USING EMPIRICAL DATA TO DESIGN AND VALIDATE HYBRID SIMULATION MODELS OF HUMAN BEHAVIOR IN SERVICE OPERATIONS

by

MOHAMMED FARHAN

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Supervising Committee:

Dr. Caroline Krejci, Supervising Professor

Dr. Brian Huff

Dr. Yuan Zhou

Dr. David E. Cantor

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ABSTRACT

USING EMPIRICAL DATA TO DESIGN AND VALIDATE HYBRID SIMULATION MODELS OF HUMAN BEHAVIOR IN SERVICE OPERATIONS

Mohammed Farhan, Ph.D.

The University of Texas at Arlington, 2021

Supervising Professor: Dr. Caroline Krejci

The purpose of this research is to examine how a change in a team member's role, team dynamics, and organizational policies impact an individual's motivation to engage in helping behavior, as well as the impact of helping behavior on service system operational performance. To analyze these behavioral dynamics in a dynamic setting, this research integrates empirical human behavioral data into a hybrid discrete event and agent-based simulation model of service operations in a restaurant. The model was then validated using Metamorphic Testing (MT), an approach that has previously been used for verification of software. Recent research shows that MT can be used to validate both agent-based models and discrete event simulation models. This research builds on that work by demonstrating that MT can also be used to validate hybrid simulation models. Metamorphic relations were systematically developed following the framework presented in this research to run different validation experiments. The experiments applied MT for validating both DES and ABM aspects of the hybrid model separately, as well as the combined overall model. Through the upholding of the predicted pseudo-oracle answers, the research shows an increased confidence in the validity of the simulation model.

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DEDICATION

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CHAPTER 1 Introduction

1.1 Background

The US Bureau of Labor Statistics estimates that nearly two-thirds of US workers are in the service industry, and these numbers are rising rapidly (Henderson, 2015). A total of 15.6 million people in the US currently work in the restaurant industry, which is 1 in every 10 working individuals (NRA, 2020a), and the employment rate for servers is projected to continue to grow (US Bureau of Labor Statistics, 2020). However, the turnover rate in the restaurant sector is very high, peaking at 74.9 percent in 2018 (NRA, 2020a). On average, a restaurant will suffer $5,864 in losses each year due to server turnover (Tracey & Hinkin, 2006). Consequently, the National Restaurant Association has identified recruitment and retention of employees as being critical to a restaurant's success, naming it as their top concern (NRA, 2020b).

One reason that server turnover is so costly for restaurants is the impact it has on employee team dynamics. A restaurant server works interdependently with other servers and the kitchen staff as a team to ensure that customers have a satisfying dining experience (US Bureau of Labor Statistics, 2020). Server turnover can disrupt team dynamics, which can result in poor customer experience. Along with recruitment and retention, restaurant managers also seek ways of improving overall team effectiveness (Haefner, 2011), in terms of performance (e.g., quality and quantity of output), member attitudes (e.g., satisfaction), and member behaviors (e.g., helping behavior and personal growth) (S. G. Cohen & Bailey, 1997; Guzzo & Shea, 1992; "Team Perform. Assess. Meas. Theory, Methods, Appl.," 1997; Tepeci, 2008). A central aspect of understanding restaurant teamwork is interdependence and coordination among team members, which correlate to each member's characteristics, the restaurant environment, and team processes (Tepeci, 2008). The team's psychosocial traits, such as manager facilitation and support, organizational esprit, workgroup cooperation, friendliness, and warmth also directly influence team effectiveness (S. G. Cohen & Bailey, 1997). A change in any of these factors can potentially disrupt team dynamics and productivity. Therefore, understanding how to minimize the impact of changes in team dynamics is critical (B. Bechky, 2006).

In particular, there is a significant gap in our understanding of what motivates a restaurant worker to exhibit helping behavior in a team. An example of helping behavior in a restaurant setting would be a server helping another server by sharing his duties without expecting to receive any monetary or social benefits in return. The concept of helping behavior is an important aspect of organizational citizenship behavior (OCB) (Bachrach et al., 2001, 2006). (Organ, 1988) describes OCB as a voluntary individual activity (i.e., not acknowledged specifically or indirectly by a formal incentive system) to facilitate the organization's efficient functioning. Although organizations can greatly benefit from an individual's willingness to engage in helping behavior (Montabon et al., 2016; Podsakoff et al., 2000), the behavioral and operational factors that motivate helping behavior are poorly understood (Doerr et al., 2004). Empirical studies (e.g., (Deakin, 2015; Nurhayati et al., 2018; Tepeci, 2008; Volkan & Meryem, 2020)) have investigated the challenges of restaurant team effectiveness via surveys and case studies, but they fail to provide an understanding of how team effectiveness dynamically impacts overall restaurant performance. Chandrasekaran et al. (2018) emphasize the inherent limitations of using only empirical research designs to solve such complex operations management problems, including data availability, unobserved variables, reliability, and the ability to analyze dynamic phenomena that occur over an extended time horizon. To address these issues, the authors recommend using simulation models to complement and strengthen an empirical study. A simulation model is a computerized simplified representation or an abstraction of a real or conceptually complex system (Kellner et al., 1999) which is governed by a set of rules that the system uses to move from its current state to the next. These rules can be flowcharts, differential equations, statements, or a combination of all (Hill, 2002). Simulation is a cost-effective strategy for experimentation on virtual systems, including systems with human behavioral elements.

Table 1-1 summarizes challenges for operations management (OM) research that is based on two archetypical research objectives and research designs. In OM, the objective of operations research is either theory building or theory testing (Hitt et al., 2015). Furthermore, depending on the kind of research question they seek to answer, OM researchers can employ two different study structures: variance design or process design (Van De Ven & Johnson, 2006). Variance design methods focus on the correlations between antecedents and outcomes, typically using cross-sectional studies and surveys, whereas process design methods are focused on understanding the dynamic relationships between independent variables and outcomes using longitudinal studies or surveys (Chandrasekaran et al., 2018).

A previous qualitative study on restaurant workers indicates that apart from monetary benefits, important motivational factors from an employee's viewpoint to remain in their current job are their relationships with coworkers, their work schedule, and their perceptions of fairness in their work environment (Dermody et al., 2004). Thus, the research described in this dissertation hypothesizes that a server’s willingness to engage in helping behavior is impacted by 1) his/her perception of fairness concerning a coworker’s promotion, 2) norms of reciprocity among servers, 3) the server's perception fairness in his/her assigned work schedule, and his/her level of work utilization.

Table 1-1 Research challenges inherent in research objectives and design (derived from (Chandrasekaran et al., 2018)).

	Variance design	Process design
Theory building	**Quadrant 1** **Examples**: cross-sectional case studies **Inherent challenge**: causal relationships **Role of simulation**: examining interactions among the variables. (e.g. (Barratt et al., 2018; Chandrasekaran et al., 2016))	**Quadrant 3** **Examples**: longitudinal case studies or surveys **Inherent challenge**: repeatability **Role of simulation**: varying decisions, boundary conditions, and parameters. (e.g. (Stauffer et al., 2018; Vries et al., 2018))
Theory testing	**Quadrant 2** **Example**: survey, secondary data work **Inherent challenge**: endogeneity issues **Role of simulation**: incorporating omitted variables and parameters. (e.g. (Sting et al., 2019))	**Quadrant 4** **Example**: longitudinal surveys **Inherent challenge**: dynamic relationships among variables **Role of simulation**: unraveling hidden dynamic relationships. (e.g. (Park et al., 2018; Sterman et al., 1997))

These hypotheses are tested via a survey, which falls under Quadrant 2 of Table 1-1. While a survey can provide useful information about the relationships between the hypothesized factors and server helping behavior, the resulting statistical model cannot predict the dynamic operational behavior that may result from the helping behavior. To overcome the inherent challenge in understanding how these behavioral outcomes manifest themselves in a dynamic restaurant setting, this research utilizes simulation modeling to obtain operational insights and reveal hidden dynamic relationships.

There are three types of system simulation methods: discrete-event simulation (DES), agent-based modeling (ABM), and system dynamics (SD) (Owen, 2013). DES is a method to model a system that changes its state solely based on a discrete set of points in time (Carson et al., 2013). During the simulation run, one's state strictly follows functions of its initial state values along with the sequence of events for that component that occurred at that time (Heath et al., 2011;

Mittal & Krejci, 2017). In ABM, simulated individuals are the decision-makers who follow programmed rules. While DES is considered a process-centric method, ABM can be considered as agent-centric, where the focus is on entities with unique characteristics making decisions, performing activities, and interacting with the environment (Badham et al., 2018). SD is a modeling technique developed by (Forrester Jay W, 1958) in the late 1950s for the purpose to study the bullwhip effect in supply chains but soon developed interests in other fields like economics, workflow management (Lättilä et al., 2010). (S C Brailsford & Hilton, 2001) define SD models as a "representation of a system as a set of stocks and flows where the state changes occur continuously over time". It defines human systems in terms of feedback and delays (Greasley, 2017).

However, real-world problems are complex, and sometimes a single simulation method is not sufficient to describe the system or problem. A hybrid simulation model is any combination of the three simulation types (ABM, DES, or SD) (Sally C Brailsford et al., 2019). Majid et al. (2016) advocate the use of a hybridized model of ABM and DES for service systems dealing with modeling human behavior. For the proposed research, a stylized restaurant model is created by combining ABM and DES. The customers in the proposed model follow a strict path that is time-dependent and do not possess decision-making capabilities, making them suitable for DES. In (M A Majid et al., 2010), the authors have shown that DES is a better modeling method for queuing customers, in comparison to ABM. The servers in the study are the decision-makers working and interacting as a team and have similar characteristics as an ABM agent. Furthermore, humans are complex social beings that have constant interaction with the world and other humans. Complex interactions can be conceptualized as social processes such as helping behavior or social influence

(Badham et al., 2018; Berkman et al., 2000). The combination of these two simulation types in a single model constitutes the hybrid simulation model for this study.

However, the validation of hybrid simulation models poses a significant challenge. Decision-makers make choices in the real-world affecting individuals based on simulation results, making the correctness of the simulation models a crucial task. The correctness of a simulation model is addressed through verification and validation. (R G Sargent, 2013) defines model verification as "ensuring that the computer program of the computerized model and its implementation are correct". (Schlesinger et al., 1979) defines model validation as "substantiation that a computerized model within its domain of applicability possesses a satisfactory range of accuracy consistent with the intended application of the model". (R G Sargent, 2013) describes that the cost and time for model validation are proportional to model confidence and its value to the modeler as shown in Figure 1-1.

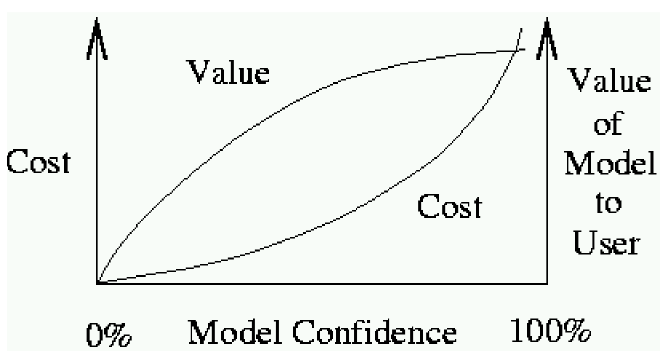

Figure 1-1 Model confidence derived from (R G Sargent, 2013).

There are over 77 techniques mentioned in the handbook of simulation for validation and verification of simulation models (Banks, 1998). All the techniques focus on the primary three types of simulation models but fail to address the validation of hybrid simulation models in specific. Out of the techniques, the most common is results validation, in which the simulation results data are compared against the real-world data for validation (M Olsen & Raunak, 2019). In most cases real-world data is not readily available and hence validating the models becomes difficult. Validation becomes even more complex for conceptual models that are not based out of a real-world environment.

Figure 1-2 derived from (Sally C Brailsford et al., 2019) shows that the use of hybrid simulation models in research has increased substantially in the last few years and the numbers are rising rapidly. However, there is a gap in the literature on hybrid simulation validation which could lead to reliability concerns with regards to these models. Previous research papers that apply hybrid simulation methodology have addressed validation by validating sub-model types in isolation. (Sally C Brailsford et al., 2019) emphasizes the urgency in research aimed at developing more rigorous methods for hybrid simulation validation when it comes to verifying the links between sub-models i.e., inter-modular verification, and validation of the exchanged information.

Metamorphic testing (MT) validation, a method first introduced in the field of computer software testing to determine if the software program's output is correct, by using a test oracle (T. Y. Chen et al., 2020). A test oracle is a mechanism that uses a test case to determine if the software program was executed correctly (Howden, 1978). (M Olsen & Raunak, 2019) proposed the use of MT validation for discrete event and agent-based simulation models using metamorphic relations (MR) and has shown promising results. MR defines the user's prediction on how the output should change based on a change in some inputs. MT validation has not been applied for hybrid simulation models and this research provides insights on future approaches for joint validation and verification via MT on simulation models by applying the approach on the helping behavior model.

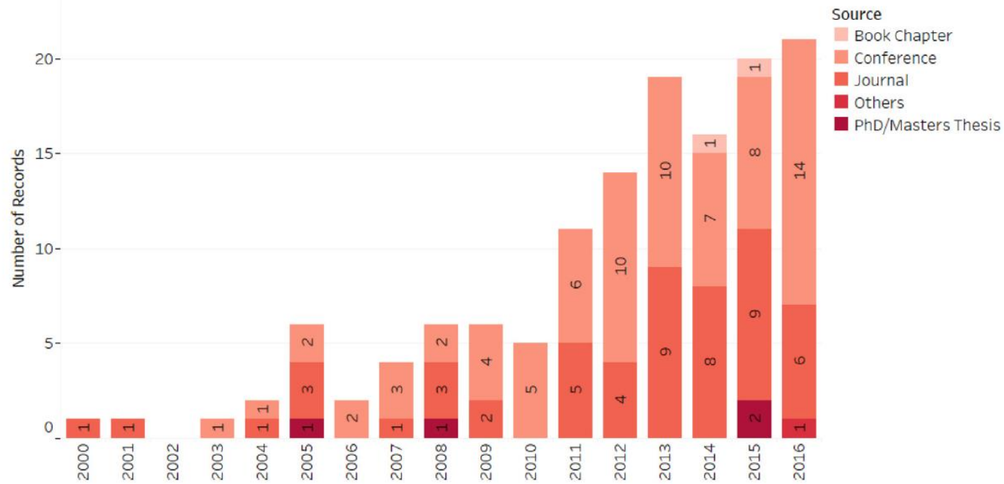

Figure 1-2 Evolution of hybrid simulation literature over time (derived from (Sally C Brailsford et al., 2019)).

1.2 Research Questions and Contributions

In this research, the following research questions are addressed:

- How do behavioral and situational factors beyond monetary benefits motivate a restaurant server to engage in helping behavior?
- How can a behavioral study of restaurant servers be extended to gain dynamic restaurant operational insights using hybrid simulation?
- How can inter-modular verification and validation be achieved in hybrid simulation models?
- How can the Metamorphic Testing technique be applied to validate hybrid simulation models?

By answering these questions, this dissertation contributes to the disciplines of operations management (OM) and simulation modeling as follows:

- Prior research in OM has not considered why and how changes in team member roles influence helping behavior. This research develops and tests a hypothesis on the behavioral factors that impede and facilitate servers to help one another in a restaurant setting.
- This research also contributes to the OM literature by developing and testing a hypothesis on the dynamic operational outcomes of a restaurant server engaging in helping behavior using hybrid simulation modeling.
- The suitability of MT validation for hybrid ABM-DES simulation models is determined, and guidelines for verifying and validating inter-modular data in hybrid simulation models are created.

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CHAPTER 2 THE IMPACT OF NON-CORE WORKERS ON HELPING BEHAVIOR AND TEAM PERFORMANCE: A MULTI-METHOD PERSPECTIVE

Mohammed Farhan, Caroline Krejci
Industrial Engineering
University of Texas at Arlington
Arlington, TX
farhanm@exchange@uta.edu,
caroline.krejci@uta.edu

David E Cantor
Supply Chain Management
Iowa State University
Ames, IA
dcantor@iastate.edu

2.1 Introduction

Improving worker productivity and overall team performance is a significant challenge for operations managers (Haefner, 2011). Poor worker productivity and team performance can have a negative impact on key performance indicators such as labor productivity, throughput time, customer service, and overall firm financial performance. Indeed, Forbes reports that 70 percent of employees are not motivated in their current position, which clearly can impact labor productivity (Strut & Nordstrom, 2018). Accordingly, firms such as John Deere and Bombardier are pursuing internal human resource strategies to encourage stronger workers to step in and provide helping behavior to low-performing workers (Delgado et al., 2012; O'Connell & Reeder, 2008)

There is scholarly interest in examining how to improve worker productivity in operations management. One stream of worker productivity research in Operations Management (OM) suggests that a production lines' structure influences worker productivity. In particular, (Doerr et al., 2002, 2004) suggest that managers can encourage helping behavior in production lines by implementing work-sharing systems. The design of these line-balancing systems requires that faster workers complete the work of slower workers. Likewise, (K. L. Schultz et al., 1998, 1999) suggest that workers are motivated to help their colleagues by the amount of inventory visible in the production system.

