker must travel *to at most* one job after finishing a job; Constraint (7) specifies that a worker must travel *from at most* one job before starting another job; Constraint (8) ensures that the number of arcs in a route of a worker must be equal to the number of jobs minus one assigned to the worker.

Constraint (9) is the big-M formulation to enforce that the time to start a job j cannot be less than the completion time of the immediate preceding job i, plus the travel time between i and j.

Constraint (10) specifies the domain of all the decision variables.

4.1.1 Implementation of the Single Assignment Model

The first case involves the Single Multi-Skilled Worker assigned to various single-skill tasks. That, is, the tasks for assignment only require a single skill. The tasks under consideration include work from 39 individual work orders, as well as 16 other tasks which comprise a Make Ready Project and are therefore co-located. The 39 jobs were selected from the group of 64 work orders that were used to develop the worker efficiency scores and process times. The included Make Ready Project was selected from within that same time period so as to reflect a job that might impact the scheduling decision from the managerial perspective.

Priority of Work Order	Number of Jobs in Each Skill Class					
	A	B	C	D	Total	Frequency
High	10	3	2	0	15	27%
Medium	6	9	4	5	24	44%
Low	6	4	3	2	16	29%
Total	22	16	9	8	55	
Frequency	40%	29%	16%	15%		100%

Table 4.1 Frequency of Jobs by Priority and Skill Level in Case Data.

Type of Job	Number of Jobs in Each Skill Class					
	A	B	C	D	Total	Frequency
Electrical	1	1	1	1	4	7.3%
HVAC	4	3	0	2	9	16%
Other	9	4	3	2	18	33%
Plumbing	4	4	5	1	14	25%
Security	4	4	0	2	10	18%
Total	22	16	9	8	55	
Frequency	40%	29%	16%	15%		100%

Table 4.2 Frequency of Jobs by Skill Class and Level in Case Data.

A frequency distribution of the jobs included for assignment shows that 40% of jobs are of the highest skill level, while the number of work orders decreases to 29% at level B, and is approximately the same at level C and D. This would indicate a requisite higher level of competence overall, if the resource availability is limited. Nearly half of all jobs are of the Medium level of priority, indicating they must be done within 72 work hours. There are about the same number of high and low priority jobs to be assigned. The mix of work class indicates that one-third of all jobs considered in the model are classified as non-traditional trade (Other), followed by one-fourth of all jobs requiring the plumbing skill, followed by HVAC, Security and then Electrical skill. Alternately, while the distribution of work orders appears to be more apportioned to the high or low priority level for HVAC, Security, and Plumbing skill classes, the work orders in the category for non-traditional skilled labor indicates these jobs are more likely to be medium-level priority. Electrical jobs are also either High or Medium level of priority only.

Type of Job	Priority Level of Work Order				
	High	Medium	Low	Total	Frequency
Electrical	2	2	0	4	7.3%
HVAC	4	2	3	9	16%
Other	2	12	4	18	33%
Plumbing	5	3	6	14	25%
Security	2	5	3	10	18%
Total	15	24	16	55	
Frequency	27%	44%	29%		100%

Table 4.3 Frequency of Jobs by Priority and Skill Level in Case Data.

The mathematical model was developed in IBM CPLEX Optimization Studio and for the Case Study was run on a MacBook Pro 2.3 GHz Intel Core i7 with 16 GB of 1600 MHz DDR3 RAM, 8 available threads, and 10,000 MB of working memory. The model consists of 10250 constraints, 33882 variables—27720 are binary and 6162 are other variables, to combine for 233,862 non-zero coefficients. The first feasible solution was achieved at around 8 minutes ($4614.62) and is within 9.11% of optimality. The program terminated at 1 hour with the best incumbent solution ($4249.46) which is within 1.3% of optimality, representing an improvement, finding 52 additional feasible solutions in the additional 52 minutes, with an improvement of $365 in total cost between the first and the last feasible solutions. The total cost of $4249.46 consisted of $3784.83 in labor wages for skilled labor, $197.07 in vehicle wear and tear; and $267.56 in travel-related wages at the standard hourly wage rate per employee. The two most expensive workers, by wage rate, had the lowest average cost of travel between any two jobs. (See Appendix, Table 4.44). The labor tied to physical completion of skilled work contributes 88% of total costs. However, at a greater than 11% contribution to costs, the travel-related costs are not insignificant. When compared to the same set of jobs at the actual cost for performance, it is interesting to note that when comparing the 39 work orders that are not part of the make ready project, the skilled labor cost to perform these jobs in the model is $2,610.74 compared to the actual skilled labor cost of assignment of $3,885.22, a cost decrease of 30.56% indicating a more efficient allocation of skilled workers to jobs as well as the additional precision with which travel costs are allocated to each ordered pair of jobs. Table 4.4 describes the cost of the Case 1 solution compared to the actual cost. Again, the objective is to minimize the total cost of the assignment decision considering the routing, skill, priority and capacity limitations of the actual operating environment. Individual worker routes, as well as the mapping of these routes, are shown in Figures 4.1 through 4.6 and Tables 4.6 through 4.14.

Costs	**Skilled Labor**	**Wear & Tear**	**Travel Labo**	**Total**
39 Work Orders	$ 3,885.22	$ 898.36	$ -	$ 4,783.58
Make Ready Project Tasks	$ 1,565.92	$ -	$ -	$ 1,565.92
Total Actual Cost 55 Jobs	**$ 5,451.14**	**$ 898.36**	**$ -**	**$ 6,349.50**
Case 1 Costs - 39 Work Orders	$ 2,610.74	$ 201.68	$ 127.52	$ 2,939.94
Case 1 Costs - Make Ready Project Tasks	$ 1,174.09	$ 65.87	$ 69.55	$ 1,309.52
Total Cost of Case 1 Solution	**$ 3,784.83**	**$ 267.55**	**$ 197.07**	**$ 4,249.46**
Savings Using Proposed Approach				**$ 2,100.04**

Table 4.4 Comparison of Actual Costs to Cost of Proposed Approach in Case 1.

	Worker								
	CW	GD	JT	NC	PD	JS	RV	JA	KS
Skilled Labor	$104.12	$1523.29	$1191.46	$94.12	$832.85	$0	$38.99	$0	$0
Vehicle Wear & Tear	$19.26	$89.73	$68.46	$14.99	$75.11	$0	$0	$0	$0
Travel Labor	$15.20	$68.87	$41.53	$14.97	$56.5	$0	$0	$0	$0
Total	$138.58	$1681.90	$1301.45	$124.08	$964.46	$0	$38.99	$0	$0

Table 4.5 Summary of Cost of Single Assignment Using Proposed Model.

In summary, the predominant bulk of the work orders are assigned to three workers (GD, JT and PD). Workers CW and NC are used sparingly and the most expensive worker (RV) is used only once. Worker CW was assigned 4 work orders, for a total of 4 hours of labor. All work is scheduled to complete within 4.74 work hours. Travel equates to 27 miles for the 4 jobs.

Worker GD is assigned 19 jobs for a total of about 55 hours of work and nearly 122 miles of travel distance. This equates to 3.24 hours of scheduled travel time. All work is scheduled to be completed before 75 work hours indicating about 15 hours of slack in the schedule. Worker JT is assigned 12 jobs with 39.09 budgeted labor hours. His travel time is the same as GD, at 122 miles and 3.24 hours. However, his stop time is 41.04 work hours, indicating no slack time in the schedule. Worker NC is assigned 4 jobs for a total budgeted labor time of 4 hours, with an additional 26.5 miles of travel at .637 travel hours. His schedule also has no slack time. Worker PD is assigned 15 jobs for a total of 55 skilled labor hours. His travel miles are also 122 and his travel time is

3.24 hours. His scheduled completion time is 75.59 indicating about 15 hours of slack time, similar to Worker GD. Worker RV is assigned one job for a total of .91 skilled labor hours. Workers JS, JA and KS were not used at all in the preliminary case. A Simple GANTT chart is constructed to show the temporal relationships between a standard work schedule and the schedule of each worker's jobs (Figure 4.7) and is shown also as Network Assignment Model (Figure 4.8) and a calendar schedule (Figure 4.9). The total compressed make-span, when integrated into a regular-time work schedule indicates 7.28 days of total make-span. This schedule considers only daytime shifts where employees are off in the evening. Work is scheduled from 7AM to 5PM, with a lunch break mid-days.

Worker CW									
Job ID	Start Time	Skilled Labor Time	Stop Time	Travel Distance	Travel Time	Skilled Labor Cost	Travel Labor Cost	Vehicle Wear & Tear Cost	Total Job Cost
22	0	1	1	18.5	.4	$26.03	$10.41	$10.45	$46.89
29	1.4	1	2.4	4.2	.17	$26.03	$4.43	$2.37	$32.83
36	2.57	1	3.57	4.2	.17	$26.03	$4.43	$2.37	$32.83
33	3.74	1	4.74	0.0	0.0	$26.03	$0.00	$0.00	$26.03
Total		4		26.90	.74	$104.12	$19.27	$15.19	$138.58

Table 4.6 Assignment for Worker CW.

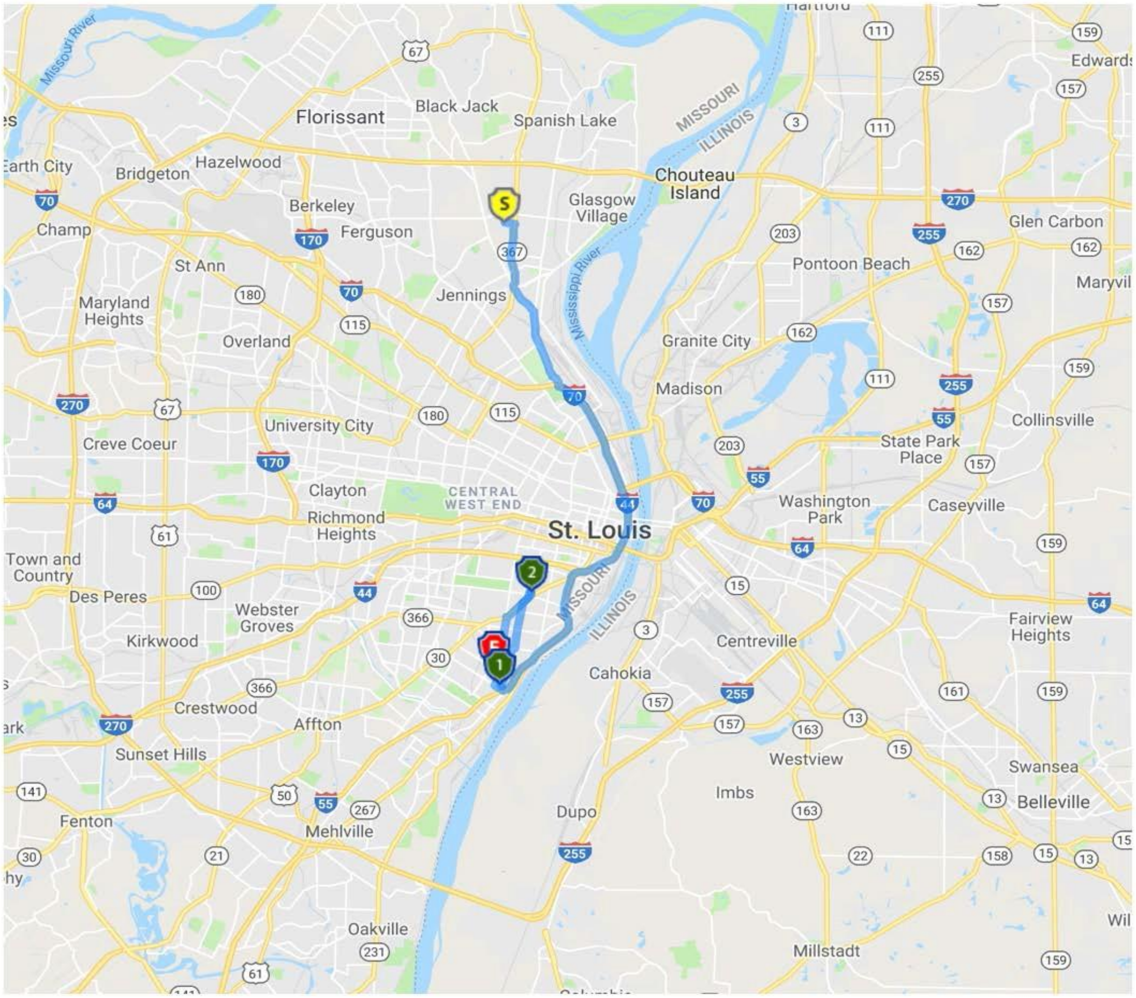


Figure 4.1 Mapped Route For Assignment to Worker CW.

Worker GD									
Job ID	Start Time	Skill Labor Time	Stop Time	Travel Distance	Travel Time	Skilled Labor Cost	Travel Labor Cost	Vehicle Wear & Tear Cost	Total Job Cost
39	0	3	3	4.2	.17	$83.16	$4.71	$2.37	$90.24
7	3.17	3	6.17	4.2	.17	$83.10	$4.71	$2.37	$90.18
12	6.34	3	9.34	4.2	.17	$83.16	$4.71	$2.37	$90.24
2	9.51	3	12.52	4.2	.17	$83.16	$4.71	$2.37	$90.24
5	12.69	3	15.69	17.8	.4	$83.16	$11.08	$10.06	$104.29
88	16.09	2.99	19.08	3.2	.15	$82.92	$4.16	$1.81	$88.88
32	19.23	2.5	21.73	3.2	.15	$69.25	$4.16	$1.81	$75.21
91	38.32	2.99	41.31	10	.17	$82.92	$4.71	$5.65	$93.28
74	41.48	2.99	44.47	10	.17	$82.92	$4.71	$5.65	$93.28
83	44.64	3	47.64	10	.17	$83.16	$4.71	$5.65	$93.52
85	47.81	3	50.82	10	.17	$83.16	$4.71	$5.65	$93.52
54	50.99	3	53.99	10	.17	$83.16	$4.71	$5.65	$93.52
71	54.16	2.99	57.15	10	.17	$82.92	$4.71	$5.65	$93.28
81	57.32	3	60.32	6.7	.217	$83.16	$6.01	$3.79	$92.95
31	60.54	2.5	63.04	2.4	.1167	$69.25	$3.23	$1.36	$73.84
16	63.16	2.5	65.66	3.9	.17	$69.25	$4.71	$2.20	$76.16
11	65.83	3	68.83	3.9	.17	$83.16	$4.71	$2.20	$90.07
27	69	3	72	4	.166	$83.10	$4.60	$2.26	$89.96
26	72.17	2.5	74.67	0	0	$69.25	$0.00	$0.00	$69.25
Total		54.99		121.9	3.24	$1,523.29	$89.74	$68.87	$1,681.90

Table 4.7 Assignment for Worker GD.

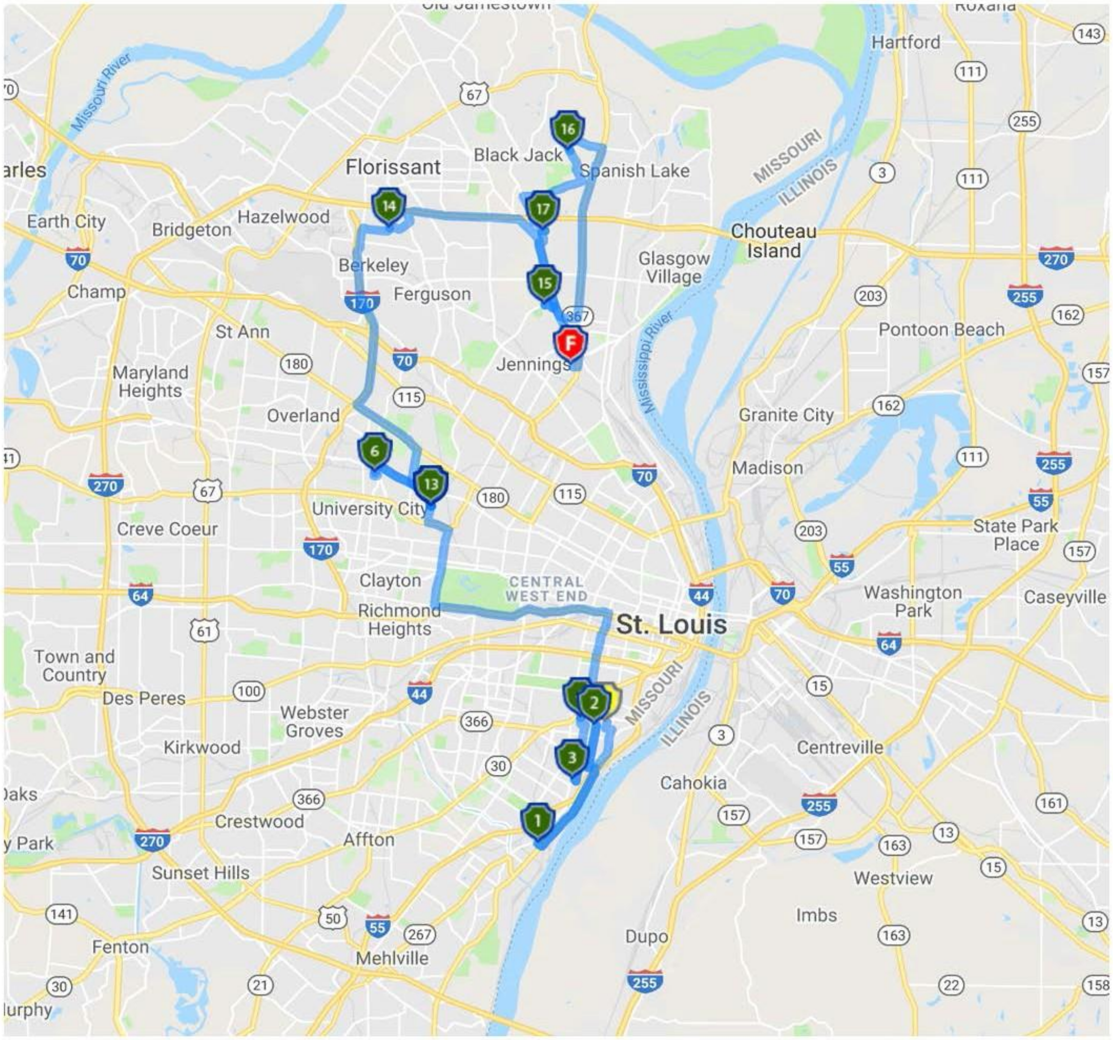


Figure 4.2 Mapped Route For Assignment to Worker GD.

Worker JT									
Job ID	Start Time	Skilled Labor Time	Stop Time	Travel Distance	Travel Time	Skilled Labor Cost	Travel Labor Cost	Vehicle Wear & Tear Cost	Total Job Cost
3	0	1.5	1.5	4.2	.316	$45.81	$9.63	$2.37	$57.81
28	1.82	5.83	7.65	15.6	.25	$177.70	$7.62	$8.81	$194.13
38	7.90	2.67	10.57	4.2	.17	$81.38	$5.18	$2.37	$88.94
24	10.74	2.67	13.41	2.3	.15	$81.38	$4.57	$1.30	$87.25
6	13.56	1.5	15.06	2.3	.15	$45.81	$4.57	$1.30	$51.68
25	15.21	5.83	21.04	4.2	.17	$177.70	$5.18	$2.37	$185.25
30	21.21	1.75	22.96	4.2	.17	$53.30	$5.18	$2.37	$60.85
19	23.13	5.83	28.96	20.1	.4	$177.70	$12.19	$11.36	$201.25
55	29.36	1.5	30.86	3.2	.15	$45.81	$4.57	$1.81	$52.19
4	31.01	1.5	32.52	3.2	.15	$45.81	$4.57	$1.81	$52.19
79	32.67	5.83	38.50	10	.17	$177.70	$5.18	$5.65	$188.53
13	38.67	2.67	41.34	0	0	$81.38	$0	$0	$81.38
Total		39.09		121.9	3.24	$1191.46	$68.46	41.53	$1301.45

Table 4.8 Assignment to Worker JT.

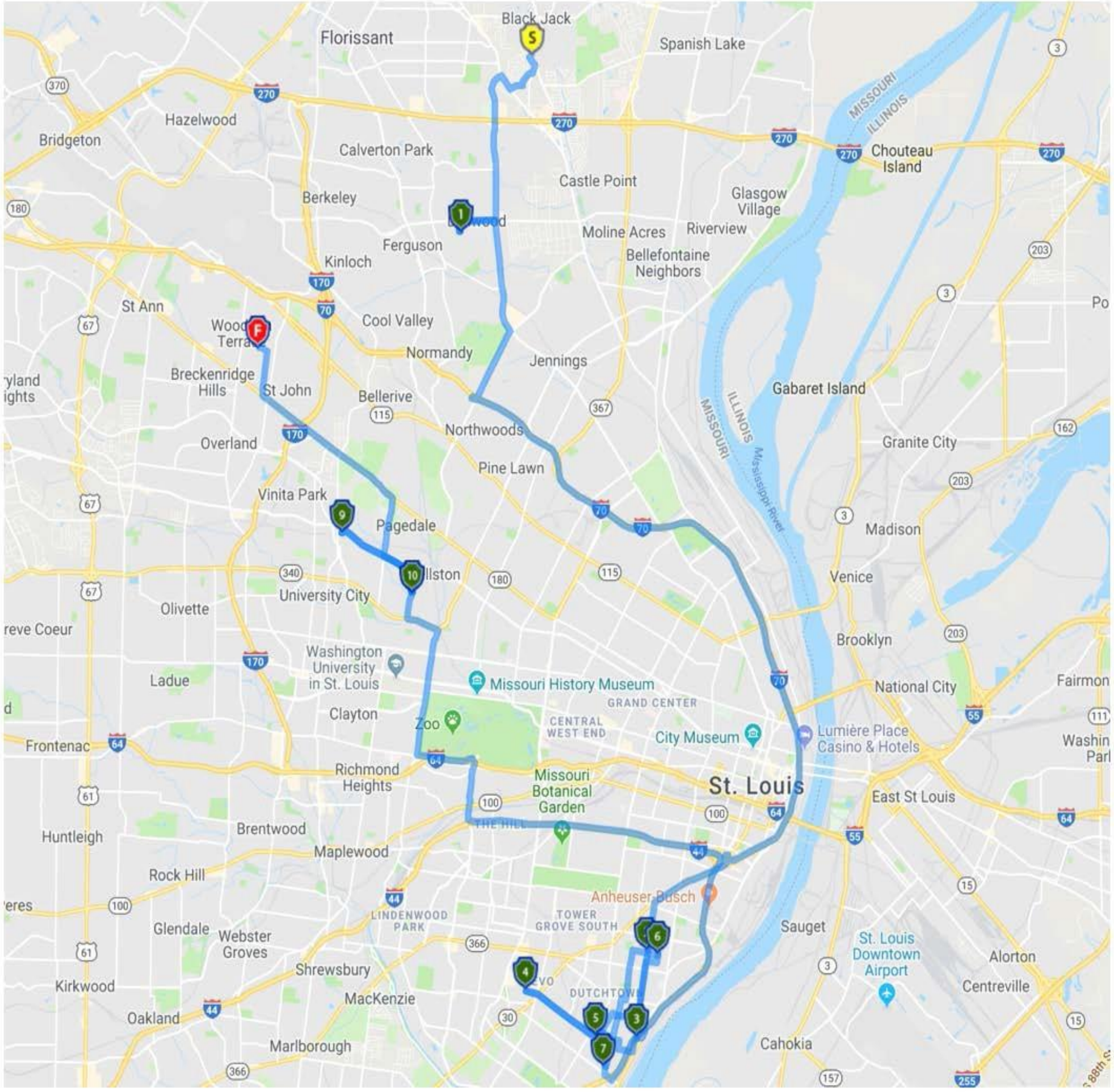


Figure 4.3 Mapped Route For Assignment to Worker JT.

Worker NC									
Job ID	Start Time	Skilled Labor Time	Stop Time	Travel Distance	Travel Time	Skilled Labor Cost	Travel Labor Cost	Vehicle Wear & Tear Cost	Total Job Cost
10	0	1	1	6.7	.217	$23.53	$5.11	$3.79	$32.42
20	1.217	1	2.217	15.6	.25	$23.53	$5.88	$8.81	$38.23
9	2.467	1	3.467	4.2	.17	$23.53	$4.00	$2.37	$29.90
21	3.637	1	4.637	0	0	$23.53	$0	$0	$23.53
Total		4		26.5	.637	$94.12	$14.99	$14.97	$124.08

Table 4.9 Assignment to Worker NC.

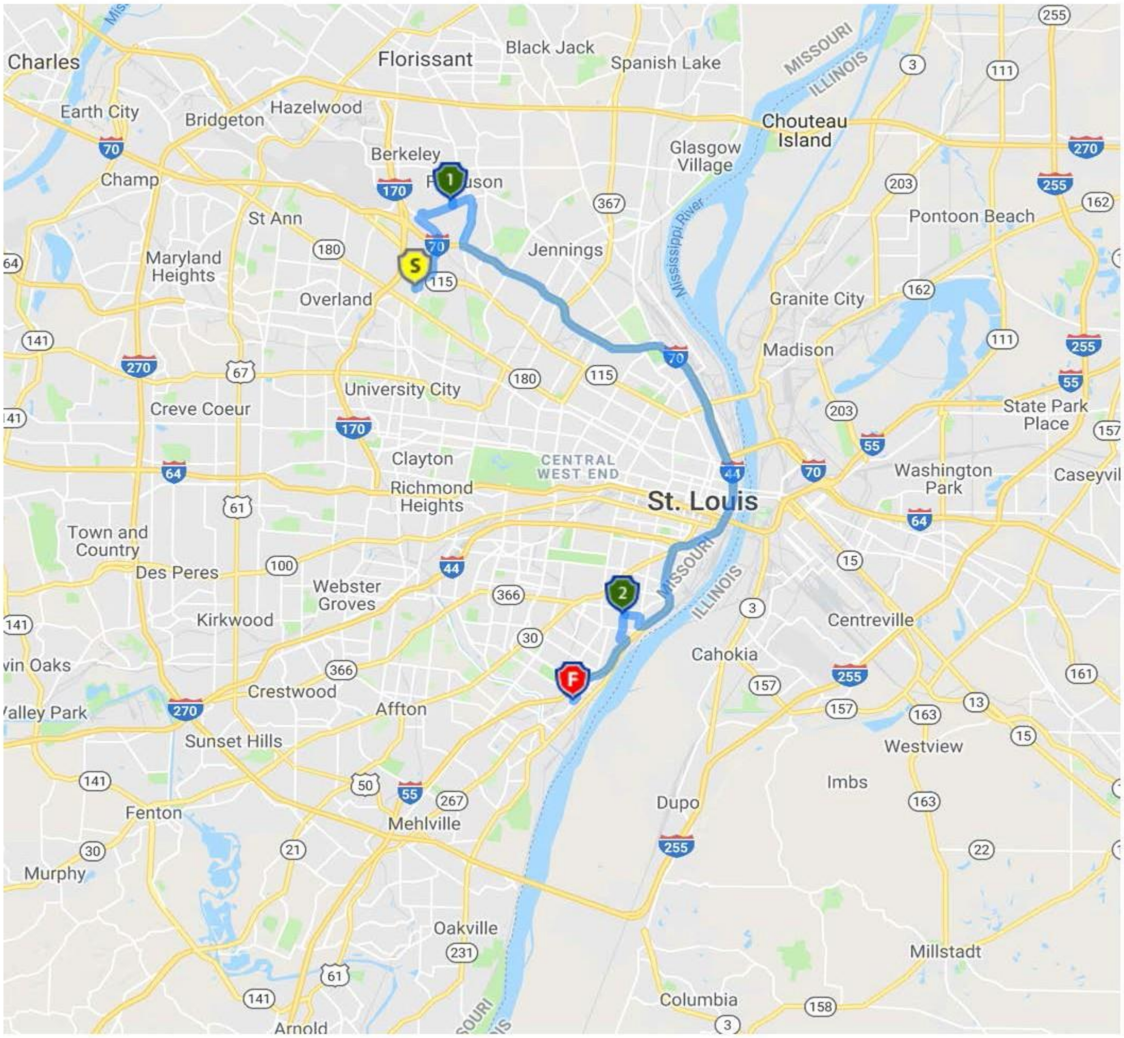


Figure 4.4 Mapped Route For Assignment to Worker NC.

