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Incorporating real-time citizen responder information to augment EMS logistics operations: A simulation study

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ABSTRACT

Minimizing response time is the key to live-saving missions of emergency medical services (EMS). As an alternative to professional paramedics, citizen responders (CRs), medically trained volunteers in the community, can use their training to help others in their neighborhood or workplace, by rendering emergency responses. Empowered by connected technologies, CRs can be promptly notified by an EMS request upon its arrival, and they may provide time-sensitive (and often life-saving) response before an ambulance arrives. Currently, many EMS agencies, though employing CRs for certain emergency situations, do not necessarily intelligently leverage real-time information of CRs (e.g., position and response propensity) when making decisions on EMS logistic operations (e.g., ambulance dispatch). As a result, opportunities arise for better coordination between CRs and ambulances. In this paper, we investigate the decision problem of dispatching ambulances for priority-differentiated emergencies. We adapt a locally optimal dispatch procedure with incorporation of real-time CR information, which is intended to balance improved response for the current emergency request via dispatching CRs and response preparedness for future requests. We evaluate the adapted dispatch procedure via a discrete event simulation and compare our procedure against the procedure without incorporating CR information and a commonly used dispatch strategy in practice. We perform a sensitivity analysis with respect to the spatial distribution and response propensity levels of CRs. The results suggest that our procedure could lead to substantial and reliable system improvement.

1. Introduction

Emergency medical services (EMS) constantly seek reductions in their response times as they currently take primary responsibility for pre-hospital care of life-threatening emergency medical conditions. In pursuit of faster emergency response and improved access to critical care, it is the key to optimize EMS logistic operations. The EMS process starts when an emergency is reported to the EMS agency, often by a medically untrained bystander. Then, the EMS dispatcher conducts a preliminary evaluation of the emergency condition and assigns an available ambulance accordingly. Once EMS staff arrive at the emergency scene, they evaluate the degree of urgency and perform initial first-aid accordingly. Next, the patient is transported to an appropriate care facility. At the operational level, an ambulance dispatch procedure needs to be used to specify which ambulance to be assigned in real time for each request. The logistic operations may be further augmented with re-routing (i.e., reassigning an already dispatched ambulance) and request preemption (i.e., placing a request in the queue, holding an ambulance for future requests).

In recent years, community-based programs are formed to recruit, train, and manage citizen responders (CRs). With the training, CRs are capable of recognizing common medical and non-medical emergencies and providing basic responses, such as hands-only cardiopulmonary resuscitation (CPR) or automated external defibrillator (AED) operation for out-of-hospital cardiac arrests (OHCA), naloxone spray administration for opioid overdoses, bleeding control for severe traumatic injuries, and epinephrine injection for allergic emergencies. As a result, patients in emergency situations could have a better chance to survive. For example, timely defibrillation assistance rendered by bystanders is strongly associated with survival increment (Hansen et al., 2015). When CRs use AED, the increase in survival probability has been found to be around a factor of 3.73, and even with just CPR, the increase would be around a factor of 1.76 (Andelius et al., 2020).

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Recently, increasing use of connected technology has made it possible to better engage community members into EMS practice in their communities. Example mobile applications include PulsePoint in the U.S. (Brooks et al., 2016), FirstAED in Denmark and Canada (FirstAED, 2021), and Heartrunner in Sweden (Heartrunner Sweden AB, 2021). CRs, if available to answer the response request of an emergency soon after its occurrence, are contacted by the dispatcher through a mobile application and tele-coached in real-time to render the response. While deploying CRs is a promising means to augment community-based response to medical and other types of emergencies, it remains challenging to coordinate service logistics of CRs with that of professional paramedics and their ambulances, especially in real-time operations. This has brought a new dimension to EMS logistic operations management.

In this paper, we investigate an EMS system with its service operations augmented by CR deployment (Fig. 1) and study the logistic operation decision problems. In such a coordinated logistic system (referred to as the CR + EMS system in the remainder of the paper), the dispatcher can request CR assistance in order to reduce the emergency response time. However, CRs can only carry out basic first-aid responses, e.g., hands-only CPRs, and they cannot completely replace professional paramedics. An ambulance must eventually arrive at the emergency scene to complete necessary life-saving operations. Further, CRs cannot be prefixed at their locations. Instead, they can be reached in real-time with the GPS tracking functionality with a mobile application upon the arrival of an EMS request. Moreover, CRs are volunteers, and as such, their acceptance of the request (i.e., response propensity) is likely random. The last two characteristics imply that CRs are independent servers in comparison to a fleet of ambulances that are centrally controlled and can stand by all time when they are on duty. With this configuration of CR + EMS logistic operations, our research problem can be viewed in the field of logistics systems as a unique service logistic coordination problem with a combination of controlled service providers (paramedics and ambulances) together with crowdsourced service supporters (CRs with their community-based transportation). This emerging EMS delivery model brings a unique opportunity to study on-demand service assignment decision rules in a logistic system. In the remainder of the paper, we refer to the two parties involved as ambulances and CRs, respectively.

Specifically, we study the decision problem of dispatching ambulances in real time for requests from patients with differentiated EMS priorities. This problem arises from a CR + EMS system that has the technological capability of acquiring real-time information on CR location and propensity. This problem aims to coordinate ambulance-based EMS with additional CR assistance to better trade-off fast and effective response to current requests against maintaining preparedness for probabilistic arrivals of future requests. Ambulance dispatch optimization has been intensively studied in the literature (Aringhieri et al., 2017) for conventional EMS. In addition, pilot studies on CR programs have been conducted. However, to the best of our knowledge, we are one of the first to study ambulance dispatch decisions in CR + EMS systems. Other relevant studies include Khalemsky and Schwartz (2017), Lancaster and Herrmann (2020), and Paz et al. (2021). We detail their differences with our work in Section 2.1.

We adapt a myopic (locally optimal) ambulance multi-priority dispatch procedure and design a discrete-event simulation to evaluate system improvement by accounting for real-time CR information. To verify the improvement, we compare the adapted procedure with a procedure of the same spirit but without incorporation of real-time CR information and with the baseline EMS practice of sending the closet ambulance to each request. In addition, we perform sensitivity analyses with respect to the spatial distribution and response propensity of CRs.

Our paper makes the following contributions. First, we introduce a new and socially impactful problem of logistic coordination between controlled service providers and crowdsourced service supporters. Second, we extend an ambulance dispatch procedure to this coordinated logistic system and show that considering CR information can lead to significant improvements in EMS responsiveness. Finally, we are among the first papers studying CR + EMS, which can help design CR programs for distinct local communities.

