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SIMULATING THE MICRO-LEVEL BEHAVIOR OF EMERGENCY DEPARTMENT FOR MACRO-LEVEL FEATURES PREDICTION

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ABSTRACT

Emergency departments are currently facing major pressures due to rising demand caused by population growth, aging and high expectations of service quality. With changes continuing to challenge healthcare systems, developing solutions and formulating policies require a good understanding of the complex and dynamic nature of the relevant systems. However, as a typically complex system, it is hard to grasp the non-linear association between macro-level features and micro-level behavior for a systematic understanding. Instead of describing all the potential causes of this complex issue, in this paper we present a layer-based application framework to discover knowledge of an emergency department system through simulating micro-level behaviors of its components to facilitate a systematic understanding. Finally, case studies are used to demonstrate the potential use of the proposed approach. Results show that the proposed framework can significantly reflect the non-linear association between micro-level behavior and macro-level features.

1 INTRODUCTION

The study of complex adaptive systems, from cells to societies, is a study of the interplay among processes operating at diverse scales of space, time and organizational complexity. The key to such a study is an understanding of the interrelationships between microscopic processes and macroscopic patterns, and the evolutionary forces that shape systems (Levin 2002). The "micro-to-macro" thinking was widely used in social science, the micro- and macro- level division concerns the capacity for theory to explain the relationship between the constitutive elements of complex systems (individual, micro-level cognitive agents) and the emergent phenomena that result from their interaction on larger scales. Discovering a complex system from micro-level behavior concept is based on an understanding of systems theory (Von Bertalanffy 1968). What accounts for the widespread use of the "micro-to-macro" thinking is that at the heart of the "micro-to-macro" behavior reflection is the fact that humans have difficulty in understanding the complexities caused by the dynamic and systemic nature of certain problems (Dorner and Palmarini 2011). Even many well-educated leaders in positions of responsibility with regard to various complex dynamic feedback systems need a lot of training to think systemically (Sterman 1994, Richmond 1993).

In this study, the term "micro units, also known as "agents or "individual, denotes the smallest components of the system according to the studied level of detail. These agents get information from environment and/or other agents, make decisions and affect the environment and/or other agents. In this way, the model of a single agent is to represent its real behavior in actual situations. Two or more agents with the same relationship form an interaction. For instance, when a patient and a doctor are in the same timeline and spatial location with the goal of healthcare provision, an interaction shows up. The key performance indicator (KPI) of the system on the macro-level is an aggregate of corresponding interaction. For example, the throughput of a service-oriented system is the sum of agents passing through the system, utilization of the system resource is a percentage of scheduled time spent on service-providing related interactions.

Hospital Emergency Departments (ED) are one of the most complex parts of hospitals to manage, and yet they are a major entry point to the healthcare system. They deal with patients arriving without an appointment and with a wide range of illnesses (Prodel, Augusto, and Xie 2014). As a highly complex, emotionally charged work environment where operational decisions can mean the difference between more life and more death. It is clearly stressful and frustrating. Nowadays, many researchers are trying to provide hospital managers with new organization and management strategies to improve performance, efficiency and quality of service. Full insight into the target system is one of the premises of efficient management. For example, the ability to accurately forecast demand in emergency departments will have considerable implications for hospitals to improve resource allocation and strategic planning. Modeling and simulating the complex healthcare system in detail plays a key role in providing insights for process improvements, capacity planning, resource allocation and appointment scheduling. In addition, a simulation model allows the user to understand and test a performance improvement idea in the context of the overall system without any impact on the real system.

In this paper, we do not intend to describe all the potential causes of complex issues in an emergency department. Rather, the goal is to provide a framework that will facilitate a systematic understanding of the emergency department operational problem. Hence, the objective pursued in this work is to discover knowledge for better understanding the science of complex ED systems and meeting the representational, educational, and decision support challenges involved in healthcare operations. This is a step forward in the contribution of modeling and simulating emergency department. We implemented and validated the agent-based emergency department model in our previous work (Liu et al. 2014) and (Liu et al. 2015). The flexible framework combines with the individual behavior simulator to observe the emergence behavior and detailed movement pattern from the simulated micro-level interactive data.

The rest of this article is organized as follows. Section 2 gives the literature review on knowledge discovery and healthcare system organization, as well as motivation of this study. Section 3 is the main part to explain the proposed framework for ED knowledge discovery. Then, two case studies on "micro-to-macro" link discovering are demonstrated in Section 4 to show the potential use of the proposed approach. Finally, Section 5 closes the article with conclusions and future work.