Worker PD									
Job ID	Start Time	Skilled Labor Time	Stop Time	Travel Distance	Travel Time	Skilled Labor Cost	Travel Labor Cost	Vehicle Wear & Tear Cost	Total Job Cost
14	0	2	2	2.3	.15	$52.02	$3.90	$1.30	$57.23
15	2.15	3.5	5.65	2.3	.15	$91.11	$3.90	$1.30	$96.31
37	6.48	2	8.48	2.3	.15	$52.02	$3.90	$1.30	$57.23
1	8.63	1	9.63	2.4	.15	$26.03	$3.90	$1.36	$31.29
8	9.78	3	12.78	15.6	.4167	$78.09	$10.85	$8.81	$97.75
35	13.20	2	15.20	10	.17	$52.02	$4.43	$5.65	$62.10
23	15.37	1	16.37	4.2	.316	$26.03	$8.23	$2.37	$36.63
18	16.68	3	19.68	4.2	.316	$78.09	$8.23	$2.37	$88.69
34	20	4	24	6.7	.2167	$104.12	$5.64	$3.79	$113.55
86	24.22	3	27.22	10	.17	$78.09	$4.43	$5.65	$88.17
78	27.39	1	28.39	10	.17	$26.03	$4.43	$5.65	$36.11
40	68.58	2.25	70.83	10	.17	$58.57	$4.43	$5.65	$68.64
17	71	1	72	10	.17	$26.03	$4.43	$5.65	$36.11
60	72.17	1	73.17	10	.17	$26.03	$4.43	$5.65	$36.11
70	73.34	2.25	75.59	0	0	$58.57	$0.00	$0.0	$58.57
Total		54.99		121.9	3.24	$832.85	$75.11	$56.50	$964.46

Table 4.10 Assignment to Worker PD.

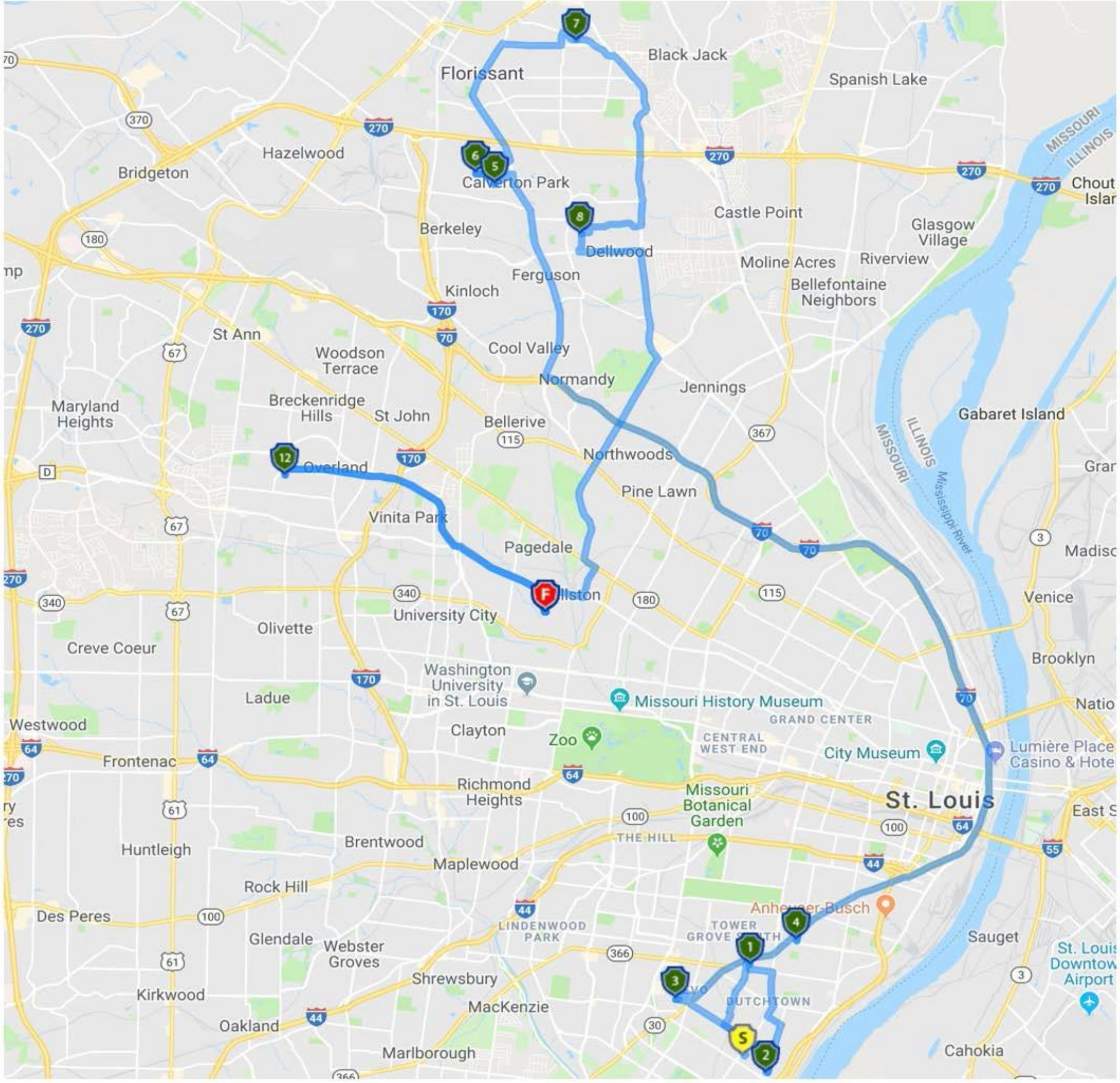


Figure 4.5 Mapped Route For Assignment to Worker PD.

Worker JS
NOT USED

Table 4.11 Assignment to Worker JS.

Worker RV									
Job ID	Start Time	Skilled Labor Time	Stop Time	Travel Distance	Travel Time	Skilled Labor Cost	Travel Labor Cost	Vehicle Wear & Tear Cost	Total Job Cost
77	0	.91	.91	0	0	$38.99	$0.00	$0.00	$38.99
Total		.91		0	0	$38.99	$0.00	$0.00	$38.99

Table 4.12 Assignment to Worker RV.

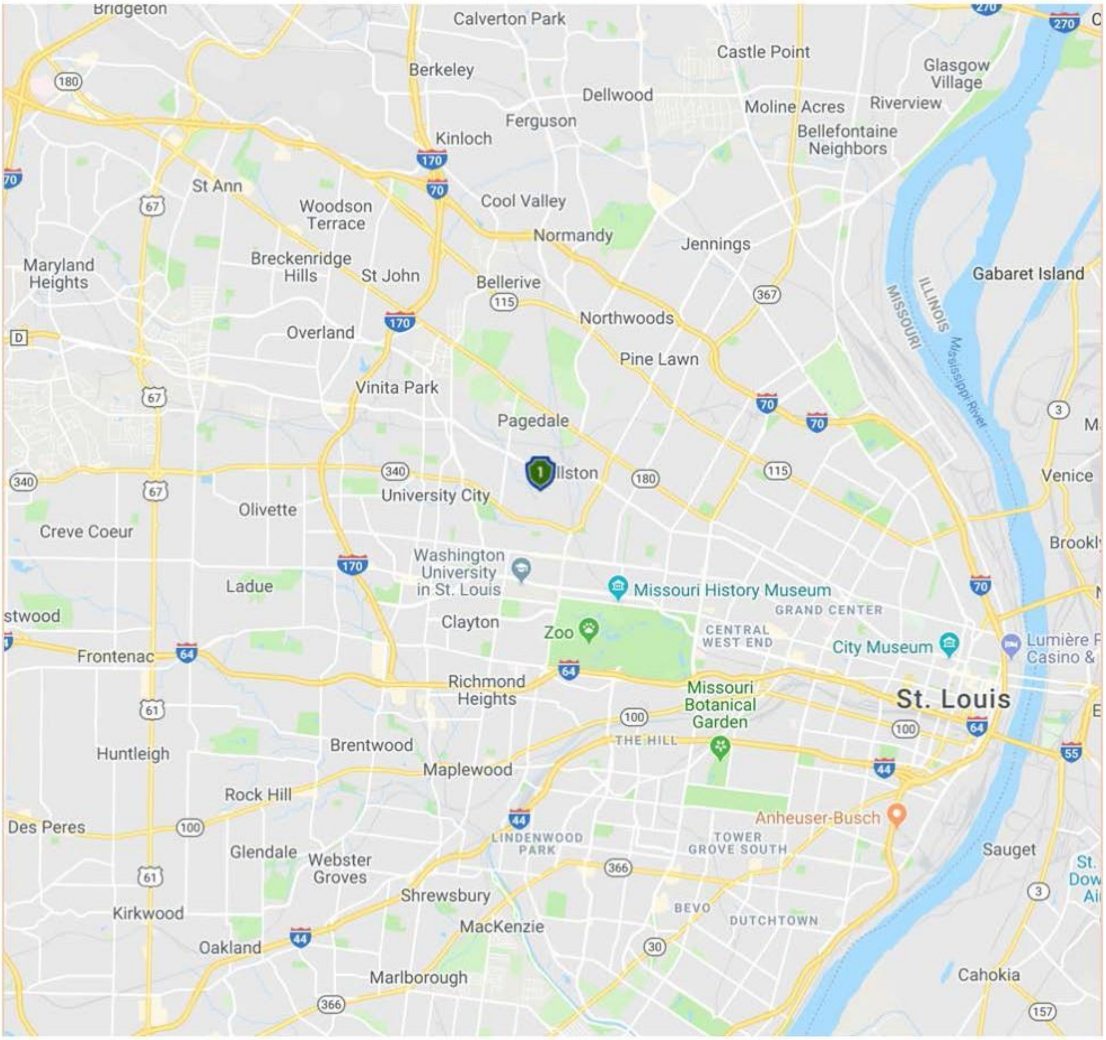


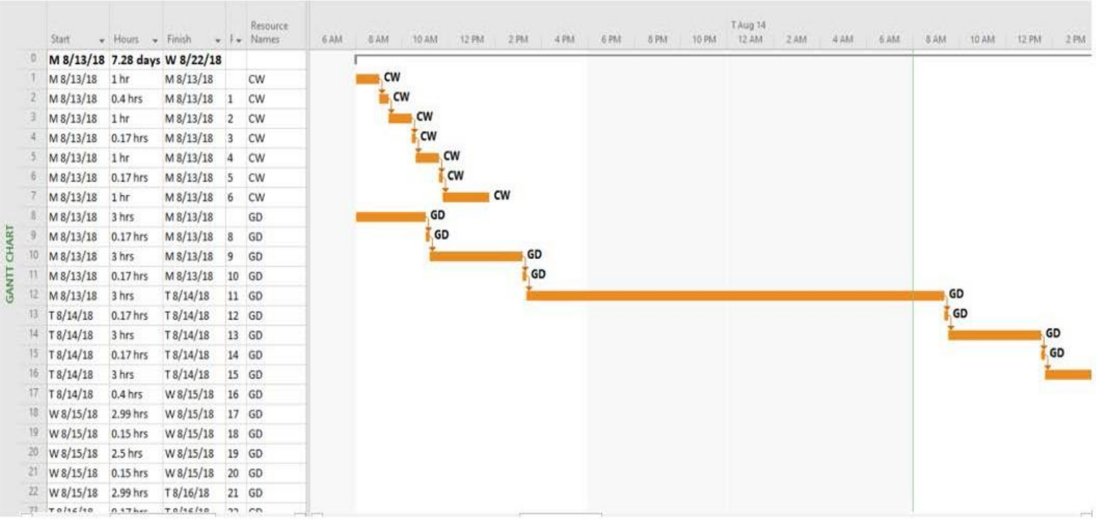
Figure 4.6 Assignment to Worker RV.

Worker JA
NOT USED

Table 4.13 Assignment to Worker JA.

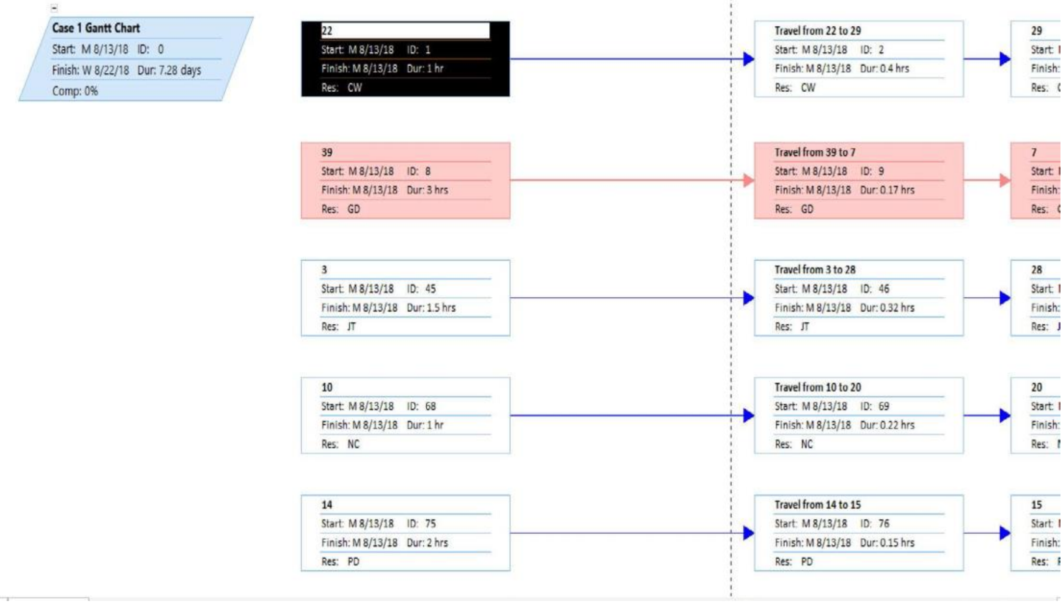
Worker KS
NOT USED

Table 4.14 Assignment to Worker KS.



	Start	Hours	Finish	P	Resource Names
0	**M 8/13/18**	**7.28 days**	**W 8/22/18**		
1	M 8/13/18	1 hr	M 8/13/18		CW
2	M 8/13/18	0.4 hrs	M 8/13/18	1	CW
3	M 8/13/18	1 hr	M 8/13/18	2	CW
4	M 8/13/18	0.17 hrs	M 8/13/18	3	CW
5	M 8/13/18	1 hr	M 8/13/18	4	CW
6	M 8/13/18	0.17 hrs	M 8/13/18	5	CW
7	M 8/13/18	1 hr	M 8/13/18	6	CW
8	M 8/13/18	3 hrs	M 8/13/18		GD
9	M 8/13/18	0.17 hrs	M 8/13/18	8	GD
10	M 8/13/18	3 hrs	M 8/13/18	9	GD
11	M 8/13/18	0.17 hrs	M 8/13/18	10	GD
12	M 8/13/18	3 hrs	T 8/14/18	11	GD
13	T 8/14/18	0.17 hrs	T 8/14/18	12	GD
14	T 8/14/18	3 hrs	T 8/14/18	13	GD
15	T 8/14/18	0.17 hrs	T 8/14/18	14	GD
16	T 8/14/18	3 hrs	T 8/14/18	15	GD
17	T 8/14/18	0.4 hrs	W 8/15/18	16	GD
18	W 8/15/18	2.99 hrs	W 8/15/18	17	GD
19	W 8/15/18	0.15 hrs	W 8/15/18	18	GD
20	W 8/15/18	2.5 hrs	W 8/15/18	19	GD
21	W 8/15/18	0.15 hrs	W 8/15/18	20	GD
22	W 8/15/18	2.99 hrs	T 8/16/18	21	GD

Figure 4.7 Critical Path Schedule as GANTT chart for Single Assignment Case.



Case 1 Gantt Chart
Start: M 8/13/18 ID: 0
Finish: W 8/22/18 Dur: 7.28 days
Comp: 0%

22
Start: M 8/13/18 ID: 1
Finish: M 8/13/18 Dur: 1 hr
Res: CW

Travel from 22 to 29
Start: M 8/13/18 ID: 2
Finish: M 8/13/18 Dur: 0.4 hrs
Res: CW

29

39
Start: M 8/13/18 ID: 8
Finish: M 8/13/18 Dur: 3 hrs
Res: GD

Travel from 39 to 7
Start: M 8/13/18 ID: 9
Finish: M 8/13/18 Dur: 0.17 hrs
Res: GD

7

3
Start: M 8/13/18 ID: 45
Finish: M 8/13/18 Dur: 1.5 hrs
Res: JT

Travel from 3 to 28
Start: M 8/13/18 ID: 46
Finish: M 8/13/18 Dur: 0.32 hrs
Res: JT

28

10
Start: M 8/13/18 ID: 68
Finish: M 8/13/18 Dur: 1 hr
Res: NC

Travel from 10 to 20
Start: M 8/13/18 ID: 69
Finish: M 8/13/18 Dur: 0.22 hrs
Res: NC

20

14
Start: M 8/13/18 ID: 75
Finish: M 8/13/18 Dur: 2 hrs
Res: PD

Travel from 14 to 15
Start: M 8/13/18 ID: 76
Finish: M 8/13/18 Dur: 0.15 hrs
Res: PD

15

Figure 4.8 Network Diagram of Worker Assignment for Single Assignment Case.

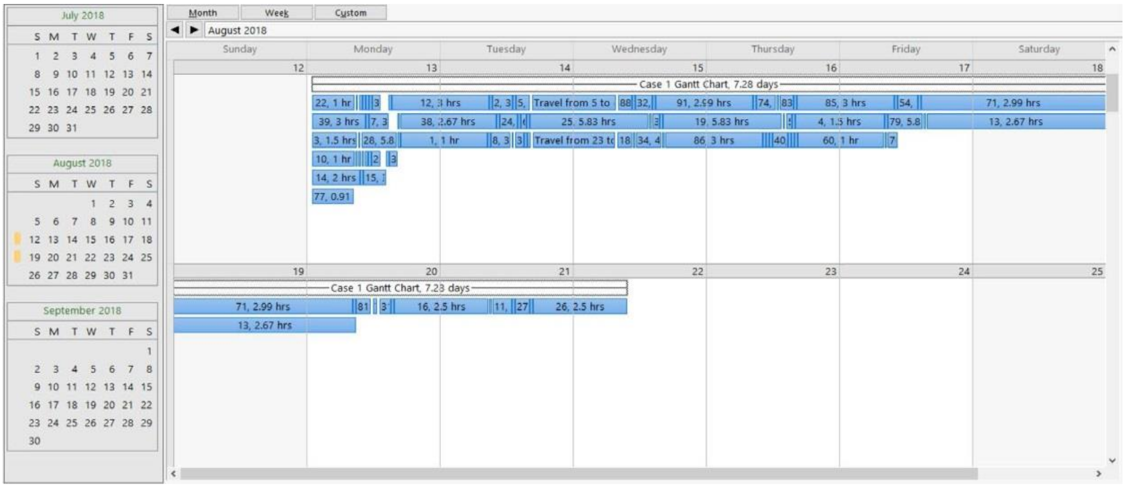


Figure 4.9 Calendar of Single Case Assignment.

4.2 Model With Precedence Relationships Among Tasks

In property management, the make-ready project occurs after a tenant moves out of a unit and prior to a new tenant moving in to that unit. The make ready is required to bring a property back to a condition suitable for rent. Such projects offer a chance for owners to reinvest in their property, upgrade and renovate the dwelling, comply with local ordinances, and prepare a property for sale. These projects are generally multi-day projects incorporating several tasks of various skill levels that must occur in a particular sequence. Because we can decompose a single make ready project into tasks, and distribute those tasks along with other single-skill jobs, we can consider assigning these tasks in line with unrelated work so as to utilize the buffer times between dependent tasks in a more efficient manner. We can adapt the general nature of the house building problem to the maintenance environment. In this scenario, tasks that comprise the make ready project are combined with all other jobs and assigned based on the previous assignment policy. This requires precedence constraints be placed on the sequence of tasks that comprise the make ready. This additional constraint is incorporated into the previous models:

$$t_j \geq t_i + \sum_{s \in S} x_{is} p_i / \delta_{k^i s} \qquad \forall \text{ (ordered i, j pairs) } \in I \times I \qquad (11)$$

(11) ensures that for every ordered pair (i, j), when job i must precede job j, there is no overlap in the start time of successor task j and the end time predecessor time i. This relationship is enforced in the mathematical model by using a key to identify the jobs of set comprising a larger project, where each sequential task must be performed in succession. The logical relationship is that, for example, demolition must occur before any other work, followed by security on the garage door for storage of materials and tools. Plumbing Rough-in must then take place so as to mitigate any water service that is necessary for other tasks where cleanup is required. This also requires accessing the framed-in utilities which may require cutting into walls and so this work must occur before drywall patching. Interior doors and trim then are finished or framed in prior to painting walls and wallpapering, followed by floors and tile, which must occur after paint dries to mitigate spills or drips onto finished flooring. This logical procession of tasks culminates in finishing the floors of the home interior and moves to the exterior tasks to include concrete finishing and walkway pouring and, finally, fencing.

4.2.1 Implementation of the Single Assignment Model with Precedence

The mathematical model expressed in 4.1 with the additional constraint in this section, is formulated in the CPLEX Optimization Programming Language (OPL). The sample data set is accessed where the prior set of 39 work orders are considered for scheduling, assignment and routing, along with the 15 tasks required to make the unit ready for rent; the prior model treats these additional tasks as independent whereas this model enforces the sequential constraints. A total number of 55 tasks are assigned—from a range of 5 work classes, and 4 work levels—to the same 9 workers from the prior example. All workers are available for up to 80 hours of assignment.

Make Ready Work and Sequence Dependencies									
Sequence	Description	Qty	Dims	Description	Hours	Skill Level	Skill Class	Precedes	Succeeds
40. DEMOLITION	Take out carpet and clear fenceline.	1			4	Misc	D	54	55
54. FRAMING, WINDOWS, AND EXT DOORS	Old English	1	Gal	Old English	2	Security	A	70	40
55. GARAGE DOOR AND EXTERIOR LOCKS	Tumblers	3	Kwikset	Kwikset	1	Security	B	40	na
60. ROUGH PLUMBING	1 diverter/2 drains	1	Kit	1-1/2" Diverter	3	Plumbing	C	78	40
70. INTERIOR DOORS AND TRIM	Polyshade: need stain swatch to match	1	Gal	Polyshade Mahogany	2	Misc	D	71	60
71. PAINT AND WALLPAPER	Interior semi-gloss color match	3	Gal	Favorite Tan	8	Misc	B	78	70
74. VINYL AND CERAMIC TILE	laminate	40	sqft.	Walnut	5	Carpentry	B	76	78
76. APPLIANCES & SPECIAL EQUIPM'T	Stove not included in price/refrigerator not included	0				Other	D	na	74, 77
77. FINISH ELECTRICAL	Cover plates	32	Duplex	White	2	Electrical	D	79	83
78. FINISH PLUMBING	Vanity	1	30"	Basin and Cabinet	2	Plumbing	C	74, 79	60
79. FINISH HVAC & FINAL HEAT	A-coil/condenser	1	set	Goodman 3.5t	6	HVAC	A	71	77
81. CARPET	Remnant	3	Rooms	Espresso	8	Misc	A	86	85
83. DRYWALL REPAIRS	Patch Plaster w/ Durham's Rock Hard Water Putty	1	Quart	Durham's Rock Hard Water Putty	4	Misc	A	71	
85. FINAL PAINT	Cabinet paint	1	Gal	Brown	1	Misc	A	86	83
86. FINAL WOOD FLOOR FINISH	Murphy's	1	Gal	Murphy's Oil Soap	2	Misc	C	88	85
88. WALKS, DRIVES, AND PATIOS	Porch cracks; thin concrete patch mix	1	Bag	Cement Mix	3	Misc	B	91	86
91. FENCING	Fenceline cleared/pickets on back right and front right	2	Panels	Cedar 4-5/8"" Picket	4	Misc	B	na	88

Table 4.15 Make Ready Project Work Classification and Sequence Dependencies.

The second case involves the Single Multi-Skilled Worker as well; however the complexity of precedence is incorporated, so that we can determine if any impact on schedule is caused by the necessity of one task being performed prior to another task. The tasks for assignment only require a single skill. The same tasks from the first case are used; however for the Make Ready Project, the real sequence dependencies are respected as paired predecessor-successor relationships between tasks. The program was run on a MacBook Pro 2.3 GHz Intel Core i7 with 16 GB of 1600 MHz DDR3 RAM, 8 available threads, and 10,000 MB of working memory; and with a limit on solution time of 1 hour. The model consists of 10270 constraints, 33882 variables—27720 are binary and 6162 are other variables, to combine for 234,262 non-zero coefficients. 49 feasible solutions were found in less than 11.5 minutes, the best solution of these ($4,265.26) being within 1.67% of optimal. An additional 15 solutions were found prior to program termination at 1 hour; the best solution of these ($4,245.12) bringing the gap to within 1.2% of optimality. This represents a savings of $20.13 for an additional 48.5 minutes of time from initial solution.

Costs	**Skilled Labor**	**Wear & Tear**	**Travel Labo**	**Total**
Case 1 Costs - 39 Work Orders	$ 2,610.74	$ 201.68	$ 127.52	$ 2,939.94
Case 1 Costs - Make Ready Project Tasks	$ 1,174.09	$ 65.87	$ 69.55	$ 1,309.52
Total Cost of Case 1 Solution	**$ 3,784.83**	**$ 267.55**	**$ 197.07**	**$ 4,249.46**
Case 2 Costs - 39 Work Orders	$ 2,605.73	$ 195.69	$ 134.19	$ 2,935.61
Case 2 Costs - Make Ready Project Tasks	$ 1,174.09	$ 65.87	$ 69.55	$ 1,309.51
Total Cost of Case 2 Solution	**$ 3,779.82**	**$ 261.56**	**$ 203.74**	**$ 4,245.12**
Difference				**$ 4.34**

Table 4.16 Cost Comparison for Model With Precedence (Case 2) and Without (Case 1).

	Worker								
	CW	GD	JT	NC	PD	JS	RV	JA	KS
Skilled Labor	$104.12	$1440.19	$1191.46	$94.12	$910.94	$0	$38.99	$0	$0
Vehicle Wear & Tear	$19.26	$82.26	$68.46	$14.99	$76.60	$0	$0	$0	$0
Travel Labor	$15.20	$67.69	$41.53	$14.97	$64.35	$0	$0	$0	$0
Total	$138.58	$1590.14	$1301.45	$124.08	$1051.89	$0	$38.99	$0	$0

Table 4.17 Cost of Assignment Considering Precedence Tasks, by Worker.

The total cost of $4245.12 consisted of $3779.82 in labor wages for skilled labor, $203.74 in vehicle wear and tear; and $261.56 in travel wages. Note that the labor tied to physical completion of skilled work increases slightly to 89% of total costs. There is a slight change in the proportion of wear and tear versus travel labor costs, most likely due to the trade-off decision to satisfy the precedence constraints inherent in the Make Ready project rules being considered in this iteration of the case. At nearly 11% contribution to costs, the travel-related costs are still significant. Workers JS, JA and KS are all not used in the assignment. The total compressed make-span, when integrated into a regular-time work schedule indicates 6.87 days of total make-span, a reduction in make-span of .41 days compared to Case 1, and all sequence dependencies were satisfied. Two employee costs change, however, to accommodate the precedence requirements of the Make Ready Project tasks. Worker GD's cost decreases by $91.76, and Worker PD cost increases by $87.43. Individual worker routes, as well as the mapping of these routes, are shown above and changes are noted below.