The remainder of the paper is organized as follows. Section 2 discusses related literature. Section 3 presents an ambulance dispatch procedure for the CR + EMS system. Section 4 presents the performance evaluation via discrete-event simulation. Section 5 draws conclusions and outlines future research directions.

2. Related work

In this section, we discuss the differences between our work and related studies in two research areas, CR + EMS systems and ambulance dispatch decision making for conventional EMS. Studies on CR + EMS systems have been primarily focused on evaluating the improvement of system performances such as response time and survival. Most studies conduct empirical research and only a few of them appear in the operations research (OR) or management science (MS) literature. We first analyze studies investigating CR + EMS in the OR-MS literature (Section 2.1) and then those from the health outcomes research literature (Section 2.2). Regarding ambulance dispatch decision-making (Section 2.3), our review implies that its research has yet to be extended to CR + EMS systems.

2.1. CR-augmented EMS systems in the OR-MS literature

The focus of the CR + EMS systems literature has primarily been on evaluating the impact of implementing CR programs (a comprehensive literature review is presented by Scquizzato et al., 2020). Among these studies, only a few can be related to OR or MS. For example, Khalemsky and Schwartz (2017) presented a Monte Carlo simulation to evaluate the impact on response time. In their work, inputs are community-

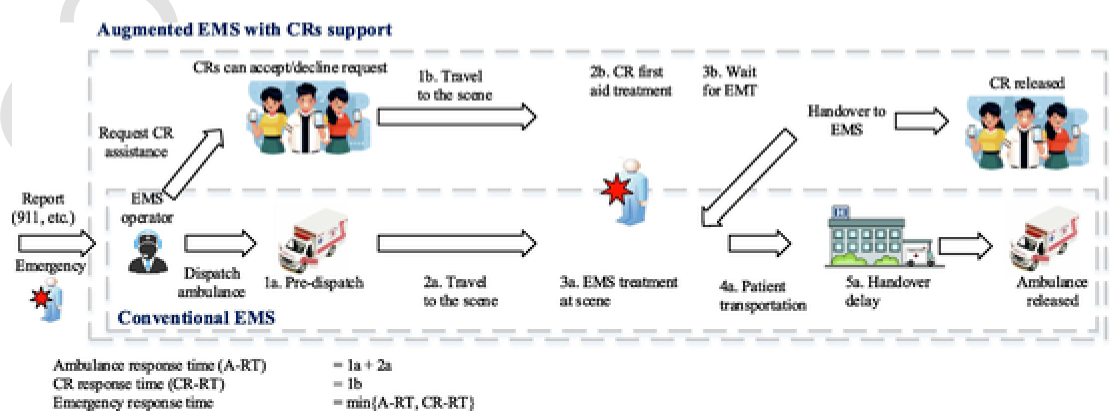

Fig. 1. Conventional EMS operational process vs CR-augmented EMS operational process.

specific characteristics such as population density. This allows for efficacy assessment of distinct CR programs. Lancaster and Herrmann (2020) presented a Monte Carlo simulation to evaluate the impact on patient survival, resulting from launching a CR program together with using drones to deliver AEDs. The authors compared the response time of CR-augmented EMS with that of conventional EMS. Neither study above simulated a stream of stochastically arrived emergency response requests. They did not capture the interplay between operational decisions and system evolution.

In addition, a few recent studies focused on solving design and operational decisions problems in CR + EMS systems. At the strategic level, Henderson et al. (2022) dealt with the problem of defining how many volunteers are needed in a CR program, and where they should be recruited from. The authors modeled the presence of volunteers with a Poisson point process, and formulated a tractable optimization model to compute the volunteer location distribution. The results of a case study with data from New Zealand demonstrated the applicability of the model to provide guidance in CRs recruitment and identify zones where recruitment would be more impactful. At the operational level, Matinrad et al. (2021) investigated the CR dispatch decision problem for OHCAs. In their setting, CRs can be dispatched either directly to emergencies or to first pick up an AED. The authors proposed a CR dispatch procedure considering the uncertainty of CRs' compliance with tasks assigned to them. Simulation experiments showed that the procedure outperforms the current practice of a CR + EMS system in Sweden. In van den Berg et al. (2021), the CR dispatch problem was defined as choosing which volunteers should receive alerts and when, in order to maximize survival rates while keeping the total number of alerts to a minimum (i.e., assuming that recurrent requests would discourage CR participation). The authors introduced a simplistic and stylistic formulation of the CR dispatch problem as a dynamic program with a state space that reflects the alerts sent, the volunteer responses received, and the departure times of request-accepting volunteers. The authors further identified two directions to expand the dynamic program: 1) incorporating availability of AED and 2) designing an efficient solution algorithm. Lastly, Paz et al. (2021) studied the problem of ambulance redeployment decisions in a CR + EMS system via discrete-event simulation to evaluate improvements on response times and survival, resulting from incorporating real-time CR information into a myopic redeployment procedure. The studies above implicitly assumed dispatching the nearest ambulance available. In addition, none of the studies systematically studied the decisions on ambulance dispatch in response to emergencies of different priority levels. In this paper we address both limits from the exiting literature.

2.2. CR-augmented EMS systems in the health outcomes research literature

There are cohort studies on CR + EMS system performance. Andelius et al. (2020) compared community responses for OHCA for which CRs arrived earlier than ambulances to those via conventional EMS operations. They found that CPR performed by CRs can increase the odds of survival by a factor of 1.76, and the increase is 3.73 times the original survival probability when CRs use AED. Similar results were found by Derkenne et al. (2020) from the data of "Staying Alive", a program with operations in a large urban area of Paris. In their study, the increase of survival odds was a factor of 5.9 for OHCA. Ng et al. (2020) examined the performance of the "myResponder" program in Singapore. The program was shown to be a feasible and promising way to improve community response for OHCA. Smida et al. (2022) analyzed dispatch data of CRs affiliated with "PulsePoint", a US-based platform focused on OHCA. The authors analyzed emergencies with CR support in a service area of Pittsburgh from July 2016 to October 2020. They found that CR-assisted responses can be associated with favorable OHCA characteristics and increased outcomes of patients receiving CPR from CRs.

Additional studies resorted to surveys or interviews on CRs. Brooks et al. (2016) conducted a survey-based study on CRs affiliated with "PulsePoint". Their study revealed that while the platform had the potential to improve EMS outcomes, increasing CR engagement would be the key. Pilemalm (2020) conducted interviews with focus groups of CRs and semi-professional first-responders in a Swedish CR program. The authors identified a set of key factors for successful implementation of the program.