A related line of research examines a worker's personality factors on helping behavior on production tasks. (Cantor & Jin, 2019) examine production factors that influence faster workers to help slower workers. (Bachrach et al., 2001) and (Bachrach et al., 2006) provide empirical evidence that feedback on task performance influences helping behavior. (Siemsen et al., 2007) theorize about how altruism (e.g., helping) influences knowledge-sharing behavior. These studies collectively advocate for the consideration of human resource strategies to improve individual and team productivity (Boudreau et al., 2003).

While the studies mentioned above, among many others, have made important contributions to the literature, prior research has not considered why and how changes in team member roles influence helping behavior. Indeed, a steady stream of research has studied the dynamics of stable team membership. However, in the real world, the operations workforce frequently experiences role changes, including an employee's job duties and responsibilities (Ancona et al., 2002). For example, in response to consumer demand changes, manufacturing and service OM team members are encouraged to adapt to new and different roles often caused by organizational upsizing and downsizing situations (DeRue et al., 2008). Because teams regularly experience changes in members' roles and responsibilities, it is critical to understand further how to minimize the resulting change in team dynamics and performance (B. A. Bechky, 2006). It is especially important to explore how procedural fairness concerns regarding a team member's change in responsibilities (e.g., role changes) impact team processes, including team member helping behavior and overall organizational performance.

The purpose of this research study is to examine how a change in a team member's role, team dynamics, and organizational policies impacts an individual's motivation to engage in helping behavior and the overall impact on system performance (e.g., service time). In so doing, we draw upon the theory of strategic core as described in the organizational behavior literature (e.g.,(Summers et al., 2012)). Briefly, the theory of strategic core suggests that some job roles in organizations have a more noticeable impact on organizational performance than others (Delery & Shaw, 2001; Emery & Trist, 1965). In particular, we leverage the theory of strategic core to explain how individuals respond to a core team member's role expansion due to an imbalanced workload resulting from an unexpected event (e.g., absenteeism, promotion decisions). We enhance our theoretical model by integrating research from the procedural fairness and equity theory literature to examine how perceptions of fairness influence an individual's motivation to help the core team member (i.e., helping behavior). We test our research questions by conducting two studies using a multi-method approach. In our first study, we conduct an online vignette-based experiment with Amazon MTurks to empirically examine how a non-core team member reacts to the core member role expansion situation regarding providing help to the team's core worker. Because we are interested in understanding how these behavioral dynamics manifest themselves in a dynamic setting, our second study then builds upon the findings from Study 1 through the development of a simulation model. In Study 2, using hybrid discrete event and agent-based simulation modeling techniques, we further explore how team dynamics influence helping behavior and overall performance.

Our study makes multiple theoretical and empirical contributions to the literature. To the best of our knowledge, this is the first study that has re-conceptualized and, hence, leveraged the theory of the strategic core in the operations management literature to study helping behavior (e.g.,(Humphrey et al., 2009; Summers et al., 2012)). In so doing, we theorize and empirically examine why and how a change in team dynamics influences helping behavior and organizational performance. Our study also provides a micro-level understanding of how team dynamics influence service time performance. Second, our study contributes to the literature by theorizing how procedural fairness concerns impact team member roles and workload management. Indeed, our study adds to the literature by providing a further understanding of how team members react to team process changes (i.e., role expansion). Thus, we enhance this perspective by theorizing on how an individual team member responds to team member fairness concerns. This study also advances our understanding of the critical importance of helping behavior in a service operations management setting. We also contribute to the literature by demonstrating the utility of a behavioral OM model using hybrid simulation modeling techniques, and in doing so, our study builds upon and extends prior helping behavior research in OM (e.g., (Cantor & Jin, 2019), etc.) and hybrid simulation literature (Sally C Brailsford et al., 2019).

2.2 Theoretical Background and Foundation

The theory of the strategic core is the theoretical foundation of this study. Previous research has developed the theory of strategic core and provided empirical evidence that some job roles and responsibilities in organizations could have a more noticeable impact on the team and organizational performance than others (Delery & Shaw, 2001; Emery & Trist, 1965; Humphrey et al., 2009; Summers et al., 2012). (Summers et al., 2012) developed the theory of the strategic core by examining how the flux in the coordination construct captures the disruption a team undergoes during team membership replacement. Following (Summers et al., 2012) and (Humphrey et al., 2009), we define the strategic core as the job role on a team that (a) encounters more of the problem that needs to be overcome by the team, (b) has greater exposure to the tasks that the team is performing, and (c) is more central to the workflow of the team. Moreover, (Humphrey et al., 2009) point out that a strategic core job role can be thought of as a continuum: the more a job role meets these criteria, the more 'core' the job role is to the team.

While the concept of the theory of the strategic core has not been previously used in the OM literature, we believe that some of the elements described in theory are present in the OM team stream of research and have applicability in this study. In operations management, leadership is a very important core role as team leaders are responsible for making critical strategic decisions that impact the team's operational and overall performance. For example, project leaders commonly find themselves serving as strategic core team members because part of their job responsibilities is to reconcile competing subordinate perspectives in new product development activities (Wouters et al., 2009). Project leaders are responsible for seeking the buy-in and resources necessary for achieving project success (Linderman et al., 2006). Undoubtedly, competing perspectives arise because some team members are more familiar with the business challenges of bringing a new product to market.

In contrast, other team members are concerned with technical hurdles. Thus, team leaders and project managers are needed to reconcile these views and facilitate critical supply chain business decisions (Bendoly et al., 2010). (Scott-Young & Samson, 2008) illustrate some of the critical success factors that project leaders need to address to impact project cost, schedule, and operability. (Easton & Rosenzweig, 2012) point out that successful Six Sigma teams are composed of project leaders that exhibit high levels of familiarity and individual and organizational experiences.

Likewise, in the production and assembly line systems literature, some workers have a greater core role than others. The OM literature points out that some team members are more central to the team's operational workflow than their colleagues. Indeed, the concept of a core role appears in a class of production systems referred to as a bucket brigade, where workers are organized in a single production line from slowest to fastest, relative to their work rates (Bartholdi & Eisenstein, 1996). Finished production work is moved downstream, and workers look to upstream stations for additional work to process (K. L. Schultz et al., 1998). OM scholars have noted that some workers become more critical to the productivity of these production lines because they work faster and become more proficient in processing work-in-progress (Doerr et al., 2002, 2004).

An important element in team processes is the fairness of decision-making policies and procedures. Previous research has thus leveraged the procedural justice literature to study the attitude and behavior of the people affected by the decisions made by organizational or legal authorities (Korsgaard et al., 1995; Lind & Tyler, 1988; Moorman, 1991; Moorman et al., 1998; Thibaut & Walker, 1978). This literature suggests that decision-making procedures should be equitable, neutral, unbiased, transparent, and fact-based and, in doing so, can potentially mitigate any potential organizational citizenship problems such as poor worker productivity and/or employee turnover (Adams, 1965). Therefore, the formation and implementation of organizational policies and decisions should follow a neutral and fact-based decision-making process to address potential worker motivation problems proactively. Procedural justice concepts have been applied in previous supply chain research (e.g., (Cantor et al., 2011; Griffith et al., 2006; Hofer et al., 2012; Y. Liu et al., 2012).

Undoubtedly, the teams and procedural justice literature have made important contributions to our theoretical understanding of team dynamics in OM. However, we believe that a significant void exists in the OM literature regarding developing a theoretical model on factors that motivate a non-core worker to provide help to a core worker. We seek to contribute to the literature by capitalizing on the theory of the strategic core to explain how perceptions of fairness influence a non-core worker to provide helping behavior to the core worker on the team. Again, a core worker has more job roles and responsibilities than non-core workers. The theory's fundamental tenet is that non-core workers who perceive that procedural fairness elements are present in the work environment will become more motivated to engage in the helping behavior of other non-core workers and the core-worker in the team. Figure 2-1 provides a depiction of our theoretical model. We now turn to describe our detailed theoretical arguments.

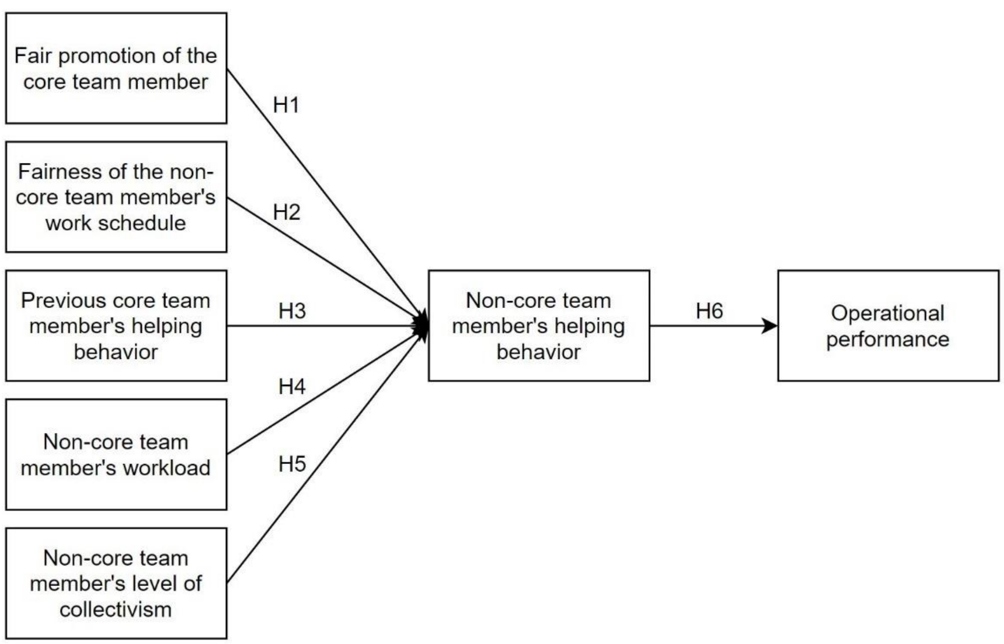

Figure 2-1 Theoretical model

2.3 Hypotheses

The first factor examined in our theoretical model is how a non-core worker's fairness perception influences their decision to engage in helping behavior [1]. In the context of our study, the research participant is the non-core worker, and she or he is told that another employee in the organization was promoted into a more prominent role and provided additional job responsibilities (e.g., stretch work). We now present our theoretical arguments in support of this hypothesized relationship by drawing-upon the theory of strategic core and procedural fairness literature (e.g., (Humphrey et al., 2009; Moorman et al., 1998; Summers et al., 2012)). We contend that the non-core worker will develop fairness impressions about the core worker's recent job promotion based on the non-core worker's interpretation of the organization's current and future organizational policies, rules, and practices (Bies, 1987; Folger & Konovsky, 1989; Moorman, 1991; Moorman et al., 1998). In many organizations, non-core workers are attentive to how core workers and supervisors create and promulgate new organizational policies and practices (Lind & Tyler, 1988). When the organization and/or leadership team designs implement new policies that are perceived to be unjust, non-core workers will react negatively and reduce their willingness to engage in pro-social behavior. Thus, the strategic core and procedural fairness literature suggest that it is important to examine how a non-core team member's fairness concerns influence team and organizational outcomes. In this study, we theorize about how procedural fairness concerns regarding promoting a team member into the core role.

There are several reasons to believe that the non-core worker would consider the fairness of the recent job promotion process involving the core worker in his or her decision to provide help to the core worker. First, in many organizations, it is important to provide both core and non-

[1] The non-core work in this study refers to the role assumed by the research participant. The core worker is the member of the team who has more responsibilities than the other team members.

core workers with the opportunity to participate in the job promotion process. By doing so, the firm can provide its workers with a voice in career advancement opportunities that can influence the actual decision-making outcome. As a result, the procedural fairness literature has shown that employees are less likely to be dissatisfied with unfavorable outcomes if they believe that the procedures used to derive those outcomes are fair and equitable, as reflected in equity theory (Adams, 1965; Folger & Konovsky, 1989; Lind et al., 1990; Lind & Tyler, 1988). Second, procedural fairness and organizational commitment literature provide insight as to why non-core workers care about the process by which core workers are promoted fairly. Through participation in the process, non-core workers should develop goodwill and, hence, form a stronger affective commitment towards the firm. As such, non-core workers should feel valued and have control over their promotion and advancement opportunities. Relatedly, greater feelings of commitment lead to a higher likelihood of pro-social behavior among non-core workers.

While we contend the perception that a core worker who was promoted fairly will lead the non-core worker to provide helping behavior to the core-worker, there are some reasons to believe that an organization's willingness to address fairness concerns regarding job promotion opportunities will not motivate pro-social behavior. Some employees do not seek promotion opportunities for several reasons. First, these individuals do not want to be burdened by the stress of managing employees or extra responsibilities. They are self-satisfied with their current role in the organization, which is especially true in industries with high job burnout, etc. (e.g., restaurants). Second, some individuals are employed in an organization for supplementary income to cover part of their post-secondary education costs. Thus, procedural fairness concerns about promotion opportunities are not a primary concern. Based on these arguments, we present the following hypothesis.

Hypothesis 1 (H1). *In the situation where there is the perception that the core worker was promoted fairly, the non-core worker is more motivated to provide helping behavior to the core worker than the situation where there is the perception that the core worker was not promoted fairly.*

The second factor in our model is the perception that the non-core worker was treated fairly regarding their preferred work schedule. As noted, non-core workers evaluate the impact of the fairness of current and future organizational policies, rules, and practices (Bies, 1987; Folger & Konovsky, 1989; Moorman, 1991; Moorman et al., 1998). Unlike in the previous hypothesis, where the non-core worker evaluated the fairness of the core-worker's job promotion, we now theorize about how the non-core worker is ***directly*** impacted regarding his or her preferred work schedule. Thus, we contend that the organization's treatment of the non-core worker's desired work schedule will directly influence fairness perceptions and pro-social behavior.

Prior theory of the strategic core and procedural fairness research has not directly investigated how work schedules' fairness concerns impact helping behavior. However, the procedural justice literature can provide insight into how an employee may react regarding organizational commitment when the employer does not respond favorably to the work scheduling desires of their employee. The US motor carrier (trucking) industry provides good examples in this regard. Briefly, in the US motor carrier industry, motor carrier employees and owner-operators (i.e., independent contractors) are responsible for hauling freight across the supply chain. These employees have a desire to perform their work based on their work scheduling preferences (e.g.,(Cantor & Terle, 2010)). However, the Federal Government desires to regulate the truck driver worker hours, including the use of technology to enforce the maximum number of hours that drivers are allowed to operate commercial vehicles (Miller et al., 2020). Commercial drivers have expressed serious procedural fairness concerns about the use of electronic monitoring technology. Indeed, (Cantor et al., 2011) theorize and empirically demonstrate that electronic monitoring technology's adoption influences employee turnover intentions among truck drivers. Relatedly, (Cantor & Terle, 2010) theorize on how employees attend to government regulators' procedural fairness practices and the subsequent impact on their voluntary compliance to a government regulation concerning the adoption of electronic monitoring technology in the workplace. Likewise, (Miller et al., 2013) studied the effects of formal controls on an employee’s work hours, which the authors suggest influences truck drivers' behavior and thereby influences the operational performance of firms in the US motor carrier industry. Collectively, these studies, among several others, demonstrate that employees are motivated to leave a place of employment rather than become subjected to the enforcement of unfair workplace rules.

In summary, the insights gleaned from the literature suggest that employees will not engage in pro-social behavior if their concerns are not attended to in a fair and just manner. Thus, we suggest that non-core workers who are not treated fairly regarding work scheduling will avoid engaging in pro-social (helping) behavior. Following this logic, we offer the following hypothesis.