- For Worker CW: 3 of four jobs change in sequence. All jobs remain with the same worker.
- For Worker GD: almost all sequence relationships change. Job 7 is reassigned elsewhere.
- For Worker JT: Job 79 and 4 are switched in sequence. All other sequence relationships remain the same.
- For Worker NC: No Change from the prior case.
- For Worker PD: added a job to his workload which was previously assigned to Worker GD. The sequence for 5 jobs was rearranged.
- For Worker RV: remained assigned to only one job.

Worker CW									
Job ID	Start Time	Skilled Labor Time	Stop Time	Travel Distance	Travel Time	Skilled Labor Cost	Travel Labor Cost	Vehicle Wear & Tear Cost	Total Job Cost
22	0	1	1	18.5	.4	$26.03	$10.41	$10.45	$46.89
33*	1.4	1	2.4	4.2	.17	$26.03	$4.43	$2.37	$32.83
36*	2.57	1	3.57	4.2	.17	$26.03	$4.43	$2.37	$32.83
29*	3.74	1	4.74	0	0.0	$26.03	$0.00	$0.00	$26.03
Total		4		26.90	.74	$104.12	$19.27	$15.19	$138.58

Table 4.18 Assignment for Worker CW.

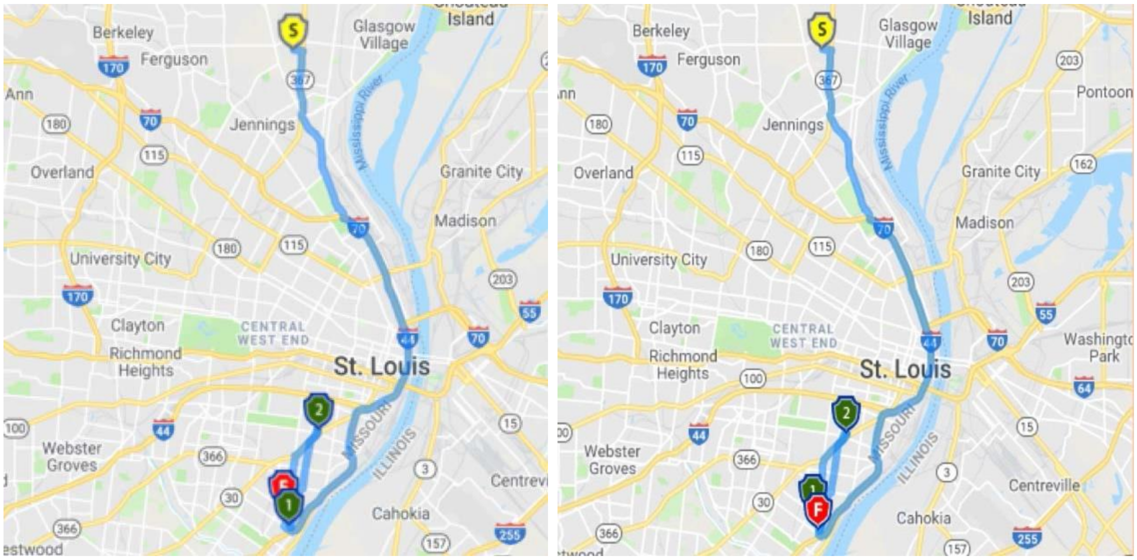


Figure 4.10 Route for CW Without Precedence (Case 1, Left); With Precedence (Case 2, Right).

Worker GD									
Job ID	Start Time	Skilled Labor Time	Stop Time	Travel Distance	Travel Time	Skilled Labor Cost	Travel Labor Cost	Vehicle Wear & Tear Cost	Total Job Cost
5*	0	3.00	3.00	10	0.17	$83.16	$4.71	$5.65	$93.52
39*	3.17	3.00	6.17	4.2	0.17	$83.16	$4.71	$2.37	$90.24
2*	6.34	3.00	9.35	4.2	0.17	$83.16	$4.71	$2.37	$90.24
12*	9.516	3.00	12.52	9.7	0.25	$83.16	$6.93	$5.48	$95.56
26*	12.77	2.5	15.27	4	0.17	$69.25	$4.71	$2.26	$76.22
16*	15.44	2.5	17.94	8.3	0.216	$69.25	$5.98	$4.69	$79.92
74*	18.15	2.99	21.15	3.2	0.15	$82.92	$4.16	$1.81	$88.88
32*	21.5	2.5	24.00	3.2	0.15	$69.25	$4.16	$1.81	$75.21
83*	26.90	3.00	29.90	10	0.17	$83.16	$4.71	$5.65	$93.52
85*	30.07	3.00	33.07	10	0.17	$83.16	$4.71	$5.65	$93.52
81*	33.24	3.00	36.24	10	0.17	$83.16	$4.71	$5.65	$93.52
54*	36.41	3.00	39.41	10	0.17	$83.16	$4.71	$5.65	$93.52
88*	53.67	2.99	56.67	10	0.17	$82.92	$4.71	$5.65	$93.28
71*	56.84	2.99	59.83	10	0.17	$82.92	$4.71	$5.65	$93.28
91*	60.00	2.99	62.99	6.7	0.217	$82.92	$6.01	$3.79	$92.72
31*	63.21	2.5	65.71	2.4	0.1167	$69.25	$3.23	$1.36	$73.84
27*	65.83	3	68.83	3.9	0.17	$83.10	$4.71	$2.20	$90.01
11*	69.0	3.00	72.00	0	0	$83.16	$0.00	$0.00	$83.16
Total		52.0		119.8	2.97	$1440.19	$82.26	$67.69	$1590.14

Table 4.19 Assignment for Worker GD.

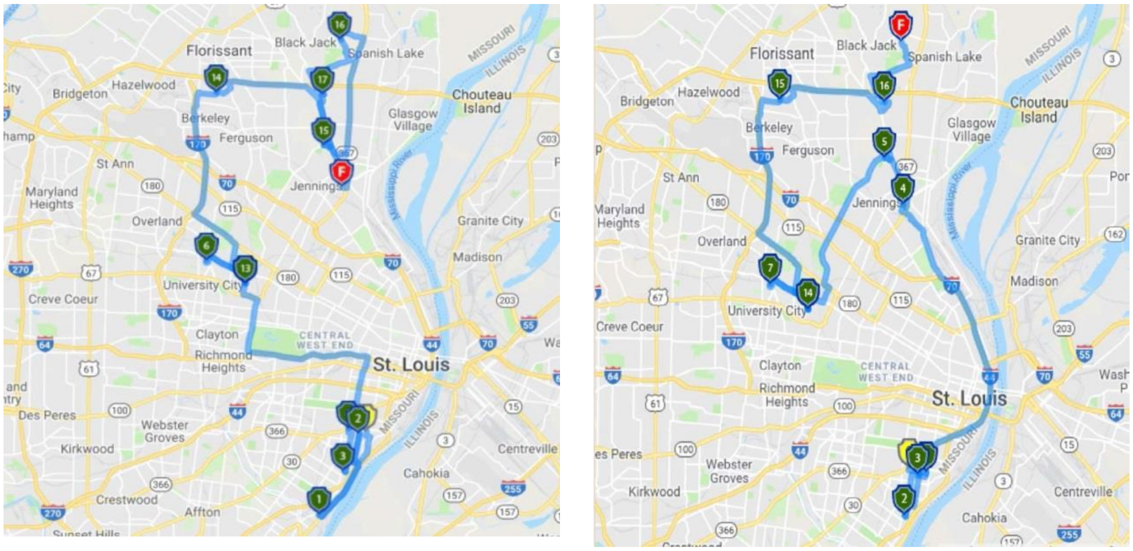


Figure 4.11 Route for GD Without Precedence (Case 1, Left) & With Precedence (Case 2, Right).

Worker JT									
Job ID	Start Time	Skilled Labor Time	Stop Time	Travel Distance	Travel Time	Skilled Labor Cost	Travel Labor Cost	Vehicle Wear & Tear Cost	Total Job Cost
3	0	1.50	1.50	4.2	0.316	$45.81	$9.63	$2.37	$57.81
28	1.82	5.83	7.65	15.6	0.25	$177.70	$7.62	$8.81	$194.13
38	10.86	2.67	13.53	4.2	0.17	$81.38	$5.18	$2.37	$88.94
24	13.70	2.67	16.37	2.3	0.15	$81.38	$4.57	$1.30	$87.25
6	16.52	1.50	18.02	2.3	0.15	$45.81	$4.57	$1.30	$51.68
25	18.17	5.83	24.00	4.2	0.17	$177.70	$5.18	$2.37	$185.25
30	24.17	1.75	25.92	4.2	0.17	$53.30	$5.18	$2.37	$60.85
19	26.09	5.83	31.92	20.1	0.4	$177.70	$12.19	$11.36	$201.25
55	32.32	1.50	33.82	10	0.17	$45.81	$5.18	$5.65	$56.64
79*	51.01	5.83	56.84	3.2	0.15	$177.70	$4.57	$1.81	$184.08
4*	70.50	1.50	72.00	3.2	0.15	$45.81	$4.57	$1.81	$52.19
13	117.33	2.67	120.00	0	0	$81.38	$0.00	$0.00	$81.38
Total		54.99		121.9	3.24	$1191.46	$68.46	$41.53	$1301.45

Table 4.20 Assignment for Worker JT.

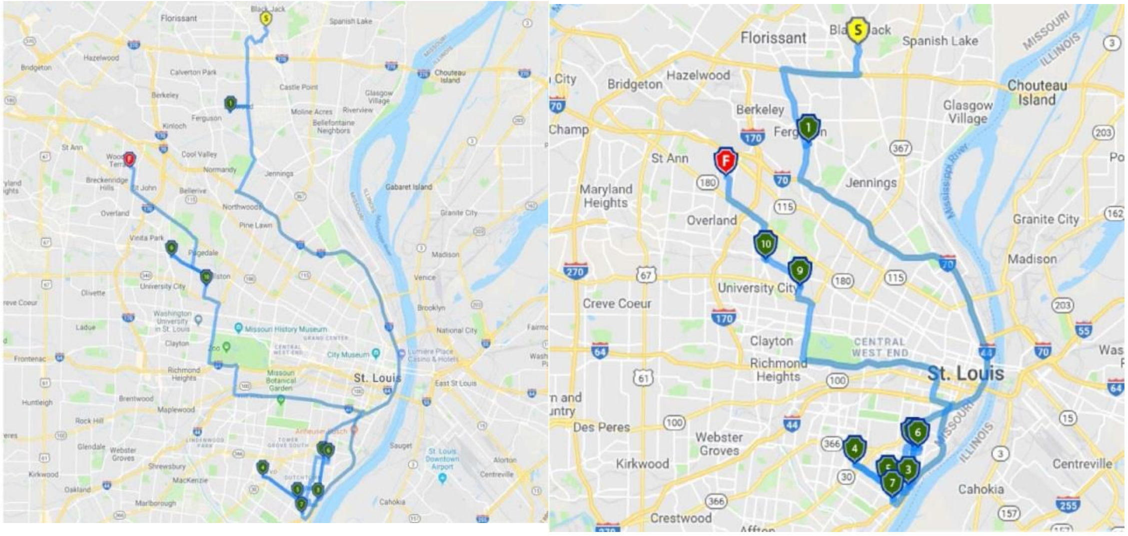


Figure 4.12 Route for JT Without Precedence (Case 1, Left); With Precedence (Case 2, Right).

Worker NC									
Job ID	Start Time	Skilled Labor Time	Stop Time	Travel Distance	Travel Time	Skilled Labor Cost	Travel Labor Cost	Vehicle Wear & Tear Cost	Total Job Cost
10	0	1	1	6.7	.217	$23.53	$5.11	$3.79	$32.42
20	1.22	1	2.217	15.6	.25	$23.53	$5.88	$8.81	$38.23
9	2.47	1	3.467	4.2	.17	$23.53	$4.00	$2.37	$29.90
21	3.64	1	4.637	0	0	$23.53	$0	$0	$23.53
Total		4		26.5	.637	$94.12	$14.99	$14.97	$124.08

Table 4.21 Assignment for Worker NC (No Change).

Worker PD									
Job ID	Start Time	Skilled Labor Time	Stop Time	Travel Distance	Travel Time	Skilled Labor Cost	Travel Labor Cost	Vehicle Wear & Tear Cost	Total Job Cost
7+	0	3	3.00	2.3	0.15	$78.09	$3.90	$1.30	$83.29
15	3.15	3.5	6.65	2.3	0.15	$91.11	$3.90	$1.30	$96.31
37	6.8	2.00	8.80	2.3	0.15	$52.02	$3.90	$1.30	$57.23
1	8.95	1	9.95	2.3	0.15	$26.03	$3.90	$1.30	$31.23
14*	10.10	2.00	12.10	4.2	0.17	$52.02	$4.43	$2.37	$58.82
8	12.27	3	15.27	15.6	0.4167	$78.09	$10.85	$8.81	$97.75
35	15.68	2.00	17.68	10	0.17	$52.02	$4.43	$5.65	$62.10
34*	17.85	4	21.85	10	0.17	$104.12	$4.43	$5.65	$114.20
23	23	1	24.00	4.2	0.316	$26.03	$8.23	$2.37	$36.63
18	24.32	3	27.32	10.7	0.25	$78.09	$6.51	$6.05	$90.64
40*	33.82	2.25	36.07	10	0.17	$58.57	$4.43	$5.65	$68.64
86	36.24	3	39.24	10	0.17	$78.09	$4.43	$5.65	$88.17
70*	39.41	2.25	41.66	10	0.17	$58.57	$4.43	$5.65	$68.64
17	41.83	1	42.83	10	0.17	$26.03	$4.43	$5.65	$36.11
60	43.00	1	44.00	10	0.17	$26.03	$4.43	$5.65	$36.11
78*	50.00	1	51.01	0	0	$26.03	$0.00	$0.00	$26.03
Total		54.99		113.90	2.94	$910.94	$76.60	$64.35	$1051.89

Table 4.22 Assignment for Worker PD.

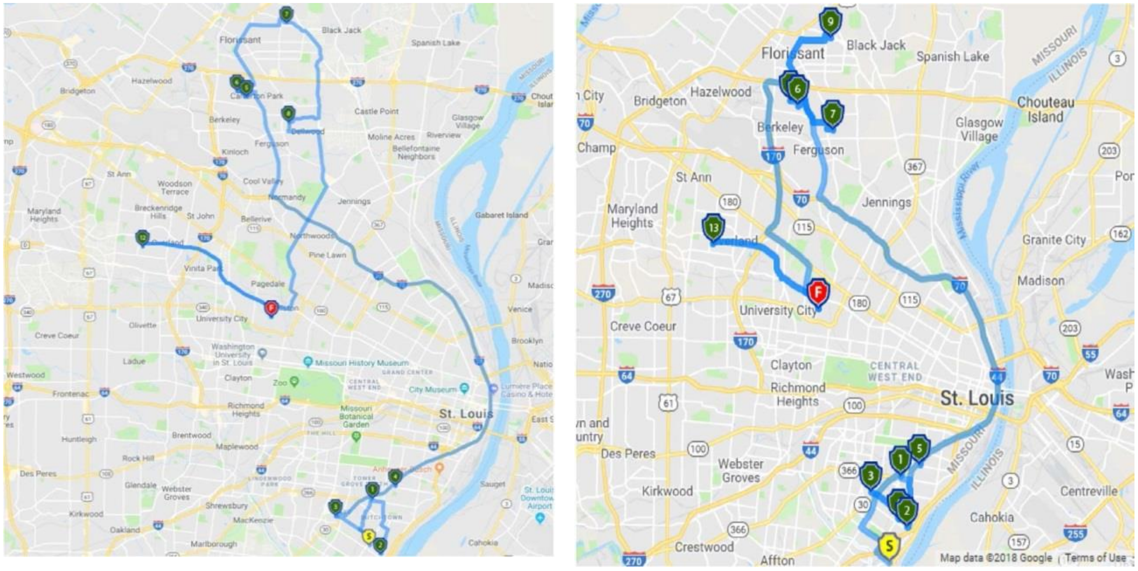


Figure 4.13 Route for PD Without Precedence (Case 1, Left); With Precedence (Case 2, Right).

Worker JS
NOT USED

Table 4.23 Assignment for Worker JS.

Worker RV									
Job ID	Start Time	Skilled Labor Time	Stop Time	Travel Distance	Travel Time	Skilled Labor Cost	Travel Labor Cost	Vehicle Wear & Tear Cost	Total Job Cost
77	0	.91	.91	0	0	$38.99	$0.00	$0.00	$38.99
Total		.91		0	0	$38.99	$0.00	$0.00	$38.99

Table 4.24 Assignment for Worker RV (No Change).

Worker JA
NOT USED

Table 4.25 Assignment for Worker JA.

Worker KS
NOT USED

Table 4.26 Assignment for Worker KS.

4.3 Model with Mentor-Apprentice Pairing

Task completion can benefit from reduced completion times or reduction of cost through the cooperation of resources co-located at a physical site; therefore, we want to evaluate the potential economies from this decision considering travel and other costs, and knowing the project durations or urgencies remain satisfied. There in fact exist many situations in routine maintenance where more than one worker assigned to the same job makes sense. For example: if the scope of work requires more than 2 workers to perform the job—such as larger scopes of work—or if the nature of the job requires a second person due to the space or physical limitations of one worker. Consider the situation where a 2.5 ton air conditioner and furnace installation requires a person to feed a line-set through a home's exterior wall while a person interior to the house guides that line set across an interstitial space. In such a scenario more than one worker is necessary. This scenario would insinuate both workers are experienced in that scope of work.

However, consider the scenario where both workers may not be competent to perform the work. In this scenario, one worker must be able to perform the task to a level of competence in order to train the other worker on that skill. The workforce can therefore be improved and skills trained into less competent workers by pairing a mentor with an apprentice. In fact, this is standard practice in the general labor environment on building construction for most trades. A novice worker begins at a lower level of expertise (assumed to be completely inexperienced) and then through assignment with formally trained masters, satisfies a time-based advancement component in that skill set. It would be ideal to have a similar structure to skill development and career advancement within the property maintenance environment. The limitation is primarily how to model the same skill development when work is not necessarily of such a volume of single-skill work to ensure the full development of any one skill. A more flexible model of skill development is required that meets the demands of a multi-skill work structure while also advancing novice skills to a level of proficiency or competence.

The following mathematical model incorporates several features to make the pairing decision in a multi-skill environment that—as shown in prior cases in this dissertation—effectively trade-off the travel and labor cost benefit of assignment and routing, while also pairing workers of low or no competence with workers of competence sufficient to be considered a mentor. An additional factor, ρ, is introduced to modulate the effective synergy of the pairing assignment, to determine at which level of combined efficiency a pairing assignment begins influences the cost of assignment. In this model, the same decisions are made as in the prior models with the addition to the option to pair workers for jobs if in fact both workers are skilled to perform the job and thus reduce the total make span of the job; also in the case where a worker paired with a mentor can complete the job at a combined efficiency based on the efficiency of the mentor and an expected performance level of the assistant equal to .5 added to the efficiency of the mentor's efficiency score. What follows is a mathematical model for the pairing of an unqualified worker with an experienced worker where all previous decisions variables and parameters still apply, and also added are some unique decision variables, parameters and constraints to ensure an optimal minimum total cost objective. The following model builds on the prior assignment, scheduling and routing decision by allowing a way to build future apprentice skill competency, more fully utilize a workforce, or better balance workforce skill mix.

Sets:

I: $set\ of\ jobs$, indexed by i.

K: $set\ of\ skills$, indexed by k.

S: $set\ of\ workers$, indexed by s.

L: $set\ of\ locations$, indexed by l.

H: $set\ of\ precedence\ relationships\ \ i, j$ indexed by $h, where\ job\ i\ must\ end\ prior\ to\ job\ j\ starts$.

Parameters:

p_i: $normal\ processing\ time\ of\ job\ i.$

k_i: $skill\ k\ required\ by\ job\ i.$

S^k: $set\ of\ workers\ who\ possess\ skill\ k.$

δ_{ks}: $efficiency\ of\ a\ worker\ s\ for\ skill\ k$ with respect to the benchmark worker for skill k When $\delta_{ks} = 1$, s is equivalent to the performance of the benchmark; when $\delta_{ks} < 1$, s is less efficient than the benchmark; when $\delta_{ks} > 1$, s is more efficient than the benchmark.

$\varphi_{kss'}$: $efficiency\ of\ a\ worker\ s\ when\ paired\ with\ worker\ s'\ for\ skill\ k.$

ρ: *discounting factor in computing the pairing*, $\rho \leq 1$.

v_{ij}: *distance to travel between job i and job j*.

τ_{ij}: *time to travel to job i from job j.*

w_s: *weekly limit for worker s in hours* $(e.g. 40)$.

c_s: *hourly wage of worker s*.

b: *travel cost per mile*.

d_i: *due date of job i*.

$\varphi_{kss'}$ can be computed as a function of each individual's efficiency score δ_{ks} depending on whether or not each individual in the pair ss' is qualified the skill k. If both s and s' are qualified for skill k, $\varphi_{kss'} = \rho(\delta_{ks} + \delta_{ks'})$; if s is qualified and s' is not, $\varphi_{kss'} = \rho(\delta_{ks} + 0.5)$; if s' is qualified and s is not, $\varphi_{kss'} = \rho(0.5 + \delta_{ks'})$. For $s = s'$, no pairing exists, thus $\varphi_{kss'} = \delta_{ks}$.

Decision Variables:

$$x_{iss'} = \begin{cases} 1 \begin{cases} s = s', s \ is\ assigned\ to\ job\ i\ by\ himself; \\ s \neq s', s\ is\ paired\ with\ s'\ and\ assigned\ to\ shared\ job\ i; \end{cases} \\ 0\ otherwise. \end{cases}$$

$t_i \geq 0$: *start time of job i*

$$y_{sij} = \begin{cases} 1, & worker\ s\ travels\ from\ the\ location\ of\ job\ i\ to\ the\ location\ of\ job\ j \\ & 0\ otherwise. \end{cases}$$

$\mu_i \geq 0$: actual duration of job i

$$z_{is} = \begin{cases} 1, & worker\ s\ is\ assigned\ to\ job\ i; \\ & 0\ otherwise. \end{cases}$$

Objective:

$$Min\ \sum_{i \in I} \sum_{s \in S} \sum_{s' \in S: s > s'} (c_s + c_{s'})\, x_{iss'} p_i / \varphi_{kss'} + \sum_{i \in I} \sum_{s \in S: s = s'} c_s\, x_{iss} p_i / \varphi_{kss} + \sum_{s \in S} \sum_{i \in I} \sum_{j \in J} y_{sij} v_{ij} b + \sum_{s \in S} \sum_{i \in I} \sum_{j \in J} y_{sij} \tau_{ij}\, c_s \tag{1}$$

Constraints:

$$\sum_{s \in S} \sum_{s' \in S: s \geq s'} x_{iss'} = 1, \quad \forall i \in I \tag{2}$$

$$\sum_{s \in S} \sum_{s' \in S: s < s'} x_{iss'} = 0, \quad \forall i \in I \tag{3}$$

$$z_{is} = \sum_{s' \in S: s \geq s'} x_{iss'} + \sum_{s' \in S: s < s'} x_{iss'} \qquad \forall i \in I, \forall s \in S \tag{4}$$

$$\sum_{i\in I}\left(\sum_{s'\in S:s\geq s'} p_i x_{iss'}/\varphi_{kss'} + \sum_{s'\in S:s<s'} p_i x_{is's}/\varphi_{kss'}\right) \leq w_s \qquad \forall s \in S \tag{5}$$

$$\mu_i = \sum_{s\in S}\sum_{s'\in S:s\geq s'} x_{iss'} p_i/\varphi_{kss'} \qquad \forall i \in I \tag{6}$$

$$t_i + \mu_i \leq d_i, \qquad \forall i \in I \tag{7}$$

$$t_j - t_i \geq \mu_i \qquad \forall (i,j) \in \mathrm{H} \tag{8}$$

$$\sum_{i\in I} y_{sij} \leq z_{js} \qquad \forall j \in I, \forall s \in S \tag{9}$$

$$\sum_{j\in I} y_{sij} \leq z_{is} \qquad \forall i \in I, \forall s \in S \tag{10}$$

$$\sum_{i\in I}\sum_{j\in J} y_{sij} \geq \sum_{i\in I}(z_{is}) - 1 \qquad \forall s \in S \text{ and } \forall \text{ ordered } (i,j) \in I \times I \tag{11}$$

$$t_j \geq t_i + \mu_i + \tau_{ij}\sum_{s\in S} y_{sij} - M\left(1 - \sum_{s\in S} y_{sij}\right), \qquad \forall (i,j) \in I \times I \tag{12}$$

$$x_{iss'}, y_{sij} \in \{0,1\}, t_i, \mu_i \geq 0 \tag{13}$$

The objective (1) is to minimize the total cost function which consists of the assignment of all jobs to qualified workers with skill *k*. When a worker is not competent to perform a skill, s/he may be considered for pairing with a competent worker in order to improve task completion times due to paired efficiency. In such a case where s>s' due to pairing, there exists a cost for each worker s' as well as a combined worker efficiency rating, $\varphi_{kss'}$.

Constraints (2) and (3) ensure that all jobs are assigned to at least one worker, paired or not. Constraint (4) ensures that if a job is assigned to a worker or a pair of workers, then each worker assigned is counted. Constraint (5) ensures that the sum of process times of all the jobs assigned to each worker *s* does not exceed that worker's capacity.

Constraint (6) computes the actual processing time of each job as a function of the assignment decision. Constraint (7) enforces that a job is completed prior to the deadline for that job.

Constraint (8) ensures that the start of the second ordered job does not start until later than the preceding job start time plus the process time for the preceding job.

Constraints (9) through (11) together ensure the correct confirmation of the rout solution.

Specifically, Constraint (9) ensures that a task has at most one predecessor in the route of the worker to which the job is assigned. Constraint (10) makes sure that a task has at most one successor in the route. Constraint (11) states that the number of arcs of a worker's route must equal the number of jobs assigned to that worker, minus one.

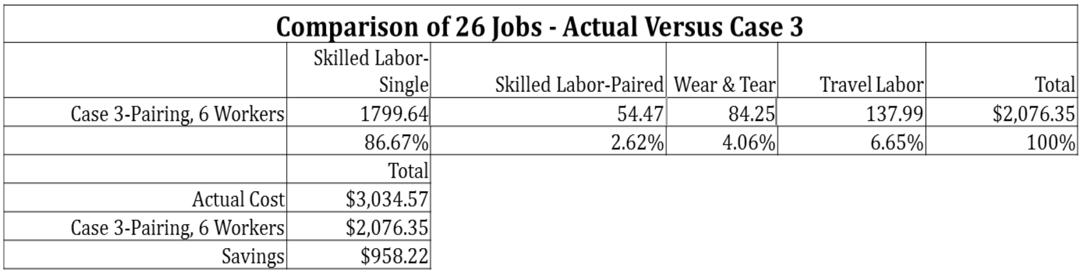
Constraint (12) guarantees no pair of jobs assigned to the same worker may overlap. Constraint (12) is the Big-M formulation to enforce that the time to start a job j cannot be less than the completion time of its immediate preceding job i, plus the travel time between i and j. Note that if job i is not an immediate predecessor of j in any route, i.e.

$\sum_{s\in S} y_{sij} = 0$, Constraint (12) is always satisfied due to the negative big number $-M$ on the right-hand-side.

(13) defines the binary decision for assignment and routing, as well as the non-negativity constraint on the start time and process times of all jobs.

