EXPLORING INFORMATION GENERATION AND PROPAGATION FROM THE POINT OF INSTALLATION ON CONSTRUCTION JOBSITES: AN SNA/ABM HYBRID APPROACH

By

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ABSTRACT

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Construction requires the knowledge and experience of craftsmen. The knowledge and experience is gained through local coordination and local adaption at points of installation, which classifies the work as complex production. Information generated at these points of installation can be valuable in understanding how and why workers make decisions, especially at points of improvisation when they encounter obstacles. However, this information often goes unrecognized at least in explicit form by the workers themselves, and is therefore not documented and not captured.

The author's experience and observations on construction jobsites, combined with literature review, show that the information generated from the point of installation has not been extensively studied or modeled in construction. However, other industries characterized as complex production have seen improvements by studying and modeling the information generated and propagated from the point where the knowledge and experience of skilled craftsmen do their work. The research postulate studied herein is that if this information is modeled and understood, the impact it has on jobsites would be known and work performance could improve.

The literature shows that observation-based studies of information generation at the worker and crew level have only recently been conducted, and not from the standpoint of information propagation. In addition, the literature led to identification of agent based modeling (ABM) and social network analysis (SNA) as sound approaches for modeling the information generation and propagation from the point of installation. The research method included developing a conceptual information model, evaluating and improving the model based on pilot jobsite observations; data collection and observations used to develop a representative model of the information generation and propagation from points of installation. A unique approach of an SNA-informed ABM was used to simulate the final model, and test the result with select jobsite scenarios.

The data collected showed that information is indeed generated and often not captured or reported from the point of installation. Workers encounter obstacles in 89% of their scheduled activities, and information about those obstacles only propagates beyond the crew level 50% of the time. The simulated SNA-informed ABM based on the data collection and conceptual model showed that there are differences in how workers handle obstacles in early vs. later stages of the jobsite, and also on large vs. small jobsites. Workers are more influenced by others in the early stages of a job and on jobsites with fewer workers.

In conclusion, by studying the information generation and propagation from the point of installation with empirical data collection, observations, and conceptual model building, a simulation showed how this information could impact work performance. In addition, explorations of the simulated model showed how the information available from the point of installation propagates and influences jobsite outcomes.

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Following on the foundation is the supporting structure, in my case this is represented by those who have taught me so much in my career and studies, not to mention supported the research herein, including Mike Holmes, Skip Perley, Kevin Lytle, Kim Mazuk, Ed Hillman, Tim Culliton and Ted Lange, Scott Harding and Richard Brooks. These are the real faces of the construction industry and I can only hope to have done justice with a work that gives back to the knowledge they have imparted me. There are also those who have helped me navigate the academic journey, including Dr. Robert Chapman, Dr. Harold Marshall, Dr. Paul Goodrum, and Muthiah Kasi.

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Chapter 1: Introduction

1.1. Problem Overview

In any work activity on a construction jobsite, there is information that is generated at the point of installation when the crew members carry out the activity, typically the outcome of on the spot improvisation. The information encapsulates what the installers did and why, what obstacles or unforeseen circumstances they encountered while trying to work, what instantaneous decisions were made to account for the unknowns in the situation, and the outcomes and impacts of those decisions. This information is not always passed on or reported outside of the installation crew, because the installers do not have a requirement or explicit advantage to pass on information. However, if the information is not reported or captured in some way, those in-the-moment learning scenarios are hidden and the information is lost to anyone other than the individual installers. Installers may or may not have the correct and appropriate information they need for installing; but regardless of what information they have and do not have, the information generated from their actions and decisions is what becomes lost. For this study, information "loss" occurs when the information generated does not propagate beyond the installation crew. The information about what they do, how they do it, why they do it, and the reasoning and outcome of decisions made, stays within the memories or experience of the installers, but these memories can never be collectively harvested to solve the problems that are either recurring or beyond the control of the installers themselves. For example, if the installer receives an incorrect drawing, he or she may install correctly and have to come back and do rework later. Even if the installer has the correct information needed for the installation, obstacles that instantaneously prevent him or her from completing the work may go unreported and therefore cannot be removed in that instant or in future similar scenarios.

From observations made while working with specialty trade contractors on several hundred jobsites, at the level of individual installation activities, the author has observed decision-making and information generated during installation that goes undocumented and becomes lost to anyone beyond the installation crew. Based on experience and the literature reviewed herein from construction and other industries, if this information and decision-making were captured, modeled and studied, the results could be used for developing real-time problem solving schemas and long-term process improvement initiatives.

To draw a parallel with other industries involving skilled-trade operators, which will be discussed in depth in Chapter 2, the *airline industry* could not develop an air-traffic control network until it could understand and model *how pilots fly*. In the *manufacturing industry*, assembly lines and automation could not be introduced until Frederick Taylor and then Henry Ford studied *how the skilled trade mechanics worked* (Taylor, 1911 and Ford, 1922). The same is true in construction. If there is a model for the skilled operator's work, and specifically the intangibles such as decision-making and improvisation, then new system-wide improvements could be made that will expand capacity to build and reduce the cost to build, just as the other skilled-trade-based industries have.

Other industries have studied this problem from several vantage points, using quantitative and qualitative models and finding that information loss from the point of installation does indeed impact the outcome of an operation. Specifically, the research in other industries that rely on technicians with a specialized professional skill or trade such as doctors, teachers, pilots, fishermen to name a few, has focused on modeling the information and situation at the point where the work takes place. In complex production where workers have to learn and adapt locally within their work environment, the information generated and exchanged in the midst of their work is rich with clues into how and why they make decisions or respond to unknowns. Without being in the middle of this information exchange as it occurs, it is impossible to know that it is happening. Without knowing that it happens, the obstacles to in the work environment are unknown, and the environment can never be completely studied and optimized for improvement.

Based on the literature available to date, modeling the information and decisions made at the point of installation does not exist in construction. Several studies have attempted to understand, quantify, and improve construction productivity, rework, and overall job performance for decades (see **Appendix A** for summary of studies). However, none have modeled the complexity of information on the jobsite from the installer's point of view. To capture the complexity, this study relied on observations and empirical data collection from jobsite installation activities. A model of information generation at the point of installation in construction was developed in this research as a first step toward understanding the degree of complexity involved with the information loss from the point of installation on construction jobsites, including whether or not the information passes beyond the point of installation, how the information passes on, and the impact of that propagation on future behavior and decisions. Modeling approaches were studied to determine what best fits the conceptual model developed in the research. Methods such as social network analysis and agent based modeling have been used elsewhere to model scenarios with a high degree of complexity and will be used to model the problem at hand.

The National Research Council formed the Committee on Advancing the Competitiveness and Productivity of the U.S. Construction Industry in 2009. According to the committee's research and published findings, one of the five key opportunities for improving the industry is through "more effective interfacing of people, processes, materials, equipment, and information." (NRC, 2009). Any additional understanding of information loss from the point of installation and its impact could help reduce the cost of construction, which would have a positive outcome on society as a whole if buildings and infrastructure could become more affordable.

Recent developments in construction modeling and simulation also acknowledge a missing element of "process" modeling, and are seeking input for modeling methods that go beyond the tangible or "product" model of the building (such as the case with building information modeling), and include intangible or "process" modeling (Daneshgari & Moore, 2012).

1.2. Problem Significance

Modeling information at the workface of construction jobsites will provide insight into the jobsite that does not currently exist. Without such a model, the situations on jobsites at the installation level escalate or reoccur, potentially causing unnecessary work and rework, additional project duration and cost. For instance, if one installation activity on one jobsite leads to a conflict between two trades and the workers representing those trades resolve the conflict (taking time to do so) and move on, there is no visibility of what happened, why it happened, and how it was corrected. The conflict, therefore, is likely to reoccur. The loss of information about the specific situation in which it was resolved hinders the overall jobsite and becomes an unknown to supervisors and the contractors for whom the installers work. At an even higher level, the industry as a whole lacks an understanding of common or special causes of jobsite performance measures because the real-time information is not captured or modeled.

The significance of the information loss from the point of installation will extend into several facets, including safety, productivity, sustainability, work performance, overall project outcomes, workforce development, to name a few. The impact of information loss from the point of installation on these factors will be known until the information is understood and modeled comprehensively.

Figure 1 shows a concept of how the problem of disruption to one scheduled activity on one project can accumulate to significant productivity loss and increased cost of construction for the industry. The disruption itself is problematic; however, the problem studied herein is the lack of information about the disruption. There is no model for the information associated with this disruption, both before and after, such as what caused the disruption, how the disruption was handled, and whether it was resolved or not. Without such an understanding, it is likely that the disruption will continue on the same day and on future days in the project, and on projects everywhere everyday to a larger degree.

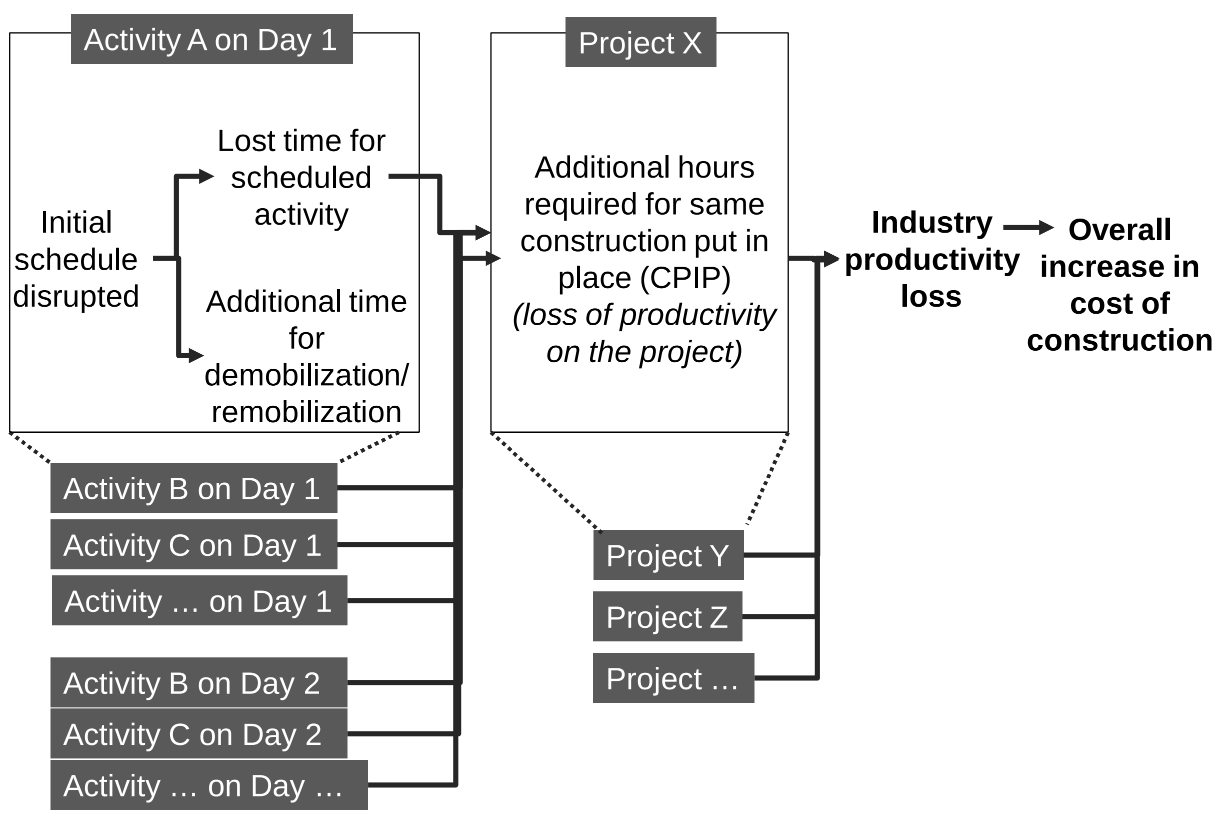


Figure 1: Potential impact of information loss from point of installation

The construction industry represents 5% of the United States GDP, $855 billion in construction spending for 2012 (United States Census Bureau: Manufacturing and Construction Division, 2012). In 2012, there were 4.2 million production and non-supervisory employees in construction (field labor), working an average of 39 hours per week, aggregating to 8.27 billion hours to produce $855 billion of construction put in place. This equates to approximately $103 construction-put-in-place (CPIP) for every labor hour expended. Data collected from thousands of work activities on different construction jobsites across the US shows that 7% of the scheduled work activities are not performed as scheduled (Daneshgari, 2009). If at least 7% of scheduled time on the jobsite is lost due to unscheduled tasks, 579 million total hours are lost. At an average hourly wage rate in construction of $25.75, the 579 million hours that could have contributed to CPIP now translate to a minimum $14 billion of cost in just raw wages in the building process that is unnecessarily burdening the industry (U.S. Bureau of Labor Statistics, 2010).

1.3. Problem Definition

When a construction worker arrives to the construction site to begin working, they have some notion of what they or their crew can complete in that day. The workers run into some unforeseen circumstance such as bad weather, manpower not being available, change of direction from supervision or customers, congestion or interference in the work area, or any of several other reasons like these. When any one of these obstacles occur, the worker or supervisor may have a backup plan and makes a shift to work on this secondary plan. These disruptions go unrecognized by the worker, or even if recognized are not reported, and are treated as typical and acceptable or "part of the work". However, these seemingly small disruptions accumulate to several hours of demobilization and remobilization to gear up for the secondary plan. Furthermore, the "initially scheduled" time for activities each day is lost on the jobsite, because those activities will now have to be rescheduled for another day, which is already spoken for with other scheduled activities and may be less opportune for the re-scheduled initial activities.

This scenario happens every day on every jobsite, and the information about what caused the obstacles and how they were handled is not well understood, let alone documented. When the workers improvise, the causes and results of the decisions made need to be modeled, using information as the dimension for capturing the decisions and their outcomes. **The accumulation and complex "net" of these decisions and information that may or may not get passed on within the possible channels available needs to be modeled and understood. Such an understanding and accompanying model will help to have insights into the day-to-day and minute-to-minute actions and impacts to installation on construction jobsites.**

Figure 2 shows a sample view of the internal hierarchy of different installation-performing contractors on a construction jobsite. This model is helpful to understand the reporting structure within various parties involved on the project, but does not represent the true information flow within the jobsite.

The work, decision making, and information propagation happen between the white space in **Figure 2**.

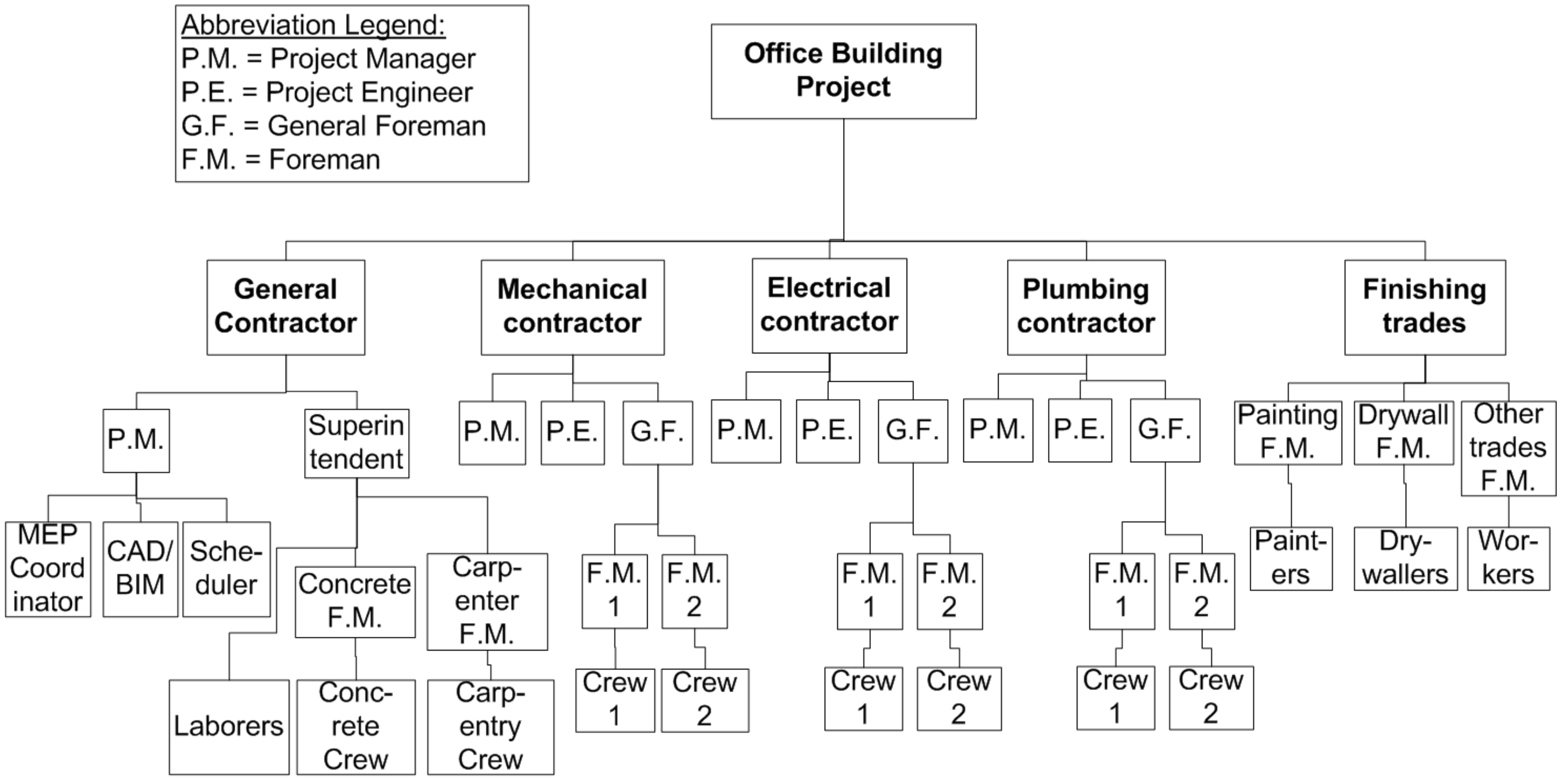


Figure 2: Sample of typical construction jobsite roles amongst trades performing work

Figure 3 shows a hypothetical model of the information flow, which occurs in the white space of **Figure 2**, between and within the trades. The model shows each trade, and key members of that trade involved at the jobsite. Using the electrical contractor crew as an example, the dotted lines indicate the connections the crew members make outside of their trade to send or receive information. The bold solid lines indicate all crew-to-crew interactions on the job. The non-bold solid lines represent additional interactions. This hypothetical model is scaled much larger on an actual jobsite to include several people representing each of the nodes shown, in addition to other roles involved on the project such as the owner, architect, engineer, contractor internal operations, authorities having jurisdiction, and more. The figure indicates that there is significant informal information propagating throughout the jobsite and within each crew. The information that passes comes from decisions, directives, knowledge of individuals, and many other sources that are tacit. Modeling the jobsite situations at the point of installation where the crew is working will make the information generated in those situations explicit so that it can be understood. In particular, situations in which the crew encounters obstacles or decision points, the information becomes more explicit and is easier to observe and document.

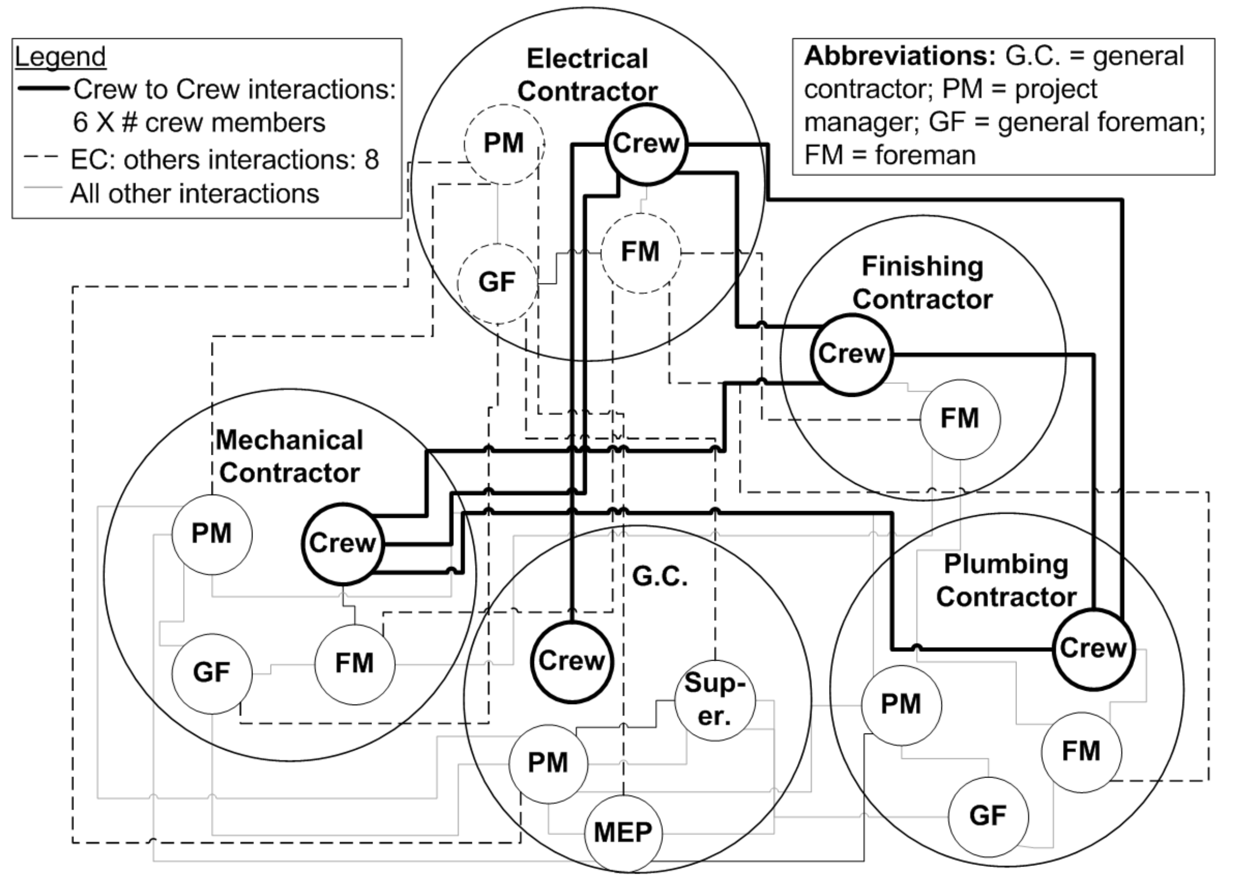


Figure 3: Hypothetical model of informal information flow on construction jobsites

In **Figure 3**, if each person involved with the project is considered as a "node" and the lines connecting them are the potential paths of information propagation, there are 153 possible channels over which information could be exchanged. This is determined by taking n as the number of nodes, which is 18 in **Figure 3**, and summing the links between them. **Equation 1** shows this calculation as the number of potential channels available in the network comprised of n nodes.

$$\frac{n(n-1)}{2} \tag{1}$$

In fact, there are potentially 18! (factorial) possible flows (6,402 trillion) of information within the network in **Figure 3** at any given time, since any node could be connecting to any other node to pass information. In other words, **Equation 1** only describes the number of links between nodes, whereas the true factorial equation describes the potential of each link sending or receiving information from every other link in the network. **Figure 3** was used as the basis for the empirical data collection in this research, with focus on information generated at the point of installation on jobsites, particularly when work was disrupted.

Based on the literature review, which is covered in detail in Chapter 2, other industries and organizations have improved performance by understanding information propagation where work is performed, especially in complex production environments such as construction. <u>The research **postulate** is that understanding information loss from the point of installation on a construction jobsite, will result in insight into how work performance can be improved.</u> The information generated at the point of installation on jobsites will be gathered through data collection and observation, then modeled to explore this postulation. Specifically, the information generated when workers face an obstacle and improvise will be studied and modeled, including how they handle the obstacle, what factors influence that handling method, and then whether the information is passed on beyond the installing crew.

1.4. Goals and Objectives

Based on the problem and postulation above, the goal of this research is to understand information loss at the point of installation on construction jobsites.

The objectives to approach the stated goal are:

- Summarize existing means and methods for modeling information generated at the point of installation
- Develop a theoretical conceptual model for information generation from the point of installation on construction jobsites
- Develop a final conceptual model through empirical jobsite observations and data collection to be used in a computer-based simulation
- Perform a simulation of the conceptual model, and conduct experiments on the model results to evaluate its ability to represent the conceptual model.
- Conduct simulation-based experiments to identify potential issues with information generation and loss and how they impact work performance

Figure 4 shows how the scope of this research was defined. The goal of this research is in the left-most box which is to understand information generation at the point of installation on construction jobsites by modeling it. The scope of this research was to develop the information model by studying skilled trades' activities on construction jobsites empirically through observations and data collection. The rest of the paths through the shaded boxes in the figure conceptualize potential impacts and further research that could extend from this work. The figure also shows on the left-most end the existing methods of studying information about jobsite activities (explained in detail in Chapter 2) through surveys or production measurements. However, none of these incorporate the instantaneous and hidden information that is generated or passed on at the point of installation and only within the crew level on a jobsite.

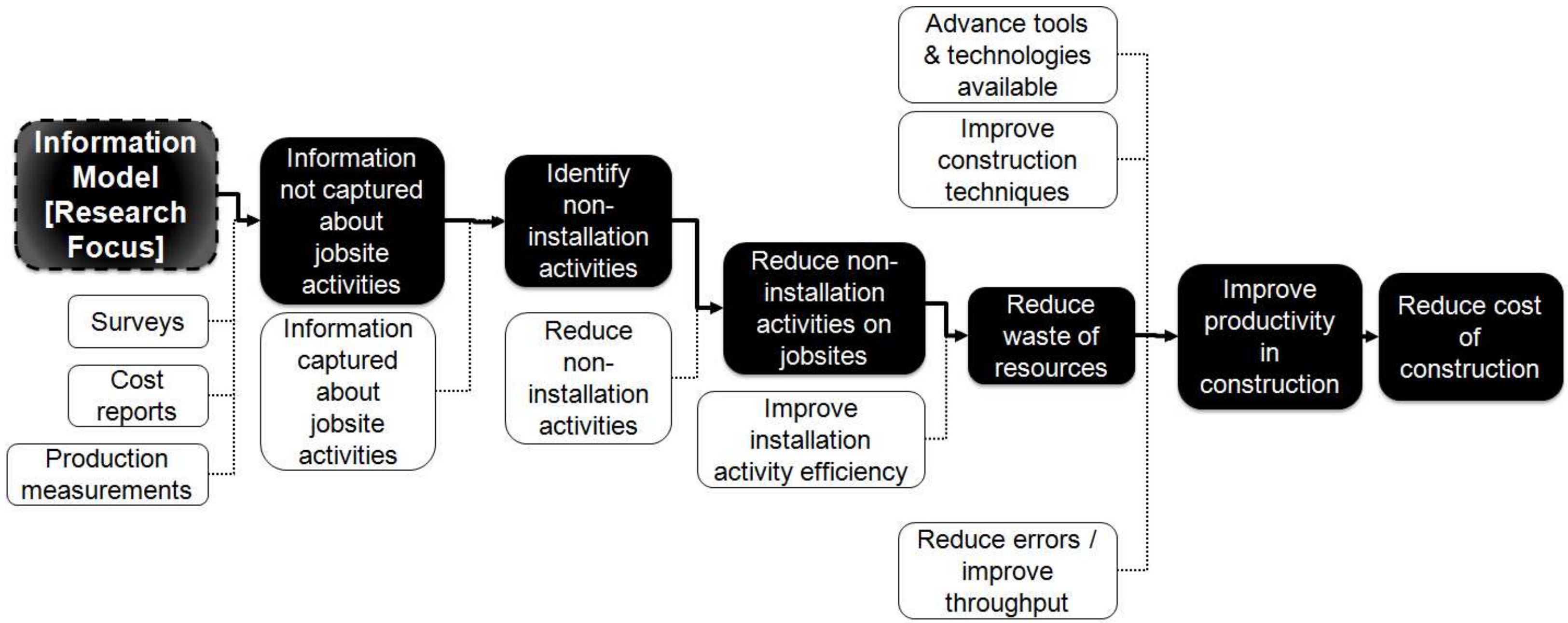


Figure 4: Research scope and potential impacts

An outline of the thesis is below, explaining what is included in each chapter.

Chapter 2: Background

This chapter includes a literature review and synthesis of topics including state-of-the-art for measuring crew-level actions and improvisation when faced with obstacles, existing systems available for mitigating disruptions to installation, studies on information on construction jobsites, perspective from other industries facing the same problem of information generation and loss at the point of production, and models and methods available for modeling information. In addition to a review of the state-of-the-art, the chapter summarizes the topics, and identified gaps addressed by this research.

Chapter 3: Research Methods

This chapter includes a review of the questions addressed and approach taken in this research. Four research questions were asked to guide the process, and research methods and work plan were developed to achieve the objectives. A map is included to show how the research goal was undertaken with five measurable objectives.

Chapter 4: Research Results and Findings: Model of Information Generation at the Point of Installation

Chapter 4 includes the results of the information generation model, developed based on empirical data collection and jobsite observations. The chapter explains the data collection process, and the findings with several examples demonstrating the information is indeed available and not passed on from the crew and workers. The chapter also includes quantitative and qualitative analysis of the data collected.

Chapter 5: Research Results and Findings: Computer-Based Simulation of Information Generation Model

Following the development of the information generation model in Chapter 4, research was conducted to determine the best approach for modeling that would appropriately simulate the complexity and individual installer interactions and behaviors found in Chapter 4. Social network analysis (SNA) and agent based modeling (ABM) were both found appropriate, and an integrated approach between the two was developed and tested with a simulation of the model.

Chapter 6: Conclusion

The final chapter concludes the study with a reflection on the research and findings. The final model of information generation is recommended, based on results of Chapter 4 and 5; specific scenarios to be modeled and future research questions are generated based on the model developed in this research. A review of how the objectives of the research were met, and listing of limitations is also included.

Chapter 2: Background

There are several facets of information at the crew level that were investigated for this research. The literature review spans topics of construction jobsite studies of factors impacting productivity, albeit this research is not directly focused on productivity, as the best source for studies that focused on installation or crew-level interactions; physics and measurement of flow; human factors; information systems; crew decision making and interactions; and lessons learned about this problem in other industries. The questions below were addressed by this review:

1. What has been measured so far related to crew-level actions when facing obstacles, and the information generated and propagating to and from those actions?

2. What has been done to mitigate disruptions to the process of installation?

3. What has been studied about information on construction jobsites?

4. What have other industries measured related to information generated and propagating from the point of installation?

5. What models and methods exist to model and measure information generation at the point of installation, and its propagation beyond the point of installation?

2.1 What has been measured so far related to crew-level actions when facing obstacles, and the information generating and propagating to and from those actions?

This question was explored in the literature to determine if any of the existing means of measurement include information generation or propagation on jobsites at the crew level. A detailed review of the literature on crew-level studies in construction revealed that many of these studies focus on defining, quantifying, and measuring production and impacts to efficiency. Some studies have correlated productivity with information flow on construction jobsites; however, this connection has not been modeled and investigated particularly at the crew or individual installer level.

In terms of measuring and defining productivity, several studies explain how this has been done in construction. Noor (1998) identified at least six major methods of measuring productivity in construction (see **Appendix A**), and Thomas and Yiakoumis (1982) identified 24 reports published since the 1940’s under the topic of construction productivity. Huang et al. (2009) performed a comprehensive study of productivity measurement methods, recognizing that the industry lacks a common method that can be used to measure productivity at the task, project, and industry level.

Some studies found that methods for measuring productivity are at a micro-level that does not focus on the overall construction project inputs and outputs (Park et al. 2005). Other studies contend that more data is needed to better understand what impacts productivity, not just measure at the end of the project (Allmon et al. 2000). In addition, several researchers have identified a need to gather data from the craft worker's point of view to understand these impacts (Dai et al. 2009), (Choy & Ruwanpura, 2006). This is similar to the identified need for the research at hand.

In studying the means to measure jobsite productivity and impacts to it, the literature can be categorized into two general methods for measuring productivity:

- Economic-based
- Industrial Engineering (IE)-based.

Economic productivity measurement compares inputs used to outputs produced. Various sources of input and output data include R.S. Means, Construction Industry Institute (CII), and the Bureau of Labor Statistics (BLS) (Allmon et al. 2000). However, the sources are fragmented and must be adjusted for various reasons, such as proprietary data and inflated values. Oglesby et al. (1989) published that "productivity….is measured primarily in terms of cost….good productivity is work accomplished at a fair price to the owner and at a reasonable cost to the contractor" (p.4). They suggested work sampling, questions, and interviews as a means of measurement, but still defined the outcome economically in terms of cost. Economic output measurements will not capture the complexity of human reasoning and behavior based on interactions in a complex production environment.

Park et al. (2005) took a different approach to economic input/output measurement, using industry input to define direct and indirect accounts of construction activities. Indirect activities such as cleanup, demolition, and testing were not included as inputs to the economic productivity calculation. Although this method attempts to capture labor activity in the measurement, it is not real-time, and relies on input from construction professionals rather than field labor.

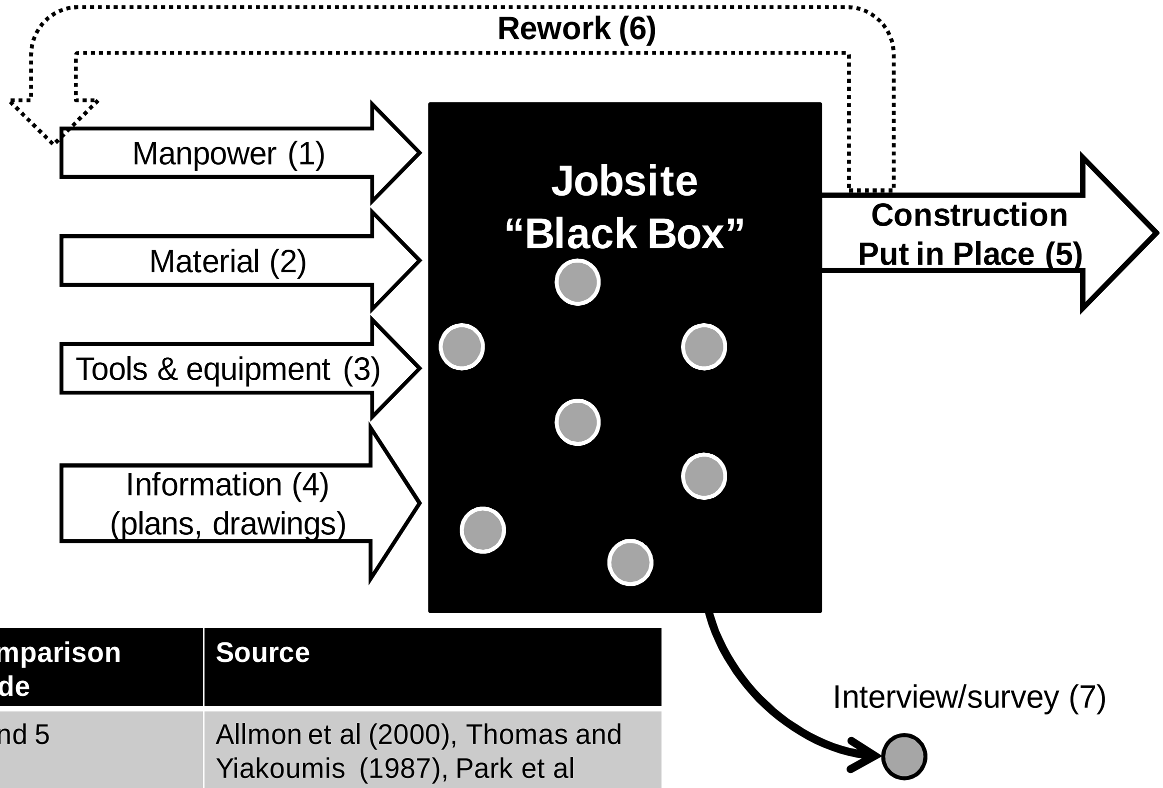
The second general method for measuring productivity is IE-based. IE measurements such as time and motion studies focus on observing, measuring, and improving workers' environments. Early IE pioneers claimed that where time and motion study was applied, worker output doubled (Gilbreth & Gilbreth, 1916). IE-based methods in the literature include work sampling, and labor impact studies. James Adrian (1976) first identified the need for direct observation and sampling from construction jobsites to measure productivity. Thomas and Yiakoumis (1987) introduced a "factor model" for measuring construction productivity, which was a first attempt to compare the completion of construction to the effort expended, whereas previous methods only used quantities installed or hours worked to denote completion. Allmon et al. (2000) studied 72 projects in Austin, Texas over a period of 25 years using work sampling, categorizing activities into direct work, supportive work, and delays. The work compared the results to economically measured productivity, and found discrepancies in the two measurement methods. This further validates the need for a non-economic measurement of the crew-level interactions. Dai et al. (2009) studied factors impacting labor productivity by quantifying input from workers. They triangulated the results by correlating the impact factors with crews' perceptions of their project's productivity, and found that the presence of negative impact factors had a negative impact on job productivity. Noor (1998) conducted studies using the daily visit method, which requires daily site visits to observe work completed through engineering drawings to show completion and any notations of causes for delay beyond fifteen minutes. Thomas et al (1992) also attempted to measure "disruptions" observed on masonry projects in seven different countries. However, the intention of this method was to remove the disruptions from the data on productivity measurement so project-to-project benchmarks could be established. In this case, the disruption data was not used to understand the causes for disruption. More recently, Menches and Chen (2013) also explored a methodology known as ecological momentary assessment (EMA), to study construction worker's thoughts and feelings when disrupted on the jobsite. This method is similar to a work sampling approach as developed in industrial engineering, where a signaling device prompts workers at intervals throughout the day to record information. Rather than focusing on work time and motion study, EMA focuses on psychological data such as feelings and mood. Menches and Chen conducted an idiographic study with the EMA method on jobsites, showing that an electrical worker encountered disruptions in 39% of the sampled recordings from his day.