Hypothesis 2 (H2). *In the situation where there is the perception that the non-core worker was treated fairly regarding her or his preferred work schedule, it is more likely that the non-core worker will be motivated to provide helping behavior to the core worker, compared to the situation where there is the perception that the non-core worker was not treated fairly regarding her or his preferred work schedule.*

The third factor in our theoretical model concerns the concept of norms of reciprocity. Briefly, norms of reciprocity are defined as the assertion that one person is willing to help another individual so long as the helping provider believes that he or she will receive help from the helped in the future (i.e., willing to engage in a norm of reciprocity) (e.g., (Eisenberger et al., 1986; Rhoades & Eisenberger, 2002; Shore et al., 1995). Stated differently, organizational behavior scholars suggest that employees will engage in behavior that supports either the organization or supervisor's goals so long as the organization is willing to reciprocate with appropriate leadership, training, and rewards. The norms of reciprocity concept have received theoretical and empirical attention in several disciplines, including organizational behavior, social psychology, and supply chain management literature. Indeed, (Cantor et al., 2012) use the norms of reciprocity theory to investigate how a supervisor's support for environmental initiatives results in an employee's commitment to the environment.

In our context, we contend that the non-core worker will provide help to the core worker based on the non-core worker's previous professional interactions with the core-worker. Based on the norms of reciprocity literature, in situations where the core worker has provided previous help to the non-core worker, the non-core worker will be more motivated to help the core worker in the future. However, should the core worker regularly need help from the non-core worker, the non-core worker may develop feelings of frustration, stress, and burnout, which will eventually reduce the non-core worker's job performance and the likelihood of providing future help to the core worker (Barnes et al., 2008; Bolino et al., 2015; Cantor & Jin, 2019). Following this reasoning, we believe that if there are violations in the non-core and core workers' reciprocity expectations in helping behavior, the non-core worker will no longer have the motivation to help the core worker in the future. Based on this theoretical basis, we offer the following hypothesis.

Hypothesis 3 (H3). *In the situation where there is the perception that the non-core worker's norms of reciprocity were not violated, it is more likely that the non-core worker will be motivated to* *provide helping behavior to the core worker, compared to the situation where there is the perception that the non-core worker's norms of reciprocity were violated.*

The next factor in our model theorizes about the role of the non-core worker's capacity to provide helping behavior. We leverage insights from the equity theory and social loafing literature to develop arguments supporting this theoretical relationship. Briefly, equity theory suggests that a worker will compare her or his capacity to carry out job responsibilities relative to other workers in the team and/or organization and utilize it to determine the amount of effort they will put forth into their job responsibilities. If the worker believes that she is not receiving her fair share of resources from other co-workers and/or supervisors, then the worker will engage in withdrawal behavior from her job. Likewise, the social loafing literature utilizes similar logic. Grounded in organizational citizenship behavior, social loafing is the tendency for workers to exert less effort when working in teams than when working alone (Li et al., 2014). (Cantor & Jin, 2019) found that workers in a production line experiment who perceived high social loafing levels engaged in lower levels of helping behavior. Similarly, (P. W. Schultz, 1999) theorizes that social loafing theory can explain why some workers operate machines slower than other workers on an inventory management task.

We contend that when non-core workers have limited resources, they will engage in lower levels of helping behavior. A worker's available resources are determined by their capacity utilization, defined as the research participant who is randomly assigned to the treatment condition where they are servicing 100 percent of her or his tables, or the research participant is servicing 25 percent of her or his tables. Our logic is that the non-core, fully utilized worker will monitor their surroundings and recognize that they contribute more to assist the team or organization than other workers. Thus, there is a non-equitable distribution of resources, making it unreasonable or unfair for the non-core worker to contribute more assistance to the team. As a result, the non-core worker will perceive it as unfair to provide helping behavior when contributing significantly to the team. Based on this reasoning, we present the following hypothesis.

Hypothesis 4 (H4). *If the non-core worker's resources are substantially utilized, the lower the likelihood that the non-core worker is motivated to provide helping behavior to the core worker compared to a situation where the non-core worker's resources are significantly underutilized.*

We now turn to theorize about how a non-core worker's predisposition to act collectively influences their helping behavior. According to (Hofstede, 1980), collectivism refers to a general desire among individuals for greater equality among society members or within the organization. Individuals who espouse the collectivist perspective believe that it is important for employees to have a voice in the workplace. In general, these individuals desire fair action, altruism, generosity, kindness to others, and a caring society.

The buyer-supplier literature has leveraged the collectivism concept. (Lee et al., 2018) find evidence that suppliers associated with collectivist cultures exert more effort and shirk less. (Cannon et al., 2010) suggest that cultural differences such as collectivism could influence purchasing strategies. (Eckerd et al., 2016) theorize that individuals from collectivist cultures (e.g., China) are more willing to trust their supply chain partners than people from individualist cultures (e.g., USA) following a psychological contract breach. (Handley & Angst, 2015) find that relational governance is more effective in collectivist societies.

Our study contends that employees who value collectivism are more likely to engage in helping behavior for several reasons. First, generally speaking, collectivist individuals are caring people and do not want others to face hardships in the workplace. When other people struggle to complete their work, collectivist employees desire to engage in pro-social behaviors, including stepping-in and assisting their overwhelmed colleagues. Next, collectivist individuals are more willing to trust their co-workers and thus seek to enhance their trusting intentions in the form of helping behavior. Lastly, collectivist individuals want to create a workplace that supports a collegial environment. By engaging in helping behavior, these individuals attempt to set an example that altruistic behavior is expected. Based on these arguments, we present the following hypothesis.

Hypothesis 5 (H5). *In the situation where the non-core worker's collectivism level is high, the greater the likelihood that the non-core worker is motivated to provide helping behavior to the core worker compared to the situation where the non-core worker's collectivism level is low.*

As mentioned, helping behavior is individual behavior that is discretionary and not directly motivated by formal rewards (Organ, 1988). We suggest that as non-core workers provide help to others, system performance should improve. The OM literature serves as a basis for this theoretical relationship. The OM literature has documented that some workers complete their job responsibilities faster than others and, indeed, help slower workers perform some of the unfinished work (Boudreau et al., 2003; Doerr et al., 2004). These OM scholars further suggest when helping behavior occurs, overall system performance should increase (Cantor & Jin, 2019; Doerr et al., 2004; K. L. Schultz et al., 1998; P. W. Schultz, 1999). To say this differently, we contend that non-core workers should have the ability to complete the slower worker's uncompleted tasks and thus remove idle time from the system. The non-core worker's performance will help to re-balance the workload so that all work is completed in a shorter amount of time, thus facilitating improvements to system performance.

While there are clear benefits of helping behavior, there isn't unequivocal evidence that system performance will improve when a non-core worker provides assistance to others. Findings from the organizational behavior literature suggest that helping providers may become fatigued or disgruntled with having to provide helping behavior. (Barnes et al., 2008) suggest that the helping requires the use of cognitive resources that can become depleted, thus rendering the individual with fewer resources to engage in helping. Barnes and colleagues suggest that helping involves communication and coordination activities which is a significant cost required by the person assisting (Barnes et al., 2008). Thus, the helping provider may reduce their future assistance because helping turns into a burden rather than a net benefit. There are also social costs associated with helping, as suggested by (Bachrach et al., 2006). Indeed, (Bachrach et al., 2006) argue that helpees become too reliant upon the helping provider are dis-incentivized to complete their work. Lastly, (Bolino et al., 2015) suggest that helping providers will develop feelings of frustration, stress, and burnout.

Notwithstanding the downsides associated with providing helping to team members, we contend that helping behavior will reduce idle time, thus improving system performance, including customer service levels and overall customer satisfaction (Podsakoff et al., 1997).

Hypothesis 6 (H6). *The greater the amount of helping behavior, the greater the system performance.*

2.4 Methods

2.4.1 Background Information about Vignette-Based Experiment

To test the hypothesized relationships depicted in our theoretical model, we conducted two studies, namely, an online vignette-based experiment to test Hypotheses 1-5 and a simulation model to test Hypothesis 6. A steady stream of research in OM has used vignette-based experiments (e.g., (Cantor et al., 2014; M. Chen et al., 2016; Eckerd et al., 2013; Polyviou et al., 2018)). OM scholars have used vignettes to test the make-or-buy decision (e.g., (Mantel et al., 2006)) and supplier switching intentions (e.g., (Mir et al., 2017)), among many other research questions.

A vignette-based experiment provides research participants with important contextual information so that the subjects can make a judgment or decision (Alexander & Becker, 1978). This research method enables scholars to control internal validity threats (Eckerd et al., 2016; Mir et al., 2017; Reimann et al., 2017; Stevens, 2011). OM scholars have also noted that the research participants are not providing sensitive information (Atzmüller & Steiner, 2010).

2.4.2 Overall Experimental Design

We followed the research guidelines as outlined in (Rungtusanatham et al., 2011). First, we became familiar with the context of our research questions before designing the vignette. We also reviewed prior service operations management, restaurant management, and consumer decision-making research studies that have appeared in the OM literature before designing our experiment. Next, we created a common module that provided the same background information to all participants. We then created the experimental modules so that they reflect an actual service OM setting (Rungtusanatham et al., 2011).

We received feedback about the clarity and realism of the vignettes from multiple doctoral students and faculty experts from marketing, management, management information systems, and supply chain management. We also interviewed managers and employees in the empirical setting of this study to improve the representativeness, readability, and functionality of our scenarios (e.g., the restaurant industry). We pre-tested our experiment using a sample drawn from the Amazon MTurk service and restaurant managers. Previous supply chain research has documented that MTurks provide high quality and reliable responses (e.g.,(Knemeyer & Naylor, 2011; Sheehan & Pittman, 2016; Shunko et al., 2017)).

Following prior OM research, we used the Qualtrics survey platform to create our common module and the experimental modules (Sheehan & Pittman, 2016). Only participants with restaurant experience were allowed to take the survey. We provided a common module to all research participants (see **Appendix A**), which contained background information about our research study. All participants were provided with the same background information regarding the restaurant, the restaurant employees, and the overall environment. We used the Qualtrics randomizer tool to assign one experimental module to each participant randomly.

2.4.3 Experimental Design

To test the study's hypotheses, we conducted a 2x2x2x2 between-subjects experiment (see **Appendix B**). Our treatment conditions are presented in Table 2-1. We asked the study participants to assume that they are a restaurant server of the fictitious restaurant, ABC Restaurant. In this role as a deciding server, the research participant was asked: "Given your role on the team, which action would you take, given that the core server has a lot of work to complete." The participant could either provide help to the core server or not provide help. If the participant agrees to provide help, a secondary question of "What percent of your time are you willing to allocate helping the core server?". The role of the restaurant server that the participants represent is that of the non-core worker from the hypotheses. As noted, each participant was randomly assigned to one of 16 vignettes. We investigated the direct effect of the experimental factors on helping behavior and percent helping.

Table 2-1 Participants by treatment condition.

Scenarios	Reciprocity	Table Occupancy	Total
Fair Promotion	144	138	282
Preferred work Schedule	141	141	282
Total	285	279	564

2.4.4 Sample

We distributed our vignette-based experiment task to MTurk participants located in the United States and are at least 18 years old. Each MTurk participant received a small monetary incentive upon completion of the experiment. To ensure that participants read the background and related information, our vignettes contained multiple attention-checking questions (Abbey & Meloy, 2017).

We recruited Amazon Master MTurks to participate in this study. Master MTurks are people who have demonstrated excellence in their performance on a wide range of tasks (Sheehan & Pittman, 2016). We received 702 completed surveys. We excluded 71 responses because the MTurk participants indicated that they do not have any work experience in the restaurant industry. We then removed observations where participants missed any of the six attention-checking questions. Our final dataset consisted of 548 observations (53 percent were female; 65 percent of the respondents were between 22 and 40 years of age, and 57 percent reported having at least an undergraduate degree).

2.4.5 Measures

Based on our between-subjects experimental design, we created four categorical independent variables: Fair promotion of the core server (*Fair promotion*), fairness of the deciding server's work schedule (*Preferred work schedule*), core server's prior helping behavior (*Reciprocity*), deciding server's workload (*Table occupancy*) and deciding server's level of collectivism (*Collectivism*). The *Fair promotion* was coded as a "1" if the vignette described that a fair process was followed to promote another restaurant worker to the core server role; this factor was coded with a value of "0" if the promotion process occurred unfairly. The *Preferred work schedule* was code with a value of "1" if the research participant was treated fairly concerning her or his preferred work schedule, “0” otherwise. *Reciprocity* was coded with a “1” if the recently promoted worker helped (assistance) the research participant in the past; this factor was coded with a value of “0” if the recently promoted worker did not help the research participant. *Table occupancy* was coded with a value of “1” if the research participant’s tables are at 100 percent capacity of her or his assigned tables; table occupancy is coded with a value of “0” if the research participant’s tables are at 25 percent capacity of her or his assigned tables. Lastly, our model also controls for an individual’s predisposition for acting collectively. The research participant’s *collectivism* level was coded with a value between “1” to “7” based on the participant's responses on the IND-COL scale.

Our two dependent variables are the research participant’s decision to help and the percent helping time. Following (Cantor & Jin, 2019), we coded the decision to help with a value of “1” if the participant provides help, zero otherwise. Percent helping time represents the percentage of the deciding server’s total time that he/she is willing to allocate for helping the core server. If the participant decided to provide help, an additional question was asked: “On a scale of 0 to 100 percent, how much of your total time would you allocate to helping Alex (core server)?” yielding a value between 0 and 100.

The items “I am willing to help the restaurant workers to complete the work,” “I will provide help to the core worker since he or she is facing problems with completing the serving activities,” and “I intend to willingly help the other worker because of the restaurant work situation” were measured on a 7-point scale (where one is “strongly disagree” and seven is “strongly agree”). The results of these responses showed a mean value of 6 with a standard deviation of 0.72 when the helping behavior variable value was one and a mean of 3 with a standard deviation of 1.15 when the helping behavior variable value was 0. These results indicate a high level of strength of result for the response helping behavior.

2.4.6 Realism checks

As described earlier, we validated that the research participants were familiar with the empirical context. 65 percent of the participants reported three years of restaurant-related work experience; 52.7 percent were kitchen staff, 74.2 percent were wait staff, 51.2 percent bussed tables, and 21.3 percent worked as a restaurant manager. 87 percent worked in a sit-down restaurant; the remainder worked at a fast-food restaurant. We also evaluated the realism of our scenarios using the three-item scale developed by (Dabholkar, 1994). The items "The scenarios are believable," "You can imagine yourself in the situation described above," and "The situation described above does occur in the real world" were measured on a seven-point scale ranging from 1 (strongly disagree) to 7 (strongly agree). Based upon the results of similar studies, our mean score of 6.27 with a standard deviation of 0.82 across these three items indicates a high level of realism as perceived by our participants (J. & M., 2017; Reimann et al., 2017).

2.5 Empirical Study Results

Statistical tests were performed using SAS 9.4 software. Because the first dependent variable (i.e., the decision to help or not help) is binary, logistic regression was used (Hosmer Jr et al., 2013). The results of this analysis are shown in Table 2. Of the 548 total observations, 419 participants (76%) decided to provide help to the core server. According to the results, the log of the odds of a non-core server providing help to the core server was positively related to the preferred work schedule ($p <.05$), reciprocity ($p <.05$), and collectivism ($p <.05$), whereas table occupancy ($p <.05$) was negatively related since higher table occupancy was coded as one and lower table occupancy was coded as zero. The reciprocity factor had a particularly strong effect.

Given the same values of fair promotion, preferred work schedule, table occupancy, and collectivism, the odds of a non-core worker helping the core worker were 19.119 times greater if help had been provided to the non-core worker in the past.

The second dependent variable in the study is percent helping time. A mean value of 22.90% was derived for percent helping time with a standard deviation of 20.18. Since the output variable has a lower bound of 0 and an upper bound of 100, Tobit regression was used, shown in Table 2 (McDonald & Moffitt, 1980). The independent variables, preferred work schedule, reciprocity, table occupancy, and collectivism, were statistically significant ($p < 0.05$).

Table 2-2 Empirical study results.

	Model 1		Model 2	
Dependent variable	*Logistic regression model* Helping behavior		*Tobit regression model* Percent helping	
	Estimate	Std. Err	Estimate	Std. Err
Constant	-2.99*	0.69	-12.57**	5.63
Fair promotion	0.33	0.2	1.16	1.93
Preferred work schedule	0.84*	0.25	5.98*	1.94
Reciprocity	2.95*	0.32	21.56*	1.99
Table occupancy	-0.57**	0.24	-12.37*	1.93
Collectivism	0.57*	0.12	4.41*	0.99
_Sigma			21.72*	0.79

*Note: *p < 0.01, **p < 0.05, ***p<0.1*

2.6 Simulation Study – Study 2

The ODD (Overview, Design concepts, and Details) protocol (Grimm et al., 2010) is used to describe the simulation model created in Study 2. The model was created using AnyLogic 8.0, which can simulate both ABM and DES simultaneously.