Lastly, some institutions performed studies to assess the potential of CR + EMS systems. For example, the McKinsey Global Institute (2018) highlighted that smart systems (e.g., CR + EMS or traffic light preemption) are a promising way to optimize field operations of EMS. Their assessment projected that smart solutions in cities with an average response time of eight minutes could be reduced by almost two minutes, whereas for cities with an average response time of 50 min, a reduction greater than 17 min could be achieved. The US National Highway Traffic Safety Administration (Schooley & Horan, 2015) identified emerging EMS delivery models based on new information and communication technologies as a disruptor, which can lead to benefits in EMS operations and patient health. However, the same report also pointed out that new vendor technologies are currently rendered by EMS leaders in a "trial and error" fashion. There is a need to conduct research to better understand how to make emerging connected concepts beneficial to EMS professionals and to establish an evidence base to decide on the implementation of these technologies in practice.

As noticed, several pilot CR programs have been evaluated with empirical research. However, not much attention has been given to the aspect of logistic operations management, and even less to the specific topic of ambulance dispatch decision making. In fact, among the pilot CR programs, real-time CR information was used to determine if a CR could reach the emergency within a specific time limit to decide the service flow diversion between ambulance and CR responses, but ambulance dispatch decisions did not change as a function of the CR status. In summary, while studies suggest that implementing a CR program can lead to improvement on response time and patient survival, to the best of our knowledge, none of them has systematically investigated how ambulance dispatch decisions should be adjusted for consistently good system performances upon the CR program implementation. Our work contributes to this area with one of the first simulation studies.

2.3. Ambulance dispatch in conventional EMS

Ambulance dispatch is one of the key EMS service operational decisions, which has been intensively studied in the EMS logistics systems literature (Aringhieri et al., 2017). Carter et al. (1972) showed that it is not necessarily optimal to dispatch the nearest ambulance to an emergency. Some recent studies applied Markov decision processes (MDP) to model the dispatch process under request arrival uncertainty and compute optimal dispatch policies (e.g., Bandara et al., 2014), whereas others evaluated local optimization-based dispatch strategies. It is challenging to formulate MDP models with incorporation of practical constraints and solve them for industry-sized instances. Meanwhile, local optimization-based strategies are more intuitive and experience-based to dispatchers, who are likely under a great deal of cognitive burden in practice. Thus, as a first attempt to study ambulance dispatch decision-making in a CR + EMS system, we focus on the latter and thereafter provide an additional literature review.

The first ambulance dispatch procedure of relevance was proposed by Andersson and Värbrand (2007), which is a procedure differentiating service priorities. When critical emergency requests arrive, the nearest ambulance is dispatched; whereas for less critical requests, the ambulance that maximizes system preparedness to future emergencies is dispatched. In their work, the notion of preparedness reflects the system ability to serve potential demand in the future. Later, Lee (2011, 2017) proposed ambulance dispatch procedures with alternative definitions of system preparedness based on node centrality in the logistic network, but did not consider different emergency priorities. Sudtachat et al. (2014) developed an ambulance dispatch procedure that directly maximizes patients' expected survival probability. Their study considered multiple priorities, a heterogeneous ambulance fleet, and the possibility of sending several ambulances to the same emergency.

The above review also shows that several locally optimal dispatch procedures have been proposed and evaluated for conventional EMS delivery. However, to the best of our knowledge, this line of research has yet to be extended to CR + EMS systems. Hence, our study expands the application range of the logistics coordination theory.

3. An ambulance dispatch procedure incorporating CR information

In this section, we introduce a multi-priority ambulance dispatch procedure incorporating real-time CR information, termed as the PP-w-CRI (i.e., priority preparedness with CR information) procedure. Real-time CR information includes each CR's position and response propensity. The procedure considers two types of emergencies, namely critical and non-critical emergencies, for which preliminary assessment can be performed by the dispatcher during the emergency call. Critical emergencies refer to those for which the CR-administered intervention can substantially improve patient survival. For example, a CR can perform hands-only CPR to someone with an OHCA before ambulance arrival, which might just provide the much-needed life-saving intervention to the person. Otherwise, the person could die within a few minutes without proper response. For non-critical emergencies, patient survival is not sensitive to fast response and unlikely improved by CR assistance.

Our procedure follows a multi-priority preparedness-based ambulance dispatch procedure proposed by Andersson and Värbrand (2007). In addition, it adapts the preparedness metric introduced by Lee (2017), with incorporation of real-time CR information to quantify each district's preparedness capacity upon a response request. For each district, real-time CR position and response propensity are used to compute the probability that a random request can be covered by a CR and its expected response time. Then, the preparedness metric is computed over the minimum response time between ambulances and CRs, over probabilistically arrived critical emergencies in the future. In a nutshell, for a critical emergency, the PP-w-CRI procedure broadcasts the emergency request to all CRs deemed available and dispatches the CR who answers the call together with the nearest ambulance. On the other hand, for a non-critical emergency, the procedure only dispatches the ambulance that can maximize the adapted preparedness metric.

We make the following assumptions on CRs and the CR program. First, when a critical emergency request is made, the dispatcher uses a prespecified threshold on the time from the real-time location of each CR to the emergency site to identify candidate CRs to broadcast the request. We also assume that each candidate CR immediately accepts or rejects the request, and only the closest CR accepting the request is selected and dispatched. Finally, we assume that all candidate CRs are identical in terms of their response propensity once being notified. Given *D*, a set of districts in a service area, the PP-w-CRI procedure is presented as follows:

)1. 1. When a new emergency request appears in district $\boldsymbol{d} \in \boldsymbol{D}$, its criticality level $\boldsymbol{r}$ is determined during the 9–1-1 call ($\boldsymbol{r}$ is 1 if it is a critical emergency and is viable to seek CR assistance, and 2 otherwise) and a set $\boldsymbol{A}$ of available (idle) ambulances are identified.
)2. 2. If the criticality level $\boldsymbol{r}$ is 1, dispatch the nearest ambulance and notify nearby CRs according to the prespecified threshold time $\boldsymbol{h^m}$.
)3. 3. If the criticality level $\boldsymbol{r}$ is 2, dispatch to district $\boldsymbol{d}$ ambulance $\boldsymbol{a}^*$ that maximizes the preparedness metric for critical emergencies, i.e., $\boldsymbol{a}^* = \arg\max_{\boldsymbol{a} \in \boldsymbol{A}} \boldsymbol{P}_{A \backslash \boldsymbol{a}}$, where $\boldsymbol{P}_{A\backslash \boldsymbol{a}}$ for each $\boldsymbol{a} \in \boldsymbol{A}$ is computed as follows:

