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ORIGINAL RESEARCH CONTRIBUTION

Review of Modeling Approaches for Emergency Department Patient Flow and Crowding Research

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Abstract

Emergency department (ED) crowding is an international phenomenon that continues to challenge operational efficiency. Many statistical modeling approaches have been offered to describe, and at times predict, ED patient load and crowding. A number of formula-based equations, regression models, time-series analyses, queuing theory–based models, and discrete-event (or process) simulation (DES) models have been proposed. In this review, we compare and contrast these modeling methodologies, describe the fundamental assumptions each makes, and outline the potential applications and limitations for each with regard to usability in ED operations and in ED operations and crowding research.

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Emergency department (ED) crowding has been shown to have many adverse consequences, including patient harm[1–6] and decreased patient satisfaction.[7] While recognized as a national crisis,[8] ED crowding is in fact an international phenomenon that calls for ED and hospital process redesigns to improve patient flow.[9] A 2009 U.S. Government Accountability Office summary report found that 1) ED crowding remains prevalent; 2) hospitals continue to divert ambulances, with 27% of U.S. hospitals reporting going on diversion at least once in 2006; 3) boarding of patients awaiting an inpatient bed is a persistent problem, with 75% of ED medical directors reporting daily boarding of ED patients; and 4) patient wait times in the ED have increased, with the average wait time to see a physician increasing from 46 minutes in 2003 to 56 minutes in 2006.[1]

Interest in this area is reflected in the number of publications related to ED crowding published in the past decade. Various approaches and outcome measures have been used to define crowding and capacity and to describe ED utilization and throughput to inform operational strategies for managing patient flow. Comparing these and arriving at some consensus is challenging because no standard definition of ED crowding exists.[10–13] Surrogate markers of crowding have been described, including occupancy rate,[14] patients who leave without being seen (LWBS),[15–17] ambulance diversion,[18–20] and staff perceptions of crowding.[21,22] The ability to predict crowding by quantitative means has been identified as a priority within the ED literature, and a handful of papers attempt to do so using various models.[23–26] Others have addressed identification of related but distinct outcomes, including predicting patient arrivals,[27,28] predicting ED census,[20,29,30] determining ED throughput,[31] forecasting wait times,[20] or some combination of these.

There are several key modeling methodologies presented in the current academic literature that attempt to analyze and forecast ED patient load and crowding, namely, formula-based equations, regression modeling, time-series analysis, and more recently, queueing theory–based models and discrete-event (or process) simulation (DES) models. Formula-based approaches, which are among the more widely known approaches to crowding research, use empirically determined equations based upon observed patterns and data.

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Regression modeling and time-series analysis are popular statistical techniques that are more mathematically justified than formula-based modeling. Queuing and DES models are used for a variety of forecasting scenarios, including call center staffing, manufacturing process design, and telecommunication system design. These tools are used to create systems that replicate or mimic ED flow operations in the hopes that 1) the model accurately reflects the current patient flow system (i.e., describes ED crowding), 2) patient wait times can be accurately predicted (i.e., forecast crowding), and 3) operational improvement strategies can be designed and tested to predict the potential effect of the improvements on the system.

Our discussion will focus on a review of each of the operational modeling techniques, including the fundamental assumptions each makes and the subsequent inherent limitations, their current use in the ED setting with regard to defining and/or predicting ED patient load and crowding, and potential future applications to ED operations research. More attention will be directed at techniques previously given less treatment in the ED literature (i.e., queuing theory and DES).