Purpose of the Study: While the results from the vignette-based experiment provide support for Hypotheses 1-5, a limitation of that method is that we do not observe dynamic operational behaviors that may result from the helping behavior. (Chandrasekaran et al., 2018) emphasize the inherent limitations of using only cross-sectional research methods to analyze complex operations management problems. To address these issues, they recommend using simulation models to complement and strengthen an empirical study. Therefore, to test Hypothesis 6, we created a simulation model that examines how helping behavior influences system performance in a dynamic service OM setting.

To represent both human behavior (i.e., the decision to help) and operational behaviors (i.e., the flow of customers through a restaurant), our model uses a hybrid combination of agent-based modeling (ABM) and discrete event simulation (DES). (Mazlina A Majid et al., 2016) advocate using hybridized ABM-DES models to capture the influence of human behavior in service systems. In (M A Majid et al., 2010), the authors show that DES is better-suited to modeling queuing customers, while ABM is more appropriate for modeling human behavior. For our study, a stylized service OM model of a restaurant is created by combining ABM and DES. While DES has been used previously to model the flow of customers in a restaurant setting (Vries et al., 2018), the servers modeled in our study are autonomous decision-makers working and interacting as a team, making it appropriate to model them as agents. Furthermore, humans are complex social beings that have frequent interactions with their environment and other humans. Complex interactions can be conceptualized as social processes, such as helping behavior or social influence (Badham et al., 2018; Berkman et al., 2000).

Entities, State Variables, and Scales: The model environment represents a restaurant with 14 tables, each of which can seat one to four customers. Each customer entity that arrives at the restaurant represents a group of one to four customers. The model also contains three server agents: the core server, the deciding server, and the non-core server. All servers have a state variable that defines the number of tables they are currently handling. All entities move at one meter per second speed in a space with dimensions of 500*500 (Width*height) meters. The model time unit is minutes, and the simulation run time is 13 hours. It is assumed that the server agents work continuously throughout the day.

Process Overview and Scheduling: Each simulation run represents a dine-in restaurant's operations, starting at 9:00 AM and ending at 10:00 PM. The restaurant servers act as resource units to customers that require assistance in filling their orders. Apart from serving duties, the deciding server periodically makes decisions about whether or not to provide help to the core server; thus, at any point during the simulation run, the deciding server is either in a state of not helping (i.e., only providing service to its own tables) or helping (providing service to its own tables and the core server's tables).

2.6.1 Design Concepts

Basic Principles: The simulation model environment represents the scenario in the vignette survey described in Study 1. The core server agent in the simulation model represents the strategic core worker who is responsible for servicing more tables, compared to the other servers. The deciding server agent and non-core server agent represent the non-core workers from the hypotheses. The deciding server agent mirrors the survey participant, who decides whether to provide help to the core server. The outputs from Study 1 (helping behavior and percent helping) serve as inputs to the decision logic of the deciding server agent.

Objectives: The objective of each server agent is to provide timely service to the customers seated at its tables. Depending on its current utility value, the deciding server may also provide help to the core server as needed.

Sensing: When the deciding server is idle, it may assess the number of customers currently being serviced by the core server to determine whether to provide help.

Stochasticity: Customer arrival times and service times are drawn from probability distributions, such as truncated Poisson or Uniform, as shown in **Appendix C**.

Observation: To gain an understanding of the restaurant's operational behaviors with respect to helping, the metrics shown in Table 2-3 were recorded at the end of each simulation run. The values of each output metric were averaged over thirty replications for each experimental scenario (Law & McComas, 1991).

Table 2-3 Operational behavior output metrics.

Metric	Description
Successful customers	Total number of customers receiving service
Total help time	Total time help was provided by deciding server to core server
Wait time on core server's tables	The average time a customer seated in the core server's area waits on the core server
Wait time on deciding server's tables	The average time a customer seated in deciding server's area waits on the deciding server
Total wait time across all tables	The average time a customer waits on any server

Initialization: The core server is assigned six tables, and the deciding server and non-core server are assigned four tables each. Each server is initially located on a node called "kitchen Node." The values of five decision variables are assigned, according to the experimental scenario that is being run: maximum table occupancy (TO; discrete values ranging from 1 to 4), whether the core server was fairly promoted (FP; binary), whether the deciding server was given his preferred work schedule (PWS; binary), whether the core server had helped the deciding server in the past, thereby triggering reciprocity (R; binary), and the level of collectivism that characterizes the deciding server (C; discrete values ranging from 1 to 7).

Input Data: The regression outputs from Study 1 (Table 2) were used to create multi-attribute utility functions that inform the deciding server's decision logic (described below). The probability distributions used to represent customer arrival rates and service times are derived from existing empirical studies on restaurant operations (See **Appendix C**) (Bell & Pliner, 2003; Brann & Kulick, 2002; Hwang, 2008; Kimes & Thompson, 2005).

2.6.2 Sub-Models

2.6.2.1 Discrete Event Simulation (DES)

The flow of customer entities is modeled using DES. The customer arrival rate is based on a truncated Poisson distribution. Each customer's path is shown in Figure 2-2. First, the entry time of the customer is recorded, and then the customer is assigned to an unoccupied table. Customers are assigned to tables in a manner to ensure an even distribution of customers across all servers, starting with two customers for the core server, followed by one customer for the deciding server, then one customer for the non-core server, and so on. If no tables are free, the customer will wait for a balk period (see **Appendix C**) before deciding to leave the restaurant without receiving service.

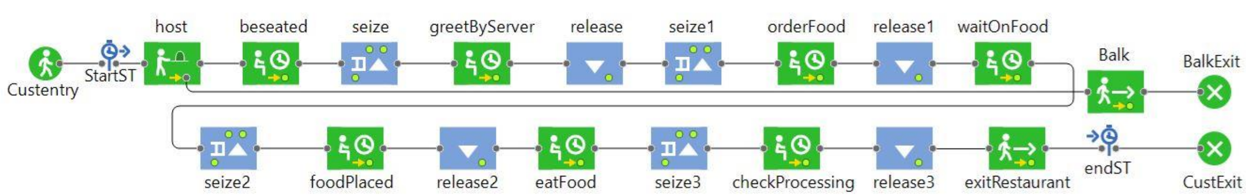

Figure 2-2 DES flowchart

After being seated, a customer receives service from server agents based on a first call, first-serve basis. First, a server greets the customer and provides menus in the "greetByServer" block, after which the customer places their order with the server in the "orderFood" block. The customer then waits for their order to be prepared by the kitchen in the "waitOnFood" block, and when their order is ready, the server delivers it to them in the "foodPlaced" block. When the customer is finished eating, the server processes their check. The server is then released, the customer leaves the table and exits the restaurant, and the customer's exit time is recorded.

2.6.2.2 Server Agent ABM flow

The logic that defines the deciding server's decision process is summarized in the flowchart shown in Figure 2-3.

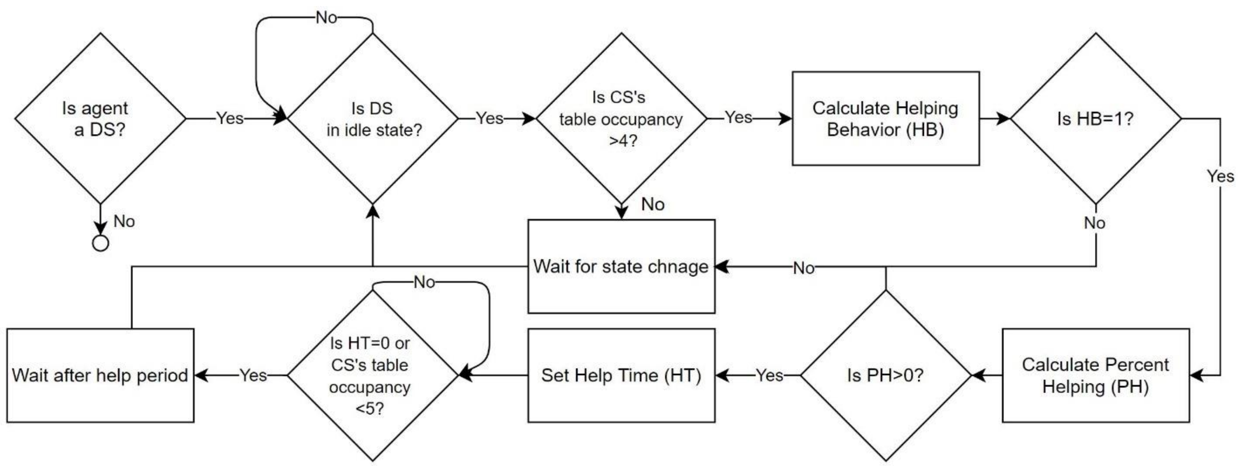

Figure 2-3 Deciding server agent decision flowchart

All three servers reside in the "kitchen Node" when they are idle (i.e., not occupied with service tasks). When the deciding server is idle, it observes the number of the core server's tables that are occupied by customers. If the core server has four or fewer tables occupied, the deciding server does not provide help and waits for its next idle state to reevaluate its decision. If the core server has more than four tables occupied, the deciding server must decide whether or not to provide help, based on the values of the five decision variables that were assigned during model initialization. These five variables are used in the formulation of a multi-attribute utility function that the agent evaluates to make its decision. Each decision variable is weighted according to the logit regression results from Table 2-2 of Study 1 and then summed to yield the predicted log of helping behavior (PLHB):

$$\text{PLHB} = -2.99 +* FP +* PWS +* R - 0.57 * TO + 0.57 * C \tag{2-1}$$

Since helping behavior is binary (i.e., the deciding server either provides help or does not provide help), the sigmoid function shown in Equation 2-2 is applied to the logistic regression output (Equation 2-1) to determine the probability of helping:

$$helping\ behavior\ value\ = \frac{1}{(1\ +\ e^{-PLHB})} \tag{2-2}$$

If the sigmoid function result is greater than 0.5, the deciding server decides to provide help to the core server; otherwise, it decides not to help, in which case the deciding server waits for the next idle state. If the deciding server decides to provide help, the next step is to determine the duration of helping, which is some percentage of sixty minutes. The helping duration (HD; Equation 2-4) is a function of data from Study 1, in which each of the five decision variables is weighted according to the Tobit regression results (Table 2-2) and summed:

$$PH\ =\ -12.56 + 1.16 * FP + 5.97 * PWS + 21.56 * R - 12.36 * TO + 4.4 * C \tag{3}$$

$$HD = 60 * PH \tag{2-4}$$

While the deciding server is helping, it shares the core server's service responsibilities, in addition to its own. The sharing of tables continues for the entire HD or until the number of the core server's occupied tables is fewer than five. Also, If the HD is less than sixty minutes, the deciding server waits for the remaining time before reevaluating the decision to provide help.

2.6.3 Simulation Study Results

To determine the impact of helping behavior on the operational metrics listed in Table 2-3, the hybrid simulation model was run for two different scenarios: one in which the deciding server is responsible for four tables in its area (i.e., 100 percent occupancy), and one in which it is responsible for only one table (i.e., 25 percent occupancy). Both of these scenarios were run for two-factor settings: one in which the deciding server is likely to provide help (with fair promotion, preferred work schedule, reciprocity factors set to a value of 1 and collectivism set to a value of 7), and one in which he is unlikely to provide help (with collectivism factor set to a value of 1 and the other factors set to zero).

Figure 2-4 shows that the average total help time for runs in which the deciding server is likely to provide help showed a 34 percent reduction when deciding server was responsible for four tables (i.e., 100 percent occupancy). This suggests that when the deciding server has fewer tables of his own, he is more willing to provide help to the core server. To observe the impact of helping behavior on the operational metrics, a two-tailed t-test with alpha equal to 0.05 was used to compare the mean values of the output metrics shown in Table 2-4. Cohen's d values were also calculated to determine the effect size of the differences in means, where d=0.2 is considered a "small" effect size, 0.5 represents a "medium" effect size, and 0.8 a "large" effect size. This means that if the two means do not differ by 0.2 standard deviations or more, the difference is trivial, even if it is statistically significant (J. Cohen, 2013).

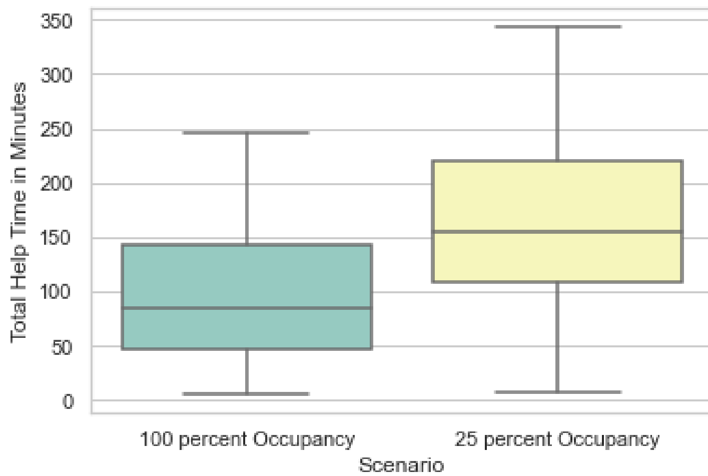

Figure 2-4 Total help time in different table occupancy scenarios

The results indicate modest improvements in nearly all operational metrics when helping behavior was present. In particular, the wait times at the core server's tables experienced a 19.2% reduction due to helping when the deciding server has four tables and a 22.4% reduction when the deciding server has one table. However, it should be noted that helping behavior increased the wait times at the deciding server's tables by 22.2% when the deciding server has 4 tables. The increase in wait times at the deciding server's tables showcases the downside of helping as the deciding server's time is also shared by the core server's tables. However, helping behavior reduced the average total wait time across all tables by 6.1% when the deciding server has four tables and 22.4% when the deciding server has only one table.

Table 2-4 T-test and Cohen D results for Study 2

Output metric	Deciding server has four tables							Deciding server has one table						
	No Helping Behavior			Helping Behavior			*d*	No Helping Behavior			Helping Behavior			*d*
	Mean	SD	N	Mean	SD	N		Mean	SD	N	Mean	SD	N	
Successful Customers	80.7	2.0	210	81.2	1.8	510	0.28*	64.2	1.7	180	66.1	1.9	540	1.2*
Average wait time on core server's tables	7.8*	0.8	500	6.3	0.8	500	1.72*	8.3	0.7	500	5.8	0.6	500	3.83*
Average wait time on deciding server's tables	2.7*	0.4	500	3.3	0.4	500	1.24*	0.2	0	500	0.7	0.2	500	8.72*
Average total wait time across all tables	4.9*	0.4	500	4.6	0.4	500	0.81*	5.8	0.2	500	4.5	0.3	500	21.2*

*Note: *p < 0.01*

2.7 Discussion

Teams operate under constant pressure to respond to changes in team member roles, responsibilities, and performance. Since many teams need to respond to disruptions in their team structures, the purpose of this study, then, is to examine how a change in a team member's role, team dynamics, and organizational policies impact an individual's motivation to engage in team member helping behavior, as well as the overall impact on system performance (e.g., service time). While previous research has recognized the influence of a worker's personality and the structure of the production line on improving production line performance, the literature has not examined how individuals respond to a core team member's role expansion due to an imbalanced workload resulting from an unexpected event (e.g., absenteeism, promotion decisions) on team performance. Leveraging the theory of the strategic core, which suggests that some job roles in organizations have a more noticeable impact on organizational performance than others (Delery & Shaw, 2001; Emery & Trist, 1965), we develop a theoretical model to conceptualize and examine how individuals respond to a change in the core team member's role expansion. We enhance our theoretical model by integrating research from the procedural fairness and equity theory literature to examine how perceptions of fairness influence an individual's motivation to help the core team member (i.e., helping behavior). We test our research questions by conducting two studies using a multi-method approach.

2.8 Conclusion

Our study makes multiple theoretical contributions to the literature. This is the first study in the operations management literature that has re-conceptualized and capitalized on the theory of the strategic core to study team member helping behavior in an OM setting (e.g., (Humphrey et al., 2009; Summers et al., 2012)). In doing so, we contribute to the literature by theorizing and empirically examining why and how a change in team dynamics influences helping behavior and organizational performance. In so doing, our study also provides a micro-level understanding of how team dynamics influence service time performance. Second, our study contributes to the literature by theorizing about how the management of team member roles and workload is impacted by procedural fairness concerns. Indeed, our study adds to the literature by providing a further understanding of how team members react to changes in team processes (i.e., role expansion). Thus, we enhance this perspective by theorizing on how an individual team member responds to team member fairness concerns. This study also advances our understanding of the critical importance of helping behavior in a service operations management setting.