2 RELATED WORKS AND MOTIVATIONS

Means and methods to obtain knowledge about the inherent uncertainties and complexities of a system to support learning, problem solving, decision making, and policy formulation have attracted a great deal of research attention. In relation to the difficulty arising from complexity and uncertainty in managing a big critical healthcare system, Barach and Johnson (2006) proposed a microsystem framework as a design concept, specifically the role of understanding and supporting process in designing and redesigning clinical care. The microsystem in their work is a group of clinicians and staff, working together with shared clinical purpose to provide care for population of patients. There are several micro-systems co-existing within a larger organization such as a hospital. Thus, the challenge for the management of the large system is transferred to the management of several relatively independent micro-systems. In this way, the behavior of the large system will be the aggregate of these micro-systems. Their work highlighted the issues of managing a complex system due to the difficulty in understanding complexities as well as the decentralized solution.

There are massive operational research (OR) results in the reviewed literatures achieved by using a simulation approach. System Dynamics (SD), Discrete Event Simulation (DES) and Agent-Based Simulation (ABS) are three widely used simulation methods in operational research community. The main differences among these three simulation methods is the level of perspective (Barnes, Golden, and Price 2013). SD is a top-down approach from the macro-level perspective; The DES is a process-oriented approach focused on workflow simulation and the ABS is a bottom-up one from an individual level. At the 2010 OR Society Simulation Workshop, there was a lively panel discussion (Siebers et al. 2010). From the discussion, we can see that actually both DES and ABS are widely used now. Neither have the absolute substituting capability in all application fields. The same workshop in 2011, as well as Ref. (Macal and North 2014) discussed the challenges of DES and several typical features of a system with which the ABS is more appropriate (Brailsford 2013). There is no fixed rule to select a suitable approach for studying a specific system, a proper combination may halve the work with double the results. Based on this idea, Djanatliev and German (2013) presented a multi-paradigm simulation method by using SD for simulations at a high abstraction level and ABS/DES at an individual level in a common simulation environment. Two examples were shown on how the new innovative technology can evaluate the “what-if” problems prospectively and how new ideas can be derived by parameter variations. Combining the reviewed discussion and simulation studies with our experience and objective, ABS was selected to simulate the emergency departments, the reason will be given in Section 3.2.

As a healthcare service provider, the functionality of an ED emerges from individual interactions among patients, healthcare staff and medical test equipments. Considering the importance of modeling and simulating the interaction between physicians and delegates in ED, Lim et al. (2013) compared two models with and without the consideration of agents interacting in an emergency department. In their hospital ED model, comparisons between the approach with interaction and without showed physician utilization increase from 23% to 41% and delegate utilization increase from 56% to 71%. They stated that neglecting these relationships could lead to inefficient resource allocation due to inaccurate estimates of physician and delegate time spent on patient related activities and length of stay. Their work strengthens the importance of accurately modeling physician relationships and the roles in which they treat patients. Furthermore, Axtell (2000) also discussed several reasons for using an agent-based modeling technique, especially compared to traditional approaches to modeling economic systems.

The review of literature reveals that a modeling and simulation technique has been applied extensively to study the patient flows in the ED systems mainly because of the complexities of patient flows and the time-dependent characteristics of such systems. However, most of these simulation based studies are oriented by specific requirements. Therefore, the simulator lacks scalability in application perspective and becomes an appropriative tool for a specific requirement. In addition, in many application domains it is extremely important to have transparency in predictive modeling because domain experts do not tend to prefer “black box” predictive models. They would like to understand how predictions are made, and possibly, prefer models that emulate the way a human expert might make a decision, with a few important variables, and a clear convincing reason to make a particular prediction (Rudin 2014).

Due to the complexity and criticality of ED systems, knowledge for full insight into the dynamics of the system will provide a great deal of help to efficient and optimum management. However, there is little work on knowledge discovery through simulating micro-level behavior. Discovering from micro-level behavior is a way to gain insight into the emergent behavior of complex systems. It is not only able to carry out prediction, but also provides knowledge on how predictions are made at individual level. Given this motivation, we tried to model an emergency department from an individual behavior perspective, the goal of this micro-level behavior model is to fully represent interactions among individuals. In view of the massive atomic data (The lowest level of detail from which the aggregate data is computed.) generated by the individual behavior simulator, we designed a layer based framework for information extraction. It can provide more flexibilities for simulator users on problem solving and it is easier to add more functionality (without always starting from scratch) than it is on a requirement specified simulator.