In summary, the IE measurements come closer than economic methods for understanding the jobsite through the vantage of the individual installer.

However, the purpose of many of the measurements has been to study productivity, and not to model information generation or propagation. Information generation or propagation has not yet been identified as a potential area that can positively improve productivity if better understood.

The literature suggests that studies of real-time situations that works face on construction jobsites and especially the information generated from those situations have not been modeled empirically. Although Dai et al (2009) emphasize the importance of the craft worker input, and quantify labor's perception of productivity impacts in terms of severity and frequency, the data is still lacking direct observation of the work. However, their results support the validity of field labor input in productivity measurement. Choy and Ruwanpura (2006) <u>come closest to studying the crew-level obstacles</u>, arguing that productivity in construction operations is due to so-called "situations", which include unexpected events, and other factors. <u>They did not find any historical real-time or ongoing measurements of these impacts on projects</u>. Recently Menches and Chen (2013) developed a method that studies the worker's psychological response to disruption. A study such as this focusing on the situational behavior of workers is needed to understand and model information at the point of installation.

In summary, **Figure 5** shows the culmination of where the sample of studies from the literature review have focused to-date on modeling the jobsite in construction, mostly for the purpose of measuring productivity. The top portion of the figure shows a model of the inputs to construction jobsites, with the output being construction put in place. The numbers label each element, and the table in the bottom left hand corner of the figure indicates which elements have been measured with which studies. While considering the input and output parameters helped in learning about the workflow disruption problem, and thusly, productivity, the problem as defined in Section 1.2 exists within the “jobsite black box and needs to be studied within the box itself. In other words, the information generation occurring on the jobsite, specifically at the point of installation, is what this research studied. Figure 5 shows that the state-of-the-art studies of productivity tended to focus on the inputs to and outputs from the jobsite only. Studies that include direct input of field labor (showing in **Figure 5** as the “gray matter” within the black box) only consist of interviews or surveys of the workers away from the work environment, rather than real-time study of how the worker interactions are occurring and what information is generated and propagated.



Comparison Made	Source
1 and 5	Allmon et al (2000), Thomas and Yiakoumis (1987), Park et al (2005), Oglesby, Parker, and Howell (1989)
1 and (5 minus 6)	Thomas, et al (1992)
5 and 7	Dai, et al (2009), Noor (1998)
4 and 7	Adrian (1995)

Figure 5: Focus point of a sample of productivity studies

2.2 What has been done to mitigate disruptions to the process of installation?

Beyond productivity studies, alternative methods have been used to try and improve jobsite productivity through preventing and making visible disruptions or obstacles to installation. The Last Planner® method was developed to shield the installer(s) from doing work that is not appropriately ready for him or her to work. Work Face Planning, based on many of the Last Planner® principles, is another approach to improve coordination of material, tools, and information needed where work is performed. The Short Interval Scheduling (SIS®) process is yet another approach to collect feedback from the skilled trade installers to determine what prevents them from working according to their own daily scheduled tasks.

The Last Planner® system is a process for project planning and production control in construction which relies on a master and phase planning effort that results in a weekly production plan that is exposed to a series of constraints analysis for activities so they are “made ready” for execution. The work assignments are shielded from being worked on if they do not pass through constraints such as being well-defined assignments, being the right amount of work or that the work can be done. Once it is determined that the assignments SHOULD be done, they then are constrained by whether or not they CAN be done. If the assignments are listed somewhere on the weekly lookahead schedule, they pass this filter. From there, once the assignments are committed to by the crew, they become in the category of “WILL” be done assignments. The percent planned complete of the assignments is measured as the number of assignments the crew completed to those that made it through the "WILL" filter (Ballard, 2000). This is a means of controlling the work so that there are minimal disruptions or in-completable tasks for any reason.

The SIS® method developed by MCA, Inc. is another means of capturing information from the point of installation. Rather than shielding tasks from being performed that have potential for being done ineffectively, this method asks the foremen or technician what activities they will plan to complete each day for no more than three days ahead. Then, the foreman or technician identifies, if the activities were not completed, what the reason was and the scheduled hours that were lost. This method is closest to capturing what the labor faces regardless of any preconceived notions of the project plan or ideal process steps (Daneshgari P. , 2009).

These three approaches have all tried to emphasize identification and removal of obstacles from the point of installation. However, they still do not provide a comprehensive model for understanding how the information generation happens which is a cause or result of the disruptions to the worker’s scheduled tasks. **Figure 6** shows a comparison of these approaches and the limitation of all that will be covered in this research. The Last Planner® approach focuses on shielding or not allowing work to be done if requirements to do the work are missing. Workface Planning asks the worker to consider what information he needs and then find out if it is available. If it is not, the worker does not perform the required tasks. Short Interval Scheduling compares what the worker schedules to perform and reasons why he cannot complete the schedule. None of the approaches truly model or study what happens in the moment of decision at the point of installation. This can only be done through observation and carefully planned data collection as well as a well-constructed conceptual model. The observations and data collection will provided empirical data to verify the conceptual model which can be represented in a computer model that can simulate the complexity of this situation encountered multiple times per day per crew on jobsites.

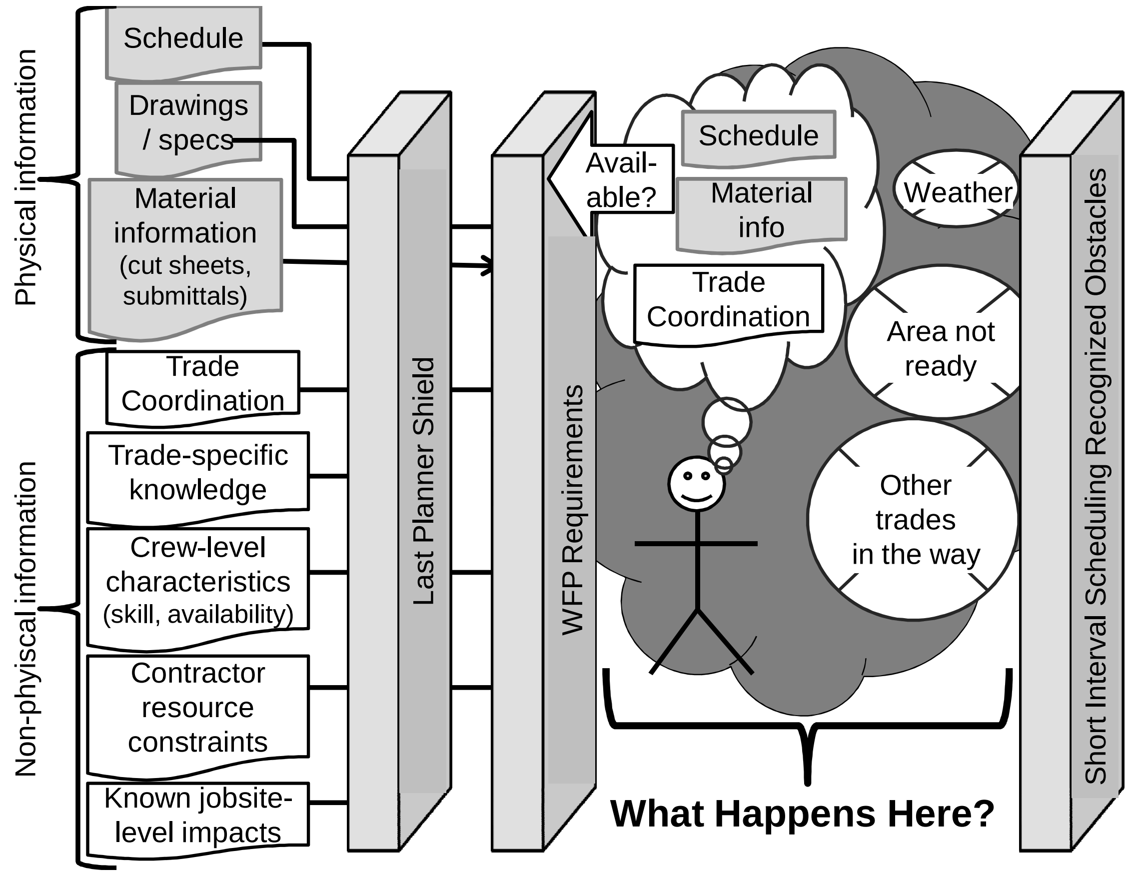


Figure 6: Comparison of how Last Planner®, Workface Planning, and Short Interval Scheduling (SIS®) work, and their limitations

2.3 What has been studied or modeled about information on construction jobsites?

Construction has always required modeling, and has a strong need for product modeling because of the complex interaction of resources required to build. However, applications such as Business Process Modeling (BPM) have only recently been applied to construction organizations. Two examples include modeling information flow in the business process within the precast concrete industry. This model used input from 14 different companies to determine what information was used for concrete production and distribution (Sacks, et al., 2004). Another example of process modeling in construction was developed by Huhnt, et al. (2008) to model changes in construction and their impact on other processes. They hypothesized that when a critical path method schedule communicates changes in means and methods, impact on downstream activities is visible, yet there are subsequent changes that go unnoticed. They postulate that including these in the model or schedule would require expert input (Huhnt, et al., 2008). Other methods for studying the problem without modeling use an ethnographic approach of direct jobsite observations, and analyze the patterns. For instance, Hallgren & Wilson (2008) studied crises on jobsites defined as interruptions to activities on the critical path. They studied 13 projects with observations, interviews, and review of project information and mapped the nature of the interruptions.

Knowledge-Based Systems approaches have been used to try to capture information from the field for use on future projects. Syal (1992) developed an approach for capturing process knowledge of firms prior to project execution, and knowledge from project-specific characteristics (Syal, 1992). This method combines static process modeling which can only characterize historic situations with information feedback from projects to improve the construction planning process. This concept could be applied closer to the activity level on jobsites to prevent information loss. However, the model needs to capture the complexity of the network of interactions that lead to information generation on jobsites, specifically at the workface. A computer-to-human interface could model these items if the input is constantly captured (such as the Google algorithm for internet searches). Just having more information available for decision-making does not make thinking and deciding unnecessary (DeBono, 1993). Davies et. al (2006) conducted a study using a web-based survey of Australian Computer Society Members, to determine how process modeling is used in practice, and found that modeling is most useful when the operator finds it useful. This means that if the model does not represent reality, is difficult to use, is too complex, among other disadvantages, it is useless.

There are more recent attempts at modeling crew-level information and decisions using approaches such as agent based modeling and social network analysis. Section 2.5.4 provides more detail of these methods. Loosemore (1998) used social network analysis for modeling information transfer during a crisis on a construction jobsite. He used this approach as a method for mapping the interactions of parties on the jobsite topologically, but still focused on the overall construction site parties and not the crew-to-crew, or within crew, interactions and decision-making rules. Son (2011) developed a theoretical approach to integrate SNA and ABM for modeling how project teams work together on jobsites. This is the closest approach to defining a model at an individual installer level and using it to understand decision-making and emergent behaviors. These models are discussed in detail in Section 2.5.

2.4 What have other industries measured related to information generated and propagating from the point of installation?

The problem of and approach to studying information generation and loss have been studied in other industries. Manufacturing, healthcare, airlines, and several other industries involve skilled operators and high risk. These industries have all recognized, studied, and attempted to measure information from the doer's perspective, focused on information flow and feedback from the operator, and developed methods for studying the information feedback and use.

Other industries have developed methods for improving an operation by modeling and understanding it from the operator's perspective and in his/her operating environment. In Fischer's exploratory study of human resources and "work process knowledge", he concluded that the person who does the work knows the most about the process. This knowledge is more important when determining how work will be done than the knowledge of an individual project or work plan (Fischer, 2005). Jackson et al. (2004) conducted a survey of production schedulers, with the outcome that the schedulers really do not sit down and work out a schedule in a structured way. They work with the available data to fit the current situation, and the knowledge they have about the situation is the critical process knowledge for the organization to learn from. With this understanding, Jackson et al. (2004) introduce a new model for scheduling in manufacturing; whereas before it was previously assumed that information technology or knowledge-based-systems would help schedulers to create the production schedule, a better model is improved organizational support to listen to what the schedulers are faced with (Jackson et al., 2004).

Healthcare has also emphasized the importance of input from the operating room. Several studies have found that surgical risks and outcomes cannot be explained or studied after-the-fact (Greenberg, et al., 2007). The direct study of handoffs between doctors, nurses, and others in surgery is needed to understand where information loss occurs.

In addition to studying problems from the point where work is performed, other industries have also focused on understanding the information and feedback from the operation that could be used to improve and reduce risk. In a study where 98 medical staff were given a scenario of cardiac arrest to react to, and observed to determine where information was lost in handoffs between doctors and nurses and residents. Their main conclusion was that “to ensure adequate transmission to an incoming group, information must be encoded and stored, accurately remembered, and accurately communicated” in the language of the incoming person (Boggenstatter, et al., 2009, p. 116). This scenario can be compared to construction, where there is information generated at the point of installation that if it is passed on, is not documented or captured in a way that is recognized or stored by anyone outside the crew.

Christian et al. (2005) studied a similar problem, with direct observations of the operating room, coding factors impacting safety of surgery and their causes. The two most important features impacting safety were: communication and information flow, and coordination of workload in auxiliary tasks. Information was most frequently lost during handoffs or interruptions, and auxiliary tasks that often require a lot of time, such as counting or sorting, result in rework. Also, the two largest problems found in Christian et al. (2005) exist in construction: information loss and impact of auxiliary activities such as material handling, which are often not measured or thought of in the design of the project and result in disrupted flow of installation or rework.

The airline industry has also studied the problem of information flow and human factors for pilots and air traffic controllers (ATC's). In the case of ATC's, Durso et al. (2008) developed a measurement of information relevance to the ATC's who are constantly faced with multiple forms of information feedback. Durso et al. (2008) defined information as “any difference that could affect the operator's understanding” and measured the information relevance for 3 tower positions, finding that the information most relevant to them related to their job (Durso et al., 2008, p. 755). At the construction jobsite, this could be translated to show that the information most relevant to the installer is the information impacting his/her work. Everything else is ancillary and only the installer knows what information is necessary.

In summary, other industries have studied information generation and propagation from skilled trades and in complex work environments. The information that is most useful is found at the “front lines” of where the work is performed. In addition, the literature pointed out that the information losses or mis-translations happen at the interfaces or handoffs between individuals involved in the process. Finally, despite information being available to the operators, the quality of the information including what is needed, when it is needed, and how it is needed has to be relevant and on the receiver's terms. Section 2.5 will explain the theory behind this as well.

2.5 What models and methods exist to model and measure information generation at the point of installation, and its propagation beyond the point of installation?

Several principles and methods can be used to model and measure information, including its generation and propagation. The formal study of information theory is summarized in section 2.5.1, which includes mathematical and physical models. These provide insight into how the information generation can be modeled quantitatively. Section 2.5.2 includes a detailed study of methods that can be used to model information generation at the point of installation, and how it propagates beyond the crew level. Agent based modeling and social network analysis are reviewed in-depth as two of the most fitting for exploring the research postulation.

2.5.1 Information Theory

The history of information theory dates back to the early twentieth century, and includes the study of human and artificial intelligence, computing, and entropy. From the literature review, two major themes arise in this field of study: quantifying and modeling information, and separating physical and social definitions of information.

Information was first defined as a measurable quantity in 1928 by Ralph Hartley in Transmission of Information (Verdu, 1998). He developed a probabilistic equation for quantifying information in a system as "H" in the form:

$$H=n\log S$$

where S is the number of possible symbols that are used in the transmission of information, and n is the number of symbols actually used in the transmission.

This relationship was used primarily for the purposes of transmission of information over electrical circuits at the time. Alan Turing used the model in the 1940's to develop the Turing machine which was the first idealization of a computer that could read and write instructions using a tape, and furthered this concept in work on cryptography during World War II (Seife, 2006). Most famously cited for developments of information theory is Claude Shannon, who published "A Mathematical Theory of Communication" in 1948, furthering Hartley's work by developing a statistical process underlying information theory (Shannon, 1948). He developed the theory to not only quantify and model information, but to use the model for understanding how to transmit information most efficiently over a channel. **Figure 7** shows an excerpt from his work depicting a system of communication (Shannon, 1948, p. 34). The attributes involved in the system are defined as:

- Information source: produces the message

- Transmitter: operates on the message in some way to produce a signal suitable for transmission over the channel
- Channel: medium used to transmit the signal from transmitter to receiver
- Receiver: reconstructs the message from the signal
- Destination: person or thing for whom the message is intended

Shannon also identified that the transmission of messages is often interrupted by a noise source. Several studies came from this depiction, including the study of channel capacity, signal-to-noise ratios, message encoding and encryption, and more. It was the basis for Bell Laboratories' development of telegraph and telephone communication systems, as well as today's wireless technologies.

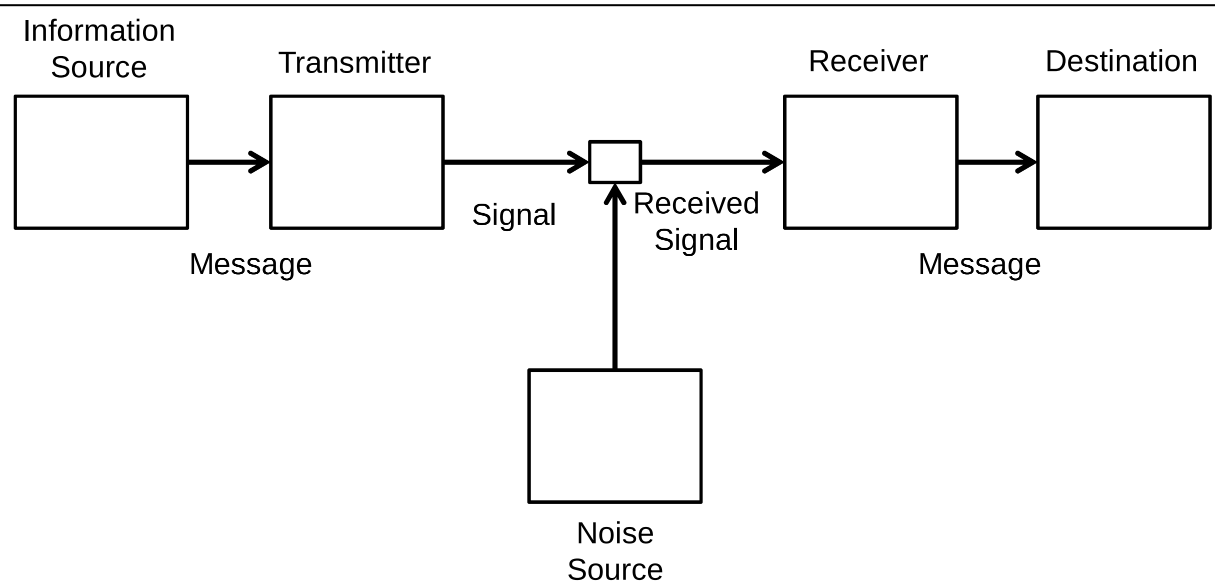


Figure 7: Claude Shannon's characterization of a communication system in 1948

The Hartley equation and Shannon's development revealed that the flow and transmission of information could be described with the physical laws that pertain to flow of any substance and characteristics, such as entropy. Hartley's equation matched Boltzmann's equation for entropy of matter, and the uncertainty involved with the information receiver's decoding of a sender's message was described using the concept of entropy (Shannon, 1948).

As first defined by Clausius (circa 1850) and then quantified by Boltzmann (circa 1877), entropy quantifies uncertainty in predicting the value of a random variable. Clausius postulated that the amount of energy released from combustion reactions is always lost due to dissipation or friction, and is not translated into useful work. He quantified this loss (entropy) as "S", and Boltzmann developed the formula for entropy as:

$$S=k_B \ln W$$

where k_B is Boltzmann's constant relating energy and temperature of a given system, and W is the number of microstates a system could potentially be in at any given time, which gives the degree of uncertainty in a system (Moran & Shapiro, 2008). The quantity "S" defines the amount of disorder in a system at any given time (Stonier, 1990).

Given the similarities between measuring the uncertainty of a state of a system and measuring the uncertainty of information transmission, entropy equations and models can be used for information as they are in physics. Ralf Landauer made this connection in 1968, and also translated the models to computational mathematics in the early 1990’s. He described how information can be “lost” when a computer has a stored memory of a computational outcome and only stores the outcome, not the path for arriving at the outcome (Landauer, 1991).

In conclusion, there are proven methods to model and quantify information; however, there is no existing literature for applying these methods to construction jobsite information.

2.5.2 Social network analysis

Beyond models of quantifying and measuring information, the literature review included study of what methods exist for modeling the construction jobsite and flow of information therein.

Social network analysis (SNA) can be used to understand the impact of information flow between individuals, particularly in complex production. This complexity renders static modeling or single-snapshot views of interactions ineffective in capturing the whole situation. Frank et al. (2011) describe complex work as requiring local adaptation and local coordination. In such complex work environments, the knowledge needed to be successful comes through a better understanding of the local work environment. Problems that arise must be solved within the local work environment or network as well. In addition, Frank and Fahrbach (1999) describe complex organizations as being able to “bounce back” from explosive situations or shocks in the work environment.

Based on the characterizations of complex production and complex work, the following characteristics of construction jobsites make them complex, and a prime candidate for SNA :

- **Multiple individual crafts with specialized skills**. This in and of itself defines the jobsite as complex; however, the required interaction of these craft workers adds another dimension of complexity to the work. The workers who become part of a jobsite network come with **depth of craft knowledge** of their own craft (e.g., steelwork, carpentry, electrical, etc), but are required to work with other trades through information exchange, physical coordination and sometimes conflict for who gets to work where at any given time. This characteristic can be classified as "local adaptability required."
- **Jobsites are temporary work organizations**. Construction projects typically have less than a three year time span. There are exceptions such as long-duration mega-projects as well as long-term maintenance work or "direct-hired' workers. In the majority of cases, this means that the workers have temporary allegiance to the local environment which they must adapt to for production on the site, but do not need to develop long-term relationships in that network. This also points to the complexity of jobsites arising due to the frequency of local adaptation that the workers experience. Not only do they require local knowledge to work, but this adaptation process happens for them every time they go to a new site. Local coordination is required on every job, and

issues are solved within the jobsite or crew environment. Information about the issues does not propagate to others who could help with coordination or problem solving.

- **Trend from, and conflict between, unit production and mass production.** The construction industry still requires heavy involvement of skilled craft workers, which characterizes the work as a "prototype shop" or unit production environment. However, the demands for reducing the cost of construction and speeding up time of delivery are forcing the industry to move toward a mass production model. This conflict arises right at the point of installation for the worker, who is trying to perform his skilled trade, but must now become an expert or follow expertise in production process design.

Below is a sample of an observed scenario of an electrician attempting to hang a light fixture in an elevator shaft, which describes the complexity of the point of installation. In order to hang the fixture, he must:

- Have technical knowledge himself about how to do this work.
- Have appropriate material available to do the work. This requires that the material is onsite somewhere, which requires that the material was delivered as requested, which requires that the material was ordered in the first place and the vendor had it in stock, which requires that the initial need for material was identified in the first place. Many of these requirements are translated through informal information systems and are missed or "lost in translation."

- Have manpower available to help with the installation. The requirements are similar to those mentioned above for material; however, the additional “human” element of manpower will come into play. In this case, one of the crew members helping was older and not able to maneuver in the shaft well so the electrician had the older helper stand outside the shaft and gather and prepare material leveraging his expertise. The decision to do this will potentially cost productivity and money for increased labor usage; however, this type of decision happens repeatedly across the jobsite every hour and nobody is there to capture or record it.
- Have most recent information about the installation, such as where to mount the fixture, what the schedule is for elevator operation and testing so not to interfere.
- Have open and accessible work areas. If this is not available, the electrician will go work elsewhere.

The frequency and impact of improvised decisions made at the point of installation is unknown, and relies on local coordination with other crews and local adaptability for the worker to be able to move forward and complete the tasks on hand. These characteristics of construction jobsites make them a good candidate for using SNA.

2.5.3. Agent Based Modeling

Simulation and modeling of any system offers several options, such as mathematical models (regression), physical models, discrete event simulation, system dynamics, and agent-based modeling (ABM). Each modeling type is used for a different purpose, depending on what the reason is for modeling and the complexity of the situation being modeled. **Figure 8** shows different approaches to modeling with simulation. Recently, simulation methods have been used to understand job productivity impacts. For example, agent based modeling (ABM) has been used to understand the real-time impacts of various jobsite scenarios (Sawhney, et al. 2003; Macal and North, 2005; Desai, A., 2011). However, the model parameters do not rely on field labor input, and have not been verified with real job results (Watkins, et al., 2009 and Kim and Paulson, 2003).

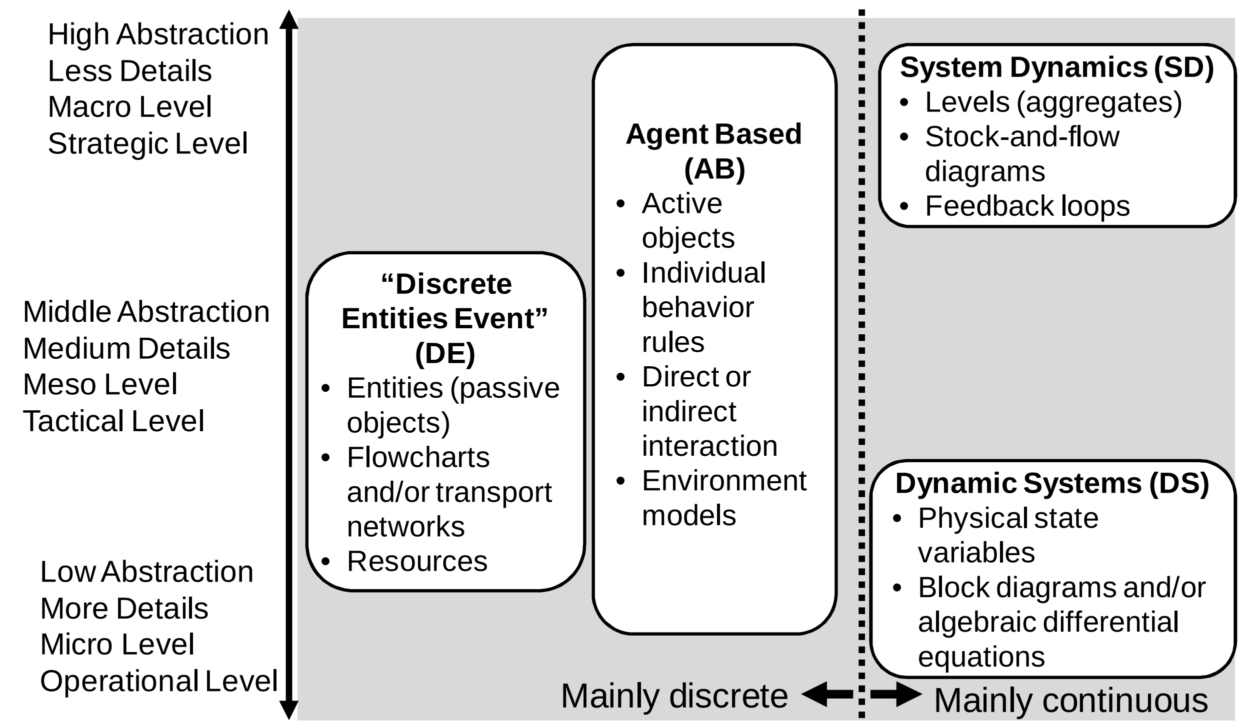


Figure 8: Approaches in simulation modeling (source: Borshchev & Filippov, 2004)

Discrete event simulation (DES) is most useful for modeling standardized processes that are repetitive, and where the process and its components are very well understood and defined (El-Gafy, 2011). The models can be used to understand system-level parameters and trends, particularly to understand the impact of changes in the system. For example, a DES model would be helpful to model the operation of a batch plant on a construction site. The DES would model the static entities of the plant, the point of pouring, and possibly resource pools for the material and labor needed. Then the transition of the resources between entities is modeled and the system metrics of resource utilization, capacity, production rate, and others. The DES modeling method is not intended for understanding the more macro-level dynamics of a system, including instantaneous changes to the environment, interaction of the resources with the environment, and feedback loops. In addition, DES does not involve active agents, rather static entities.

System Dynamics (SD) is another powerful modeling technique. Different than DES, SD is intended to model the overarching system to study its overall behavior and characteristics (El-Gafy, 2011). Another distinction is that SD can be used to model soft factors such as trust, confidence, learning, and more, whereas DES only models entities and tangible factors such as time, distance, quantities, to name a few. SD also models the continuous behavior of the system rather than discrete events and time. SD does not require in-depth knowledge about the system being modeled; rather it requires an understanding of the interactions potentially occurring. SD models these interactions using the concept of stocks and flows to see how changes to the system will impact the system. SD does allow, and in fact emphasizes, the study of feedback loops. It also allows for more abstraction in the model development.

Agent Based Modeling (ABM) is a third method for modeling systems that models the system on a micro level, but provides results at both micro and macro levels (Ligmann-Zielinska, 2010). It does not require in-depth or extensive data that would be required by DES, but it does require more understanding of the individual interactions within the system than is required by SD. It provides a means for modeling interactions and feedback loops at the local level, impacts of changes to the system and, most uniquely, a method to allow the system-wide behaviors to emerge. This is different than modeling with SD, which requires that the modeler already knows and understands how the system behaves and model it as such (El-Gafy, 2011).

Based on the review of the available methods, ABM is an appropriate choice for modeling the research problem as defined in Chapter 1 for a few reasons. First, it is useful for modeling individual interactions and studying their aggregate effects. Other modeling methods will not be able to capture the individual decision making and reactions to scenarios like the above-mentioned scenario, and then determine what the overall effects are on the jobsite and productivity. Related to this, ABM is a good choice because it can capture complexity. The research problem is complex because it occurs in localized situations and the actions and decisions made are dependent on many factors, both quantitative and qualitative (Frank, et al., 2011). Lastly, ABM can model the “learning loops” within the jobsite and show why the information does or does not get captured when labor encounters obstacles. **Table 1** shows selected characteristics of the three modeling types, and an indication with circles of the characteristics needed to model the problem of this research (adapted from Du & Ligmann-Zielenska, 2013).

Characteristics	SD	DES	ABM
Threads of control	Few	Few	Many
Aggregation	High	Medium	Low
Autonomous actors	No	No	Yes
Heterogeneous decision making	No	No	Yes
Multi-scale abstractions	Narrow (Macro-Meso)	Narrow (Macros-Micro)	Wide (Macro-Micro)
Normative decisions	Maybe	Yes	Maybe
Well-defined macro processes required	Yes	Yes	No

Table 1: Comparison of characteristics for different model types, with those circled that apply to the model that will be developed in this research

2.5.4 Combining SNA and ABM

This section reviews the state-of-the-art regarding how the SNA and ABM approaches have been combined. In addition, the literature points to some common challenges in modeling, such as the lack of robust empirical data. Potentially related to the challenge of collecting empirical data about social networks, the models studied in this review have agents using economic utility only for making decisions with no input for their social utility or other factors such as geo-spatial considerations. **Table 2** shows a codification of the literature in terms of which study relates to which of the aspects that will be covered in detail further in this report.

	Addresses SNA	Addresses ABM	Integrates SNA & ABM	Uses empirical data	Models social utility	Study of construc-tion
Banerjee, et al. (2012)	X	X				
El-Sayed, et al. (2012)	X	X				
Evans, Jane (2012)	X	X				
Frank and Fahrbach (1999)	X	X			X	
Frank, et al. (2011a)	X	X		X	X	
Frank, et al. (2011b)	X			X	X	
Gemkow and Neugart (2011)	X	X				
Loosemore, M. (1998)	X			X		X
Nishizaki, et al. (2009)	X	X	X		X	
Son, J. (2011)	X	X	X			X

Table 2: Summary of primary sources used from the literature and aspects covered in detail in the review

The first significant finding from the literature is that in models where SNA and ABM were used together, the <u>combination tends to be dominated by one method or the other</u>. Most often, the ABM is developed traditionally with static rules for agents or agent sub-groups, and then SNA is used as an analysis tool prior to or following the ABM simulation. For instance, Evans (2012) used an agent based model of the social response to the spread of infectious disease.

The ABM results were then mapped onto a network to show how the diseases spread throughout a society. However, the agents in the ABM were not endowed with any logic derived from SNA modeling methods. El-Sayed, et al. (2012) also explores both ABM and SNA approaches to model social epidemiology. They see both approaches valuable in their own right, but there is no recommendation to combine or integrate them. In the single study where both SNA and ABM were explored in the construction environment (Son, 2011), the use of SNA was topological and did not include an integration of the analytical models of the social network as prescribed in Frank and Fahrbach (1999).

The second commonality of the literature reviewed is that <u>attempts made to integrate the ABM and SNA approaches use economic utility of the agents as a measure or variable for decision making</u>. Frank et al. (2011a and 2011b) proved through empirical data collection and SNA modeling that economic utility is not the only motivation for human interactions and decisions. Whether it is teachers adopting new technologies (Frank et al. 2011a), or fishermen choosing with whom to interact (Frank et al. 2011b), the research shows social utility is as or more important than economic utility for human decision-making, especially in complex production environments with a high degree of local adaptation and local coordination. For example (Frank et al. 2011b) concludes that fishermen are more likely to spread knowledge in exchange for social utility than they are for economic utility such as time, effort, or money.

In the literature, attempts to develop an integrated SNA-informed-ABM rely on maximizing only economic utility of the agents. These methods do not use interactions of individual agents to influence beliefs or spread knowledge without consideration of economic payoffs. Banerjee (2012) for example, developed a model for how people are influenced to shop online based on their interactions with others in their social network who shop online. The agents in the model work to "reduce their transaction costs" for shopping, even though Banerjee was trying to study impact of the social network on the individuals in the network. Gemkow and Neugart (2011) model the influence of a social network on job seekers, by building an ABM of the labor market endogenizing the market's social network. Their premise is that the agent behavior is a result of the network itself and not individual interactions between friends. They have agents programmed to maximize their economic utility, using a measure of "per unit time cost for maintaining friendships." Although these are good advances in the development of an integrated approach to ABM and SNA, the model logic relies heavily on economic influences and incentives.

Nishizaki, et al. (2009) is the best example from the literature of usage of sociological decision-making and logic in developing the rules for the ABM. This research expanded on work done by Akerlof (1980) and Naylor (1989) by using ABM as a tool for modeling the adaptive nature of agents over time and exposure to multiple iterations of a scenario, which may not be feasible to model in a purely SNA approach due to complexity. The research coded the agents in the ABM to include "chromosomes" for how agents carry out decision based on their (a) decision-making preferences, and (b) history of actions and decision outcomes. These two characteristics were implemented and updated using a genetic algorithm where the individual agents remain unique and heterogeneous and actually learn and evolve within the model. This is unique when compared with a typical ABM where agent logic is homogeneous both between agents and also over time with each agent.

