A Method for Projections of the Emergency Department Behaviour by Non-Communicable Diseases From 2019 to 2039

Elham Shojaei, Alvaro Wong, Dolores Rexachs, Francisco Epelde, and Emilio Luque

***Abstract*—In this paper, a new method for prediction of future performance and demand on emergency department (ED) in Spain is presented. Increased life expediency and population aging in Spain, along with their corresponding health conditions such as non-communicable diseases (NCDs), have been suggested to contribute to higher demands on ED. These lead to inferior performance of the department and cause longer ED length of stay (LoS). Prediction and quantification of behavior of ED is, however, challenging as ED is one of the most complex parts of hospitals. Using detailed computational approaches integrated with clinical data behavior of Spain's ED in future years was predicted. First, statistical models were developed to predict how the population and age distribution of patients with non-communicable diseases change in Spain in future years. Then, an agent-based modeling approach was used for simulation of the emergency department to predict impacts of the changes in population and age distribution of patients with NCDs on the performance of ED, reflected in ED LoS, between years 2019 and 2039. Results from different projection scenarios indicated that Spain would experience a continuous increase in total ED LoS from 5.7 million hours in 2019 to 6.2 million hours in 2039 if same human and physical resources, as well as same ED configuration, are used. The results from this study can provide health care provider with quantitative information on required staff and physical resources in the future and allow health care policymakers to improve modifiable factors contributing to the demand and performance of ED.**

***Index Terms*—Agent based modeling, population aging, projection of emergency department, non-communicable disease, simulation.**

I. Introduction

EMERGENCY Department (ED) is the main entrance for patients in the healthcare system and should provide 24-hour services, 365 days a year, to people experiencing medical conditions, trauma, or injury. Patients usually visit ED without an appointment and are expected to receive services and treatment. Overcrowding, and its resultant pressure on ED, is a global problem leading to increased ED waiting times and hence decreased quality of services, poor clinical outcomes, and patients' dissatisfaction [1] and [2]. An inferior performance of ED reduces efficiency of the whole healthcare system and is a threat to patients' safety. The quality of care in ED is often evaluated using ED length-of-stay (LoS), which is calculated from when a patient arrives at ED to the time they depart from the ED [3]. LoS is the most extensively used and accepted index in literature for ED service quality and performance such that a longer LoS can be an indicator of growing demand of ED and insufficient resources or delayed service delivery and inefficient use of resources [4] and [5]. Increased life expediency and population aging, along with their corresponding health conditions, have been recognized to contribute to higher demands on ED and healthcare system, leading to a longer LoS.

Non-communicable diseases (NCDs) are the leading cause of disability and death. When determining global burden of disease, NCDs are categorized as one of the emergency conditions and reasons for visiting ED and healthcare system. It has been reported that the incidence of non-communicable diseases increase with age such that ageing is a dominant predictor of death for NCDs in rapidly aging regions [6]. In addition to more frequent readmission of the elderly in healthcare system that causes overcrowding in ED (Fig. 1(a)), the elderly needs more medical tests (Fig. 1(b)) and consultation (Fig. 1(c)) leading to a higher burden on ED and longer LoS (Fig. 1(d)) [7] and [8].

Spain is experiencing population aging and reported to be the world's oldest country by 2050, with about 30% of its population being aged over 65 years [9]. In Spain, NCDs have increased from $\sim$ 85.8% in 2007 to $\sim$ 87.8 % in 2017 resulting in increases in NCDs-related mortality/disability from 91.6% to 92.4% [10] and [11]. As such, it is predicted that NCDs-related mortality/disability further increase by 2050 as Spain experiences population aging. Management of ED for timely and appropriate primary care and efficient use of medical resources is vital to provide patients with satisfactory services and achieve best clinical outcomes in minimum LoS. ED, however, is one of the most complex parts of hospitals to manage as several unpreventable and unpredictable contributing factors are involved in designing ED managing system [12]. In recent years, many studies have

Manuscript received September 25, 2019; revised January 15, 2020, February 21, 2020, and April 16, 2020; accepted April 17, 2020. Date of publication May 11, 2020; date of current version September 3, 2020. This work was supported by the MICINN/MINECO Spain under Contract TIN2014-53172-P and in part by the Agencia Estatal de Investigación, Spain and the Fondo Europeo de Desarrollo Regional UE, under Contract TIN2017-84875-P and in part funded by a research collaboration agreement with the Fundacion Escuelas Universitarias Gimbernat (EUG). *(Corresponding author: Elham Shojaei.)*

The authors are with the Computer Arcitecture and Operating System, Universitat Autonoma de Barcelona, Barcelona 08193, Spain (e-mail: elham.shojaei@e-campus.uab.cat; alvaro.wong@uab.cat; dolores.rexachs@uab.cat; fepelde@tauli.cat; emilio.luque@uab.cat).

Digital Object Identifier 10.1109/JBHI.2020.2990343

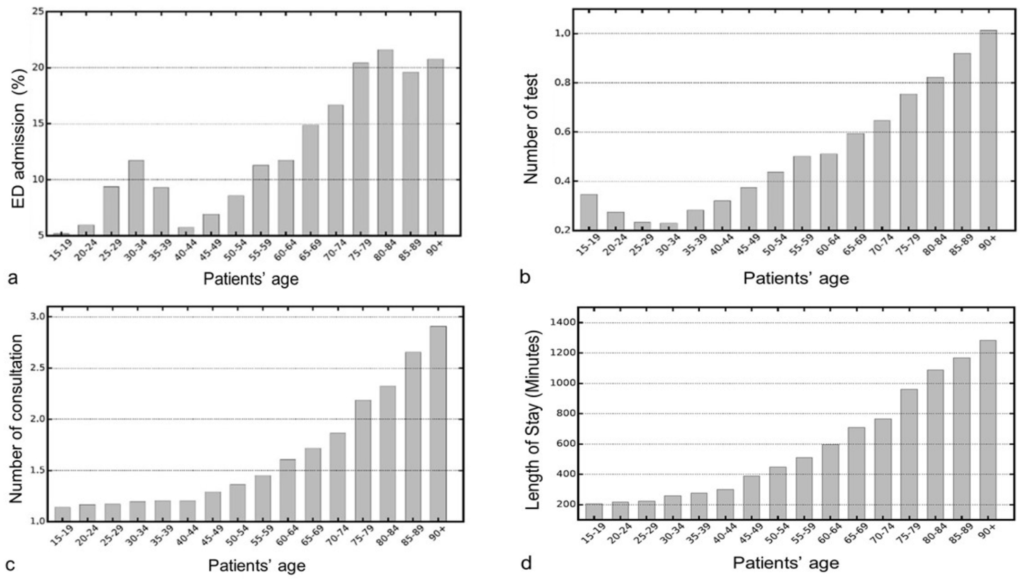

Fig. 1. Histograms of patients' ages versus: Total hospital admission (a), average medical-tests (b), and average consultations (c), and Average Length of Stay (d). Data collected from Parc Tauli hospital in Sabadell/Spain [8].

been conducted to provide Spanish hospital managers with new executive and management strategies to improve performance, efficiency, and quality of service in hospitals [13] and [14].