We further contribute to the OM literature by juxtaposing the theory of strategic core with theory from the procedural fairness literature. We do so by theorizing and providing empirical evidence about how the perceptions of fairness about the core worker's promotion could influence the non-core worker's motivation to provide helping behavior. We theorized that non-core workers are attentive to how core workers and supervisors create and promulgate new organizational policies and practices (Lind & Tyler, 1988). When non-core workers observe that the formation and implementation of these policies as unjust, non-core workers will react negatively and reduce their amount of helping behavior. It is clearly important for organizational and team leaders to solicit feedback on the performance of other team members before bestowing rewards and recognitions for a worker's job performance. Doing so will create greater levels of organizational and team commitment. Future research should investigate how the issues of worker personality, team promotion policies, and frequencies of team member changes could impact helping behavior.

Perceptions of fairness are impacted by the assignment of work schedules to team members. To say this differently, we contend that the organization's treatment of the non-core worker's desired work schedule will have a direct bearing on fairness perceptions and pro-social behavior. We provided theoretical and empirical support for the work scheduling hypothesis based on previous research that has found that logistics workers who believe that their work scheduling preferences are violated have a greater intention to engage in counter-productive behaviors (e.g., engage in poor job performance, quit their job, leave the industry (e.g., (Cantor et al., 2011; Miller et al., 2013)). The implications of this hypothesis suggest that a non-core worker's helping behavior will be impacted by not only strategic human resource (HR) decisions such as the firm's promotion practices but also the team leader's implementation of operational HR policies such as daily or weekly scheduling policies.

We theorized that norms of reciprocity influence a non-core worker's decision to engage in helping behavior. As explained earlier, norms of reciprocity are defined as the assertion that one person is willing to help another individual so long as the helping provider believes that he or she will receive help from the helped in the future (e.g., (Eisenberger et al., 1986; Rhoades & Eisenberger, 2002; Shore et al., 1995)). We applied this theoretical basis to suggest that the non-core worker will provide help to the core worker based on the non-core worker's previous interactions with the core worker. Indeed, while we found empirical support for this relationship, we suggest that future research should develop a theory about situational factors in which the norms of reciprocity concept may result in the reduction of providing help. For instance, future research could explore the circumstances that arise where the non-core worker may develop feelings of frustration, stress, and burnout from the providing of repeated help to the core worker.

We next theorized about the role of the non-core worker's capacity to provide helping behavior. In so doing, we leveraged insights from the equity and social loafing literature to develop arguments in support of this theoretical relationship. Briefly, we suggested that non-core workers who had allocated most of their capacity to servicing assigned customers would not engage in helping behavior. We found empirical support for this relationship because we theorized that a worker would compare her or his capacity to carry out their job responsibilities relative to other workers in the team. Workers will find it unfair to invest more effort into completing their job responsibilities than their peers. The implication of this finding is that managers should create greater levels of equity in work assignments to reduce these loafing concerns. Future research should investigate the effectiveness of balancing workloads in a service operation setting and the subsequent opportunities for helping behavior.

We also hypothesized and found empirical support about the role of a non-core worker's predisposition to act collectively. Collectivism, an individual difference personality trait, refers to a general desire among individuals for greater equality among members of society or within the organization (Hofstede, 1980). Indeed, there is a steady stream of research in OM that has begun to examine how this personality trait enhances individual and team performance (Cannon et al., 2010; Eckerd et al., 2016; Handley & Angst, 2015; Lee et al., 2018). We integrate this base of literature into our model to increase our understanding of how an individual's personal values influence helping behavior (e.g., individualist attitudes versus collectivist attitudes). We hope that our findings will encourage scholars to investigate additional theoretically relevant personality characteristics that could influence helping behavior.

Our final hypothesis is in regard to how helping behavior can improve service time performance. There are upsides and downsides associated with encouraging helping behavior. Clearly, it is important for team leaders to encourage more productive (e.g., faster) workers to provide help to other workers in need of help. More productive workers complete their assigned tasks faster and more effectively than others. However, team leaders recognize that doing so may create situations of resentment, stress, and burnout if more productive workers are regularly asked to step-in and assist less productive workers. Moreover, evidence suggests that increased levels of helping behavior way led to poorer overall team performance. While we found empirical support for our hypothesis, we suggest that managers should exercise caution in supporting helping behavior because there can be negative consequences of doing so. It is important for future research to examine the conditions under which helping behavior can degrade systems performance.

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Appendix A Common Module

Random Background

Imagine that you work at a restaurant named "ABC Restaurant" as a server. Just before the start of dinner service on a Friday evening, one of your co-workers, Sam, calls the restaurant manager to say that he will not be able to come to work. The restaurant manager tells another co-worker named Alex (who has recently been promoted to senior server) that, in addition to his new responsibilities of recruiting and interviewing restaurant staff members, he is required to take on the serving duties of the absent co-worker, Sam. Because of the promotion to a senior server, Alex has a much higher salary than any other server at the restaurant. Moreover, you believe that the restaurant manager **did not follow a fair process (or did follow a fair process)** when making the promotion decision because Alex was not qualified for the position. Each waiter is normally responsible for serving four tables. Since Sam was a new employee, he was only responsible for two tables. Thus, Alex is assigned two additional tables to service because of Sam's unexpected absence from work. You and your other co-worker Kelly are busy serving customers at each of your respective four tables. You are aware that the level of service that you provide to your own customers has a direct impact on your ability to earn high-quality tips. You and Kelly face an important decision: **While continuing to provide service to the customers seated at your own tables, will you also provide help to Alex by providing service to his tables as well? You will not get any tips for helping Alex.**

Who is absent from work at the restaurant?

1) Alex 2) Caroline 3) Dave 4) Sam 5) None of the above

Which worker has the greatest amount of work to complete at the restaurant?

1) Alex 2) Caroline 3) Dave 4) Yone 5) None of the above

Did the restaurant manager follow a fair process when making the promotion decision?

1) Yes 2) No

How many tables does a waiter normally serve?

1) 1 2) 2 3) 4 4) 30

How many tables were assigned to Sam?

1) 1 2) 2 3) 3 4) 4 5) 5

Will you get any tips for helping Alex?

1) Yes 2) No

Please answer the questions below regarding how fair it is for Alex to work two additional tables:

I think it is fair that the restaurant manager assigned Alex the extra work.

I think it is fair to require Alex to service two additional tables.

I think it is fair that Alex is covering two more tables.

1) Strongly agree 2) Agree 3) Somewhat agree 4) Neither agree nor disagree 5) Somewhat disagree 6) Disagree

Appendix B Random Scenarios (Treatment Conditions)

Fairness of the non-core team member's work schedule	
Preferred work schedule	Undesirable work schedule
At ABC restaurant, you believe that you are treated fairly with respect to your preferred work schedule. You are always assigned to your preferred days and times.	At ABC restaurant, you believe that you are treated unfairly with respect to your preferred work schedule. You are always assigned to undesirable days and times.

Previous core team member's helping behavior	
Previous Experience with Receiving Help: Yes	Previous Experience with Receiving Help: No
There have been several situations in the past where you needed help from your co-workers. In those cases, it was very common for Alex to provide you with help and assistance when you needed it.	There have been several situations in the past where you needed help from your co-workers. In those cases, it was not very common for Alex to provide you with help and assistance when you needed it.

Non-core team member's workload	
Non-core worker's resources are overutilized	Non-core worker's resources are underutilized
All of your tables are currently occupied by customers. Specifically, you are currently servicing 100% of your assigned tables.	Very few of your tables are currently occupied by customers. Specifically, you are currently servicing 25% of your assigned tables.

True or False:

You are treated fairly with respect to your preferred work schedule.

In previous situations, it was common for Alex to provide you with help and assistance when you needed it

You are currently servicing 100% of your assigned tables.

Given the scenarios (fictitious story) described above, please rate the realism of the story as presented:

The scenarios are believable.

You can imagine yourself in the situation described above.

The situation described above does occur in the real world.

1) Strongly agree 2) Agree 3) Somewhat agree 4) Neither agree nor disagree 5) Somewhat disagree 6) Disagree

Given your role on the team, which action would you take given that Alex has a lot of work to complete?

1) I am willing to provide help to Alex. 2) I am unwilling to provide help to Alex.

Additional Questions:

On a scale of 0 to 100 percent, how much of your total time would you allocate to helping Alex? Please use the scale button to provide your response:

0 5 10 15 20 25 30 35 40 45 50 55 60 65 70 75 80 85 90 95 100

If you decided to help, please explain in as much detail as possible your reasoning behind your decision to help.

If you did not decide to help, please explain in as much detail as possible your reasoning behind your decision not to help.

Please indicate your level of agreement to the following items.

I am willing to help the restaurant workers to complete the work.

I will provide help to the worker since he or she is facing problems with completing the serving activities.

I intend to willingly help the other worker because of the restaurant work situation.

1) Strongly agree 2) Agree 3) Somewhat agree 4) Neither agree nor disagree 5) Somewhat disagree 6) Disagree

Appendix C Customer Agent State Variables

State variables for customer agent (*Group Size (GS) , poisson (p) (min, max, mean, shift, stretch) , uniform distribution (ud) (min, max)*).

State variables	Description	Type	Possible values
table	Stores the number of the table that the customer group is seated in	Table agent	*0 - 13*
startTime	Time of entry of customer	minutes	*0 - 780*
Inter-arrival time	Time between two subsequent customer arrivals.	minutes	*p(5,10,8,1,1)*
groupSize	The number of people in a party of customers	int	*ud (1,4)*
BalkTime	Amount of time customer waits to be seated before balking the system	minutes	*p(0,30,20,-6,1)*
greetTime	Time taken by server to greet customers	minutes	*GS 1 - p (2, 3, 2.5, 2, 0.2)* *GS 2 - p (3, 5, 4, 3, 0.2)* *GS 3 - p (4, 5, 4.5, 4, 0.1)* *GS 4 - p (5, 6, 5.5, 5, 0.1)*
orderFood	Time taken by customers to order food	minutes	*GS 1 - p (3, 5, 4, 3, 0.2)* *GS 2 - p (4, 7, 5, 3, 0.5)* *GS 3 - p (6, 8, 7, 5, 0.3)* *GS 4 - p (7, 10, 8, 6, 0.3)*
waitOnFood	Time taken by customers to wait on food	minutes	*GS 1 - p (15, 20, 18, 11, 0.3)* *GS 2 - p (16, 20, 18, 12, 0.3)* *GS 3 - p (15, 25, 20, 13, 0.4)* *GS 4 - p (15, 25, 20, 13, 0.4)*
placeFood	Time taken by server to place food on table	minutes	*GS 1 - p (2, 3, 2.5, 2, 0.2)* *GS 2 - p (3, 5, 4, 3, 0.2)* *GS 3 - p (4, 5, 4.5, 4, 0.1)* *GS 4 - p (5, 6, 5.5, 5, 0.1)*
eatFoodTime	Time taken by customers to eat food	minutes	*GS 1 - p (30, 60, 40, 0, 1)* *GS 2 - p (45, 70, 50, 0, 1)* *GS 3 - p (45, 70, 50, 0, 1)* *GS 4 - p (45, 70, 50, 0, 1)*
checkProcessing	Time taken by customers to process checks after eating	minutes	*GS 1 - p (1, 2, 2, 1, 0.2)* *GS 2 - p (1, 3, 1.5, 1, 0.5)* *GS 3 - p (2, 4, 3, 2, 0.3)* *GS 4 - p (2, 5, 2.5, 3, 0.3)*

CHAPTER 3 Metamorphic Testing for Hybrid Simulation Validation

Mohammed Farhan, Caroline Krejci
Industrial Engineering
University of Texas at Arlington
Arlington, TX
farhanm@exchange@uta.edu,
caroline.krejci@uta.edu

Megan Olsen
Computer Science
Loyola University Maryland
Baltimore, MD
mmolsen@loyola.edu

M S Raunak
Information Technology Laboratory
National Institute of
Standards and Technology
Gaithersburg, MD
raunak@nist.gov

3.1 Abstract

Proper validation of a simulation model is essential to have confidence on its accuracy and credibility. However, many of the most effective approaches for simulation validation require access to data that may not always be available. Metamorphic Testing (MT), an approach from traditional software testing, has been shown to be useful for verification of software in similar situations. Recent research shows that MT can be applied to the validation of agent based and discrete event simulation models. In this paper we build on that work and show how MT can be applied to hybrid simulation models. We demonstrate the effectiveness of our approach by applying it on a case study of helping behavior among servers in a restaurant.

3.2 Introduction

Simulation is an integral part of many research, development, and implementation projects across a wide range of domains and application areas, particularly when real-world analyses are too large, complex, dangerous, or expensive to perform. Recent advances in modeling techniques allow for hybrid simulation, which includes combinations of discrete event simulations (DES), system dynamics models (SD), and agent based models (ABM), to enable the creation of more detailed models of complex real-world systems. As a result, hybrid simulation has become an increasingly popular approach (Sally C Brailsford et al., 2019).

Validating simulation models is critical to creating trust in and reliance on the generated outputs. However, simulation researchers and practitioners often do not perform or report model validation in their publications (Sally C Brailsford et al., 2019; Raunak & Olsen, 2014). One potential reason is that simulation model validation is a challenging process, especially when real-world data is unavailable for 'result validation' (Balci, 2010; Banks, 1998). Moreover, executable simulation models fall under the definition of 'non-testable' systems (Weyuker, 1982). Such systems lack the presence of an oracle, which can be used to judge whether a simulation model is behaving correctly and producing the expected results.

Metamorphic Testing (MT), a relatively new idea from software verification, has been shown to be effective in validating both DES and ABM simulations (M Olsen & Raunak, 2019; Megan Olsen & Raunak, 2016; Raunak & Olsen, 2015). MT addresses the 'oracle problem' by running the System/Software Under Test with multiple input and parameter combinations that are used as pseudo-oracles of each other. To the best of our knowledge, this approach has not been applied to hybrid simulation. In this paper we build on the prior work of MT as a technique for validation of DES and ABM and show its applicability on hybrid models through a case study on the effects of helping behavior among restaurant waitstaff. The case study also provides insights on future approaches for joint validation and verification via MT on simulation models.

3.3 Background and Related Work

Hybrid simulation has become popular, but few validation techniques have been developed specifically for it. (Mustafee & Powell, 2018) argued that researchers should consider using the Hybrid Systems Modeling approach and should incorporate techniques from computer science for proper verification and validation. Simulation model validation is often divided into conceptual, data, and operational validation (Robert G Sargent, 2010). Conceptual validation analyzes the validity of the conceptual model's assumptions. Data validation assesses whether the data used for developing the conceptual model and for running the experiments are consistent and realistically represent the System Under Study (SUS). Operational validation assesses whether the model's behavior correctly represents the behavior of the SUS. The work presented in this paper focuses on operational validation. Many of the commonly used operational validation techniques require either an expert in the studied system who can determine if the behavior is as expected (review, inspection, face validation), or data on the expected behavior of the system (traces and results validation), and these resources are not always available (Banks, 1998; Robert G Sargent, 2010; Sokolowski & Banks, 2010).

One of the reasons simulation validation is considered difficult is that simulation models suffer from what is known in the software testing community as the 'oracle problem'. Testing is the primary mechanism for finding bugs in computer software, and generally requires a *test oracle* to verify that the output or behavior for a given system input is as expected (Howden, 1978). Most software testing approaches assume the presence of a test oracle, where a set of test cases are selected to execute on the software system (often called Software/System Under Test or SUT), and results are checked against the expected behavior or output as specified by the oracle. The term *oracle problem* refers to the situation where a deterministic way of asserting and checking the expected or “correct behavior” of the SUT is not available and cannot be built easily (Barr et al., 2015). Programs without an oracle are often labeled as ‘non-testable programs’ (Weyuker, 1982), and include machine learning algorithms, cryptographic programs, search engines, certain scientific computations, and executable simulation models (Murphy, 2012).

In software testing research, Metamorphic Testing (MT) is one approach that has been proposed for dealing with the oracle problem (T Y Chen et al., 1998). MT is used to perform verification of software systems that lack an oracle or where developing an oracle is expensive (T Y Chen et al., 1998, 2003; H. Liu et al., 2014; Raunak et al., 2011). To perform MT, properties referred to as metamorphic relations (MRs) are identified for the SUT, utilizing the knowledge of the underlying application domain and/or the software. An MR defines how the output should or should not change, given some change to the inputs or configuration. MT has been shown to be applicable to ‘non-testable programs’ such as those listed above (Tsong Yueh Chen, 2015; Kanewala & Bieman, 2013; Mouha et al., 2018; Pugh et al., 2019; Segura et al., 2016; Xie et al., 2011). MT has also been applied to verification in specific simulation case studies, such as Sim et al.’s usage of MT for verifying physics equations in a casting simulation (Sim et al., 2005), Ding et al.’s case study on using MT with code coverage for verifying a Monte-Carlo simulation (Ding et al., 2011), and Lindvall et al.’s verification of autonomous drone software with MT (Lindvall et al., 2017). Ahlgren et al. showed the use of MT to automate the search for bugs in an industrial level continuous testing and integration setting where thousands of simulated agents interact on Facebook’s platform (Ahlgren et al., 2020).