- 3.1 Compute α_d, the probability that a request in district d can be assisted by some CR, i.e., $\alpha_d = 1 - \prod_{c \in C_d} (1 - \tau_c)$. Denote τ_c to be the probability that a request is accepted by a CR $c \in C_d$, where C_d is a subset of CRs that can reach district d in less than some prespecified threshold value h^m (i.e., candidate CR set).
- 3.2 Compute $\overline{t_d^c}$, denoted as the expected response time of CRs in C_d to district d, $\overline{t_d^c} = \sum_{K \in F} \left(\left(\prod_{c \in K} \tau_c \prod_{c \in K^c} (1 - \tau_c) \right) \min_{c \in K} t_{cd} \right)$, where t_{cd} is denoted as the time of CR c to reach district d. Denote F to be the set of all subsets of C_d, K is a subset of C_d representing the set of CRs willing to respond to the emergency, and K^c the complement of K.
- 3.3 Compute w_{kd}, denoted as the minimum response time to a critical emergency occurring at district d if attended by ambulance k or the candidate subset of CRs. That is, $w_{kd} = \min \left\{ t_{kd}, \alpha_d \bullet \overline{t_d^c} + (1 - \alpha_d) \bullet t_{kd} \right\}$, where t_{kd} is the travel time of ambulance k to district d.
- 3.4 Then, for each ambulance $a \in A$, the system preparedness metric to critical emergencies $P_{A\backslash a}$ is computed by setting ambulance a unavailable (resulting from dispatching it). For this purpose, where π_d is the proportion of calls in district d, then $P_{A\backslash a} = \frac{1}{\sum_{d \in D} \pi_d \left(1 + \min_{k \in A\backslash a} w_{kd} \right)}$.

4. Performance evaluation

4.1. Simulation model

A discrete event simulation was developed to evaluate the EMS system performance of PP-w-CRI and two other dispatch procedures under different spatial distributions and response propensity levels of CRs. The other two procedures are 1) dispatching the nearest ambulance (termed as the closest procedure), a common EMS practice, and the 2) multi-priority procedure for CR + EMS systems without incorporating CR information (termed as PP-w/o-CRI). Compared to PP-w-CRI, PP-w/o-CRI also dispatches CRs to critical emergencies, but it ignores real-time CR information in computing the system preparedness metric.

The discrete event simulation model represents the CR + EMS system evolution over time in which ambulances and CRs follow a given dispatch procedure as they respond to a stochastic process of emergency arrivals. Three types of entities appear in the simulation, namely ambulances, CRs, and emergencies. The entity locations are continuously computed and tracked. The entities have the following attributes: ambulances have location and state ∈ {idle, deployed, moving to emergency, moving to station}; CRs have location, response propensity, and state ∈ {available, not available}; and emergencies have location, occurrence time, emergency type, on-site time of the response, response time, and state ∈ {assigned to ambulance, not assigned to ambulance}. These attributes, tracked and updated in the simulation, are variables that instantly change according to seven events that occur at discrete times, namely *emergency arrival*, *dispatch CR*, *start ambulance service*, *finish ambulance service*, *start idle ambulance redeployment*, *finish ambulance redeployment* and *CRs change locations*. In the following, we describe the simulation mechanics as the logic process used by the events to change the entities' attributes. Later we describe the input parameters of the simulation along with the specific values used in a case study.

The simulation process changes the entities' attributes as it iterates through an event list (Banks et al., 2010; Fishman, 2013). At each iteration, the simulation updates its clock variable with the occurrence time of the earliest event, triggers the instructions associated with the at-hand event and updates the simulation-time-persistent statistics (e.g., average number of emergencies in system). This process begins with the arrival of emergencies that is represented by *emergency arrival* events. The occurrence time of these arrival events is read from a demand instance randomly generated according to the emergency arrival rate of a Poisson process and the spatial distribution of emergencies. The scheduling of other events is based on the conditions specified by the logic process of each event type. In the following, each event logic process is explained in detail. In addition, we include a more detailed flowchart of the simulation events in Fig. 2.

- Each time an *emergency arrival* event takes place, two other events could be immediately scheduled subject to resource availability, namely *dispatch CR* and *start ambulance service*. If no ambulance is available, the emergency is kept in queue until one is released (i.e., after a *finish ambulance service* event).
- The *dispatch CR* event assigns a CR to the request, following the process described in Section 3. If the CR can reach the emergency before the ambulance, the CR is dispatched and its state is updated to *not available*. In addition, its response time is registered as the time traveling to the emergency.
- The *start ambulance service* event assigns an ambulance to the emergency using a dispatch procedure considering ambulances