Simulation is a powerful tool that has been used to model, predict, and design ED in order to improve quality of health care system [13]. An ED simulator can take into account various aspects of behavior and capacity of ED to optimize safety and quality of healthcare system. Several modeling approaches including Discrete Event Simulation (DES), Analytic Queuing Models (AQM), System Dynamics (SD), and Agent-based Modeling (ABM) has been used in literature to simulate complex systems like EDs. DES is a traditional established method that has been used in $\sim$75% of earlier ED simulation studies. Compared to AQM and SD methods, DES is more capable to model complex non-linear systems [15]. This method, however, has limitations on modeling of individual entities and their behavior leading to an unrealistic representation of ED [15], [16], [17], [18] and [19]. To overcome such a limitation, in recent years ABM has been used to represent people (e.g., physicians, patients), their behavior, and the environment in which they can operate actively. In this method, a complex system can be modeled as a set of independent entities called agents who can interact with each other, make self-governing decisions, and indicate proactive behavior based on their goals [15], [16], [17], [18] and [19]. Linear and non-linear analyses with different levels of modeling complexities have been used in earlier studies to investigate impacts of patient's behavior, number of ED visits [20], [21] and [8], aging population and NCDs [22], on LoS and ED quality of care [23], [24]. Liu at [21] simulated ED using ABMS where patients were classified according to their level of acuity. In this model, patients, ED staff, and hospital physical resources were agents whose actions and interactions were modeled in the ED simulator. One limitation of earlier ABMS studies is that patients with any types of diseases were considered as a same group of patients so that simulation outcomes could not provide decision-makers with information on a desired group of patients (e.g., NCDs) or specific types of diseases. Furthermore, to the best of our knowledge, the literature is scant on prediction and projection of growth of NCDs in ED in future.

The first objective of this study was to improve an existing agent-based ED simulator [21] by taking into account patients with NCDs, in addition to regular patients, as inputs into the model. Hence, new variables and attributes were added to the patient's agent characteristics of which were obtained through clinical data (collected from Parc Tauli Hospital in Sabadell/Spain and from GDB, WHO) [21] as well as data from statistical models that we developed to predict how population and age distribution of patients with NCDs changes in Spain in future years. The second objective of this study was to use the ED simulator to investigate and predict impacts of changes in population and age distribution of patients with NCDs on ED performance through estimations of LoS between years 2019 and 2039. It was hypothesized that aging of Spain population in future years would impact the number of patients with NCDs and their age distribution Such changes, along with the clinical evidence on the positive relationship between age and LoS in an existing configuration of ED (Fig. 1(d)), further suggested an increase in the saturation of ED and a longer LoS.

In recent years new technologies and innovations have substantially improved care delivery, quality, and outcomes. However, the fast population, social, and economic transformations of the upcoming years will need deployment of advanced tools and technologies that will allow us to lead healthier, longer, and more productive lives while controlling the associated cost and providing everyone across the world with better access to care. The focus of the current study is on prediction of future performance and demand on ED through detailed modeling approaches integrated with statistical learning and clinical

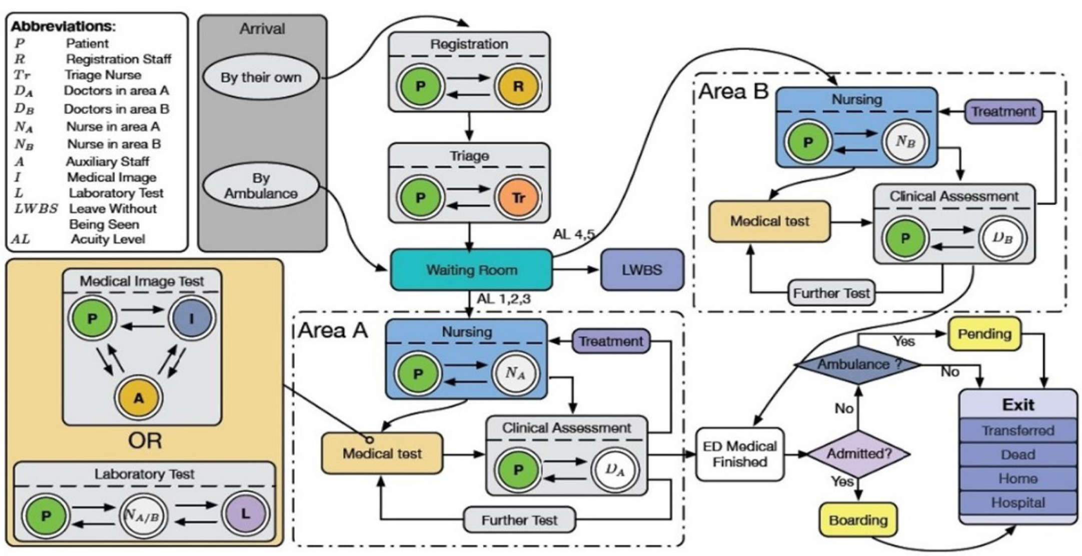

Fig. 2. Workflow of ED and the interaction between its components elements. An agent-based modeling approach is used to simulate the ED where the agents are patients, healthcare staff, and physical resources of ED. Eight service processes (i.e., green circles) drive various aspects of patient flow. There are both independent (registration, triage, diagnosis, and treatment (i.e. nursing and clinical assessment in both areas)) and dependent (medical image test and laboratory testing) service processes, and duration of each service process is different from other processes. Two separate zones have been designed for urgent (zone A) and non-urgent (zone B) patients. Each zone has its own group of staff who work independently from the other group [21].

data. This research can answer several questions in regards to demand and performance of ED in future and provides health care providers with quantitative information on required staff, physical resources, schedule and timing, and optimization of the healthcare processes in ED in coming years. Such efforts are in line with the current efforts and technologies on modelling, scheduling and optimization of healthcare processes for the healthcare 4.0, and contribute to the technologies in health engineering and informatics for the new revolution of healthcare 4.0 by providing information on how ED environment will change in future through the aging population.