3 KNOWLEDGE DISCOVERY FROM SIMULATED MICRO-LEVEL BEHAVIOR

One benefit of simulating the micro-level behavior is that it provides a potential to know the root cause of macro-level features. For an existing macroscopic phenomenon, it is possible to trace back to the micro-level behavior that accounts for it. In addition, compared with a direct macro-level behavior simulator, adding more functionality to the micro-level behavior simulator is easier because an overall knowledge of the whole system will not be mandatory. Moreover, real data collecting for refining the individual model is easier and more straightforward because real data for defining an individual component model can be used directly with few or even without systemic abstraction. For instance, real data collecting for defining the behavior model of a doctor and admission staff can be done separately without an overall knowledge of the emergency department system.

3.1 Architecture

For a complex system like an emergency department, the macro-level features of the system emerge from the corresponding micro-level interactions. However, the interaction data generated from the agent simulator is massive and unreadable without being analyzed. To meet the massive simulation data generated by micro-level simulator as well as constantly changing requirement, we designed a layer architecture to simulate, monitor and discover knowledge for full insight into the complex system (see Figure 1).

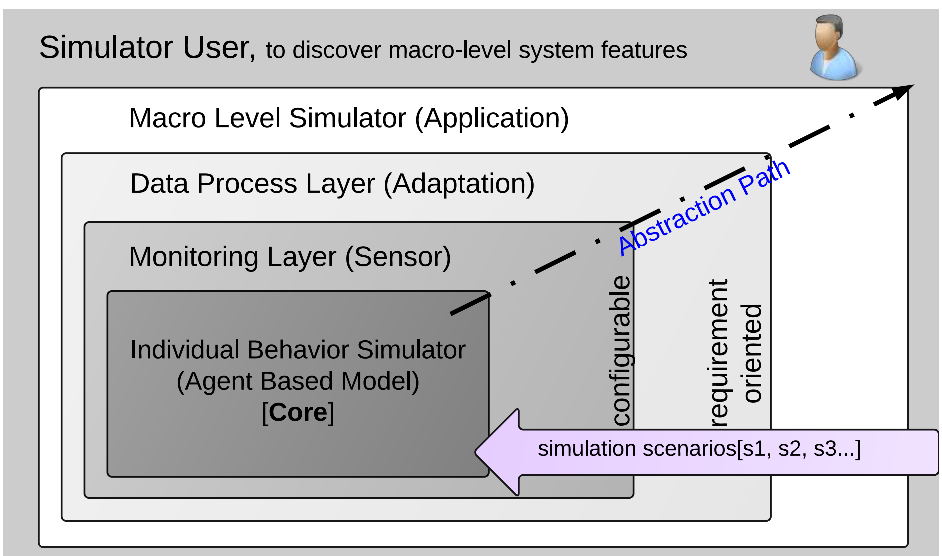


Figure 1: Layer architecture of application framework for knowledge discovering from micro-level behavior simulator. The micro-level simulator generates interaction information among the system components, configurable monitoring layer records all the needed interaction information and state information in a given format for the upper processing layer.

As shown in Figure 1, the core of the knowledge discovery system is an agent-based micro-level behavior simulator. It can provide detailed interaction information among the smallest components of the ED as well as state information of the simulated environment. This information is the source of knowledge to understand behavior of the entire system. However, not all the data is required for specific analysis, thus the monitoring layer is designed to provide the flexibility on micro-level data collecting and processing. Moreover, the simulation scenario is defined as a set of parameter configurations for the agent-based model and environment. Therefore, from the perspective of the simulator users, the whole system is a macro-level features simulator because what the users get is the macro-level information extracted from the micro-level data. The detailed function of each layer will be explained in the following subsections.

3.2 Micro-level Agent-Based Simulator

Agent-based simulation (ABS) is an approach to model systems comprised of individual, autonomous, interacting "agents". The interacting is a key characteristic since that is the smallest element emerges the functionality of the system. Such interaction data has incredible potential to address complex features and dynamics of the objective system. Agent-based modeling offers ways to model individual behaviors more easily and to see how behaviors affect others in ways that have not been available before (Macal and North 2014). Furthermore, in the micro-level, the spatial agent-based simulator is not a design for any specified application. Instead, it is just a general behavior simulator to simulate interaction among the smallest components of the ED system. Thus, it is customizable for different emergency department simulation requirements.