OVERVIEW OF COMMON APPROACHES TO MODELING ED CROWDING

The mathematical modeling approaches to ED crowding may be more easily understood when applied to a simple nonmedical analogy, such as development of a novel airplane wing design. In a formula-based analysis, this wing design may be generated from calculations based on previous engineering experience with older wing designs and other observed phenomena. For regression modeling, data might be collected on existing wing designs, variables such as lift and wingspan defined, and the desired statistical model constructed to demonstrate how the dependent variables (e.g., lift) relate to the independent variables (e.g., wingspan). Time-series modeling could relate the current position of the airplane wing in space to its velocity of motion and position in space a few seconds prior. Physics-based formulas may also be used to predict lift as a function of wingspan, but instead of relying on data, the relationships are mathematically derived (much like queuing models). Finally, an actual model of the wing could be constructed and analyzed in a simulated environment, such as a wind tunnel, to determine the adequacy of the proposed device. The application of these mathematical models to ED operations mirrors this analogy. A comparative summary of the model inputs, outputs, and methodologies is summarized in Table 1. A review of the quantitative method, ability to define and forecasting crowding, ability to predict process improvement effect on ED operations, ease of model development, and model complexity of development is presented in Table 2, based on the authors' assessment of the various modeling approaches discussed in this article. Institutional review board approval was not required for this review, as no human subjects or data are involved.

Formula-based Methods

Formula-based approaches are constructed from observable facts, such as the number of beds and providers. The investigator treats these inputs as a "figure of merit" that are considered to be empirically useful, but without a statistical basis. Selected formula inputs are assumed to be important and relevant determinants of the output. Some of the most widely known ED crowding

Table 1
Comparison of Conceptual Models Used to Describe and Forecast ED Patient Load and Crowding

	Inputs	Outputs	Methodology
Formula-based	Important factors selected based on experience (e.g., number of staff and beds)	Measures of crowding	Past experience of ED flow performance is used to posit appropriate formulas
Regression-based	Uses multiple independent input variables (e.g., patient arrivals per hour)	Dependent variables (e.g., ED crowding)	Statistically predicts dependent variables based on independent variables
Time-series analysis	Recently observed ED flow performance (e.g., ED bed occupancy levels)	Current ED flow performance (e.g., ED census)	Statistically uses recent past performance to predict current and immediate future performance
Queuing theory	Patient arrival behavior, number of servers (e.g., staff), and service priorities (e.g., first come first serve)	ED flow (e.g., mean wait times)	Mathematical formulas are derived from general system principles and used to convert inputs to outputs
DES	Patient arrival behavior, number of servers (e.g., staff), and service priorities (e.g., FCFS) and routing	ED flow (e.g., mean wait times)	A computer generated model (typically with graphical interface) is used to sample inputs and generate outputs.

DES = discrete-event (or process) simulation; FCFS = first-come-first-serve.

Table 2
Summary of Mathematical Models Used to Describe ED Operations: Authors' Assessment

	Quantitative Method	Used to Define Crowding	Ability to Forecast ED Crowding (Short-term)	Ability to Predict Process Improvement Impact	Ease of Model Development	Ease of Use	Comments
Formula-based	Mathematical formulas	Good	Poor	N/A	Good	Good	Readily available inputs
Regression-based	Statistical analysis	Fair	Fair	Poor	Fair	Fair	Widely understood
Time-series analysis	Statistical analysis	N/A	Fair	Poor	Poor	Fair	Requires computational resources
Queuing theory	Mathematical formulas	N/A	Poor	Good	Poor	Fair	Significant number of underlying assumptions
DES	Computer programming code	N/A	Fair	Good	Poor	Poor	Costly to implement and maintain

DES = discrete-event (or process) simulation; N/A = does not allow, is not applicable.

assessment tools (EDWIN,[21] Work Score,[32] occupancy level,[33] and READI[34]) use readily available inputs (ED data metrics) and mathematical conceptual formulas to detect or quantify crowding. Some of these formula-based models have also been evaluated for their ability to forecast crowding.[33,35] Several studies have compared different scoring systems with one another. They have been found to correlate with one another as to when crowded conditions exist[26] and to correlate with ambulance diversion,[20] with LWBS numbers,[36] and with clinicians' perceptions of crowding.[21,30] One of the strengths of these tools is in their use of commonly available information and relative ease of use. Some, such as occupancy level, are very simple both in concept and in calculation, while others such as READI require additional inputs.