II. Emergency Department: Performance and Modeling

A. Agent-Based Modeling of ED

Agent-based models are a class of microscale computational models that simulate operations, actions, and interactions of multiple independent entities (i.e., agents) in an attempt to reproduce and predict the behavior of a complex phenomenon/system as a whole. Our research group has developed and validated a simulator using an agent-based design of system to predict behavior and performance of ED. A detailed description of the simulator and its configuration can be found in [21]. Briefly, in this simulator a spatial agent-based modeling approach has been used to simulate actions and interactions between patients, healthcare staff, and physical resources of ED as the three types of agents in the model. Each agent possess a set of attributes and behaviors, individually assesses its own situation, and makes decisions based on a set of rules [25]. Attributes and behavior of each agent are a function of agent type and interactions between

TABLE I
An Example of an If-Then Rule for Patient's Agent. Patients in ED Are Guided by Information System (IS), Which Is a System for Communicating and Coordinating Among Staff, Patients and Test Room. Patients Go to a Relevant Place to Receive Treatment/Service When They Are Notified or Stay in Their Current Place Otherwise. During the Process in ED, Patients Alternate Between Two States: Waiting (e.g., for a Doctor, Nurse, Medical Testing Service/Result, etc.) or Receiving Treatment/Service

IF	THEN
Notified by IS (before entering treatment area)	Go to the corresponding place as notified
No requests from IS (before entering treatment area)	Keep staying in waiting room
Notified by IS (in area B)	Go to diagnosis room or medical image test-room as notified

agents (Fig. 2). Specifically, the non-linear behavior and actions of agents in our ABM has been characterized by if-then rules based on signals the agents receive: If [signal vector x is present], Then [execute act y]. If an agent is busy with an interaction while a signal is received, the signal will be pushed into its task queue [26]. An example of an if-then rule for patient's agent has been shown in Table I. Patients in the model are divided into 5 acuity levels (ALs) of I-resuscitation, II-emergent, III-urgent, IV- less urgent, and V-non-urgent , according to Spanish triage system [27] and [28]. ALs prioritize incoming patients and identify those who cannot wait to be seen based on patient's condition and resource needs. Patients with a higher AL (level I or II) have a higher priority to receive treatment and/or use physical resources of ED. The triage results of a patient also determines their treatment area in ED. As such, in our model ED is divided into zones A and B (Fig. 2) [21].

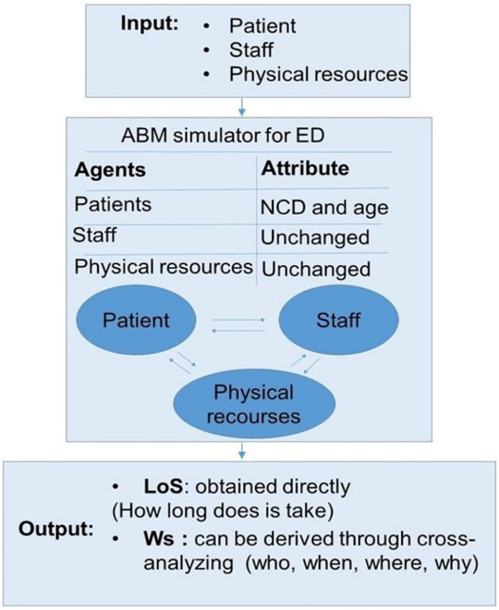

Fig. 3. General workflow of ABM simulator wherein patients, ED staff, and hospital physical resources were considered as agents. NCDs and age distribution were attributed to the patients, and actions and interactions between the agents were modeled in the ED simulator. LoS of ED, as an index of health care quality, was directly obtained from the simulator [21].

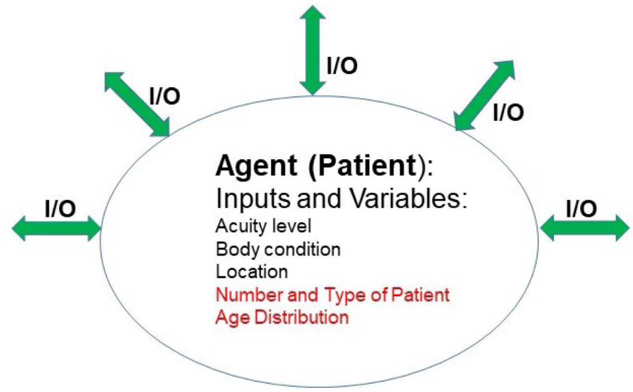

Fig. 4. Inputs (acuity level, body condition, and location) and variables (number and type of patients and their age distribution) of patient's agent into the model. Acuity level involves 5 levels from AL1 (the most sever condition: resuscitation) to AL5 (non-urgent condition). Percentage of ED visits for each acuity level was 0.5%, 5.5%, 30.0%, 51.0%, and 13.0% from AL1 to AL5, respectively. Body condition determines the severity of disease for a patient while receiving treatment. It defines the next service and location for a patient until being discharged from the ED. Location input has a set of possible values (register, triage, waiting room, laboratory, area A, B, etc.) and specifies the current location and next move of a patient based on required services. Number and type (regular or NCD) of incoming patients each year (from 2019 to 2039) and their age distribution (5-year intervals from 15 to 100 years old) were introduced as new variables into the patient's agent. The predictions from statistical modeling were assigned as attributes to these new variables.

Patients with ALs I, II, and III are hospitalized/treated in zone A and stay in their own care-box during all diagnosis and treatment processes whereas patients with ALs IV and V are hospitalized/treated in zone B. For all patients, admission and triage phases are conducted by same nurses and healthcare staff. After triage, in diagnoses and treatment stages, different doctors and assistant nurses serve at each zone while sharing same test service resources such as X-Ray, laboratory test, etc. [21]. https://www.overleaf.com/project/5e9821f5aea68b0001f55001

Outputs of the agent-based simulator are: 1) interaction information of all agents (such as who, when, where, why and how long it takes), and 2) performance information of ED environment including number of waiting patients, utilization of physical resources, and occupation of healthcare staff. Therefore, such information should be provide through cross-analyzing of different simulation scenarios.

In summary, in our ED simulator we used the results in Table IV (age distribution of patients with NCDs for both scenarios) and Table V (percentage/number of patients with NCDs and total number of patients) as inputs into the model for the patient's agent. The general workflow of ABM simulator after implementing new variables and attributes has been shown in Fig. 3

B. Impacts of Patients With NCDs on Behavior of ED

1) Simulation of Patients With NCDs: To investigate the relationship between number of patients with NCDs and pressure on ED, we have tracked and modeled these patients when visiting ED. As soon as a patient (i.e., regular or NCD) enters the healthcare system, the simulation runs according to the patient flow. Each simulation scenario is characterized by a set of Environment Configuration Parameters which are specific inputs of agents into the service. The inputs of patient's agent into the model are composed of acuity level, body condition, and location. Specifically, number and type (regular or NCD) of incoming patients each year (from 2019 to 2039) and their age distribution (5-year intervals from 15 to 100 years old) were introduced as new variables into the patient's agent (Fig. 4). These projection information, and were provided through statistical analysis and statistical modeling of clinical data and the of data from Our World in Data [29] and Spain demography [30] (see sections below). The predictions from the statistical models were then assigned as attributes to the new variables (i.e., number and type of patients and their distribution) of patient's agent in the ASB model. In ED simulator the steps for admission, triage, diagnoses, treatment, and finally discharge of patients with NCDs are similar to those of regular patients. Also, same staff configuration and physical resources are used for both NCDs and regular patients.