The reasons why ABS was selected to model an emergency department in this study include: (1) in an emergency department system, agents have dynamic relationships with other agents. For example, patients have dynamic relationships with sanitary staff, doctors have dynamic relationships with nurses and medical test rooms. These dynamic relationships are important to consider and, by their nature, well suited to be modeled as part of agent-based model. (2) The agents have a spatial component to their behaviors and interactions, i.e., most of the agents in ED need to move around and the spatial location is one of the key states which determines their potential interacting object and state transferring. (3) A large numbers of agents, agent interactions and agent states are important for information extraction. In an ED, services are provided via multiple interactions, patients pass through ED with a series of non-deterministic interactions. These interactions can deeply reflect the functionality of the target system. (4) Model reusability. Agent-based model directly represents behavior of the system components, so it can provide the all-side atomic data needed for analyzing the macro-level behavior of the system.

In this study, the micro-level behavior simulator for emergency departments is a pure spatial agent-based model. It is formed entirely of the rules governing the behavior of the individual agents which populate the system, no higher-level behavior is modeled. Thus, the system behavior emerges as a result of micro-level actions and interactions. Without loss of generality, we consider all the components of the emergency department as agents. In this way, there are two kinds of agents, passive and active. The passive agents include the test service (laboratory and medical imaging) and information center (work as a task detacher and information exchange center). Active agents include all the staff and patients. Concerning the staff, we considered: admission staff for registration service, triage nurses for classifying patients according to their body condition, doctors, nurses and auxiliaries for helping patients move around the ED for medical tests. The sanitary staff are modeled as junior or senior according to their expertise. As for the environment model, except waiting rooms, admission desk and triage box, there are two areas which work independently for treatment: area A for high acuity patients with some careboxes (a room with bed and essential equipment) and area B for low acuity patients with some chairs. Doctors and nurses are specified for different areas but test rooms are shared by all the patients. All of these agent models are parameterized to be configurable for simulator users. A detailed description of the entire emergency department model using the agent-based paradigm can be found in our previous publication (Liu et al. 2014) and (Liu et al. 2015). This model is carried out with the participation of the ED Staff Team of the Hospital of Sabadell (one of the most important Hospitals in Spain, that gives care service to an influence area of 500,000 people, and attends 160,000 patients/year in the ED) who are knowledgable about the actual system, and implemented in Netlogo (Wilensky 1999) simulation environment.

The input of the model is the patients who arrive for emergency service. The patient arrivals were modeled by a time-dependent Poisson process (uniquely defined by its time-dependent arrival intensity). This intensity function was created by using a step function generated from hourly ED arrival rate data obtained from our cooperating emergency department. This hourly ED arrival rate was given weekly, i.e., the arrival model repeats with an interval of one week in model execution. When a patient has arrived and registered by the admission staff, a triage nurse will assign the patient a priority level based on the severity of their condition. The priority consists of five levels, with one being the most critical (resuscitation), and five being the least critical (non-urgent). Patients with acuity level one to three will be assigned to area A, with level four and five will be assigned to area B. The reference arrival rate and acuity level distribution is obtained from our cooperative ED and configurable for simulator users.

3.3 Micro-level Data Monitoring

Simulation output from the agent-based simulator is subjected to extract the system-level behavior information. However, the interaction data and the state information of the system are massive and some of it may not be necessary for specific analysis. In data collection process of a real system, we tend to collect as much data as possible in order to cover as much information as possible. Whereas in simulation, data monitoring should be focused on the goal of analyzing because the simulation process is reproducible, more data usually means greater difficulty to analyze and a waste of resources. Therefore, we designed a configurable data monitoring layer between the micro-level behavior simulator and data processing layer from a point view of "sensor".

