**ABSTRACT**

**Objectives.** Large-scale incidents such as the 2009 H1N1 outbreak, the 2011 European *Escherichia coli* outbreak, and Hurricane Sandy demonstrate the need for continuous improvement in emergency preparation, alert, and response systems globally. As questions relating to emergency preparedness and response continue to rise to the forefront, the field of industrial and systems engineering (ISE) emerges, as it provides sophisticated techniques that have the ability to model the system, simulate, and optimize complex systems, even under uncertainty.

**Methods.** We applied three ISE techniques—Markov modeling, operations research (OR) or optimization, and computer simulation—to public health emergency preparedness.

**Results.** We present three models developed through a four-year partnership with stakeholders from state and local public health for effectively, efficiently, and appropriately responding to potential public health threats: (1) an OR model for optimal alerting in response to a public health event, (2) simulation models developed to respond to communicable disease events from the perspective of public health, and (3) simulation models for implementing pandemic influenza vaccination clinics representative of clinics in operation for the 2009–2010 H1N1 vaccinations in North Carolina.

**Conclusions.** The methods employed by the ISE discipline offer powerful new insights to understand and improve public health emergency preparedness and response systems. The models can be used by public health practitioners not only to inform their planning decisions but also to provide a quantitative argument to support public health decision making and investment.
The inevitable threat of natural disasters and manmade attacks has made emergency preparedness an issue of constant concern. Large-scale incidents such as the 2009 H1N1 outbreak, the 2011 European *Escherichia coli* outbreak, and Hurricane Sandy demonstrate the need for continuous improvement in emergency preparation, alert, and response systems across the globe. Industrial and systems engineering (ISE) techniques are well suited to address these challenges. Industrial and systems engineers solve problems by examining the way an entire system works together rather than just focusing on individual parts. They look at decision making as well as technical processes to figure out how to do things better. Systems engineers work with models to show the big picture of how processes are connected and interdependent, while focusing on the value of each action to achieve the desired result. ISE techniques involve the ability to quantify performance and readiness metrics of a system and translate data into real-time information quickly and accurately. Considering the importance of timely and accurate information during an emergency, these techniques have the potential to greatly enhance both the design and operation of current emergency systems and serve as an aid in identifying unforeseen and counterintuitive deficiencies or bottlenecks within a system that may be undetectable to the naked eye. The power of this approach comes from the ability to conduct what-if scenarios to examine modifications to systems without implementing the change.

The primary objective of this study was to use systems engineering techniques to develop Markovian, optimization, and simulation models to address public health preparedness problems. Specifically, we developed tools for visualizing emergency events and modeling the emergency response process. These models seek to capture the interdependencies at a system level, enabling public health stakeholders to evaluate the impact of various potential threats, compare/quantify the impact of response strategies, and explore what-if scenarios. Although these models began as rough sketches on a white board, they eventually became sophisticated mathematical/computer simulations of events that can be used to maximize efficiency, productivity, and effectiveness. Other studies have employed modeling techniques and operations research for public health preparedness, 

Methods

We employed three tools of ISE—Markov chain modeling, computer simulation, and optimization—to facilitate the development of a more effective and efficient emergency response system. In addition, we conducted in-person and phone interviews with public health staff, observed public health events to collect data, and examined system-generated data from public health electronic systems to inform model development.

Public health alerting and notification

We explored the relationship between local and state health departments with respect to issuing alerts and responding to a potential disease outbreak such as influenza. We modeled the public health system as a multi-agent partially observable Markov decision process (POMDP), where local and state health departments are decision makers. There are many applications of POMDPs to health-care problems. The surveys by Monahan, Cassandra, and Yaylali and Ivy provide reviews of this literature. The model is used to determine when local and state decision makers should issue an alert or initiate mitigation actions such as vaccination in response to a disease threat.