While these scoring systems enjoy the most familiarity in the ED literature, they have been subject to a number of criticisms, including the use of the subjective "clinician perception" of crowding as a primary outcome measure (READI) in validating the presence of crowding. Not all tools use clinician perceptions of crowding as endpoints. However, even when other endpoints, such as ambulance diversion (based on explicit criteria), are used as the outcome measure, the tools studied have not consistently outperformed simpler measures such as occupancy level. Other criticisms have included lack of scalability to different site types, with low positive predictive values despite site-specific adjustments.[26]

Regression Modeling

Regression-based modeling is a commonly used statistical technique that may offer a more robust approach to identifying and describing variables that affect or forecast crowding, offering a more mathematically justified approach compared to formula-based modeling methods. In regression-based approaches, the inputs of the "regression formula" are derived in reproducible, statistical ways from a set of observations. A thorough description of regression techniques has been published elsewhere.[24] However, broadly speaking, regression is a tool used to either evaluate or describe the effect of multiple variables (also known as independent variables or covariates) on some outcome (dependent variable) or to determine a collection of independent variables or covariates that "predict" an outcome based on a derived mathematical formula.

Although a regression model can validate to what degree selected inputs are significant determinates of the desired output, it cannot identify all inputs that affect the output. Thus, there is inherent imperfection in the ability of regression models to forecast the output (e.g., anticipate crowding). What is attractive about this methodology is that it can incorporate a range of variables in predictive models, including average patient wait time, available beds, radiology turnaround time, etc. Proposed regression models have demonstrated that ED census is cyclical (following hourly, daily, and seasonal patterns determined by arrivals); is determined by prior arrivals, current arrivals, and current departures; and that sudden unexpected arrivals ("surge") can have long-lasting results on census levels. Experimental models of ED census have been created relating a number of these concepts.[37] However, only a few regression-based models attempt to forecast ED crowding.[30,33,36,38] This has led to the suggestion that time-series modeling techniques might provide better forecasting than those achieved with a more formula- or regression-based approach.

Time-series Based Approaches

A basic and intuitive approach to forecasting uses historical averages to make predictions about future conditions. Time series analysis primarily uses recent historical time series data to model future ED behavior, reducing or eliminating the need for multiple data streams to populate the model variables. The ability to correctly handle serially correlated observations (e.g., arrivals, occupancy, length of stay [LOS], boarding time) that are common among a wide variety of ED measures is valuable for ED operations research. An example time series might consist of daily ED census by hour, and a model might use the preceding 5 days. Time-series models can use a number of different techniques in analyzing data. These frequently include autoregression, moving average regression, exponential smoothing, and other variants and combinations of these techniques; a description of these techniques has been previously published.[24] A handful of studies have used various time series modeling techniques with some success in long- and short-term prediction of ED work load or census.[39–43] This method provides a fair estimate that can be useful for tracking trends or anticipating workload, but by their nature, such averages often fail to capture the level of short-term variability that may be important in operations management in the setting of surge conditions.[43]

Queuing Models

Queuing theory makes basic assumptions about a system to create mathematical equations that describe system flow and thus can help to predict waits (i.e., crowding). At the most basic level, queuing systems consist of four components—arrivals, servers, service principles (described as the ''queuing discipline'' or rules as to whom a server serves next), and the flow or routing through the system.[44] Many queuing models exist (hundreds to thousands), but relatively few have been described in the literature pertinent to ED flow.[45–55]

Inputs into the system are described based on (patient) arrival time intervals, patterns, and distributions. A central tenet of queuing theory is that variability in the arrival process is unpredictable or predictable but unmanageable. It is the variability in arrivals and service times around their means that creates congestion and causes wait times to increase.[56] Arrivals are usually assumed to be ''Markovian'' or random, in the sense that past arrival histories do not probabilistically affect future arrival patterns. This assumption implies that the number of arrivals in a given interval of time may be described by a Poisson probability distribution (which is the probability of a number of events occurring in a fixed period of time with a known average rate, independent of the last event,[51] and whose appearance has an early peak with a long right skew). To create a queuing model, it is also almost universally[52] assumed that the arrival patterns are ''stationary'' over the period under consideration, so that the underlying rate of arrivals is constant, although the actual realization of arrival times may be highly variable. To satisfy this assumption, data used for deriving queuing theory models are often truncated for periods when arrival rates are relatively constant. The derived model can still perform quite well despite the actual variability seen in arrival times for the entire data set. Service takes into consideration the number of servers (i.e., single or multiple physicians), the number of queues formed waiting to be served, and the probability distributions of service processing time. Service processing time is frequently described by an exponential distribution.