III. Projection Scenarios

Since we have taken into account the behavior of patients with NCDs in our ED simulator, we needed to forecast how population and age distribution of patients with NCDs changes in future years. Demographics (2019 to 2040) show that Spain's population is decreasing with a gentle gradient. If the current demographic trends continue, Spain would experience a decrease

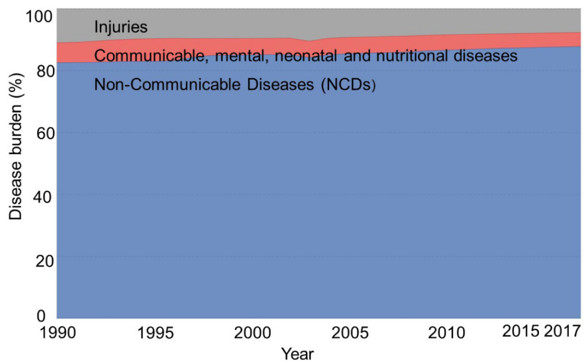

Fig. 5. Total disease burden by cause, Spain (1990–2017). Total disease burden measured as the number of DALYs (Disability-Adjusted Life Years) per year [29].

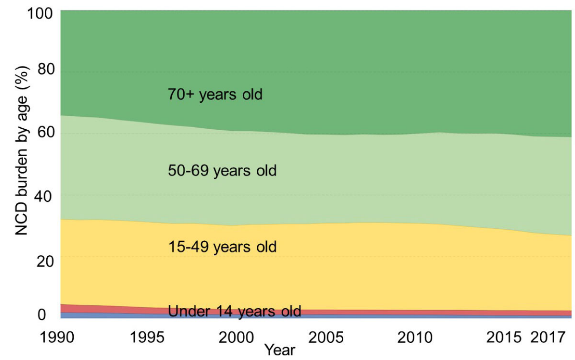

Fig. 6. Disease burden from non-communicable diseases (NCDs) by age. Disease burden is measured in DALYs (Disability-Adjusted Life Years) [29].

of ~ 0.5 million people in the next 20 years (Fig. 13) [30]. On the other hand, as Spain's population is ageing, patients are more likely to have multiple comorbidities and chronic conditions leading to NCDs [31], [32] and [33]. Therefore, gentle decreases in an aging population can result in increases/no changes in number of patients with NCDs and changes in their age distribution in health care system. Analyzing data from Parc Tauli Hospital in Sabadell/Spain [13], [8] indicated that the ED had a total number of 137,757 visits in 2014. We considered this number as the total number of visits in our model and assumed there is trivial variations in the number of patients , and therefore number of visits, from year to year. Other data from Parc Tauli hospital used in our model included the number of arrival patients (hourly, daily and weekly), number of staff, number and type of physical resources, type of interaction and behavior between agents, etc. We have conducted data analyses and constructed optimistic and pessimistic projection scenarios to predict upper and lower ends of percentage of patients with NCDs and their age distribution in future years. The predictions from each scenario were then used as inputs into the ED simulator.

A. Pessimistic Scenario: Increases in Percentage of Patients With NCDs and Changes in Age Distribution

Data from the Our World in Data shows that the number of patients with NCDs has increased from 2010 to 2017 (Fig. 5) [34] and [29].

Using these data and computational methods (see below), it was predicted that the number of patients with NCDs will further increase by 2039. Also, through combining data from Spain demography (Table VI) [30] and disease burden from non-communicable disease by age (Fig. 6), it was predicted that number of patient with NCDs in different age categories (collectively called age distribution hereafter) will change from 2019 to 2039 (see below).

Therefore, a pessimistic scenario with two variables (i.e., more patients with NCDs and changes in age distribution) was considered.

We have used Least Squares Regression to find a line of best fit to data on patients with NCDs from 2010 to 2017 (Fig. 5 and

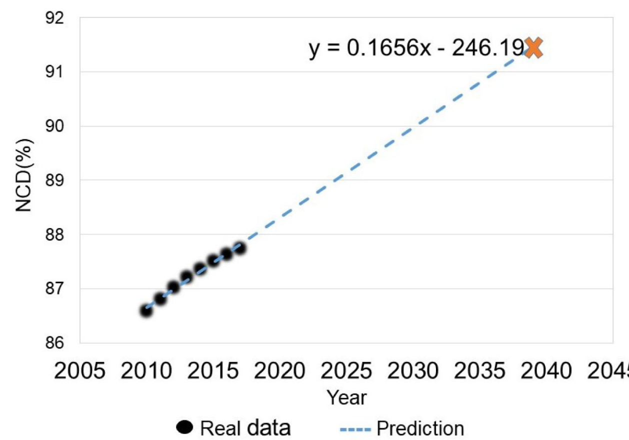

Fig. 7. Projection of percentage of patients with NCDs from 2019 to 2039 in Pessimistic scenario. Least Squares Regression is used to find a line of best fit to data on patients with NCDs from 2010 to 2017 ($R^2 = 0.9851$). The asterisk indicates the upper limit (i.e. 2039) for using the linear regression.

Fig. 7). Mathematically, we can write this linear relationship as:

$$y = \beta_0 + \beta_1 x$$

where x represents the year, y represents percentage of patients with NCDs, and $\boldsymbol{\beta}_0$ and $\boldsymbol{\beta}_1$ are unknown coefficients. To be able to use the linear model to make predictions, we used our data from 2010 to 2017 to estimate the coefficients. We defined the residual sum of squares (RSS) as:

$$RSS = (Y_1 - \beta_0 - \beta_1 x_1)^2 + (y_2 - \beta_0 - \beta_1 x_2)^2 + \cdots + (y_8 - \beta_0 - \beta_1 x_8)^2$$

where (x_1, y_1) to (x_8, y_8) are year-NCD(%) training data points from 2010 to 2017, respectively. Finally, $\boldsymbol{\beta}_0$ and $\boldsymbol{\beta}_1$ were obtained through minimizing the RSS. Mean (SD) of the training data points (2010 to 2017) for NCD values were (87.24%) (0.41%). This line was then used to predict rate of patients with NCDs for every consequent 5 years from 2019 to 2039 (Fig. 7). NCDs by age's data (2010 to 2017) from age categories of 0–14, 15–49, 50–69, and above 70 (Fig. 6) were used [29] to