4.3.1 Implementation of the Pairing Assignment Model

The pairing model using the same data and computer specifications as in prior cases (55 tasks, 9 workers, 5 classes of skill and 4 levels) ran for over 10 hours without converging on even a feasible solution, indicating the complexity of this model. In order to evaluate a model within a reasonable time period, I performed a case using a reduced data set. The data set for evaluation consists of only 26 tasks, 5 workers, and no precedence relationships. ρ, the discounting factor for synergy among pairing assignment, is set at a factor of 1.1 to indicate a gain of 10% due to synergy above and beyond the basic level of paired efficiency. At an increased benefit of paired assignment of 1.1, all jobs were assigned to one worker, except for Work Order 8679, which was assigned to worker RV as the mentor and worker KS as the apprentice. The total skilled labor cost for work assigned to one worker was $1799.64 and the cost for paired assigned of labor was only $54.47, for a total of $1,854.07. Travel costs were $84.25 for wear and tear vs $137.99. The model at a ρ of 1.10 reduces the total assignment cost by $958.22, a reduction of 46%.



Comparison of 26 Jobs - Actual Versus Case 3

	Skilled Labor-Single	Skilled Labor-Paired	Wear & Tear	Travel Labor	Total
Case 3-Pairing, 6 Workers	1799.64	54.47	84.25	137.99	$2,076.35
	86.67%	2.62%	4.06%	6.65%	100%
	Total				
Actual Cost	$3,034.57				
Case 3-Pairing, 6 Workers	$2,076.35				
Savings	$958.22				

Table 4.27 Comparison of Actual Work Costs to Cost of Model Considering Pairing

A mapping of the routes shows that Worker KS (Figure 4.14, Top Left) is paired with Worker RV for Work Order 8679. This is the only job Worker KS is assigned. Note that another non-skilled worker, Worker JA, was not assigned at all. Workers GD, JT and NC (Figure 4.14, Bottom Left to Right) were assigned 7, 9 and 7 jobs respectively.

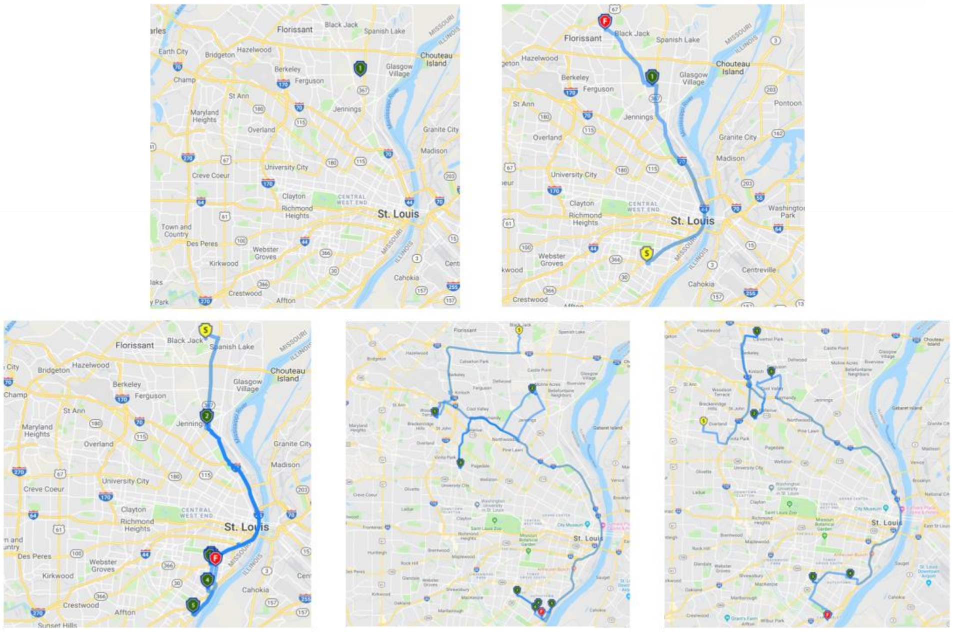


Figure 4.14 Mapping of Worker Routes for Model Considering Pairing (Clockwise from top left: KS, RV, NC, JT, GD. Worker JA was not used.)

4.3.2 Computational Experiment to Test Varying Levels of Synergy

The pairing model on its own will not find an incentive to pair a non-skilled apprentice to a mentor for the development of a skill. Because the objective is to minimize the total cost, if there is a worker available to perform the job that is competent, while still satisfying the priority deadline, the model does not know the future benefit of a so-called up-trained worker. If the wage of two workers who are competent is equal, then the pairing of two competent workers results in increased travel costs for the additional worker. In a naïve approach to motivating pairing, we assume that the value of ρ (the measure of conation, measured in some factor of synergy, motivation or potential increase in productivity as a by-product of pairing) exists, and it can be measured. In order to test the sensitivity of the pairing model to this scenario, I use ρ as a tuning parameter with a range of values from .6 to 1.4. We assume (and it is proven) that any value of ρ less than 1 will result in no potential increase in conative potential. At values above 1.0, we expect an additional benefit to the pairing beyond the simple formulation we provide where the synergy level increases.

In order to determine the impact of the mentor-apprentice pairing on total cost, I use the data from previous cases to run the same pairing program iteratively, updating the efficiency scores of select apprentice workers with each round of assignment. I develop a path to competency whereby for each non-competent worker, if they are assigned to the pairing of work with a mentor, they receive a credit towards competency equal to the following table. In all successive jobs, the apprentice can be assigned individually to any job for which he is now competent, including the new competence earned through performance with a mentor.

I run the pairing model on a selection of 26 jobs from the Pairing case study, tuning the ρ measure in .10 increments from .6 to 1.4. Here 1.0 would equate to a baseline measure of synergy equal to the mentor's efficiency score plus .5. So, for example, if a job were to take, on average, 5.83 hours and the mentor—paired with an apprentice—is able to perform the job himself with an efficiency rating of 1.10, then the process time for the job would be 5.83 hours / 1.10+.5, or 3.64 Hours. As two workers are assigned to the job, at a ρ measure of 1.0, the total time for two workers is 7.2875 hours. While a mentor may be compensated greater than the pay of the apprentice, this scenario can—despite requiring more hours to perform the work—approximate the cost if the mentor does the work on his own, with added benefits. For this example, when the mentor-apprentice synergy is set at 1.00, the skilled worker would perform the job in 5.3 hours at a cost of $227.32 where the paired assignment would take a total of 7.2875 hours, but only 3.64 hours in make span and at a total cost of 232.67. The $5.35 savings is the cost of moving a non-competent worker up in skill acquisition (training/learning effect) while also reducing overall make span.

I run the scenario for 6 consecutive rounds using the same set of workers. I use 6 workers of varying skill competence. However, I ensure that one worker, the Mentor, is able to do all jobs in a process time better than the average in all cases. This worker has an efficiency rating of 1.10. Other workers may also be considered for pairing both with each other and with those workers considered of low overall competence. The program was run on a MacBook Pro 2.3 GHz Intel Core i7 with 16 GB of 1600 MHz DDR3 RAM, 8 available threads, and 10,000 MB of working memory; and with a limit on solution time of 1 hour. I begin with a ρ of .6 and in all rounds, no pairing occurs. For all ρ values up to 1.1, no pairing occurs. However, at a ρ value of 1.1, pairing does occur for Rounds 1-3 and then stops. For values of ρ at 1.2-1.4, pairing occurs in all rounds. Over subsequent increases in ρ from 1.1 to 1.4, the frequency of pairing increases.

As an example of how well this model advances a non-skilled apprentice worker to the level of competence: at a ρ of 1.4, Worker KS was able to attain the level of competence in both HVAC Level A and Other Level A tasks. This indicates that in 6 rounds of work assignment he was assigned to that same class and level of skill at least 8 times, paired with a mentor. It would be reasonable to expect that after this many assignments to the same class and level of task, competence is achieved. At a ρ of 1.4, Overall Efficiency increased by 4.6417%, an improvement of 10% efficiency after 6 consecutive rounds. This improvement only includes the isolated impact of mentor-apprentice pairing and the building of apprentice competence. Other worker efficiencies were not updated and in a practical scenario would be calculated from work orders and included in the mean process times of work by class and level.

There are implicit tradeoffs in this approach regarding the level of complexity for such a decision. First, the model considers many more potential scenarios for each pairing decision. Therefore reasonable solution times require fewer jobs for assignment. However, it is promising to realize that a process toward a practical learning method for non-repetitive tasks can be achieved.

We would expect to see the normal characteristics of a reduction in total cost for a higher round of computation. As the value of ρ increases, the cost of pairing increases, indicating more pairing at higher levels of ρ. Alternately, the cost of single assignment decreases as fewer jobs are performed by individual workers. There is a tradeoff in the solution time and the overall fit of a final solution, with the total cost of assignment when pairing is included as part of the solution. Models appear to run much faster when only single assignment is accessed.

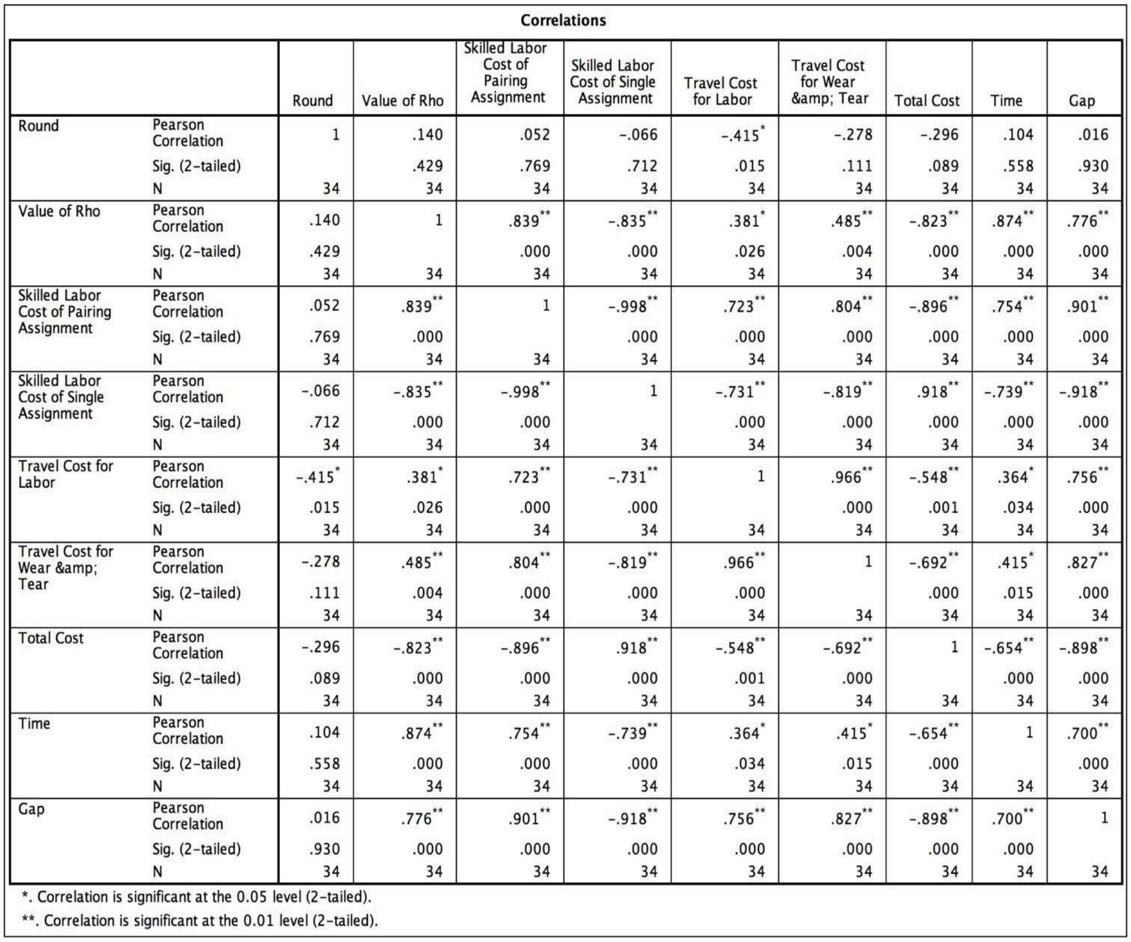
When considering the output of the consecutive rounds of pairing, we notice there is a strong correlation between the later rounds and the reduction in the travel cost for labor (significant at .05 level). This insight indicates that as subsequent pairing, updating and training occurs, more adequate resources are available within a sufficient distance from a job to reduce costs or travel. Not only does the firm benefit from the improvement of skill within the workforce, as well as the potential reduction in overall project timeline; the non-value added time for driving between jobs is also reduced.

Even though the scope of this example is limited, we are able to derive a sense of how training impacts the workforce composition. Future work needs to include the consideration of all score improvement—mentor, apprentice, and paired competent workers alike—and how the model performs under such considerations as workforce size, skill depth and breadth, and skill chains where individual skills contribute to the hierarchy of skill development.

Initial Base Score (Completely non-competent)	.010
After first assignment requiring skill class and level	.300
After 2nd Assignment of same skill class and level	.500
After 3rd Assignment of same skill class and level	.600
After 4th Assignment of same skill class and level	.650
After 5th Assignment of same skill class and level	.675
After 6th Assignment of same skill class and level	.6875
After 7th Assignment of same skill class and level	.695
After 8th Assignment of same skill class and level	.69875, conversion from non-competence to Competence, and considered for individual assignment.

Table 4.28 Process for Achieving Basic Skill Competence through Recurring Assignment

Statistical inferences from the 34 solutions of the Pairing assignment also show that an increase in pairing when skill competency is updated with each paired training experience, is very strongly correlated with the reduction in total cost (-.896, $p<.000$) while at the same time increasing both travel cost components (.723 and .804, respectively, both $p<.000$). However, the decision to pair workers is at the expense of a greater gap between a feasible solution and the optimal solution, when one hour is allowed to generate a solution. (.754 and .901, respectively, both $p<.000$). In fact, once workers achieve the level of competence, this reduces total travel cost in later rounds, so that the later round is strongly correlated with reduced travel labor cost (-.415, $p<.015$).



Correlations

		Round	Value of Rho	Skilled Labor Cost of Pairing Assignment	Skilled Labor Cost of Single Assignment	Travel Cost for Labor	Travel Cost for Wear & Tear	Total Cost	Time	Gap
Round	Pearson Correlation	1	.140	.052	-.066	-.415*	-.278	-.296	.104	.016
	Sig. (2-tailed)		.429	.769	.712	.015	.111	.089	.558	.930
	N	34	34	34	34	34	34	34	34	34
Value of Rho	Pearson Correlation	.140	1	.839**	-.835**	.381*	.485**	-.823**	.874**	.776**
	Sig. (2-tailed)	.429		.000	.000	.026	.004	.000	.000	.000
	N	34	34	34	34	34	34	34	34	34
Skilled Labor Cost of Pairing Assignment	Pearson Correlation	.052	.839**	1	-.998**	.723**	.804**	-.896**	.754**	.901**
	Sig. (2-tailed)	.769	.000		.000	.000	.000	.000	.000	.000
	N	34	34	34	34	34	34	34	34	34
Skilled Labor Cost of Single Assignment	Pearson Correlation	-.066	-.835**	-.998**	1	-.731**	-.819**	.918**	-.739**	-.918**
	Sig. (2-tailed)	.712	.000	.000		.000	.000	.000	.000	.000
	N	34	34	34	34	34	34	34	34	34
Travel Cost for Labor	Pearson Correlation	-.415*	.381*	.723**	-.731**	1	.966**	-.548**	.364*	.756**
	Sig. (2-tailed)	.015	.026	.000	.000		.000	.001	.034	.000
	N	34	34	34	34	34	34	34	34	34
Travel Cost for Wear & Tear	Pearson Correlation	-.278	.485**	.804**	-.819**	.966**	1	-.692**	.415*	.827**
	Sig. (2-tailed)	.111	.004	.000	.000	.000		.000	.015	.000
	N	34	34	34	34	34	34	34	34	34
Total Cost	Pearson Correlation	-.296	-.823**	-.896**	.918**	-.548**	-.692**	1	-.654**	-.898**
	Sig. (2-tailed)	.089	.000	.000	.000	.001	.000		.000	.000
	N	34	34	34	34	34	34	34	34	34
Time	Pearson Correlation	.104	.874**	.754**	-.739**	.364*	.415*	-.654**	1	.700**
	Sig. (2-tailed)	.558	.000	.000	.000	.034	.015	.000		.000
	N	34	34	34	34	34	34	34	34	34
Gap	Pearson Correlation	.016	.776**	.901**	-.918**	.756**	.827**	-.898**	.700**	1
	Sig. (2-tailed)	.930	.000	.000	.000	.000	.000	.000	.000	
	N	34	34	34	34	34	34	34	34	34

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Table 4.29 Bivariate Correlations between Variables in the Pairing AssignmentModel.

Chapter 5

Computational Experiments and Hypothesis Testing

5.0 Introduction to Computational Experiments

I perform a computational experiment on the initial case study data set and evaluate several hypotheses as well as the fitness of the proposed models. The ability to analyze such a robust data set using mathematical optimization provides significant relevant insight into the operational nature of the workforce involved as well as general perspective on the operating environment.

5.1 Computational Experiment on Single Assignment Model

The 55 job instances excluding the additional make ready tasks comprise a 39 job data set. I use these 39 jobs for an evaluation of the model's solution capability. I develop variations to the data set based on the following factors for evaluation:

Number of Jobs: I evaluate 3 variations. I consider the first 13 jobs, the first 26 jobs, and then all 39 jobs. This allows me to determine if the addition of more jobs to the existing data changes the solution complexity or performance measures, as well as the time to solve the model, the increase or decrease in solution gap, and the scalability of the cost measures.

Hour Limit: I want to determine if the number of allowed working hours per worker is a constraining factor on the overall performance of the model. When fewer workers are involved it may be that more hours improves feasibility. Also, if there is a tradeoff between more fully allocated workers and workforce size, we would want to know those cost implications.

Workers: I evaluate the number of workers from as few as 3 to as many as 9. For larger data sets I would expect fewer workers to result in a greater solution gap as well as greater incidence of infeasibility in general. I would also expect for costs to be generally higher with fewer workers, due to the reduced number of assignment choices available.

Skill Classes: I consider three variations of Skill Class. First we want to determine what solutions result when no skill classes are considered. In this scenario all jobs are unclassified for skill. This means that a worker who has performed any job of a certain degree of skill (A, B, C, or D) may perform any other job that requires that same level of skill. The performance times and efficiency levels are calculated based on the reclassification scheme so we can determine the actual cost implication of this decision. In a second variation of Skill Classes, we consider all those jobs which are generally considered Mechanical, Electrical and Plumbing tasks, including HVAC jobs, in a category called "MEP", whereas Security and Other miscellaneous jobs are classified into the "Other" category. This allows us to determine at least a difference between trade and non-trade task requirements. Then, we finally decompose all tasks into the 5 skill classes used in the case studies: HVAC, Electrical, Plumbing, Security and Other. Of primary interest here is whether the level of skill class division changes the overall total cost of assignment, as well as other cost components and also the solution time and gap.

Skill Levels: Finally, we consider the variation of skill level. First, we evaluate those scenarios where no skill level exists. All times of performance for a job of a certain skill class can be performed by any worker who has performed a job in that class, regardless of skill level or task complexity. In a subsequent variation, we evaluate the division of all jobs into those which require "higher" skill class aptitude and those which require "lower" skill class aptitude. In a third iteration we divide all jobs into each of four skill levels, where level "D' would be considered jobs that require a basic understanding of skill within a skill class, followed by subsequently higher levels of skill complexity through level "C", "B", and "A". Each job is evaluated and reclassified so as to be appropriately classified to the correct level of skill required. All performance times and efficiency scores are likewise re-calculated based on actual performance data inputs from the data set. Again, it will be of interest to determine how the division of the tasks into skill levels effects the overall total cost of assignment, as well as other cost measures and the solution time and gap.

The data is reconstituted to provide the appropriate qualities of each of these 324 variations of workforce, classification and constraint. Then, the single assignment model is implemented to solve for each data set, and the solution is documented for inclusion in an overall data repository. This data is then evaluated in IBM SPSS Statistics software to determine what, if any, relationship exists between variables. Variables for evaluation included:

- **Jobs:** number of jobs.
- **Classes:** number of skill class divisions.
- **Levels:** number of skill level divisions.
- **Workers:** number of available workers.
- **Hours:** number of available hours per worker.
- **Solution Time:** the total time required to reach a solution.
- **Total Cost:** the total cost objective.
- **Labor Cost:** the total skilled labor cost.
- **Travel 1:** the vehicle wear and tear cost.
- **Travel 2:** the travel labor cost.
- **Solution Gap:** the percentage difference from the best possible solution within the time allotted compared to the best optimal solution.

Parameter	# Variations	Description
Number of Jobs	3	-13 -26 -39
Hour Limit	3	40 Hours 60 Hours 80 Hours
Workers	4	-3 Workers -5 Workers -7 Workers -9 Workers
Skill Classes	3	-Specialized (0 Classes) -Mixed (2 Classes) -Diversified (5 Classes)
Skill Levels	3	-0 Skill Levels -2 Skill Levels (Hi-Low) 4 Skill Levels (A-B-C-D)

Table 5.1 Structure of the Computational Experiment.

The data sets were run on a workstation computer with a limit on solution time of 1 hour using PC Intel Quad-Core with 3GHz CPU and 8G RAM. Only 291 instances were feasible, indicating that 33 instances were such that resources were so constrained as to make solution impossible. All infeasible instances involved 39 jobs for assignment, and 3 or 5 workers. Summary Statistics for the 324 instances indicate the mean solution time was just over 19 minutes, with a standard deviation of solution time nearly equal to that (just shy of 18 minutes). General characteristics of the overall data set include a proportion of labor as a percentage of total cost equal to 87.74%, where travel costs combine for an average of 12.26% of total cost. The overall solution gap is very low at a mean of .80%, indicating sufficient time allotted to solve--or at least derive a sufficiently feasible sub-optimal solution for--the single assignment model within 1 hour. Furthermore these mean cost proportions from the total data set are remarkably similar to the results of the prior cases. Case 1 skilled labor was 88.23%; Case 2 skilled labor was 89.03% and case 3 skilled labor was 89.29% of total costs. The bivariate correlations are included for comparison between the full experiment and the three sub-experiments of 13, 26 and 39 jobs. They are located in the Appendix.

Descriptive Statistics for 324 Data Instances, Single Assignment Model

	Mean	Std. Deviation	N
Jobs	24.53	10.221	291
Classes	2.68	1.717	291
Levels	2.35	1.257	291
Workers	6.26	2.146	291
Hours	60.00	16.526	291
Solution Time	1904.02	1766.88	291
Total Cost	1440.08	765.88	291
Labor	1263.54	712.22	291
Travel 1	69.78	31.25	291
Travel 2	106.76	46.53	291
Gap	0.80%	1.47%	291

Table 5.2 Descriptive Statistics for Computational Solutions.

5.2 Hypothesis Testing and Results of Computational Experiment

The following hypotheses were evaluated based on the collection of solutions for 324 variations of data, of which 291 were found to have a solution and are considered in the analysis. While this is not an exhaustive summary of hypotheses (we do not address the large number of statistically significant yet very obvious correlations between individual cost variables) I attempt to identify the more interesting variable relationships within and between the 4 computational experiment data sets. They are listed here with my findings:

- **Number of Jobs:** A greater number of jobs will result in a reduced cost to travel between jobs, and fewer jobs may result in more travel costs, while labor costs may be lower, as a proportion of total costs.

H_0: The number of jobs does not correlate with the travel cost of worker assignment.

H_1: The change in total cost correlates significantly with number of jobs to assign.

For the total data set, Reject the null hypothesis. In fact, all elements of cost are very highly positively correlated with the increased number of jobs to be assigned. While travel costs are nearly perfectly correlated with the number of jobs to be assigned (.978, p<.000 for Vehicle Wear & Tear; .970, p<.000 for Travel Labor), the cost of skilled labor is also strongly correlated, though not as perfectly. (.547, p<.000) and has a much greater impact on the correlation of total cost and number of jobs (.608, p<.000).

- **Number of Hours Available Per Worker:** It is assumed that if each worker has fewer available hours, a greater pool of labor will be required. In some cases, the solution may be infeasible when too few workers are available for job assignment. It is also possible a severe penalty will occur when a non-competent worker is assigned to a job due to lack of a qualified worker available. It is also assumed that with more available hours, more jobs can be scheduled. As long as the resource capacity is sufficient for a problem instance to be feasible, we did not find statistical significance of resource capacity on the total optimal cost for the test instances. We could envision that in an environment with more tasks and tighter deadlines, resource capacity can be an important factor. Because of the priority constraints, it may be that some jobs cannot be performed within the time required, resulting in an infeasible solution.

H_0: The number of available hours per worker does not have any effect on cost of assignment.

H_2: Total cost correlates significantly with the change in the available hours per worker.

For all experiments, we do not reject the null hypothesis. The number of available hours in this experiment does not correlate significantly with cost of assignment. Managerial insight would indicate testing with fewer workers or comparing the difference between costs utilizing workers with various competences and skill mixes, as well as different performance times. This would be an ideal opportunity for a time study.

- **Number of Workers:** This research assumes that if fewer workers are available, they will be more fully utilized, but at an increase in cost; and with more workers, we expect that the cost of work completion will be decreased.

H_0: The number of workers does not have any effect on cost of assignment.

H_{3a}: The cost of assignment correlates significantly with the number of workers.

For the full data experiment, we reject the null hypothesis. Total cost is very strongly correlated with the number of workers available for assignment, indicating that more workers reduces the cost (-.336, p<.000). The significance of the total cost is composed of the significance of skilled labor (-.372) which reduces total cost, and of principal interest, the increase in vehicle wear and tear cost as more workers are considered for assignment (.137, p<.02).

When evaluating the individual experiment sets, we find that when only 13 jobs are evaluated, there is no statistically significant relationship between the number of workers and the total cost. We cannot reject the null hypothesis for the 13 job set.

However, as we evaluate the 26 job set, I observe that not only does total cost very strongly correlate with the number of workers (-.698, p<.000), but all costs are strongly correlated, including both travel cost components. Of these, vehicle wear and tear is the least significant component, though also very highly correlated with the number of workers. (-.317, p<.000). All costs components are negatively correlated indicating that as more workers are available for assignment, the total cost of assignment decreases.

Again, when evaluating the 39 job data set, we find there is no statistically significant correlation between the number of workers available for assignment, and the cost components of assignment. Therefore we cannot reject the null hypothesis for the 39 job data set. The implications of this targeted approach are interesting. We can isolate the specific dimension of data sample size where a significant relationship exists.

Considering the relationship between the number of workers and the solution time, we want to understand if considering more workers for assignment makes finding the optimal solution easier, faster.

H_0: The number of workers does not have any effect on solution time.

H_{3b}: The solution time is significantly correlate with a change in the number of workers.

When considering the full experiment, we find no statistically significant relationship between the number of workers available for assignment and the time required to solve to optimality. The same finding holds for the 13 job experiment, and therefore we cannot reject the null hypothesis. However, when looking deeper and evaluating the 26 and 39 job experiments, we observe a very weak statistically significant correlation (-.204, p<.034, one-tailed, and .268;p<.020, one-tailed, respectively). For the fewest number of jobs considered: the number of workers does not correlate with solution time. For the greatest number of jobs considered, the increase in workers significantly correlates with a faster solution time; however for the 26 job experiment, the increase in available workers results in a slower solution time.

Considering the relationship between number of available workers and solution gap when solving models of increasing complexity, we also want to know if the number of workers has any significant relationship with the percentage difference between the best feasible and the target optimal solution. If the consideration of more workers does not improve solution times, we may weigh the trade-offs of the solution gap with the model complexity and reduce the available workers for assignment, especially if more workers do not significantly reduce total cost.

H_0: The number of workers does not have any effect on solution gap.

