In our opinion, a good forecasting model is a key feature to provide an efficient and effective EMS management. A counter-intuitive example – which supports our remark – is discussed in Aringhieri et al. [132]. In this paper, the authors show that demands that heavily fluctuate in time and space can lead to managerial solutions that worsen the EMS performance even if more resources are used. The literature mostly deals with demand forecasting, i.e., how call volumes vary over time and space. However, only few contributions are available on forecasting travel times and workload.

7.1 Forecasting the demand

One of the earlier models, proposed by Hall [149], uses basic statistics in order to determine daily demand. Its main shortcoming is the lack of accounting for daily or weekly trend data, or other causal factors. Aldrich et al. [150] develop a model capable to predict the total demand using a large set of independent variables reflecting socio-demographic characteristics using least squares regression. Other regression models were developed by Siler [151] and Kvalseth and Deems [152]. Recently, McConnel and Wilson [153] developed a regression model that takes the age distribution of the population into account.

Another stream of forecasting models are those based on time series, which are able to overcome some weaknesses of regression techniques. Baker and Fitzpatrick [154] propose a Winters exponential smoothing model whose optimal parameters are defined through a goal programming model. The model is able to combine the forecast of emergency calls with *routine calls*, i.e., non-urgent calls. Channouf et al. [155] develop and compare several time series models to generate daily and hourly forecasts of EMS calls in Calgary, Alberta. The authors' objective is to provide a simple and effective model that can be used to develop effective simulation models.

Setzler et al. [156] are the first to recognize that EMS demand depends on the day of the week and the time of day. They develop an artificial neural network to forecast demand volume for specific areas during different times of the day. The forecasted demand is compared with current practice to determine the accuracy of the prediction.

The paper by Vile et al. [157] aims at exploring new methods to produce accurate forecasts. The authors propose a non-parametric technique for time series analysis known as singular spectrum analysis. The model – tested on data provided by the Welsh Ambulance Service Trust – produces superior long-term forecasts and comparable short-term forecasts to well established methods.

An alternative method is presented by Micheletti et al. [158]. The authors assume that the time and location of an emergency call are outcomes of a space-time marked point process. They estimate the process intensity by exploiting a rich database covering three years, from 2005 to 2007. Further, they relate the daily number of emergency call to various exogenous variables.

Since the problems discussed in Section 2 are NP-hard, a common practice is to aggregate demand points in order to reduce the computational burden. Aggregation makes the size of the problem more manageable, but may also reduce the quality of the solution when applied in practice. Identifying and controlling this quality loss is the subject of the study reported in [159]. Considering the importance of covering models in emergency location problems, Emir-Farinas and Francis [159] develop aggregation methods supported with a priori error bounds, which facilitate the identification and control of errors in covering location models. A survey of different aggregation approaches has been reported in Francis et al. [160] where Francis et al. provide a framework for different aggregation approaches applied to various location models, including covering, p-median, and p-center models. This study also discusses the efficiency and inefficiency of different aggregation error measures via a comparative study.

EMS data is a classical example of a spatio-temporal dataset. In these kind of datasets, it is possible to define a path in its embedded spatio-temporal framework. Examples of such paths are the sequence of the calls served by an EMS vehicle or the sequence of emergency calls in a given area. The analysis of such paths could lead to the detection of interesting sub-paths in spatio-temporal data [161], where not only the spatial features are considered but also time. As a result, the most frequently used sub-paths could provide evidence for a lack of coverage and, as a consequence, the need to restructure the EMS vehicle deployment. Further, regional co-location patterns (representing collections of feature types frequently located together in certain localities or regions [162]) could constitute a characteristic rule that is only valid in the detected regions and not in the overall dataset. These patterns might form the basis of a classification rule that can be used to identify a class of interesting situations (such as for the prediction of emergency situations with a high demand of healthcare services). Finally, the combination of spatial analysis with data mining techniques can identify regions or districts with a high level of demand, as in [163]. This can be determined by analyzing the districts with respect to their geographical neighborhood and the uniformity of the geographical features distribution in the space. Based on this spatial model, data mining might allow the development of a prediction system for emergency demand, i.e., to identify the most likely region from where the next emergency request could arrive.