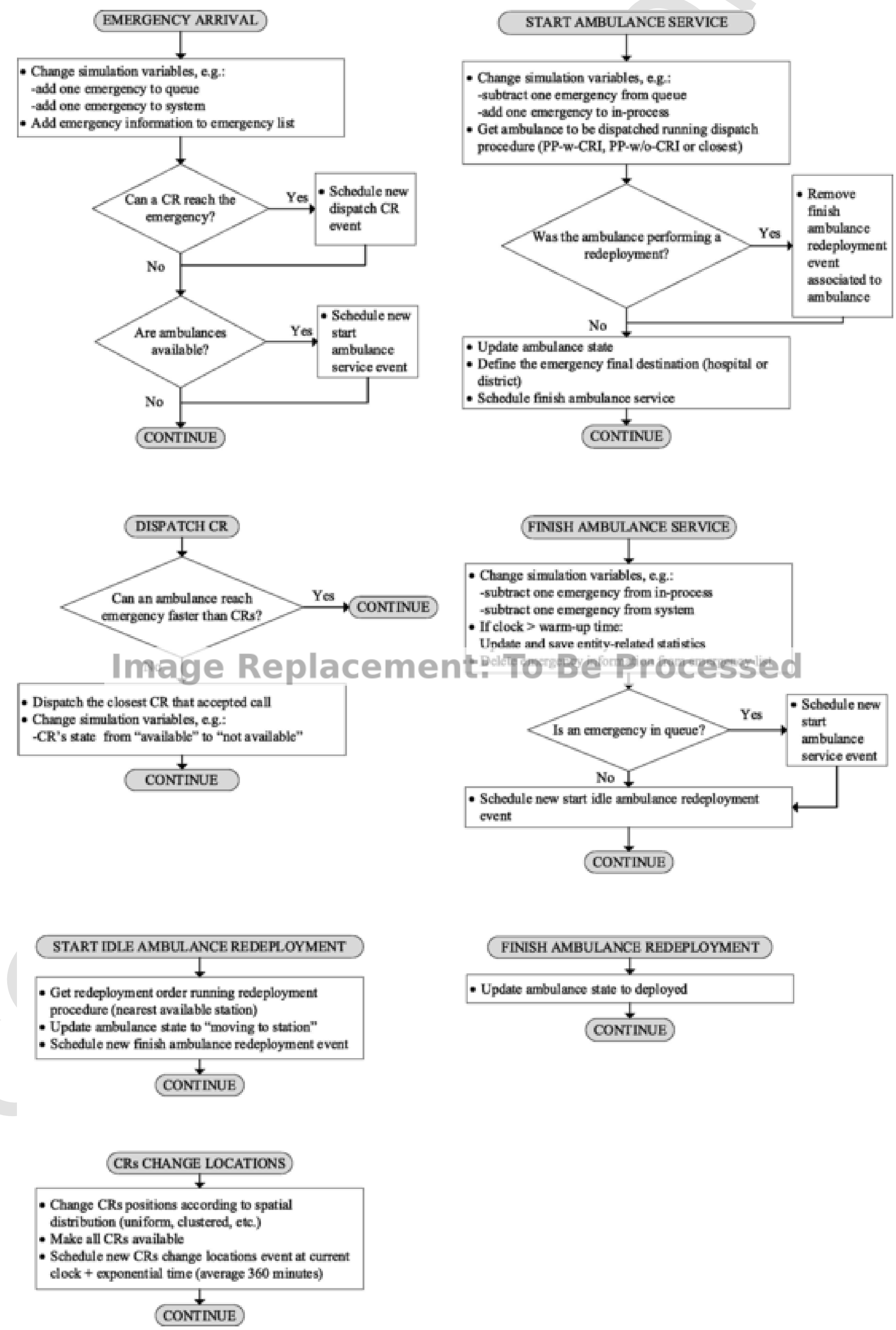

Fig. 2. Flow-chart representation of the simulation model – events and steps.

available for dispatch (i.e., its state is *idle*, *deployed* or *moving to a station*). If an ambulance is dispatched, the simulation changes the ambulance state to *moving to emergency*, and the emergency state to *assigned to ambulance*. If the ambulance is moving to a station, its corresponding *finish ambulance redeployment* event is discarded from the event list. Finally, the simulation schedules a *finish ambulance service* event with the occurrence time computed as the current simulation clock time plus: 1) a random emergency on-site time for the response, which is generated according to an exponential distribution, and 2) a deterministic transportation time (from the current location to the emergency and then to the hospital).
- When the *finish ambulance service* event takes place, the simulation deletes the information about the emergency just attended, and updates entity-related statistics (e.g., average response time to emergencies). Then, if there are emergencies in the queue, the simulation immediately schedules a *start ambulance service* event. If there are no emergencies in the queue, the simulation immediately schedules a *start idle ambulance redeployment* event.
- The *start idle ambulance redeployment* event assigns a station to the idle ambulance using a redeployment procedure, and changes the ambulance state to *moving to a station*. In this simulation, an ambulance is redeployed to the nearest station when sufficient capacity is available, but different redeployment strategies could be easily implemented. Finally, the simulation schedules a *finish ambulance redeployment* event with the occurrence time computed as the current simulation clock time plus the deterministic transportation time from the current location to the assigned redeployment station.
- The *finish ambulance redeployment* event updates the state of the ambulance just redeployed.
- Finally, the *CRs change positions* event updates the random locations of CRs based on their spatial autocorrelation. The state of each CR is then changed to *available* and a new *CRs change positions* event is scheduled with an occurrence time computed as the current simulation time plus a sthocastic time interval between changes, which is generated according to an exponential distribution.

Specific input values used for the case study are described as follows: The simulation model represents a service area on an 8 by 8 grid and with one hospital at the center. Each grid point represents a district, which is a one mile by one mile square area. Twenty-five ambulances are randomly positioned in the service area at the beginning of each simulation replication. They move between districts with a constant travel speed of 30 miles per hour. One hundred CRs are randomly positioned in the service area at the beginning of each simulation replication based on their spatial autocorrelation (0: uniform, between 0 and 1: partially clustered, and 1: clustered). No spatial pattern associated with negative autocorrelation is considered due to counter intuitiveness of such pattern in which regions with many CRs would have neighboring regions with few CRs (e.g., chessboard pattern). The CRs can move at an average speed of five miles per hour and the time threshold for any CR to be contacted is set to be five minutes from the emergency. A *CRs change locations* event is used to introduce a disturbance to CR locations, occurring within the time interval between events and following an exponential distribution with an average of 360 min (every 6 h). With the event, CRs randomly perturb their locations but preserving the level of spatial autocorrelation among them. Emergency requests occur at a rate of 2.5 requests per hour. They are assigned to districts following a uniform distribution and the on-site time is simulated according to an exponential distribution with a mean of 65 min. These case study parameters lead to a relatively uncongested system. Once an emergency request is generated, it is deemed a critical emergency with 40% of chance, and a non-critical emergency with 60% of chance. In addition, critical emergencies need to be transported to the hospital without diversion, and non-critical emergencies do not require transportation. The above system configuration is inspired by Enayati et al. (2018) and most of the parameters are extracted or adapted from the paper.

Table 1 shows a summary of the parameters used in the simulation model. The service rate was directly taken from the synthetic simulation of Enayati et al., (2018), and the original arrival rate of emergencies and the percentage of critical emergencies used by the authors were proportionally reduced to our simulation size (64 districts vs 240). The speed values of ambulances and CRs were assumed to be fixed. Note that ambulances have a relatively constant average speed when it is assumed that ambulances move with their lights andsirens enabled (Lupa et al., 2021). Thus, this assumption does not hinder the relative comparison between the different dispatch procedures investigated. The CR threshold was set following the common threshold of 5 min response to OHCA (Huang et al., 2021; Lee et al., 2019). Given the parameters above, the number of hospitals, district size and number of ambulances were set to represent a relatively uncongested system. We fixed the number of CRs as well as the average time between events of change position of CRs (following an exponential distribution). But, the response propensity of CRs was varied in the sensitivity analysis (Section 4.3). Thus, different levels of CR program capacity were evaluated.

4.2. Experiment design

We offline-generated 30 demand profiles (synthetic values according to a Poisson process; arrival rate in Table 1). Each profile comprises a set of emergency occurrence times and locations, emergency types, and on-site times of the response. We set a simulation duration of 7,000 min to ensure the statistical significance in a comparative study between the procedures. We set a warm-up period of 360 min for the simulation to achieve a steady state of the emergency request queue.