H_{3c}: The solution gap is significantly correlated with a change in the number of workers.

In the full experiment, there exists no statistically significant correlation between the number of workers and the solution gap. We also cannot reject the null hypothesis for the 39 job experiment. However, when evaluating the 13 and 26 job experiments we do find a statistically significant correlation between the number of workers and the solution gap (-.266, p<.005, two-tailed; and -.230, p<.017, one-tailed, respectively). This indicates that as more workers are considered in the assignment decision, the model is able to achieve a reduced solution gap. It appears that as these resources are constrained by the addition of more jobs, the benefit from additional resources dwindles to insignificance.

- **Skill Classes:** It is assumed that when more skill classes exist, there is more accuracy in assignment and therefore a reduced cost. It is assumed that with fewer skill classes, a greater total cost will occur.

H_0: The number of skill classes does not have any correlation with cost of assignment.

H_{4a}: Total cost is significantly correlated with a change in the number of skill classes.

For the full data experiment, we can reject the null hypothesis. As the number of skill classes increases, we observe a significant increase in total cost. (.321, p<.000). Likewise, we also note that the cost of labor increases with the inclusion of more skill classes (.332, p<.000) and the cost of travel labor increases as well, though not as significantly, (.141, p<.000). Vehicle wear and tear, though scaled proportionally with distance and time to travel, is not significantly correlated with the increase in the number of skill classes, indicating that the individual cost of labor options matters here, where it is tied to skill mix.

For 13 and 39 job data sets, the travel wear and tear component is not statistically significantly correlated with the number of skill classes; however, total cost, skilled labor cost, and travel labor cost are all positively correlated with an increase in the number of skill classes. All four cost components are statistically significantly correlated with the number of classes in the 26 job data set.

When comparing the change in significance between the 13, 26 and 39 job experiments, we observe that between the 13 and 26 job experiments, the level of significance for skilled labor and total cost remain relatively stable, .298 to .283, and

.294 to .274, respectively); however, the significance of travel labor increases from .380 to .487, and in the 26 job experiment the cost of wear and tear becomes very significant at .577 of all variation explained between this variable and the number of skill classes. Then, from the 26 job experiment to the 39 job experiment, we note the great increase from.263 to .812 for correlation between total cost and number of skill classes. P-value also improves from p<.003 to p<.000. Skilled labor cost significance jumps from .274 to 814. Travel labor increases in significance from .487 to .824; however the cost for vehicle wear and tear is no longer significantly correlated with the number of skill classes. The increase in cost tied to skill class can be explained primarily by the reduction of individual worker qualification for job assignment as work is further divided into skill classes.

Considering the impact of skill classes on solution time, it would be reasonable to expect that if data is divided into more categories for consideration in a solution space, the model will take longer to solve to optimality. Intuition argues that more pieces to a puzzle may take longer to assemble. If it can be shown that a varying degree of skill class division results in a more timely solution, the potential for solving solutions of greater job numbers, workers and other inputs becomes more attractive. Therefore we test the following hypothesis related to skill class.

H_0: There is no correlation between the number of skill classes and the solution time.

H_{4b}: The number of skill class divisions is correlated with a change in solution time.

We find that for the full experiment, there is a weak correlation (p<.02, one-tailed) between the number of skill classes and the solution time. The two variables are negatively correlated and only 13.8% of the variation can be attributed to something other than chance. This finding in fact contradicts intuitive expectations. As data is parsed into more divisions of labor by class, the solution time improves. The benefit of this finding is that as more sophisticated processing techniques allow for models of greater complexity to be solved, there may exists a benefit of greater division of labor when the time to solve a model is more costly than the time to perform the work.

Considering the impact of skill classes on solution gap, the gap is a measure of the difference between the best feasible solution identified in the decision tree, compared to the target optimal solution. When time is a limiting factor for model solution—as is the case with models of greater complexity, more coefficients and a greater number of variables— then the gap is a measure of how close we come to an optimal target. With more precision in the model development considering the results of other variables and their performance on the model, we can achieve a greater level of optimality in a reasonable solution time. Therefore we want to know if the number of skill classes considered in the model increase or decrease this percentage gap.

H_0: There is no significant correlation between the number of skill classes and the solution gap.

H_{4c}: The number of skill class divisions is significantly correlated with a change in solution gap.

In the full experiment, we observe that the number of skill classes is negatively correlated with the solution gap. The very strong negative correlation (-.151, p<.01, two-tailed) indicates that additional skill class divisions actually improves the percentage difference between the best feasible solution and the optimal solution, when time is a limiting factor in the model. This relationship holds up in the 13 and 39 job data sets, and is even more impactful, explaining 39% of the variation (p<.01, two-tailed) in the 39 job set, and 48.4% of the variation (p<.000, two-tailed) in the 13 job set. However, the 26 job set does not support rejecting the null hypothesis as there is no statistically significant correlation between number of skill classes and the solution gap.

When evaluating the underlying causes for such findings, we can observe that the 13 job experiment benefits from overall simplicity due to fewer job instances. The 39 job experiment includes many more decisions regarding assignment; however, the number of feasible solutions was much less, with all 33 instances of infeasibility at lower levels of available workers. The research would benefit from a more robust data set incorporating even greater number of jobs and more accurate process times and efficiencies based on a wider longitudinal data set.

- **Skill Levels:** As with Skill Class, it is assumed that with more divisions of labor levels, there will be a lower total cost of assignment, and with fewer levels of skill, a higher total cost.

H_0: The number of skill levels does not have any effect on total cost of assignment.

H_{5a}: Change in total cost is significantly correlated with the number of skill levels.

For the relationship between the number of skill levels considered, and the total cost component, we in fact reject the null hypothesis for the full data experiment. While not as significant as the number of skill classes, the increase in number of skill levels is positively correlated with total cost (.169, p<.000) along with the cost of skilled labor (.171, p<.000) and the cost of vehicle wear and tear (.118, p<.000). However, in the full data experiment, the cost of travel labor is not statistically correlated with a change in the number of skill levels.

For the experiment considering only 13 jobs, there is no significant correlation between total cost and the number of skill levels, and if only considering those data solutions, we do not reject the null hypothesis; however with only 13 jobs for consideration we should be cautious in doing so without further evaluation. Further analysis reveals that while skilled labor and total cost are not significantly correlated with the number of skill levels, there does exist a significant positive correlation between both travel cost components and the number of skill levels (.782 for vehicle wear and tear, and .605 for travel labor, both p<.000).

For the 26 job experiment, we do not reject the null hypothesis for total cost correlated with the number of skill levels. This appears to reinforce the findings of the 13 job experiment. Furthermore, the only cost component that is now significantly correlated with the change in skill levels is vehicle wear and tear, which itself decreases in significance (from .782, p<.000 to .309, p<.001).

Then, when evaluating the 39 job experiment, all cost components become significantly correlated with the number of skill classes and levels. Total cost is very strongly correlated with number of skill levels (.457, p<.000) along with skilled labor, vehicle wear and tear, and travel labor (.455, p<.000; .545, p<.000; and .273, p<.018 respectively). Vehicle wear and tear is the only cost component that remains significantly correlated with the number of skill levels over all experiments. Skilled labor does not become significantly correlated with the number of skill levels until at least 39 jobs are considered, and neither does total cost. However, while the labor cost of travel is very strongly correlated among the 13 job experiment (.605, p<.000) it is not significant in the 26 job experiment, indicating that when fewer jobs are considered, the travel cost matters more as a proportion of total cost, when more skill levels are included.

We also want to investigate the possible relationship between the number of skill levels and the time to find a solution.

H_0: The number of skill levels does not have any effect on solution time.

H_{5b}: Solution time is significantly correlated with the number of skill levels.

For the full experiment, we find that—much like the case for division of skill classes—the increased number of skill levels results in a quicker solution time, though the relationship is weak (p<.02, one-tailed) and only 14% of the variation between these variables is not random. When evaluating only the 39 job experiment, the correlation does not exist, and we cannot reject the null hypothesis. However, there is a marked improvement in correlation at both the 26 and 13 job experiments (.459 and .549, respectively, both p<.000, two-tailed) indicating a very strong correlation between the addition of skill levels and the improvement of solution times. It appears that as more jobs are included for evaluation, the importance of increased skill levels in the reduction of solution time diminishes.

We likewise want to evaluate the division of skill levels and the potential relationship with the solution gap. Again, a reduction in the solution gap is preferable when an optimal solution cannot be obtained in the allotted solution time.

H_0: The number of skill levels does not have any effect on solution gap.

H_{5c}: Solution gap is significantly correlated with the number of skill levels.

In the full experiment we observe a very strong negative correlation (-.324, p<.000, two-tailed) indicating that as more skill level divisions are incorporated to the model, the percentage difference between the best feasible solution and optimality is reduced. As more jobs are considered, the solution gap is reduced with the inclusion of more skill level divisions. From -.238, p<.013, one-tailed) in the 13 job experiment, to -.510, p<.000, two-tailed) in the 26 job experiment, and finally to a -.620, p<.000, two-tailed in the 39 job experiment; indicating the very strong significance of skill level division on obtaining as close to an optimal solution as possible.

Chapter 6

Extensions of the Proposed Model and Areas of Future Research Interest

6.0 Introduction to Future Research

It is my intention to provide some direction for others who want to pursue this area of research. In evaluation of the current trends in industry as well as natural extensions of this research, it is with certainty that future development of this work will result in adoption of the approaches and methods among academics and practitioners alike.

6.1 Areas of Research Opportunity

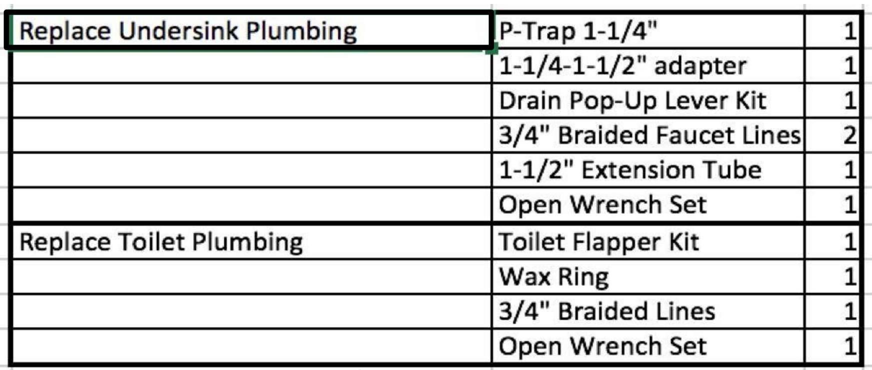
With the development of new computer processing technologies and the sophistication of modeling software, its integration into the workspace for building, facilities and property maintenance, and the development of lightweight solutions like handheld device applications, tracking methods that are cost-effective and disposable, and the growth of adoption of technology in the skilled labor environment, there exist many extensions of this work. I propose some areas of personal interest and propose some hypotheses on the existing models that may result in practical insights.

6.1.1 The Consideration of Overtime Costs, Shift Duration, and Various Planning Horizons

As work orders may be prioritized as emergencies and need immediate attention, there may exist a cost of attending to work orders after hours. Because the current model only considers standard wage rates, we may also add the potential to charge overtime rates after a full 8-hour work shift is assigned to an individual. We may also evaluate the longer range planning horizon, incorporating more complex multi-task jobs, and planned preventative maintenance.

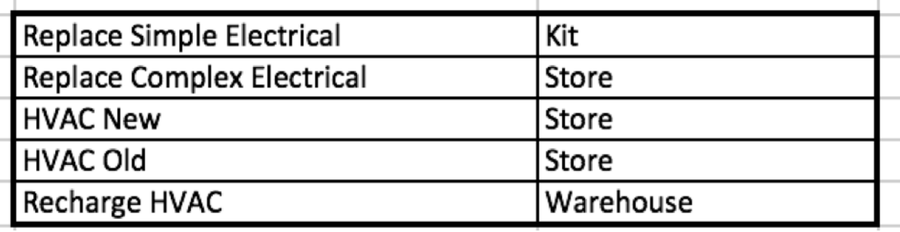
6.1.2 The Inclusion of Trips to the Store or Warehouse and Relevant Costs

The stated model does not consider the time and resource necessary to procure materials from either a warehouse location, or a store. Because work may require special materials, a store purchase may be required. However, if a job is of a more standard nature, then we would either possess the necessary materials to perform the work on hand, or they may be provided from the warehouse location. In most cases this would be a policy decision due to resource constraints. However, in some cases there may exist a cost benefit of buying supplies from the store as opposed to driving to the warehouse.



Replace Undersink Plumbing	P-Trap 1-1/4"	1
	1-1/4-1-1/2" adapter	1
	Drain Pop-Up Lever Kit	1
	3/4" Braided Faucet Lines	2
	1-1/2" Extension Tube	1
	Open Wrench Set	1
Replace Toilet Plumbing	Toilet Flapper Kit	1
	Wax Ring	1
	3/4" Braided Lines	1
	Open Wrench Set	1

Table 6.1 Kit Requirements for Common Maintenance Repairs.



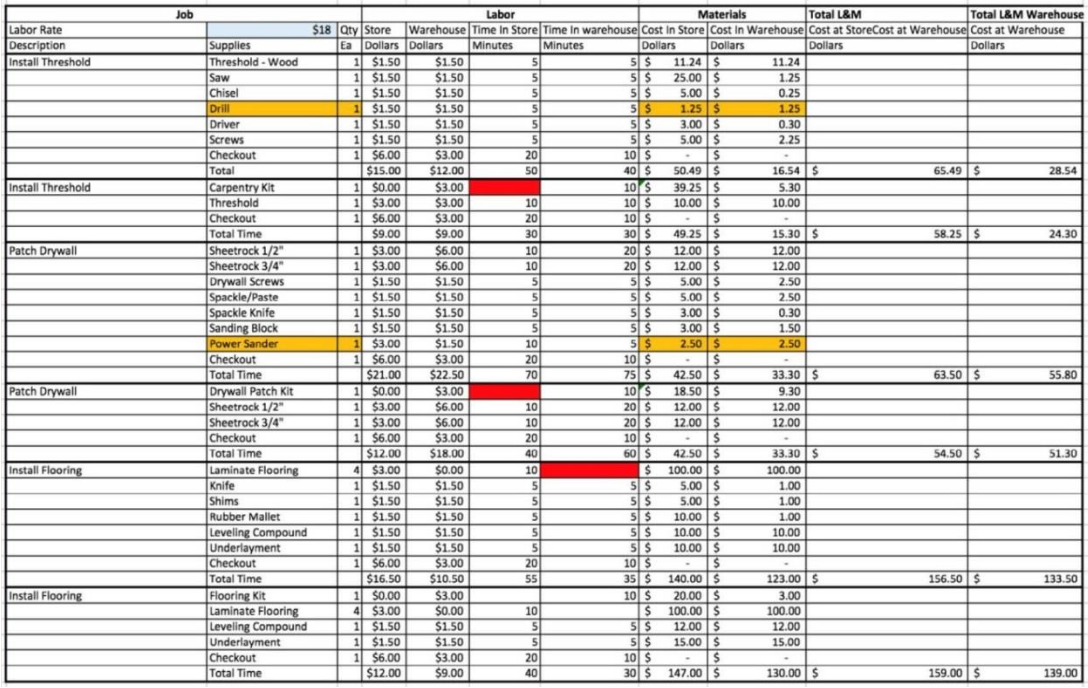
Replace Simple Electrical	Kit
Replace Complex Electrical	Store
HVAC New	Store
HVAC Old	Store
Recharge HVAC	Warehouse

Table 6.2 Examples of Where Materials May Be Sourced.

If we assume power tools are on hand, all or most of the material and hand tools required for a job can be kitted. We can distinguish between typical warehouse visit requirements and store visit requirements, each with their inventoried items so as to indicate one visit versus the other, and schedule that visit into the work plan, if necessary.

6.1.3 Assignment Considering Multiple Periods.

What is the impact of task assignment in this time period on the solution of future states considering updated skill sets? Does the assignment of workers at a higher cost of pairing result in a lower total cost of operation over the longer term planning horizon? Discrete time horizons or work planning allow for the evaluation of the total cost of human resource allocation. This extension can include the evaluation of learning curve concepts as they are applied to the non-traditional work structure addressed in this model.



Job			Labor				Materials		Total L&M	Total L&M Warehouse
Labor Rate	$18	Qty	Store	Warehouse	Time In Store	Time In warehouse	Cost In Store	Cost In Warehouse	Cost at StoreCost at Warehouse	Cost at Warehouse
Description	Supplies	Ea	Dollars	Dollars	Minutes	Minutes	Dollars	Dollars	Dollars	Dollars
Install Threshold	Threshold - Wood	1	$1.50	$1.50	5	5	$ 11.24	$ 11.24		
	Saw	1	$1.50	$1.50	5	5	$ 25.00	$ 1.25		
	Chisel	1	$1.50	$1.50	5	5	$ 5.00	$ 0.25		
	Drill	1	$1.50	$1.50	5	5	$ 1.25	$ 1.25		
	Driver	1	$1.50	$1.50	5	5	$ 3.00	$ 0.30		
	Screws	1	$1.50	$1.50	5	5	$ 5.00	$ 2.25		
	Checkout	1	$6.00	$3.00	20	10	$ -	$ -		
	Total		$15.00	$12.00	50	40	$ 50.49	$ 16.54	$ 65.49	$ 28.54
Install Threshold	Carpentry Kit	1	$0.00	$3.00	🟥	10	$ 39.25	$ 5.30		
	Threshold	1	$3.00	$3.00	10	10	$ 10.00	$ 10.00		
	Checkout	1	$6.00	$3.00	20	10	$ -	$ -		
	Total Time		$9.00	$9.00	30	30	$ 49.25	$ 15.30	$ 58.25	$ 24.30
Patch Drywall	Sheetrock 1/2"	1	$3.00	$6.00	10	20	$ 12.00	$ 12.00		
	Sheetrock 3/4"	1	$3.00	$6.00	10	20	$ 12.00	$ 12.00		
	Drywall Screws	1	$1.50	$1.50	5	5	$ 5.00	$ 2.50		
	Spackle/Paste	1	$1.50	$1.50	5	5	$ 5.00	$ 2.50		
	Spackle Knife	1	$1.50	$1.50	5	5	$ 3.00	$ 0.30		
	Sanding Block	1	$1.50	$1.50	5	5	$ 3.00	$ 1.50		
	Power Sander	1	$3.00	$1.50	10	5	$ 2.50	$ 2.50		
	Checkout	1	$6.00	$3.00	20	10	$ -	$ -		
	Total Time		$21.00	$22.50	70	75	$ 42.50	$ 33.30	$ 63.50	$ 55.80
Patch Drywall	Drywall Patch Kit	1	$0.00	$3.00	🟥	10	$ 18.50	$ 9.30		
	Sheetrock 1/2"	1	$3.00	$6.00	10	20	$ 12.00	$ 12.00		
	Sheetrock 3/4"	1	$3.00	$6.00	10	20	$ 12.00	$ 12.00		
	Checkout	1	$6.00	$3.00	20	10	$ -	$ -		
	Total Time		$12.00	$18.00	40	60	$ 42.50	$ 33.30	$ 54.50	$ 51.30
Install Flooring	Laminate Flooring	4	$3.00	$0.00	10	🟥	$ 100.00	$ 100.00		
	Knife	1	$1.50	$1.50	5	5	$ 5.00	$ 1.00		
	Shims	1	$1.50	$1.50	5	5	$ 5.00	$ 1.00		
	Rubber Mallet	1	$1.50	$1.50	5	5	$ 10.00	$ 1.00		
	Leveling Compound	1	$1.50	$1.50	5	5	$ 10.00	$ 10.00		
	Underlayment	1	$1.50	$1.50	5	5	$ 10.00	$ 10.00		
	Checkout	1	$6.00	$3.00	20	10	$ -	$ -		
	Total Time		$16.50	$10.50	55	35	$ 140.00	$ 123.00	$ 156.50	$ 133.50
Install Flooring	Flooring Kit	1	$0.00	$3.00		10	$ 20.00	$ 3.00		
	Laminate Flooring	4	$3.00	$0.00	10		$ 100.00	$ 100.00		
	Leveling Compound	1	$1.50	$1.50	5	5	$ 12.00	$ 12.00		
	Underlayment	1	$1.50	$1.50	5	5	$ 15.00	$ 15.00		
	Checkout	1	$6.00	$3.00	20	10	$ -	$ -		
	Total Time		$12.00	$9.00	40	30	$ 147.00	$ 130.00	$ 159.00	$ 139.00

Table 6.3 Cost to Acquire Small Tools and Materials for Various Maintenance Work Scopes.

6.1.4 Assignment Considering Three-Dimensional Workflow.

When work is performed within a Cartesian coordinated space, we can utilize the path of progress in determining the shortest path to perform work while avoiding conflicts or clashes in work by various skilled workers in the same space.

6.1.5 Assignment Utilizing Automated Work Processes

With the advent of Artificial Intelligence and Machine Learning, we can augment the performance of work with robots, automated machinery and processes, and Automated Guided Vehicles, to assist in the delivery of resources, materials, and assistive semi-autonomous labor drones.

6.1.6 Sample Hypotheses for the Current Data Sets and Models

I propose some general hypotheses that may serve as extensions of the existing research performed as part of this dissertation. These hypotheses form the basis on immediate advances on insight into the existing data sets. I number them as natural extensions of the already defined hypotheses:

- The experiment with Mentor-Apprentice pairing: with each iteration of job assignment, we want to determine the extent to which repetitive skill acquisition leading to competence is preferred over paired assignment.

H_0: The option to pair a mentor (competent worker) with an apprentice (non − competent worker) has no significant correlation with the total make span of a project..

H_{6a}: The option to pair a mentor with an apprentice in the worker assignment correlates with a reduction in project make span.

H_0: The option to pair a mentor (competent worker) with an apprentice (non − competent worker) has no significant correlation with the total cost of assignment.

H_{6b}: The option to pair a mentor with an apprentice is selected in the worker assignment decision correlates significantly with a total cost of assignment.

- The House Building extension of the model, where the sequence of dependent tasks that comprise a larger project is determined and those tasks are included in the aggregate of task assignment:

H_0: The option to decompose and combine the house building assignment into the assignment of other assigned tasks is no better than the separate assignment of house building and other tasks.

H_{7a}: The inclusion of housebuilding in the assignment of other tasks correlates significantly with the change in total cost.

H_0: The total makespan to decompose and combine the house building assignment into the assignment of other assigned tasks is no better than the separate assignment of house building and other tasks.

H_{7b}: The inclusion of housebuilding in the assignment significantly correlates with the change in total makespan.

- The decision where materials are procured. If materials are to be purchased at the store, kept on hand, or got from the warehouse, this will have a time and travel implication for schedule solution.

H_0: The decision where to acquire materials has no impact on the total cost of assignment.

H_{8a}: The decision to classify where and when to acquire materials correlates significantly with greater (lesser) total cost.

H_0: The decision where to acquire materials has no correlation with total cost of assignment.

H_{8b}: The decision to classify where and when to acquire materials will correlate significantly with a change in total project makespan.

6.2 Final Comments on Plans for Future Research

At what rate does a change in worker skill mix correlate with a change in the total cost of assignment over time? Certainly, up to a point, the division and specialization of skill and the subsequent advancement of skill would result in a decrease in total project make span, at the expense of skill development. When evaluating the sequential assignment decisions as states of the system in time, with one state's inputs the result of a prior state's outputs, what sort of progress and to which point does learning, forgetting and reforming the workforce influence the cost, timeline, solution time and solution gap? This requires extension of the existing model into discrete sequential time intervals of assignment with an objective to optimize the total cost of assignment for all states, with the ability to train up workers for needed skills as well as dissociate workers from prior skills when sufficient time has passed between skill acquisition and skill use. When simultaneously considering the conative synergies of working pairs and teams, we may want to blend the various behavioral skill qualities to achieve a greater level of efficiency, with subsequent skill reinforcement and experience modification.

Finally, the research will definitely benefit from the development of efficient and effective algorithms for obtaining quality solutions to large instances.

Chapter 7

Summary and Conclusions

This dissertation proposes a general model for the assignment of jobs of varying skill requirements--both in terms of skill class and skill level--to the most cost-appropriate worker capable of performing that task while simultaneously considering the temporal, spatial and resource constraints of the assignment, scheduling and routing decision.

A total cost objective considering both skilled and unskilled labor costs, as well as travel costs, is incorporated to minimize the cost of these decisions. The model was implemented and the resulting cost objective is a marked improvement on the original assignment decisions. The model was then extended to include precedence tasks that comprise a separate class of job within the property maintenance environment--the make ready project. The inclusion of the decomposed project tasks and subsequent assignment in parallel with routine work orders was found to not significantly increase the cost of assignment, suggesting that the decomposition of tasks for assignment within temporally and spatially demanding environments like property maintenance offer excellent practical benefit.

The single assignment model was expanded to include the common scenario where more than one worker may be assigned to a job; however, the model goes one step further and incorporates a method for determining the combined synergy or resonance of the pairing decision. I implement variations of the pairing model within CPLEX where through successive iterations of updated efficiency scores I emulate the possible path to skill development, the precursor to knowledge transfer and a bridge for training in the tacit learning environment. The measure of synergy or resonance in the pairing assignment helps to determine the most precise level of cooperation among paired assignments. The results show that over 6 rounds of successive assignment of the same jobs, the model can achieve up-training an incompetent worker to basic competence, at which point the worker is assigned to individual jobs of that skill class and level.

Finally, I perform an extensive computation experiment with 324 instances and 291 solutions from variations of the initial data set. I also separate the overall data set into three sub-sets based on the number of jobs to be assigned; I then delineate the similarities and differences between these data sets, using SPSS Statistics to derive meaningful relationships between variables.

I offer several potential extensions of the model and suggest several hypotheses for future development of this research as well as areas that can be developed using this research as a platform for a more comprehensive research initiative. Truly, the phenomenon of practical skilled labor, multi-skilling and trade-based or team-based project environments can benefit from such research. I also suggest areas of future technological expansion of this work, including automation, artificial intelligence, machine learning, three-dimensional workflow and knowledge transfer and learning.

There is much more in the area of data analysis and insights to be gained from statistical analysis of both the given 18 months of data as well as the outputs from various schemes of work assignment and considering various priority, pre-emption and duration rules. These varying approaches also would benefit from a more elaborate visualization. Maps, Gantt charts and travel times depending on days of the week may all add more definition to the solutions gained from this model. We would also gain from isolating certain aspects of the model for revaluation of how this may affect outcomes. For example, we may want to pursue the solution for when all work is isolated to a smaller or larger geographic region to determine if results scale in proportion to spatial, temporal or other geographical ranges. While we have discussed the standard of practice for financial comparison, we have not explained the complete heuristic used for the rule of thumb decisions being made at the daily assignment level. In order to get our model closer to the working example of the business, the more accurate the scheduling and assignment function will be; therefore, running several scenarios and comparing and contrasting these scenarios and data inputs to determine how these scenarios will behave, allows us to more accurately adapt the model. When with greater accuracy we can predict the actual performance of the model results, we are able to compress the schedule and leverage that efficiency. Furthermore, what is the impact of the job mix based on different times of the year to evaluate the effect of seasonal demands? And what of the impact of the worker mix under seasonal pressures, both during routines of preventative and corrective maintenance? For example, the high demand of heating system service during the winter, or the air conditioning service in summer, demands a greater level of HVAC skilled workers. However, preventative maintenance, which occurs in spring and fall, does not necessarily require the more advanced skills as emergent HVAC service does.