The Nishizaki model was built and compared to the pure SNA mathematical model built by Naylor, in which actors gain social capital (a better reputation) by obeying the social norm. Naylor's model ended in an equilibrium state where a stable fraction of the population believe in the social norm and follow it. The results of Nishizaki's ABM differed from Naylor's in the long run. Nishizaki found that the social norms either became extinct over time, or reached a steady-state adoption rate. The difference in outcomes of the models was attributed to the ability of ABM to model a series of an agent's actions in the long run, whereas Akerlof and Naylor were only able to model and infer from one set of agents and agent interactions. The ABM allows for an evolution of the agents and therefore more complexity than a static SNA model allows.

The third finding that was common in the literature <u>is minimal use of empirical data in either modeling approach</u>, and no use of empirical data in any attempt to use the ABM and SNA models in combination. Loosemore (1998) went furthest in an SNA approach utilizing empirical data, by observing the results of a crisis in a construction project with a case-study based approach. The data was used to develop a network structure, yet the result could only be used to infer correlation to project outcomes. Loosemore did not combine ABM or SNA in an integrated approach to using the empirical data. Evans (2012) developed the model for social response to infectious disease spreading hypothetically, and Son (2011) also developed the model without use of empirical data. Banerjee's (2012) model was built conceptually based on hypothetical actions of online shoppers influencing non-online shoppers. Gemkow and Neugart (2011) did not use any empirical data, and the Nishizaki et al. (2009) model was purely theoretical.

The use of empirical data is very valuable as it will provide real-world inputs to the model parameters, leading to model results that can be validated against the real-world environment. <u>A model built based on theory will, to some degree, lead to a result that has a foregone conclusion based on the modeler's conception and assumptions made in the theory and hypothetical data used.</u> However, the effort and cost to collect such data is challenging, particularly for SNA development and even more-so to have data for developing an empirical SNA and real-world ABM parameters.

Regarding use of an SNA-informed ABM in construction, Loosemore (1998) and Son (2011) are useful references. Son (2011) provides a theoretical foundation for an integrated approach of SNA and ABM, on construction projects. Son outlines how ABM's can take advantage of SNA in two ways: (1) the analysis of relational data within networks to examine the processes of project teams and how they work together, and (2) building the ABM rules based on the SNA explanation for forming, maintaining, and dissolving relations in networks. The latter is what this research built on, as explained in Chapters 3 and 4. Son defined three layers of networks amongst agents as social network, knowledge network, and institutional network, all of which are so complicated that they cannot be described with simple static rules. Despite the limitation of modeling only economic utility, Son has recognized the need for an approach within the construction environment to integrate SNA and ABM due to the industry's complexity, particularly on large projects where despite up-front planning for the physical installation process, the projects suffer due to lack of a model for information handling.

Using an SNA approach, Loosemore evaluates the response to a crisis on a jobsite with a map of the network of various players involved at a macro level (e.g. the engineer, clerk of the works, project manager, surveyor, etc.) and who interacts with whom in response to the crisis. The individual influences of decisions or outcomes within those positions are not modeled, and mathematical models used in influence and selection models such as in Frank and Fahrbach (1999) are not incorporated in this macro view. SNA is used only for a topological view of the social network, not as a means to define why agents interact and the resulting influences.

In summary, there were several techniques uncovered in the literature search that can be built upon for the research method used in Chapters 3 and 4. The approach of an SNA-informed ABM is novel, given the limited research and empirical examples in the literature. In terms of direct usage for the research, most notable is the model developed by Nishizaki, et al. (2009). The approach of modeling the learning and adaptive behavior of agents using “chromosomes” and accounting for social interactions will be useful for the research herein. The Nishizaki research also demonstrated the need for clearly identifying the model inputs and parameters. Lectures and content from Dr. Ken Frank’s CEP 991 course show how the selection and influence models developed in Frank and Fahrbach (1999) can be developed to connect to the ABM for this research, and also how empirical data can be collected and used in these models (Frank, K. , 2010).

2.6 Summary of Literature Review

To summarize Chapter 2, there are several references that were studied and relied on to characterize and research the problem described in Chapter 1. The literature reviewed revealed what has been done and what could be done to study the information generation and losses of that information from the location of installation on jobsites. None of the studies have led to an understanding of the information generation at the workface and its impact on construction productivity or project performance. However, other industries such as healthcare and aviation, which are both skilled-trade-based environments, have studied this problem and similar approaches could be referenced for this research. Furthermore, the techniques of studying complex environments such as agent-based modeling and social network analysis were used in developing the conceptual model to explore the research postulate.

Chapter 3 explains how this background literature review and study was used to design and conduct the research.

Chapter 3: Research Methods

3.1 Research Questions

The research **postulate** is that understanding information generation and loss from the point of installation on a construction jobsite will result in insight into how work performance can be improved.

Therefore, the relevant operational **research questions** to be addressed are:

1. What are the characteristics and examples of information available to and from the worker, during a work activity, especially when the worker has to improvise?
2. How does information get generated at and propagated from the point of installation?
3. How can this information generation and propagation be effectively modeled, including implementation of the model with real jobsite scenarios?
4. What is the relationship between the information flow and work performance?

The map shown in **Figure 9** shows how the research questions are associated with the objectives of the research as outlined in Chapter 1, and how the data collection and observations as well as the literature review were used to address each question.

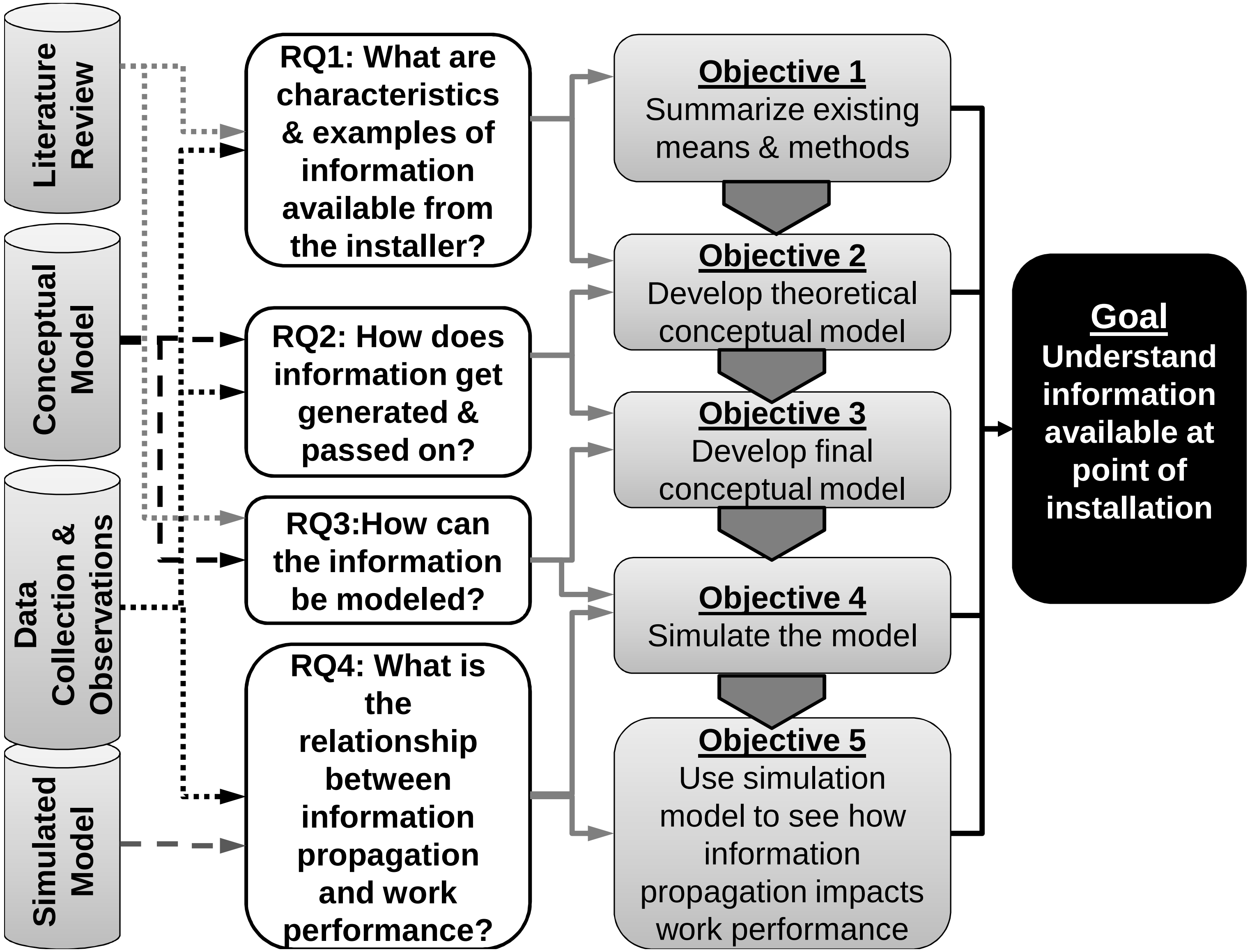


Figure 9: Map of research approach including method, research questions, objectives, and goal

3.2 Research Plan

To achieve the research objectives and address the research questions, the following work plan was followed:

1. Review existing means and methods for modeling information generation and propagation.
    1.1. Conduct a literature search, addressing the questions listed in Chapter 2.
    1.2. Review and summarize literature search, identifying existing means and methods for modeling information available at the crew and installer level of construction jobsites.
    1.3. Identify what can be used from the literature as a reference for modeling information generation. As discussed in Section 2.5, an SNA-informed ABM was identified as the most appropriate method for this model.
2. Develop a conceptual model for information generation from the point of installation on construction jobsites using a deductive approach.
    2.1. Create a conceptual model based on historical jobsite observations and experience working with crew members. This model mapped the conceived information flow during a work activity, and with particular focus on what happens when workers encounter obstacles. Information is available with the workers all the time, but when obstacles are encountered, this information and decision-making become more explicit for the timeframe while they are handling the obstacle and improvising. A high level conceptual model was developed based on this.

2.2. Test the conceptual model by evaluating it against new jobsite observations. The conceptual model from step 2.1 was taken to seven jobsites to determine if the conceptual model was an accurate and representative model of what happens at the jobsite. This pilot evaluation process tested whether the actions and information available from the crew were captured conceptually. Based on these observations, the conceptual model was further refined to include any discrepancies between the original conceptual model and what was observed.

2.3. Refine the conceptual model, and use it to develop a final SNA-informed-ABM model that accurately represents the jobsite actions and information generation.

3. Develop and implement a computer-based simulation for the conceptual model.

3.1. Collect data to determine model parameters and detailed model logic.

3.1.1. Develop a detailed data collection plan, including when, how, and where data will be collected, with considerations for data needed for both SNA and ABM design. An initial data collection plan was developed and used simultaneous as part of the observations in step 2.2 above. The final data collection instrument and plan was approved by the Institutional Review Board, and is shown in **Appendix B**. This is the plan that was used for data collection.

3.1.2. Collect data from direct jobsite observations of mechanical, electrical, or plumbing trades, including what, when, and how information is generated and propagated. This data was used for quantitative and qualitative input into the final conceptual model development, and also used to parameterize the final computer simulated model.

3.1.3. Collect data from direct jobsite observations of mechanical, electrical, or plumbing trades, about the social network(s) that exist on jobsites at the point of installation. This data was used for understanding the interactions and influences between workers on the jobsite so they could be modeled using SNA.

3.2. Synthesize data collected to develop data inputs and logic for the computer-based simulation. The data was analyzed with summary statistics to determine the distributions of worker / agent attributes such as age and experience as well as crew attributes such as crew size and crew ratio (foreman, journeyman, apprentice). Timing data was also analyzed to determine the impact of obstacle handling on completion time of activities as well as the impact of obstacle reporting to supervision on completion time. The data was also used for developing a social network model that could be embedded within an ABM that captured heterogeneous worker decisions and actions.

3.3. Develop an agent-based model (ABM), with integration of social network analysis (SNA) for modeling the information generation at the point of installation on construction jobsites. Model outputs and inputs were defined, as well as model logic built based on what was observed and collected from the jobsite. An influence model was also developed and embedded into the ABM model.

3.4. Integrate real jobsite data from the conceptual model into the ABM. In this step, the model was simulated using AgentAnalyst which is a programming application used for simulation of ABM. The data collected from jobsites was used for model parameterization, and the SNA-informed-ABM was coded.

3.5. Test the model by demonstrating and evaluating the ability for the model to lead to an understanding of the impact of information generation at the point of installation, and the loss of this information when it does not propagate beyond the crew level. The output of the final model was analyzed with a demonstration case of a jobsite, where scenarios were tested to see what the information model explained. Shortcomings of the model were identified to be explored in future research and through additional validation and verification.

4. Suggest a final model for information at the point of installation on jobsites. Based on observations, data analysis, and simulation modeling results, a final model was suggested representing the information generated and available at the point of installation on jobsites, and how that information becomes lost (e.g., does not get passed on from the crew).
5. Explore potential issues with information generation from the point of installation and how the loss of this information impacts work performance. Develop scenarios that could be explored within the final model, including

further studies of information generation and information loss and its impact on work performance. In addition, describe the limitations and boundary conditions of the model that could be explored in future research.

In summary, Chapter 3 defined the proposed research method, work plan to achieve the outcomes of this research described in the next chapters. To achieve the stated goal of Chapter 1, four research questions were addressed through a plan of literature review, data collection and observation, conceptual model building and verification, a computer-based simulation of the model, and a final set of guidelines for how information from the point of installation can be modeled on jobsites.

Chapter 4: Research Results and Findings:

Model of Information Generation at the Point of Installation

To work toward the goal of understanding information generated at the point of installation, the first objective was to study and summarize existing means and methods of capturing the information. This objective was partially met with the literature review covered in Chapter 2, but was further verified in this research through empirical data collection and observations at jobsites. The second objective to develop a conceptual model was achieved by characterizing the information available from the worker at the point of installation, and then modeling how that information is generated and passed on.

Section 4.1 outlines a conceptual model that was developed, and then evaluated in a pilot study of observations on seven jobsites. These observations led to improvements in the conceptual model, particularly in modeling the social network and influences on worker decision-making. Following revisions to the model of information propagation at the point of installation, data was collected on 25 different installation activities of mechanical, electrical, and plumbing work and workers. Analysis of this data parameterized the conceptual model, and provided insight into worker behavior and decision-making when faced with obstacles to their work. Analysis of the data and synthesis of observations indicated that information is indeed lost from the point of installation, and there is an impact to the work performance.

4.1. Model Development

Based on the literature review and problem definition, a high level conceptual model was developed as a basis for the actions and information to model in the research. This model was validated with jobsite observations in a pilot study, where seven jobsite observations were conducted to determine if the concept matched the information that is generated at the point of installation. These observations were also used to develop a data collection plan that was then used to collect data about information generation and propagation when obstacles are encountered at the point of installation. The observations and findings are included, proving that information is indeed available at the point of installation that may or may not be propagated beyond the crew level.

4.1.1 Conceptual Model Development

The information available at the point of installation includes any thoughts, decisions, and actions made where work occurs. This information is ever-present in the minds of the workers, and is therefore impossible to see unless they make the information explicit through writing or speaking. However, drawing a parallel to physical elements that exist and are not visible, moisture is in the air and can now be measured but is only visible in physical presence when certain conditions are present (e.g. precipitation, cloud formation). The same is true with information at the point of installation. It is always there in the minds of the workers, but can be seen and measured when pressurized conditions are present, such as when the installers need to improvise due to obstacles or unforeseen circumstances. Therefore, the conceptual model of information at the point of installation is developed for the special case of when workers face an obstacle.

Figure 10 shows a depiction of the concept for worker and crew actions and decision making when they encounter an obstacle while working. In the model, a worker has work scheduled (either by him/her or for him/her), and then attempts to work. When an obstacle is encountered, the worker goes through a series of decisions about how to handle the obstacle. He/she either chooses to work around the obstacle, or to have the obstacle removed either by resolving it himself/herself or reporting it and getting help elsewhere. This scenario involves several pieces of lost information, if the obstacle is not reported beyond the worker or the crew level, including:

- What the obstacle was and what caused it?
- How the worker resolved the obstacle?
- What was the impact of the obstacle?
- What is the likelihood of obstacle reoccurrence?

Regardless of the obstacle handling choice, there is a loss of time. The lost time has two impacts: (1) workers lose effective time on installation, and (2) the scheduled work takes longer than expected to complete. One or both losses could occur. The result of both is additional cost to the project. In the case of number one, if a task was scheduled to take 20 man-hours and the workers encounter an obstacle, they could still complete the task in 20 man-hours but actually spent 5 of the 20 hours resolving the obstacle. In the case of number two, the same task that was scheduled to take 20 man-hours ends up taking 30 hours because there is additional effort incurred either to resolve the obstacle, wait for clarification, or deal with other consequences.

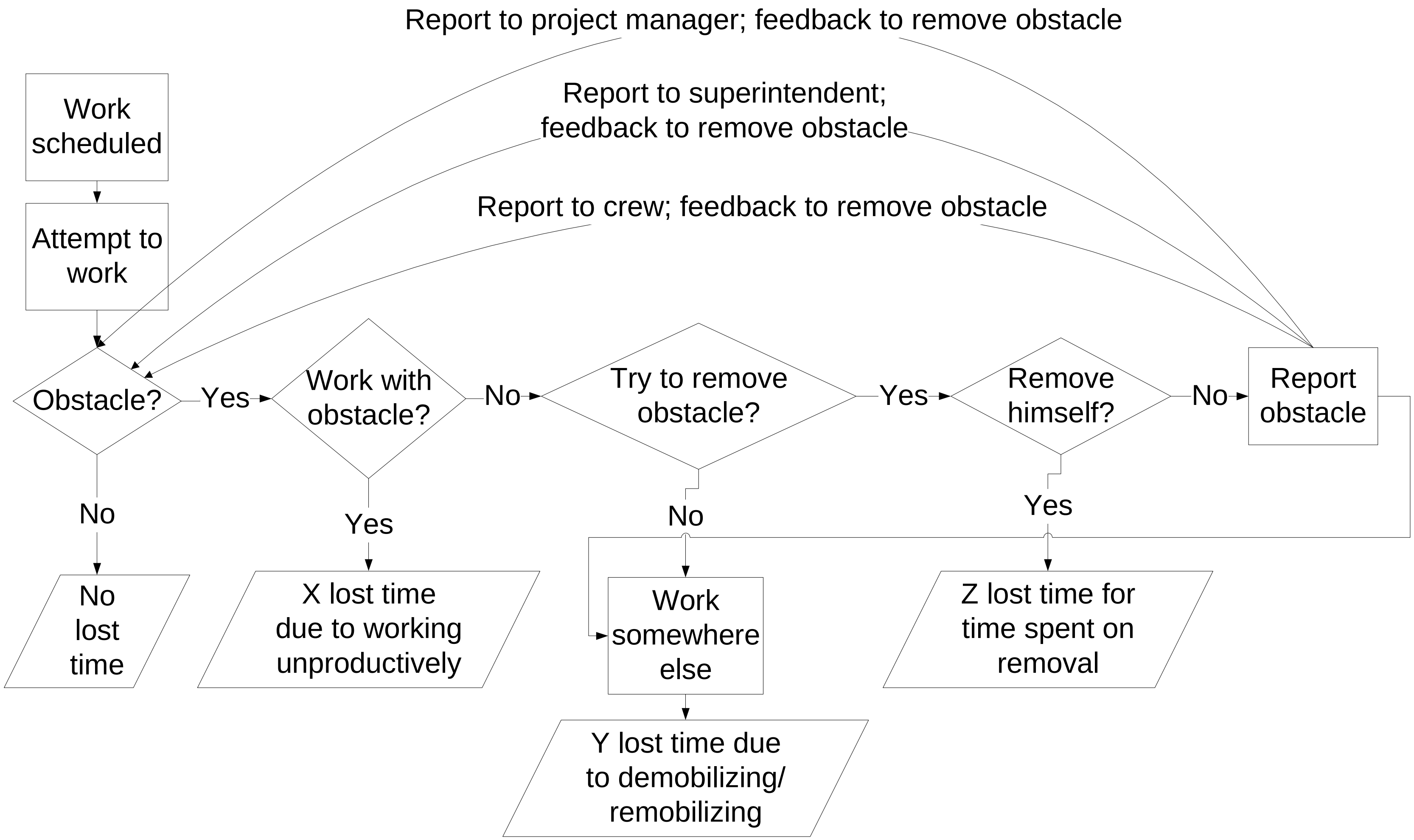


Figure 10: Conceptual model of the jobsite information propagation in the specific scenario where workers encounter obstacles

4.1.2 Conceptual Model Evaluation

Prior to data collection and analysis, the conceptual model developed in section 4.1.1 was evaluated. This was done through observations on jobsites as listed below, which led to some revisions to **Figure 10**.

The evaluation was accomplished through observations of seven construction jobsites. The observations, which were performed at the crew level of individual installation activities, resulted in visual models of each jobsite scenario as well as a review of what information was generated in the observations. This helped to identify how to build a robust data collection plan for collecting this information through interviews and observations. A review of each observation is listed below, followed by a synthesis that resulted in revisions to the conceptual model from **Figure 10**.

Observation #1

The first observation was made on a very large jobsite with 800+ workers onsite. The observation was of a crew made up of a crew lead and three or four electricians. The crew was installing conduit and pulling wire in a room and corridor area. The observation was made while one of the jobsite supervisors walked by the installation area, and the supervisor inquired of the lead about installation progress. The crew lead explained that it was taking them double the expected production rate to install in that room. The supervisor asked the lead why, and the lead explained that some of the problem was due to individual workers who were not meeting expectations on installation rates. The lead also explained that the room was full of other trades' equipment, tools, materials as well as their own; plus there were obstacles in the ceiling that they hadn't anticipated working around.

The items below were noted as information generated at the point of installation. In this observation, the information would have been lost had the supervisor not walked by and inquired.

- Crew running into physical obstacles in installation space
- Crew running into obstacles with debris in the work area
- Crew not installing as fast as expected

Observation #2

The second observation was on a mid-sized commercial jobsite, where the core and shell of the building was being constructed. On this jobsite, an observation of interaction between trades demonstrated the information loss at the point of installation. The electrical foreman walked by a crew of sprinklerfitters, who stopped him to ask a question. They were preparing to run a sprinkler line and asked the electrical foreman to move his temporary light that was installed in the concrete ceiling deck, so that they could run the pipe. The electrical foreman informed the sprinklerfitters that it would not be possible, because if they were to run the sprinkler pipe where they intended, it would interfere with a stairwell and not pass inspection.

When electrical foreman was asked about what would have transpired had he not walked by, he indicated the sprinklerfitters probably would have run the pipe and taken down his temporary light, causing additional problems and rework later. The information generated in this interaction and not passed on beyond the two crews includes:

- Conflict for sprinklerfitters for running pipe as expected
- Knowledge about the code allowances for pipe in the stairwells
- Conflict with temporary light and the sprinkler pipe

If the electrical foreman had not walked by and the sprinklerfitters went ahead with the pipe install, information losses could have included:

- Why the temporary lights are damaged or removed
- How the sprinklerfitters determined that they should install the pipe despite the conflicts
- What the impact was for all of the additional work required to work around conflicts, and later resolve conflicts caused by the pipe not installed to code requirements

Observation #3

This was a second observation on the jobsite from observation #2. In this case, there were three crew members (journeymen and apprentices) installing conduit racks in the ceiling. They were encountering a conflict with a beam to which they needed to attach the racks. They were working together for several minutes, talking and reviewing how they could get around the conflict. The contractor's chief estimator and engineer happened to be walking the job at the same time and walked by the crew. He noticed their work stoppage and asked what was going on. They explained the conflict to him and he explained how the same type of conflict was solved a week prior by another crew who had encountered the problem. This brief encounter demonstrated several pieces of information not passed on from the crew, had the estimator not walked by, including:

- Physical conflict of installation between the rack and the beam
- Information on how to resolve the conflict from another prior encounter (e.g., that information hadn't been passed on completely to those who could use it, other than the human-to-human interface and tacit memory)
- How the crew ended up resolving it in this instance

This observation validated the model of lost time when the conflicts arise, and depending on how the obstacle gets handled. The fact that someone who had an answer walked by potentially saved the time the crew would have deliberated over the decision, and potentially saved the time they would have spent on finding a solution.

Observation #4

Observation four was on a commercial tenant fit-out jobsite. The crew observed consisted of three people: a lead journeyman, another journeymen, and an apprentice. The observation began with each of the three workers working independently on their own tasks. It ended with them all working together, in addition to a foreman's involvement, to resolve and decide on a conflict. The lead journeyman discovered the conflict when leaving his workspace to go check on the other journeyman's progress. In doing so, he ended up helping on the conflict for about fifteen minutes, and then recognizing that the conflict would be repeated for other similar install applications (fishing cable down a covered wall from ceiling), the lead journeyman called the foreman to come and help resolve the problem. The group worked together to review prints, and also explained part of the issue was that the material they had to use was owner-purchased so they did not have the same flexibility in how to resolve the problem. The owner-supplied cables were already cut to-length and so the decision of how to handle the conflict had to be made with the material assemblies in mind.

Simultaneous to the conflict above, the apprentice reported his prior task was done and came to the lead foreman for a new assignment, taking about five minutes from each of them to review work, review prints, and review new assignment. Immediately following, another electrician came over to the lead journeyman asking to borrow a tool. This observation was rich with examples of information that is generated at the point of installation; some was passed on beyond the crew level, and other information was not:

- Decision on how to handle cable install through the wall, given the owner-supplied material limitations. This decision and information was passed on to the foreman, but the material issue was not passed on beyond where the decision was made

- Secondary crew needing tools and taking time from this crew to borrow and look for them
- Information and direction about how to proceed with work to the apprentice

Observation #5

This observation did not occur *at* the point of installation on the jobsite, but it was included as an example of information loss. The observation was made at a jobsite where a new industrial facility was being constructed. There was a meeting being held between the crew leaders, project manager, and project executive of the electrical contractor. The crew was reviewing results of their Short Interval Scheduling process, where items such as other trades, design conflicts, and other items were showing up as the top reasons why they could not complete their daily scheduled work. Following the review of these results, the project executive asked the crew if there were any other issues on the projects. A heated exchange followed where the crew leaders brought up several issues they were having with tools and material, such as not having tools/material, having wrong tools/material, having broken tools, not being able to find tools/material, and more.

In regards to information loss, this observation was interesting because the issues about the tools and material issues the crew leaders were not being passed on in any other means other than in this meeting verbally. This indicated that either (a) the information about the tool and material issues is not passed on when the issues occur, or (b) the information about the actual obstacles as captured in the SIS process indicates the tools and materials may be problematic, but there are larger issues causing more lost time and unscheduled work on a daily basis.

Observation #6

This was an observation on a small commercial project, where the electrical foreman was explaining problems he had when prefabricated conduit racks were delivered to his jobsite from the prefab shop. The racks were designed and built without the foreman's involvement; not only were the racks built differently than the foreman expected, in addition the conduits in the racks were jostled during shipping. Because of these unknowns, pieces of racking needed to be reworked onsite. This could be considered a minor problem, and likely happens with materials or assemblies whether or not they come from prefabrication, the focus on the information available and not passed on observed in this exchange included:

- Information about how racks were expected was not passed from foreman to prefab shop before the shop began building
- Information about the problems with the racks, both in design and shipping was not passed on
- Information about the issues encountered onsite and resulting rework was not passed on

Observation #7

This observation was made on a new construction commercial project, where several trades were working in the same areas, and working to get the project done on time. The electrical construction crew consisted of an apprentice and journeyman working to install conduit in the ceiling. The apprentice was on a scissor lift installing pipe, and was running into conflicts with the plumbers, painters, and other electricians. Most of his time was spent moving up and down on the lift to maneuver around the others who were shouting at him to get out of their way. The apprentice did no installation work in this timeframe because of the conflicts. This observation validated the lost time involved with working around obstacles and information generated and lost because he did not record or report anything included:

- Conflicts with other trades in the same working space
- Impact of the conflicts and how much time was lost to move around

In summary, the observations proved that there is information generated and available at the point of installation that is often not passed on beyond the worker or crew level. Even if the information is passed on to the foreman, there are impacts of the information beyond the foreman level and the information often does not go beyond the foreman. Based on the observations, and prior experience of the author, the information generated and available at the point of installation was mapped onto two dimensions, shown in **Figure 11**. The two dimensions characterize the information as:

1. Within vs. between trades; if the information was pertaining to a situation that only involved one trade, it is “within trade” only and if the information pertained to situations involving other trades, it is “between trade” only.
2. Building vs. work related; if the information was pertaining to the physical structure being built or worked on, it is “building” only, and if the information pertained to the work including how, where, when, who, and what is involved in the building, it is “work related” only.

Some of the observations map to multiple locations if the observation consisted of multiple types of information generated. The information generated that was lost, or not passed on beyond the crew included:

- Information about the obstacle encountered including who, what, why, where, and when,
- Information about how the situation is handled, including decision making and reasoning,
- Information about the outcome and impact of the obstacle encountered, including lessons learned, lost time, and other impacts.

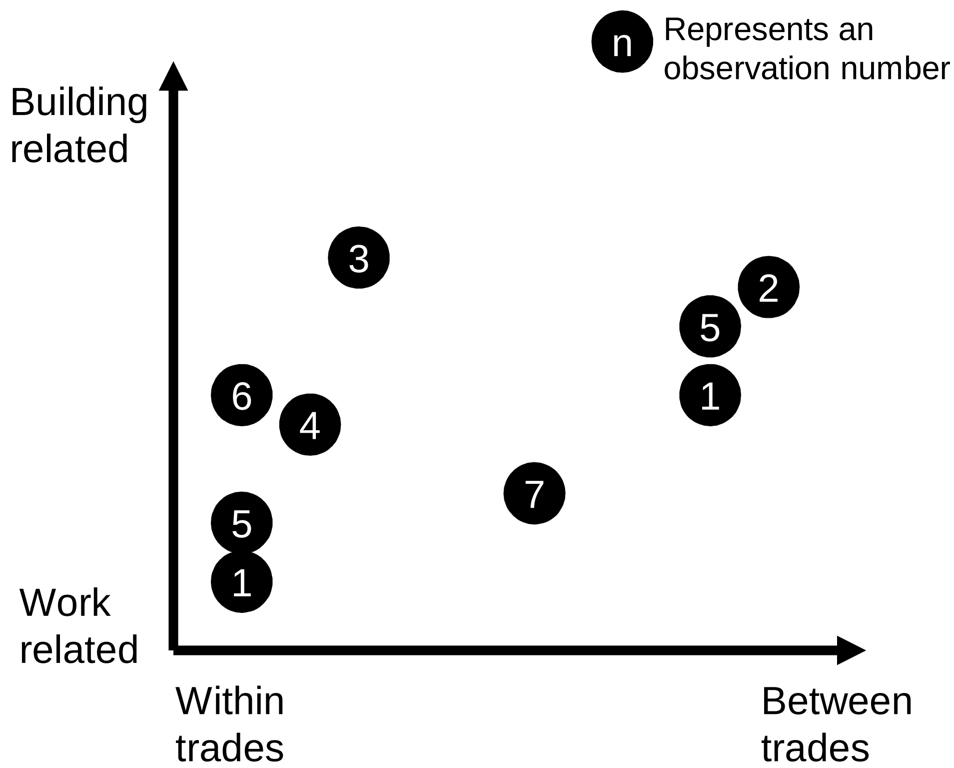
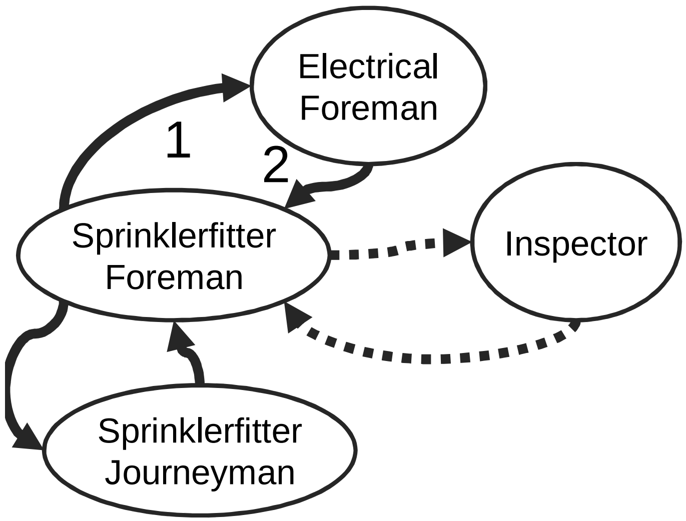


Figure 11: Map of type of information generated at the point of installation based on observations, and in two dimensions

The purpose for the jobsite observations was to evaluate the conceptual model shown in **Figure 10**. Each observation was mapped with a depiction similar to that of **Figure 12** to see the ABM considerations, the physical and network interactions, as well as the social network aspects.



SNA Considerations:

-Reasons for selecting to interact, or leading to influence in decision:

- -"line of interaction" (the interaction happened because the electrical foreman physically walked by)
- -Technical knowledge (e.g. of the code)
- -Favors/dis-favors/ego
- -Risk in asking forgiveness vs. permission

Interaction

- Electrical FM (EFM) walks by sprinklerfitter foreman (SFFM)
- SFFM stops EFM (**note 1** in network above) to ask if the EFM will move a temporary light because the sprinklerfitters have to install a pipe there
- EFM says sprinklerfitters. cannot do that anyway because it is against code since the pipe would end up running through the stairwell (**note 2** in network above)
- QUESTIONS RAISED:
    - How would this have happened differently if electrical FM hadn't walked by? (EFM answer: "they would have run the pipe")
    - What is the relationship between sprinklerfitters and electricans prior to this interaction?

ABM Considerations:

-Logic for agents:

(1) Do work
(2) Use selection model to determine who to interact with
(3) Run into obstacle and determine how to resolve using selection model and geo-spatial impact
(4) Outcome of obstacle handling influences next decision; agents may change belief about how to handle next time

Figure 12: Sample of how each pilot observation was characterized

The results of the evaluation proved that more detail was needed in the conceptual model to describe the situation. There were three functions identified to be understood and included in the information model, since information pertaining to each is generated and could be lost:

1. Prepare for work
2. Do work
3. Handle obstacles

Figure 13 was developed to add these functions and additional detail to the original conceptual model, based on the observations done for model evaluation. In addition, the specific impacts of handling method selection are separated, and parameters are introduced that will later be used to collect data. If a worker chooses method 1, and resolves the obstacle, they are assumed to complete the task and then start a new task if the day is not over. If a worker chooses method 2, they may or may not move on to another task. The model in **Figure 13** does not depict the reporting feedback loops as were shown in **Figure 10**, but those are included in the final model.

The revised conceptual model for information available at the jobsite was reviewed against the seven jobsite observations collected in the original evaluation. All situations followed one pathway through the model in **Figure 13**, which confirmed that the concept was acceptable as a starting point for data collection to match the scenarios. With the model improved, the next step was developing a plan to collect data that populates the model.