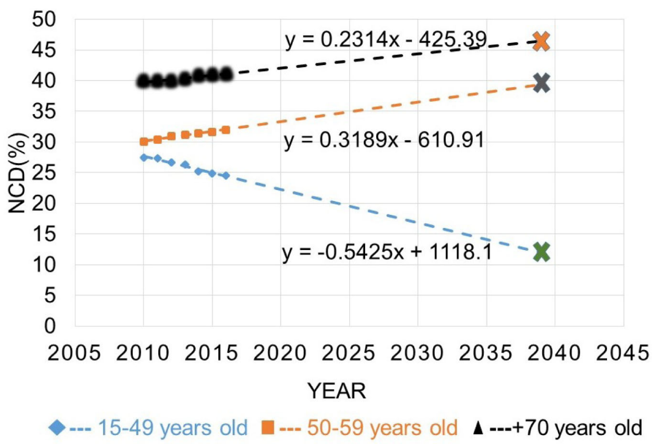

Fig. 8. Projection of percentage of patients with NCDs by age from 2019 to 2039. NCDs by age's data (2010 to 2017) from age categories of 15–49, 50–69, and above 70 were used [29] and [35] to predict same data in future (2019 to 2039). Using Least Squares Regression methods, we estimated the disease burden from NCDs by age for each age categories (R2 equals 0.9746, 0.9812, and 0.8991 for age categories of 15–49, 50–69, and above 70, respectively). Mean (SD) of the training data points (2010 to 2017) for NCDs by age values were 26.21% (1.27%), 30.94% (0.77%), and 40.37% (0.58%) for 15–49, 50–69, and above 70, respectively. The asterisk indicates the upper limit (i.e. 2039) for using the linear regression.

TABLE II
PREDICTED VALUES FOR PERCENTAGE OF PATIENTS WITH NCDS FROM 2019 TO 2039 FOR PESSIMISTIC SCENARIO. THE LINE OF BEST FIT TO DATA ON PATIENTS WITH NCDS FROM 2010 TO 2017 ($y = 0.1656x$–246.19) WAS USED FOR PREDICTIONS

age	2019	2024	2029	2034	2039
NCDs(%)	88.15	89.98	89.81	90.64	91.47

TABLE III
PERCENTAGE OF PATIENTS WITH NCDS FOR EACH AGE CATEGORY FROM 2019 TO 2039 EVALUATED FROM EQUATIONS IN FIG. 8

	NCD(%)		
Age / Year	15-49	50-69	+70
2019	22.79	32.95	41.80
2024	20.08	34.547	42.96
2029	17.37	36.14	44.12
2034	14.6	37.73	45.28
2039	11.94	39.33	46.43

predict same data in future (2019 to 2039). In ED, children have a different department and are treated separately so we considered only patients above 15 years in our model. Similarly, using Least Squares Regression methods, we estimated the disease burden from NCDs by age for each age categories (Fig. 8 and Table III). However, since in our ED simulator, and consistent with Spain demography, we had age categories of 5-year intervals, we accordingly mapped the predicted NCDs by age data (Fig. 8 and Table III) to these intervals (see the algorithm in appendix section).

Our predictions from percentage of patients with NCDs (Fig. 7, Table II) and their age distribution (Table IV) were then used as inputs into the ED simulator. The value for the rest of input parameters including staff configuration (number of staff in each shift) and various physical resources remained unchanged.

TABLE IV
THE PREDICTED NCDS BY AGE FOR 5-YEAR INTERVALS

	NCDs by age: $P(incd)$				
age	2019	2024	2029	2034	2039
15-19	3.10	2.60	2.22	1.80	1.39
20-24	2.85	2.40	2.50	2.04	1.56
25-29	3.16	2.30	2.32	2.29	1.76
30-34	3.54	2.50	2.22	2.12	1.96
35-39	2.85	3.43	2.54	2.08	1.72
45-49	2.85	4.07	3.18	2.33	1.76
50-54	9.64	9.77	9.78	8.52	7.63
55-59	9.03	9.07	9.55	10.22	9.20
60-64	7.81	8.49	8.74	9.98	11.05
65-69	6.46	7.21	8.05	9.00	10.52
70-74	13.27	13.42	14.46	14.51	14.03
75-79	10.73	11.54	11.27	11.91	12.45
80-84	8.19	8.32	8.82	8.66	9.28
85-89	6.21	5.63	5.63	6.06	5.92
90-94	2.54	3.22	2.94	3.03	3.35
95-100	0.84	0.80	0.98	0.86	1.18
100+				0.21	0.19

TABLE V
THE TOTAL NUMBER OF PATIENTS (PARC TAULI HOSPITAL, 2014) AND PERCENTAGE/NUMBER OF PATIENTS WITH NCDS FROM 2019 TO 2039. THE TOTAL NUMBER OF PATIENTS WAS ASSUMED TO REMAIN UNCHANGED. TOTAL NUMBER OF PATIENT: NO. OF PATIENT, PS: PESSIMISTIC SCENARIO, OS: OPTIMISTIC SCENARIO

Year	2019	2024	2029	2034	2039
No. of patients	137757	137757	137757	137757	137757
NCD (%): PS	88.15	89.98	89.81	90.64	91.47
No. of NCD: PS	121433	123954	123719	124863	126006
NCD (%): OS	88.15	88.15	88.15	88.15	88.15
No. of NCD: OS	121433	121433	121433	121433	121433

B. Optimistic Scenario: Constant Percentage of Patients With NCDs and Changes in Age Distribution

Data from Spain demography indicates that population of Spain, from 2010 to 2017, is almost unchanged while aging. Therefore, we considered an optimistic scenario wherein we had 1) a constant percentage of patients with NCDs and 2) a changing age distribution. Specifically, we estimated that percentage of patients with NCDs for each year from 2019 to 2939 is equal to that of 2017. For disease burden from NCDs by ages, we used the same results we obtained from pessimistic scenario (P(incd)) in the ED simulator. In summary, in our ED simulator we used the results in Table IV (age distribution of patients with NCDs for both scenarios) and Table V (percentage/number of patients with NCDs and total number of patients) as inputs into the model for the patient's agent.

IV. SIMULATION RESULTS AND DISCUSSION

As mentioned, an ED simulator can have various outcomes including interaction information of patients, healthcare staff, and physical resources. One of such interaction information is patient's LoS that is an objective indicator of the quality of care. We have quantified and predicted LoS from 2019 to 2039 for the two projection scenarios we considered. Results from both

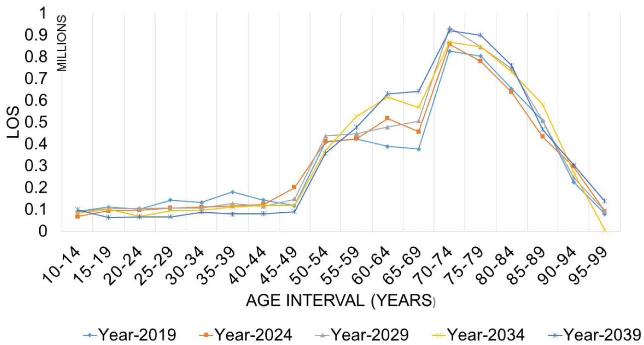

Fig. 9. Contribution of each age interval into the LoS from 2019 to 2039 for pessimistic scenario.