MT has also been studied for use in simulation validation. Raunak and Olsen first presented a preliminary process for applying MT toward simulation validation (Raunak & Olsen, 2015). In their subsequent work, the authors elaborated the validation process, developing a full set of guidelines for using MT on ABM and DES (M Olsen & Raunak, 2019; Megan Olsen & Raunak, 2016). Other related work provides guidelines for using MT for both simulation verification and validation across a continuum (Raunak & Olsen, 2021). In this paper we build on the MT validation approach from Olsen and Raunak (M Olsen & Raunak, 2019) to extend it to hybrid simulation models, and demonstrate its success on a previously unpublished restaurant model.

3.4 Model Description

To demonstrate the application of MT on hybrid (DES and ABM) simulation validation, we apply the validation process to a restaurant simulation model. The model's purpose is to examine the effects of a server's willingness to help an overly busy server on customer wait times and customer throughput. There are two distinct entities in the model: customer entities, which have no decision-making capabilities and follow a strict time-dependent flow; and server agents, which have autonomous decision-making capabilities. Data from an empirical study is used to parameterize the utility functions that represent a server agent's logic when deciding to help a co-worker. AnyLogic 8.0 was used to create the model.

3.4.1 DES Customer Model

The restaurant has 14 tables, each seating 1 to 4 customers. Three server agents, named Core Server (CS), Deciding Server (DS), and Non-Core Server (NCS), provide service to customers on a first come, first served basis. Each party of 1-4 customers is represented by a single customer entity. Customers pass through several service blocks that require a server in the DES model, with the customer group size determining the duration of each block (Figure 3-1). Customers' arrival and service times are stochastic, following Poisson or Uniform distributions as per prior restaurant literature (Vries et al., 2018); exact times are described in Section 3.6. Each server has pre-assigned tables to service, with CS having more tables (6) than the other servers (4). In initial table assignments, two customer entities are assigned to CS, followed by one customer entity for DS, and then one for NCS. This process is repeated once, then one table is assigned in order to each server, followed by future assignments based on availability. The model time unit is minutes.

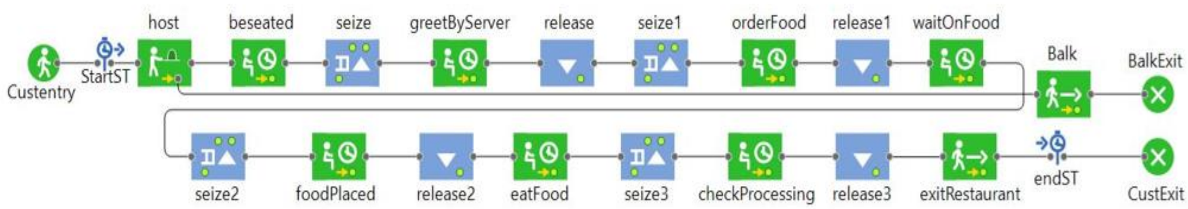


Figure 3-1 The DES restaurant workflow. Blue boxes represent queue blocks where the customers wait for a server, and green blocks are wait blocks in which the customers wait for a specified period of service time.

3.4.2 Agent-Based Server Model

The ABM defines the logic used by DS to decide whether to help CS (Figure 3-2), based on literature on helping behavior. During their idle time, servers reside on a "kitchen node". When idle, DS can decide to help, depending on the number of CS's tables customers occupy. If CS has fewer than five occupied tables, DS does not help and waits for the next idle state to again consider helping. Otherwise, DS's decision to help depends on the evaluation of Equation 3-1, which contains five user-entered decision variables from the literature: whether CS had been fairly promoted in the organization *FP* (0: no, 1: yes), whether DS was given their preferred work schedule *WS* (0: no, 1: yes), whether CS had helped DS in the past (i.e., a measure of reciprocity

RC, (0: no, 1: yes), DS's maximum allowed table occupancy TO (1-4), and DS's level of collectivism CO (1-7). The parameters are derived from data collected from a vignette survey, in which participants were asked whether they would help a co-worker who was assigned extra work.

$$\text{Predicted log of HB} = -2.99 + 0.33 * FP + 0.84 * WS + 2.95 * RC + -0.57 * TO + 0.57 * CO \quad (3\text{-}1)$$

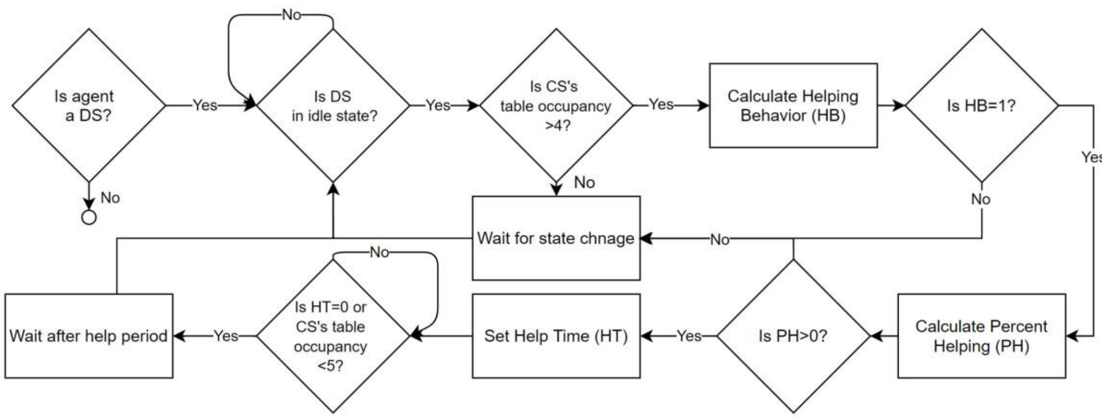


Figure 3-2 ABM: How Deciding Server (DS) decides if, and for how long, they help the core server (CS).

The sigmoid function is used to convert the predicted log of helping behavior obtained from Equation 1 to a probability of helping. DS will provide help only if the resulting probability is greater than 0.5. Once DS decides to help CS, it calculates what percentage of the maximum time of 60 minutes (Equation 3-2) to share CS's serving duties. DS shares CS's duties for the entire calculated help time or until CS's table occupancy drops below five tables, whichever occurs first. During helping, either server can attend to customers seated at CS's tables, based on their availability. If the total help time is less than 60 minutes, DS waits until 60 minutes past the start of the help time before considering helping again.

$$\text{Percent Helping} = -12.56 + 1.16 * FP + 5.97 * WS + 21.56 * RC - 12.36 * TO + 4.4 * CO \quad (3\text{-}2)$$

3.5 Our Hybrid Model Validation Approach

3.5.1 Applying Metamorphic Testing for Validation on Hybrid Models

Olsen and Raunak described the application of MT for validation of agent based and discrete events simulation models, arguing that the process could be adapted and applied to other simulation types (M Olsen & Raunak, 2019). This paper expands on that work, applying the same principles to hybrid simulation. One of the challenges of using MT for validation is to discover the MR in the system that is being modeled. In addition to providing a detailed process for performing simulation validation using MT, (M Olsen & Raunak, 2019) also provides specific categories that one should look into for discovering MR in an ABM or DES model. These source categories will be used while discovering MR for hybrid models.

For hybrid simulation, we propose applying MT on different model components individually. The resulting MR, however, will generally be defined using the results from the entire model, not only the Sub model. The exact categories of MR will continue to be based on the model definition. The MR elicited in ABM or DES categories will describe a change within that submodel, with a result that may be testable either within the submodel, within another submodel, or within the system overall (Figure 3-3). The unique aspect to validating hybrid models is that it may be possible to predict outcomes outside of the submodel being validated. Indeed, the uniqueness of validation in hybrid models is in the relationship between submodels. It is becoming common for submodels to be well integrated within the simulation software, and thus easier to validate as a whole as opposed to only as separate parts. This process supports both the validation of individual submodels, as well as the model overall, as will be seen in our case study.

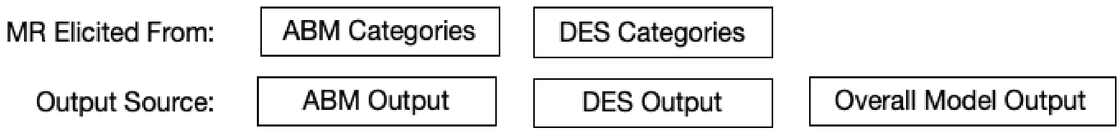


Figure 3-3 MRs can be elicited from either category, and each could use output from any aspect of the model.

3.5.2 Metamorphic Relations (MRs) for the Restaurant Helping Model

To define the MR for this model, we first define the available metrics:

1. Average customer queue time to be seated (ACQ): Average time a customer spends waiting in the queue before being seated.
2. Average customer seated wait time (ACSW): Average time customer waits on server after being seated.
3. Average overall server utilization (AOSU): Average percentage of time servers are assisting customers during the entire simulation run.
4. Individual average server utilization rate (IASU): Each server's average utilization during the entire simulation run.
5. Throughput: Total number of customers successfully dining during the entire simulation run.
6. Balk rate: Total number of customers who decided to exit before being seated.
7. HB Count (HBC): Total number of times help was provided by DS to CS.
8. Total Help Time (THT): Total number of minutes DS helped CS.

Using these metrics, we elicit MR that represent a predictable change when we do not have an oracle (Table 3-1). As described in Section 3.5, we can define MR for both the DES and ABM Submodels. In this particular simulation model, the ABM describes behavior of server agents that flow within the DES sub model, and thus only the last two metrics are specific to the ABM's logic; the remaining metrics are affected by the ABM, but not directly calculated within it.

The DES MR utilize all three categories from (M Olsen & Raunak, 2019): resource availability MR (D1) relate to availability of servers; process parameter MR (D2) relate to arrival of customer entities, customer group size, and delay times within service blocks; and workflow step MR (D3) relate to how servers are assigned, customers are seated, and service blocks are managed. The type of change to the parameter or property is paired with the expected type of change in outputs, as predicted by expert knowledge on the studied real world system. Only those changes that are predictable are included; if the effect on an output metric is not predictable, it cannot be included in the MR.

Table 3-1 Metamorphic Relations or validation. DES coded MRs are for the discrete-event model, and ABM coded MRs are for the ABM model. Category labels and format are from (M Olsen & Raunak, 2019)

Cat.	Code	Parameter or Property	Type of change	Pseudo-oracle Answer
D1	DES1	Number of servers attending a table	Increase	ACSW decreases, AOSU increases, IASU equal, Throughput increases, balk rate decreases
D2	DES2	Inter-arrival time for customers	Decrease	ACQ increases, balk rate increases
	DES3	Maximum customer group size	Decrease	ACSW decreases, balk rate decreases, throughput increases
	DES4	Delay time for single service block	Increase	ACQ increases, ACSW increases, throughput decreases, balk rate increases
D3	DES5	Combine service blocks	Food Order & Check Processing	ACSW decreases, AOSU decreases, throughput increases, balk rate decreases
	DES6	Server preference in table assignment	CS over others when all servers have same number of tables	IASU for CS highest of all servers, ACSW for CS tables highest of all servers
	DES7	Assignment of customers to servers	Random	IASU equal for all servers
A2	ABM1	Number of helping servers	Increase	individual HBC decreases, total HBC increases, balk rate decreases, throughput increases, overall THT increases, DS THT decreases
A4	ABM2	Helping time frame	Increase	THT increases, ACSW for CS decreases
A6	ABM3	Table occupancy check level	Decrease	THT increases, ACSW for CS decreases
	ABM4	Wait after help time frame	Increase	HBC decreases, THT decreases
	ABM5	Server walking speed	Decrease	Throughput decreases, balk rate increases, ACSW increases, HBC decreases

The ABM MR focus on changes to DS's helping behavior, as that is the only aspect controlled by the ABM. The MR utilize three of the ABM categories: agent parameter (A2) MR are the number of servers; interactions between agents (A4) MR relate to the amount of time help is provided; and individual agent behavior (A6) MR relate to how helping is provided and how quickly agents can choose to move in the system. Two other ABM MR categories are irrelevant in this model as they are defined by the DES instead: the environment category, and the interactions between agents and the environment category. A third ABM MR category is irrelevant for the model overall: agent topology. A number of potential ABM MR were also rejected as they were verifying implementation details instead of validating that the model matched the system being studied. For instance, making minor changes to the helping logic, in which the only predictable change was due to implementation and not due to the real world system being studied. We propose that the overall approach will be similar for applying MT for validation in other hybrid models.

3.6 Experimental Design

To validate our hybrid model using MT, we first test all DES MR while disabling the ABM logic, and then test the ABM MR while including the DES (Table 3-1). For each MR, we experiment by varying the given parameter or property and examining the results to determine if the expected change in output occurs, while holding all other values constant. For validation with MT, we must check a variety of scenarios to increase our confidence that the MR is upheld. Thus, in situations where a model change is made, some other influencing parameter should be varied to ensure that the MR's expected change in output occurs in more than a single situation of the model. In the following subsections we describe how parameters and/or the model are changed to validate with each of the MR from Table 1.

3.6.1 DES Experimental Design

Helping behavior is disabled for DES validation experiments as it could change the study's dynamics to be less predictable. The default model parameter values are customer group size (uniform distribution with min:1, max:4), customer inter-arrival time (truncated Poisson distribution with min:5, max:10, mean:8, shift:1, stretch1), service delay times varied by customer group size, server table assignments (CS:6, DS:4, NCS:4 tables), and simulation run-time (simulated 13 hours).

For **DES1**, instead of assigning the tables to always be served by a single server, the customer requests are handled by whichever server is free first. At the simulation start customers are randomly assigned to tables. DES1 was tested against seven different cases of customer inter-arrival times. Case 1 has a truncated Poisson distribution (min:7, max:12, mean:10 minutes), and each increasing case number has a reduction of one minute for each value, with case 7 having values min:1, max:6, and mean:4 minutes.

DES2 is tested with the same inter-arrival times as DES1. We test **DES3** by altering the maximum customer group size, from Case 1 at Uniform (min:1, max:8) to Case 8 (min:1, max:1). For **DES4**, the service block *orderFood* is modified. The default delay time is a truncated Poisson distribution that varies by group size: group size 1 is (min:3, max:5, mean:4); group size 2 is (4,7,5); group size 3 is (6,8,7); and group size 4 is (7,10,8). We test DES4 with six cases where Case 1 uses the default values, and each increasing case number increases min/max/mean by one minute for all group sizes.

For **DES5** the service blocks *orderFood* and *checkProcessing* are combined into one service block called *orderandBilling*. The service block *orderFood* uses the DES4 delay times.

The service block *checkProcessing* uses a delay time of truncated Poisson distribution that varies by group size: group size 1 is (min:1, max:2, mean:2); group size 2 is (1,3,1.5); group size 3 is (2,4,3); and group size 4 is (2,5,2.5). The service block *orderandBilling* adds together delay times from the other two service blocks. Similar to DES4, six cases are used with Case 1 using the default delay times and the additional cases adding 1 minute each.

For **DES6** and **DES7**, the model is modified so that each server handles only four tables. For **DES6**, customers are always seated at the CS's tables if possible. If no CS tables are free, customers are randomly seated at DS or NCS tables. For **DES7**, the customer seating order is random. The assigned server owns that customer table and handles all requests of customers seated in their area. For testing DES6 and DES7, the seven different cases of customer inter-arrival times from DES1 are used.

3.6.2 ABM Experimental Design

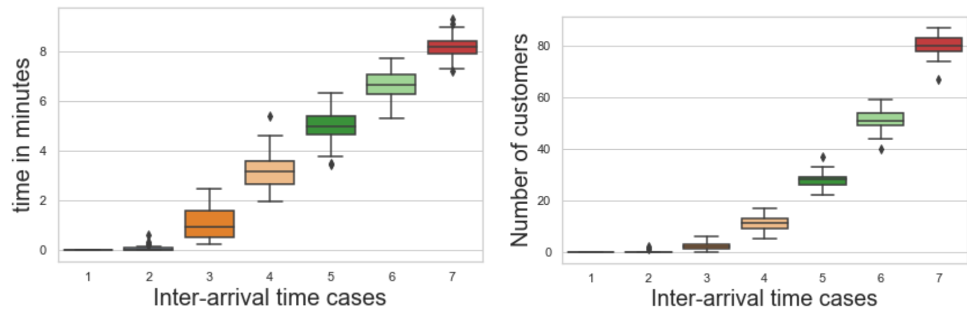
To validate the ABM sub-model, we run the simulation model in a mode that exhibits helping behavior. To achieve this setting, DS's behavioral parameters are initialized for maximum helping: maximum table occupancy allowed for DS: 1 table; CS was fairly promoted: yes; DS was given preferred work schedule: yes; CS had helped DS in the past: yes; and the collectivism level of DS: high.