We remark that, in most EMS relocation and dispatching models, demand is considered as discrete points in space. However, it is more realistic to consider the problem space as a network in which the emergency requests arrive both on the links and the nodes [78]. Therefore, an extension of demand forecasting models dealing with this issue will be welcomed. Although some researchers have addressed the demand aggregation problem by bounding it or removing some of the factors causing aggregation errors, this problem is worth to be studied in more detail (see Goldberg [3]).
Combining spatial analysis and data mining in EMS modeling could help to identify the most likely region from where the next emergency request could arrive. Such a forecasting tool could improve real-time EMS fleet management. To the best of our knowledge, there is no literature on the application of such techniques to EMS systems.

7.2 Forecasting travel times and workloads

The first model aimed at forecasting travel times was developed by Kolesar et al. [164]. They propose a model for fire engines, which was validated by a field experiment. Their main finding is that regional traffic conditions and hourly variations have only minor effects on average travel times.

Alanis et al. [56] estimate the dependence of travel times on distance by using data of high-priority calls in Calgary, Alberta. The EMS system is represented as a two-dimensional Markov chain model and EMS vehicle redeployment is included by using a compliance table policy as discussed in Section 3. First, Alanis et al. prove that the mean fire engine travel times reported in [164] are a valid and useful description of median ambulance travel times through a non-parametric estimate of the median and coefficient of variation. Then, they propose a new specification for the coefficient of variation, which decreases with distance. The validated model is capable to provide accurate estimates of the travel time distribution, the distribution of the number of busy ambulances, and other system performance measures. The results of the model largely depends on the compliance table used, and therefore, the authors emphasize the importance of a good redeployment policy.

Westgate et al. [165] propose an innovative approach to evaluate travel times based on a Bayesian model that uses global positioning system (GPS) data from the Toronto EMS system. The paths, travel times, and parameters of each road segment travel time distribution are estimated simultaneously by using Bayesian data augmentation. They also consider two simpler estimation methods based on GPS speed data. The proposed approaches outperform estimates from alternative methods and their robustness with respect to GPS location errors. Finally, as in [166], the authors construct probability-of-coverage maps for ambulances.

Workload is concerned with how long an ambulance and its crew are occupied with a call. As discussed in [8], workload is a service time that could largely influence the performance of an EMS system. For instance, ambulances with non-urgent patients can wait longer than average when an ED is overcrowded which has an impact on the EMS system as discussed in [56].

> To the best of our knowledge, workload forecasting has not yet been discussed in the EMS literature. This research could take inspiration from similar work in the hospital setting as the one discussed by Kc and Terwiesch [167].

8 Workforce Management

Workforce management is closely related to personnel scheduling and rostering (see, e.g., Ernst et al. [168, 169]). In healthcare, the nurse scheduling problem is probably the most studied problem in the field of workforce management (see review of Cheang et al. [170]). Even though many models have been published in this field, the application of these models in practice is limited as argued by [171]. However, there are only a few papers that consider workforce management in the field of EMS systems.

Bradbeer et al. [172] use an evolutionary algorithm approach to determine an acceptable roster for the EMS vehicle crew duties while assuming that the number and locations of the EMS vehicles are given. In contrast, other authors deal with both the crew rostering problem and EMS vehicle location problem. Erdogan et al. [173] apply a neighbourhood search to locate EMS vehicles and use the solution found as input for two integer programming models to solve the crew rostering problem. Vile et al. [174] propose interrelated advanced statistical and operational research methods to recommend minimum staffing requirements and generate low-cost rosters. Rajagopalan et al. [175] also present a two-stage approach for crew rostering and EMS vehicle location planning. In the first stage, they solve a dynamic expected coverage model using tabu search while an integer programming model is presented in the second stage to solve the crew rostering problem. Finally, Li and Kozan [176] propose two-stage models that use non-linear integer programming techniques. In the first stage, shift start times and the number of staff required to work during each shift are determined. The results of the first stage are used as input for the second stage, which determines a balanced scheduled for the EMS vehicle crew.

In this section, we consider a new approach for workforce management in healthcare and its possible application to the management of personnel employed along the ECP by using demand forecast.

A new way of thinking and of organizing health care delivery is to focus on the patient instead of on facilities. A patient-centered approach to health care means to deliver a service which is "*closely congruent with and responsive to patients' wants, needs, and preferences*" [177]. In May 2004, the International Alliance of Patients' Organizations (IAPO) conducted a consultation with its member patients' organizations in order to investigate which health care policy issues were most important to them. The final report showed that 74% of the respondents indicated that "*defining patient-centered healthcare was very relevant to their organization*" [178]. Along the lines of patient-centered health care delivery, approaches for medical workforce management that guarantee efficiency and fairness of the delivered services becomes crucial as pointed out by Aringhieri [179].