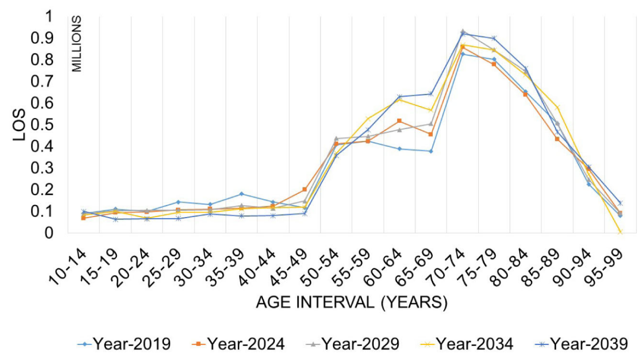

Fig. 10. Contribution of each age interval into the LoS from 2019 to 2039 for optimistic scenario.

projection scenarios indicated that Spain would experience a continuous increase in total LoS (sum of LoS among all age intervals for one year) from 5.7 million hours in 2019 to 6.2 million hours in 2039 if same human and physical resources as well as same ED configuration are used (Fig. 9). The constant increase in total LoS for optimistic scenario (constant NCDs) (Fig. 9) indicates that the changes in age distribution alone play a key role in the increase of total LoS. Increases in NCDs in addition to changes in age distribution (i.e., pessimistic scenario) exacerbates the total LoS by 1.58% on average from 2019 to 2039 when compared to the optimistic scenario. However, we observed smaller differences in total LoS between pessimistic and optimistic scenarios for years 2019, 2024, and 2039 (<0.31%) and larger difference between the scenarios for years 2029 and 2034 (>3.1%) (Fig. 9). Such a behavior indicates that there are interactions between the two variables (i.e., NCDs and age distribution).

Significant increases in LoS started after age 50 with the maximum values of LoS being observed in 70–74 and 75–79 age intervals (Fig. 10 and Fig. 11). Comparison of four marginal conditions (i.e., optimistic 2019, pessimistic 2019, optimistic 2039, and pessimistic 2039) indicated that, due to changes in age distribution, LoS in elderly people is increasing along the time for both optimistic and pessimistic scenarios (Fig. 12).

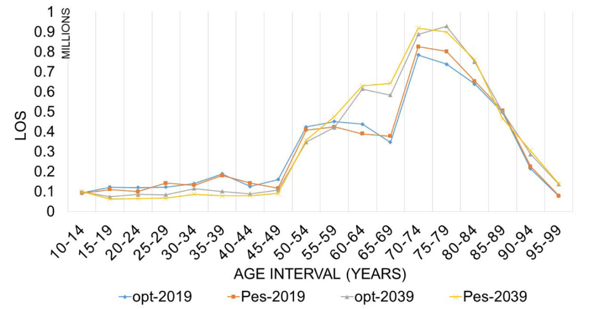

Fig. 11. Comparison of LoS between four marginal conditions for different age intervals.

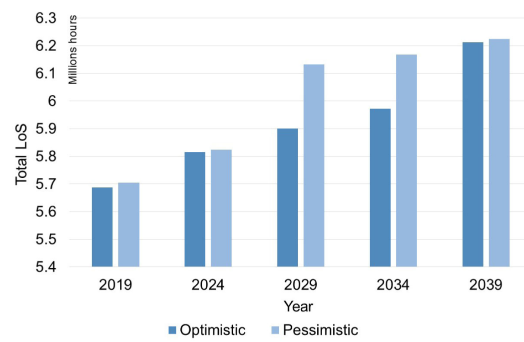

Fig. 12. Total LoS for optimistic versus pessimistic scenarios from 2019 to 2039.

V. Conclusion

This research can answer several questions in regards to demand and performance of ED in future and provides health care provider with quantitative information on required staff and physical resources in coming years. There are several solutions to reduce overcrowding of ED and improve its performance. These solutions include 1) increasing resources (e.g., physicians, nurses, physical resources such as beds, etc.), 2) managing patients through redirecting them to different wards, and 3) applying operational research methods to increase the efficiency of the resources [36]. The traditional approach for decision-making in continual improvement process to improve ED performance is based on trial and error procedures and experience of the decision makers. However, this approach includes several limitations such as the amount of time needed, the cost, and the unclear outcomes. The problem becomes even more challenging when it comes to long-term and future planning. Integration of computational methods and simulations with statistical models, as conducted in this study, provide decision makers with a powerful tool that can help them predict the results of changes in the ED system or designing different scenarios without actually altering the ED. Such results will have implications for optimizing resources, planning, and improving the quality of care. Despite uncertainties in projection scenarios, indicating percentage of patients with NCDs and their age distribution in future years, the impacts of the scenarios on ED were fairly certain and consistent. Specifically, as a result of population aging along the time, ED LoS increases and ED saturation will occur for both optimistic and pessimistic projection scenarios if same human and physical resources as well as same health care policies are used.

The results predicted by simulation allow health care policy-makers to improve modifiable factors contributing to the demand and performance of ED before reaching a critical point. Since most EDs in Spain has the same configuration and structure, and follow guidelines from the Spanish triage system (Sistema Español de Triage) [37], the results from this study can be generalized and used nationally to forecast future of all EDs in Spain [38] and [39]. Similarly, the method developed in this study can be used to asses and predict performance and quality of service of EDs in other countries provided that required data and information are available. Our findings should be interpreted with consideration of our study limitations. First, our predictions of long term projection of patients with NCDs and their age distribution are based on the assumption that the current behavior/pattern of Spain demography and disease burden continues in upcoming years. Nevertheless, to reduce uncertainties in our predictions, we have considered two projection scenarios (i.e., pessimistic and optimistic) to be able to capture extreme conditions. It should be noted that the clinical data used in this study were collected from only a few resources (i.e., from Parc Tauli Hospital in Sabadell/Spain and from GDB, WHO). Therefore, collecting data from more hospitals and using these data as inputs into the model can further improve predictions of the long term projection of ED Behavior Second, in this study the total number of visits (as the total patient demand regardless of number of unique patients) was considered in the model. Since our regressions and statistical models are based on reports on number of patients and not number of visits (e.g., Fig. 5 and Fig. 6), there was an assumption in our study that the number of visits are proportional to the number of patients. As future works, since it is hard at this stage to fully validate our outcomes and conclusions, we plan to compare the predictions by our model (e.g., NCDs (%) and LoS of ED) against the real data in coming years (let's say data collected in the next 5 years). This help us not only evaluate the performance of our model but also update and adjust adaptively the modifiable parameters of our model to further improve its performance. Finally, we used linear regressions to estimate the projection of percentage of patients with NCDs in future years. Given that there was only a few data points available to fit a curve, linear regression was likely a reasonable choice. However, by including more data points from coming years into the model, we can use curves with higher degrees of freedom to better estimate the true relationship for future projection of patients with NCDs. Also, we plan to study how changes in modifiable risk factors such as life style can decrease the number of patients with NCDs and help improve the quality of service and reduce LoS of EDs.