We test **ABM1** by defining 3 cases on number of deciding servers: 1) no server can help; 2) DS can help; and 3) both the DS and the NCS can help. This MR is tested across seven different customer inter-arrival times with the same values used for DES1, resulting in 21 total combinations of number of helping servers and arrival times. For **ABM2** we test a total of 6 cases of maximum helping time, with Case 1 being at 60 minutes, and each increasing case number increasing that time by 30 minutes. **ABM3** is tested by altering the number of CS's tables that must be occupied for DS to consider helping. A total of 6 cases are tested for ABM3. For ABM3 Case 1, CS's tables must be greater than five for DS to share one of CS's table duties if he/she decides to help. With every increase in the case number, the CS's table occupancy value for the condition is dropped by one. For ABM3 Case 6, the condition is that CS's tables must be greater than zero, which implies that if the DS decides to help, he/she will share all the core server's tables. For **ABM4**, instead of the DS going through a state of helping and waiting after helping for a total of 60 minutes, a total of six cases are run, each adding 15 minutes of additional wait time after the help time frame cycle. Case 1 adds zero minutes. For **ABM5**, the default server walk speed of 1 meter per second is reduced by half in each of the six cases, with Case 6 using a walking speed of 0.03125 meters per second.

3.7 Results

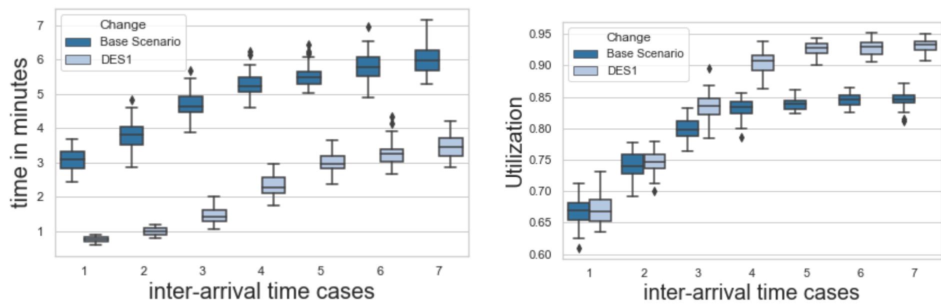
To validate the model, each case for every MR is run with 30 replications to obtain the average and standard deviations of the pseudo oracle answers. Box-and-whisker plots are generated for every pseudo-oracle output to visualize the predicted change. A trend of increase or decrease is the predicted result for an MR; thus, the direction of change between cases is the focus of this analysis. The order of the experiments was chosen based on complexity and its use for another experimental setup.

DES2 is tested first as DES1 uses a similar experimental design. The DES2 MR results support the pseudo-oracle answers corresponding to changes in customer inter-arrival time (Figure 3-4), except for Case 1 and Case 2, which have higher inter-arrival times (i.e., customers arrive less frequently). However, the outputs for these cases are reasonable because fewer customers should lead to customers always being serviced as soon as they arrive. Further examination of the output confirmed this was the case. Therefore, DES2 is upheld. We next test DES1, which upholds the MR following a similar pattern to DES2 regarding the customer inter-arrival time (Figure 3-5). Figure 3-6 shows the expected direction of change in ACSW, throughput, and balked customers for DES3.

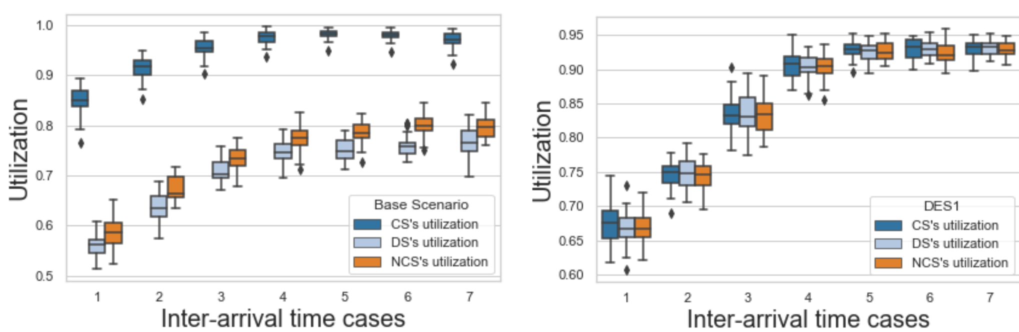


(a) ACQ (b) Number of balked customers

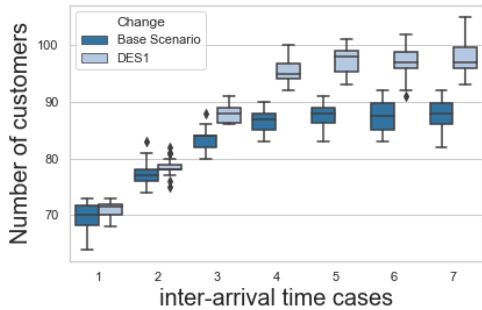
Figure 3-4 DES2 MR results show the expected increase in ACQ and balk rate



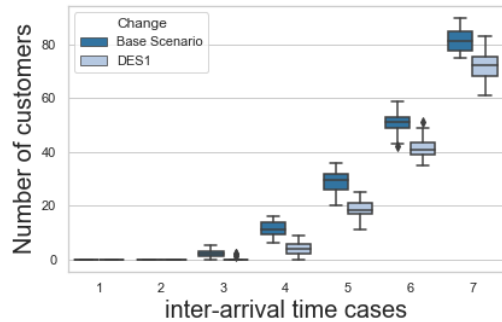
(a) ACSW (b) AOSU



(c) IASU in base scenario (d) IASU in DES1

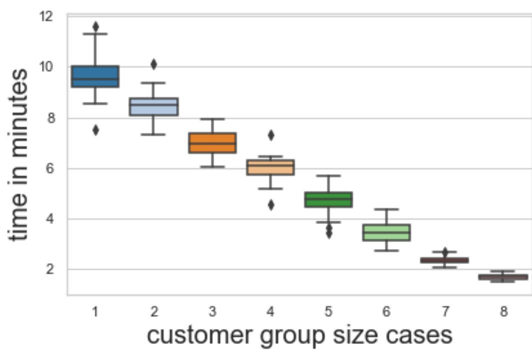


(e) Throughput

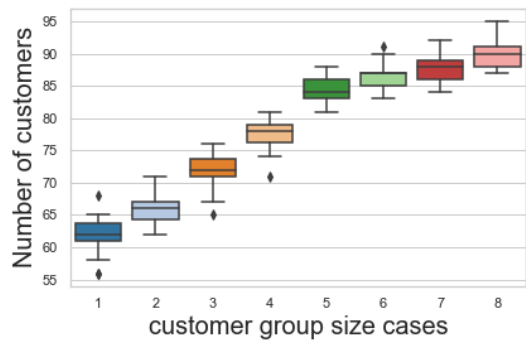


(f) Balked customers

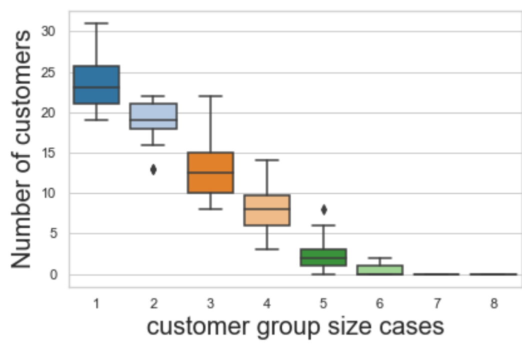
Figure 3-5 DES1 MR results on varying arrival rates show the expected changes in each output



(a) ACSW



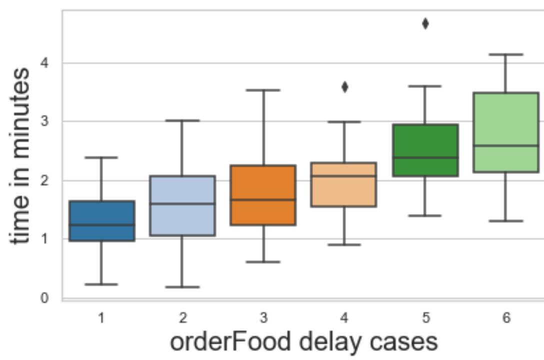
(b) Throughput



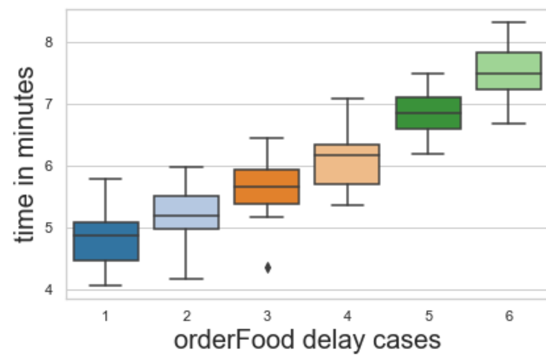
(c) Balked customers

Figure 3-6 DES 3 MR results for different customer group sizes

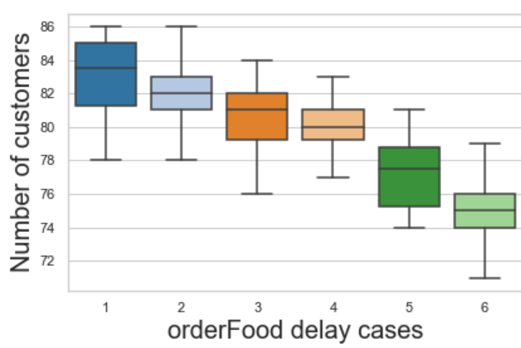
DES4 alters the delay time of a single service block. The resulting outputs in Figure 3-7 show increasing/decreasing trends that appear to correspond to the pseudo-oracle answers. Although the spread of averages of the outputs is close, the delay times used for each case only differed by a minute, and thus the gradual upward/downward trend is reasonable. The DES5 MR is tested by combining two service blocks. Initially, the pseudo-oracle answers for DES5 were expected to exhibit no change in the results for different cases of delay times. But the outputs in Figure 3-8 show varied results, implying that either there is a bug or the person drafting the MRs needs better domain expertise. Upon investigation, it was found that combining two service blocks in the system by adding their delay times reduces server utilization as servers now spend less time moving between customers. This MR was further tested by combining various other service blocks, yielding similar results as Figure 3-8. Hence DES5 MR was updated accordingly to the version in Table 3-1, as the issue was in domain expertise instead of a bug. Finally, DES6 and DES7 are tested (Figures 3-9 and Figure 3-10), and upheld due to the expected change in output.



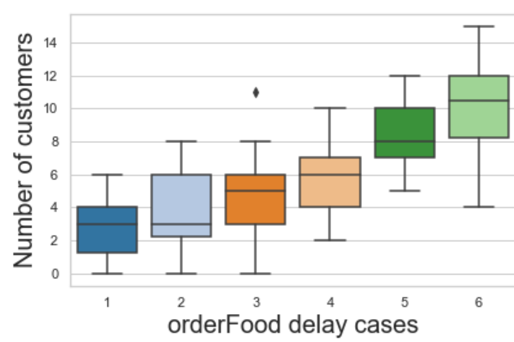
(a) ACQ



(b)ACSW

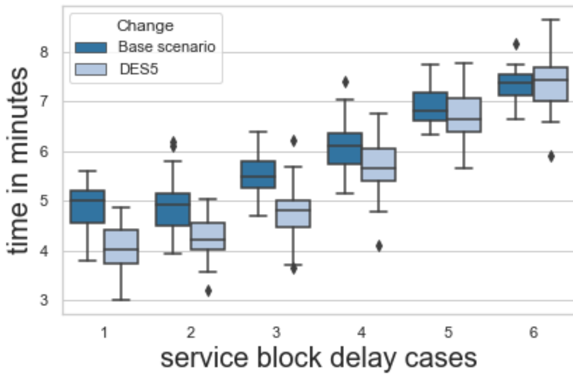


(c)Throughput

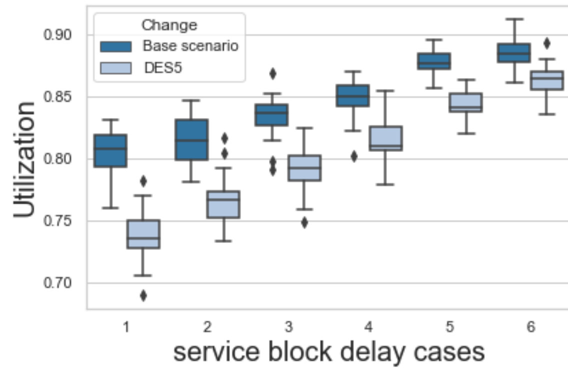


(d) Balked customers

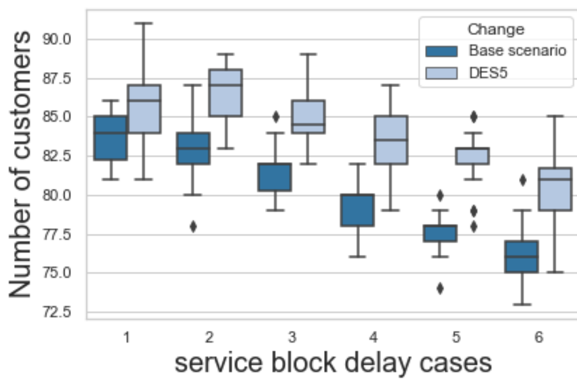
Figure 3-7 DES4 MR results for orderFood delay times



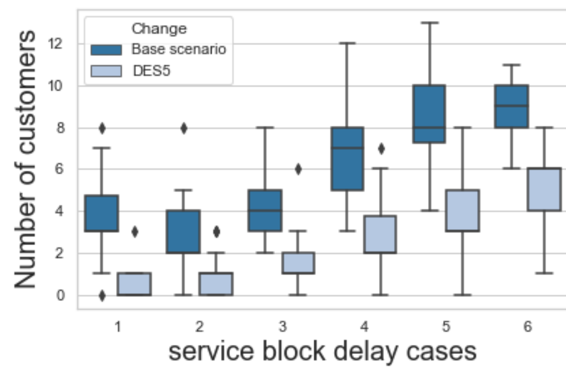
(a) ACSW



(b) AOSU

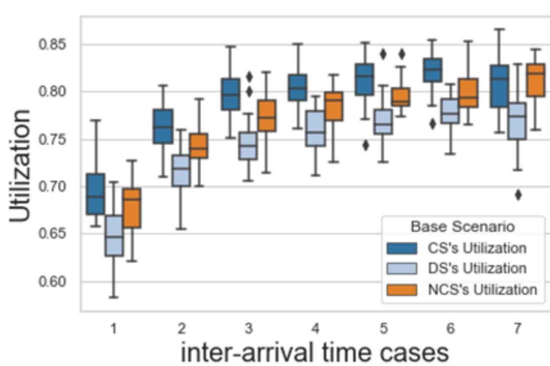


(c) Throughout

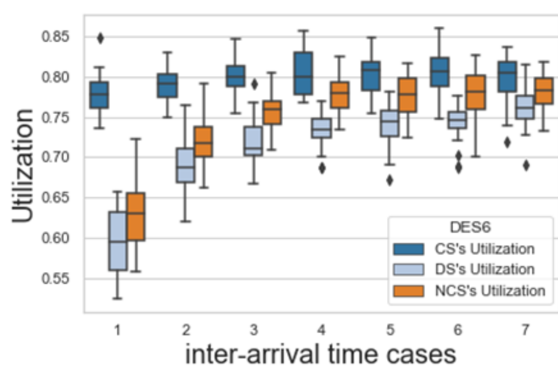


(d) Balked customers

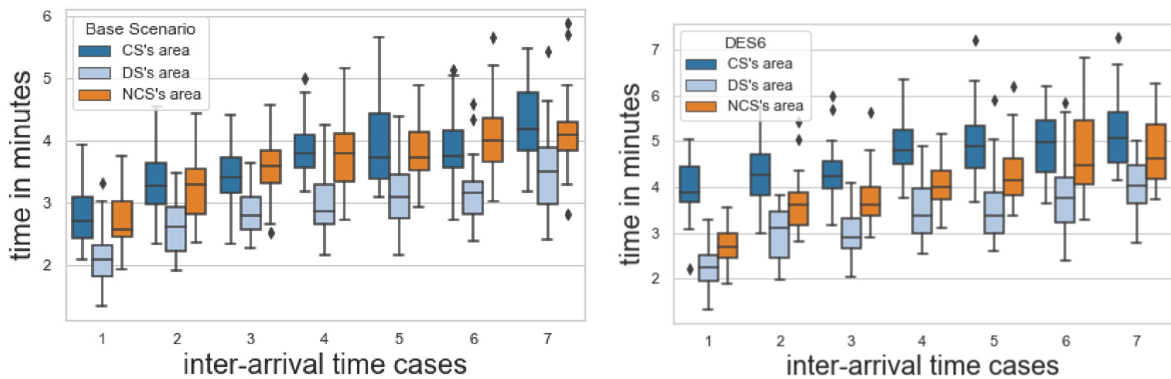
Figure 3-8 DES5 MR results for each service block delay time