Usually, health care is delivered by a team of individuals who work together and who share knowledge, experiences and skills. As reported in [180], higher patient volumes lead to superior outcomes for hospitals, teams of physicians and single physicians. Similar insights are discussed by Grantcharov et al. [181] who reports the learning rate for laparoscopic skills when trained on a virtual reality system. McIntosh and Sheppy [182] argue that skill maximization (e.g., increasing the responsibilities of healthcare practitioners) is the key to increase productivity and quality of care. They also argue that an improvement in the output (number of cases treated) and quality of care is not just necessary, but essential. Because of this, McIntosh and Sheppy conclude that maximizing the use of human resources is key in the future of health care.

In order to increase the responsibilities of healthcare practitioners, we need to measure the efficiency of individuals and teams with respect to the service demand. Various metrics can be used to measure the efficiency of one individual (such as the number of patients visited per hour, the volume of surgical patients per year, the probability of making an incorrect decision, etc.). These measures can be used to evaluate the overall team performance with respect to the service demand forecast. Actually, a good demand prevision plays a fundamental role when health care managers want to guarantee the efficiency and fairness of the provided service. Demand forecast is crucial in the work of Feyter [183, 184], where the author focuses on the long-term supply of employees in a company based on forecasted needs of recruitments, lay-offs and retraining of the current workforce.

In [185], Addis et al. deal with managing the personnel working at the operation center of the EMS system of Milano by taking demand forecast into account. The staff members work together in teams according to predefined shift patterns. The considered problem consists in assigning individuals to teams and teams to shifts while providing the best service to citizens by guaranteeing the needed number of operators with respect to the demand forecast. The authors provide mixed integer linear programming models solved by a general purpose solver.

Outside the field of health care, there are a few papers that consider, in some way, demand forecast in their planning. Billionnet [186] discusses scheduling a hierarchical workforce with variable demands under the restriction that a higher qualified worker can substitute a lower qualified one, but not vice versa. An ILP model has been proposed which is solved using a general purpose solver. In [187, 188], Atlason et al. consider the problem of minimizing staffing costs in an inbound call center while maintaining an acceptable level of service in multiple time periods. The staffing level in one time period can affect the service levels in subsequent periods. The authors present an iterative cutting plane method for minimizing staffing costs in a service system which must meet service level requirements over multiple time periods. Furthermore, it is assumed that the service level cannot be computed a-priori, and thus, it is evaluated using simulation. More recently, Gurvich et al. [189] address the problem of staffing call centers with multiple customer classes, agent types operating under probabilistic quality-of-service constraints, and uncertainty in demand rate. The proposed formulation of the problem is solved by a two-step solution method. In the first step, a random static planning problem is solved which provides an approximation of the optimal staffing levels and a staffing frontier. In the second step, a finite number of staffing problems is solved with arrival rates provided by the staffing frontier of the first step. The output of the procedure is a solution that is feasible with respect to the chance constraints. For large call centers, the solution method provides near-optimal solutions.

Including demand forecast in workforce management poses several challenges. In many real-life settings, teams have to be composed in a fair manner (see [185]) to guarantee a (quasi) constant quality of health service. This opens the debate (already introduced in Section 2.1 for the location problems) on how fairness should be incorporated when assigning shifts to medical crews. From a methodological point of view, the problem of composing teams has an intrinsic stochastic nature that should be addressed by adopting unconventional approaches as discussed in Aringhieri et al. [190].

9 Big EMS, big data, big challenge

In the previous sections, many challenges were highlighted such as those arising when dealing with the problem of incorporating equity and uncertainty aspects, the need for reliable forecasts and new methodological hybridizations.

In our opinion, the biggest challenge is to adopt a holistic outcome-based approach for the ECP, which should be conceived as a methodology that details all decisions, treatments, and reports related to a patient. From this point of view, one of the main difficulties is the collection of information regarding all events involving the patient before, during and after the EMS intervention. Usually, EMS systems collect a large amount of data, but this does not include data on what happens before and after the involvement of an EMS vehicle. Therefore, the main challenge is to develop new reliable models (probably hybrids and supported by new ICT solutions) that are capable to represent the inherent complexity behind the definition of an ECP.