Appendix A
Spanish Demography and Mapping Algorithm

The predicted NCDs by age data were mapped to age categories of 5-year intervals through the following algorithm:

- In our ED simulator, and consistent with Spain demography, an age range between 0 to 100 years was assumed. The age range was then classified into 20 age categories of 5-year intervals.
- An index for each age distribution was defined $(i = 1 : 20)$. For instance, the index for age category of $[0-4]$ is equal to 1. Because we only studied adults older than 15 years, i started from 4.
- If $P(i)$ is population of Spain for category index i, according to Spain demography (Table I), the population from 15 to 49, 50 to 69, and above 70 is respectively calculated through $Pop_{15-49} = \sum_{i=4}^{i=10} P(i)$, $Pop_{50-69} = \sum_{i=11}^{i=14} P(i)$, and $Pop_{+70} = \sum_{i=15}^{i=20} P(i)$ for each year.
- An index for each age category was defined $(j = 1 : 4)$. For instance, the index for age category of $[0 - 14]$ is equal to 1. For our study, j started from 2 so that $Pop(j = 2)$ means Pop_{15-49}.
- Consider the total number of patients with NCDs in age category j as $Pop(jNCD)$ (known from Fig. 7 and Table III), and number of patients with NCDs in age category i as $P(incd)$ (to be calculated). Then we can approximate $P(incd)$ from 2019 to 2039 through $\frac{P(i)}{Pop(j)} =$

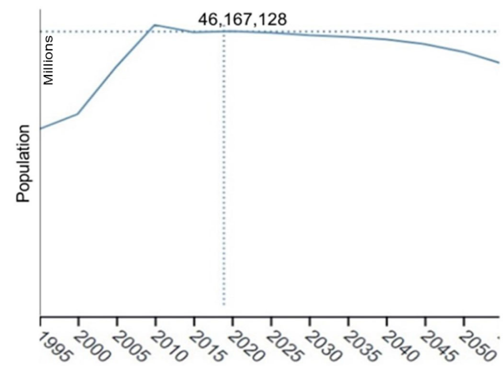

Fig. 13. Spain demography from 1995 to 2050 which shows Spain population from 2019 to 2039 is decreasing with a gentle gradient [30].

TABLE VI
Spain Demography and Its Projection From 2014 to 2039 for Different Age Intervals. Population Pyramid Prediction Issued By The Spanish National Statistics Institute [30]

	Percentage of population in each year						
age	2014	2017	2019	2024	2029	2034	2039
15-19	4.5	4.7	4.9	5.3	4.6	4.5	4.2
20-24	4.9	4.7	4.5	4.9	5.5	5.1	4.7
25-29	5.5	5.1	5.0	4.7	5.1	5.7	5.3
30-34	7.1	6.0	5.6	5.1	4.9	5.3	5.9
35-39	8.6	7.8	7.0	5.6	5.2	4.9	5.4
40-44	8.6	8.7	4.5	7.0	7.0	5.2	5.1
45-49	7.9	8.3	4.5	8.3	8.5	5.8	5.3
50-54	7.6	7.8	7.9	8.4	8.3	7.0	5.8
55-59	6.5	7.1	7.4	7.8	8.3	8.4	7.0
60-64	5.4	6.0	6.4	7.3	7.6	8.2	8.4
65-69	4.8	5.2	5.3	6.2	7.0	7.4	8
70-74	4.2	4.5	4.7	5.0	5.9	6.7	7.1
75-79	3.5	3.6	3.8	4.3	4.6	5.5	6.3
80-84	3.1	3.0	2.9	3.1	3.6	4.0	4.7
85-89	1.7	2.0	2.2	2.1	2.3	2.8	3
90-94	0.7	0.9	0.9	1.2	1.2	1.4	1.7
95-100	0.1	0.3	0.3	o.4	0.	0.4	0.6
100+	0.0	0.0	0.0	0.0	0.0	0.0	0.0

$\frac{Pop(incd)}{(Pop(jncd)}$ or equally $P(incd) = \frac{Pop(i)*pop(jncd)}{Pop(j)}$ (Table IV) where P(i) and Pop(j) for each year are known from Table I and third bullet point above.

References

[1] N. Jayaprakash, R. O'Sullivan, T. Bey, S. S. Ahmed, and S. Lotfipour, "Crowding and delivery of healthcare in emergency departments: The European perspective," *Western J. Emerg. Med.*, vol. 10, no. 4, p. 233, 2009.

[2] M. H. Yarmohammadian, F. Rezaei, A. Haghshenas, and M. Tavakoli, "Overcrowding in emergency departments: A review of strategies to decrease future challenges." *J. Res. Med. Sci.*, doi: 10.4103/1735-1995.200277

[3] B. E. Driesen, B. H. Van Riet, L. Verkerk, H. J. Bonjer, H. Merten, and P. W. Nanayakkara, "Long length of stay at the emergency department is mostly caused by organisational factors outside the influence of the emergency department: A root cause analysis," *PloS One*, vol. 13, no. 9, p. e0202751, 2018.

[4] S. L. Bernstein *et al.*, "The effect of emergency department crowding on clinically oriented outcomes," *Acad. Emerg. Med.*, vol. 16, no. 1, pp. 1–10, 2009.

[5] J. W. Thomas, K. E. Guire, and G. G. Horvat, "Is patient length of stay related to quality of care?" *J. Healthcare Manage*, vol. 42, no. 4, p. 489, 1997.

[6] C. Y. Chang, S. Abujaber, T. A. Reynolds, C. A. Camargo, and Z. Obermeyer, "Burden of emergency conditions and emergency care usage: New estimates from 40 countries," *Emerg. Med. J.*, vol. 33, no. 11, pp. 794–800, 2016.

[7] L. Hui, "Assessment of the role of ageing and non-ageing factors in death from non-communicable diseases based on a cumulative frequency model," *Sci. Reports*, vol. 7, no. 1, p. 8159, 2017.

[8] Z. Liu, D. Rexachs, F. Epelde, and E. Luque, "Support managing population aging stress of emergency departments in a computational way," *Procedia Comp. Sci.*, vol. 108, pp. 149–158, 2017.