We defined our experiments with three spatial distributions of CRs (i.e., uniform, partially clustered, and clustered), five CR response propensity levels, and three dispatch procedures. Thus, we had a total of 45 experiments. For each of the 45 experiments, we ran the simula-

Table 1
Parameters of the simulated system.

Parameters	Value	Measurement unit	Type	Source
Service rate according to exponential distribution with mean of	65	min/request	Real	(Enayati et al., 2018) (adapted)
Arrival rate of emergencies (Poisson distribution)	2.5	requests/hr	Real	(Enayati et al., 2018) (adapted)
Critical emergencies	40	%	Real	(Enayati et al., 2018) (adapted)
Miles per hour	30	mph	Real	Assumed
CRs speed	5	mph	Real	Assumed
CR threshold	5	min	Real	(Huang et al., 2021; Lee et al., 2019)
Districts	64	units	Synthetic	(adapted)
Hospitals	1	units	Synthetic	(adapted)
District size	1	sq mi	Synthetic	(adapted)
Ambulances	25	units	Synthetic	(adapted)
Number of CRs	100	units	Synthetic	Fixed for sensitivity analysis
Time between events of change position of CRs according to exponential distribution	6	hrs	Synthetic	Fixed for sensitivity analysis

tion for each of the 30 demand profiles generated, and recorded the response time for each emergency request, measured as the time lapse between the time of emergency occurrence and the time of service arrival. Note that the service arrival time for a critical emergency is the first arrival of either a CR or an ambulance.

Using response time as the outcome instead of survival is due to the following reasons. First, survival functions are associated with specific clinical conditions, and our study was intended to all time-sensitive emergency conditions. Second, survival outcomes depend on several external factors (patient health condition, healthcare system quality, etc.). Modeling them precisely would increase the complexity of the study without significant advantages in relation to this paper's research objectives. Finally, our proposed procedure considers patient prioritization, which has been known to be associated with improved patient survivals (Bandara et al., 2014).

4.3. Results

We had two objectives for our computational experiments. The first objective was to compare the changes in response time to emergency between the proposed procedure (PP-w-CRI) and the procedure without integration of CR real-time information (PP-w/o-CRI), against the baseline closest dispatch procedure. The second objective was to analyze the sensitivity of the response-time outcome with respect to varying spatial distributions and response propensity levels of CRs, for each of the above procedures. As a result, this sensitivity analysis assessed the effect of implementing a CR program by setting the propensity level to zero as a reference. We present four types of results for the analyses: 1) a base 100 index chart showing the response times to critical emergencies (Fig. 3); 2) a trend graph of relative changes in average response time to critical emergency against the baseline procedure (Fig. 4), with respect to spatial distribution and response propensity level of CRs; 3) a summary of relative changes in response time between PP-w-CRI and PP-w/o-CRI (Fig. 5 and Table 2); and 4) a summary of outperformance robustness results with PP-w-CRI and PP-w/o-CRI against the baseline procedure as well as between them (Table 3).

Fig. 3 shows the average response time to critical emergencies obtained with the three dispatch procedures: Closest, PP-w/o-CRI, and PP-w-CRI, and for different response propensity levels and spatial distributions of CRs. The base value (100%) is the average response time to critical emergencies obtained with the baseline procedure and no CRs. Fig. 3 shows a decrease in response time that is sensitive to the spatial distribution and response propensity of CRs. When CRs are uniformly distributed and highly responsive, the best reductions in response time are achieved, whereas clustered distribution and low responsiveness decrease the magnitude of the reductions.

Fig. 4 shows the trend in relative changes in the average response time to critical emergency of PP-w-CRI and PP-w/o-CRI over the closest procedure for different response propensity levels and spatial distributions of CRs. The PP-w-CRI procedure constantly outperforms the

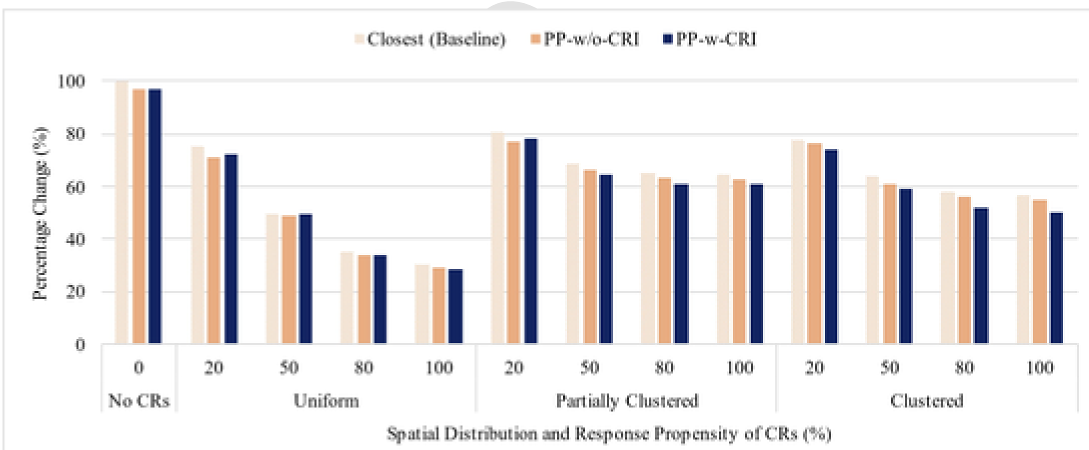

Fig. 3. Base 100 index chart - base value: average response time to critical emergencies obtained with the baseline procedure and no CRs.