The model incorporates the fact that health departments have imperfect information about the exact number of infected people. The objective of the model is to minimize both false alerts and late alerts while identifying the optimal timing for alerting decisions. Providing such a balance between false and late alerts has the potential to increase the credibility and
efficiency of the public health system while improving immediate response and care in the event of a public health emergency. We used data from the 2009–2010 H1N1 influenza outbreak, including data from CDC’s FluView and Influenza Sentinel Provider Network reports,15 the North Carolina Division of Public Health (NC DPH) state laboratory results,16 and North Carolina State University (NCSU) Student Health Services data, to estimate model parameters such as observation distributions and transition probabilities. To gain insight regarding the structure of optimal alerting policies at the local and state levels, we explored various model parameters including false and late alerting costs. A detailed discussion of these models can be found elsewhere.17,18

Outbreak investigation contact tracing and control of disease spread

While there is extensive literature on the use of simulation to model the epidemiology of infectious diseases19–21 and various interventions such as contact tracing,22–26 relatively little work has examined the effect of resource availability and different resource deployment policies on the spread and containment of disease outbreaks. We developed a discrete-event simulation model in C/C++ computer programming language of an LHD and its response to a pertussis outbreak. As shown in Figure 1, the model begins with an initial infected patient and follows the flow of contacts through becoming infectious, infecting others, seeking care, being contacted, and potentially becoming a confirmed case.

We took a comprehensive view of public health actions, beginning with detection of an individual patient, confirmation of the case by physician and laboratory tests, and contact tracing and isolation of contacts by LHD personnel. We explicitly modeled the information transfer among providers, laboratories, and LHDs and examined the effect of different alerting strategies on the number of confirmed cases encountered. Contact tracing, a key mitigation method for pertussis, was modeled and the effect of limited resource availability for contact tracing was examined. We explored the impact of the time to initiate response and the resource availability of the health department on outbreak management policies. The model was parameterized using NC case data as well as information from the NC Public Health Information Network. We ran the simulation model for 500 replications until contact tracing stopped. The threshold for the number of confirmed cases required before contact tracing began was varied and different resource levels were evaluated. A detailed discussion of this model can be found in Yaylali17,18 in addition to an earlier version of this model, which is presented in Worth et al.27

Mass vaccination clinic/POD planning

One of the challenges in implementing mass vaccination clinics during the H1N1 pandemic included setting appropriate staffing levels to vaccinate an unknown number of community members on any given day a vaccination clinic was offered. Some other challenges to this type of clinic planning include determining the most efficient patient flow pattern, minimizing patient time spent filling out forms, and reducing bottlenecks.28 Computer simulation models are tools that can help planners address some of these challenges.29–32 This research describes a collaborative effort to try to recreate (via computer simulation models) several different types of clinics implemented during the H1N1 pandemic to help health directors and frontline staff explore opportunities for improved vaccination clinic efficiency.

In spring 2010, the Southern Piedmont Partnership for Public Health (SPPPH), a voluntary association of LHDs collaborating to improve public health practice,33 partnered with the NCPERRC to explore the use of systems engineering modeling to help understand and improve their implementation of mass vaccination clinics. Using local data and information derived from...
discussions with SPPPH, a set of six county-specific computer simulation models of the local public health clinics (e.g., drive-through and school-based) set up during the H1N1 pandemic were developed and validated for accuracy by the health department staff. The NC LHDs shared the details of their clinic operations to inform development of the discrete event simulation (DES) models and facilitate the creation of reasonably accurate 3D depictions of the clinics using Simio® simulation software.34 A sample model is shown in Figure 2.

RESULTS

Public health alerting and notification
Figure 3 plots the optimal alert policy as a function of the no-threat probability and the decision-time horizon as defined by the time remaining in the problem horizon. The no-threat probability represents the public health decision maker’s uncertainty or belief regarding the level of threat that is present. As shown in Figure 3, the optimal alerting thresholds for the state and local levels are different. If the decision maker believes there is no threat to the public, the probability of no threat is 1; as the decision maker’s concern about a public health threat grows, the no-threat probability decreases (where 0 means the decision maker feels certain that there is a public health threat). The alert thresholds are affected by the penalties associated with late alerting and false alerting, and the effect differs at the state and local levels.

The relationship between late alerting and false alerting is defined as relative weights associated with the actions chosen in the model. Because it is difficult to accurately estimate the cost of different alert types and the penalty for late alerts, these weights are not absolute cost values for alerting; rather, they are marginal values.