[9] M. R. José Luis Fernández and C. Parapar, "Population ageing," Accessed on: May 27, 2019. [Online]. Available: http://www.fgcsic.es/lychnos/en_EN/articles/population_ageing

[10] J. M. Haro *et al.*, "The burden of disease in spain: Results from the global burden of disease study 2010," *BMC Med.*, vol. 12, no. 1, p. 236, 2014.

[11] *Institute for Health Metrics and Evaluation (IHME)*, [Online]. Available: http://www.healthdata.org/spain.

[12] J. S. Olshaker, "Managing emergency department jayaing," *Emerg. Med. Clinics*, vol. 27, no. 4, pp. 593–603, 2009.

[13] Z. Liu, E. Cabrera, M. Taboada, F. Epelde, D. Rexachs, and E. Luque, "Quantitative evaluation of decision effects in the management of emergency department problems," *Procedia Comp. Sci.*, vol. 51, pp. 433–442, 2015.

[14] Z. Liu, E. Cabrera, D. Rexachs, F. Epelde, and E. Luque, "Simulating the micro-level behavior of emergency departments for macro-level features prediction," in *Proc. 2015 Winter Simul. Conf.*, 2015, pp. 171–182.

[15] M. E. Lim, A. Worster, R. Goeree, and J.-É. Tarride, "Simulating an emergency department: The importance of modeling the interactions between physicians and delegates in a discrete event simulation," *BMC Med. Inform. Decis. Making*, vol. 13, no. 1, p. 59, 2013.

[16] S. Sumari, R. Ibrahim, N. H. Zakaria, and A. H. Ab Hamid, "Comparing three simulation model using taxonomy: System dynamic simulation, discrete event simulation and agent based simulation," *Int. J. Manag. Excellence*, vol. 1, no. 3, pp. 54–59, 2013.

[17] A. Borshchev and A. Filippov, "From system dynamics and discrete event to practical agent based modeling: Reasons, techniques, tools," in *Proc. Int. Conf. Syst. Dyn. Soc.*, vol. 22. Citeseer, 2004.

[18] R. Maidstone, "Discrete event simulation, system dynamics and agent based simulation: Discussion and comparison," *System*, vol. 1, no. 6, pp. 1–6, 2012.

[19] H. Stainsby, M. Taboada, and E. Luque, "Towards an agent-based simulation of hospital emergency departments," in *2009 IEEE Int. Conf. Services Comput.*, 2009, pp. 536–539.

[20] E. Bruballa, A. Wong, D. Rexachs, E. Luque, and F. Epelde, "Scheduling model for non-critical patients admission into a hospital emergency department," in *2017 Winter Simul. Conf.*. IEEE, 2017, pp. 2917–2928.

[21] Z. Liu, D. Rexachs, F. Epelde, and E. Luque, "A simulation and optimization based method for calibrating agent-based emergency department models under data scarcity," *Comp. Ind. Eng.*, vol. 103, pp. 300–309, 2017.

[22] G. L. Freed, S. Gafforini, and N. Carson, "Age distribution of emergency department presentations in victoria," *Emerg. Med. Austral.*, vol. 27, no. 2, pp. 102–107, 2015.

[23] K. W. Tan, H. C. Lau, and F. C. Y. Lee, "Improving patient length-of-stay in emergency department through dynamic queue management," in *2013 Winter Simul. Conf.*. IEEE, 2013, pp. 2362–2373.

[24] J. Wang, J. Li, K. Tussey, and K. Ross, "Reducing length of stay in emergency department: A simulation study at a community hospital," *IEEE Trans. Syst., Man, Cybernet.-Part A: Syst. Humans*, vol. 42, no. 6, pp. 1314–1322, 2012.

[25] E. Bonabeau, "Agent-based modeling: Methods and techniques for simulating human systems," *Proc. Nat. Acad. Sci.*, vol. 99, no. suppl 3, pp. 7280–7287, 2002.

[26] J. H. Holland, "Studying complex adaptive systems," *J. Syst. Sci. Complex.*, vol. 19, no. 1, pp. 1–8, 2006.

[27] N. A. Green, Y. Durani, D. Brecher, A. DePiero, J. Loiselle, and M. Attia, "Emergency severity index version 4: a valid and reliable tool in pediatric emergency department triage," *Pediatr. Emerg. Care*, vol. 28, no. 8, pp. 753–757, 2012.

[28] R. Sánchez Bermejo *et al.*, "El triaje en urgencias en los hospitales españoles," *Emergencias*, vol. 25, no. 1, pp. 66–70, 2013.

[29] H. R. J. H. D. G. Max Roser, Esteban Ortiz-Ospina, "our world in data."

[30] R. at the University of Oxford, "Spain population pyramid," Accessed on: Sep. 18, 2019. [Online]. Available: https://www.populationpyramid.net/spain

[31] M. J. Divo, C. H. Martinez, and D. M. Mannino, "Ageing and the epidemiology of multimorbidity," 2014.

[32] C. Hajat and E. Stein, "The global burden of multiple chronic conditions: A narrative review," *Prevent. Med. Rep.*, 2018.

[33] J. L. Wolff, B. Starfield, and G. Anderson, "Prevalence, expenditures, and complications of multiple chronic conditions in the elderly," *Arch. Int. Med.*, vol. 162, no. 20, pp. 2269–2276, 2002.

[34] C. D. Mathers and D. Loncar, "Projections of global mortality and burden of disease from 2002 to 2030," *PLoS Med.*, vol. 3, no. 11, p. e442, 2006.

[35] C. J. Murray *et al.*, "Global comparative assessments in the health sector: disease burden, expenditures and intervention packages," 1994.

[36] S. Di Somma, L. Paladino, L. Vaughan, I. Lalle, L. Magrini, and M. Magnanti, "Overcrowding in emergency department: An international issue," *Int. Emerg. Med.*, vol. 10, no. 2, pp. 171–175, 2015.

[37] Ò. Miró, "State of emergency medicine in spain," *Int. J. Emerg. Med.*, vol. 3, no. 4, p. 219, 2010.

[38] C. Duguay and F. Chetouane, "Modeling and improving emergency department systems using discrete event simulation," *Simulation*, vol. 83, no. 4, pp. 311–320, 2007.

[39] B. R. Asplin, D. J. Magid, K. V. Rhodes, L. I. Solberg, N. Lurie, and C. A. Camargo Jr, "A conceptual model of emergency department crowding," *Ann. Emerg. Med.*, vol. 42, no. 2, pp. 173–180, 2003.

[40] J. M. McGinnis and W. H. Foege, "Actual causes of death in the united states," *Jama*, vol. 270, no. 18, pp. 2207–2212, 1993.

[41] M. M. Gunal and M. Pidd, "Understanding accident and emergency department performance using simulation," in *Proc. 38th Conf. Winter Simul.*, 2006, pp. 446–452.