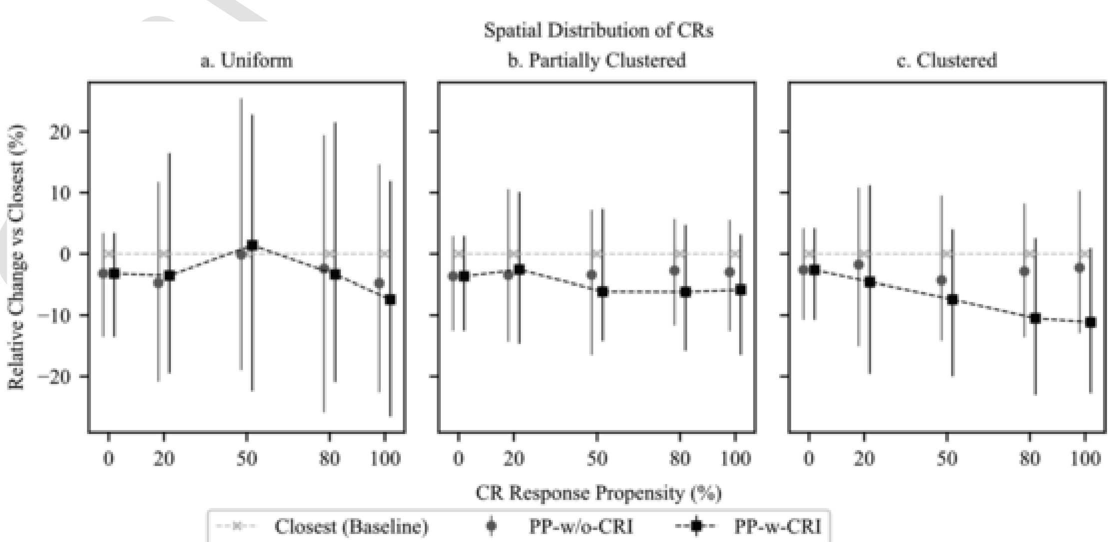

Fig. 4. Trend of the relative change vs dispatching the closest ambulance - average and 2.5/97.5 percentile over 30 demand profiles.

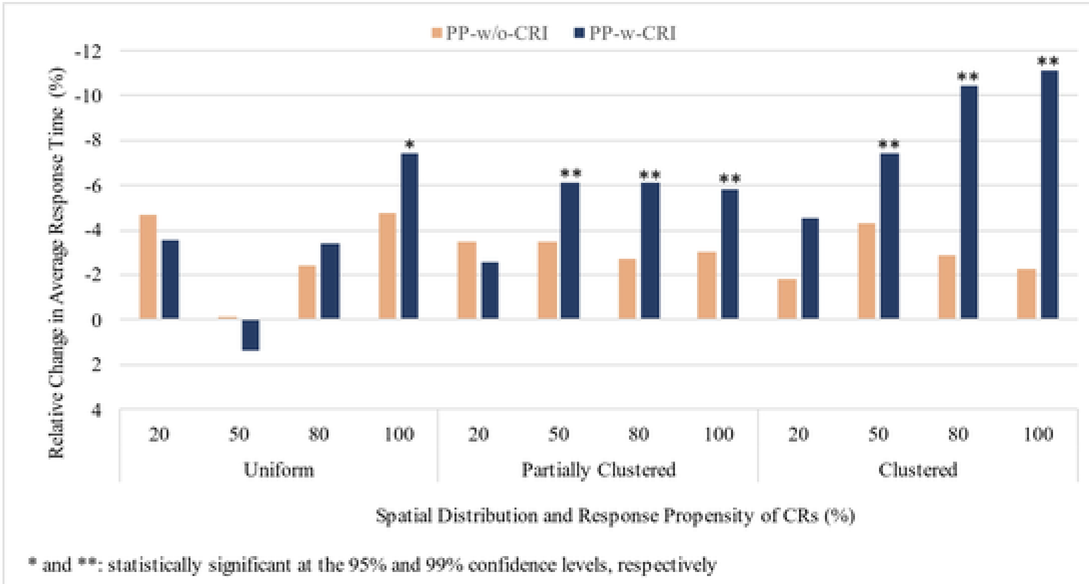

Fig. 5. Relative change in the average response time for critical emergencies over the baseline procedure with respect to spatial distribution and response propensity of CRs.

other two procedures when CRs are relatively more spatially clustered and responsive to critical emergencies. When CRs are more clustered, PP-w-CRI tends to dispatch ambulances in zones that have more CRs while leaving ambulances in zones with fewer CRs. This tendency would push the system to a more balanced distribution of servers (ambulances and CRs), resulting in lower response time to critical emergency in comparison with the other procedures that do not consider CR information.

Fig. 5 and Table 2 show more reduction in the average response time of PP-w-CRI compared to PP-w/o-CRI, ranging from 2.63% to 8.86%. In all cases but one, the PP-w-CRI leads to reduction in response time. The slight increase, which occurs in the case where CRs are uniformly distributed and have a response propensity level of 50%, is nevertheless not statistically significant as indicated by the p-value of the paired-sample *t*-test. This is likely due to the noise introduced to the simulation-based comparison. Among the statistically significant cases, the outperformance of PP-w-CRI is more noticeable and reliable under the following conditions: 1) when CRs are spatially clustered in the service area and their response propensity levels are 50% or higher; or 2) when CRs are uniformly distributed and they are quite responsive to emergencies that appear in their neighborhood. It is also worth pointing out a slight increase (2.12%) in the response time difference for non-critical emergencies. However, this may be less harmful to the whole EMS system with marked response time reduction among critical emergencies, which require substantially more care resources if not attended sooner. However, a statistically significant increase among non-critical emergencies does not occur often (2 out of 15). Note that when the response propensity level is zero, the two procedures are identical, so there is no difference in performance.

Next, we assessed the robustness of the two priority-differentiated dispatch procedures outperforming the closet dispatch procedure for critical emergencies. Table 3 reports the percentage of 150 cases (combination of propensity level and demand profile) with a reduced response time against the benchmark. The table also reports the relative time changes, both in terms of its average and range, but only for cases with a time reduction. Table 3 also shows that PP-w-CRI outperforms the baseline procedure more often than PP-w/o-CRI. In addition, PP-w-CRI more likely outperforms PP-w/o-CRI with partially and completely clustered CRs.

In summary, our results show that PP-w-CRI is more reliable than PP-w/o-CRI in system performance improvement, and its average reductions are more significant. In addition, our results show that when CRs are more clustered and their response propensity level decreases, the response time worsens in general, but PP-w-CRI is less sensitive to this worsened performance.

4.4. *Managerial insights and practical limitations*

In this study, we have evaluated the performance of a CR + EMS system under different dispatch procedures and with respect to diverse spatial distributions and response propensity levels of CRs. We found that:

- Under a CR program, response time reductions for critical emergencies are sensitive to the spatial distribution and response propensity of CRs. The most marked reductions occur when CRs are uniformly distributed and they have a high response propensity level. The least marked reductions occur when CRs are more clustered and their response propensity level is low.
- A CR program can lead to substantial reductions in response time for critical emergencies. When compared to the configuration with no CR program in place and using the closest dispatch procedure, the program implementation together with either of the two dispatch procedures, namely PP-w/o-CRI and PP-w-CRI, can lead to about 20% reduction in response time even in scenarios with low level of responsiveness (e.g., 20%) and unbalanced spatial distribution (e.g., clustered). The best scenario (responsiveness of 100% and uniform spatial distribution) showed a reduction above 60%, by either procedure.
- The proposed PP-w-CRI dispatch procedure yields lower response times for critical emergencies by intelligently utilizing the real-time information of CRs. The computational results suggest that PP-w-CRI can lead to at least equal results in response time in comparison to the baseline and PP-w/o-CRI procedures, and moreover, leading to significantly lower response times in case where CRs are highly responsive and spatially clustered.