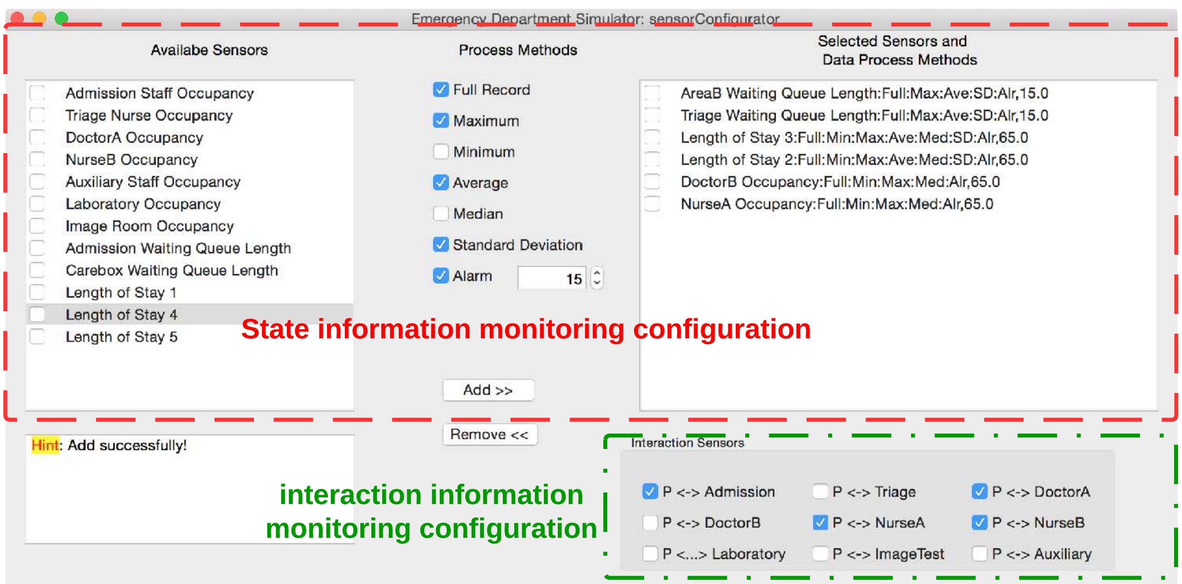


Figure 2: Interface of application for configuring the micro-level interaction information monitoring.

This layer is implemented in two parts: a separate application (shown in Figure 2) for data-monitoring configuration and a data-collection program, along with the core simulator to record and store data in a predefined format. The two parts communicate through a configuration file before simulation started. Since this layer is considered as a set of sensors to monitor states of the core simulator, all of which are customizable, e.g., enable/disable and sampling frequency. Moreover, some of the sensors also provide some simple data processing methods to carry out some basic analysis (e.g., maximum, minimum, standard deviation.) in order to reduce the size of micro-level simulation results without affecting final knowledge discovery. Figure 2 demonstrates the user interactive application interface for configuring these "sensors".

According to the character of an agent-based simulator, we classified the raw simulation data as two categories: environment state and interaction information. The state information includes the state indicator of the simulated environment as well as the agents. It is sampled and averaged in a given time interval. The interaction information contains records of all the interaction among agents, this information is recorded as five Ws (Who, What, When, Where, Why) and one H (How long it takes). The simulator only records and stores information from "sensors" that has been enabled by user.

3.4 Data Processing

The data generated by the micro-level behavior simulator is massive and unreadable, whereas what the simulator users need is the macro-level system key performance indicator, thus we must convert data into information and information into knowledge. The data process layers are application-specific which transfer the massive micro-level information to macro-level features of the complex system. Moreover, as shown in Figure 1, the scenario is a set of parameter configurations for the agent-based model as well as simulated environment. It has been defined as the smallest unit of simulation experiment in this study. Specifically, knowledge discovery of the complex system may depend on several executions, we organize one execution as one scenario. Therefore, there are two ways to process the data generated by agent-based simulator, single scenario and cross-scenario for different requirements. Single scenario analysis is mainly used to reproduce existing phenomenas, i.e., ground the agent-based model as close as possible to the real system, then replay the system to identify root cause of macro-level phenomena (reverse direction of the abstraction path in Figure 1). The cross analysis is used to analyze the influence trend of micro-level model indicator, e.g., resource sensitivity analysis. Since the processing method is application-specific and due to lack of space, we will not detail the methods here. Moving on from here, the steps to do simulation mainly include: design scenarios (parameter variation), config micro-level data monitor, simulation and process data.

4 CASE STUDY: DISCOVER MACRO-LEVEL FEATURES FROM MICRO-LEVEL BEHAVIORS

Decision making in the field of healthcare service management assessment is not a simple task and it is important for different stakeholders. For example, patients are expecting efficient services, insurers are aiming for cost-effectiveness and the health industry is primarily interested in yield maximization. Understanding the complexity of such a system requires more than experience and intuition alone. In this section, we will demonstrate two case studies. The first one (4.1) is from the point view of resource configuration. The second one (4.2) is about the influence of micro-level behavior on macro-level functionality.