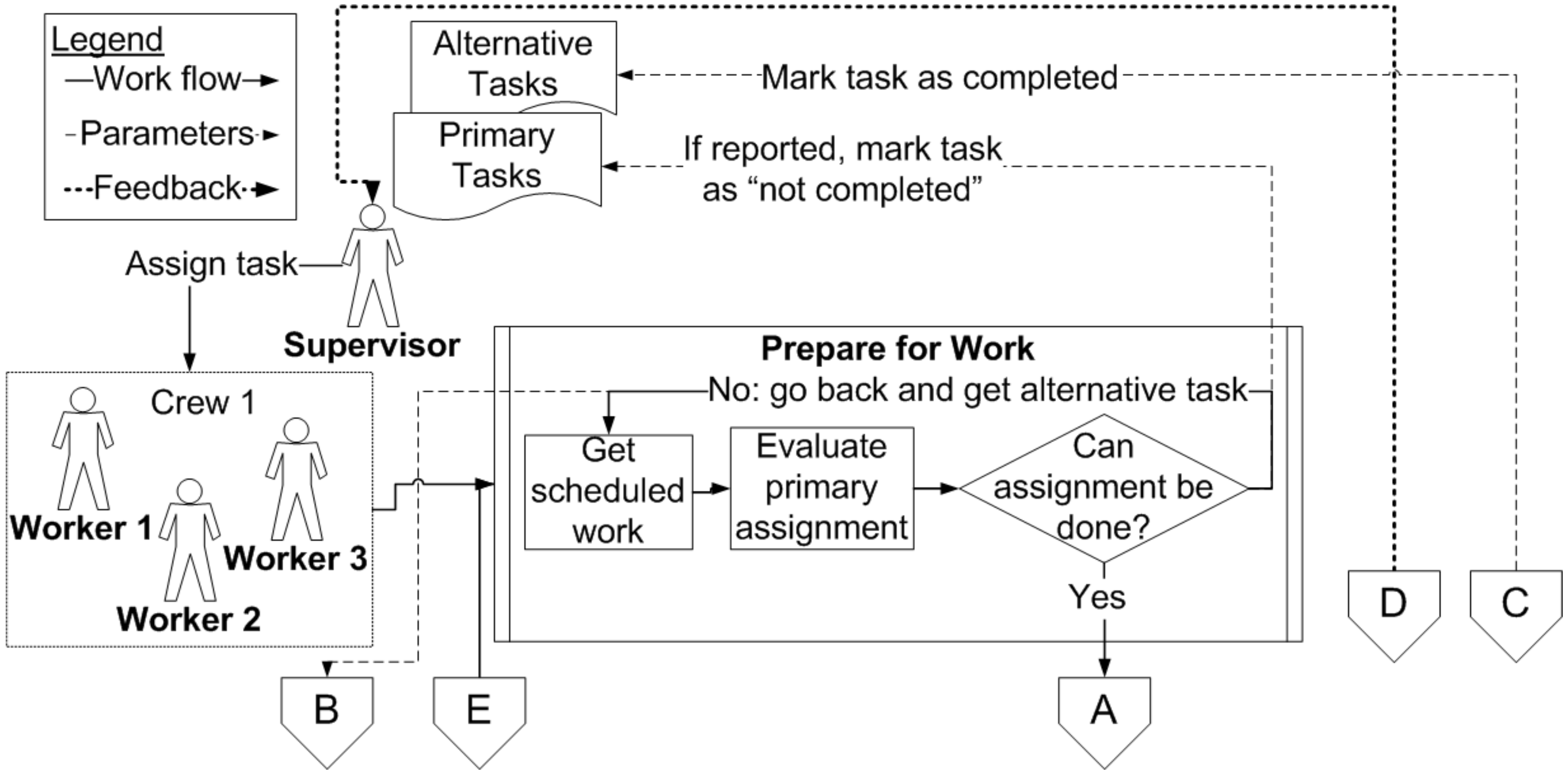
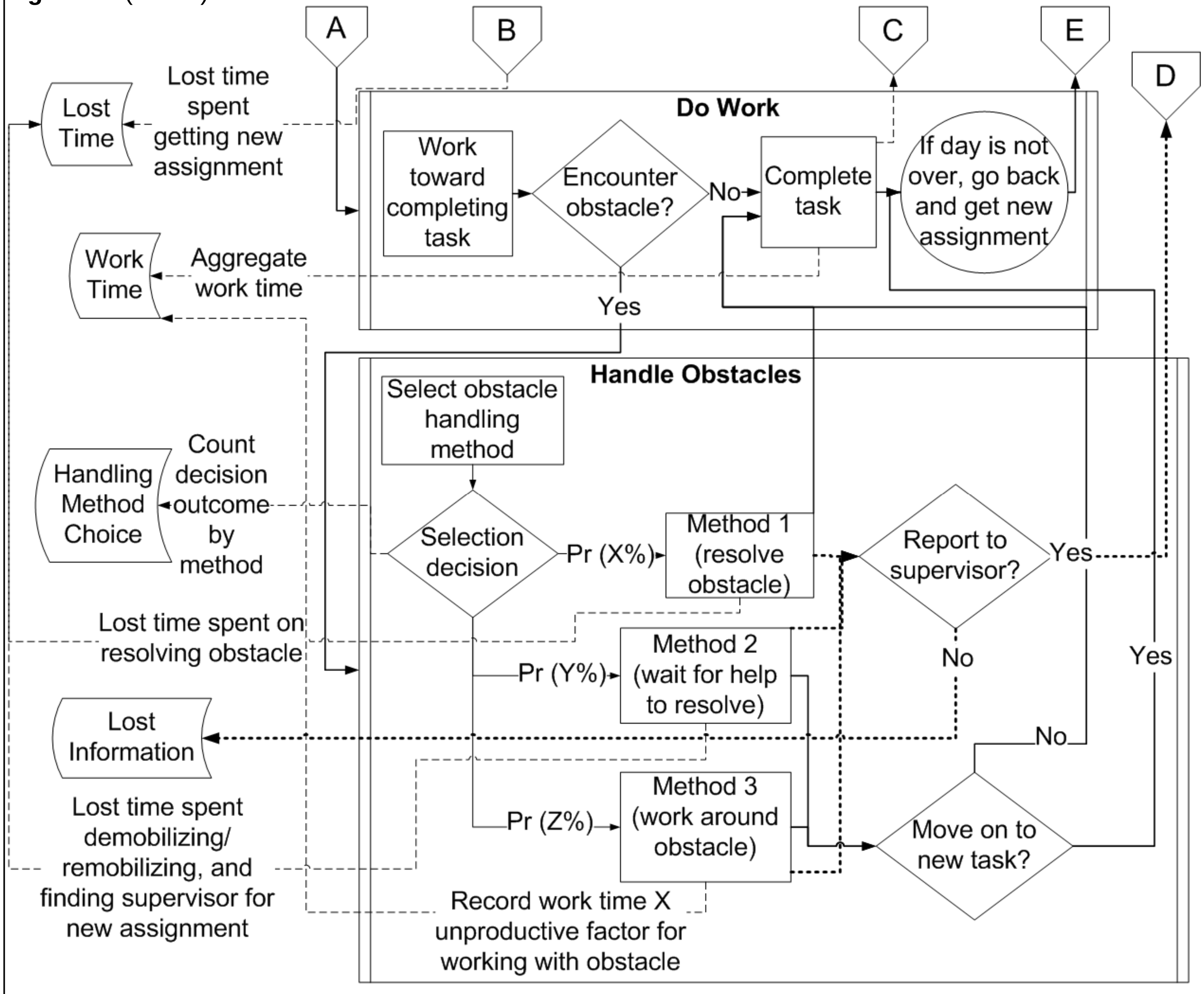


Figure 13: Revised conceptual model for situation at the point of installation, and information generated

Figure 13 (cont'd)



4.2. Data Collection and Analysis

A draft data collection instrument was created (see **Appendix B**) based on the jobsite observations used to evaluate and refine the conceptual model, and consideration for the type of data that would be needed to construct a model using ABM and SNA approaches. The instrument consists of a three page form that was used to gather data for the ABM and SNA components of the model, respectively. The form consists of two sections and the following general information:

Part I: Jobsite demographics, including information about the project being observed.

Part II: Observed work activity information, including:

- Information about the activity
- The social network of the involved crew members
- Longitudinal questions about the method used for handling obstacles
- Description of and reaction to an obstacle if encountered including impact on activity duration and installation time

The jobsite observation and data collection process included four phases listed below:

Phase 1: Pilot data collection instrument (covered in section 4.1.2)

Phase 2: Collect preliminary data, and improve collection method

Phase 3: Collect data with improved method and better quantification of variables for obstacle handling by separating handling method from reporting/no reporting

Phase 4: Collect and analyze data by separating the dependent variables of change in obstacle handling method and change in knowledge

4.2.1. Data Collection

The Phase 2 data collection plan included a plan for jobsite visits to conduct the data collection and observations. This research is unique due to its inclusion of actual observations and empirical data in the development of the information propagation model. The author has access to jobsites due to her company, MCA, Inc.'s engagement with contractors across the United States and Canada. Given MCA, Inc.'s engagements at the time of this research, a plan was developed to collect data from jobsites to which she could request access through the IRB process.

The following data collection was identified to develop the parameters needed for the final model, and to be used in the computer-based simulation:

- Specification of the installation activity, in terms of the number of agents present, and their characteristics including skill level, experience, and trade
- Specification of the installation activity, in terms of the environment including expected task duration and manpower effort required
- Agent-to-agent interactions and agent-to-environment interactions, including:
    - Time intervals and duration of actions

- Characteristics of the decisions made, such as reasoning for the decision, the resulting actions, as well as what information (if any) is disseminated

- Map of each of the observed workers' social networks within their crew, including who is in the crew together, whether they have worked together before, and each crew members' attributes
- In an individual installation activity, specific identification of workers' prior information about the belief on how they will resolve obstacles if encountered in the work activity
- Once an obstacle is encountered and handled, longitudinal data about how this impacted each crew members' future decision-making and knowledge about the obstacle and how it should be handled

The final listing of jobsite demographics from the data collection is in **Appendix C.** The jobsites encompassed a wide range of installation activities primarily electrical and mechanical construction. A random approach could not be used to represent the full population of all variables and aspects of jobsites, due to the fact that the author's access to jobsites was limited and it would have been impractical to gather data about and observe specific installation activities on a representative sample of jobsites. However, the data collection approach is valid and is a random representation of the variables within individual jobsites, including time of day, phase of the project, size of the project, and area of the project worked on.

The process for data collection involved:

1. Speak with responsible party for the construction site and its resources (typically the owner or senior manager of the contracting company). Explain data collection process and IRB protocol and gain permission to collect data on the jobsite.
2. Go to the jobsite and speak with site foreman, explaining methodology and IRB protocol. Receive introduction to installation crew and area of work. Complete part I of data collection instrument for jobsite demographics.
3. Fill out part II of data collection instrument, through inquiries of workers and observations of work activity, especially obstacles encountered and the response to the obstacles. Obstacles were defined as any observed significant disruption to work. For instance, if a worker put down his or her tools and left the work area, this was noted as an obstacle. If the worker stopped working to answer questions or have discussion with other workers on the site, or if the worker could physically not continue with his work, these were noted as obstacles.

The approach used for observation and data collection on the jobsites relied on industrial engineering principles of work sampling and work studies. Observations and interviews of workers can be disruptive to the work and/or worker, rendering the results inaccurate if care is not taken. To avoid this outcome, the observations were carried out with the following guidelines (Sellie, 2001):

- Be clear and open about the purpose and design of the study and observations. This was achieved using points 1 and 2 above, according to the IRB protocol.
- Observations were conducted discretely, by observing the work and interactions as a “by-stander”, without interruption to the work or worker; the observations were made and noted, and if questions arose, they were asked non-chalantly to understand the situation or reasoning of the workers being observed.
- Observations lasted between 30-60 minutes, which allowed enough time for the workforce to become accustomed to the observation approach, and hopefully to feel comfortable that they could and should carry on with their work as usual.

Figure 14 shows a completed data collection form. There was one component of the conceptual model that was not observed in the pilot and therefore removed from the final data collection, analysis, and simulated model, which was the evaluation of the primary assignment by the worker to determine if it can be done.

Part II: Activity Observation

Activity Description and Background

1. Activity Information

A. Activity description (e.g. pulling wire, setting carriers, etc.)
Pulling wire to generator

B. Location on jobsite (describe) Generator with site contractor working in area

C. Questions of installers:
Do you have an alternate task in mind if primary task cannot be finished? (Y/N): Y

D. If you run into an obstacle in completing this, what is your most likely response?

Circle one: (1) Resolve it, (2) Wait for help/resolution, (3) Work around it or move on

Circle one: (A) Report it, (B) Don't report it

2. Tradesmen involved in activity being observed

Sub-ject	**Trade**	**Position**	**Approx. age**	**Experience**		**Subjects worked with before** (Y/N)	**Subjects know each other outside of work** (Y/N)
	(elec, plumbing, carpenter, etc.)	(App, FM, JM)		In trade (# yrs)	In this activity (Y/N)	*(see note 1 below)*	
1	Electrician	JM	42	20	Yes	Yes	No
2	Electrician	App	23	2	Yes	Yes	No
3	Site contractor	JM?	52	Don't know	No	No	No

3. Activity Expectations vs. Actual Results

	Start Time	**Comp-letion Time**	**Total Effort** (see note 2 below)	**Manpower Effort on the Task**	
				# People involved	Total Effort (# people X effort per person)
Expected	6:00	12:00	4	2	2 x 4 = 8
Actual	6:00	12:00	6	2	2 x 6 = 12

Note 1: have the crew members worked together before on this job (on another task) or on another job?

Note 2: fill in the start & completion time OR the total duration (whichever is easier to collect)

Figure 14: Example completed data collection form (set in type with original handwritten data collection for legibility)

Figure 14 (cont'd)

4. **Obstacle Handling (if encountered)**

A. Obstacle encountered: Site contractor wanting to work in same area

B. Reaction to obstacle (circle):

Circle one: (1) Resolve it, (2) Wait for help/resolution, (3) Work around it or move on

Circle one: (A) Report it, (B) Don't report it

C. If reported, who reported by: JM to: Foreman

D. Time from obstacle discovery until next productive work (per subject):

Subject	Stop work	Re-start work	Other action or reaction to obstacle
1	6:30	6:40	Talk to site contractor
2			
3			
4			
5			
6			

E. Detailed Description of obstacle and handling: Site contractor wanting to work next to where we are pulling wire; wanting us to move it

F. Change in belief for next encountered obstacle (e.g. given the outcome of how the obstacle was handled/resolved, what would each person do to handle the next obstacle?)

Subject	Next decision (1-resolve), (2 - wait), or (3–work around); and (A – report) or (B – don't report)	Details / Comments on change in decision or approach and why
1	2A	Report to foreman
2	1A	Report to GC
3	3A	Site contractor to work around us

4.2.2. Data Analysis

The data analysis includes the general results of the data collected from jobsite observations, and analysis leading to parameters based on the final conceptual model in section 4.1. The analysis has both qualitative and quantitative components which are included in the subsequent sections. Detailed summary statistics are listed in **Appendix D**.

4.2.2.1. Summary statistics

The observations were collected over a period of 6 weeks across 11 jobsites by observing primarily electrical and mechanical trades. The observations ranged from 10-60 minutes each, and the jobsites observed were a mix of commercial and industrial construction sites in 3 states and 1 Canadian province. The construction project sizes ranged between $1,000,000 and $10,000,000, and a mix of new construction and renovation of existing buildings. The project delivery methods were equally mixed between design-build, design-bid-build, and design-assist. All except one project had a fixed-price contract; the exception was a guaranteed-maximum-price (GMP) project. Two projects had a project manager onsite full time, and two of the eleven projects did not have any onsite construction trailer or office for the crew. All activities involved installations performed by a combination of journeymen and apprentices. Foremen and other parties were involved for reporting obstacles when encountered.

The data was tabulated and both qualitative and quantitative results are included in the following sections. Some of the quantitative results were used to develop the final model parameters. Most significant is that 22 out of 25 observed installation activities (89%) encountered an obstacle, resulting in a sum of about 7-8% of the scheduled installation time spent handling obstacles. This matches closely with MCA, Inc.'s statistics on over 1,300 jobsites submitting SIS® data for over 6 years, showing an average of 6% of hours not worked as scheduled due to obstacles.

Half of the observations resulted in workers reporting the obstacles when they occurred, and the other half did not report. Only 2 of the 11 reported were reported beyond the foreman level. In sum, from the 22 obstacles encountered, information propagated beyond the crew level in only 2 instances, or about 9% of the time. This finding supports the significance of this research and need for a model of information generation, that emulates what happens at the point of installation when obstacles occur, which is not recognized or reported by workers half of the time. Furthermore, one project manager explained during a jobsite observation that installers often leave work incomplete without telling anyone, or without making decisions needed to complete installations, which contributes to the lack of quality and lack of productivity on that particular jobsite.

4.2.2.2. Qualitative Patterns

The data analysis also pointed to the following qualitative patterns that happened on two or more occasions of observation. These qualitative patterns were not used explicitly in the final model, but stand alone as observations that could be incorporated in future research to expand on the final model in Chapter 5.

1. Line of interaction.

    This was observed when an installer would engage another for help because they were in proximity. For example, during the pilot observations, an electrician walked by a plumber and the plumber asked the electrician to move a temporary light installed in the ceiling so that the plumber could install a pipe there. The electrician told the plumber that he would not be able to put a pipe in that location because it would go through the stairwell which would not meet code. When asked what the plumber would have done if the electrician hadn't walked by, the electrician surmised that the plumber would have installed the pipe anyway.

    Four other installation observations resulted in other forms of this pattern. One foreman explained that "texting" is helpful for them on the jobsite now so that the journeymen can always reach him (see pattern #3 below for potential reasoning). Several journeymen and apprentices explained that they would report an obstacle "if the foreman or interfering trade was around." In summary, geospatial distance between workers is an important factor in deciding with whom to interact on a jobsite, particularly when an obstacle is encountered.

2. Issue escalation paths.

   Four of the observations showed a common path of issue escalation, from installer (journeyman or apprentice) to foremen to GC to owner's representative. One instance excluded the GC node. This path can be modeled probabilistically for information propagation.

3. Giving or taking responsibility for a decision.

   When asked about the likely response to an obstacle, several installers mentioned that they would report it to their foreman (supervisor) and let him or her make the decision about handling it. Some installers said their likelihood of reporting would depend on the type of obstacle encountered. The reasoning for reporting is because the installers expressed that the foreman has responsibility for the decisions. In fact, one person stated that "if I report it to my foreman, it's his problem not mine." On the other hand, a crew of installers who knew each other personally outside of their jobsite environment avoided reporting obstacles to their foremen because they didn't want to burden him and take up his time. Either way, there is a level of responsibility that the crew members either avoid taking or willingly take, likely dependent on their relationship with the rest of the crew.

4. “Surrogate” foremen.

On two jobsites where an obstacle was encountered, one member of the crew that was not technically a foreman acted as a foreman in taking responsibility for crew decisions and actions. In both cases, the foreman for the jobsite was not nearby, so there may be a tendency in crews for one “lead” to take this role. Therefore, the role of foreman can be played without holding the title when obstacles are encountered.

5. The buddy factor.

In several observations, installers spoke of their decision-making reasoning in relation to their “buddies” on or off the jobsite. On the jobsite, the buddy factor is significant between trades. For instance, if the electrician encounters an obstacle with the concrete worker, he may resolve the obstacle amicably without escalation if they have history. One foreman described this relationship as “we work well with that crew; we have worked together a lot on other jobs and we help each other out a lot.” In construction, this is typically seen as “doing favors” between trades.

Relationships outside the jobsite are significant as well. One crew which was highly productive in their work and also was the single crew who “avoided having to get the foreman involved” (see pattern #3) was one where the entire crew is friends outside of the jobsite. In fact, the foreman described that knowing the subject outside of work increases his level of trust, and the crew respects each others' work and pushes each other accordingly.

6. Recognition of obstacles

The definition of obstacle for the data collection included anything that prevented an installer from completing installation or necessary work in general. This includes material handling, interference with other trades, having to find the appropriate information or tools, etc. When installers encountered these non-installation activities, they did not recognize them as obstacles. For example, when an installer was taking measurements for pipe installation and then walking to another room to cut and bend, he forgot the measurements and had to go back to re-do them. When asked about reporting the "obstacle" of having to leave his work to go find material, cut, re-measure, he replied that these activities are all "part of the work" and not obstacles. Another example of an apprentice who was asked several times to interrupt his work to move out of the way, come down from his lift to gather material, and more showed that these activities were his definition of "work" and didn't recognize those obstacles to respond to at all. This is discussed further in pattern #7.

7. Fraternity structure

In both union and open shop jobsite observations, there were occurrences of a "hazing" structure for the jobsite ranks, whereby less experienced installers are used by the more experienced to do the "gopher" work such as material seeking or whatever the more experienced installers ask. This structure also seems to include an informal training mechanism, whereby less experienced workers learn "the hard way" how to avoid or handle obstacles by having to go through them.

4.2.2.3. Quantitative Analysis of Obstacle Handling and Impact on Work Time

Analysis of the tasks, workers, and obstacles was done to determine how the data could be used in model development. The first step in the analysis was to understand the nature of obstacle handling. Of the observed installation activities 89% encountered an obstacle, defined as a "significant stoppage to work". **Figure 15** shows the proportioning of obstacle handling methods when obstacles are reported and **Figure 16** shows that when obstacles are encountered, there is an equal probability (50%) that workers will report or not report the obstacle.

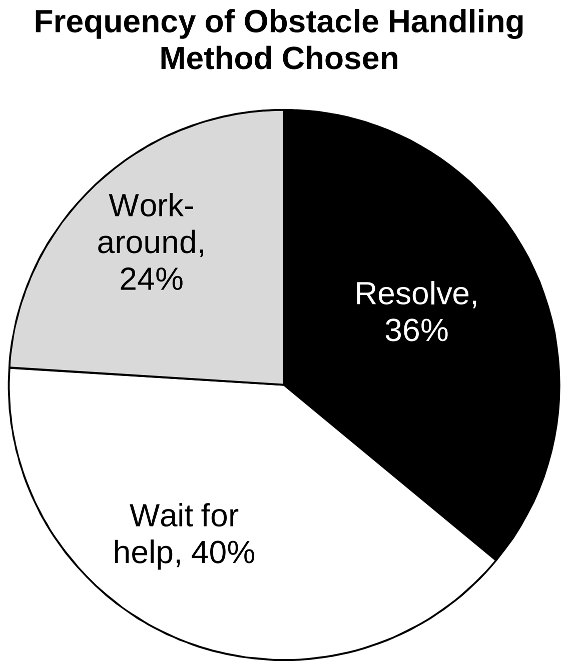


Figure 15: Likelihood of method for handling obstacles

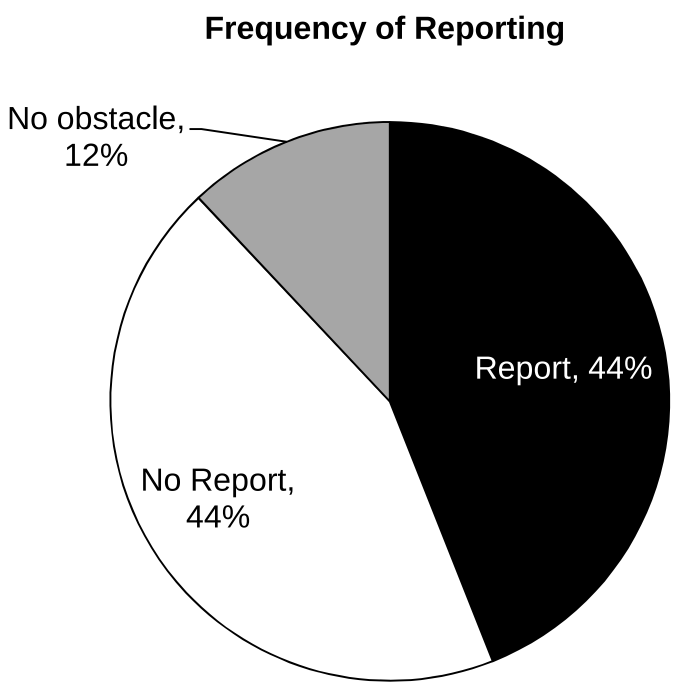


Figure 16: Likelihood of reporting obstacles

Analysis of the handling and reporting decisions was done to determine if any worker or crew attributes correlated with the decisions of obstacle handling. **Table 3** shows six different attributes and their correlation with the obstacle handling method. There were only two attributes that were somewhat significant: number of people in a crew and whether or not the crew members have individual experience with the activity being worked on. In both cases, if there are more people in a crew and if the members have experience with the activity, they are more likely to resolve the obstacle. Age, individual tenure in the trade, and aggregate crew experience do not appear to make any difference on how obstacles are handled. There is some difference in handling depending on whether or not the crew members know each other, but not significant enough based on the data collected to be included in the model.

<table>
<tr><th>Variable reviewed for inclusion as parameters in the final model</th><th>Data Analysis</th><th>Consider for model?</th></tr>
<tr><td>Number of people involved in crew</td><td><table>
<tr><th></th><th>1 person</th><th>2+ people</th></tr>
<tr><td>Resolve</td><td>3</td><td>6</td></tr>
<tr><td>Report</td><td>4</td><td>3</td></tr>
<tr><td>Workaround</td><td>1</td><td>4</td></tr>
<tr><td>Wait for help</td><td>0</td><td>1</td></tr>
<tr><td>No obstacle</td><td>1</td><td>2</td></tr>
<tr><td>Sum</td><td>9</td><td>16</td></tr>
<tr><td>Sample</td><td colspan="2">25</td></tr>
</table>If more than 1 person involved, more likely to resolve.</td><td>Yes</td></tr>
</table>

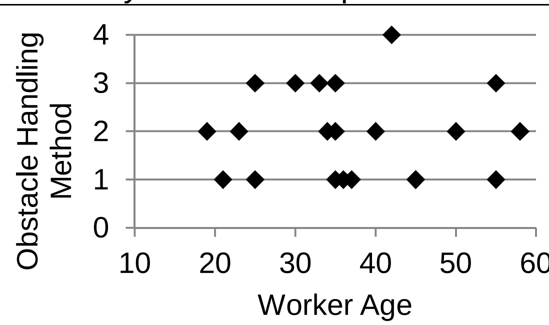
Table 3: Factors considered for impact on obstacle handling method used

Table 3 (cont'd)

<table>
<tr><th>Variable reviewed for inclusion as parameters in the final model</th><th>Data Analysis</th><th>Consider for model?</th></tr>
<tr><td>Crew members' relationship with each other

Note to interpret table: "Yes" means crew members have worked together prior to the observed work activity, "No" means that they have not worked together before, n/a means that the data was not collected or available.</td><td><table>
<tr><th></th><th>No</th><th>Yes</th><th>n/a</th></tr>
<tr><td>Resolve</td><td>3</td><td>5</td><td>1</td></tr>
<tr><td>Report</td><td>3</td><td>3</td><td>1</td></tr>
<tr><td>Workaround</td><td>0</td><td>3</td><td>2</td></tr>
<tr><td>Wait for help</td><td>0</td><td>1</td><td>0</td></tr>
<tr><td>No obstacle</td><td>2</td><td>1</td><td>0</td></tr>
<tr><td>Sum</td><td>8</td><td>13</td><td>4</td></tr>
<tr><td>Sample</td><td colspan="3">25</td></tr>
</table>If crew members know each other, somewhat more likely to resolve.</td><td>No</td></tr>
<tr><td>Crew members' experience at the activity

Note to interpret table: "Yes" means crew members have performed the observed work activity before, "No" means that they have no experience with the observed work activity, n/a means that the data was not collected or available.</td><td><table>
<tr><th></th><th>Yes</th><th>No</th><th>n/a</th></tr>
<tr><td>Resolve</td><td>9</td><td>0</td><td>0</td></tr>
<tr><td>Report</td><td>4</td><td>2</td><td>1</td></tr>
<tr><td>Workaround</td><td>3</td><td>0</td><td>2</td></tr>
<tr><td>Wait for help</td><td>1</td><td>0</td><td>0</td></tr>
<tr><td>No obstacle</td><td>2</td><td>1</td><td>0</td></tr>
<tr><td>Sum</td><td>19</td><td>3</td><td>3</td></tr>
<tr><td>Sample</td><td colspan="3">3</td></tr>
</table>If have experience with the activity, more likely to resolve. If no experience, will always choose to report obstacles.</td><td>Yes</td></tr>
<tr><td>Age of the person handling the obstacle

Note to interpret table: obstacle handling methods are plotted as
1 = resolve, 2 = report, 3 = workaround, 4 = wait for help</td><td>
</td><td>No</td></tr>
<tr><td>Crew members' total experience in the trade

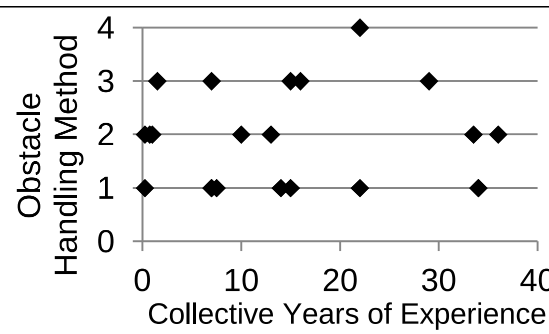
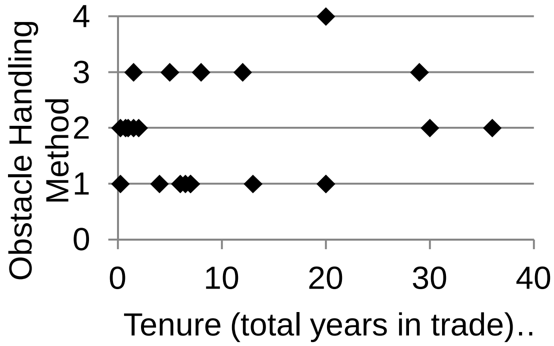
Note to interpret table: obstacle handling methods are plotted as
1 = resolve, 2 = report, 3 = workaround, 4 = wait for help</td><td>
</td><td>No</td></tr>
</table>

Table 3 (cont'd)

Variable reviewed for inclusion as parameters in the final model	Data Analysis	Consider for model?
Tenure of the person handling the obstacle in the trade Note to interpret table: obstacle handling methods are plotted as 1 = resolve, 2 = report, 3 = workaround, 4 = wait for help		No

Although the factors in Table 3 showed that there are individual attributes of workers that play a role in the obstacle handling method, these attributes were not included in the final SNA-informed-ABM model described in Chapter 5.

The next step in analysis was to determine the activity and work time, and the impact of obstacle handling on time parameters. **Table 4** shows the minimum, median, and maximum task duration for the observed tasks, and for when obstacles occur. Overall, a task will take 29% longer and 13% of the worker's time is spent not installing when an obstacle occurs.

	Min	Median	Max
Assigned Activity Duration (hours)	0.50	6.00	24.00
If obstacle encountered, additional duration required	-8%	29%	200%
If obstacle encountered, time spent not installing	0.5%	12%	66%

Table 4: Median and range for additional time involved when obstacles are encountered

Table 5 shows the additional duration required, and time spent not installing for each of the three obstacle handling methods used. In the table, Method 1 is resolving the obstacle, Method 2 is waiting for help, and Method 3 is working around the obstacle.

Additional task duration	**Min**	**Median**	**Max**
Method 1	0%	21%	100%
Method 2	-8%	42%	100%
Method 3	25%	25%	100%

Time spent not installing	**Min**	**Median**	**Max**
Method 1	2%	17%	66%
Method 2	0%	5%	25%
Method 3	5%	15%	25%

Table 5: Median and range for time parameters by obstacle handling method

The additional activity duration and non-installation time vary depending on the obstacle handling method used. **Figure 17** shows the additional effort in terms of manpower required for each observation coded based on obstacle handling method. There is not enough data in each category of handling method to draw a conclusion of statistical significance; however, the extreme points in **Figure 17** can be explained. Once they are explained, the remaining data pattern can be used to draw more meaningful conclusions.

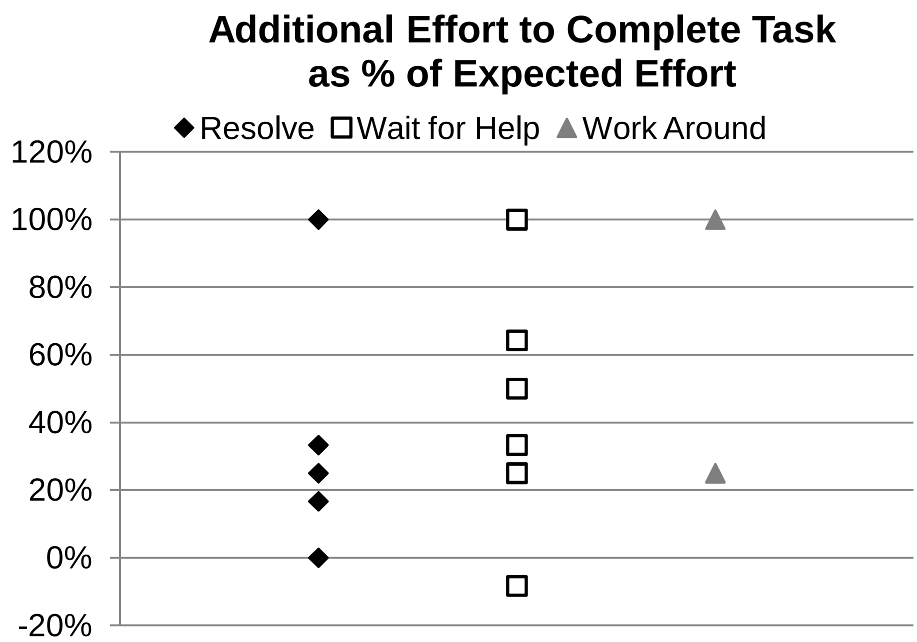


Figure 17: Range of additional effort required to complete tasks depending on obstacle handling method used

The data point in the “resolve” category that took 100% additional effort was from one observation of a crew of four people that were constantly interrupting each other to review and resolve problems together during installation. In addition, the task was expected to take only 30 minutes, representing the shortest duration task in the sample. Once the obstacle was encountered, the task took an additional 30 minutes to complete (100% longer than expected). With this extreme data point explained, all other crews that resolved obstacles themselves required **0% to 33% more effort** to complete the work.

The data point in the “wait for help” category that took 100% additional effort to complete the task was an observation made of a very inexperienced crew (less than 4 years each in the trade). The negative additional effort required (-8%, or required 8% less effort than expected) occurred when a crew encountered an obstacle yet was able to finish the task in less time than originally planned. With these two extremes explained for the “wait for help” category, all other observations in this category required an **additional effort of 25% to 64%.**

The work around category was not used as frequently so no conclusion was drawn about additional effort required in this handling method. With the extreme data points removed, the analysis indicates that **waiting for help will result in more time added to complete the task than if the crew resolves it on their own**. This conclusion is also supported by research conducted by Ankur Desai on the crew behavior when faced with obstacles (Desai & Abdelhamid, 2012 and Desai A., 2012). A deductive conclusion could be that if an obstacle is not resolved by the crew when encountered, the work on the encumbered task will need to be completed at a later date, so the time to complete the task from start to finish is extended. However, even if the crew spends additional time than expected to resolve the obstacle, the task can still be completed in the same window of time (e.g. within the same work day). The impact that this could have is on other tasks that needed to be completed that day and can no longer be worked on since the effort to resolve an obstacle spills over into time allotted to work on other tasks.

Figure 18 shows that the **time spent not installing is independent of the type of method used to handle the obstacle**. When an obstacle is encountered regardless of how it is handled, workers spend between 0 to 25% of their time not installing while handling the obstacle. The observation that showed 66% of time not installing was the same observation discussed above with the crew of four workers constantly interrupting each other to resolve problems together.

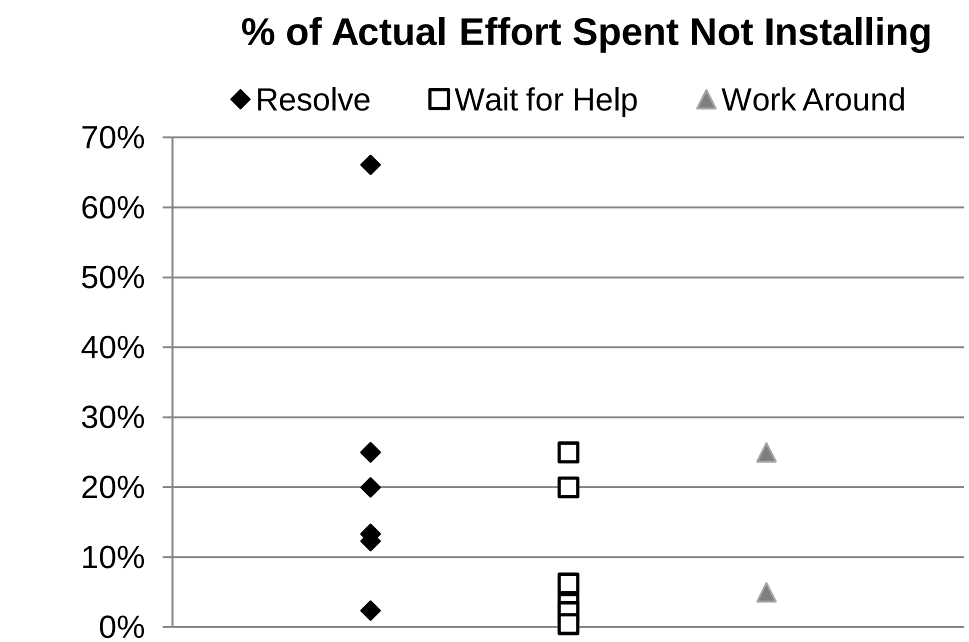


Figure 18: Range of non-installation time depending on obstacle

Beginning with observation #20, the obstacle handling method (resolve, work around, or wait for help) was separated from the reporting choice (report, no report). Prior data collected was coded as “reported” if the obstacle method chosen in the earlier phase of data collection was “reported.” If the obstacle handling method used was “resolve” or “work around”, it was assumed that the obstacle was not reported. With this new coding of data, **Figure 19** and **Figure 20** show that whether or not the obstacle is reported has an impact on the time of installation. **Figure 19** shows that obstacles that are **reported tend to take more effort to complete** than those that are not reported.