Figure 2. Snapshot of a Simio® Discrete Event Simulation model animation of a mass vaccination clinic

*Waiting clients are guided into the clinic by a crowd control agent. Inside, clients are assisted with completing forms before entering one of the vaccination areas staffed by nurses.
chosen between 0 and 1 for two types of alerts, Type 1 (active surveillance) and Type 2 (active surveillance and mitigation), and late alerting. Combining these weights with the state of the system in the model, we observed timely, late, or false alerts. For example, the penalty of late alerting occurs when the system is in the outbreak state and the decision makers choose to wait to take action. Similarly, the decision makers incur the cost of alerting (Type 1 or Type 2) when they choose one of these actions. For example, we could consider the situation of being in a no-threat state and choosing to alert to be false alerting. In Figure 3, the following relationship is assumed: cost of a Type 1 Alert < cost of late alerting < cost of a Type 2 alert with values of 0.1, 0.2, and 0.3, respectively. For the local level, when the penalty associated with late alerts increases, the system issues Type 1 alerts more frequently. For the state level, when the penalty associated with late alerts increases, the threshold for the wait action increases.

### Outbreak investigation contact tracing and control of disease spread

We established a base case where the LHD has three communicable disease (CD) nurses and initiates contact tracing upon detection of one confirmed case. We then varied these base levels of resources and thresholds to analyze the effect on the outbreak spread, which is measured by the number of confirmed cases and the time that the outbreak ends. The number of contacts traced is used to measure the change in the workload of the LHD as a function of the contact tracing policy. Figure 4 shows the frequency distributions for the number of confirmed cases, the number of contacts traced, and the length of the outbreak (i.e., the time until no cases/contacts remained to trace) for 500 replications for each scenario. We used the simulation model to evaluate scenarios with thresholds of one, two, and three confirmed cases when three CD nurses are available for four hours a day, seven days a week. When the LHD starts contact tracing with one confirmed case, the number of confirmed cases is usually in the range of one to four. The frequency decreases as the upper bound of the interval increases. When the LHD starts contact tracing with two or three confirmed cases, the number of confirmed cases resulting from the outbreak increases, with the most frequent intervals for these thresholds being 5–8 cases and 17–20 cases, respectively. There is a similar trend in the number of contacts traced and time to control outbreak, as seen in Figures 4b and 4c. As the contact tracing threshold increases, the number of contacts is more likely to be greater, and the outbreak is more likely to last longer.

To determine the effect of resource capacity and the availability of the LHD on pertussis outbreak management, we varied the staffing levels of the LHD and examined three performance measures generated by
500 replications for each scenario. The nurse schedule in the base case assumes that each nurse is able to allocate four hours a day, seven days a week exclusively to contact tracing of pertussis. This assumption may be unrealistic because of recent budget cuts, understaffed LHDs, and CD nurses often juggling different responsibilities. Therefore, we tested nurse schedules of four hours, five days a week to one hour, one day a week with a threshold of 1–3 cases and 1–3 CD nurses. The Table presents the average and standard deviation for the number of confirmed cases when the resource capacity is varied (both with the number of CD nurses available and the nurse schedule) and the contact tracing threshold is varied.

**DISCUSSION**

**Public health alerting and notification**

Our findings suggest that understanding the cost associated with alerting as well as the cost of failing to alert is particularly important for public health preparedness at the local level. We have shown that optimal alerting thresholds can differ for the state and local levels and still be optimal. Implementing the same emergency management strategy for different levels of a public health system may not result in the most efficient response to an outbreak. Our results suggest that the optimal policies of the local and state levels are sensitive to the changes to cost values and parameters.
that model the uncertainty in the system. Thus, it is important to estimate the parameters related to the dynamics of the system as accurately as possible to obtain thorough optimal policies at both levels.

### Outbreak investigation contact tracing and control of disease spread

Our results suggest that resource availability as well as information delays at various stages of the process have a significant impact on the evolution of a disease outbreak. Additionally, our results suggest that the time to initiate the response and contact tracing as well as resource capacity significantly affect the duration of the outbreak. The confirmed case threshold for the initiation of contact tracing significantly changes the total number of confirmed cases as well as the number of contacts traced and the time to control outbreak. Further, there is a direct relationship between the public health resources available for contact tracing and the size of a pertussis outbreak.