The emergency department studied in the case studies uses a five-level triage system that is very similar to the worldwide Canadian one to prioritize patients (Centeno et al. 2013), in which patients are dispatched arbitrarily to the relevant area on their acuity level determined by triage nurses. Hence, the priority of patients for doing a specific test is based on their acuity level and for patients with the same acuity level, the priority is based on their arrival time. Here, we do not concentrate on complete study descriptions and detailed validation steps, as it would be beyond the scope of this paper, but focus on practical use of the presented methods. The base configuration of the simulated emergency department, such as number of doctors, nurses as well as average attention time are fully specified in Table 1.

In these case studies, as the staff work shifts, we consider that the medical test technicians, admission staff and triage nurse group run on two shifts and the number of staff is different during the day (6:30 - 18:30) and night (18:30 - 6:30) because the patients arrival rates are quite different. The rest of the staff work on one shift by turns. We simulate one scenario for 1464 hours, to avoid initialization bias, the simulation allowed a warm-up period of 24 hours, then monitoring was carried out during the following 1440 hours. Considering that the agent-based modeling methodology has one significant disadvantage vis-a-vis mathematical modeling, i.e., despite the fact that each run of such a model yields a sufficiency theorem, a single run does not provide any information on the robustness of such theorems (Axtell 2000). One way to deal with this problem in agent computing is through multiple runs, systematically varying initial conditions (different random seeds) and taking the average of indicators in order to assess the robustness of results. Therefore, this study requires the execution of a huge amount of multi-parametric simulations (same model, different parameter value configuration), for one scenario to make the results statistically reliable. Specifically, we repeated one scenario for 50 times and took the average for each indicator. Given this, a 18-node cluster with 648 cores in total was used and the execution task was assigned as one core for one scenario repetition. According to our statistics, the average execution time for one scenario repetition

Table 1: Configuration of the emergency department (environment) and individual behavior model.

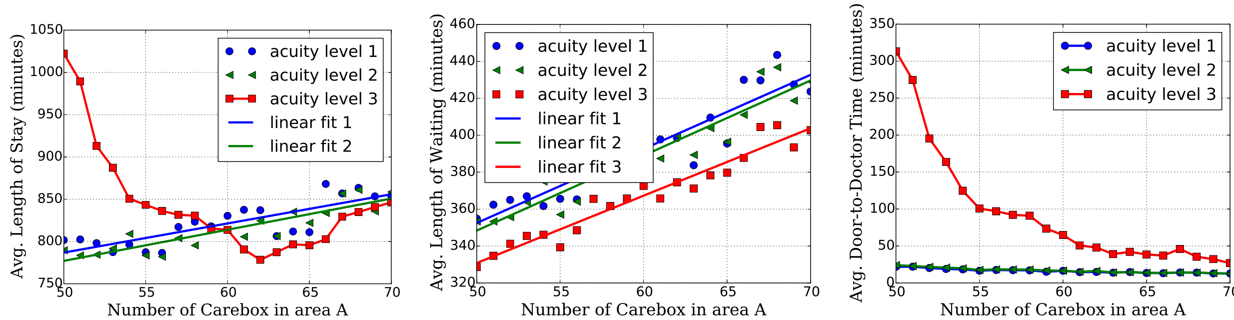
Resource	Capacity (#)		Avg. Attention Time (AT, minutes)		AT Distribution
	day	night	first interaction	follow-up	
junior admission staff	3	2	5		Gamma
senior admission staff	2	0	3		Gamma
junior triage nurse	3	1	8		Gamma
senior triage nurse	2	1	6		Gamma
junior doctor in area A	2		20	15	exponential
senior doctor in area A	4		15	13	exponential
junior nurse in area A	5		25	18	exponential
senior nurse in area A	5		20	14	exponential
junior doctor in area B	2		8	7	exponential
senior doctor in area B	5		6	5	exponential
junior nurse in area B	4		11	7	exponential
senior nurse in area B	4		7	5	exponential
medical imaging test room	5	2	45		Beta
laboratory test place	4	2	30		Beta
carebox in area A	50		-		-
chair in area B	60		-		-
auxiliary nursing staff	3		15		exponential

is about 15 minutes. Thus, one simulation scenario with 50 repetitions can be done in about 20 minutes (due to individual difference as well as extra time for mapping and reducing).