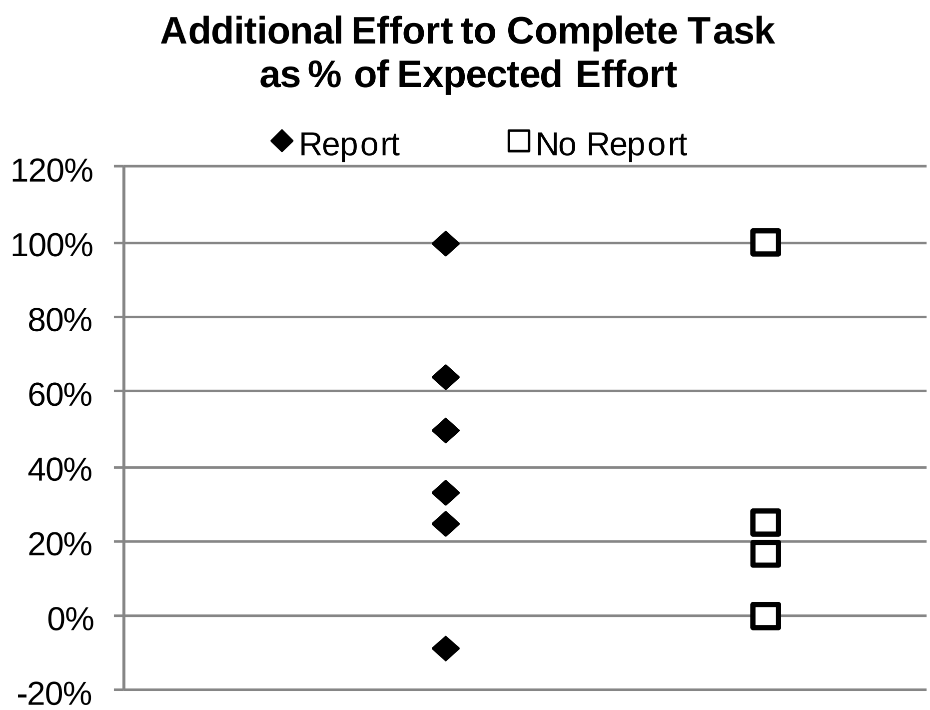


Figure 19: Range of additional effort required to complete tasks depending on whether obstacle reported or not

Figure 20 shows that tasks that are **reported result in less non-installation** time than those that are reported. This analysis leads to the conclusion that workers reporting obstacles will be able to move on more effectively, spending less non-installation time to handle the obstacles. However, when obstacles are reported, it does take longer overall for the tasks to be completed.

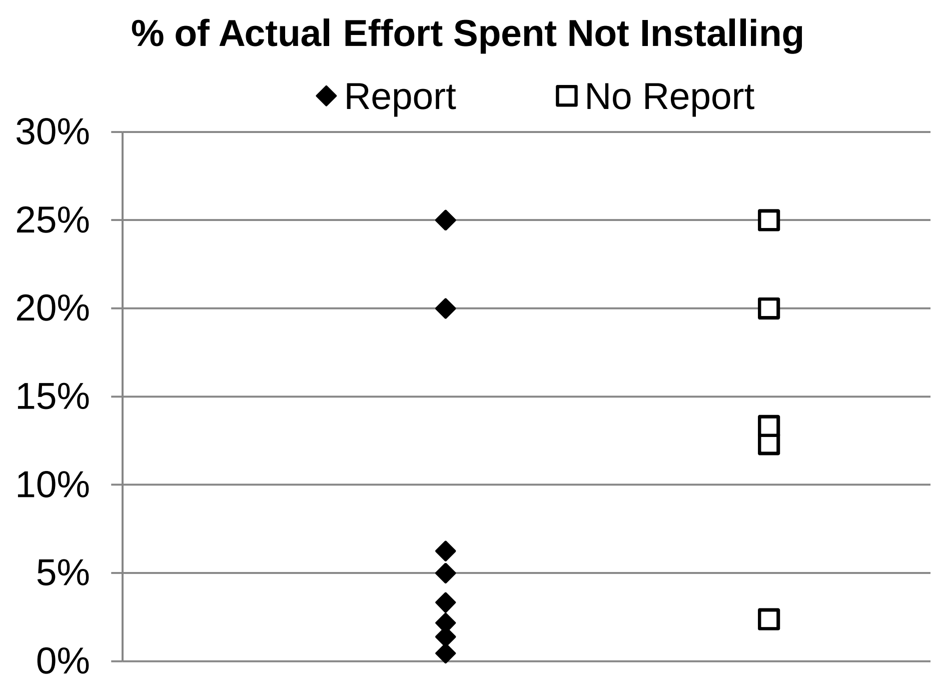


Figure 20: Range of non-installation time depending on whether obstacle reported or not (Note: one observation removed from chart, representing “No Reporting” category and 66% effort not installing)

Combining the analysis shown in **Figures 17 through 20,** the following conclusions are drawn about obstacle handling and its impact on work performance:

- Obstacles that are handled by **resolving** obstacles and **not reporting** take less additional effort to complete (e.g. are completed sooner).
- Obstacles that are handled by **waiting for help** and **are reported** take longer to complete.
- Obstacles that are **not reported** lead to more non-installation time spent by workers to handle the obstacles.

Overall, this shows that workers should resolve obstacles on their own without reporting for work to be done “sooner”; however, if obstacles are handled without reporting, the workers’ time is not used as effectively on installation.

In summary, the research results as explained in Chapter 4 show that there is information available at the point of installation on construction jobsites, and that this information is multi-dimensional. Although the information available at the point of installation is always present to the crew itself, it often goes unreported and unknown outside of the installation crew and is therefore a loss to the rest of the jobsite or even beyond the jobsite to others who could benefit from it.

To understand the information, the research conducted and explained in this chapter included development and evaluation of a model for the information, including how the information is generated, what are its characteristics, and how it gets passed on if at all. This study and resulting model addressed research questions 1 and 2. Data collected and analysis quantified the relationship between information generation, propagation and work performance in terms of additional time and non-installation effort required to resolve obstacles.

The data collected indicates that almost 9 out of 10 scheduled activities encounter an obstacle, which the installers handle in different ways. How these obstacles occur, what causes them, how they are handled, and what they impact are all lost information if the decision and handling is not reported beyond the crew level. The final model explained in this chapter depicts this flow. Chapter 5 will use modeling approaches to simulate the impact of this information loss on a broad scale of an entire jobsite when these obstacles and interactions are happening constantly.

Chapter 5: Research Results and Findings: Computer-Based Simulation of Information Generation Model

As described in Chapter 2 (section 2.5), there are several existing methods for studying and modeling information flow, as was studied and better understood through the research explained in Chapter 4. The approaches studied that were selected to be the best fit for the model of information flow are social network analysis (SNA) and agent based modeling (ABM). After developing the information generation model depicted in Chapter 4, this chapter explains how ABM and SNA models were used to understand the impact of the model. Although each modeling approach was found to be useful in representing aspects of the model in Chapter 4, an integrated approach became necessary to truly depict the complexity of the information generation model. This integrated approach was developed, and applied to the information model, using some of the parameters found in data collection and analysis. Finally, the ABM was simulated using AgentAnalyst to further investigate and explore the modeling approach.

5.1 Agent-Based Model Development

This section explains how the conceptual model in **Figure 10** (see p.69) was translated into an ABM. As discussed in Section 2.5.3, ABM is an appropriate approach at modeling the problem at hand because it has these characteristics:

- The complex environment of construction jobsites, particularly at the crew and individual task level, can be captured best with ABM. Other modeling methods have limits to the frequency, quantity, and degrees of freedom of decisions and options that are taken in a given system. ABM allows for this level of complexity to be modeled, which will be required to accurately model the information propagation.

- ABM is noted for its ability to model learning and feedback, which other modeling methods do not easily capture. This will also be important since the conceptual model in **Figure 10** (see p. 69) includes the feedback loops when obstacles are encountered. These loops will also be a connecting point to the 'influence and selection' models developed using SNA.
- ABM endows individual agents with unique behaviors, which can be studied in aggregate to determine if there are any system-wide outcomes that emerge as a result of the individual rules and interactions. The micro-to-macro level of study can be accomplished with ABM, which is one of its strengths.

5.1.1 Model Description and Components

An ABM consists of the following components: agents, their behavior, their environment, and interactions (Gilbert, 2007). These model components were applied to the final information model displayed in **Figure 13** (see p. 82) and based on the data collected and analyzed.

Agents

The primary agent in the model is a skilled-trade construction craftsman, such as electrician, plumber, mechanic, or mason. Their attributes include age, experience in the trade, experience in the task at hand, and skill level (apprentice, journeyman, foreman). Other attributes are later developed in the social network model pertaining to the agent-to-agent relationships.

Agent behavior

The agent behavior at the point of installation includes preparing for daily tasks to be accomplished, performing work, encountering obstacles, and responding to the obstacles. When an agent encounters an obstacle, he chooses one of the following three methods for handling the obstacle:

1. **Resolves it**, by removing the obstacle himself, and then continuing to work on the activity. In doing so, completing the task may take longer and the installer ends up spending unproductive time resolving the problem.
2. **Waits for it to get resolved**, either in the short term which means he stops work and idles until it is resolved; or long term which means he moves to another location and leaves the task unfinished and loses time to demobilize and remobilize.
3. **Works around it,** in this case he continues to work despite the obstacle, but loses productivity due to the obstacle being present.

In any of the three reactions to the obstacle, the worker either **reports** the obstacle or **does not report** the obstacle to a supervisor.

The outcome of this combination of events has an impact on the worker's lost time (captured as "non-installation" time), the task duration, and likelihood of choice of response the next time an obstacle is encountered.

Environment

The environment modeled is a single point of installation on a construction jobsite, and the agent will work in one space such as an electrical room, a hospital patient room, or an office room. Each activity will be assigned to a "crew" of worker agents representing one trade. Obstacles are encountered and handled by each crew probabilistically. Crews shuffle everyday so the workers do not necessarily work with the same crew members from one day to the next.

Interactions

There are agent-to-agent, and agent-to-environment interactions. According to **Figure 13,** the only agent-to-agent interactions are the supervisors assigning tasks to the crew, and the feedback from the crew to the supervisor if they elect to report an obstacle. The agent-to-agent interactions will be further defined by the social network models included in section 5.2. The agent-to-environment interactions include how tasks and obstacles are handled throughout the model. Once a task is assigned to a crew, the crew works on the task until it is completed, or an obstacle is handled. Once an obstacle is handled, the agent carries the memory of that handling method with him to the next obstacle encounter. This is similar to the "chromosome" model of Nishizaki (2009) described in Chapter 2.

5.1.2 Need for SNA-informed ABM

The information model described in Chapter 4 is one of complex production as was described in Chapter 2. In that case, each agent locally adapts and locally coordinates to solve problems and do his or her work. A pure ABM model will introduce logic to homogenous agents or groups of agents. Although it is possible to include a "learning" behavior to the agents or in the model, the cross-agent interactions and influences are challenging to represent without the inclusion of a network model. This limitation is addressed with the integration of the social network model that will be explained in section 5.2, and integrated into the final ABM model logic.

5.2 Social Network Analysis Model Development

The social network model defines the micro level network interactions of the agent, and provides a model of the influence each agent has on other agents and the crew decisions. During data collection, it became clear that the relationships that workers have with each other influence how decisions are made. The influence may be normative (e.g., "I chose to keep working in a crowded area because the rest of my crew mates aren't moving or saying anything either.") or informative (e.g., "I chose to stop installing the sprinkler pipe because another tradesman told me it would not pass inspection."). These influences on belief and knowledge in the crew about how to handle obstacles were applied in each instance of a work activity and within each agent's rules for interaction and decision making.

To develop the social network model, the networks to which a worker belongs were defined based on observations and data collection. **Figure 21** shows three networks to which a worker belongs. The networks include the **jobsite** network, which consists of workers on the same jobsite together who may or may not be of the same trade affiliation or from the same contracting company; the **contractor** network which represents people working for the same contracting firm; the **trade affiliation** network which represents workers who are a particular trade such as masons, carpenters, laborers, excavators to name a few, but may or may not be on the same job together or work for the same contractor. The overlap of any of these networks could have an influence between members.

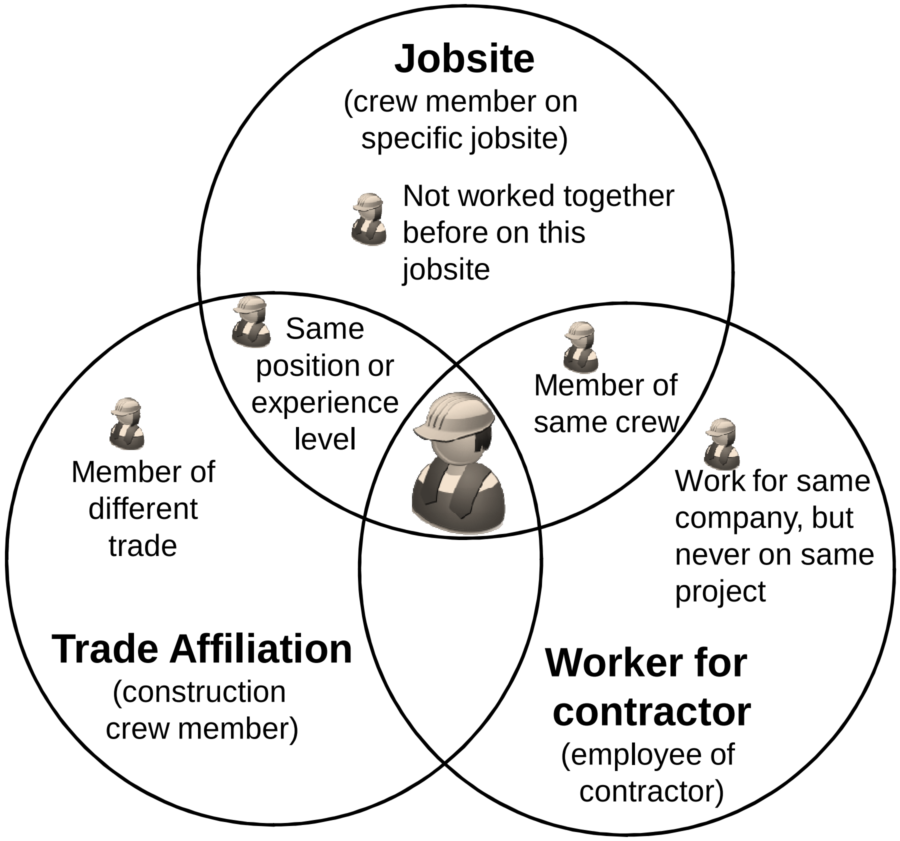


Figure 21: Overlapping social networks to which a construction worker belongs

The choices about with whom to interact on the jobsite can be driven by social or economic utility, and those choices could be different based on the network characterizing each agent-to-agent interaction as shown in **Figure 21**. The worker interactions were modeled with social network methods to capture how information and knowledge propagates within the jobsite network, specifically at the time when workers are working on assigned tasks and encounter obstacles. When the obstacles are encountered, each worker has a “chromosome” of prior knowledge and belief on the best method for handling the obstacle. This chromosome is recalled to handle the obstacle, and then depending on the outcome of the handling method, the worker’s belief and knowledge change and accumulate over time and with experience. The influence model captures this behavior within the social network. The SNA model captures the agent-to-agent influences on belief for best handling method. In addition, and more significantly in terms of information propagation, the model captures change in knowledge because of the obstacle handling and reporting.

5.2.1 Influence Model

An influence model is used to model the change in knowledge or belief about what is happening on the jobsite and how to react, based on the information that is received from, or an encounter with, others on the jobsite.

The basic influence model is shown in **Equation 2**.

$$y_{it}=\rho \sum_{i'=1}^{n} w_{ii'} y_{i't-1}+\gamma y_{it-1} \qquad (2)$$

The variables for the generic influence model (Frank K. , 2010) for the jobsite situations are described below, including the generic description and how they were used in the influence model to capture worker interactions and their influence on each other's obstacle handling method choice.

y_{it} : belief or knowledge of agent i at time t

Each agent (i) carries a belief about the best method for handling an obstacle. Prior to encountering an obstacle, he has belief y_{it-1}. This is a function of his past experience and interactions. In each interaction, he or she interacts with other crew members who have the same or other beliefs about the best handling method, and depending on their degree of influence and the outcome of the obstacle handling, agent i may change his belief for future obstacle handling. The belief of agents with whom agent i interacts are represented by $y_{i't-1}$.

$w_{ii'}$: matrix of n agents on the jobsite, and indicator of relationship between each agent i-i´ agent pair

The matrix of network interactions between n agents in the network is represented by the w variable and an n by n matrix. Each agent, i, has or does not have a relationship with each corresponding agent i´ in the network. This matrix indicates each agent i on the row, and then the relationship to the other i´

agents in the columns. In this case, agent 1 does not consider agent 2 or agent 3 a “friend” (they do not have a relationship with each other). Agent 2 is friends with agent 3, and agent 3 is friends with agent 1 and not agent 2. A sample of this matrix is shown below.

$$w_{ii'} \text{ for } n = 3: \quad \begin{array}{cc} & i' \\ i & \begin{array}{|ccc|} \hline 1 & 0 & 0 \\ 0 & 1 & 1 \\ 1 & 0 & 1 \\ \hline \end{array} \end{array}$$

There are two observations about the matrix that are important assumptions made for this research: (1) each i agent has a 1 in the reflective position of himself (e.g. position 1-1 = 1, position 2-2 = 1, and position 3-3 = 1), and (2) relationships are not necessarily reciprocal (e.g. position 1-3 = 0 but position 3-1 = 1). Both of these assumptions could be further explored and changed in future research.

ρ: extent to which agent’s beliefs are influenced by interactions in the network

This term is based on data collected about the strength of influence within the network. If agent-to-agent interactions result in change in y_{it} belief, then ρ will be high. The influence can be either normative or informative. If the influence is normative, agents are influenced by each other only because they have a relationship with each other (e.g. they are “friends”). They are changing beliefs perhaps because they respect the decision of a crew member or a supervisor in their network, or because of "peer pressure" in a situation. If the influence is informative, the agents are influenced in their decision because they learned something new from those with whom they interacted in the network. Whether or not they are friends with the other agents, they chose to change their belief because it had a positive outcome.

γ: extent to which each agent retains his/her belief

This term is also based on data collected about how strongly agents go with their own belief or knowledge about a situation when making decisions on how to handle obstacles.

Overall, the model in Equation 2 determines the outcome of each agent's belief based in part on their own "chromosome" which they bring to the situation when handling obstacles, and in part on the exposure to chromosomes of belief that their crew member agents bring to the situation. The choice to "go with their gut" versus follow their crew member's decision is dictated by how strongly they are influenced and on whether or not they consider the other members in their crew part of their social network as depicted conceptually in **Figure 21.**

Y_{it} was modeled as a function of the pieces of information, or decision opportunities, to which an individual worker is exposed. Frank and Fahrbach (1999) showed that an individual's knowledge is comprised of their own prior beliefs based on the information they carry individually, plus the information to which they are exposed within their social network. This also matches

Nishizaki's (2009) model of "chromosomes" for agents. Their own knowledge changes based on either a normative or informative exposure to information carried by others in their network, and how likely the agents are influenced by exposure to others in the network. So the individual knowledge of a worker will be a function of the information available to them individually plus the information present among all of the workers on the project plus the average knowledge (Y_{it}) of all others on the project, which represents the prior information to which all workers are individually exposed.

5.2.2 Selection Model

The selection model shows the nature of relationships or the network built among different jobsite personnel (Frank K. , 2010). **Equation 3** shows the generic selection model and its components are described below. This model was considered for determining how the individual attributes of workers in the jobsite network become "friends" or not to populate the w-matrix of the influence model in section 5.2.1.

$$\log\left[\frac{p(w_{ii'})}{1-p(w_{ii'})}\right]=\theta_0+\theta_1\left|y_i-y_{i'}\right|+\rho w_{i'i} \tag{3}$$

The model is established as a logistic regression model with the θ coefficients representing the weight of the attribute upon which an agent will select to interact with another agent. The final element of the equation is a measure of reciprocity among the agents.

This selection model is built with different θ's representing the weight of each attribute an agent has that determines whether or not he is friends with another agent. For instance, θ_1 can be based on the weight of interaction when two crew members have the same experience level. θ_2 can be based on the weight of interaction when two members are the same age. θ_3 can be based on the weight of interaction when two members have experience working together on an activity prior to their current assignment. Essentially the θ's represent the degree of importance that a worker puts on selecting to interact with another person based on the similarity of an attribute.

5.2.3 Need for ABM to integrate with SNA

SNA allows for depiction and analysis of the social utility and influences in a network of people. The models developed by Frank and Fahrbach (1999) are useful in modeling complex production, where people must locally adapt and locally coordinate to accomplish their work. The observations in Chapter 4 show that points of installation on jobsites are complex production, and therefore similar social network models can apply. Although the influence and selection models are developed above to model the network interactions, a computer-based simulation of the macro-level impact of these models in concert with other environmental and agent interactions was needed for this research. These social network models can explain how workers make their choice about handling obstacles and whether to report them, but the network model alone cannot simulate and allow experimentation on the entire information model shown in Chapter 4.

An integrated approach was needed in which ABM is used to model the worker agent behavior in the information generation model, and SNA is used to model the complexity of the network interactions and influences among the workers. A fully integrated model was considered to provide a better and more accurate representation of the information generation model than the SNA models alone.

5.3 SNA-Informed ABM Integrated Model

An integrated SNA/ABM model was developed for further evaluation and exploration of the conceptual information generation model discussed in Chapter 4 and developed based on empirical data collection as well as deductive research. To develop the SNA-informed ABM model, recall the literature review in Chapter 2, which found that the Nishizaki et al. (2009) approach was the closest at truly integrating an SNA model into agent behavior in the ABM. A similar approach was used herein.

A conceptual SNA-informed-ABM model is shown in **Figure 22**. This figure represents the same three phases described in the conceptual model of Chapter 4. It shows the ABM logic as well as the integration of the influence and social network models for agent interaction into the heterogeneous population of workers. To finalize and simulate the model, a model was developed in the next section to represent the stochastic choices and behavior of agents that will be used in the final influence model.

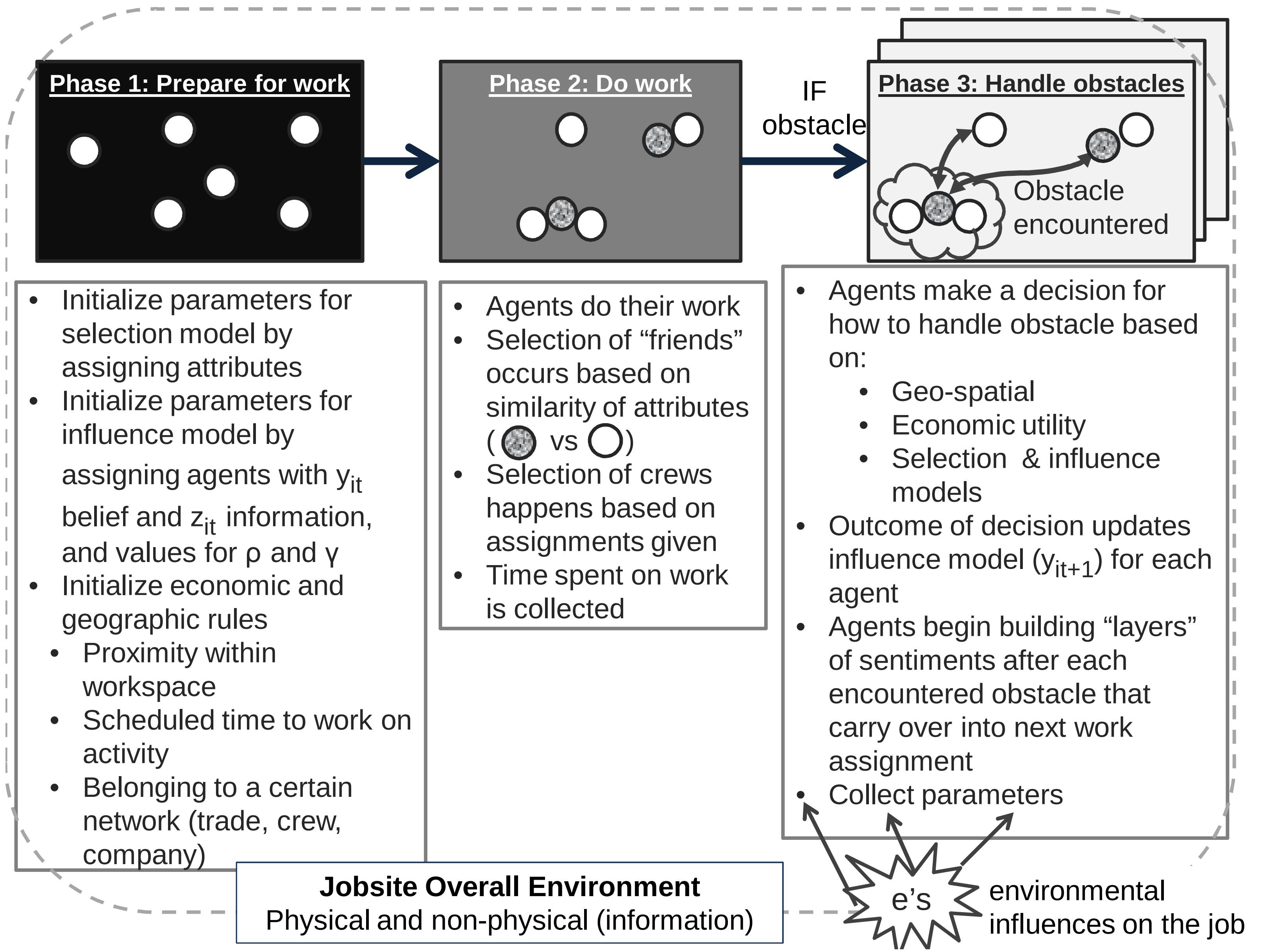


Figure 22: Conceptual model of SNA-informed ABM

5.3.1 Stochastic Modeling of Obstacle Handling Choice

One of the aspects of the conceptual model is that the outcome of handling an obstacle impacts a worker's future belief in obstacle handling and potentially influences the crew of workers if the obstacle is reported to a supervisor and the supervisor can respond to resolve it. Both of these outcomes will be modeled using the influence model described in section 5.2.3. To determine the model parameters for the stochastic behavior, longitudinal data was gathered in the data collection. Data representing three timeframes were collected as follows:

1. Ask the worker how he believes he would handle an obstacle if it occurred; this was asked prior to observation of the actual installation activity. This belief is denoted $\mathbf{y_{it-1}}$.
2. Observe how the worker handles the obstacle. This is denoted $\mathbf{y_{it}}$.
3. Ask the worker how he would handle the obstacle if encountered in the future, given the outcome of the current obstacle. This is denoted $\mathbf{y_{it+1}}$.

Figure 23 shows the number of workers choosing each belief about obstacle handling in the three timeframes. Observations listed as "n/a" occurred when the longitudinal data was not collected on all three timeframes.

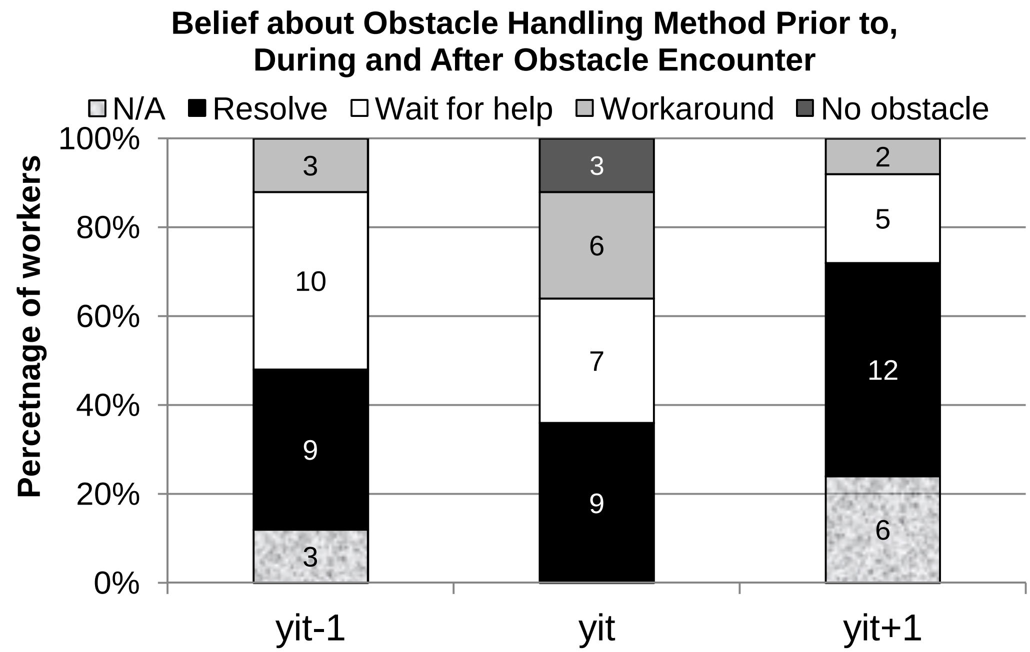


Figure 23: Change in belief about obstacle handling method from yit-1 (prior to encountering an obstacle), yit (during obstacle encountered), and yit+1 (following obstacle encounter)

Figure 23 represents the beliefs of all workers in each timeframe in the aggregate. To model the individual worker belief transition from the three timeframes, which was used for the ABM model logic as part of the influence model, the individual paths of workers were assessed. In addition, to model the decision-making probabilities, the categorical data needed to be translated into a probabilistic representation of a worker's decisions before, during, and after handling obstacles. **Figure 24** shows the number of observations that took each y_{it-1}, y_{it}, and y_{it+1} progression as a path. **Figure 25** shows the same longitudinal information for the decision of whether or not to report obstacles. Each decision tree starts with the total number of observed activities. Figure 24 shows that of the 25 activities in which a worker said he would handle an obstacle using one of the three methods, denoted as "X method", he actually ended up using "X method” in 8 instances and in another 8 instances he used something else, denoted as a “non-X method.” For the 8 instances where he said he would use X method and actually used X method, when asked after handling an obstacle what method would he chose in the next obstacle encounter, 7 of the responses were that he will use the same X method.

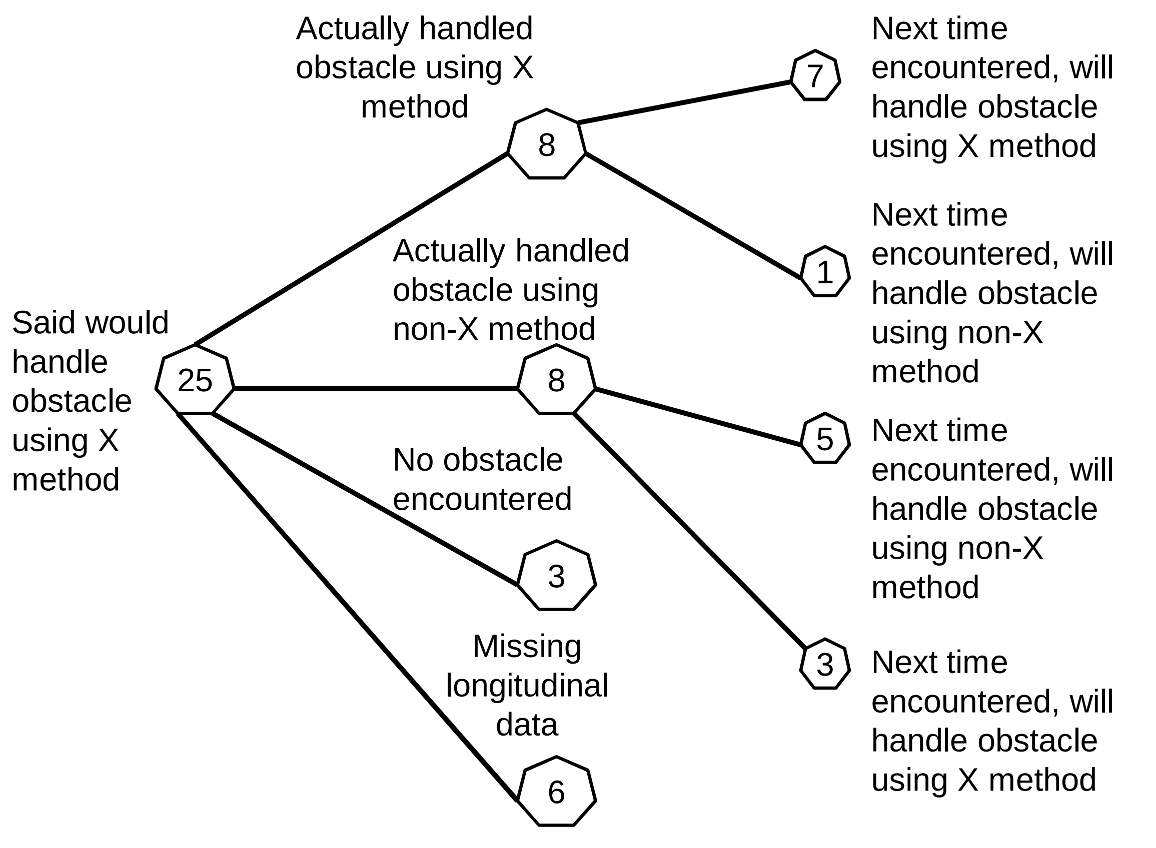


Figure 24: Stochastic model for longitudinal obstacle handling decisions

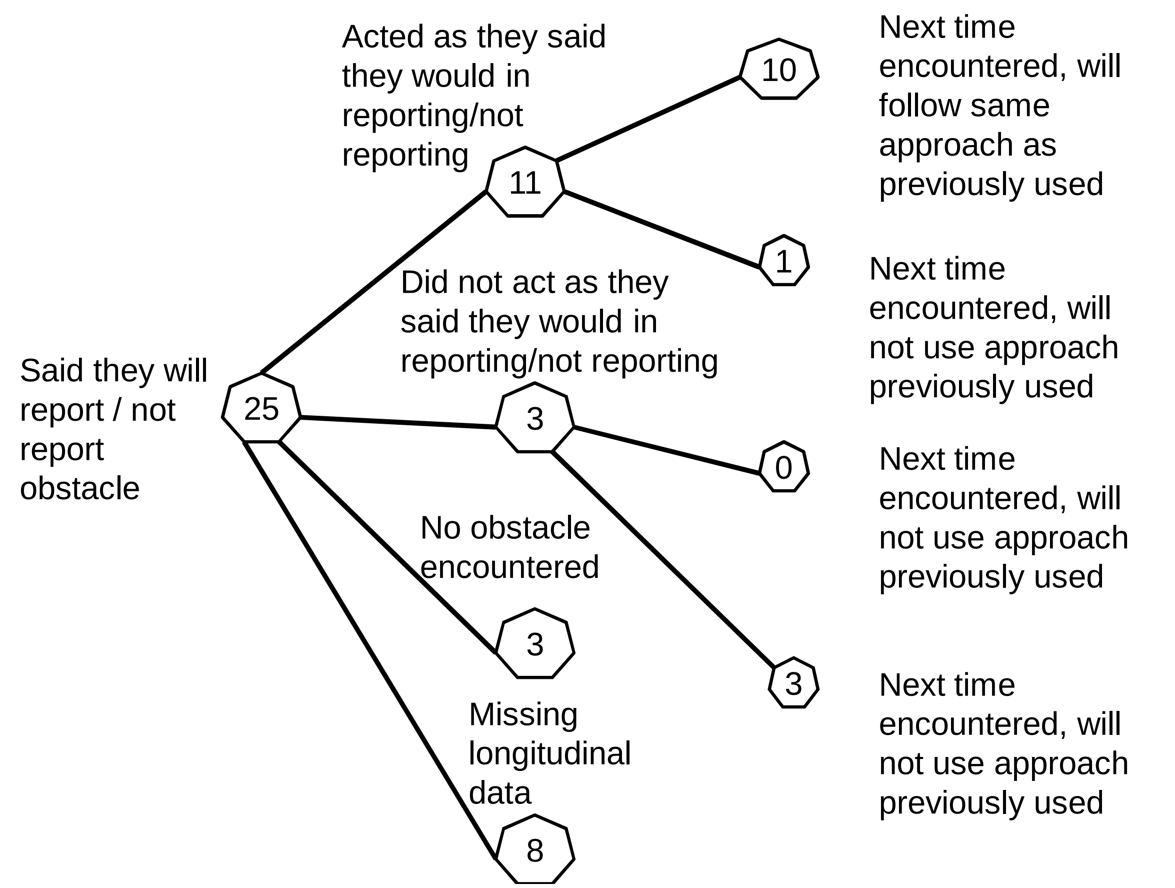


Figure 25: Stochastic model for longitudinal reporting decisions

5.3.2 Final Influence Model

The influence model outlined in Chapter 2 is applied to the information model of Chapter 4 based on the observations and data analysis results. Agents in the final model are influenced based on who is in their crew, and those crew members' beliefs.