However, the following practical limitations should be noted:

- Implementation of the PP-w-CRI procedure would require to setup a reliable and fast communication network to enable real-

Table 2
Summary of relative change in average response time over the baseline procedure with respect to spatial distribution and response propensity of CRs – significant differences are shaded.

Response Propensity (%)	μ PP-w-CRI (%)	μ PP-w/o-CRI (%)	μ PP-w-CRI (%) – μ PP-w/o-CRI (%) (95% Confidence Interval)		P-Value
Critical Emergencies					
Uniform					
0	-3.22	-3.22			
20	-3.57	-4.72	1.15	(-2.27, 4.57)	0.4976
50	1.41	-0.13	1.53	(-3.20, 6.26)	0.5130
80	-3.37	-2.43	-0.94	(-5.20, 3.32)	0.6556
100	-7.41	-4.78	**-2.63**	(-5.49, 0.23)	0.0702
Partially Clustered					
0	-3.67	-3.67			
20	-2.57	-3.48	0.91	(-1.72, 0.05)	0.4861
50	-6.12	-3.44	-2.68	(-4.45, -0.57)	**0.0041**
80	-6.16	-2.75	-3.42	(-5.45, -5.75)	**0.0018**
100	-5.82	-2.99	-2.83	(-4.83, -6.69)	**0.0070**
Clustered					
0	-2.63	-2.63			
20	-4.57	-1.77	-2.80	(-5.64, 0.05)	0.0536
50	-7.41	-4.31	-3.10	(-5.63, -0.57)	**0.0181**
80	-10.48	-2.86	-7.62	(-9.48, -5.75)	**0.0000**
100	-11.14	-2.28	**-8.86**	(-11.03, -6.69)	**0.0000**
Non-Critical Emergencies					
Uniform					
0	57.10	57.10			
20	58.98	56.87	2.12	(0.75, 3.48)	**0.0036**
50	57.26	56.75	0.51	(-1.20, 2.22)	0.5456
80	57.31	56.93	0.38	(-1.56, 2.32)	0.6933
100	58.90	57.73	1.18	(-0.41, 2.77)	0.1392
Partially Clustered					
0	57.09	57.09			
20	57.82	56.65	1.18	(-0.51, 2.30)	0.1644
50	57.94	57.54	0.40	(-1.58, 2.04)	0.6810
80	58.37	56.53	1.84	(-0.05, 1.54)	0.0564
100	59.52	57.43	2.10	(0.48, 3.19)	**0.0127**
Clustered					
0	57.39	57.39			
20	58.05	57.64	0.41	(-1.48, 2.30)	0.6601
50	56.92	56.56	0.36	(-1.32, 2.04)	0.6668
80	57.23	57.03	0.20	(-1.14, 1.54)	0.7629
100	57.73	56.68	1.05	(-1.09, 3.19)	0.3232

time decision making and information exchange between CRs and the EMS dispatcher.

- PP-w-CRI needs access to detailed historical data of CRs, which requires their consent, and be appropriately stored and protected from leaks or cyber-attacks.
- The PP-w-CRI applicability should be limited to emergencies that CRs have been trained to attend, and happening in public spaces. This is because public spaces are more accessible than residential areas. Allowing CRs to access residences and help someone in distress would require further differentiation on individual CRs' capability. Therefore, such requests would only be assigned to a subset of "star" CRs.
- In a CR + EMS system, reliable reports of emergencies are demanded when considering dispatch of CRs. False alarms have long been a common issue in all EMS systems, but a CR program would likely be more prone to the resultant disruptions. Dispatching CRs to false alarms could easily discourage their volunteer participation in the program.

5. Conclusions and Future Work.

In this paper, we study an emerging context of EMS logistics where conventional EMS is augmented by the volunteer involvement of citizen responders in providing first aid to a subset of emergencies deemed critical. This is an application of logistic coordination in service systems with controlled agents (ambulances) together with crowdsourced agents (CRs). We extend an ambulance dispatch procedure to CR + EMS systems with consideration of the spatial location and response propensity of CRs. Results from a discrete event simulation confirm the significant advantages of the new procedure in comparison with a procedure without considering information about CRs and the closest ambulance dispatch procedure. Insights from our simulation study on the outperformance of our procedure with respect to the spatial distribution and response propensity of CRs can help to design the CR programs.

Future work can be oriented towards the design of a more flexible dispatch procedure on prioritization of critical patients. Dealing with the trade-off between critical and non-critical emergency response times can be a plausible extension. Additionally, even though the proposed procedure provides an abundant amount of cases with response time reduction in comparison with the closest procedure, there is still room for improving the dispatch procedure design especially under a changing environment. In this case, machine learning techniques could be a plausible option to alleviate the potential computational burden encountered in real-time decision making. Alternatively, we plan to formalize the sequential decision problem with a Markov Decision process model and solve it offline to benchmark the system performance.

Table 3
Outperformance robustness of the two procedures.

	Percentage of cases with time reduction vs baseline (%)	Average response time change (%) *	Range (%) *
Uniform			
PP-w-CRI	64.7	-9.7	(-28.60, -0.08)
PP-w/o-CRI	65.3	-8.9	(-28.43, -0.08)
Partially Clustered			
PP-w-CRI	**81.3**	-6.8	(-19.17, -0.13)
PP-w/o-CRI	66.7	-6.5	(-20.79, -0.20)
Clustered			
PP-w-CRI	**81.3**	-9.6	(-24.13, -0.28)
PP-w/o-CRI	66.7	-6.3	(-18.75, -0.03)
Overall			
PP-w-CRI	**75.8**	-8.6	(-28.60, -0.08)
PP-w/o-CRI	66.2	-7.2	(-28.43, -0.03)
Cases of time reduction, PP-w-CRI vs PP-w/o-CRI (%)			
Uniform	51.6		
Partially Clustered	**67.6**		
Clustered	**81.5**		
Overall	**67.8**		

* Only for cases with time reduction against the baseline procedure.

CRediT authorship contribution statement

Juan Camilo Paz: Conceptualization, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. **Nan Kong:** Methodology, Investigation, Writing – original draft, Writing – review & editing. **Seokcheon Lee:** Methodology, Investigation, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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