(a) IASU in base scenario

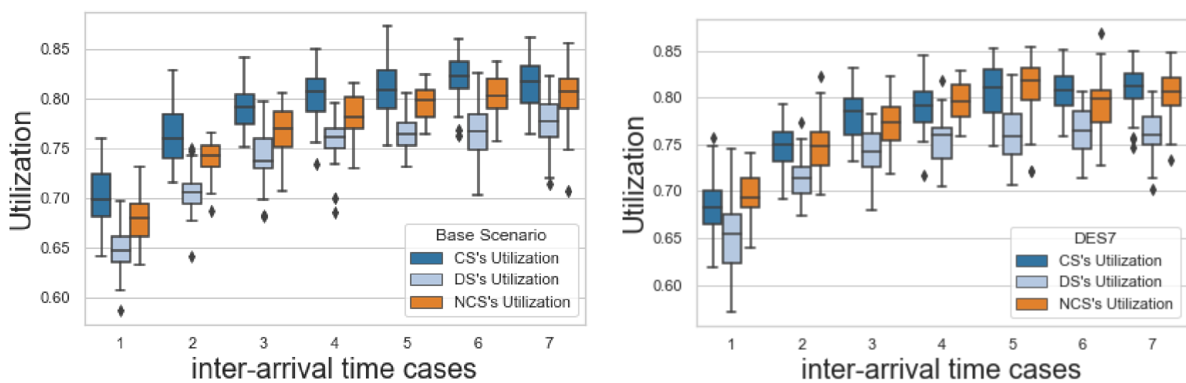


(b) IASU in DES6



(c) ACSW in base scenario (d) ACSW in DES6

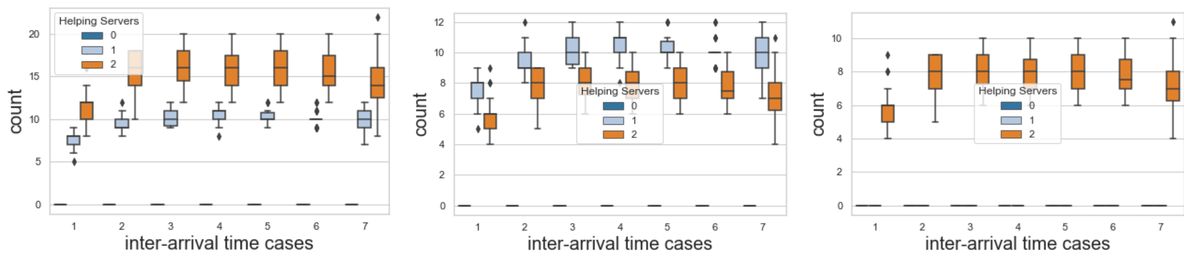
Figure 3-9 Results of Experiments MR DES6 pseudo oracle outputs vs. different customer arrival rates



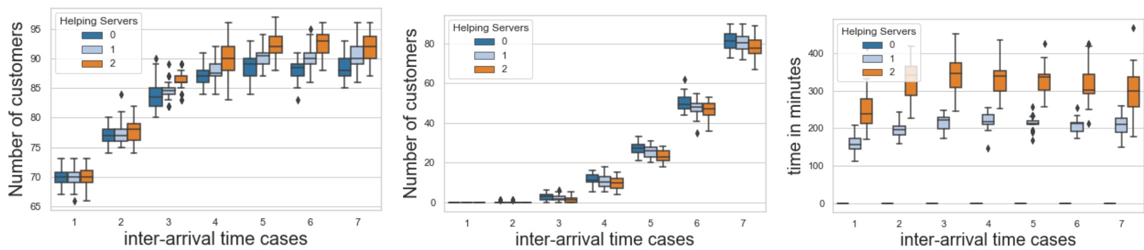
(a) IASU in base scenario (b) IASU in DES7

Figure 3-10 DES7 MR results for each customer arrival rate

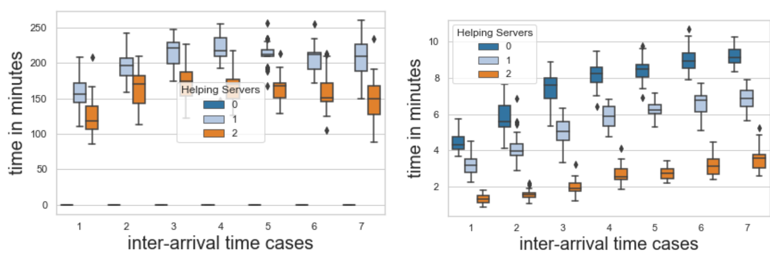
For ABM1, an increase in the number of deciding servers shows the expected increase in overall HBC and an expected drop in Individual HBC across all cases of customer inter-arrival time. All other pseudo-oracle outputs for ABM1 also show supporting results as seen in Figure 3-11. The ABM3, ABM4 and ABM5 results are shown in Figure 3-12. For ABM3, an increase in the number of tables shared by DS shows the expected increase in THT and an expected drop in ACSW for CS's tables. For ABM4, an increase in the wait time after the help time frame shows the expected drop in overall HBC and THT. For ABM5, a decrease in the server walking speed shows the expected decrease in throughput and overall HBC, and an expected increase in the number of balked customers and ACSW.



(a) overall HBC (b) DS's HBC (c) NCS's HBC

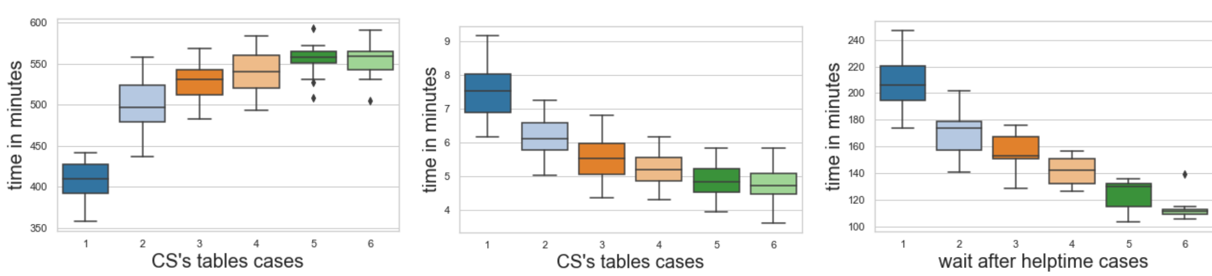


(d) Throughput (e) Balked Customers (f) THT

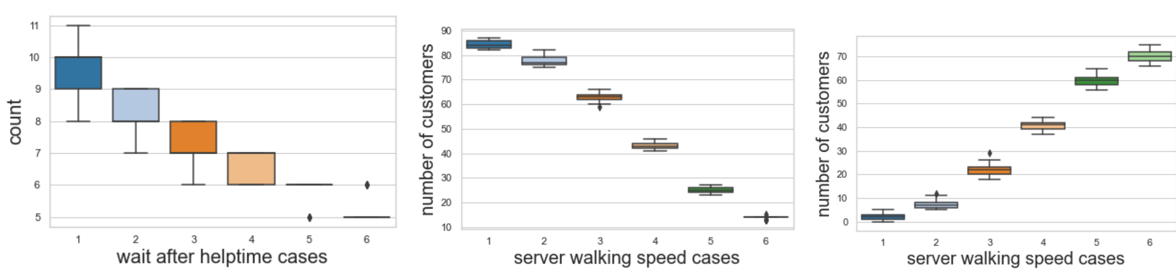


(g) THT for DS (h) ACSW for CS's tables

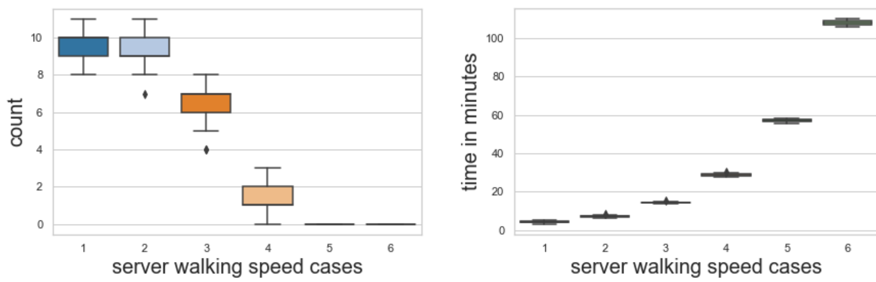
Figure 3-11 ABM1 MR results for each customer inter-arrival time



(a) ABM3 THT (b) ABM3 ACSW for CS's tables (c) ABM4 THT



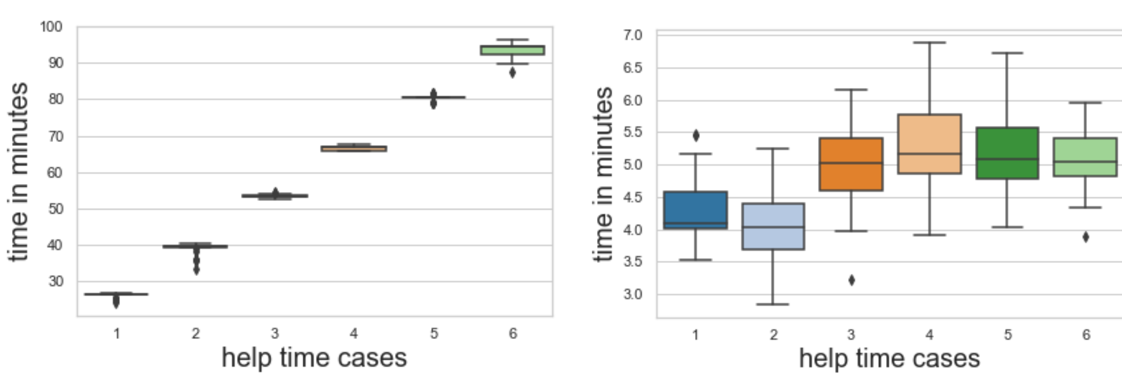
(d) ABM4 HBC (e) ABM5 Throughput (f) ABM5 Balked Customers



(g) ABM5 HBC (h) ABM5 ACSW

Figure 3-12 Results of experiments for A6 ABM MR pseudo oracle outputs. All MRs are upheld.

ABM2 MR results show that THT has the expected increase, but ACSW for CS's tables shows no significant change, contrary to the expected decrease (Figure 3-13). In the ABM2 experiment the only helping server is the DS, DS only shares two of CS's tables, and DS only helps if CS has at least 5 tables occupied. Therefore, ACSW for CS's tables cannot be predicted only by altering the helping time frame in ABM2 with the default setup due to confounding factors. It is likely that a different experimental setup is needed: DS should help with all of CS's tables, and not be limited to only helping when CS has at least 5 tables occupied. The MR would need to be updated once the full situation is determined from additional experiments. This MR demonstrates a common step of the MT process for simulation validation.



(a) THT (b) ACSW for CS's tables

Figure 3-13 Results of Experiments for A6 ABM MR pseudo oracle outputs. All MRs are upheld.

3.8 Conclusion

In this paper we presented an approach for applying metamorphic testing to validate hybrid simulation models, with a focus on ABM/DES hybrid models. We applied MT on a hybrid restaurant simulation model, where servers carry out their responsibility of servicing their assigned customers, and under certain scenarios, decide to help other servers. We systematically developed metamorphic relations following our framework presented in the paper and used those MRs to run different validation experiments. Our experiments applied MT for validating both DES and ABM aspects of the hybrid model separately, as well as the combined overall model. Through the upholding of the predicted pseudo-oracle answers, we have shown an increased confidence in the validity of our hybrid model. In prior work, MT has been demonstrated to be effective in validation of individual ABM or DES simulation models. Through this study, we have demonstrated its effectiveness on validation of hybrid model as well. In our future work, we plan to utilize MT for both verification and validation of hybrid models. We also intend to apply our approach on other hybrid models using different combinations of modeling techniques and from different domains.

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CHAPTER 4 CONCLUSION

This dissertation makes multiple theoretical contributions to the operations management (OM) literature. Firstly, this research conceptualizes the theory of the strategic core to study the behavioral factors that influence a team member to provide helping behavior to his/her coworker. Secondly, this research empirically examines why and how changes in team dynamics and organizational policies influence restaurant employees' altruistic behavior. This dissertation also leverages the power of hybrid simulation modeling to provide a greater understanding of how team dynamics influence overall operational performance in a service system. Specifically, this dissertation uses a combination of agent-based and discrete event simulation to design a human behavioral model of restaurant servers in an operational setting. This dissertation also contributes to the simulation modeling literature by showcasing how empirical human behavioral data from vignette-based surveys can be used to build conceptual simulation models for dynamic operational insights. This dissertation further demonstrates a new approach to validating hybrid simulation models (DES and ABM) using the Metamorphic Testing (MT) technique.

The answers to the research questions addressed in the Introduction are summarized below:

- *How do behavioral and situational factors beyond monetary benefits motivate a restaurant server to engage in helping behavior?*

  According to the results, the log of the odds of a non-core server providing help to the core server was positively related to the preferred work schedule ($p <.05$), reciprocity ($p <.05$), and collectivism ($p <.05$), whereas table occupancy ($p <.05$) was negatively related since higher table occupancy was coded as one and lower table occupancy was coded as zero. The reciprocity factor had a particularly strong effect: Given the same values of fair promotion, preferred work schedule, table occupancy, and collectivism, the odds of a non-core worker helping the core worker were 19.119 times greater if help had been provided to the non-core worker in the past.

- *How can a behavioral study of restaurant servers be extended to gain dynamic restaurant operational insights using hybrid simulation?*
  To facilitate the representation of both human behavior (i.e., the decision to help) and operational behaviors (i.e., the flow of customers through a restaurant), the dissertation uses a hybrid combination of agent-based modeling (ABM) and discrete event simulation (DES). By utilizing the regression outputs from Chapter 2, two multi attribute utility functions were used to describe the server agent logic in the simulation model. The simulation model extends the limitations of an empirical study by providing dynamic insights of helping behavior on the overall operational performance of the restaurant such as customer service times and throughput.

- *How can inter-modular verification and validation be achieved in hybrid simulation models?*
  For hybrid simulation, the dissertation proposes applying MT on different model components individually. However, the resulting MR will generally be defined using the entire model's results, not only the sub-model. The MR elicited in ABM or DES categories will describe a change within that sub-model, which may be testable within the sub-model, within another sub-model, or the system overall. The unique aspect of validating hybrid models is that it may be possible to predict outcomes outside of the validated sub-model. Indeed, the uniqueness of validation in hybrid models is in the relationship between submodels. It is becoming common for submodels to be well integrated within the simulation software and thus easier to validate as a whole as opposed to separate individual components. This process supports both the validation of individual submodels as well as the model overall. This technique can very well be used for verification of the model logic.

- *How can the Metamorphic Testing technique be applied to validate hybrid simulation models?*

  This dissertation presented an approach for applying metamorphic testing to validate hybrid simulation models, focusing on ABM/DES hybrid models. MT was applied on a hybrid restaurant simulation model, where servers carry out their responsibility of servicing their assigned customers, and under certain scenarios, decide to help other servers. 12 metamorphic relations following the MT framework presented in Chapter 3 were systematically developed and using those MRs to run validation experiments on a variety of model scenarios to increase the confidence that the MR was upheld. The experiments applied MT for validating both DES and ABM aspects of the hybrid model separately and the combined overall model. A trend of increase or decrease or no change was the predicted result for an MR; thus, the direction of change between the various experimental designs was the focus of this analysis. Out of the 12 MRs, 10 MRs were upheld. The remaining 2 MRs were further investigated to either update the MR or make necessary assumptions about the dynamics of the model. The upholding of the predicted pseudo-oracle answers has shown increased confidence in the validity of the study's hybrid model. It was observed that the MT technique can very well be applied for model verification as well.