An initial influence model was developed that began with each agent having probabilities of choosing obstacle handling choices based on the probabilities shown in **Figure 15.** The w-matrix was populated for whether crew members were "friends". In the final simulation model, this population happens randomly with each pair having a 50/50 chance at being friends. The decision for how to handle an obstacle has a component of the individual agent beliefs from **Figure 15**, and also a component based on interaction with other agents. In the initial influence model, the value of ρ is 0.62, based on the data collected that indicated 62% of the decisions on how to handle obstacle are influenced by other crew members. In this initial model, the value of γ is 0.5, meaning that workers retain their own belief in obstacle handling method 50% of the time, also an outcome of the data collection. The final initial SNA model as described for the initial iteration is shown in **Equation 4.**

$$y_{it}=0.62\sum_{i'=1}^{n} w_{ii'}y_{i't-1}+0.5y_{it-1} \tag{4}$$

After the initial iteration of the model, workers that have encountered an obstacle now carry a “chromosome” with them for future decision-making. Their belief in handling the next obstacle included their y_{it} from the prior obstacle encounter (y_{it-1}) as well as the beliefs other agents brought to the crew based on their individual obstacle encounter outcomes. In this model which was applied after t = 0, ρ = 0.43 representing the normative influence of other crew members on the worker. This was based on data collected, indicating that 43% of the time workers were influenced in their decisions based on their interactions with other workers, but only to the extent that they had a social relationship with the other workers. In other words, a worker would be influenced in his/her decision because they are crew-mates only, not because the other crew member passed on new information to the worker.

To model the impact of information propagation in the jobsite network, an additional parameter was included in the model. The parameter used is a binary variable S_r representing whether or not the workers reported in the obstacle in the y_{it-1} beyond the crew level. There is a 50% probability of this reporting based on the data collected. When a supervisor is informed, there will be a higher likelihood that the obstacle will get resolved by the crew since the supervisor has information that can be passed on to the crew for them to resolve on their own. The weight of this influence is modeled as a "weight" of ρ_2 to the binary S_r variable as 0.19 based on the data collected that showed 19% of the influence of others on a worker was informative, meaning that workers were influenced by others because the others passed on new information to them. This weight is not as high as the weight of the other workers' influence from normative influence, which was mentioned above as $\rho_1 = 0.43$. The final SNA model described above as used in all iterations after t=0 is shown in **Equation 5**.

$$y_{it}=0.19S_r + 0.43\sum_{i'=1}^{n} w_{ii'}y_{i't-1}+0.5y_{it-1} \qquad (5)$$

5.3.3 Computer-Based Simulation of SNA-Informed ABM of Information Generation Model

The final model represents the conceptual ABM model depicted in **Figure 13**, with an integration of the social network analysis as shown conceptually in **Figure 22**. The social network integration is specifically the final influence model explained in section 5.2.3. The model parameters were derived from the data collection and analysis from section 4.2.2. Model logic explains what happens in each iteration of the model, with the agents, obstacles, tasks, and the "chromosomes" of beliefs and information that are or are not passed on within the crew members and to outside supervisors.

5.3.3.1 Model Parameters

Parameters were identified for model input and output. The input consists of data needed to simulate the ABM behavior described in section 4.1.2. To integrate the social network component, the influence model was also parameterized with the values based on the data collection and analysis. **Appendix D** shows tables of the parameter identification used for model input. Output parameters were driven by what questions the model was required to answer, including:

- How much time do workers spend installing versus not installing?
- How many tasks are left unfinished at the end of each day?
- How much information is propagated beyond the crew level, and how much information is lost?

- How does the information propagation impact future obstacle encounters for the entire jobsite and for each worker?

Appendix D includes a table of the output parameter identification based on these questions.

5.3.3.2 Model Logic

The model included logic for the initial iteration ("tick") and separate logic for each iteration thereafter. The model tick represents one day of work on a jobsite. Before the model begins, the agents and environment were initialized. The agents were initialized with parameters listed in **Table 9** (see **Appendix D**). For the social network initialization, each worker was assigned to a crew, with crew size distributed according to the data collected. Within the crews, workers were "friends" with a 50% chance. If they were friends, the w matrix was populated with a "1" for the pair of workers. The crew makeup of individuals changed in each iteration of the model, to simulate workers being assigned to new crews from one day to the next. However, the workers still carry with them their "chromosome" of exposure and belief about obstacle handling from one day to the next.

The crews were assigned tasks which then became unavailable for assignment to any other crew. Task duration was assigned with the distribution developed from data collection. Each crew had an 89% likelihood of encountering an obstacle.

T0 model

In the initial tick, each worker (agent) had the same distribution of probability for handling obstacles with each of the three methods, based on probabilities shown in **Figure 15**. Each agent brought with them their own belief in how to handle the obstacle, and then the influence model described in Equation 4 was invoked for the crew. Since the obstacle handling method data was categorical, an influence model representing the likelihood of each decision method was used, as:

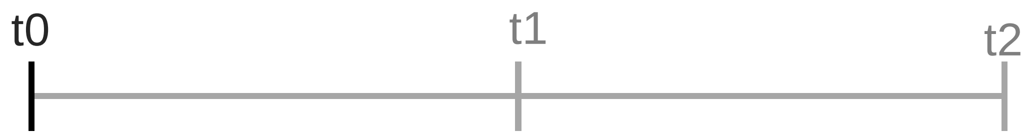
$Y_{it}1$ = crew belief that method 1 should be used (resolve the obstacle)

$Y_{it}2$ = crew belief that method 2 should be used (wait for help)

$Y_{it}3$ = crew belief that method 3 should be used (work around the obstacle)

- Whichever of the three Y_{it} values was the highest was the decision made by the crew. Each worker in the crew "remembered" this method and carried it as his or her new belief or preference for obstacle handling to the next iteration of the model.

An example of the calculation carried out using the model described above for t0 is shown in **Figure 26**, for a network of 3 agents.



3				i				yi't-1				yit-1
			i'	**1**	1	1		0				0.41
yit1	0.62	X		0	**1**	1	X	1	+	0.5	X	0.41
				1	1	**1**		0				0.41
	0.62	X	0.39	+	0	=	**0.45**					
3				i				yi't-1				yit-1
			i'	**1**	1	1		0				0.36
yit2 =	0.62	X		0	**1**	1	X	0	+	0.5	X	0.36
				0	1	**1**		1				0.36
	0.62	X	0.44	+	0	=	**0.46**					
3				i				yi't-1				yit-1
			i'	**1**	1	0		1				0.23
yit3 =	0.62	X		1	**1**	0	X	0	+	0.5	X	0.23
				1	1	**1**		0				0.23
	0.62	X	0.44	+	0	=	**0.4**					

Figure 26: Example of SNA model in t=0 for a 3 x 3 w-matrix

In each tick after t=0, the T1 influence model was used, which had different values for ρ and γ as explained in Equation 5. In addition, the variable representing the influence of reporting to the supervisor (S_r) was included in the

T1 model. The value of $y_{i´t\text{-}1}$ represented an array of each i´ agent's method for handling obstacles in the prior encounter. For instance, in a crew of 3 workers:

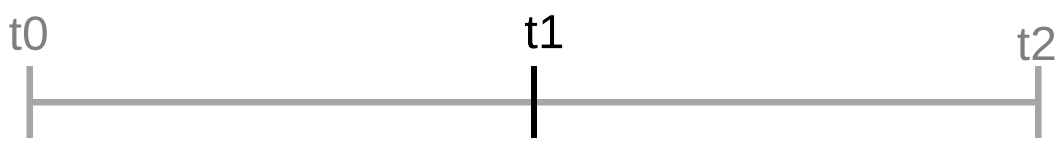
If agent 1 chose method 1 in t-1, the $y_{i't\text{-}1}1$ array is 1,0,0

If agent 2 chose method 2 in t-1, the $y_{i't\text{-}1}2$ array is 0,1,0

If agent 3 chose method 3 in t-1, the $y_{i't\text{-}1}3$ array is 1,0,0

In t=1, $y_{it\text{-}1}$ represents the probability of methods chosen by agent i in t=0. For instance, if $y_{it}1 = 0.42$ in t1 for agent 1, then the first row of the $y_{it\text{-}1}1$ matrix is 0.42. The other rows are populated with resulting probabilities in the prior step of each i agent. If $y_{it}2 = 0.20$ in t1 for agent 1, then the first row of the $y_{it\text{-}1}2$ matrix is 0.20. The other rows are populated with resulting probabilities in the prior step of each i agent.

S_r represents the impact of reporting obstacles to the supervisor beyond the crew. If the obstacle was reported by a crew on a given task that was left unfinished either because it was not resolved or the day ended before it was complete, when the supervisor next gives the task assignment to the next crew to finish, he passed on the information to the crew being assigned, and they became more likely to resolve it. Therefore, the S_r variable was only included in the $y_{it}1$ equation which represented a crew's likelihood to choose "resolve" as their obstacle handling method. The fact that the supervisor passes on the information to the next crew was also an assumption made for this research; future research could explore this assumption further by collecting appropriate data and modeling the results. An example of the t=1 calculations made based on the model listed above is shown in **Figure 27**.



											Y1				
								i			yi't-1				yit-1
							0	1	0		1				0.5016
yit1 =	0.19 X	0	+	0.4	X	i'	1	0	0	X	0	+	0.5	X	0.5000
							1	1	0		0				0.2000
yit1 =	0	+	0.4	X	1	+	0.200								
yit1=	**0.41526**														
											Y2				
								i			yi't-1				yit-1
							0	1	0		0				0.4556
yit2 =			+	0.4	X	i'	1	0	0	X	1	+	0.5	X	0.0000
							1	1	0		1				0.7000
yit2 =			0.4	X	1	+	0.193								
yit2=	0.40759														
											Y3				
								i			yi't-1				yit-1
							0	1	0		0				0.0000
yit3 =			+	0.4	X	i'	1	0	0	X	0	+	0.5	X	0.5000
							1	1	0		0				0.1000
yit3 =			0.4	X	0	+	0.100								
yit3=	0.1														

Figure 27: Example of SNA model in t=1 for a 3 x 3 w-matrix

The functions used by AgentAnalyst (the software used to build the ABM) are shown in **Appendix E.**

5.3.4 Simulation Results

The information model was simulated in AgentAnalyst with various settings of parameters to determine the impact of those settings on the behavior and information generation and propagation from the point of installation. **Appendix F** shows a sample of the model output that was used for analysis. The following data was available from the model output:

- Time scheduled for work for all agents in all crews
- Total time spent working for all agents in all crews
- Total time by all agents spent not installing
- Number of tasks that were assigned and left unfinished
- Total unfinished tasks (including those assigned and left unfinished, and those not yet assigned at the model stopping time)
- Tasks completed
- Total tasks attempted (the sum of completed tasks and tasks that were assigned and left unfinished)
- Total count of obstacles encountered
- Number of obstacles reported to the supervisor
- Count of each of the 3 obstacle handling methods chosen

The simulation was first used to explore the behavior of worker decision-making and information propagation when obstacles are encountered. Three variables were explored for their impact on this outcome:

1. Crew size and structure

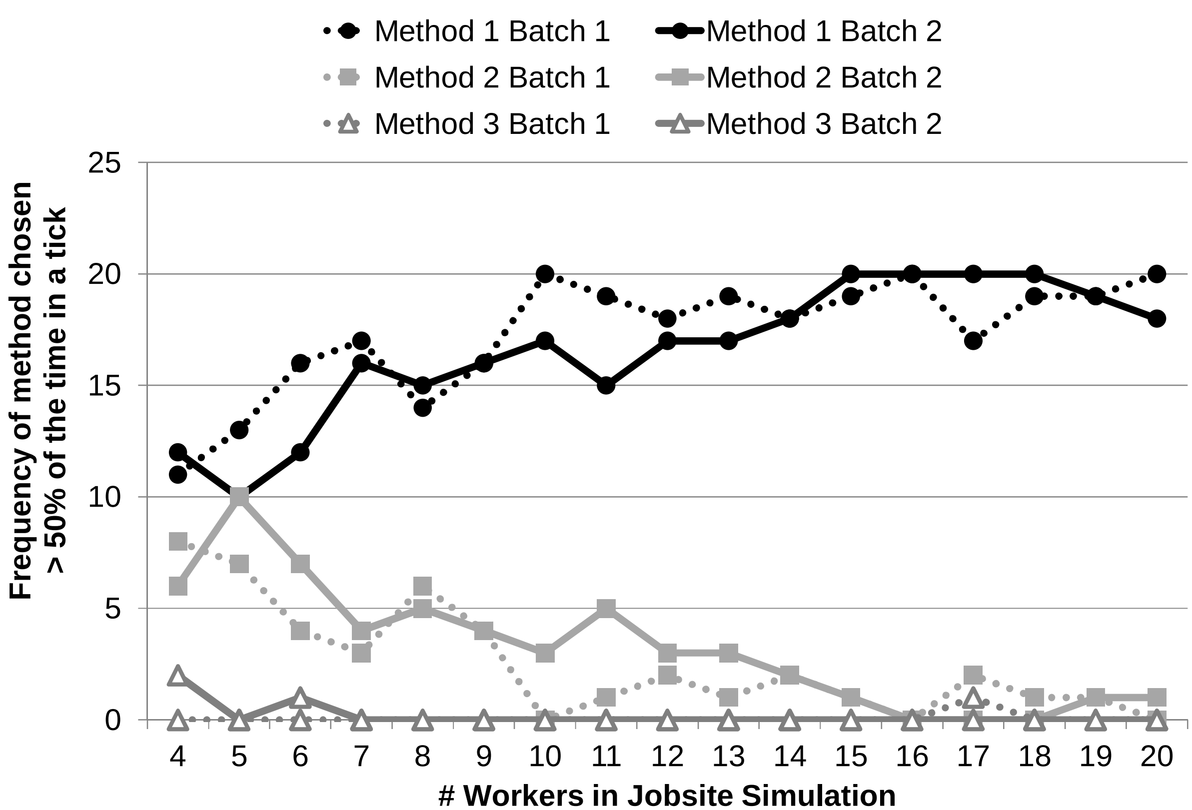
2. Time, in the sense of how many interactions workers have and their exposure to each other and information as the project progresses

Reporting structure and impact of reporting

5.3.4.1 Crew size and structure exploration

To answer the first question, various runs of the model explored the difference in outcomes in terms of obstacle handling methods chosen, given the size and structure of the crew. The primary distinction was that on runs with a larger number of workers, there was a higher likelihood that the workers would select method 1 ("Resolve the obstacle") than other methods. Independent of the crew size, jobsites with fewer workers tended to resolve obstacles with a mix of each method. However, method 1 was still the most popular method chosen among the runs.

The model was designed such that 1 "tick" in the model, representing 1 event, should somewhat resemble 1 day on a jobsite. Each worker crew is assigned one set of tasks; in the even they encounter an obstacle, they are assigned a new set of tasks until the crew works 8 hours. Once they have worked 8 hours, they are done for the day. **Figure 28** shows the final decision-making behavior of a crew after 200 "ticks" on a jobsite (or about 6+ months onsite). The figure plots, for jobsites with a range of 4 to 20 workers, how often method 1, method 2, and method 3 are the chosen method for obstacle handling more than 50% of the time. Two different batch runs with the same settings were conducted using a parameter file for input, to account for model "burn-in" behavior. This sometimes occurs in simulations where the value used as a seed for the simulation parameters can impact the first few iterations of the model run. In this case, Batch 1 was run with an ascending number of workers iterating by 1 from 4 to 20, and Batch 2 was run with a descending number of workers iterating by -1 from 20 to 4. Figure 28 shows that for jobsites with fewer than 10 workers, the obstacle handling decisions have a lot more variation than in jobsites with more than 10 workers.



Note: Method 1 = Resolve, Method 2 = Wait for Help, Method 3 = Work Around
Output shows end-of-model results after 200 ticks

Figure 28: Dominant obstacle handling method chosen by workers, on jobsites with a workforce between 4 and 20

This finding was also tested in batch simulations for various crew sizes (the above analysis was done with a crew size of one), as well as batches with larger number of workers (up to 100). The results were very similar to Figure 28. See **Figure 29** for the output of a run with batches involving one and two crews for comparison. The number of crews was irrelevant to the behavior that is a result of total number of workers onsite.

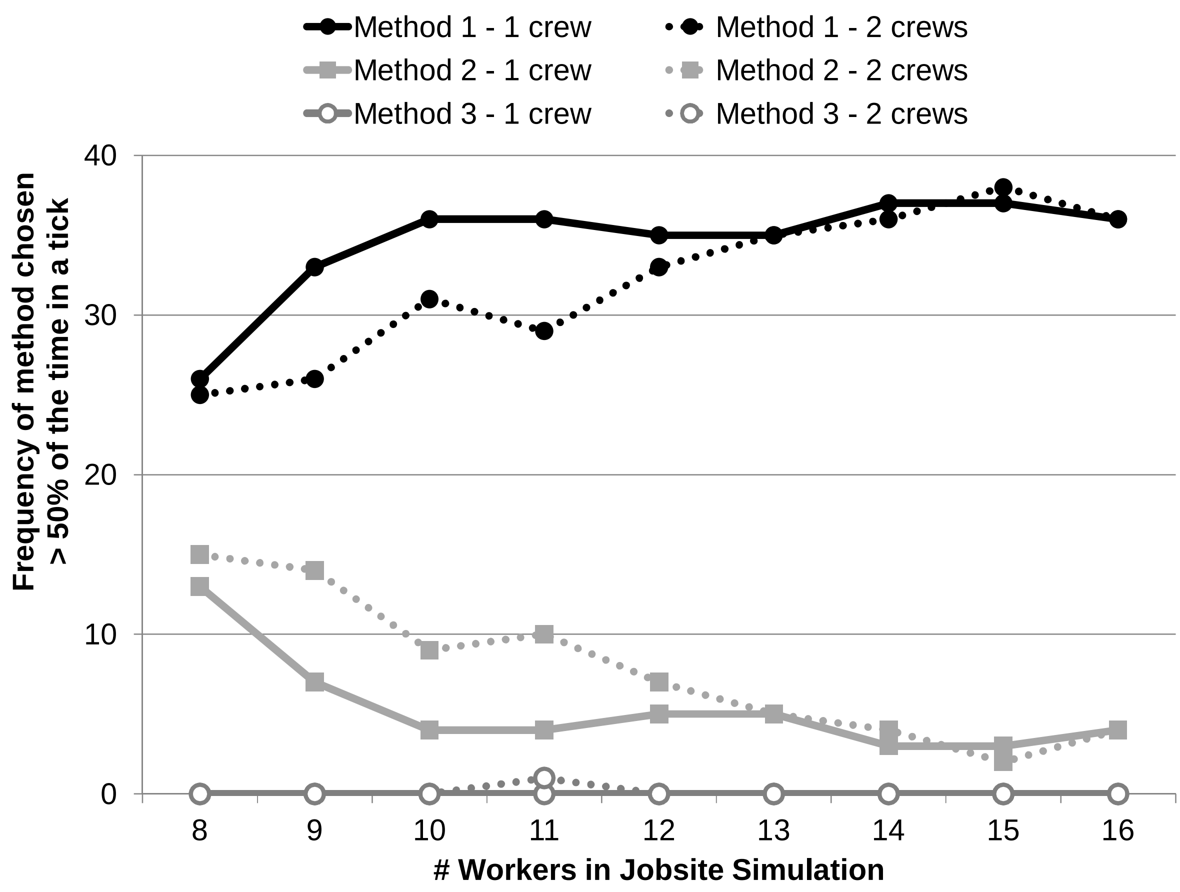


Figure 29: Dominant obstacle handling method chosen by workers, on jobsites with a workforce between 8 and 16 workers, with a comparison of 1 versus 2 crews

5.3.4.2 Crew size and structure exploration

This finding led to the question of whether any methods other than "Resolve" (method 1) were used predominantly on the jobsite. In the long run, after 30 days (or "ticks") on the jobsite, the predominant method on the entire jobsite turns out to be method 1. However, in addressing question 2 regarding the impact of time on the decision-making behavior, the model showed that the behavior of agents in the first 30 days on the jobsite is much more variable than in the longer-run stages of the site. This was further supported through a simulation of the short-interval behavior of the workers in their decision making from early to longer-run stages on the jobsite. **Table 6** shows a the frequency of various patterns seen on jobsites with a workforce ranging from 4 to 20 workers, by observing intervals of 5 ticks up to 200 ticks, for 10 runs of each size workforce. This behavior still matches the long-run behavior of Figures 28 and 29, indicating that jobsites with fewer workers vary in their predominant handling method, whereas jobsites with 10 or more workers primarily choose method 1 for resolving obstacles. Throughout the runs though, there are other patterns that emerge, and it is also noted that method 3 ("work around") is the least frequently selected handling method.

	Number of workers																
Pattern of Method Selection	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
Method 1 dominates and always dominates	4	4	4	10	8	5	7	9	9	9	9	8	7	8	8	9	6
Method 2 dominates and always dominates	6	6	2		1	1	2		1	1	1	2	3				
Method 1 & Method 2 both dominate			2				1	1							1		4
Method 1 & Method 3 both dominate			2			4								2	1	1	

Table 6: Frequency of obstacle handling pattern chosen on jobsites with 4 to 20 workers

The model output statistics file was altered to read results at intervals of 5 ticks up to 30 ticks. The result showed that the worker behavior in the first 30 ticks (days) was more variable than in the long run. **Figure 30** shows a series of plots for the percentage of workers choosing method 1, method 2, and method 3 at intervals of 5 ticks. Each plot represents a different simulation run in its first 30 ticks, and the plots show that there are various scenarios of worker behaviors on the jobsite in terms of the methods chosen for handling obstacles. This result led to the interpretation that the early stages on a jobsite and the interactions between agents play a key role in how obstacles are handled. Over time, perhaps once the workers “settle in” or learn or gather information about the jobsite and local environment, they find it easier to resolve obstacles on their own. In the first 30 days of the simulated jobsite, the workers sometimes maintain their original method for handling, and other times are influenced by the other crew members or obstacle outcome to change their approach.

The same finding that was uncovered in the long-run model simulation (see Figure 28) also showed up in the early stages (less than 30 ticks) of the simulation results as shown in Figure 30. That is, jobsites with more workers tend to chose method 1 (“resolve”) more frequently than jobsites with fewer workers. When the same simulation was run for intervals of 5 ticks, jobsites with 4 to 8 workers had 35% of their decision outcomes dominated by method 1, meaning that they chose it more than half the time in only 35% of the tick intervals. Jobsites with 10 to 50 workers had 94% of their decision-making outcomes dominated by method 1. In other words, jobsites with more workers still tend to choose to resolve obstacles, even in the early stages of the jobsite. This could be indicative of more frequent interactions and learning between the workforce. This outcome was yet independent of crew size, and only a reflection of the total number of workers onsite.

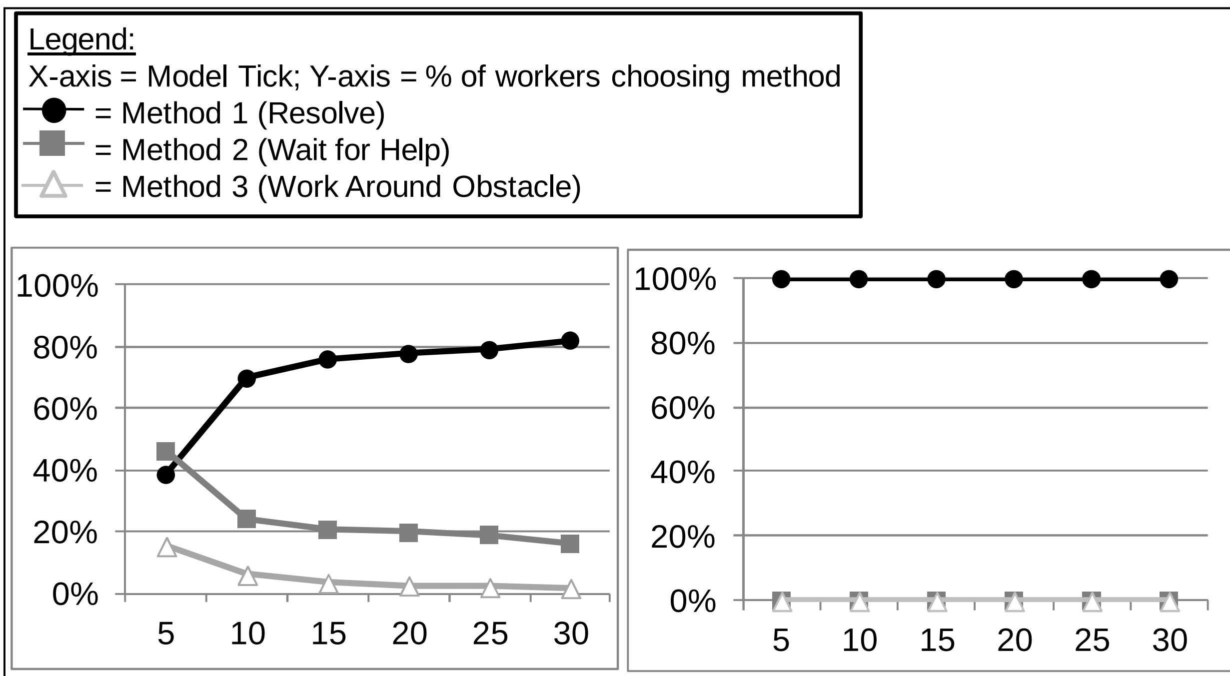
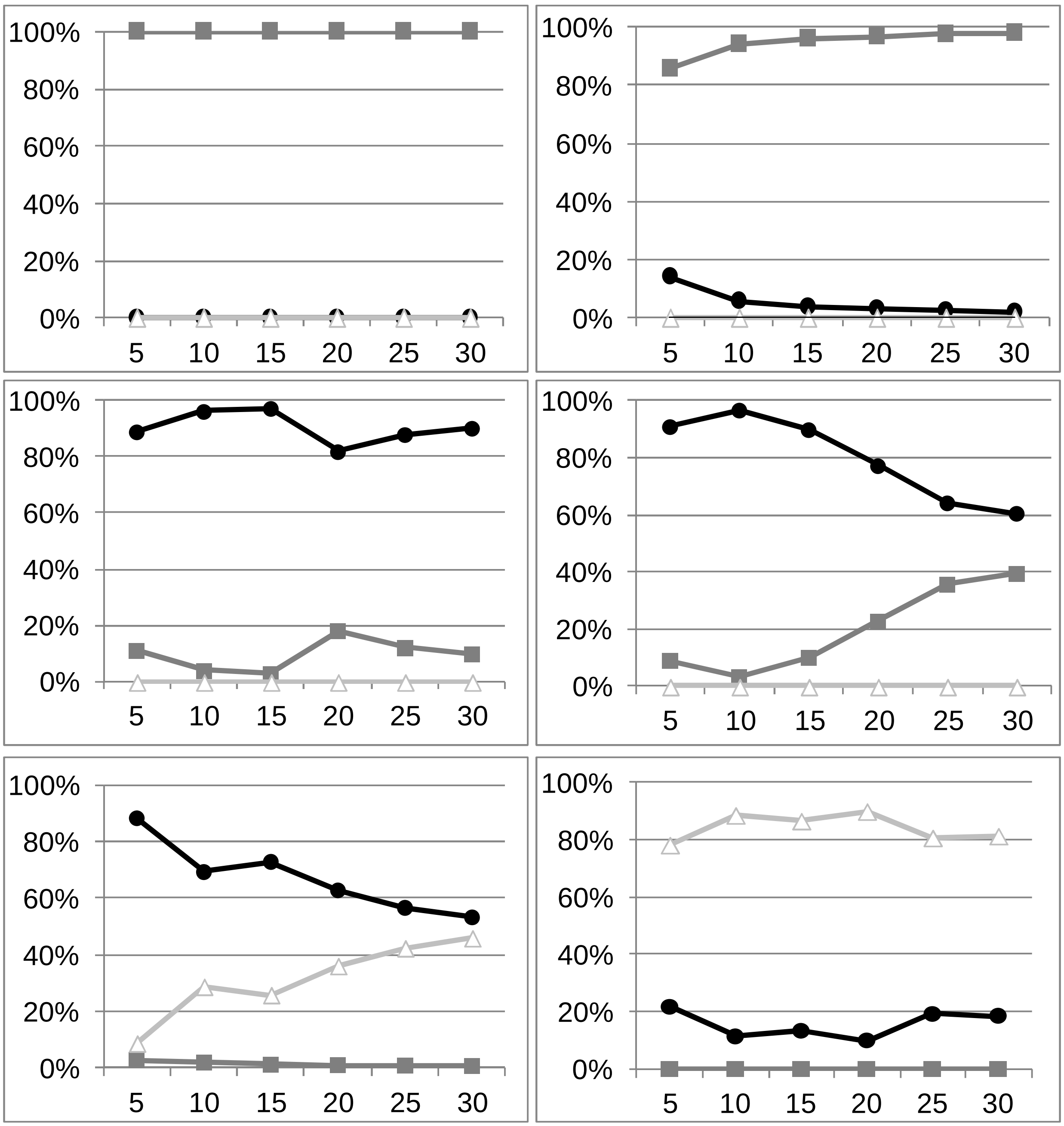


Figure 30: Various simulation runs for a 4-person jobsite, plotting the percentage of workers choosing each method at 5-tick intervals in the first 30 ticks of the model runs

Figure 30 (cont'd)

Legend:
X-axis = Model Tick; Y-axis = % of workers choosing method
= Method 1 (Resolve)
= Method 2 (Wait for Help)
= Method 3 (Work Around Obstacle)



5.3.4.3 Impact of Supervisory Reporting Structure

This interpretation from 5.3.4.2 further implored question #3 of the model outcome, which was to determine the impact of supervisory structure in the model. The role of the supervisor in this model was someone to whom the workers can report obstacles. When obstacles are reported, the influence model increases its S_r coefficient, making it more likely that the next workers to encounter obstacles can resolve them on their own because the supervisor can pass on information either about the obstacle or about how to resolve it. There are two factors in the ABM logic that were studied for supervisory impact: (1) the number of supervisors in the crew structure to whom reports can be made and information propagated, and (2) the likelihood of reporting an obstacle to the supervisor. The number of supervisors to which a worker could report made no difference in the outcome of the simulation. However, an increase in the likelihood of reporting led to a higher portion of workers choosing to "resolve" the obstacles themselves. In simulation runs where workers have a 50% likelihood to report obstacles, which matches empirical data collected, method 1 is chosen by more than 50% of the workforce in 85% of the runs. When the workers increase their likelihood to report to 80%, the method is chosen predominantly in 83% of the runs. When the likelihood to report is decreased to 20%, method 1 represents more than half of the worker's choice 77% of the time.

5.3.4.4 Impact of Obstacle Handling on Work Performance

In terms of the impact of reporting and obstacle handling on time, the method chosen did lead to a difference in the lost time and in the additional effort required for task completion. **Figures 31 and 32** show the plot of time impacts depending on the frequency of using method 1 (“resolve”) for obstacle handling. The x-axis represents the percentage of obstacles that are handled with method 1, with each dot representing these results at the end of a 5-tick interval. Both figures indicate that there is not a significant relationship between the method chosen and the work performance. When obstacles encountered and the workers chose to wait for help or work around, they do generally spend less time not installation, and the task takes less additional effort to complete. However, the figures also indicate there is a wide range of performance in both measurements of time when workers chose to resolve the obstacle. The cause for this variation correlates with the finding of the first point from the simulation exploration. The variation, especially when method 1 is chosen by more than 50% of the workers as shown in Figure 29, is related to the number of workers on the jobsite. **Figure 33** shows this with a view of the non-installation time when workers chose to resolve more frequently, indicating that the variation in non-installation time is distinguishable between small and large workforce sizes. A view of the same result is shown in **Figure 34**, zoomed in on the window where the variation is greatest (x-axis greater than 50%, and y-axis less than 12%). The interpretation of this result is that when smaller workforces chose to resolve obstacles, they end up losing more time than when large workforces try to resolve obstacles on their own. This could be related to the interpretation drawn from Figure 28, which is that smaller workforces have less information and knowledge to share with each other, and therefore their behavior and outcomes from this behavior is different.