The system is designed based on select ''queuing disciplines'' (i.e., principles) that describe the order in which service is provided. Some commonly used disciplines include first-come-first-serve (FCFS) or equivalently first-in-first-out; priority service, where patients are stratified and the highest priority class who has been waiting the longest is served next; preemptive service where a high priority arrival is immediately serviced; or nonpreemptive service where high priority patients must wait for the next free server. If the arrival distribution, service distribution, and queuing discipline are known, then under assumptions such as those detailed, characteristics of the queue can be calculated based on the steady state, including average number (and duration) of waiting patients and service utilization (e.g., staff, laboratory, radiology services).[51]

The most basic queuing model is the M/M/1 queue. In this model:

- First ''M''—assumes Markovian (random) demand of customers (patients) with a Poisson arrival distribution at a constant rate lambda (λ).
- Second ''M''—service time assumed to follow exponential distribution.
- ''1''—assumes single queue forms for a single server (e.g., a doctor) following a FCFS service principle.

It is assumed that patients will wait as long as it takes to be seen, then depart after treatment. The fraction of time the doctor is busy, or ''server utilization,'' equals the arrival rate of patients (λ) multiplied by the mean or expected service time (ES), i.e., the average time for a patient to be treated by the doctor. However, if the rate of demand (arrival) exceeds the rate of services provided by the server ($\lambda > 1/ES$), then wait times in the queue quickly increase, and projected utilization of the servers increase above 100% (an impractical proposition that many may find familiar; Figure 1). It is this curve that gives insight into common staffing rules of thumb, such as targets of 80% utilization,[47,53] where a patient's expected time in system (LOS) can be seen to be five times the time spent in service (treatment). And

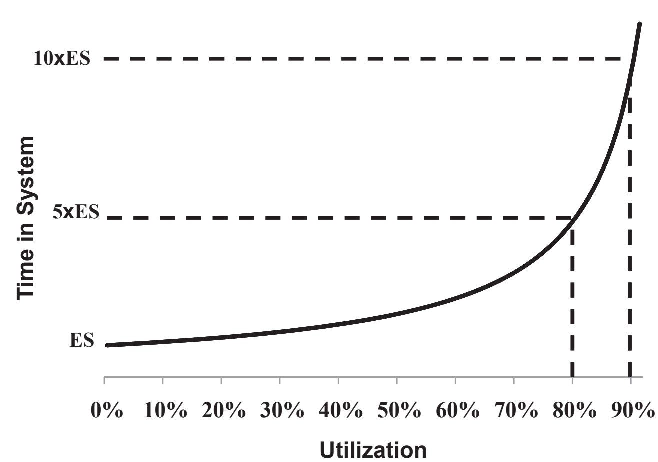

Figure 1. Time in system (LOS) versus utilization in the M/M/1 queuing model. LOS = length of stay.

at 90% utilization, the total LOS will be 10 times the actual treatment time. Queuing theory has little (but not nothing[57]) to say about situations when server utilization is at or above 100%.

With regard to patient flow, *queuing network models* describe systems with a number of server pools, each with their own queues and queuing disciplines, that patients may be routed between. Typically such patient flow occurs 1) in a fixed fashion (e.g., triage to bed placement, with a queue forming in the waiting area if beds are fully occupied), 2) probabilistically (e.g., 25% of patients must go to radiology), or 3) dependent on the patient's ''class'' or type (e.g., acuity or presenting complaint). Flow is typically ''feed-forward'' where patients do not revisit a server pool. However, more complex routings have been proposed in the queuing literature.[58]