4.1 Influence of Capacity in Area A

Emergency department overcrowding is defined as a situation where the demand for emergency services exceeds the ability of an emergency department (ED) to provide quality care within appropriate time frames. By observing more than 20 million patient visits to emergency departments over five years, Guttmann et al. (2011) determined that the risk of death and hospital readmission increases with the degree of crowding in the emergency department. When an emergency department meets an overcrowding problem, usually there are many patients waiting in the waiting room or even receiving attention in a corridor. Thus, it takes up more patient time and results in worse satisfaction. From intuition, when there are many patients waiting to enter the treatment zone, one way to solve this problem is by expanding the capacity. In this case study, a cross-scenario analysis was used to discover the influence of additional careboxes in area A with the goal of solving the overcrowding problem. Regarding this requirement, "sensor" to monitor patient's behavior and carebox utilization are enabled via the user interactive application shown in Figure 2.

As one of an important KPIs of an emergency department, the patient's length of stay (LoS) is the time when a patient arrives at the ED to the time they depart from the ED. From the point view of the patient's state, the LoS consists of two parts: the total length of waiting time (LoW, total length of time on waiting for services) and the length of attention time (LoAt, total length of time on interacting), i.e., $LoS = LoW + LoAt$. Since the arrival patients keep the same in this case study and we assumed that the service a patient needs is determined entirely by properties of patient, i.e., the average $LoAt$ will keep no change among scenarios, the LoS differences among different scenarios are the length of waiting (LoW) time. The influence of area A capacity (carebox number) from the point of view of LoS is visualized in Figure 3. Due to the randomness, slightly small changes may somewhat result in inconsistent change, linear fit was used to demonstrate the trend in Figure 3(a, b).



(a) length of stay (b) length of waiting time (c) “door-to-doctor” time

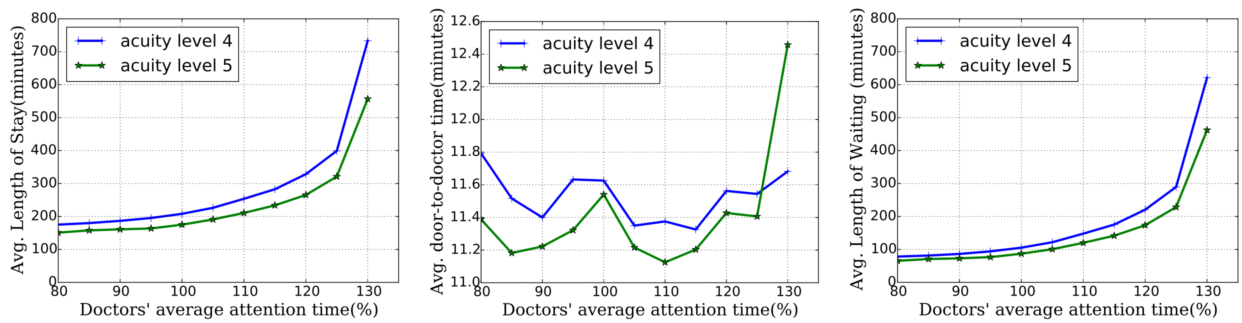
Figure 3: The influence of additional carebox on patients’ behavior. (note: the scale of vertical coordinates are different.)

In this case study, we set the start point as an overcrowding scenario, i.e., when the number of careboxes is 50, the studied ED is facing with overcrowding. Since patients with acuity 3 have the lowest priority to be assigned a free carebox in area A, they will be delayed first (Figure 3(a)). From Figure 3(a), it is clear to see that additional careboxes provides good results in patients with acuity level 3, the overcrowding problem is solved. However, different from what we would expect, patients with higher acuity meet bad influence because their LoS increased. As shown in Figure 3(b), all the patients met increasingly longer waiting times for service with additional carebox. Therefore, the root cause is: after adding more careboxes, as the number of corresponding nurses and doctors did not increase accordingly, they cannot provide service to patient as instantly as before, so the patients need to wait more for their doctor and nurse (Figure 3(b)), which results in the increased LoS. Additionally, a resource with a high occupation rate will be more sensitive to fluctuations in its arrival process than a resource with a lower occupation rate. Tracing back to the micro-level indicator by single scenario analysis, the average occupancy of doctors in area A (percentage of scheduled time spent on patient related activities) is 89.9%, and average occupancy of nurses is 92.3%. However, one benefit of additional careboxes is the reduced length of “door-to-doctor” time (i.e., the number of minutes from patient arrival until seeing a doctor). That is to say, the patients can enter the treatment zone earlier and they may feel happier than waiting helplessly in the waiting room. Furthermore, as shown in Figure 3(a), an additional 12 careboxes (i.e., 62 in total) in the ED may be a good choice for current staff configuration if there is no cost constraint, because the patients with acuity level 3 (about 30% of arrival) meet with the shortest *LoS*. Moreover, further studies could be done to find the tradeoff between patient satisfaction and cost constraint.