When considering the constraints of managerial pressures in the real operating environment, where the daily decision is made based on skilled worker availability, it may not necessarily make decisions to forego plan work based on priority, duration, costs and skill level at the same time. We would want to identify the phenomenological nature of any influencers from the evaluation of the operating environment. We anticipate the ability to identify other similar patterns of decision making in practice, to compare to the same decisions as the model predicts them, from which comparisons can be made and better operational objectives, strategic goals and development schemes can be created. Further, because of the extensive data collected, we have the ability to develop historical examples of decision making for time periods, and can compare these to our model results. Subsequent research would emphasize simulation of distributed performance times and the impact on solution feasibility. Our model is able to approximate the optimal decision for work assignment given the available workforce at that point in time. By performing the sensitivity analysis on the variation of job locations, job times, available workers, and various skill sets, we can compare the performance of the model versus historical performance as well as simulated scenarios.

Appendix A. Summary of Literature Review

Authors (Year)	Publication	Industry Focus	Application/Approach	Results
Brusco and Johns (1998)	Decision Sciences	Paper Mill Maintenance	Multiple Integer Linear Program (MILP); Interviews and Department of Labor (DOL) Data; Semi-Structured Interviews with Managers.	Partially Skilled Workers can cover more than 50% of 100% productivity assignments. Using 50% training in a second skill achieves 86.9% of the savings as cross training at 100% productivity.
Hegazy (2000)	Journal of Engineering and Construction Management	Construction Project Management	Multiskill Resource Scheduling Algorithm (MURSA) program using Microsoft Project and SAS/OR and earliest Late Start (ELS) Rule	Unconstrained resource scheduling resulted in 32 days total Project duration (TPD). Application of one substitution rule for multi-skill labor resulted in a TPD of 39 days by MURSA versus 47 by SAS/OR. Utilization of 5 substitution rules resulting in a TPD of 35 days for MURSA and 47 (same) for SAS/OR. Project Delay is reduced bymulti-skilled resource substitution.

Authors (Year)	Publication	Industry Focus	Application/Approach	Results
Burleson et al (1998)	Journal of Construction Engineering and Management	Petrochemical Plant	Plant Data Development; Dual-Skill Versus Four-Crafts Strategy	Multi-Skilling offers 5%-20% total project labor cost reduction, 35% workforce reduction, and 47% average employment duration increase.
Gomar et al (2002)	Journal of Construction Engineering and Management	Construction	GAMS Model using CII Plant data	After one or two additional skills are obtained, additional benefits are marginal. Tests should be run with natural affinities in order to evaluate the most effective combinations. Multi-skilled workers were always in the optimization model over single skilled workers.

Authors (Year)	Publication	Industry Focus	Application/Approach	Results
Haas (1999)	Center for Construction Industry Studies	Construction	Site Visits and Interviews	Multi-Skilling depends on Superintendent ability to assign appropriate tasks to workers and build effective work crews; 20% productivity gain found among 6 companies surveyed. Multi-Skilling Benefits marginal after 10-20% multiskill workforce composition; benefits marginal after 2-3 craft competency.
Carley (1999)	Center for Construction Industry Studies	Construction	Data Analysis	70% of workers have skills in other trades; 79% of these workers are interested in more primary trade training; 57% would pursue training in another trade.
Tam et al (2001)	Construction Management and Economics	Public Works/ Housing Authority Construction	Genetic Algorithm and Labor Optimization Model	Limited Multi-Skilling increased cost of performance 3.7%.

Authors (Year)	Publication	Industry Focus	Application/Approach	Results
Fitzpatrick and Askin (2007)	Computers and Industrial Engineering	Cellular Manufacturing	Kolbe Conative Index and Multiple Integer Programming (MIP)	Average deviation from lower bound was less than 11%; maximum deviation was lower than An increase in members may overstate the weighted values and might not be a good indicator of potential problem areas; inertia is not a good indicator of synergy.
Bennour and Crestani (2005)	Computers in Engineering, International Journal of Production Research	Industrial Engineering	MOVES Model; Human Resource Competency Based Assignment	With increased experience, the duration of the implementatio of a process decreases and reaches a stable state when all involved actors attain their maximal competence level. The definition of multiple weight factors is difficult to manage and tends to reduce their impact on performance.
Bennour and Crestani (2007)	International Journal of Production Research	Industrial Engineering	Performance Estimation Using Competencies	The human factor is a key element to ensure the survival of an enterprise.

Authors (Year)	Publication	Industry Focus	Application/Approach	Results
Elfwing et al (2007)	IEEE transactions on Evolutionary Computation	Robotic Automation, Artificial Intelligence	Reinforcement Learning, Heierarchical Learning Structures, MaxQ, Semi-Markov Decision Process	Robot will execute a minimal strategy that minimizes the number of primitive subtasks to perform a goal to remove the need to re-learning behaviors; learning time is reduced when higher order routines are decomposed into lower order behaviors.
Canini et al (2010)	Proceedings of the 27th International Conference on Machine Learning	Human categorization, Transfer Learning	Hierarchical Dirichlet Process	Humans are able to accurately reconstruct taxonomy structures in category systems from a limited number of examples.
Janiak et al (2009)	Computers and Industrial Engineering	Job Scheduling	Experience Based Learning Model and Single Processor Make-Span Minimization	The model solves for an optimal schedule for up to 30 jobs in a few minutes.
Hyari et al (2010)		Small to Medium Sized Contracting Firms Using data from Tam et al (2001)	Single Versus Multi-Skill Work Groups and Multiple Integer Linear Programming (MILP)	Solution time improvement from 10 hours to 1 second Tam et al Genetic Algorithm Approach; all three solutions improved over 2001 results.

Authors (Year)	Publication	Industry Focus	Application/Approach	Results
Janiak and Rudek (2010)	Omega	Processor Scheduling	Make Span Minimization Problem with Multi-Ability Learning Effect (SAMALE)	An exact polynomial time algorithm was run and found to solve optimally; jobs where learning can be advanced were assigned before jobs where no learning could occur.
Pitiot et al (2010)	Engineering Applications in Artificial Intelligence	Product/Project Integration Model	Hierarchical Decomposition, Evolutionary Algorithm Organized by Knowledge (EAOK); Expectation-Maximization Algorithm	Using qualified individuals first helps to ensure learning capabilities are not saturated among individuals with a poor fit; fast learning is good for global guidance whereas longer learning can cause over-guidance. Work should incorporate actual information to develop a network model.
Wongwai and Malaikrisanachalee (2010)	Automation in Construction	Human Resource tion	Single and Multi-Skill Substitution; Project Timeline Minimization	Sacrifices minimum cost for shortest project duration.

Authors (Year)	Publication	Industry Focus	Application/Approach	Results
Czyz et al (2011)	International Journal of Electronics and Telecommunications	Computer and Industrial Systems	Total Tardiness Minimization using Automated Learning System (ALS)	Parallel Tabu Search (PTS) is more efficient as the number of jobs increases; Efficiency gains from PTS are greater compared to Parallel Nawaz-Enscore-Ham (PNEH) or Parallel Simulted Annealing (PSA).
Florez et al (2012)	Construction Research Congress	Construction	Multimode Resource Constrained Project Scheduling Program (MRCP-SP) using MILP	Mathematical Modeling may help to stabilize the hiring and firing of workers. The solution time for multi-skilling was more than 10 versus less than a minute for single skilling.
Liu and Wang (2012)		Construction	Constraint Programming for Crew Scheduling	Crew schedule durations are minimized.
Zha and Zhang (2012)			Learning Function (Induced and Autonomous) with Multi-Skilling; Project Scheduling	Learning effect can contribute to shorter makespan. Cost of assignment decreases before increasing as induced learning increases.

Authors (Year)	Publication	Industry Focus	Application/Approach	Results
Alikhani and Fazlollahtabar (2014)	Advances in Operations Research		Organizational Learning/Cost Minimization; Epsilon Constraint Method	Computation results confirm model effectivenes; methodology wasvalidated.
Lucko (2014)	Automation in Construction	Construction	Temporal-Spatial Task Scheduling	Creates a foundational model (algorithm) for 3D spatial scheduling of sequenced tasks. A 31.3% reduction in project duration was achieved when considering spatial modeling compared to Critical path method (CPM).
Abotaleb (2014)	Canadian Society for Civil Engineering	Construction	Multi-Skilling	Total Project Duration (TPD) was 31.5% shorter; and labor cost was less using Multi-Skilling.

Authors (Year)	Publication	Industry Focus	Application/Approach	Results
Małachowski, B., & Korytkowski, P. (2016)	Computers & Industrial Engineering	Manufacturing	Multi-Skilling and Learning Curve	Advancement of one competence loads itively on other interrelated competences. Learning can be calculated as skills are adopted. Elementary competence compound competences. Research needs to apply learning performance models to various areas of workforce scheduling and assignment.

Authors (Year)	Publication	Industry Focus	Application/Approach	Results
Ottoman, G. R., Nixon, W.B., & Lofgren, S. T. (1999)	Journal of Management in Engineering	Building & Facilities Maintenance	Literature Review: Life-Cycle Costing and Property Valuation Approaches	Maintenance costs are primarily overlooked; Annual budgeting can conflict with short-term maintenance requirements. 18 estimating approaches are presented. Sophisticated data-modeling approaches are uncommon in practical use. Analysis relies more on professional evaluation and proportional Maintenance and Repair (M&R) value, life-cycle expected cost condition-assessment.

Authors (Year)	Publication	Industry Focus	Application/Approach	Results
Army Corps of Engineers Construction Engineering Research Laboratory (1991)	USACERL Technical Report P-91/10	Building and Facilities Maintenance	Facility Life-Cycle Costing and Maintenance Resource Prediction	Definition and Standardization of a data base of maintenance components and costs. Predictive models/methods and their and disadvantages are discussed. Buildings account for over 60% of the maintenance expenditures annualy. Housing and Unaccompanied Personnel Housing alone contribute 26% of yearly maintenance expenditures.

Authors (Year)	Publication	Industry Focus	Application/Approach	Results
Army Corps of Engineers Construction Engineering Research Laboratory (1990)	USACERL Technical Report M-90/19	Building and Facilities Maintenance	Conception of the BUILDER Engineered Management System (EMS)	Assesment of the various other Operation Related Software systems use at State and Federal Institutions. Provides a framework for advancement of the ARMY property maintenance program. Because building components use different technology disciplines, the BUILDER EMS must be multi-displined. The system must be created in steps or modules.
Sun and Che (2012)	Applied Mechanics and Materials	Construction Engineering Building Information Modeling (BIM)	Process Model detailing the functional structure of an Engineering management system reference practical use for maintaining a water chiller unit.	Comprehensive application of a BIM database can aid planners in efficient maintenance response rate and guarantee appropriate human, material and financial resources.

Authors (Year)	Publication	Industry Focus	Application/Approach	Results
Burcin-Becerik Gerber et al (2011)	Journal of Construction Engineering and Management	Facilities Management	Building Information Modeling (BIM)	BIM adoption rate has increased and its vizualization of facilities management goals and controls holds undeveloped possibilities. Facilities Management Oragnizations have already stared incorporating BIM or plan to implement BIM in the immediate future.
Wu, Neale, Williamson, Hornby (2010)	Journal of Quality in Maintenance Engineering	Industrial Maintenance	Workshop-based review of practitioner's insights on maintenance policy.	Practioners want simple tools to aid in Maintenance Planning; Academic research aims to be published and may not be suitable for practical use. The gap between practical and ic application needs to be narrowed. Case study is one suggestion for bridging this gap.

Authors (Year)	Publication	Industry Focus	Application/Approach	Results
Saranga (2004)	Journal of Quality in Maintenance Engineering	Opportunistic Maintenance	Genetic Algorithm applied to Mathematical Model	The GA approach was validated using an aircraft maintenance scenario and depending on useful life of components and whether all or each component are to be evaluated considering risk of failure, downtime cost, and replacement cost; If considering individual items, it is more cost effective to replace now; if one considers grouping items it may be more cost effective to delay replacement until a later point in time.

Authors (Year)	Publication	Industry Focus	Application/Approach	Results
Wu and Clements-Groome (2006)	Engineering, Construction and Architectural Management	UK Construction Industry	Modified version of Pride's Scheduled Maintenance Logic Tree	The term "failure-based maintenance" may be misunderstood. Only 23% of firms apply maintenance whereas 45% of firms apply preventative maintenance, which may be more costly. Data analysis should be applied in maintenance strategy development.
Lind and Muyingo (2012)	Property Management	Review of Swedish studies on building maintenance strategies.	Alternative Model of Maintenance Strategy	Identifies a "before-fault" and "after-fault" classification of most commonly applied maintenance strategies.
Kuhn and Madanat (2006)	Computer-Aided Civil and Infrastructure Engineering	Single Facility/ Project Maintenance and Rehabilitation	Markov Decision Process with MAXI-MIN and Hurwicz Criterion Robust Optimization	Optimal management policies in MAXIMIN robust optimization are more conservative than those employed in non-robust optimization, especially as uncertainty is more significant.

Authors (Year)	Publication	Industry Focus	Application/Approach	Results
Ahuja and Khamba (2008)	International Journal of Quality and Reliability Management	Total Productive Maintenance (TPM)	Literature Review	TPM might be considered one of the best proactive strategic initiatives that can lead the organization to success over failure. TPM must be regarded as a "change process."
Tsui and Fong (2012)	Knowledge and Process Management	Hong Kong Housing Organization (Property Management Division)	Combined Qualitative and Quantitative Approach Using Survey instrument and Follow-Up Discussion	Business Information was largely the preferred collaboration tool for Property Management Division (PMD) knowledge management. Suggests a two-phase adoption plan with to Knowledge Management (KI) and Business Information (BI) Tools
Lambie-Hanson (2015)	Journal of Urban Economics	Property Maintenance	Statistical Analysis including Multi-Level, Longitudinal Regression Model estimated as a logit model.	Magnitude of code violation is increased as property falls into Indicates benefit of maintaining occupied properties.
Chen et al (2017)	European Journal of Operational Research	Urban Drainage	Risk-driven Preventative and Corrective Maintenance, Dynamic Optimization	Policies that include condition based maintenance can reduce risk of blockages or breakages by over 90%.

Authors (Year)	Publication	Industry Focus	Application/Approach	Results
De Jonge et al (2017)	Reliability Engineering and System Safety	Time Based Performance (TBP) versus Condition Based Performance (CBP)	Comparison of numerical examples from Literature-review	Cost benefit of Condition Based Maintenance (CBM) over Time Based Maintenance (TBM) decreases as uncertainty of the risk of failure increases. Large amount of uncertainty may actually make CBM perform worse than TBM.
Keizer et al (2017)	European Journal of Operational Research	Equipment Maintenance	Literature review of Condition-Based Maintenance (CBM)	Resource-dependence is still ill-researched. Most pooled resource research considers constant availability over time.
Mehrgani et al (2016)	Applied Mathematical Modeling	Flexible Manufacturing Systems	Dynamic Approximation Model Considering Lock Out Tag Out for Preventative and Corrective Maintenance	Increasing production speed and reducing worker training increases human error and subsequently the total production cost while decreasing worker safety.

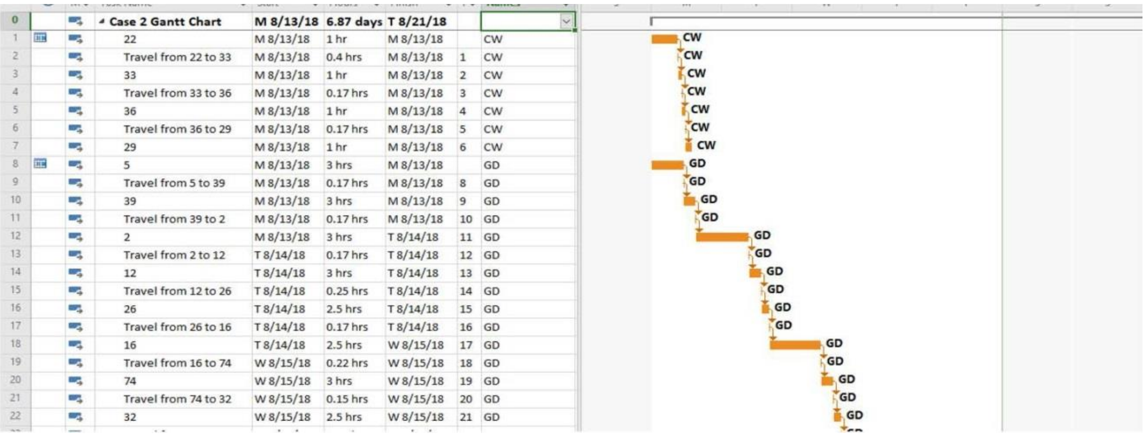
Authors (Year)	Publication	Industry Focus	Application/Approach	Results
Pun et al (2017)	2017 proceedings of Portland International Center for Management of Engineering and Technology '17: Technology Management for Interconnected World	Facility Management	Fuzzy Analytics Hierarchy Process Decision Support System	There is a lack of a systematic approach to determine how maintenance strategies are recorded in most companies. The suggested approach uses cloud based data management to provide clear direction in formulating various maintenance plans.
Sheng and Baharum (2015)	International Journal of Property Sciences	Property Management	Survey Rank of 20 Criteria each for both Client (40 of 59 respondents) and Service Provider (19 of 59 respondents).	Quality (best possible affordable and sustainable level) and Flexibility (meet changes with existing resource base) are the two most important criteria by both clients and service providers.
Reischl et al (2015)	Journal of Community Psychology	Neighborhood Development, Property Maintenance	Parcel Maintenance Observation Tool (PMOT)	Unsecured and broken windows and doors are a main observation of unoccupied properties, and also contribute to 19.9% of occupied property observations reported.

Authors (Year)	Publication	Industry Focus	Application/Approach	Results
Han et al (2014)	Applied Mechanics and Materials	Construction management; Property Maintenance	Evaluation of Building Information Technology	Introduction of technical capabilities of BIM as applied in construction and property management. Technology is expected to be adopted more widely in the future.
Li and Monkkonen (2014)	Property Management	Property Management	Experimental Survey Methodology of 150 experts in Hong Kong Property Management Market.	Moderate increases in appreciation of value of property management among respondents over 34 years in age.
Tan et al (2014)	Facilities	Building and Facilities Maintenance	Critical Success Factor Analysis Using Varimax , Oblimin, Quartimax and Equimax Rotation Methods	Concentration of 28 factors into 8 distinct principal factors. The top factors were Client Satisfaction (1), Certification of the Company (2) and Reliability (3) and Quality (4) of service. Cost management, Work execution control, communication and responsiveness also scored in the top 10 factors.

Authors (Year)	Publication	Industry Focus	Application/Approach	Results
Muczynski and Gawron (2014)	Technical Transactions Civil Engineering	Property Management	Elicitation of a Property Management Plan	A methodology for planning property management with emphasis on immediate and long-term objectives should ensure the optimal method of property usage and management.
Liu (2013)	Mathematical Problems in Engineering	Parallel Unrelated Machines Project Management	Hybrid Genetic Algorithm using data from a Priority Rule Based Algorithm	HGA performs accurately and efficently for small-size cases (<30 jobs); performs better than Conventional Genetic Algorithm (CGA) for large size problems (30, 90 jobs).
Kuo et al (2013)	Production and Operations Management	Airline Agent Staffing	Multi-Skill Staffing Across Multiple Locations	Valid Inequalities reduce CAPU time considerably. Using partialy skilled workers whose skills are in short supply offers almost the same coverage as utilizing only fully skilled workers.

Authors (Year)	Publication	Industry Focus	Application/Approach	Results
Methlouthi et al (2017)	CIRRELT	Electronic Transaction Equipment	Technician Routing and Scheduling Program	When technician skills are more restricted, a larger number of solutions exists. When stops are required to pick up special parts, the number of solutions increases. Only instances of a small size can be solved to optimality.
Chen et al (2016)	Omega	Home Services	Technician Routing and Scheduling Problem (TRSP) using a variant of the Record to Record (RTR) Travel Algorithm and Learning Effect	Modeling learning and technician heterogeneity leads to better and different solutions than homogenous learning curves and/or static productivity. Inexperienced technicians specialize the most and experienced technicians the least.
Biskup (2008)	European Journal of Operational Research	Manufacturing Scheduling	Literature Review on Learning Curve Literature	The well known sum of processing time sequence yields strong results for competition time goals.

Authors (Year)	Publication	Industry Focus	Application/Approach	Results
De Breucker (2015)	European Journal of Operations Management	Workforce Planning	Literature Review of Workforce Planning Considering Multiskilling.	It is almost impossible to solve problems of realistic complexity to optimality. Often, management of a company Will sacrifice optimality for feasibility. Suggests using assumptions based on sound empirical evidence and with consideration for uncertainty, for a balance of both fast and good solutions.



0		Case 2 Gantt Chart	M 8/13/18	6.87 days	T 8/21/18		
1		22	M 8/13/18	1 hr	M 8/13/18		CW
2		Travel from 22 to 33	M 8/13/18	0.4 hrs	M 8/13/18	1	CW
3		33	M 8/13/18	1 hr	M 8/13/18	2	CW
4		Travel from 33 to 36	M 8/13/18	0.17 hrs	M 8/13/18	3	CW
5		36	M 8/13/18	1 hr	M 8/13/18	4	CW
6		Travel from 36 to 29	M 8/13/18	0.17 hrs	M 8/13/18	5	CW
7		29	M 8/13/18	1 hr	M 8/13/18	6	CW
8		5	M 8/13/18	3 hrs	M 8/13/18		GD
9		Travel from 5 to 39	M 8/13/18	0.17 hrs	M 8/13/18	8	GD
10		39	M 8/13/18	3 hrs	M 8/13/18	9	GD
11		Travel from 39 to 2	M 8/13/18	0.17 hrs	M 8/13/18	10	GD
12		2	M 8/13/18	3 hrs	T 8/14/18	11	GD
13		Travel from 2 to 12	T 8/14/18	0.17 hrs	T 8/14/18	12	GD
14		12	T 8/14/18	3 hrs	T 8/14/18	13	GD
15		Travel from 12 to 26	T 8/14/18	0.25 hrs	T 8/14/18	14	GD
16		26	T 8/14/18	2.5 hrs	T 8/14/18	15	GD
17		Travel from 26 to 16	T 8/14/18	0.17 hrs	T 8/14/18	16	GD
18		16	T 8/14/18	2.5 hrs	W 8/15/18	17	GD
19		Travel from 16 to 74	W 8/15/18	0.22 hrs	W 8/15/18	18	GD
20		74	W 8/15/18	3 hrs	W 8/15/18	19	GD
21		Travel from 74 to 32	W 8/15/18	0.15 hrs	W 8/15/18	20	GD
22		32	W 8/15/18	2.5 hrs	W 8/15/18	21	GD

Figure 4.15 Critical Path GANTT Project Schedule for Assignment Considering Precedence.

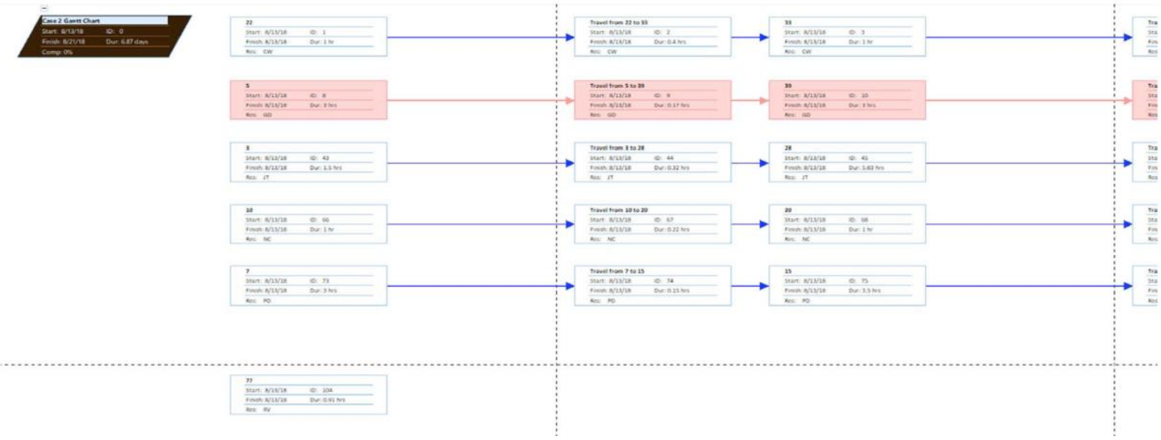


Figure 4.16 Network Diagram for Assignment Considering Precedence.

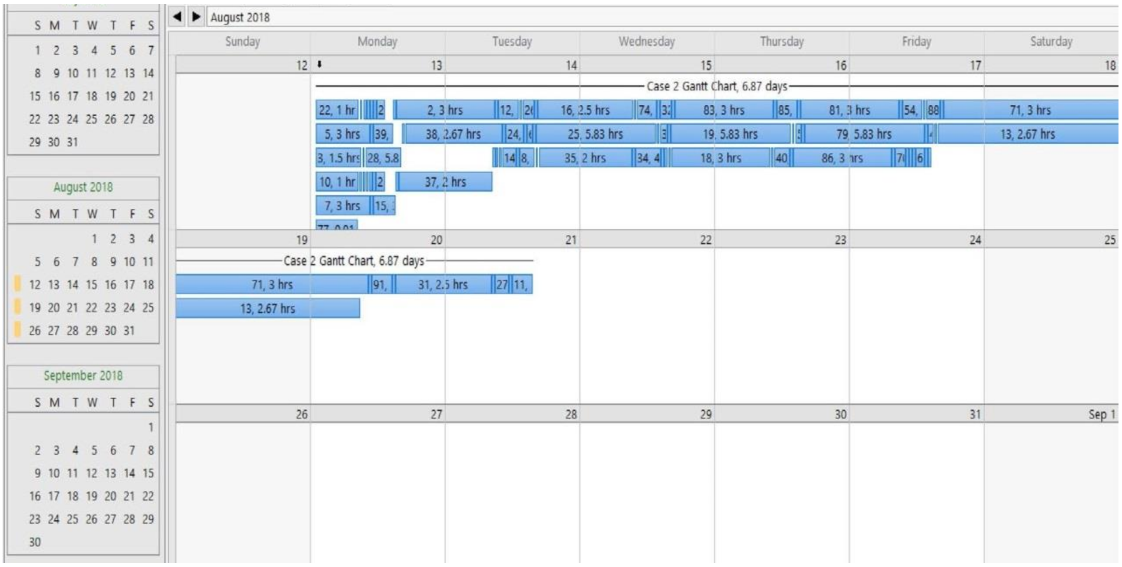
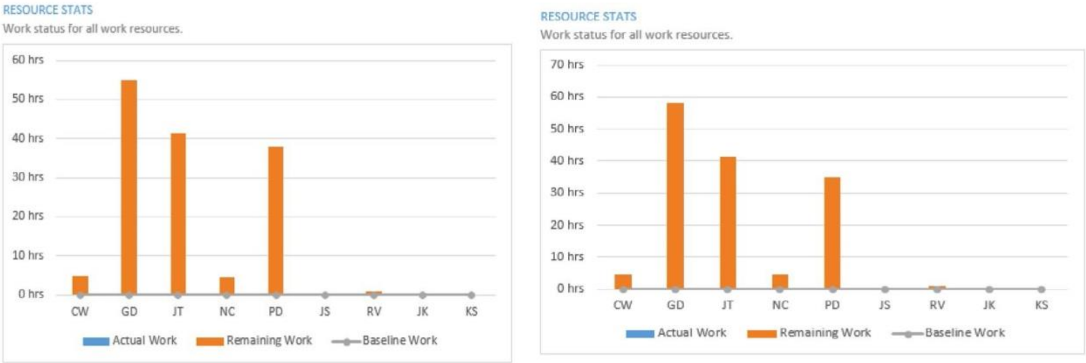
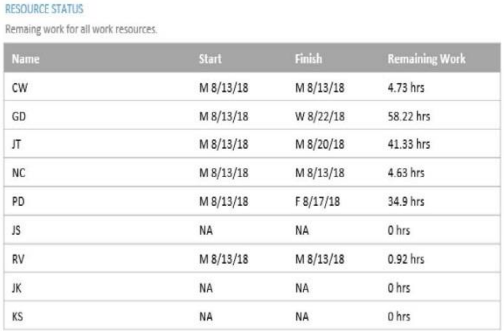


Figure 4.17 Calendar of Assignment for Model Considering Precedence.