Focusing on the ECP means to shift the attention from the EMS system to the whole Emergency Care Delivery System (ECDS) in order to enhance the quality of care, which will improve patient outcomes, promote patient safety, increase patient satisfaction, and optimize the use of resources. In this respect, the interplay between the EMS system and other stakeholders of the ECDS plays a crucial role. Due to budget cuts, this challenge is faced by reorganizing the EMS system to better exploit the availability of other resources or by taking advantage of economies of scale. In the first case, especially in North America, the idea is to involve firemen services, which usually have low utilization rates: after a training, it will be possible to use firemen to provide ELS until a BLS provider arrives at the scene. In the second case, especially in Europe, the idea is to merge several EMS systems into one organization. Apart from economies of scale, another benefit of this is that it solves the problem of dealing with emergency requests arising from contiguous EMS systems.

One of the main consequences of taking the whole ECDS into account could be the need to analyze large amounts of data from different data sources. Smart cities are more and more connected, which provides interesting information such as real-time traffic conditions. Another example is related to the ED workload: to deal with ED overcrowding, ICT solutions are used that provide real-time information on the ED workload. An experimental project on this subject is ongoing in the Piedmont region in Italy. Therefore, the *big challenge* is to connect the obtained data with the EMS systems to deliver more effective and efficient emergency care.

As an example, consider the development of a new dispatching decision support system. Such a system should at least deal with the following decisions. The first decision is to dispatch an EMS vehicle that can reach the patient in time and that reduces the overall coverage of the region the least. To support this decision, the spatial analysis discussed in Section 7 could be fruitfully used. The quality of this analysis is expected to be high, because accurate data is available. The second decision is to select the most appropriate ED to transport the patient to. For instance, in case of a non-urgent request, the dispatcher can select the ED with the lowest workload among the nearest EDs to evenly distribute the workload. The possibility of selecting non-overcrowded EDs may be crucial in the case of urgent requests. Finally, the third decision encompasses the positioning of the EMS vehicle after serving an emergency request. Again, a good forecast, in particular in combination with a spatial analysis, could be crucial in indicating the least covered area given the expected emergency demand. To some extent, this decision is connected with the second decision, i.e., the dispatcher can select a specific ED to cover the area around this ED after the patient is transported to the hospital. It is evident that the exploitation of real-time traffic information is crucial when determining the set of the "nearest" EMS vehicles or EDs.

Glossary. In this paper, we have used several acronyms. To help the reader, we list them here, in alphabetical order: Advanced Life Support (ALS), Agent-Based Simulation (ABS), Approximate Dynamic Programming (ADP), Automated External Defibrillator (AED), and Basic Life Support (BLS), Clinical Pathway (CP), Discrete Event Simulation (DES), Double Standard Model (DSM), Dynamic DSM at time t (DDSM^t), Emergency Care Delivery System (ECDS), Emergency Care Pathway (ECP), Emergency Department (ED), Emergency Life Support (ELS), Emergency Medical Service (EMS), European Emergency Data Project (EED), Fuzzy Goal Programming (FGP), Geographical Information System (GIS), Global Positioning System (GPS), Health Technology Assessment (HTA), Hypercube Queueing Model (HQM), Low-Priority Calls Coverage (LPCC), Markov Decision Process (MDP), Maximal Covering Location Problem (MCLP), Maximal Covering Location Problem including Probabilistic Response times (MCLP+PR) Maximal Expected Coverage Relocation Problem (MECRP), Maximum Availability Location Problem (MALP), Maximum Expected Covering Location Problem (MEXCLP), Maximum Expected Covering Location Problem including Probabilistic Response times(MEXCLP+PR), Maximum Expected Covering Location Problem Probabilistic Response times and Station Specific Busy Probabilities (MEXCLP+PR+SSBP), Mixed Integer Program (MIP), National Health Service (NHS), Queueing Maximum Availability Location Problem (Q-MALP), Queueing based Probabilistic Location Set Covering Problem (Q-PLSCP), Response Time (RT), Response Time Threshold (RTT).

Acknowledgements. The authors would like to thank the numerous colleagues who suggested useful references. In particular, we would like to thank Rosa Meo to help us in identifying the link between data mining techniques and EMS forecasts, Vito "Franco" Fragnelli for his useful suggestions in the field of game theory, Derya Demirtas for introducing the authors to the AED location problem and Angela Testi and Elena Tànfani for introducing the authors to the Health Technology Assessment. Further, the authors would like to thank the anonymous reviewers for their really accurate work and for providing such useful suggestions, which really improved the quality of this review.

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