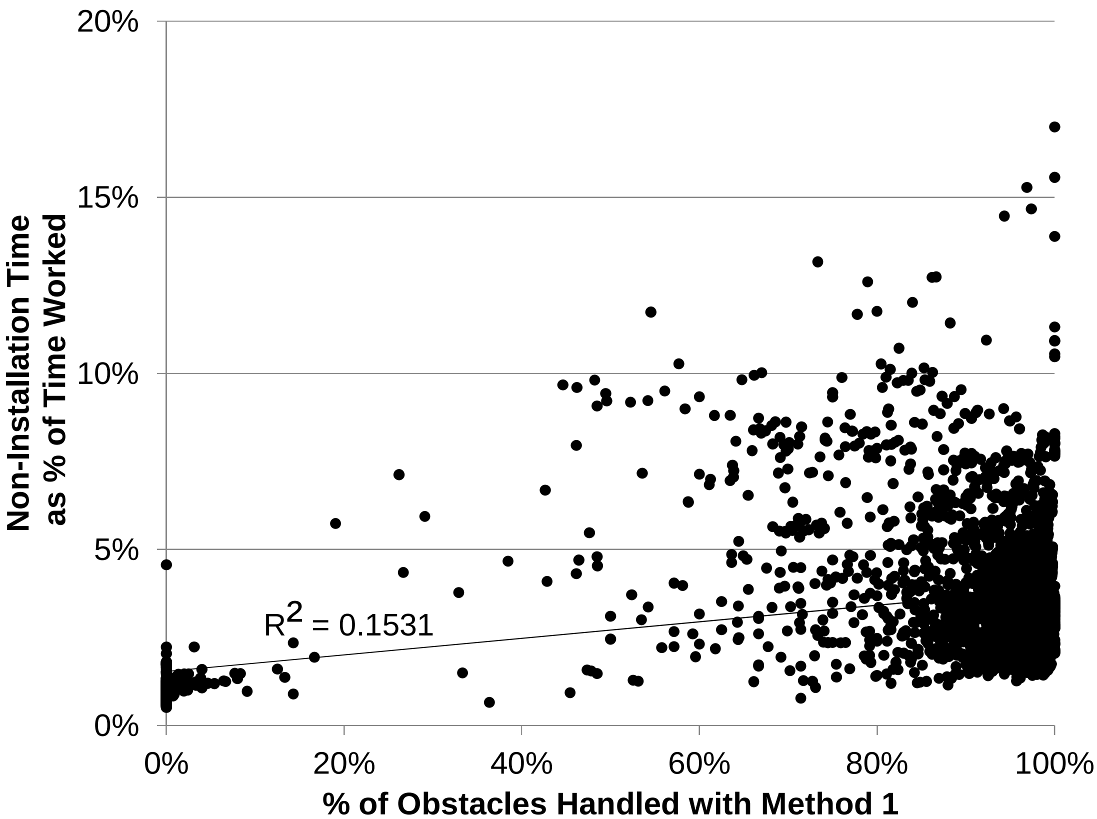


Figure 31: Correlation between frequency of method 1 used and the lost time when obstacles are encountered

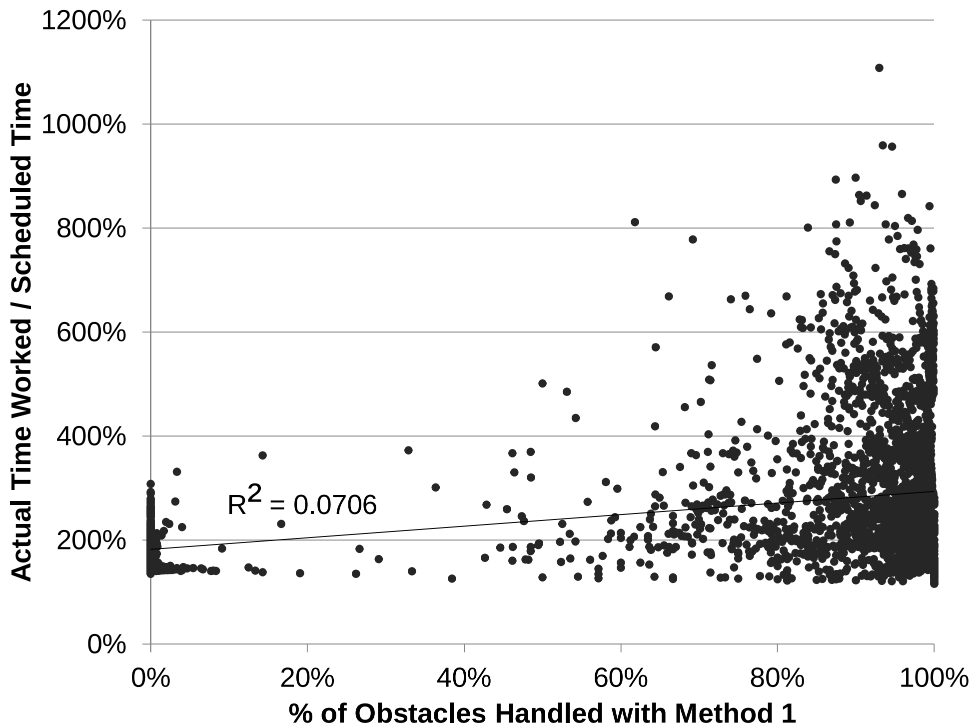


Figure 32: Correlation between frequency of method 1 used and the additional effort required when obstacles are encountered

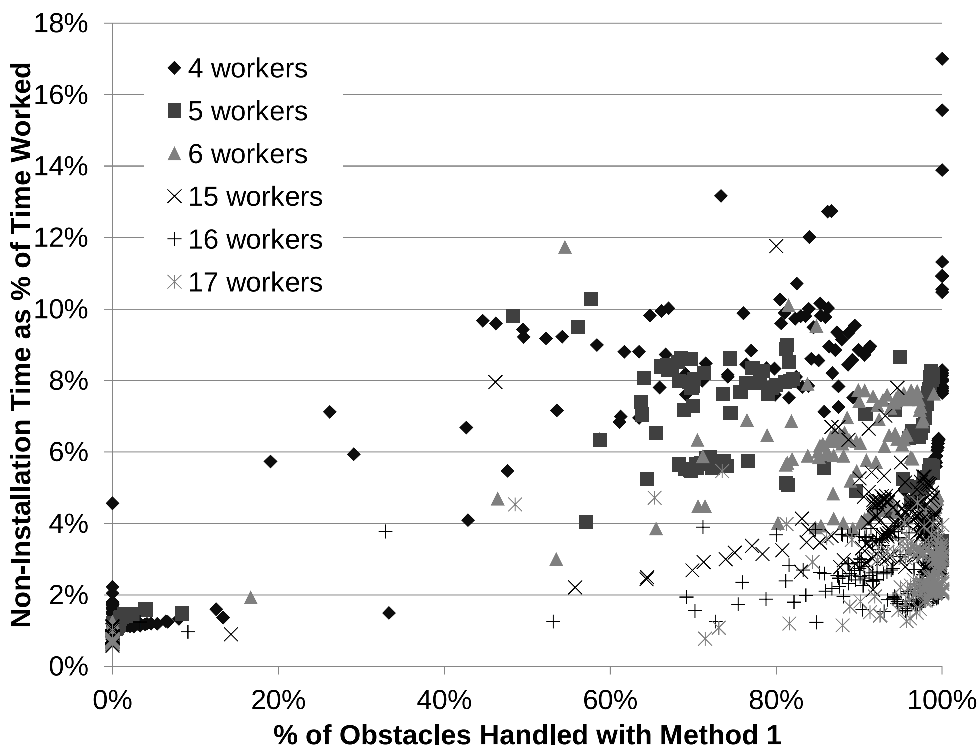


Figure 33: Distinction of small vs. large workforce sizes, as an explanation of variation in non-installation time resulting from obstacles when workers chose method 1

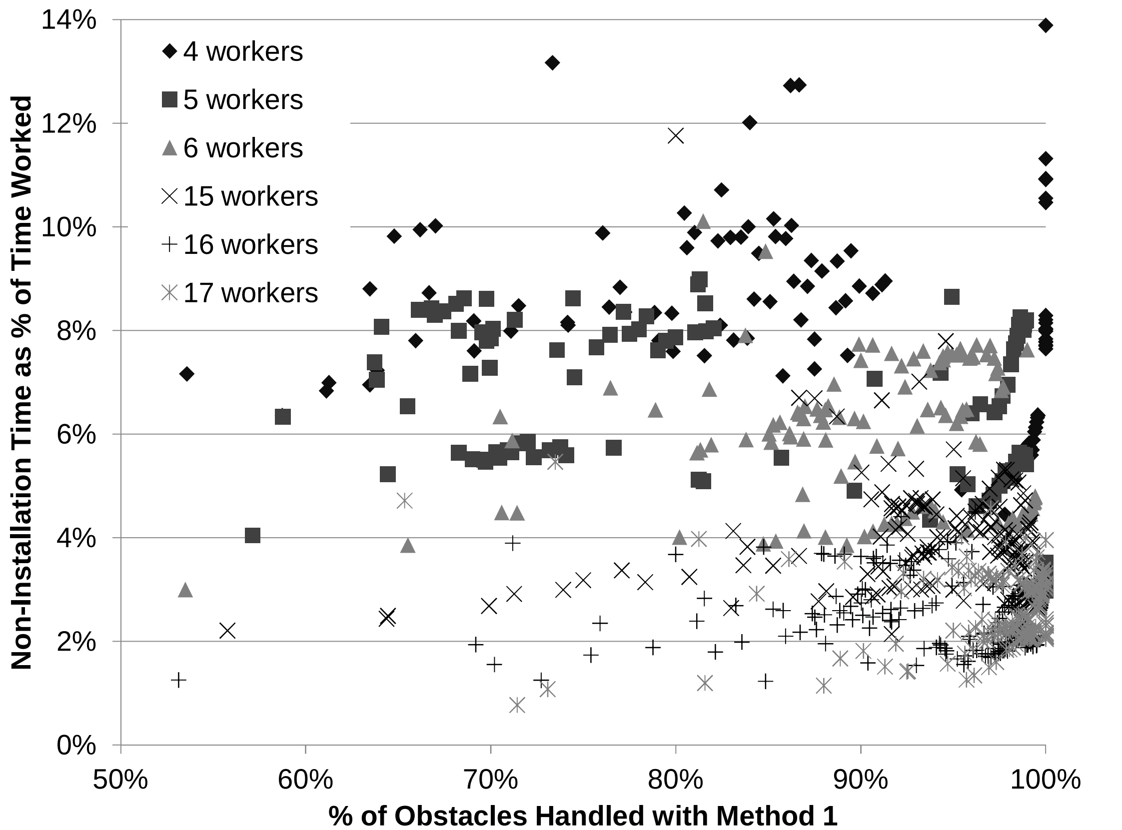


Figure 34: A zoomed view of the distinction of small vs. large workforce sizes, as an explanation of variation in non-installation time resulting from obstacles when workers chose method 1

5.3.4.5. Exploration of Model Parameters and Assumptions

Three aspects of the model parameters and assumptions were explored, all related to the SNA component of the SNA-informed ABM. The first was the values for ρ and γ, coefficients in the model used for workers influencing each others' decisions for obstacle handling, as explained in Equation 4 (section 5.3.2). The values used in the simulation results shown above match the values listed in Equations 4 and 5. Literature indicates that ρ is typically between 1/10 and ½ of γ (Frank, et al. 2011a, 2001b). The values in Equations 4 and 5 have ρ > γ. An explanation for this difference is included in Chapter 6. However, for testing the model outcome, the values for ρ and γ were changed to represent the typical relationship between the two numbers. This change resulted in the majority of obstacles (greater than 80% of the time) being handled with method 1 (“resolve”) in both the short-term and long-term of the simulation. This is explainable with reflection on the influence model from Equation 4. The equation was altered such that $\rho = 0.05$ and $\gamma = 0.5$, which indicates that each worker will rely on their own prior information and experiences to make decisions ten times more than that of their peers when interacting and exchanging information. Their individual preferences in the initial 5 days (ticks) may begin with the static probability of Figure 15, where the distribution of obstacle handling method choices is almost equal. However, after the 5^{th} tick, the handling choices of the workforce all tend to “resolve” obstacles more than 95% of the time, regardless of the size of the workforce.

Figure 35 shows a comparison of the distribution for obstacle handling choices with $\rho = 0.62$, $\gamma = 0.5$ with the minimum of obstacle handling choice chosen when $\rho = 0.05$, $\gamma = 0.5$. For the distribution of handling choices using equation 4, the figure shows the minimum, first quartile (Q1), median, and third quartile (Q3) of all results within a given tick among 170 different runs of the model at that tick point. The figure indicates that the small rho model initiates with no less than 28% of the obstacles handled using method 1. The results model the Q1 results of the Equation 4 simulation runs.

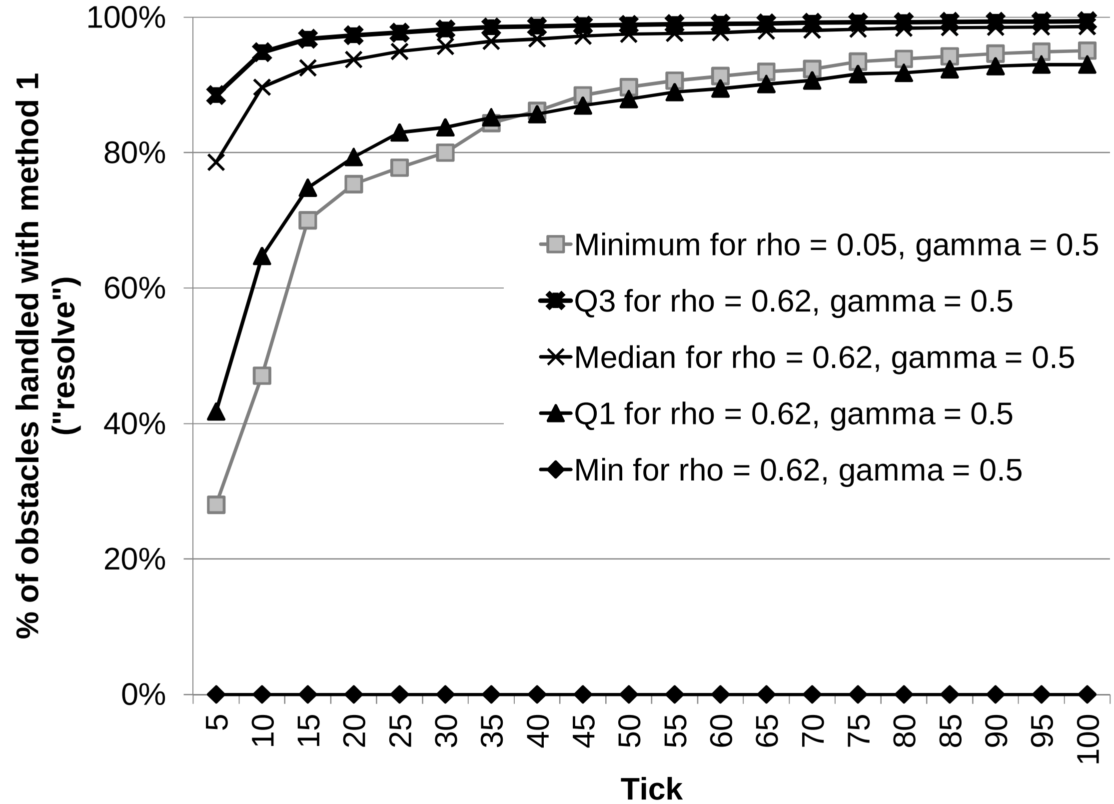


Figure 35: Model results comparison for Equation 4 (ρ = 0.62, γ = 0.5) vs. small rho (ρ = 0.05, γ = 0.5)

The second change made in the model to understand its impact was to remove the SNA aspect altogether, and run the simulation as a pure ABM. This was run with varying crew sizes, and studied in tick intervals of 5 up to 100 ticks per run. No information was passed between workers, and the decision for agents was purely probabilistic and static. The results showed that the obstacle handling choices in both the short and long term mirror the probabilities for handling choice from the data collection (see Figure 15). **Figure 36** shows short-term behavior, which can be compared to the behavior in Figure 28 where the ABM did include the SNA model. The comparison shows that the short term in both cases has more volatility than the long term behaviors of workers;

however, Figure 36 also shows that the workers are more likely to have a more evenly distributed mix of handling methods than when the ABM does not include the SNA. In Figure 28, there were some runs where workers did not use one or two of the methods at all, whereas Figure 36 shows that all runs start and run through at least 30 ticks with some usage of each of the three methods. In addition to the short term behavior differences, the long-term model results differ when the SNA model is not included.

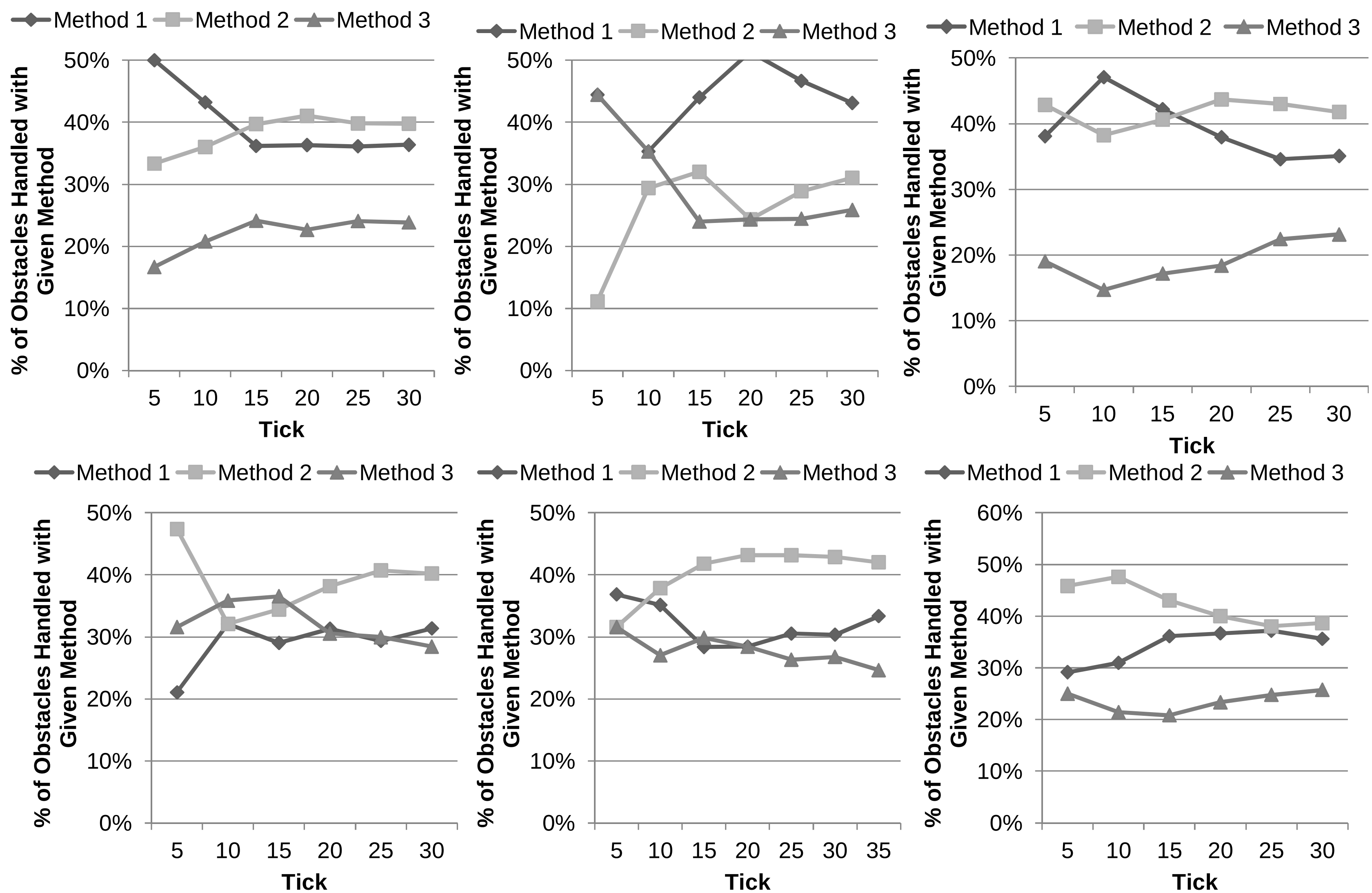


Figure 36: Simulation results for 6 runs, showing % of obstacles handled with each method in the short run (30 ticks), when the SNA model is not included in the ABM

Figure 37 shows a comparison of the handling method choices for the long-run (after 100 ticks) results with SNA and without SNA included in the ABM. When SNA is included, method 1 dominates the outcome and when SNA is not included, method 2 dominates. According to the data collection, method 2 should dominate as it was the most frequently used in observations. However, by including the SNA model in ABM, method 1 becomes used more as the jobsite evolves, since the model led to more resolutions (use of method 1) if the obstacles were reported at the end of each day / tick.

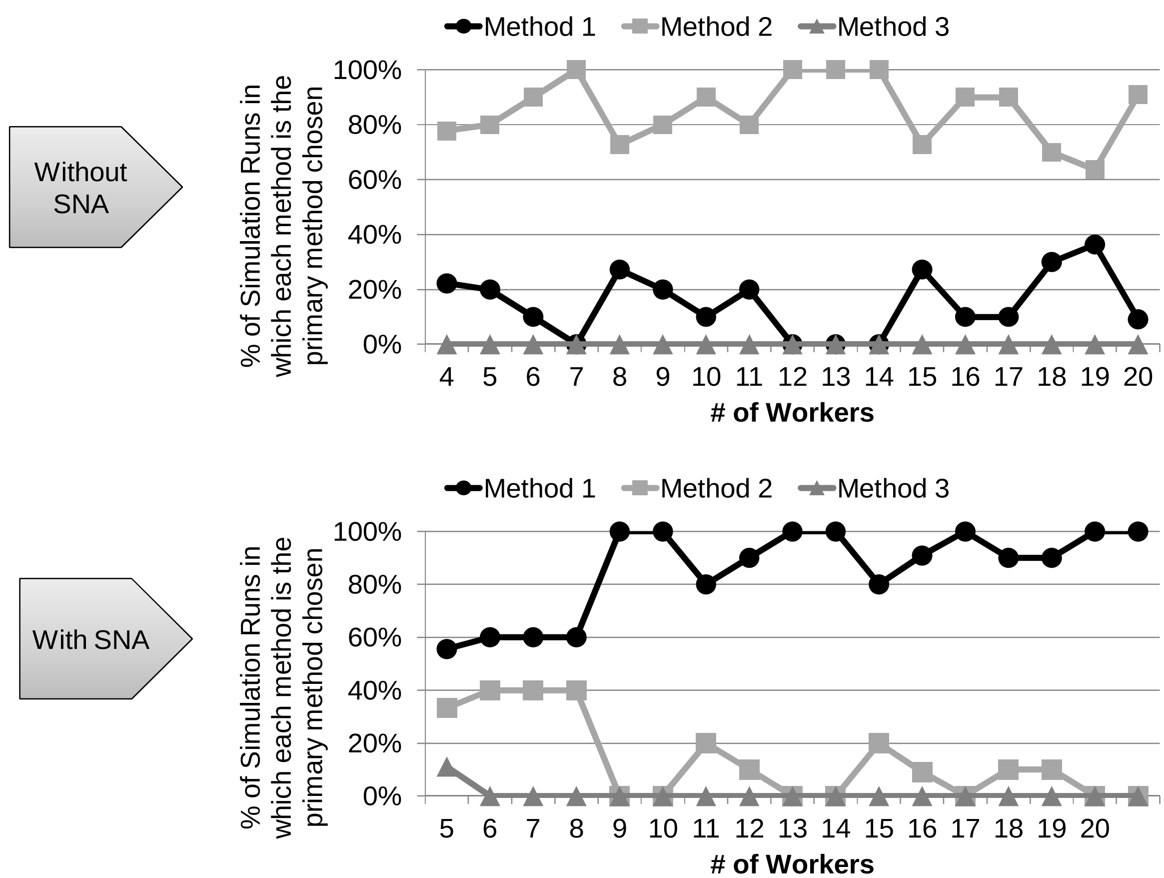


Figure 37: Comparison of long-run simulation results for obstacle handling choices with and without SNA used in the ABM

The third element explored was the impact of crew shuffling between ticks (representing days on the jobsite) in the model. The crew shuffling element included in the model allowed information to be exchanged and carried by workers who move between crews from one day to the next. This behavior matches what happens on the jobsite; however, if crew members stay together and do not shuffle, the simulation shows the impact on information propagation and decision-making behavior. In Frank and Fahrbach (2011), the notion of "exploding equilibrium" occurs when individuals from different social networks become part of the same network, and through their interactions develop similar beliefs that escalate sometimes to a cultic level. In the simulation model, this could be tested by removing the crew shuffling, to determine if the tendency toward a given method for resolving obstacles as explained in sections 5.3.4.1 and 5.3.4.2 was not present if workers do not share information and knowledge across the jobsite.

The results indicated different behavior in obstacle handling over time than was shown in Figure 30. Some runs showed similar behavior, but in 40% of the runs, independent of the workforce size, patterns such as the ones shown in **Figure 38** showed that the workforce changed their behavior abruptly at one point in the jobsite. Although these transitions appear to match those in Figure 30, the difference is the time interval. Figure 30 showed short-term shift in behavior, but long-run pattern in all model runs matched Figure 28, where the obstacle handling method always tended toward method 1 in the long run (after

100 ticks). Another finding from this change in the model was that method 3 was used more frequently than in other results.

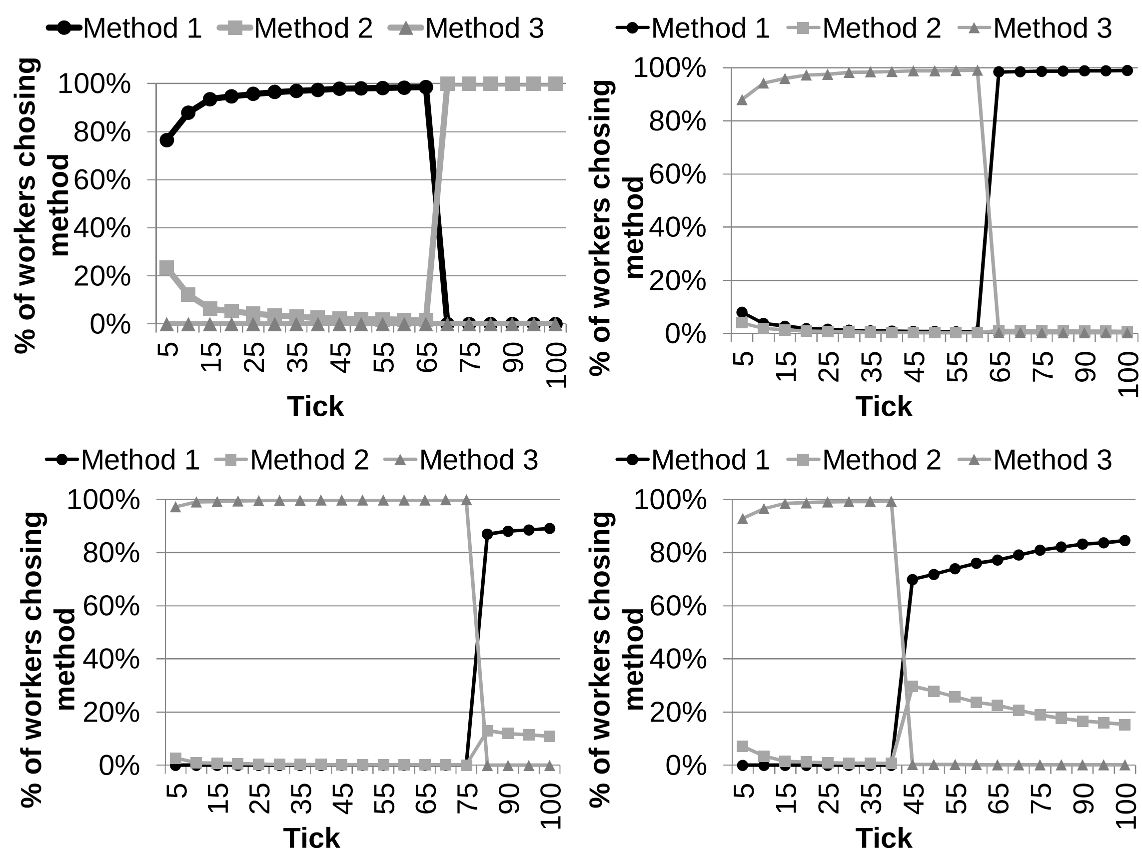


Figure 38: Model output results from simulations where workers did not shuffle between crews from day to day

These results indicate that the crew shuffling does have an impact on the information propagation that leads to decisions for handling obstacles. The patterns indicate that the crews handle obstacles a certain way, and then the decision-making flips. For this simulation result, the change in decision-making is somewhat driven by the probabilistic choice of handling method, and the SNA model. The inference is that when crew members do shuffle, the overall jobsite information is what causes decision-making, since workers and their inherent knowledge is passing through. When crew members do not shuffle, the network of information is restricted, and crews rely more on their own individual experiences and knowledge which is more limited. This could be explored further in future research to determine if the abrupt change is related to certain types of obstacles, or other factors.

An example model and scenario illustrates why exploding equilibrium does not occur on construction jobsites, and also the impact of information propagating throughout the jobsite. The interactions on a construction project and the information propagation depend on influence as well as selection within a worker's social network. Frank and Fahrbach (1999), showed that an "equilibrium" effect can occur when the selection and influence models are intertwined (Frank & Fahrbach, 1999).

In the case of a jobsite, **Figure 39** shows, the networks and agents within them interacting on a project according to the overlap described in Figure 21:

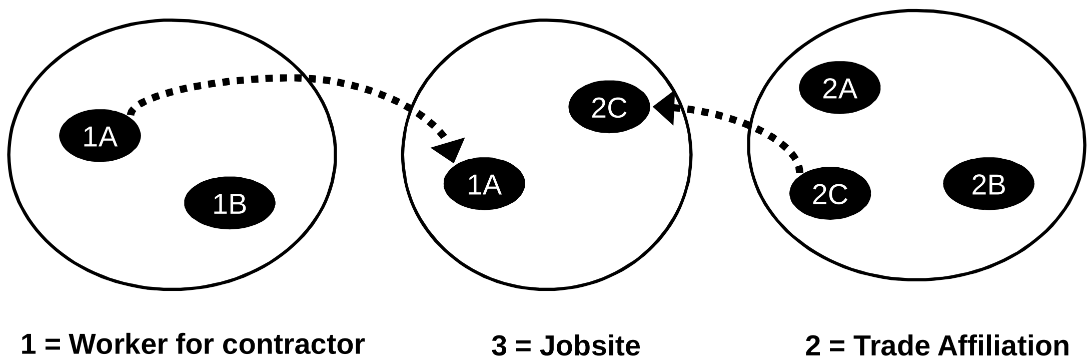


Figure 39: Sample interaction of individuals on a jobsite representing three different social networks

In this case, the labor “donates” an individual from its trade affiliation network to do the work (shown as “1A” in Figure 39), and the contractor “donates” an individual from its network to run the project (shown as “2C” in Figure 39). 1A and 2C have influence over each other while they are involved in group 3, but they are allegiant to their respective groups 1 and 2. However, both groups 1 and 2 could use information from group 3 to help the jobsite improve productivity. Frank and Fahrbach identified information such as this as a “resource” that is expandable (Frank & Fahrbach, 1999). In other words, once the information from individual 1A in group 3 goes back to group 1, individual 1A retains the information and group 1 now adds the information to its network. If the influence model is run iteratively, it shows that group 1 would be more and more influenced by group 3 with the more information that they have, to a cultic level.

On a jobsite, information from group 3 does not cause a revolution when passed on to group 1 because as new information enters group 3, it recirculates in the network, and may only become influential if the information receivers in group 1 have selected the information as it is being generated within the network of group 3, which is made up of “donated” group 1 and 2 individuals interacting.

To demonstrate, **Figure 40** shows an example of an issue on a jobsite, where there are problems with accessibility to restrooms. The issue is impacting individual 2C (from Figure 38) on a daily basis, and he notifies individual 1A. This happens on a daily basis, and the iteration of the influence model for this scenario would lead to the two group 3 individuals starting a rally on the jobsite because of the restroom shortage. This does not happen in reality, as was shown in Frank and Fahrbach, because the redundancy of the information about the bathroom problem does not affect behavior as strongly (Frank and Fahrbach, 1999).

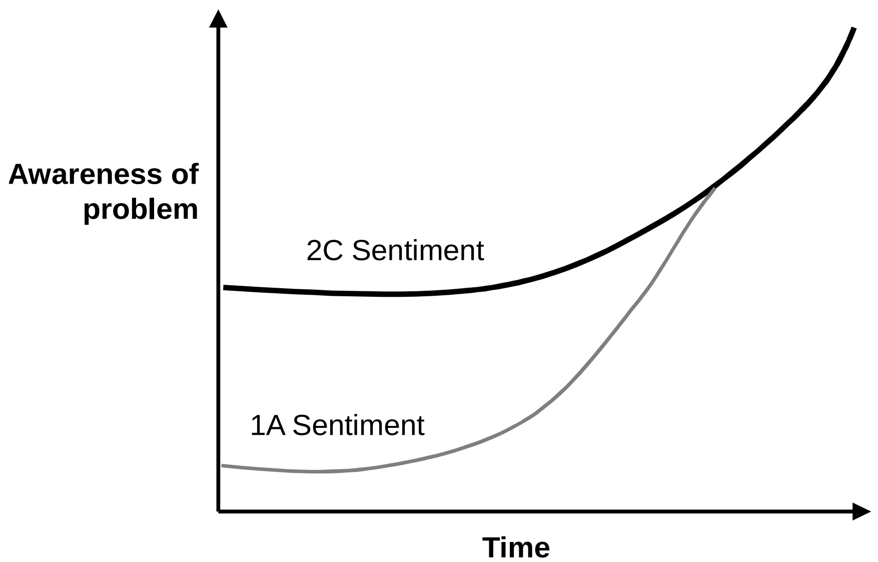


Figure 40: Iterative influence model toward explosive reaction

The situation that is more typical of jobsites is in **Figure 41**. In the same bathroom shortage scenario, the issue is raised by individual 2C and he constantly informs group 2 of the problem. However, individual 1A is never informed, and therefore group 1 can offer no help.

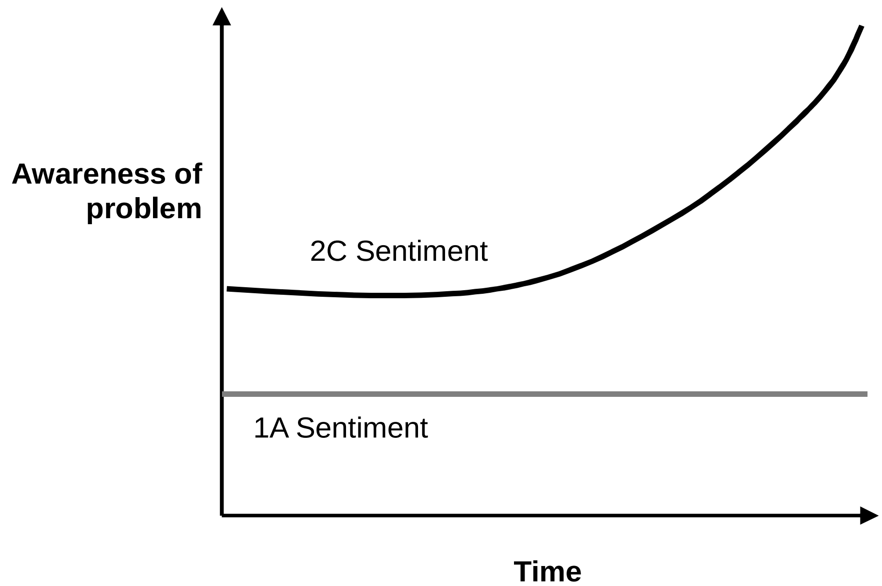


Figure 41: Iterative influence with no selection (information flow) between groups 1 and 2 while part of group 3

Figure 42 shows how obstacles could be resolved depending on the path of information propagation. Here, individual 2C encounters the issue consistently over time, and individual 1A becomes aware once information is passed to this individual. At this heightened awareness, a resolution is put in place, and the awareness stabilizes until the issue is ultimately resolved and no longer raised between the two parties.

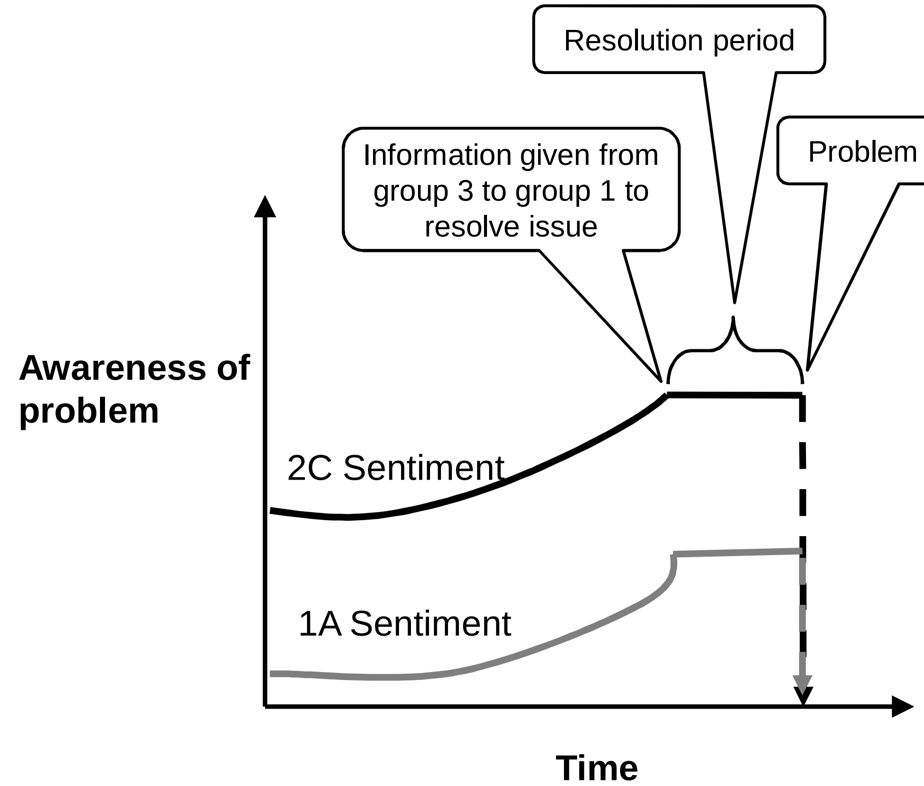


Figure 42: Iterative influence with selection (information flow) between groups 1 and 2 while part of group 3

The means for achieving Figure I-4 comes through a “third party” information carrier, as shown in Frank and Fahrbach, which would connect the information noticed by the “donated” group 1 individuals to the “donated” group 2 individuals, while maintaining balance in the system (Frank & Fahrbach, 1999). However, this third party would need to be very carefully structured and introduced to the system in order for groups 1 and 2 to converge to a perfect balance without exploding.

In summary, the simulation results show that there are unique behaviors among the workers for obstacle reporting, primarily based on the size of the workforce and based on empirically driven model design. With the data and assumptions used in the model, the crew structure and supervisory structure had less impact on the obstacle handling method chosen, lost time, and additional effort required for tasks, than the number of workers and the time into the job. The early stages of the simulated jobsite showed more variation in the likelihood of obstacle handling method selection. In addition, jobsites with smaller crews had more variation in their choice of method.