It is possible to have too few resources, resulting in an outbreak that can never be contained. It is also possible to use the model to identify the minimum number of public health resource hours necessary to control an outbreak. While the effect of the resource level is not as large as the effect of the contact tracing threshold, we observed a drop in the number of confirmed cases when more CD nurses are available in the LHD. The effect of this reduction is more significant for the second schedule, where the nurse(s) only devotes one hour per week to contact tracing of pertussis. This finding suggests that the resource availability significantly increases the size of the outbreak if a small percentage of the nurse’s time is assigned to contact tracing. It is likely that these results would translate to other disease outbreaks. Further, the model structure we have developed can be extended to other CDs. This model enables the estimation of the public health resources (in terms of time, which may be translated to cost) required to control a CD outbreak.

### Mass vaccination/POD planning

The 3D DES models representing a diverse collection of mass vaccination clinic configurations have been created to inform the development, design, and configuration of future vaccination or mass care clinics. These models also create an opportunity to explore the impact of alternate staffing levels and clinic flow, for example, without having to conduct a full exercise to test a number of different scenarios. In fact, some health departments have used the models to inform their seasonal influenza clinics. In addition to providing insight regarding the performance of different clinic configurations with respect to metrics such as throughput and waiting time, the models created a computer animation that allowed LHDs to discuss their clinic configurations within and among other counties, and work together to discuss best practices and opportunities for maximizing efficiency and patient satisfaction. These animations may also be beneficial in pre-event and just-in-time training.

### CONCLUSION

We found that the methods employed by the disciplines of operations research and ISE offer powerful new insights to understand and improve public health emergency preparedness and response systems. The
models and tools developed can be used by public health practitioners not only to inform their planning decisions but also to provide a quantitative argument to support public health decision making and investment. While the methods and findings are promising, one limitation of this research was that the research was not translated into direct improvements to public health. Despite this limitation, systems engineering-based tools, specifically techniques that have the ability to model (i.e., mathematically represent) the system, simulate (i.e., run multiple what-if scenarios), and optimize (i.e., select the best course of action or system design for) complex systems, even under uncertainty, are necessary to address public health preparedness problems now and in the future. As cost pressures increase and demands on public health resources grow, it will be increasingly important to identify efficient and effective solutions for public health preparedness problems. The need to optimize, develop simulated models of potential realities, and perform what-if analyses will be necessary.

This research was conducted by the North Carolina Preparedness and Emergency Response Research Center (NCPPERRC), which is part of the University of North Carolina (UNC) Center for Public Health Preparedness at the UNC at Chapel Hill Gillings School of Global Public Health, and was supported by the Centers for Disease Control and Prevention (CDC) grant #1P01TP000296. The contents and views expressed in this article are solely the responsibility of the authors and do not necessarily represent the official views of CDC.

The authors thank the members of the Southern Piedmont Partnership for Public Health for their valuable input in this project; the six counties that allowed their clinics to be modeled; Dr. Edward Baker, NCPPERRC Principal Investigator and Director of the North Carolina Institute for Public Health; Heather Gates, former member of the UNC Center for Public Health Preparedness; Carol Gunther-Mohr, NCPPERRC Project Manager; and the six counties that allowed their clinics to be modeled; Mr. Travis Worth, Physician, North Carolina Division of Public Health; Dr. Rehana Ness; Carol Gunther-Mohr, NCPERRC Project Manager; Dr. Edward Baker, NCPERRC Principal Investigator and Director of the North Carolina Institute for Public Health; Heather Gates, former member of the UNC Center for Public Health Preparedness; Carol Gunther-Mohr, NCPPERRC Project Manager; Dr. Jean-Marie Maillard, Communicable Disease Branch Medical Unit Physician, North Carolina Division of Public Health; Dr. Reha Uzsoy, Clifton A. Anderson Distinguished Professor in the Edward P. Fitts Department of Industrial and Systems Engineering (ISE) at North Carolina State University (NCSU); and Mr. Travis Worth, a former graduate student in the Edward P. Fitts ISE Department at NCSU for their invaluable assistance.

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