There are a number of limitations of forecasting models based on queuing theory principals for the ED patient population. Queuing equations are often based on a number of simplifying assumptions, which differ depending on the particular model being employed. First, many queuing models assume that the priority of services provided follows a FCFS format. Clearly, in the ED population where acuity, in addition to the time of presentation, determines the order that patients are serviced (i.e., the sickest patients are prioritized over the less acute patients), this assumption can be problematic. Thus, a model based on priority principles is more appropriate for the ED setting. The priority queuing discipline assumes that the choice of prioritization is from one of a fixed number of classes (e.g., acuity level) and that order within a class is FCFS. However, in practice, the order of service is more complex than this assumption as well. For example, a patient's condition may deteriorate, leading to prioritization for treatment, which is not well modeled by the fixed class system. Second, many queuing models, including the M/M/1 model, assume that both the arrival rate and the service rate of the system are stationary and constant over time. This would mean that patients present to the system at a constant rate that does not vary throughout the day, which clearly is not the case with most EDs. For models that do not assume a fixed rate, there are those that break the day into intervals and model each interval separately, those that try to smooth the intervals,[52] and those that explicitly model the variable input.[59] Third, one common (albeit often unrealistic) assumption for the ED is that no patients leave the system without treatment complete. Queuing models typically assume that patients will wait as long as is necessary to be served in the system, which is obviously not the case in the ED, as patients LWBS and against medical advice, particularly during times of crowding.[60] However, violation of this assumption tends not to be particularly problematic either, because this often has minimal effect on the model outputs or because reneging patients decrease ED congestion, actually making the model more conservative (e.g., predict longer waits than real waits). Finally, most queuing models assume that the patient moves through the system from one service to the next (queue) with no unscheduled delays for resources other than the one server they are queuing for. Typically, patients boarding in the ED waiting for transfer to an inpatient bed are either not modeled or assumed to follow some independent external distribution. Further, the modeler must pick either the physician or the bed as the critical resource to be queued for, as the model does not allow for patients to queue for multiple types of resources.

A handful of queuing models have been designed to describe ED patient flow[47,49] and forecast demand in the ED.[46,48] Once flow predictions have been made, such models can then be used to predict the effect of changes on the system (such as patient reprioritization[51] or addition of fast-track services,[55]) or determine optimal ED staffing.[52] Despite their limitations, queuing models are useful for ED operations research and forecast modeling because they allow for the application of simple equations to model patient flow. In most ED applications these equations can be easily input into a spreadsheet. Such equations can then guide system design and yield general principles about the relationship between variables such as capacity, patient wait, and treatment times. Further, the limitations created by assumptions can often be minimized by mathematical approximations (e.g., variable [nonstationary] arrival patterns,[52] flow blockages,[61] and patients who leave the system without treatment complete[54]). These approximations usually require validation using data from the actual system being modeled or with a DES.[62]

Discrete-event Simulation

Discrete-event simulation, sometimes called a process simulation, is a computer model that seeks to ''mimic'' the behavior of a system or a queuing model. The title ''discrete event'' comes from the core programming assumption in the simulation. Most of these are written in process-focused simulation packages with a graphical interface. There are numerous such proprietary packages available for this type of modeling. Some are health care–focused and others have more broad business operations applications as well as health care (e.g., ProcessModel, Arena, Extend, etc.) where any flow of entities (patients, customers, etc.) may be modeled. Figure 2 is a ''snapshot'' of a DES-based commercial software product. Less common than process-based simulations are spreadsheet-based simulations (which tend to be limited in scope) and simulations written in a general programming language, such as C++, which are very flexible but also complex to program. DES models define activities as a network of interdependent discrete events.[63]

The simulation stores what is known as the ''event list,'' i.e., the desired model inputs, (e.g., patient arrivals, patient departures, staff breaks, laboratory and imaging studies, etc.). The simulation then steps from one discrete event (one step in the system flow) to the next, updating the system clock (which always moves forward in time) and system variables and recording relevant system data. Events are randomly generated by the program in real time, based on input probabilities.