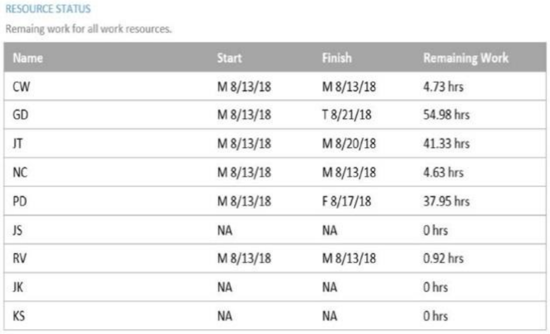




RESOURCE STATUS

Remaing work for all work resources.

Name	Start	Finish	Remaining Work
CW	M 8/13/18	M 8/13/18	4.73 hrs
GD	M 8/13/18	W 8/22/18	58.22 hrs
JT	M 8/13/18	M 8/20/18	41.33 hrs
NC	M 8/13/18	M 8/13/18	4.63 hrs
PD	M 8/13/18	F 8/17/18	34.9 hrs
JS	NA	NA	0 hrs
RV	M 8/13/18	M 8/13/18	0.92 hrs
JK	NA	NA	0 hrs
KS	NA	NA	0 hrs



RESOURCE STATUS

Remaing work for all work resources.

Name	Start	Finish	Remaining Work
CW	M 8/13/18	M 8/13/18	4.73 hrs
GD	M 8/13/18	T 8/21/18	54.98 hrs
JT	M 8/13/18	M 8/20/18	41.33 hrs
NC	M 8/13/18	M 8/13/18	4.63 hrs
PD	M 8/13/18	F 8/17/18	37.95 hrs
JS	NA	NA	0 hrs
RV	M 8/13/18	M 8/13/18	0.92 hrs
JK	NA	NA	0 hrs
KS	NA	NA	0 hrs

Figure 4.18 Resource Utilization for Single Assignment Without Precedence (Case 1 Left) and With Precedence (Case 2, Right).

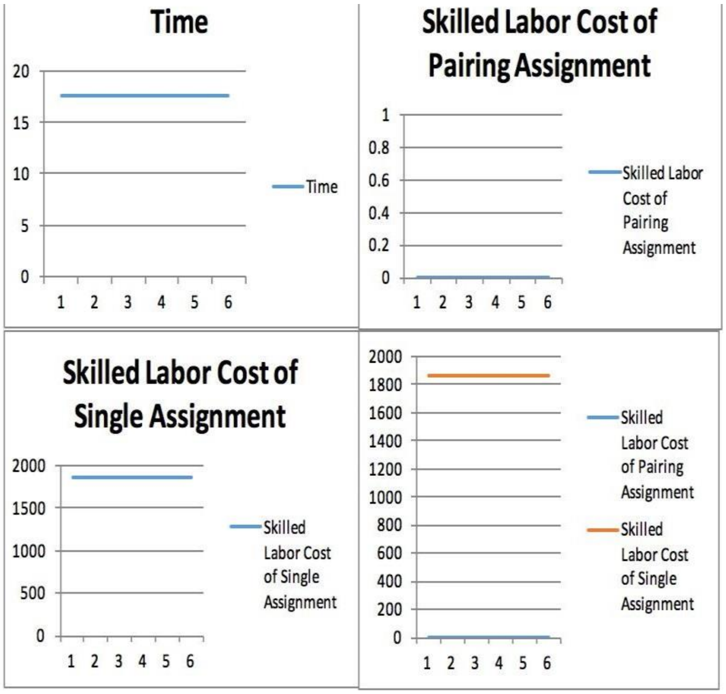


Figure 4.19a Results of 6 Rounds of Assignment when ρ = .6

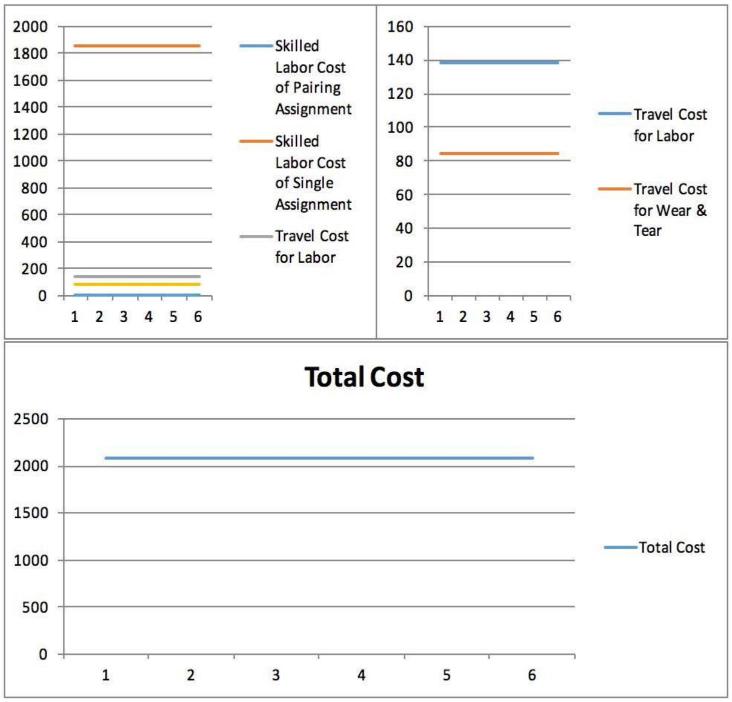


Figure 4.19b Results of 6 Rounds of Assignment when ρ = .6

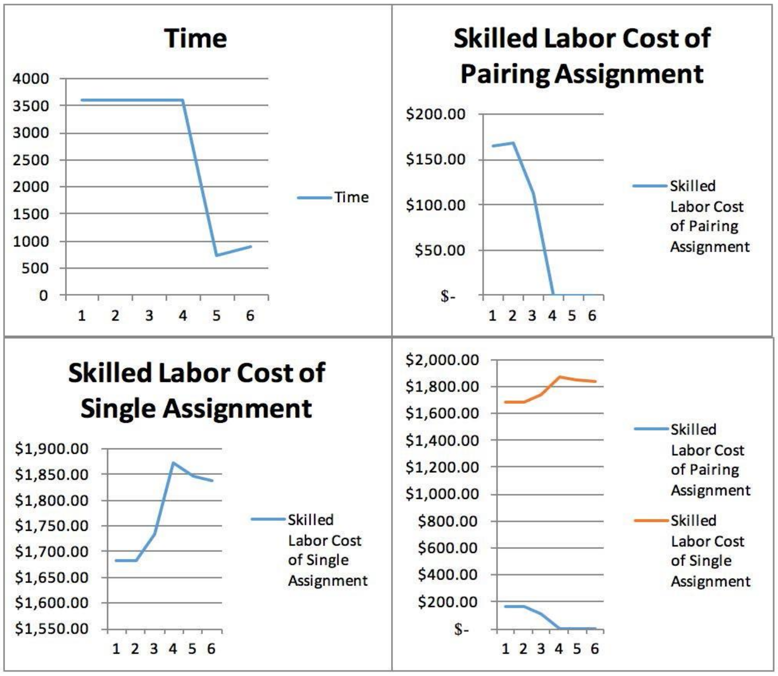


Figure 4.20a Results of 6 Rounds of Assignment when ρ = 1.1

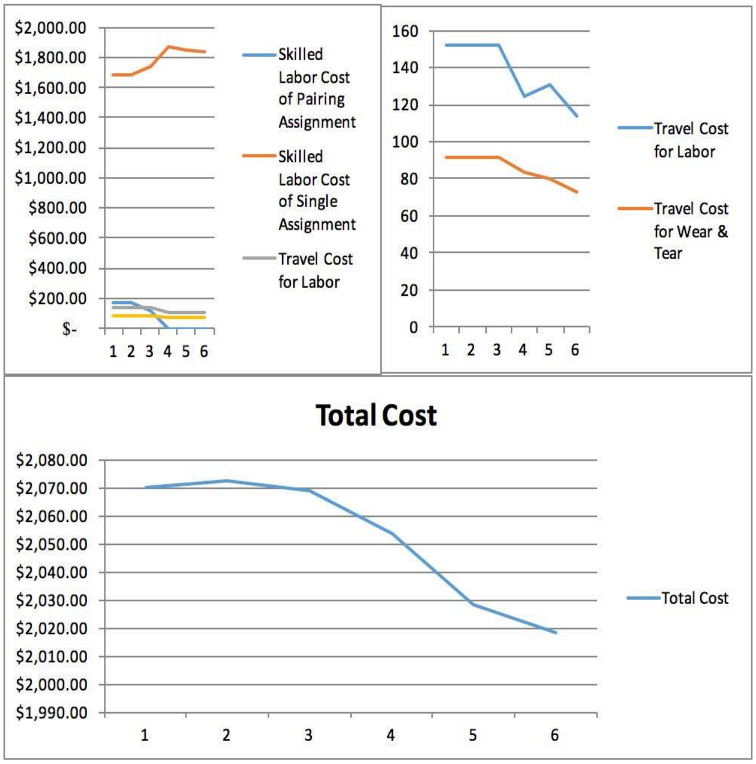


Figure 4.20b Results of 6 Rounds of Assignment when ρ = 1.1

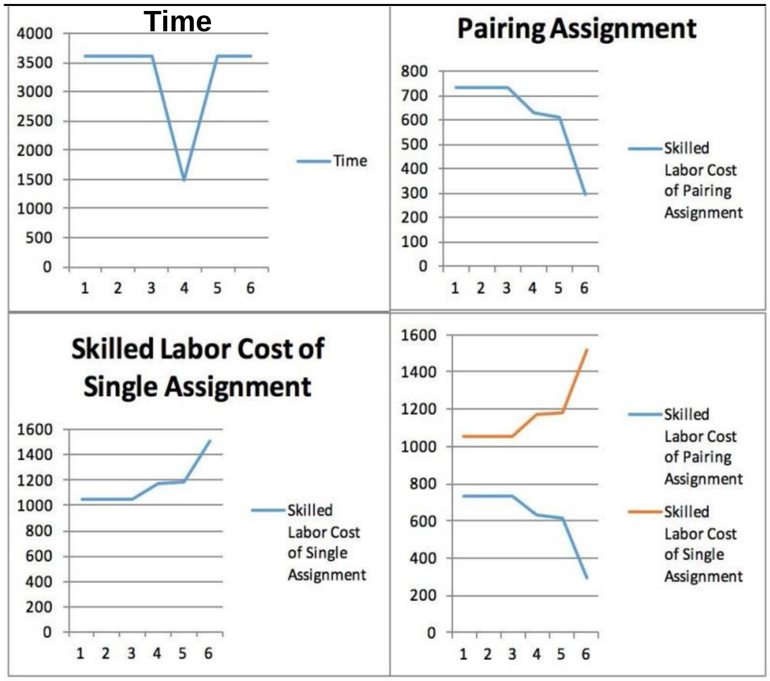


Figure 4.21a Results of 6 Rounds of Assignment when ρ = 1.2

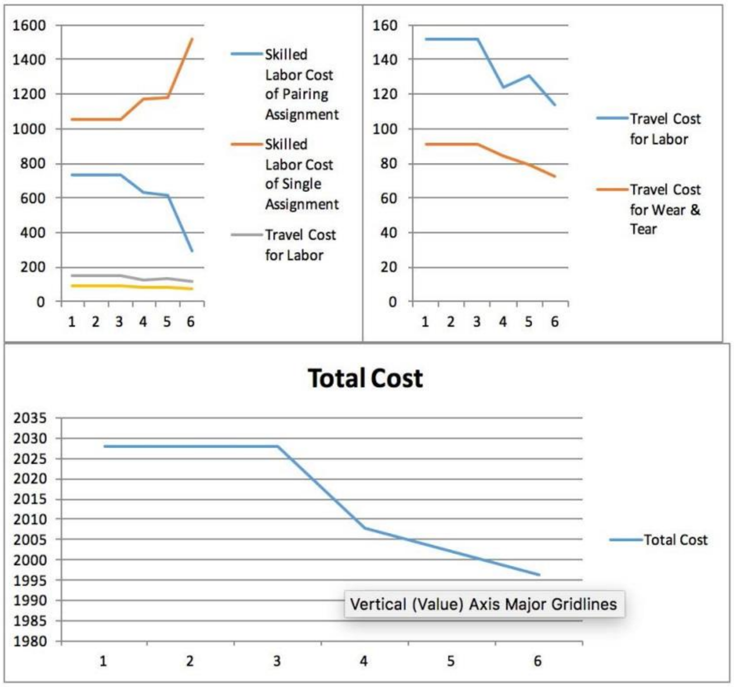


Figure 4.21b Results of 6 Rounds of Assignment when ρ = 1.2

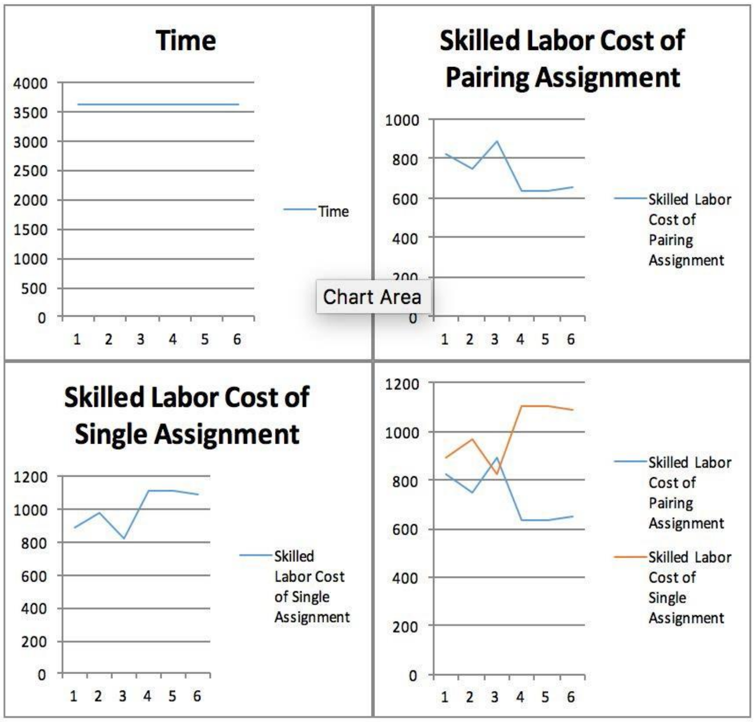


Figure 4.22a Results of 6 Rounds of Assignment when ρ = 1.3

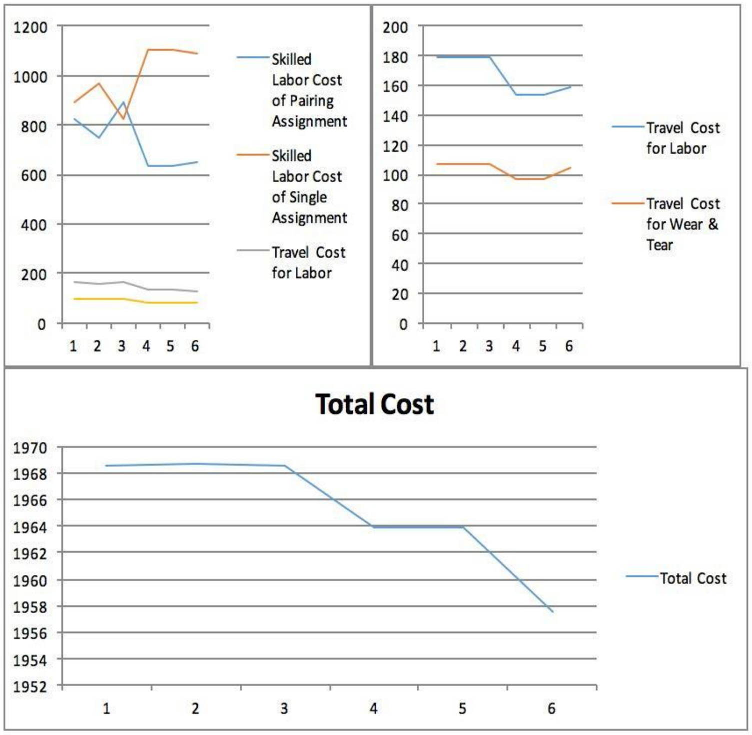


Figure 4.22b Results of 6 Rounds of Assignment when ρ = 1.3

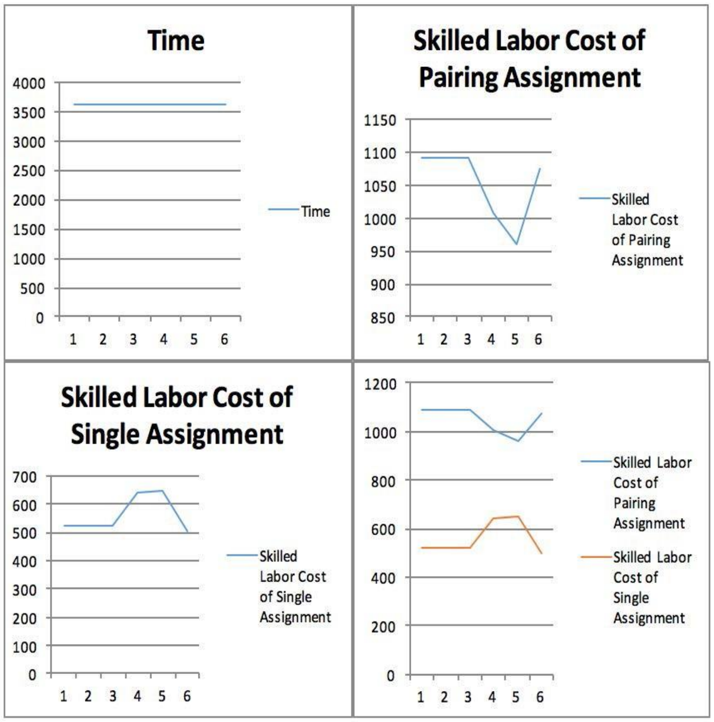


Figure 4.23a Results of 6 Rounds of Assignment when ρ = 1.4

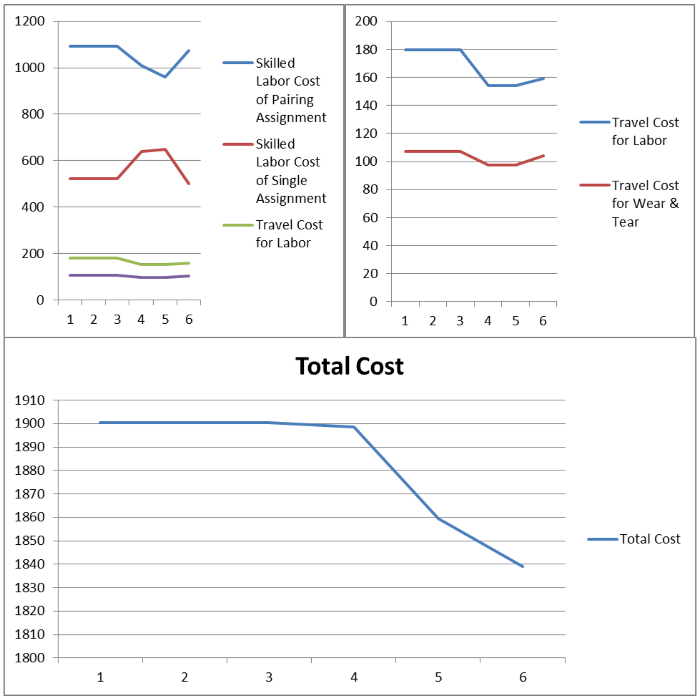


Figure 4.23b Results of 6 Rounds of Assignment when ρ = 1.4

Ranking of Costs For Travel Among Workers, Wage and Travel Cost Per Job (1=Least, 5=Most)

	Worker Wage	Wage Rank	Travel TimeCost	Travel Time Cost Per Job	Travel Time Cost Rank	Travel Distance Cost	Travel Distance Cost Per Job	Travel Distance Cost Rank	Composite Rank For Travel Cost
CW	$ 26.03	2	$ 19.26	$ 6.42	5	$ 15.20	$ 5.07	5	4
GD	$ 27.70	3	$ 89.74	$ 4.99	2	$ 68.87	$ 3.83	2	2
JT	$ 30.48	4	$ 68.46	$ 6.22	1	$ 41.53	$ 3.78	1	1
NC	$ 23.53	1	$ 14.99	$ 5.00	4	$ 14.97	$ 4.99	5	4
PD	$ 26.03	2	$ 75.11	$ 5.36	3	$ 56.50	$ 4.04	3	3

Table 4.44 Ranking of Costs For Travel Among Workers, Wage and Travel Cost Per Job

		Jobs	Classes	Levels	Workers	Hours	Solution Time	Total Cost	Labor	Vehicle Wear	Travel Labor	Gap
Jobs	Pearson Correlation	1.00	0.01	0.02	.171**	-0.02	.821**	.608**	.547**	.978**	.970**	.556**
	Sig. (2-tailed)		0.85	0.79	0.00	0.79	0.00	0.00	0.00	0.00	0.00	0.00
	Sum of Squares and Cross-products	30294.56	57.90	57.90	1085.57	-780.00	4299137.10	1379597.87	1155249.25	90591.91	133756.70	2428.09
	Covariance	104.46	0.20	0.20	3.74	-2.69	14824.61	4757.23	3983.62	312.39	461.23	8.37
Classes	Pearson Correlation	0.01	1.00	0.00	0.00	0.02	-.138*	.321**	.332**	0.08	.141*	-.151**
	Sig. (2-tailed)	0.85		0.94	0.96	0.71	0.02	0.00	0.00	0.18	0.02	0.01
	Sum of Squares and Cross-products	57.90	855.28	-2.72	2.97	180.00	-121503.52	122413.67	117933.48	1214.06	3266.13	-110.79
	Covariance	0.20	2.95	-0.01	0.01	0.62	-418.98	422.12	406.67	4.19	11.26	-0.38
Levels	Pearson Correlation	0.02	0.00	1.00	0.00	0.02	-.140*	.169**	.171**	.118*	0.09	-.324**
	Sig. (2-tailed)	0.79	0.94		0.98	0.69	0.02	0.00	0.00	0.04	0.15	0.00
	Sum of Squares and Cross-products	57.90	-2.72	457.95	-1.03	140.00	-90236.47	47275.49	44483.30	1349.19	1443.00	-173.93
	Covariance	0.20	-0.01	1.58	0.00	0.48	-311.16	163.02	153.39	4.65	4.98	-0.60
Workers	Pearson Correlation	.171**	0.00	0.00	1.00	0.00	0.05	-.336**	-.372**	.137*	0.07	0.10
	Sig. (2-tailed)	0.00	0.96	0.98		1.00	0.42	0.00	0.00	0.02	0.22	0.08
	Sum of Squares and Cross-products	1085.57	2.97	-1.03	1335.67	0.00	51743.41	-160309.52	-165036.83	2660.18	2067.13	93.16
	Covariance	3.74	0.01	0.00	4.61	0.00	178.43	-552.79	-569.09	9.17	7.13	0.32
Hours	Pearson Correlation	-0.02	0.02	0.02	0.00	1.00	-0.01	-0.01	-0.01	0.00	-0.02	0.03
	Sig. (2-tailed)	0.79	0.71	0.69	1.00		0.92	0.91	0.91	0.97	0.74	0.58
	Sum of Squares and Cross-products	-780.00	180.00	140.00	0.00	79200.00	-47927.56	-25751.21	-21693.02	296.06	-4354.25	231.83
	Covariance	-2.69	0.62	0.48	0.00	273.10	-165.27	-88.80	-74.80	1.02	-15.01	0.80
Solution Time	Pearson Correlation	.821**	-.138*	-.140*	0.05	-0.01	1.00	.535**	.489**	.773**	.791**	.520**
	Sig. (2-tailed)	0.00	0.02	0.02	0.42	0.92		0.00	0.00	0.00	0.00	0.00
	Sum of Squares and Cross-products	4299137.10	-121503.52	-90236.47	51743.41	-47927.56	905342856.91	209772994.74	178532579.30	12376600.95	18863814.49	392096.59
	Covariance	14824.61	-418.98	-311.16	178.43	-165.27	3121871.92	723355.15	615629.58	42677.93	65047.64	1352.06
Total Cost	Pearson Correlation	.608**	.321**	.169**	-.336**	-0.01	.535**	1.00	.997**	.674**	.744**	.190**
	Sig. (2-tailed)	0.00	0.00	0.00	0.00	0.91	0.00		0.00	0.00	0.00	0.00
	Sum of Squares and Cross-products	1379597.87	122413.67	47275.49	-160309.52	-25751.21	209772994.74	170104479.47	157734958.29	4681039.27	7688481.91	62246.98
	Covariance	4757.23	422.12	163.02	-552.79	-88.80	723355.15	586567.17	543913.65	16141.51	26512.01	214.64
Labor	Pearson Correlation	.547**	.332**	.171**	-.372**	-0.01	.489**	.997**	1.00	.617**	.692**	.149*
	Sig. (2-tailed)	0.00	0.00	0.00	0.00	0.91	0.00	0.00		0.00	0.00	0.01
	Sum of Squares and Cross-products	1155249.25	117933.48	44483.30	-165036.83	-21693.02	178532579.30	157734958.29	147103893.77	3984160.55	6646903.97	45319.91
	Covariance	3983.62	406.67	153.39	-569.09	-74.80	615629.58	543913.65	507254.81	13738.48	22920.36	156.28
Travel 1	Pearson Correlation	.978**	0.08	.118*	.137*	0.00	.773**	.674**	.617**	1.00	.981**	.524**
	Sig. (2-tailed)	0.00	0.18	0.04	0.02	0.97	0.00	0.00	0.00		0.00	0.00
	Sum of Squares and Cross-products	90591.91	1214.06	1349.19	2660.18	296.06	12376600.95	4681039.27	3984160.55	283277.89	413600.84	6995.82
	Covariance	312.39	4.19	4.65	9.17	1.02	42677.93	16141.51	13738.48	976.82	1426.21	24.12
Travel 2	Pearson Correlation	.970**	.141*	0.09	0.07	-0.02	.791**	.744**	.692**	.981**	1.00	.500**
	Sig. (2-tailed)	0.00	0.02	0.15	0.22	0.74	0.00	0.00	0.00	0.00		0.00
	Sum of Squares and Cross-products	133756.70	3266.13	1443.00	2067.13	-4354.25	18863814.49	7688481.91	6646903.97	413600.84	627977.09	9931.25
	Covariance	461.23	11.26	4.98	7.13	-15.01	65047.64	26512.01	22920.36	1426.21	2165.44	34.25
Gap	Pearson Correlation	.556**	-.151**	-.324**	0.10	0.03	.520**	.190**	.149*	.524**	.500**	1.00
	Sig. (2-tailed)	0.00	0.01	0.00	0.08	0.58	0.00	0.00	0.01	0.00	0.00	
	Sum of Squares and Cross-products	2428.09	-110.79	-173.93	93.16	231.83	392096.59	62246.98	45319.91	6995.82	9931.25	628.74
	Covariance	8.37	-0.38	-0.60	0.32	0.80	1352.06	214.64	156.28	24.12	34.25	2.17

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

c. Listwise N=291

Table 5.3 Correlations for Full Computational Experiment.

Descriptive Statistics for 108 instances with 13 Jobs, Single Assignment

	Mean	Std. Deviation	N
Jobs	13.00	.000	108
Classes	2.67	1.708	108
Levels	2.33	1.253	108
Workers	6.00	2.246	108
Hours	60.19	16.519	108
Solution Time	19.91	34.31	108
Total Cost	832.40	421.10	108
Labor	741.66	414.74	108
Travel 1	35.39	4.29	108
Travel 2	55.3530	8.02	108
Gap	0.00522%	0.004230%	108

Table 5.4 Descriptive Statistics of Output, 13 Job Set.