4.2 Behavior of Doctor in Area B

Identifying the primary causes of overcrowding in an ED is a critical step in knowing how to increase throughput. In this case study, the quantitive association between a doctors’ micro-level behavior and macro-level patients’ average LoS was discovered via cross-scenario analysis.

Attention time, also known as service time, is the length of time for one interaction. The length is determined by service provider drawn from an exponential distribution. Taking the interaction among doctor and patient as an example, it is different in terms of doctors’ expertise, the patients’ condition (patient’s acuity level, age) and interaction times (fist interaction or follow-up). The initial average value for the exponential distribution was shown in Table 1. As we assumed that the relationship between the patients and doctors is always static, only when doctors change shifts do they detach their patients to other doctors on the next shift. In addition, according to empirical data, the first interaction with a patient always takes longer. Thus, there are two values for the attention time model of a doctor and this will result in four for the group of doctors (consisting of junior and senior) in area B. Therefore, to study the overall influence of doctor group in area B, in scenarios' design step, we change the average length of attention time of doctor in area B by percentage independently. As micro-level data monitor configuration, only a "sensor" for recording patients' behavior was enabled through the separate application shown in Figure 2. The effects of doctors' behavior on LoS and "door-to-doctor" time are illustrated in Figure 4.



(a) length of stay (b) "door-to-doctor" time (c) length of waiting time

Figure 4: The effect of length of doctors' attention time on macro-level LoS and the root cause identification. The horizontal axis is the percentage against the normal configuration show in Table 1. (note: the vertical coordinate scale of (b) is quite different as (a) and (c).)

Figure 4(a) clearly shows the significant impact of doctors' behavior on systemic functionality. With the increasing length of doctors' attention time (e.g., working with lower efficiency or more carefully diagnose), average patient LoS increased dramatically in area B. After analyzing the "door-to-dctor" time (Figure 4(b)), we find that the patients enter the treatment area after a very short waiting time, which means that the increased LoS is not because of "door-to-doctor" time. Thus, the patient spent most of their LoS in the treatment area. Moving on from here, we analyzed the length of waiting time in treatment phrase (Figure 4(c)). It is clear that waiting for doctors' attention is the root cause of the increasing LoS. Furthermore, Figure 4(a) also provides the singularity of this micro-to-macro association, that is to say, if doctor's attention increases more than 125%, patients' LoS will increase very fast. This information is useful for managers to avoid mistake in intuitive thinking. In summary, this case study quantifies the effects of micro-level behavior on macro-level LoS, further study can be done to balance the quality of service and efficiency of ED system under specific situations.

5 CONCLUSIONS AND FUTURE WORK

This article presents an approach to discover knowledge of emergency department through simulating individual behavior of its components. Agent-based modeling technique was used to simulate the behavior of system components. The behavior simulation model can generate interaction information under various configuration scenarios. Analyzing this interaction information thoroughly enables knowledge discovery towards a better understanding of the complex systemic behavior. This makes it possible to explore association between micro-level behaviors of individuals and macro-level patterns that emerge from their interactions, thus assisting users to better understand a system's behavior under various conditions. Additionally, a layer-based architecture was used to achieve flexibility and configurability. The demonstrated case studies show the potential use of the presented approach as well as how small changes in procedure yield important changes in flow. This proposed framework can be used to promote learning, hypothesis testing, decision making support, and policy formulation after being properly validated, offering the user and organization the ability to understand the complexity of healthcare systems and to facilitate the redesign of optimal outcomes. It is also capable of predicting and quantifying how a particular emergency department will respond to a given "what if" scenario and what could be the well-targeted changes to make for a "how-to" (simulation optimization) issue via cross-scenario analysis. In addition, looking deep into the system is one side to provide information, another challenge for supporting critical decision is to find a tradeoff between different parameter configurations, such as service satisfaction of patients and efficiency for providers. Accordingly, an optimization based framework for managing complex processes in the healthcare domain is a scope of future work.

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