In process-based simulation, the specific events are autodefined by the software, which schedules the event list as indicated. From the user's perspective, the core

Figure 2. ''Snapshot'' of a commercially available discrete event simulation graphical user interface (ModModel, ProModel Corp., Orem, UT; used with permission).

of the simulation is driven by ''entities'' (usually patients) that move through ''locations'' (e.g., waiting room, clinical spaces, etc.) while requesting ''resources'' (e.g., staff, beds, etc.) as needed. The user maps the flow of the entities and must also input probability distributions for each step in the patient flow process. Waiting times are not directly input; instead, they are an output that comes from the request/demand of resources or locations that are shared by multiple entities or patients. When demand supersedes resources (i.e., crowding), bottlenecks and delays are created in the modeled system. Flow can follow any pattern specified. For example, patients may be routed from ED bed to radiology and then back to ED bed, either releasing the bed for another patient or holding the bed for the original patient until that patient returns.

Each run of the simulation, referred to as a ''trial,'' uses one stream of samples from the input distributions. Thus, the resulting data is for one time-based scenario with forecasted outcome(s). Multiple trials are required to generate valid system statistical estimates (e.g., average LOS). Because simulations are typically initialized with no patients in the system, care needs to be taken when choosing the run length for a trial and when choosing what portion of that trial on which to base the estimates. Note that simulation models use statistical sampling rather than mathematical formula(s) and therefore the choice of run length affects the accuracy of the estimates. However, because no exact formulas need to be derived mathematically, simulation can provide estimates for a much wider range of models than queuing models and thus may more accurately model many applications. For example, it makes no difference to the DES model whether arrivals are ''Markovian,'' whereas this assumption is key to making the mathematics tractable in most queuing models.[58,64]

DES is an ideal tool for performing ''what-if'' analysis (e.g., what effect would an increase/decrease in ED bed capacity have on patient wait times?[65]). It is less well designed to perform a ''best-fit'' analysis, where many trials need to be performed to identify the superior system design, which may be very time-consuming. However, if the range of possible values is small (e.g., deciding between one to three on-call teams or choosing within a small range of bed capacities) it can be reasonably effective.

In theory, any scheduling rule or queuing discipline may be modeled using DES.[47] Unlike queuing models, models of patient boarding and waits for consultants are relatively easy to add to a DES. However, many of the more sophisticated modeling programs assume only simple scheduling rules (e.g., FCFS prioritization). Further, even seemingly simple aspects of human behavior can be very challenging to model (e.g., jockeying between queues, prioritization of service based on changing acuities), although they are usually not impossible with a flexible software tool.

A number of simulation models described in the medical literature address elements germane to ED crowding. DES models have been used to identifying optimal ED flow patterns,[66,67] predict (forecast) ED crowding,[25,50,63] and evaluate the effect of resource modifications on ED flow systems, including a fast-track service line,[68] on-call specialists,[69] staffing levels and changes in ED bed capacity,[65] facilities management,[64] patient arrival patterns,[70] natural disaster surges,[71] ED observation units, mandatory inpatient transfer of ED boarding patients,[67] and elective cardiac catheterization scheduling smoothing.[72]

There are a number of limitations of forecasting models based on DES principals for the ED patient population. First, DES models are very time-consuming to develop. They also require a significant amount of data input, in particular for ED operations modeling, because each step in a patient's flow through the ED must be modeled. Finally, they do not provide any explicit mathematical description or formula from which to understand the modeled flow dynamics (e.g., how waiting times depend on capacity); thus, multiple simulations must be conducted with varying parameters (e.g., levels of capacity) and then the collected data (e.g., waiting time outputs) must be analyzed as a separate process.

CONCLUSIONS

The ability to model, forecast, and predict ED patient load and crowding has valuable application to real-time ED operations. Because of the complex nature of ED operations, including unscheduled patient demand, variable resources including providers, and relatively fixed functional capacity, precise modeling of the ED environment is challenging. As such, formula-based approaches, regression modeling, time-series analysis, queuing theory-based models, and discrete-event (or process) simulation models have been offered as ways to describe the ED system. Each approach has its strengths, but also notable limitations that do not fully capture the complexities of the ED system. A summary of the quantitative method, ability to define and forecasting crowding, ability to predict process improvement effect on ED operations, ease of model development, and model complexity of development are summarized in Table 1 based on the authors' assessment of these various modeling approaches. As the demand for ED services increases, the need to anticipate ED patient load and crowding becomes more important. More collaboration between operations management experts and emergency medicine researchers is needed to improve existing approaches.

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