		Jobs	Classes	Levels	Workers	Hours	Solution Time	Total Cost	Labor	Travel 1	Travel 2	Gap
Jobs	Pearson Correlation	.[a]	.[a]	.[a]	.[a]	.[a]	.[a]	.[a]	.[a]	.[a]	.[a]	.[a]
	Sig. (2-tailed)											
	Sum of Squares and Cross-products	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Covariance	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Classes	Pearson Correlation	.[a]	1	.000	0.000	.015	-.272**	.298**	.294**	.101	.380**	-.484**
	Sig. (2-tailed)			1.000	1.000	.874	.004	.002	.002	.299	.000	.000
	Sum of Squares and Cross-products	0.000	312.000	.000	0.000	46.667	-1705.502	22944.233	22308.181	79.044	557.008	-.374
	Covariance	0.000	2.916	.000	0.000	.436	-15.939	214.432	208.488	.739	5.206	-.003
Levels	Pearson Correlation	.[a]	.000	1	.000	.015	-.549**	.101	.083	.782**	.605**	-.238*
	Sig. (2-tailed)		1.000		1.000	.877	.000	.296	.392	.000	.000	.013
	Sum of Squares and Cross-products	0.000	.000	168.000	.000	33.333	-2526.291	5729.689	4630.384	449.345	649.960	-.135
	Covariance	0.000	.000	1.570	.000	.312	-23.610	53.548	43.275	4.199	6.074	-.001
Workers	Pearson Correlation	.[a]	0.000	.000	1	.005	-.014	-.715**	-.717**	-.183	-.382**	-.266**
	Sig. (2-tailed)		1.000	1.000		.959	.883	.000	.000	.058	.000	.005
	Sum of Squares and Cross-products	0.000	0.000	.000	540.000	20.000	-118.436	-72376.006	-71451.557	-188.654	-735.796	-.270
	Covariance	0.000	0.000	.000	5.047	.187	-1.107	-676.411	-667.772	-1.763	-6.877	-.003
Hours	Pearson Correlation	.[a]	.015	.015	.005	1	.029	-.006	-.008	.081	.021	.026
	Sig. (2-tailed)		.874	.877	.959		.765	.949	.939	.407	.825	.788
	Sum of Squares and Cross-products	0.000	46.667	33.333	20.000	29196.296	1766.567	-4590.238	-5505.456	610.985	304.238	.195
	Covariance	0.000	.436	.312	.187	272.863	16.510	-42.899	-51.453	5.710	2.843	.002
Solution Time	Pearson Correlation	.[a]	-.272**	-.549**	-.014	.029	1	-.045	-.038	-.306**	-.255**	.618**
	Sig. (2-tailed)		.004	.000	.883	.765		.641	.696	.001	.008	.000
	Sum of Squares and Cross-products	0.000	-1705.502	-2526.291	-118.436	1766.567	125989.962	-70142.143	-57816.418	-4812.503	-7513.222	9.595
	Covariance	0.000	-15.939	-23.610	-1.107	16.510	1177.476	-655.534	-540.340	-44.977	-70.217	.090
Total Cost	Pearson Correlation	.[a]	.298**	.101	-.715**	-.006	-.045	1	1.000**	.326**	.633**	.227*
	Sig. (2-tailed)		.002	.296	.000	.949	.641		.000	.001	.000	.018
	Sum of Squares and Cross-products	0.000	22944.233	5729.689	-72376.006	-4590.238	-70142.143	18973682.490	18681882.920	62924.960	228874.610	43.315
	Covariance	0.000	214.432	53.548	-676.411	-42.899	-655.534	177324.135	174597.037	588.084	2139.015	.405
Labor	Pearson Correlation	.[a]	.294**	.083	-.717**	-.008	-.038	1.000**	1	.304**	.615**	.234*
	Sig. (2-tailed)		.002	.392	.000	.939	.696	.000		.001	.000	.015
	Sum of Squares and Cross-products	0.000	22308.181	4630.384	-71451.557	-5505.456	-57816.418	18681882.920	18405186.691	57829.856	218866.373	43.842
	Covariance	0.000	208.488	43.275	-667.772	-51.453	-540.340	174597.037	172011.091	540.466	2045.480	.410
Travel 1	Pearson Correlation	.[a]	.101	.782**	-.183	.081	-.306**	.326**	.304**	1	.850**	-.063
	Sig. (2-tailed)		.299	.000	.058	.407	.001	.001	.001		.000	.516
	Sum of Squares and Cross-products	0.000	79.044	449.345	-188.654	610.985	-4812.503	62924.960	57829.856	1967.099	3128.004	-.123
	Covariance	0.000	.739	4.199	-1.763	5.710	-44.977	588.084	540.466	18.384	29.234	-.001
Travel 2	Pearson Correlation	.[a]	.380**	.605**	-.382**	.021	-.255**	.633**	.615**	.850**	1	-.111
	Sig. (2-tailed)		.000	.000	.000	.825	.008	.000	.000	.000		.251
	Sum of Squares and Cross-products	0.000	557.008	649.960	-735.796	304.238	-7513.222	228874.610	218866.373	3128.004	6880.238	-.404
	Covariance	0.000	5.206	6.074	-6.877	2.843	-70.217	2139.015	2045.480	29.234	64.301	-.004
Gap	Pearson Correlation	.[a]	-.484**	-.238*	-.266**	.026	.618**	.227*	.234*	-.063	-.111	1
	Sig. (2-tailed)		.000	.013	.005	.788	.000	.018	.015	.516	.251	
	Sum of Squares and Cross-products	0.000	-.374	-.135	-.270	.195	9.595	43.315	43.842	-.123	-.404	.002
	Covariance	0.000	-.003	-.001	-.003	.002	.090	.405	.410	-.001	-.004	.000

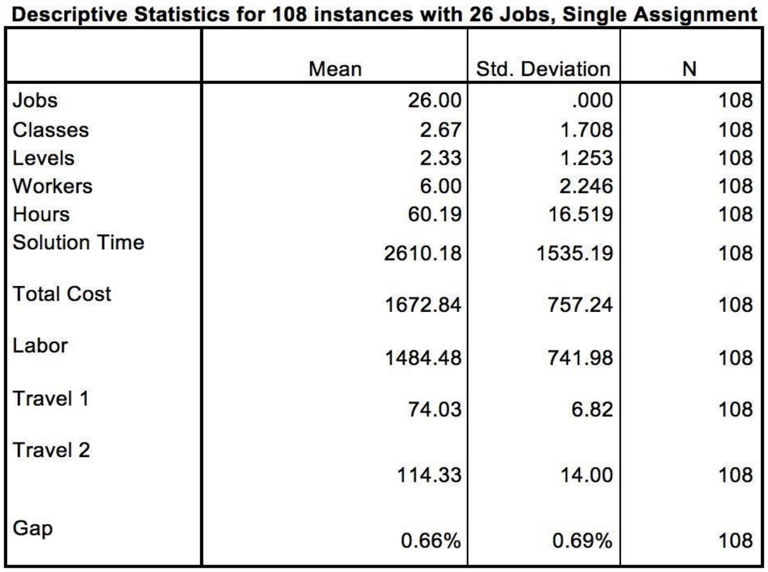
**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

a. Cannot be computed because at least one of the variables is constant.

d. Listwise N=108

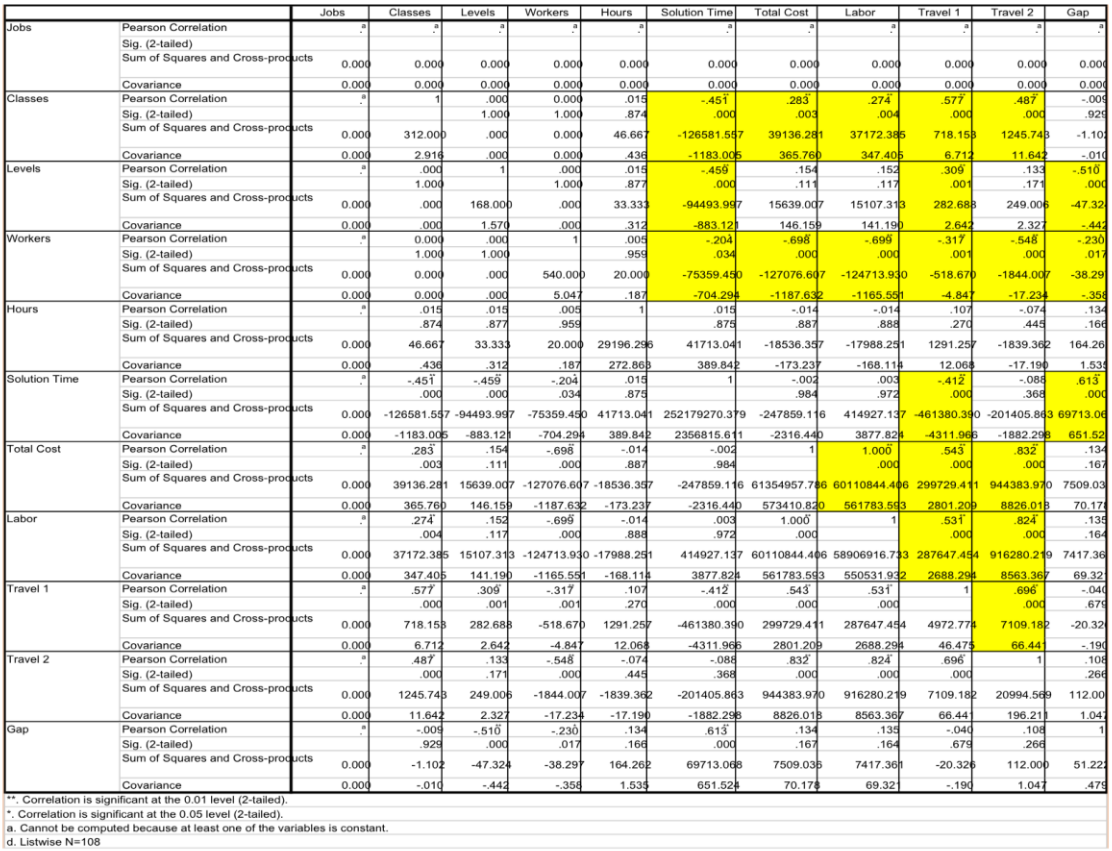
Table 5.5 Correlations for Output of 13 Job Computational Experiment.



Descriptive Statistics for 108 instances with 26 Jobs, Single Assignment

	Mean	Std. Deviation	N
Jobs	26.00	.000	108
Classes	2.67	1.708	108
Levels	2.33	1.253	108
Workers	6.00	2.246	108
Hours	60.19	16.519	108
Solution Time	2610.18	1535.19	108
Total Cost	1672.84	757.24	108
Labor	1484.48	741.98	108
Travel 1	74.03	6.82	108
Travel 2	114.33	14.00	108
Gap	0.66%	0.69%	108

Table 5.6 Descriptive Statistics of Output, 26 Job Set.



		Jobs	Classes	Levels	Workers	Hours	Solution Time	Total Cost	Labor	Travel 1	Travel 2	Gap
Jobs	Pearson Correlation	.[a]	.[a]	.[a]	.[a]	.[a]	.[a]	.[a]	.[a]	.[a]	.[a]	.[a]
	Sig. (2-tailed)											
	Sum of Squares and Cross-products	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.00
	Covariance	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.00
Classes	Pearson Correlation	.[a]	1	.000	0.000	.015	-.451[**]	.283[**]	.274[**]	.577[**]	.487[**]	-.009
	Sig. (2-tailed)			1.000	1.000	.874	.000	.003	.004	.000	.000	.929
	Sum of Squares and Cross-products	0.000	312.000	.000	0.000	46.667	-126581.557	39136.281	37172.385	718.153	1245.743	-1.10
	Covariance	0.000	2.916	.000	0.000	.436	-1183.005	365.760	347.405	6.712	11.642	-.010
Levels	Pearson Correlation	.[a]	.000	1	.000	.015	-.459[**]	.154	.152	.309[**]	.133	-.510[**]
	Sig. (2-tailed)		1.000		1.000	.877	.000	.111	.117	.001	.171	.000
	Sum of Squares and Cross-products	0.000	.000	168.000	.000	33.333	-94493.997	15639.007	15107.313	282.688	249.006	-47.32
	Covariance	0.000	.000	1.570	.000	.312	-883.121	146.159	141.190	2.642	2.327	-.442
Workers	Pearson Correlation	.[a]	0.000	.000	1	.005	-.204[*]	-.698[**]	-.699[**]	-.317[**]	-.548[**]	-.230[*]
	Sig. (2-tailed)		1.000	1.000		.959	.034	.000	.000	.001	.000	.017
	Sum of Squares and Cross-products	0.000	0.000	.000	540.000	20.000	-75359.450	-127076.607	-124713.930	-518.670	-1844.007	-38.29
	Covariance	0.000	0.000	.000	5.047	.187	-704.294	-1187.632	-1165.551	-4.847	-17.234	-.358
Hours	Pearson Correlation	.[a]	.015	.015	.005	1	.015	-.014	-.014	.107	-.074	.134
	Sig. (2-tailed)		.874	.877	.959		.875	.887	.888	.270	.445	.166
	Sum of Squares and Cross-products	0.000	46.667	33.333	20.000	29196.296	41713.041	-18536.357	-17988.251	1291.257	-1839.362	164.26
	Covariance	0.000	.436	.312	.187	272.863	389.842	-173.237	-168.114	12.068	-17.190	1.535
Solution Time	Pearson Correlation	.[a]	-.451[**]	-.459[**]	-.204[*]	.015	1	-.002	.003	-.412[**]	-.088	.613[**]
	Sig. (2-tailed)		.000	.000	.034	.875		.984	.972	.000	.368	.000
	Sum of Squares and Cross-products	0.000	-126581.557	-94493.997	-75359.450	41713.041	252179270.379	-247859.116	414927.137	-461380.390	-201405.863	69713.06
	Covariance	0.000	-1183.005	-883.121	-704.294	389.842	2356815.611	-2316.440	3877.824	-4311.966	-1882.298	651.52
Total Cost	Pearson Correlation	.[a]	.283[**]	.154	-.698[**]	-.014	-.002	1	1.000[**]	.543[**]	.832[**]	.134
	Sig. (2-tailed)		.003	.111	.000	.887	.984		.000	.000	.000	.167
	Sum of Squares and Cross-products	0.000	39136.281	15639.007	-127076.607	-18536.357	-247859.116	61354957.786	60110844.406	299729.411	944383.970	7509.03
	Covariance	0.000	365.760	146.159	-1187.632	-173.237	-2316.440	573410.820	561783.593	2801.209	8826.018	70.17
Labor	Pearson Correlation	.[a]	.274[**]	.152	-.699[**]	-.014	.003	1.000[**]	1	.531[**]	.824[**]	.135
	Sig. (2-tailed)		.004	.117	.000	.888	.972	.000		.000	.000	.164
	Sum of Squares and Cross-products	0.000	37172.385	15107.313	-124713.930	-17988.251	414927.137	60110844.406	58906916.733	287647.454	916280.219	7417.36
	Covariance	0.000	347.405	141.190	-1165.551	-168.114	3877.824	561783.593	550531.932	2688.294	8563.367	69.32
Travel 1	Pearson Correlation	.[a]	.577[**]	.309[**]	-.317[**]	.107	-.412[**]	.543[**]	.531[**]	1	.696[**]	-.040
	Sig. (2-tailed)		.000	.001	.001	.270	.000	.000	.000		.000	.679
	Sum of Squares and Cross-products	0.000	718.153	282.688	-518.670	1291.257	-461380.390	299729.411	287647.454	4972.774	7109.182	-20.32
	Covariance	0.000	6.712	2.642	-4.847	12.068	-4311.966	2801.209	2688.294	46.475	66.441	-.190
Travel 2	Pearson Correlation	.[a]	.487[**]	.133	-.548[**]	-.074	-.088	.832[**]	.824[**]	.696[**]	1	.108
	Sig. (2-tailed)		.000	.171	.000	.445	.368	.000	.000	.000		.266
	Sum of Squares and Cross-products	0.000	1245.743	249.006	-1844.007	-1839.362	-201405.863	944383.970	916280.219	7109.182	20994.569	112.00
	Covariance	0.000	11.642	2.327	-17.234	-17.190	-1882.298	8826.018	8563.367	66.441	196.211	1.047
Gap	Pearson Correlation	.[a]	-.009	-.510[**]	-.230[*]	.134	.613[**]	.134	.135	-.040	.108	1
	Sig. (2-tailed)		.929	.000	.017	.166	.000	.167	.164	.679	.266	
	Sum of Squares and Cross-products	0.000	-1.102	-47.324	-38.297	164.262	69713.068	7509.036	7417.361	-20.326	112.000	51.22
	Covariance	0.000	-.010	-.442	-.358	1.535	651.524	70.178	69.321	-.190	1.047	.479

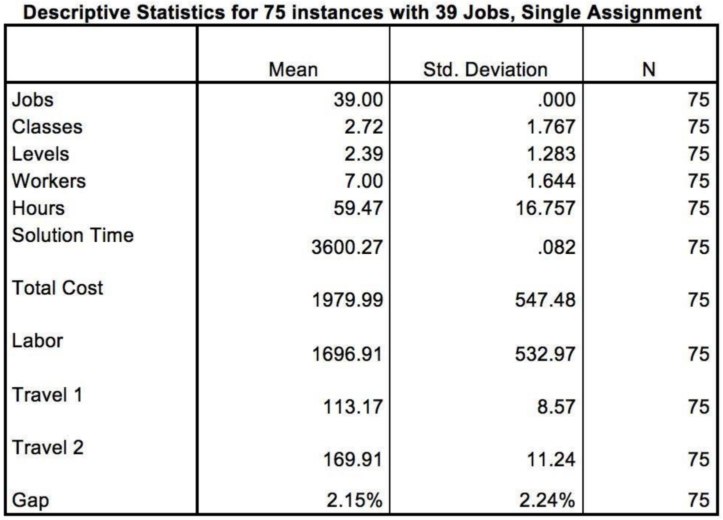
**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

a. Cannot be computed because at least one of the variables is constant.

d. Listwise N=108

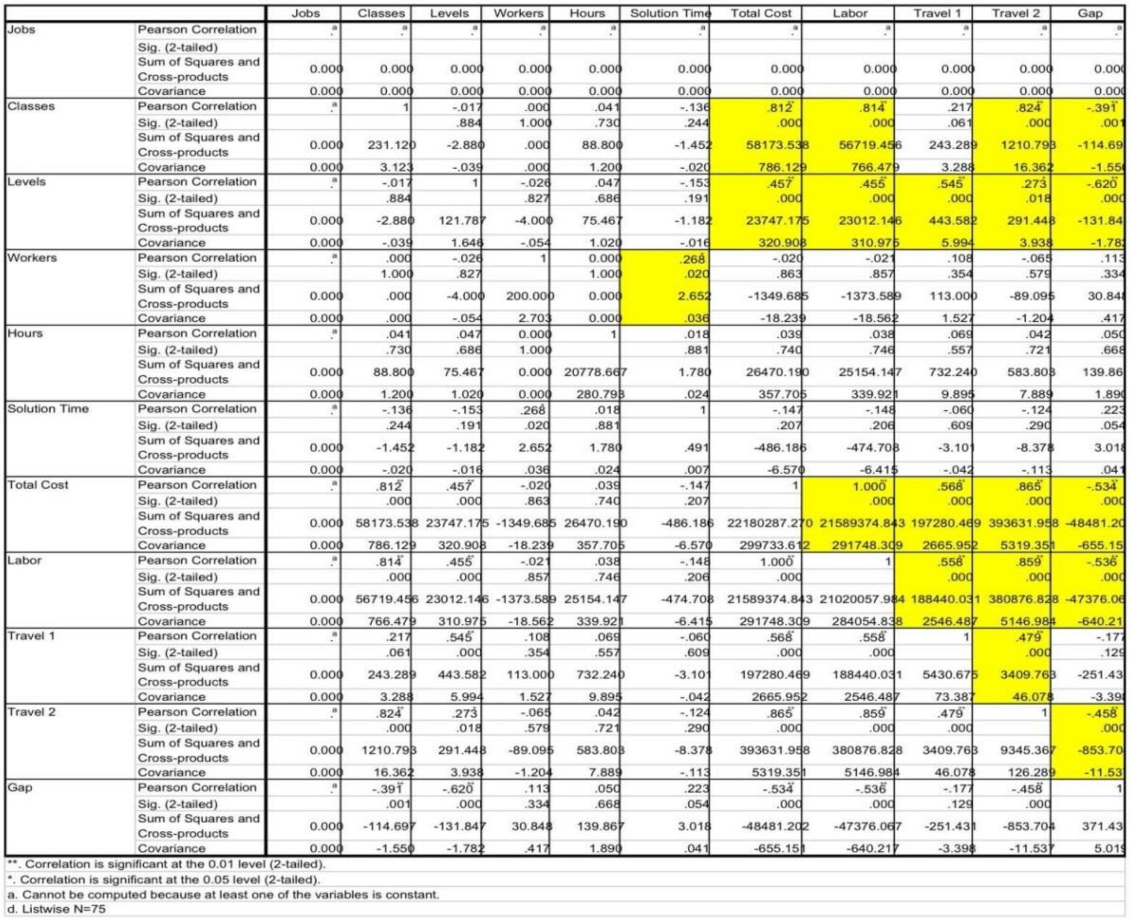
Table 5.7 Correlations for Output of 1396 Job Computational Experiment



Descriptive Statistics for 75 instances with 39 Jobs, Single Assignment

	Mean	Std. Deviation	N
Jobs	39.00	.000	75
Classes	2.72	1.767	75
Levels	2.39	1.283	75
Workers	7.00	1.644	75
Hours	59.47	16.757	75
Solution Time	3600.27	.082	75
Total Cost	1979.99	547.48	75
Labor	1696.91	532.97	75
Travel 1	113.17	8.57	75
Travel 2	169.91	11.24	75
Gap	2.15%	2.24%	75

Table 5.8 Descriptive Statistics of Output, 39 Job Set.



		Jobs	Classes	Levels	Workers	Hours	Solution Time	Total Cost	Labor	Travel 1	Travel 2	Gap
Jobs	Pearson Correlation	.a	.a	.a	.a	.a	.a	.a	.a	.a	.a	.a
	Sig. (2-tailed)											
	Sum of Squares and Cross-products	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.00
	Covariance	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.00
Classes	Pearson Correlation	.a	1	-.017	.000	.041	-.136	.812**	.814**	.217	.824**	-.391**
	Sig. (2-tailed)			.884	1.000	.730	.244	.000	.000	.061	.000	.001
	Sum of Squares and Cross-products	0.000	231.120	-2.880	.000	88.800	-1.452	58173.538	56719.456	243.289	1210.793	-114.69
	Covariance	0.000	3.123	-.039	.000	1.200	-.020	786.129	766.479	3.288	16.362	-1.55
Levels	Pearson Correlation	.a	-.017	1	-.026	.047	-.153	.457**	.455**	.545**	.273*	-.620**
	Sig. (2-tailed)		.884		.827	.686	.191	.000	.000	.000	.018	.00
	Sum of Squares and Cross-products	0.000	-2.880	121.787	-4.000	75.467	-1.182	23747.175	23012.146	443.582	291.448	-131.84
	Covariance	0.000	-.039	1.646	-.054	1.020	-.016	320.908	310.975	5.994	3.938	-1.78
Workers	Pearson Correlation	.a	.000	-.026	1	0.000	.268*	-.020	-.021	.108	-.065	.113
	Sig. (2-tailed)		1.000	.827		1.000	.020	.863	.857	.354	.579	.334
	Sum of Squares and Cross-products	0.000	.000	-4.000	200.000	0.000	2.652	-1349.685	-1373.589	113.000	-89.095	30.84
	Covariance	0.000	.000	-.054	2.703	0.000	.036	-18.239	-18.562	1.527	-1.204	.417
Hours	Pearson Correlation	.a	.041	.047	0.000	1	.018	.039	.038	.069	.042	.050
	Sig. (2-tailed)		.730	.686	1.000		.881	.740	.746	.557	.721	.668
	Sum of Squares and Cross-products	0.000	88.800	75.467	0.000	20778.667	1.780	26470.190	25154.147	732.240	583.808	139.86
	Covariance	0.000	1.200	1.020	0.000	280.798	.024	357.705	339.921	9.895	7.889	1.89
Solution Time	Pearson Correlation	.a	-.136	-.153	.268*	.018	1	-.147	-.148	-.060	-.124	.223
	Sig. (2-tailed)		.244	.191	.020	.881		.207	.206	.609	.290	.054
	Sum of Squares and Cross-products	0.000	-1.452	-1.182	2.652	1.780	.491	-486.186	-474.708	-3.101	-8.378	3.01
	Covariance	0.000	-.020	-.016	.036	.024	.007	-6.570	-6.415	-.042	-.113	.041
Total Cost	Pearson Correlation	.a	.812**	.457**	-.020	.039	-.147	1	1.000**	.568**	.865**	-.534**
	Sig. (2-tailed)		.000	.000	.863	.740	.207		.000	.000	.000	.00
	Sum of Squares and Cross-products	0.000	58173.538	23747.175	-1349.685	26470.190	-486.186	22180287.270	21589374.843	197280.469	393631.958	-48481.20
	Covariance	0.000	786.129	320.908	-18.239	357.705	-6.570	299733.612	291748.309	2665.952	5319.351	-655.15
Labor	Pearson Correlation	.a	.814**	.455**	-.021	.038	-.148	1.000**	1	.558**	.859**	-.536**
	Sig. (2-tailed)		.000	.000	.857	.746	.206	.000		.000	.000	.00
	Sum of Squares and Cross-products	0.000	56719.456	23012.146	-1373.589	25154.147	-474.708	21589374.843	21020057.984	188440.031	380876.828	-47376.06
	Covariance	0.000	766.479	310.975	-18.562	339.921	-6.415	291748.309	284054.838	2546.487	5146.984	-640.21
Travel 1	Pearson Correlation	.a	.217	.545**	.108	.069	-.060	.568**	.558**	1	.479**	-.177
	Sig. (2-tailed)		.061	.000	.354	.557	.609	.000	.000		.000	.129
	Sum of Squares and Cross-products	0.000	243.289	443.582	113.000	732.240	-3.101	197280.469	188440.031	5430.675	3409.763	-251.43
	Covariance	0.000	3.288	5.994	1.527	9.895	-.042	2665.952	2546.487	73.387	46.078	-3.39
Travel 2	Pearson Correlation	.a	.824**	.273*	-.065	.042	-.124	.865**	.859**	.479**	1	-.458**
	Sig. (2-tailed)		.000	.018	.579	.721	.290	.000	.000	.000		.00
	Sum of Squares and Cross-products	0.000	1210.793	291.448	-89.095	583.808	-8.378	393631.958	380876.828	3409.763	9345.367	-853.70
	Covariance	0.000	16.362	3.938	-1.204	7.889	-.113	5319.351	5146.984	46.078	126.289	-11.53
Gap	Pearson Correlation	.a	-.391**	-.620**	.113	.050	.223	-.534**	-.536**	-.177	-.458**	1
	Sig. (2-tailed)		.001	.000	.334	.668	.054	.000	.000	.129	.000	
	Sum of Squares and Cross-products	0.000	-114.697	-131.847	30.848	139.867	3.018	-48481.202	-47376.067	-251.431	-853.704	371.43
	Covariance	0.000	-1.550	-1.782	.417	1.890	.041	-655.151	-640.217	-3.398	-11.537	5.01

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

a. Cannot be computed because at least one of the variables is constant.

d. Listwise N=75

Table 5.9 Correlations for Output of 39 Job Computational Experiment

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