The simulation outcome indicated that information generation at the point of installation has a higher impact when passing locally within the social network, through the influence model, than it does when passed on to a supervisor. This surfaced in two ways. First, the fluctuations in obstacle handling methods for the first 30 days in the jobsite could indicate that workers come to the jobsite and to an assigned work activity with their own beliefs, and it takes some time for them to adapt and coordinate with their local environment of work. Once they do that, the workers are able to resolve obstacles faster. Second, the impact of reporting to supervisors had a small impact in the simulation. The number of supervisors to report to within the crew structure did not matter at all. The likelihood of reporting did make a difference, with a higher likelihood leading to more workers resolving obstacles than working around them or waiting. However, this impact was also minimal; even when the workers were only likely to report 20% of their obstacles; the workers still selected method “1” 77% of the time in the long run. This conclusion is supported with the literature from Frank et al. 2011a and 2011b, showing that in complex production environments, agents use local coordination and local adaption for knowledge transfer. The simulation results show that this is the case, given the SNA-informed ABM model of the jobsite information generation.

By exploring three model assumptions, the model design was shown to be a contributing factor in its results and interpretations listed above. Parameters used such as rho and gamma, as well as assumptions about crew shuffling and the overall underlying SNA model embedded in the ABM all lead to different modeling results.

There are also two important assumptions about the environment modeled in the ABM. First, the model assumes there are no newcomers to the site. All agents modeling workers start the model and end the model together. The learning for all workers is simultaneous and homogenous to the jobsite, although unique to individual installation and crew interactions. The second assumption is that the tasks assigned to workers are repetitive and homogenous. This research did not study or model the impact of different types of tasks, and all tasks were treated the same in the model as they were assigned, with the exception of their expected duration. This means that the learning about tasks and obstacles to tasks was completely transferrable between all workers. An alternative to this assumption would be to model tasks that are isolated to single workers or crews, where there is no learning between those crews and between the tasks. A corollary of the second assumption is that the social networks on the jobsite did not distinguish networks by type, as was shown in Figure 19 (jobsite, trade affiliation, and worker for contractor). The network used in the SNA was a very small subset representing crews working on a single task together. Although members of the crew brought their own history and experience with them, this history and experience was still defined by the jobsite itself and nothing outside since that was beyond the scope of the data collection and model developed in this research.

5.4. Suggested Final Model

The final model for information generation at the point of installation is the SNA-informed-ABM simulated model of the concept as explored in Chapter 5, derived in Chapter 4 based on empirical data collection and observations. The model incorporates the logic of the workers at the point of installation, when they work on a task and encounter an obstacle, which occurs in 89% of scheduled tasks. The steps of the workers at each tick (representing each day) include preparing for work, doing work, and handling obstacles. The steps within these phases are homogenous for each worker as an agent in the ABM. The influence model of SNA is used to model the impact that workers have on each other's beliefs as they interact on jobsites. In the initial interaction in the worker social network on the jobsite, each worker is assigned a probabilistic belief about which obstacle handling method to select, based on empirical data collected in this research.

In successive interactions, workers chose a method based on their own knowledge of what method they chose in the past, and based on the influence of other crew members and their methods of obstacle handling. Also in successive iterations, if the supervisor(s) on the jobsite have been informed in the past about obstacles, the supervisor will pass on the information about obstacles to the crews, and the crews will have an easier time resolving the obstacles on their own. This is taken into account as an additional variable with coefficient derived from data collection on the impact of obstacle reporting to supervisor(s).

There are some aspects not included in the simulated SNA-informed ABM model that should be included in the final model, including:

- Influence of non-workers; this includes others belonging to the various social networks of a jobsite, such as shown in Figure 19, section 5.2., as well as other environmental influences that were not included in the simulation of Chapter 5. These externalities include any events that are outside the control of the jobsite workforce, such as weather or labor strikes. These impacts should be modeled collectively as an error term in the influence model.
- Use of the selection model for determining which workers are "friends" in their w-matrix of the social network. In the simulated model, the likelihood that workers were friends was 68% in every pair of workers, due to lack of full network data. The final model should have the workers selecting friends based on a selection model as described in section 5.2.2.
- Data collection representing longer-term longitudinal results for the workers; the data collected and used herein was based on a one-time interaction with the workers. The long-term change in belief of each worker on the jobsite should be collected and included in the model.

There are additional limitations and future improvements that can be made on this model, discussed in section 6.4. However, the above-listed are those that were not included in the simulation of the conceptual model developed for information generation.

5.5. Model Validation and Verification

Validation and verification are topics that are inherently important in any use or discussion of simulating reality. Validation asks the question of “did you build the right model?” whereas verification will question “did you build the model right?” The former requires testing of whether the model represents reality, whereas the latter requires testing of whether the model is providing the correct output based on its foundation and inputs. Neither of these were a significant requirement for the scope of this research, and in fact model validation for the simulation in Chapter 5 would take several more observations and longer-term analysis of results to validate that the model represents the fullness of jobsite conditions. The model evaluation process conducted and explained in Chapter 4 provided some validation for a select set of jobsites; yet the model results in Chapter 5 would need to be validated to confirm that the model design and model results match reality. Based on the jobsite observations conducted herein in additional to historical observations and literature review, the model results do match reality and can be used to explore the model design and assumptions; however, the model should not be used to predict outcomes without further validation.

Model verification was included in the simulation process, through exploration of boundary conditions explored by varying parameter values and run settings. The simulation results matched conceptual model assumptions, indicating that the simulation was designed and coded accurately.

All models are tools to think with; they will not think for you. The model developed conceptually and then with simulation was used herein to explore what could not be explored in simple linear models; however, the inferences drawn are still dependent on the model assumptions. A model built based on theory will, to some degree, lead to a result that has a foregone conclusion based on the modeler’s conception and assumptions made in the theory and hypothetical data used

5.6. Summary

The model used for the analysis in section 5.3.4 was evaluated by demonstrating its ability to lead to an understanding of the impact of information generation in the complex production on jobsites. The SNA-informed ABM model was developed to show the impact of workers encountering obstacles on the time to complete a task and the time spent by workers not on installation due to the obstacle and obstacle handling. The model also needed to show the information generation and propagation between workers to demonstrate if this propagation had an impact on the time parameters, and on the system behavior of the jobsite over time. As was demonstrated in the results of section 5.3.4, these requirements were met by the modeling approach.

The model was also evaluated by demonstrating the ability to simulate jobsite scenarios. The scenarios developed in section 5.3.4 represent the projects for which data was collected in this research, including the project durations (total number of ticks) and the project sizes as parameterized with the number of workers. The outcome of the simulated jobsite scenarios can be explained with typical jobsite behavior, such as how workers learn from each other and over time on the jobsite; the impact of obstacles on production and on the duration of tasks. Model assumptions were reviewed according to scope that was not included in the model, to clarify that some provisions could not be tested in the simulations developed for this research but could be explored in future research.

Chapter 6: Conclusion

6.1. Reflections on Research

This research began with a postulate that understanding information loss from the point of installation on a construction jobsite will result in insight into how work performance can be improved. To address this postulate, four research questions were developed, to be answered with five objectives. The research methods used included a literature review, development of a conceptual model, and then evaluation of that model through jobsite observations and data collection at the point of installation. A conceptual model was developed for how information is generated at the point of installation, when workers encounter an obstacle, and how that information propagates. ABM and SNA approaches were identified as viable methods for further development and exploration of the conceptual model. The conceptual model was adapted to the characteristics of ABM, and the influence model of SNA was used to model the social network interactions among workers on the jobsite. A final conceptual SNA-informed ABM integrated model was developed and then simulated using Agent Analyst. Several jobsite scenarios were simulated and tested to verify that the model was built correctly to match the empirical data and conceptual model assumptions already developed. Model assumptions and results were also explored to determine the model sensitivity to various parameters and assumptions. The answers to the research questions are explained below as a reflection to the research, as well as a recommendation for the industry based on this research.

Each research question was addressed throughout the research. The first question was **what are the characteristics and examples of information available to and from the worker, especially when the worker has to improvise**? This question was answered through literature review of existing studies of information on construction jobsites, and through the data collection and observations. Literature led to the classification of the environment being studied herein as “complex production”, where craft workers who are specially trained locally adapt and locally coordinate at the point of installation in order to learn and solve problems. Other industries who have similar characteristics have studied this through direct observation and learning from the in-the-moment scenarios of the craft workers. The information available and generated by the workers at the point of installation was identified, mapped, and distinguished in two dimensions: (1) relationship to the work vs. the physical construction or building, (2) information shared within a trade vs. between trades. Information generated by the workers when an obstacle is encountered was gathered through direct jobsite observations, indicating that 36% of the time, workers resolve the obstacles they encounter on their own; 40% of the time the workers wait for help, and they work around the obstacle without any resolution 24% of the time. In addition, the workers report the obstacle beyond their crew 50% of the time. This and more quantitative data was used for the final model development.

In addition, qualitative data with seven patterns of behavior were recognized and explored in the analysis. These patterns included the impact of a physical line of interaction, meaning that workers interact to solve problems just because others who *could* help happen to be walking by. Another example that was seen in over half of the observations was that there is a common path for escalation when obstacles occur, from trade worker to trade foreman to jobsite general contractor to owner's representative. A third case is the differences in how workers take or give responsibility for a decision. In some cases, workers avoid handling obstacles because they do not want the responsibility of making the decision and living with a potentially negative outcome. In other cases, workers avoid reporting obstacles because they do not want to burden their supervisor. Although the intricacy of these patterns was not included in the final SNA-informed ABM model simulation, they are interesting findings that point to the unknown and tacit information available from workers on construction jobsites.

The second question was **how does information get generated at and propagated from the point of installation?** This question was answered through the direct jobsite data collection and observations. Specifically, workers were asked about how they would handle an obstacle if encountered, prior to the author's observations of their work. Once an obstacle arose, the worker choice for handling method was observed and noted, as well as other behaviors or information exchanges between or within crews and trades. Following the obstacle handling and aftermath, the workers were asked about the influence of that event on their next decision about handling obstacles. These data points were collected and synthesized in the final model development.

The research showed that information is generated based on a combination of the workers' prior knowledge and experience, and the local conditions at their point of installation. In most cases, once workers resolved or learned of the resolution to the obstacle, they were more informed about how they would resolve that obstacle in future cases. Data collected indicated that 43% of the time workers were influenced in their decisions based on their interactions with other workers, but only to the extent that they had a social relationship with the other workers. In other words, a worker would be influenced in his/her decision because they were crew-mates only, not because the other crew member passed on new information to the worker

The third question was **how can this information generation and propagation be effectively modeled, including implementation of the model with real jobsite scenarios?** Based on the combination of literature review on modeling methods, and the data collected to validate the conceptual model, it was determined that the SNA-informed ABM model was most appropriate for modeling the information generation and propagation, capturing the complexity and social interactions of the jobsite scenarios.

SNA was deemed useful due to its ability to capture the complexity of the worker decision making and information propagation. Knowledge diffusion in organizations and particularly in complex production is a concept often modeled with SNA; these methods were studied and used in the research. A method was also needed to simulate and model the micro and macro behavior of the conceptual model developed through observations in the research. ABM was selected as the candidate for this requirement because it allows simple logic rules to be built in for many agents that, when simulated over the long run, can result in emergent effects that do not appear in other modeling approaches. The two methods were both needed, and at a full level of integration (not just used subsequent to each other). This led to the development of a unique approach in which the SNA model was developed and integrated into the logic of agents in the ABM such that each agent was uniquely endowed with decision-making behavior based on their own history in prior obstacle encounters. The results of the implemented model suggest that the approach was successful in matching real jobsite scenarios.

Various parameters and assumptions of the model were tested by comparing alternative approaches. Within the SNA model, different values for ρ and γ were used, matching more closely to the typical values used in SNA. The values for ρ and γ are typically derived for an influence model using regression analysis to predict the value for y_{it} based on the network (w-matrix) and behaviors within the network ($y_{i't}$ and y_{it-1}) Typically ρ turns out to be no greater than 1/10 the value of γ, whereas the empirical values used in the SNA model herein had ρ > γ. The outcome showed that the worker behavior outcomes would be much different with the typical ρ and γ relationship, such that the workers would move much faster toward one obstacle handling method than they do based on the empirically-driven values for ρ and γ. However, the relationship between ρ and γ, as derived by empirical probabilities, can be explained given the nature of the construction jobsite. Construction does have a more hierarchical and authoritarian structure than perhaps other environments of complex production. The “apprentice/foreman” relationship in construction tends to promote workers following their peers or elders more strongly than they would their own beliefs. In addition, because the jobsites are long-term temporary workplaces, the workforces may have a social need to “conform” to a norm or information more than to stick with their own prior belief.

A second assumption explored was the impact of crew shuffling in the model. The model was run with this assumption removed, and due to less shuffling, there was less exposure to information gained between crews. The results showed without shuffling, the workers change their obstacle handling choice suddenly and drastically, potentially because of lack of exposure to “outside influences” within each worker’s network. A third test was performed within the model to show the impact of having the ABM informed by SNA. The model was run without the SNA underlying logic for each agent, and the outcome showed that the model without SNA was much closer to a static and probabilistic outcome in the ABM based on the parameters. Although emergent behavior did occur, in the long run of the simulation, the long run behavior is different when the SNA is included. This points to the usefulness of the SNA-informed ABM, in which each worker acts and learns dynamically according to their interactions with other agents.

The fourth question was **what is the relationship between the information flow and work performance?** This question was answered with analysis of the data collected from jobsites, and analysis of the simulated model for information flow on jobsites. In this research, the work performance metrics included the time workers lost, or in other words were not doing installation, due to handling obstacles; it also included the extension of effort required to complete a task when an obstacle is encountered, depending on the method chosen for handling and whether or not reporting the obstacle had an impact. The simulation showed that the information flow that impacted work performance most was the worker-to-worker information sharing.

Through answering the research questions, the postulation was verified. For one, the research showed that information is indeed generated from the point of installation on jobsites, which was verified through empirical data collection and observation, and analysis. The information that the workers have about their own experiences on jobsites, as well as their technical trade and skill is kept to themselves and used by themselves to locally adapt and coordinate in their daily work. This information becomes explicit particularly in the face of obstacles, when they have to improvise and decide how to handle the obstacles, either through resolving on their own, waiting for help, or working around the obstacle. As the obstacle is being handled or following its handling, information about the obstacle or incident is sometimes passed on beyond the crew. If passed outside the crew, it can help others on the jobsite to resolve future obstacles. If the information is not passed on outside the crew that faced the obstacle, the only other means for information passing is through the social network of the workers onsite. In this case, the information is still not carried out beyond the workforce or the jobsite, and therefore cannot be understood to solve work performance problems onsite.

The data collected in the research showed the gravity of these impacts on jobsite. Workers encounter obstacles in close to nine out of ten scheduled work tasks. This finding was interesting, because the data from state-of-the-art methods for measuring obstacles at the point of installation through surveys or asking the workers to report does not reflect this same quantity of obstacles. This indicates that the workers themselves do not recognize work-stoppage. To the workers, if the obstacle can be resolved, it may not be reported as an obstacle at all. This research treated anything that stopped workers from completing their work uninterrupted as obstacles, which showed the significance of the problem. Qualitative analysis of the observations showed that the behavior of the workers follows a few patterns that could also be modeled and studied individually in future research.

The second major conclusion from the research is that information propagates on the jobsite, but not consistently. Although workers encounter obstacles in nine out of 10 installation activities, they only report the obstacles 50% of the time, and they often choose to resolve the obstacles without outside help or support. In addition, the conceptual model and data collection and analysis used to populate the model showed that information is more likely to propagate through the workers onsite than through the formal hierarchy of the jobsite or crew structure.

The third conclusion is that there are many motivations for crew interactions and influences, including social, economic, and geospatial. Influences are both normative and informative, and based on a combination of past experience and current influence. This is due to construction being an environment of “complex production”, which is why the modeling methods used in this research were chosen.

The fourth conclusion from the research is that an SNA-informed ABM can represent the complexity of the interactions at the jobsite and information propagation and are therefore useful to study the information propagation and its impact. In addition to the data collection findings, the use of both ABM and SNA as methods for studying the model developed was proven to be beneficial. The method was developed uniquely in this research as an integrated model, where the SNA influence model was integrated in the ABM, including the logic and the worker network. Explorations of the model allowed for assumptions and parameters to be tested, further verifying that the SNA-informed ABM approach does best capture the jobsite conditions. Although a pure ABM approach or pure SNA approach would have provided useful models of the information generation and propagation, the simulation results indicated that an SNA-informed ABM model led to different results. Although the pure ABM model matched closer to the empirically collected data for handling and reporting obstacles, adding the SNA component allowed for a model of information propagation throughout a worker’s network and influence within and between crews. The worker interactions were not based on purely economic rules, and the SNA model implied that none of the workers including supervisors have fixed knowledge; it evolves over the life of a project as information propagates.

The model itself is to understand obstacles and information generation, and the impact that they have. The model will not likely be able to prevent the obstacles from occurring. The simulation output and future models will show the impact so that the highest impacts on work performance can be addressed.

6.2. Contributions

There are four main contributions of this research. The first contribution is the learning through empirical data collection about the jobsite information and obstacles from direct jobsite observations. The research proved that there is information available and generated from the workers, and that this problem is even more significant than what is shown in the current literature. Analysis of the data from the observations and data collection also allowed for the quantification of the conceptual model.

The second contribution is the development of a conceptual model for information generation and propagation from the point of installation. The research results of Chapter 4 explain how this model was developed conceptually, evaluated with observation to match actual jobsite behaviors. Finally, the conceptual model of how the information flows between and within workers on the jobsite was built to capture interactions that are not known or modeled in state-of-the-art research.

The third contribution is the development of an integrated SNA-informed ABM model. Research has been done to develop models that use both ABM and SNA models, but they have shortcomings that were addressed in this research. Specifically, the model developed herein relied on empirical data from jobsites, and the two methodologies were truly integrated, where the influence model of SNA was embedded in the ABM logic and used for agents in the model to carry on information to their next decisions, based on their prior experiences and current interactions with other workers. Other attempts to use both ABM and SNA used the two methods in a complementary way but not in a completely integrated way. Although the final simulation method could be improved upon, the concept of the integration is in itself a contribution.

The fourth contribution is the analysis and interpretation of the simulation results indicating that emergent behavior of a jobsite could be explained based on how information propagates or does not propagate through the various social networks.

6.3. Limitations

Despite the contributions of the research as listed above, there are some limitations that should be noted, in the categories of data collection and simulation development. In data collection, the long-run belief and behavior of agents was not captured in the data collected, because observations were done within one work day. This limited the ability to develop a full influence model for SNA. Longer-term data would provide information about whether or not agents truly change their behavior based on social network influence. The data collection sample was also limited to the jobsites and crews to which the author had access. A more stratified sample with additional samples would allow for more statistical rigor in the analysis and model parameters.

The simulation development was limited in scope for this research. For instance, the qualitative patterns were not included in the final simulation, and the full extent of the quantitative parameters from individual workers was not included. In addition, the final model used in the research did not account for several aspects of worker characteristics such as age and experience. These attributes could be used within a selection model as well to determine whether or not worker agents decide to interact. The model developed herein used a static probability of 50% likelihood for workers to become “friends” and therefore influenced by each other. Additionally, the exploration of cross-trade learning, the impact of various dimensions of workers’ social networks, and increasing heterogeneity of tasks would be interesting for future study. The model simulated was limited to the data collected and used as the basis for model development. There was also a challenge in the ABM, which is a common challenge in ABM, which is the synchronization of time and events. In modeling, typically a choice needs to be made on whether the model will be time-based or event-based. Given the conceptual model, the ABM used in this research attempted to develop a time-based model, but the stopping condition to be event based. When a random worker in the crew completed 8 hours of work, all workers in the crew stopped working. When all crews met this condition, the model should stop. The limitation of this is that tasks that take longer than 8 hours could not be modeled.

These limitations show that the model does not represent the full reality of the jobsite conditions; however, it is very challenging if not impossible for any model to fully represent reality. However, the model developed is still useful to see the impact of information generation and propagation at the point of installation. Model validation would be a useful future endeavor to bring the model closer to reality.

6.4. Future research

The work and results of this research has led to several potential future research opportunities and questions to be answered. Although the model proved useful in answering the questions for this research, several questions remain unstudied and additional questions raised through the research results. The additional data collection in the limitations section could be extended in future research, as well as the modeling limitations including development of an influence model populated with parameters based on a full regression of data collected. Further to this, the following questions could be explored:

- What is the impact of different types of obstacles encountered on the outcome of the model?
- What is the impact of worker turnover on the information generation and propagation? In other words, what happens when a new worker joins a jobsite? Does the jobsite overall knowledge change?

- Can the science of information theory models and their corollaries be used as extensions of the model developed here?
- Does the model developed herein apply to all general conditions on jobsites? What scenarios do not fit? What are the boundaries outside of which the model does not apply? What is the outcome of changes to the coefficients of the influence model?
- What is the impact of geospatial distance considerations in the model?
- What is the impact of information propagation from the point of installation on work performance?
- Can the models here apply outside the construction point of installation? This can be answered both for the information model and the SNA-informed ABM model.

In conclusion, this research has contributed greatly to the knowledge about information at the point of installation, which has been modeled with an integrated SNA-informed ABM model, which is also a unique contribution. However, there are several future research opportunities that can build on and expand on the questions left opened in this research.

6.5. Recommendation for Industry

Based on the results of this research, there are two practical recommendations that can be made to the construction industry. First, given that the research results confirmed the postulate that information does get lost from the point of installation on jobsites, construction practitioners representing all aspects of the construction process (e.g. owners, developers, contractors, suppliers, consultants) should recognize the need for building a channel through which information, particularly about the situations encountered and decisions made at the point of installation, can be captured and transferred from the worker. This channel should be designed to contain what was presented in this research as a conceptual model for how information propagates throughout the jobsite. In other words, existing means for capturing information and preventing disruptions are still missing a majority of the information available, as was discovered in empirical observation. Therefore, existing means and methods are not providing an adequate channel for information capture. The second recommendation is based on the results of the data collected, analyzed, and used in the simulation of the conceptual model. The analysis showed that jobsites with fewer workers result in different information propagation than those with more workers, independent of crew structure. Smaller workforces are more unpredictable in terms of how they will handle obstacles, potentially because of their worker network is so small so they are limited to the experience and knowledge to which they have access. In addition, when they do handle obstacles, they tend to lose more time and take longer to complete a task that encountered an obstacle. Based on this, the recommendation for industry is to understand and segregate types of work based on these findings, supporting smaller jobsites with a different infrastructure, especially for resolving conflicts and having access to the knowledge and experience that can help them resolve obstacles more effectively.

APPENDICES

Appendix A: Methods of Measuring Construction Productivity

Table 7: A summary of construction productivity measurements (summarized from Noor, 198)

Measure-ment Method	**Brief Description**	**Advantages**	**Disadvantages**
Direct observation	Observe workers throughout the day, identify contributory and non-contributory activities	1. Accurate time inputs 2. Detailed data for analytical purposes	1. Laborious and expensive 2. Sampling limitation in observation 3. Potential interference with the work during observation
Work study	Intermittent observations during work cycles	1. Not as intrusive to observe during full work period 2. Accurate time inputs 3. Detailed data for analytical purposes	1. More suited to work that has repetitive/continuous cycles 2. Sampling limitation for not observing all cycles
Audio-visual	Use time-lapse photography to capture and review observations in detail	1. Easier to collect and analyze data 2. Permanent record of activity	1. High initial cost, potential equipment failure 2. Time lag between capturing and interpreting video may lead to misinterpretation 3. Restriction on space monitored by camera setup
Activity sampling (including 5-minute rating technique)	Make periodic observations at the work site, focusing on the activities done by the workers during observation.	1. Simultaneous monitoring of labor productivity in various trades 2. Multiple observations made, still captures productive/non-productive time of the workers	1. Laborious and expensive 2. Sampling limitation in observation 3. Potential interference with the work during observation

Table 7 (cont'd)

Measure-ment Method	Brief Description	Advantages	Disadvantages
Craftsman's questionnaire survey or interviews	Survey workers for factors affecting their performance	1. Solicits view of workers 2. Gather input across several workers from sites	1. Data collection process complicated 2. Inaccurate information because based on memory and not real-time
Foreman delay survey	Foreman questioned on extent and type of delays	1. Data collection more accurate & less disruptive than from all workers 2. Only records delays, so inexpensive	1. Inaccurate information because based on memory and not real-time 2. Foreman may not know all of the delays on the site or their impact
Daily visit method	Observer visits site at end of every day and notes completion and causes for delays longer than 15 minutes	1. Frequency of collection 2. Data gathered from all sources of work on the jobsite	1. No reference point for "delay"; is just a listing of items, not relating to what was supposed to happen 2. Data collection and coding is extensive

Appendix B: Data Collection Instrument

Part I: Jobsite Demographics

Date:__________________

Job Name:____________________________________

Job Location:__________________________________

Job Information:

- Market category
  - o Commercial
  - o Residential
  - o Industrial
  - o Other
- Building structure
  - o # stories:
  - o Superstructure:
  - o Sq. ft:
  - o Footprint:
  - o Project size ($ / hrs):
- Delivery method
  - o Design-Bid-Build
  - o Design-Build
  - o Design-Assist
  - o IPD
- Contract type
  - o Lump sum / fixed price
  - o Cost plus
  - o T&M
  - o GMP
  - o Other

Project team:

- Owner / developer:________________________
- Architect:________________________________
- Engineer:________________________________
- GC / CM:________________________________

o Observed trade(s):____________;________________;______________________

___________;________________;____________________________

- **Project team structure:**

o PM onsite PM offsite

o Trailer Construction office No office

o Project team worked together before: Yes No

Part II: Activity Observation

Activity Description and Background
1. Activity Information

A. Activity description:____

B. Location on jobsite (describe):____________________________________

C. Do you have an alternate task in mind if primary task cannot be finished?:__________

D. If you run into an obstacle in completing this, what is your most likely response?
(1) resolve it, (2) report it and wait, (3) work around it

2. Tradesmen involved in activity

Subject	**Trade**	**Position**	**Approx. age**	**Experience**		**Subjects worked with before**
				In trade	In this activity	

3. Activity Expectations vs. Actual Results

	Start Time	**Completion Time**	**Manpower Involved**	
			Members / Positions	Total Effort
Expected				
Actual				

4. Obstacle Handling (if encountered)

A. Obstacle encountered:_____________________________________

B. Reaction to obstacle (circle): (1) resolve it, (2) report it and wait, (3) work around it

C. Time from obstacle discovery until next productive work (per subject):

Subject	Stop work	Re-start work	Other action or reaction to obstacle

C. If reported, who reported by:______________ to:_____________________

D. Detailed Description:____

____

E. Change in belief for next encountered obstacle

Subject	Next decision (1), (2), or (3)	Details / Comments

Appendix C: Data Collection Statistics

Table 8: Detailed statistics from jobsite data collection

Obs #	Date	City	State/Province	Market Category	# Stories	Sq. Ft.	Project Size ($) (italics if estimated)
1	5/2/2013	Waterloo	ON	Commercial	1	n/a	*$ 1,000,000*
2	5/2/2013	Waterloo	ON	Commercial	1	n/a	*$ 1,000,000*
3	5/2/2013	Waterloo	ON	Commercial	1	n/a	*$ 1,000,000*
4	5/2/2013	Kitchener	ON	Commercial	1	n/a	*$ 1,000,000*
5	5/2/2013	Kitchener	ON	Commercial	1	n/a	*$ 1,000,000*
6	5/2/2013	Georgetown	ON	Commercial	1	n/a	*$ 1,000,000*
7	5/10/2013	Denver	CO	Commercial	39	n/a	*$ 3,000,000*
8	5/10/2013	Denver	CO	Commercial	39	n/a	*$ 3,000,000*
9	5/10/2013	Denver	CO	Commercial	13	100,000	*$ 10,000,000*
10	5/10/2013	Denver	CO	Commercial	13	100,000	*$ 10,000,000*
11	5/10/2013	Denver	CO	Commercial	13	100,000	*$ 10,000,000*
12	5/10/2013	Denver	CO	Commercial	13	100,000	*$ 10,000,000*
13	5/10/2013	Denver	CO	Commercial	39	n/a	*$ 3,000,000*
14	5/10/2013	Denver	CO	Commercial	39	n/a	*$ 3,000,000*
15	5/10/2013	Omaha	NE	Commercial	n/a	n/a	$ 1,000,000
16	5/11/2013	Lincoln	NE	Commercial	2	n/a	$ 3,500,000
17	5/11/2013	Lincoln	NE	Commercial	2	n/a	$ 3,500,000
18	5/22/2013	London	ON	Industrial	2	n/a	n/a
19	5/22/2013	London	ON	Industrial	2	n/a	n/a
20	6/13/2013	Rockville	MD	Commercial	15	500000	*$ 3,600,000*
21	6/11/2013	Rockville	MD	Commercial	15	500000	*$ 3,600,000*
22	6/13/2013	Rockville	MD	Commercial	15	500000	*$ 3,600,000*
23	6/13/2013	Rockville	MD	Commercial	10	500000	*$ 10,000,000*
24	6/13/2013	Waterloo	ON	Commercial	1	n/a	*$ 1,000,000*
25	6/13/2013	Waterloo	ON	Commercial	1	n/a	*$ 1,000,000*

Table 8 (cont'd)

Obs #	Renovation /new	Delivery method[1]	Contract type	Observed trades	PM Onsite?	Trailer/office onsite?	Team worked together before?
1	New	DBB	Fixed price	Electrical	No	Trailer	n/a
2	New	DBB	Fixed price	Plumbing	No	Trailer	n/a
3	New	DBB	Fixed price	HVAC	No	Trailer	n/a
4	New	DBB	Fixed price	Electrical	No	Trailer	Yes
5	New	DBB	Fixed price	Mechanical	No	Trailer	Yes
6	Renovation	DBB	Fixed price	Electrical	No	Trailer	Yes
7	Renovation	n/a	Fixed price	Electrical	Yes	Construction Office	n/a
8	Renovation	n/a	Fixed price	Electrical	Yes	Construction Office	n/a
9	Renovation	DA	Fixed price	Electrical	No	No office	Yes
10	Renovation	DA	Fixed price	Electrical	No	No office	Yes
11	Renovation	DA	Fixed price	Electrical	No	No office	Yes
12	Renovation	DA	Fixed price	Electrical	No	No office	Yes
13	Renovation	n/a	Fixed price	Electrical	Yes	Construction Office	n/a
14	Renovation	n/a	Fixed price	Electrical	Yes	Construction Office	n/a
15	Renovation	DB	Fixed price	Electrical	No	No office	No
16	New	DB	GMP	Electrical	No	Construction Office	Yes
17	New	DB	GMP	Electrical	No	Construction Office	Yes
18	New	n/a	Fixed price	Electrical	No	Trailer	n/a
19	New	n/a	Fixed price	Electrical	No	Trailer	n/a
20	New	DA	Fixed price	Electrical, mechanical, drywaller	No	Construction Office	Yes
21	New	DA	Fixed price	Electrical, mechanical, drywaller	No	Construction Office	Yes
22	New	DA	Fixed price	Electrical, mechanical, drywaller	No	Construction Office	No
23	New	n/a	Fixed price	Electrical, sprinkler, duct, steamfitter, plumber, drywall	Yes	Construction Office	Yes
24	New	DBB	Fixed price	Electrical	No	Trailer	n/a
25	New	DBB	Fixed price	Electrical	No	Trailer	n/a

1 DBB = Design/Bid/Build, DA = Design/Assist, DB = Design/Build

Appendix D: Modeling Parameters

Table 9: Input parameters for model

ABM Element	Parameter	Step or model initialize	Value	Distribution (if needed)	Source
Agent	# agents	Model	Vary with model run		Consideration based on job sizes observed
	Position	Model	Apprentice, Journeyman, Foreman	App: 38%, JM: 54%, FM: 8%	Data collection
	Age	Model	Variable		Data collection
	Experience in trade	Model	Variable		Data collection
	Experience in activity	Model	Yes/No		Data collection
	Crew size	Step	1, 2, 3, or 4 people; used for initializing selection model (for the network arrangement)		Data collection
	Crew buddy	Step	68% of the time, workers are "friends"		Data collection
	Likely resolution method - initial	Step	1. Resolve, 2. wait for help, 3. work around, based on initial influence model	1: 41%, 2: 36%, 3: 23%	Data collection
	Likelihood to report - initial	Step	A. Report, B. No Report	A. 50%, B. 50%	Data collection
Environ-ment	Expected activity durations	Model	Variable	See "Time" tab	Data collection
	# tasks in the job	Model	4000		

Table 9 (cont'd)

ABM Element	Parameter	Step or model initialize	Value	Distribution (if needed)	Source
Behavior	Get work	Step	Assigned primary task		
	Do Work	Step	Work on task over time, if and until obstacle encountered		
	Handle Obstacles	Either	89% of agents encounter obstacle in their activity; if can't complete, can work on alternative 71% of time. Remaining 29% of time have to go back to supervisor to get new primary task.		Data collection
		Step	When encountered, % time spent not working	See "Time" tab - use median	Data collection
		Step	When encountered, additional task duration	See "Time" tab - use median	Data collection
A-A Inter-actions	Selection model	Model	Method used for determining whether agent i interacts with agent i'	See "Selection Model" tab	Data collection
	Influence model - initial	Step	Method used for obstacle handling	see "Influence Model Initial" tab	Data collection
	Influence model - initial at t0	Step	Method used for obstacle handling	See "Influence Model after t0" tab	Data collection

Table 10: Output parameters for model

Information Needed	Variable Description	Variable, Function, or Analysis	Variable Name	Variable type
Time of work	Time installing	Variable	t_Inst	Double
	Time not intsalling	Variable	t_NotInst	Double
	Total time	Function = t_Inst+t_NotInst	t_tot	Double
Impact of obstacle handling method	Frequency of decision type (1,2,3)	Analysis = Pr(each method)	resolve, report, workaround	Boolean (binomial?)
Correlation of decision with time of work		Analysis =Correlation between frequency of each decision and t_tot; Correl between each decision and t_Instl		
Correlation of decision with tasks left unfinished	Tasks left incomplete		task_incomplete	Integer
	Total tasks assigned		task_assigned	Integer
Correlation of decision with obstacle perpetuation	Obstacle recurrence	Function=if(obstacle left unresolved for task assignment and task left incomplete, if(next agent encounters obstacle in task assignment))	obs_reoccur	Integer

Table 10 (cont'd)

Information Needed	Variable Description	Variable, Function, or Analysis	Variable Name	Variable type
Change in agent belief about method for obstacle handling	y_{it}	Variable	y_{it}	Boolean (binomial?)
		Function = y_{it} - y_{it-1}		
		Function = y_{it} - y_{it+1}		
Amount of information lost (e.g. not passed on beyond work location); does this follow H=nlogS		Function = sum(report)log(sum(resolve,report,workaround))		
Aggregate outcomes; effect of model parameters	e, age, experience, etc.	Variable	e_present	Boolean
Aggregate outcomes: salience of economic, geographic, social utility (what has bigger impact)				

Appendix E: Functions from AgentAnalyst for final model

1. Model level
    a. InitAgents
        i. Initialize the attributes of the agents that don't change throughout the model, including:
            1. Worker characteristics (age, experience, position/skill level)
            2. Crew characteristics (number of people in crew)
            3. Calls electrician.befriend() to assign friends across or within crews
    b. StepIni
        i. Initializes every tick with time worked, crew assignments, etc.
            1. Crew assignments are based on randomizing the workers in a crew, and assigning random workers until the crew "size" is filled up as identified as distribution of crew sizes in step 1.a.2 above.
        ii. Calls action function
    c. Action
        i. Calls step function for crew, triggering work

2. Crew agent
    a. Step
        i. Record time, run into obstacles
        ii. Call influence models for workers: T1 and Tn
        iii. Includes stopping condition
    b. T1 influence model
    c. Tn influence model

3. Worker agent
    a. Befriend
        i. Populate network model (randomly with 68% chance)

Appendix F: Example simulation output used for analysis

Example output from excerpt of ticks 5 and 10 for one model run

```
START MODEL
-----------------SUMMARY STATISTICS---------------
Time scheduled to work: 695.0
Total time spent working: 2088.4000000000015
Total lost time: 55.08780000000004
Tasks assigned and left unfinished: 5
Tasks unfinished: 3980
Tasks completed: 76
Total tasks attempted: 81
Total count of obstacles encountered: 74
Total obstacles reported to the supervisor: 34
Method 1: 63
Method 2: 6
Method 3: 5
End of Summary Statistics for tick 5.0
-----------------SUMMARY STATISTICS---------------
Time scheduled to work: 1340.0
Total time spent working: 3360.8900000000053
Total lost time: 128.93409999999983
Tasks assigned and left unfinished: 5
Tasks unfinished: 3996
Tasks completed: 182
Total tasks attempted: 187
Total count of obstacles encountered: 169
Total obstacles reported to the supervisor: 81
Method 1: 158
Method 2: 6
Method 3: 5
End of Summary Statistics for tick 10.0
```

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