Proceedings of the 2019 Winter Simulation Conference
N. Mustafee, K.-H.G. Bae, S. Lazarova-Molnar, M. Rabe, C. Szabo, P. Haas, and Y.-J. Son, eds.

COMBINING SIMULATION TECHNIQUES TO UNDERSTAND DEMOGRAPHIC DYNAMICS AND FORECAST HOSPITAL DEMANDS

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ABSTRACT

An ageing population directly affects the volume and structure of hospital demands while raising concerns about both short- and long-term medical service accessibility. In this context, simulations can be used to facilitate understanding about population dynamics and the mechanisms driving healthcare service demands. This study's primary goal was to determine, using a hybrid simulation technique, how demographic changes influenced the demand for inpatient hospital services. The studied model was used to predict how changes in the age-gender population distribution would affect future hospital inpatient service use among 17 hospital located in a large administrative region in Poland. The population model was constructed as a system dynamics model while patient pathways were modeled using a discrete event approach. Results showed that the hybrid model enabled analyses and insights that were not delivered by each sole method.

1 INTRODUCTION

The demographic changes are the key challenges for the European healthcare system. They include population ageing, very low fertility rates, unfavorable proportions of employed and unemployed people, and problems associated with epidemiologic forecasts (i.e., an increase in the cost of treating the contemporary civilization diseases, including cardiovascular diseases, cancer, respiratory illnesses, musculoskeletal disorders, and mental health issues). In addition, a characteristic feature of an ageing population is an increase in the number of chronic diseases and higher treatment costs due to injuries. Such demographic transitions directly affect the volume and structure of hospital demands while raising concerns about medical equity and service accessibility. There is thus a strong need for credible forecasts of potential medical demands. This issue is strongly articulated in the strategic national health policy programs of many European countries.

Modeling and simulation methods offer a good way to understand both population dynamics and the mechanisms driving demand for healthcare services. Population projections and demand forecasts are performed within different simulation paradigms. Demographic phenomena have been successfully modeled using system dynamics (SD) (Eberlein and Thompson 2013), discrete event simulation (DES) (Olsson and Hössjer 2015), agent based simulation (ABS) (Singh and Ahn 2017), the Monte Carlo method (MC) (Tian and Zhao 2016), and microsimulation (MSM) (Onggo 2008).

Studies on healthcare demands have similarly used an extensive variety of methods and models, including simulation techniques. Simulation models are used to forecast population needs and determine the resources needed to cover expected demands. For example, DES models enable short-term predictions of near-future patient arrivals to emergency departments (Hoot et al. 2008). On the other hand, MC simulations can predict future demands and long-term care services utilization (Cardoso et al. 2012). An SD model has also been used to predict annual health care consumption rates (Pavlova et al. 2012), while a

MSM allowed to forecast the number of visits to family doctors under different demographic options (Davis et al. 2010).

Simulation approaches differ significantly. While each is capable of delivering adequate and credible support for healthcare decision makers, they all contain weak points and lack features that other techniques provide. For instance, the MC model simulates a range of potential scenarios and works very well when uncertainties are the main influencers of the studied problem. However, this fails when decisions require changes to be tracked over time. The SD is a deterministic approach that aids in understanding complicated and dynamic system interactions. It does not require detailed or high quality data, but can still be used to provide adequate knowledge about trends and future tendencies. ABS models can be used to consider individual human behavior. The agent-based approach is thus a perfect choice when participation cannot be ignored. DES models simulate processes over time and follow individual dynamic objects that interact with system resources and each other. They provide a unique opportunity to carefully trace patient movements through the system, however an increased number of details hinders the ability to make decisions at the macro level.

The combined application of different simulation methods can overcome the limitations of a single approach (Mustafee and Powell 2018). Here, a hybrid model can be arranged to integrate different methods and constructs. Such a tool is capable of delivering benefits that are unavailable when using each component separately. For instance, according to a previous study (Bae et al. 2016), wherein modeled population dynamics used MSM and ABS, a hybrid model emphasized the strengths and reduced the weaknesses of each individual simulation method.

This study's primary goal was to determine the influence of demographic changes on the demand for inpatient hospital services using a hybrid simulation method. The resulting model was used to predict how changes in the age-gender population distribution of the Wrocław Region (WR) would affect future hospital inpatient services use among 17 area hospitals. WR is located in the highly populated southwest part of Poland. Here, a combined simulation approach enabled us to construct a new tool while preserving the paradigms of each original methodology. This was expected to significantly enhance the research possibilities. This study expanded on our previous research (Mielczarek et al. 2018) reporting on the use of combined simulation methods to support healthcare demand predictions. The population model was constructed as an SD model while patient pathways were modeled using a DES approach. We overcame limitations to not only successfully study demands and future trends at the macro (regional) level, but also focused on main classes of diagnoses among different age-gender cohorts.

The remainder of this paper is organized as follows: Section 2 provides background information on demographic and healthcare-demand simulation modeling. Section 3 discusses an extended and modified version of the model presented at Winter Simulation Conference 2018. According to a classification provided by (Mustafee and Powell 2018), this model represents type A (i.e., a *Multi Methodology Hybrid Simulation*). Section 4 focuses on this study's simulation experiments and results for different scenarios. Finally, Section 5 draws conclusions and summarizes the contributions of this research.

2 BACKGROUND

Ageing populations have known effects on hospital demands. These have been explored in the literature from different angles. The most common approach forecasts the number of treatments using age-group projections and by applying different scenarios that describe potential population dynamics. The age-group projection approach assumes that the demands of each cohort remain constant (Vrhovec and Tajnikar 2016) and that the volume of future demand can be estimated if the size of particular age-gender group is properly predicted. This type of study is usually performed at the macro level and is based on demographic projections for a whole country. Such an analysis may focus on main healthcare services groups (e.g., primary, secondary, daycare, and hospitalization (Vrhovec and Tajnikar 2016)), main disease groups according to International Classification of Diseases (ICD) or Diagnoses Related Group (DRG) classification (Strunk et al. 2006), and particular types of services such as those related to visits to family doctors (Starkiene et al. 2005).

The relationship between population changes and healthcare demands can be captured using analytic or simulation models. The study by (Burkett et al. 2017) used linear least-squares curve fitting with uncertainty estimates for fit values to predict patient arrivals to emergency departments. Time series analysis and linear rate model were also applied (Aboagye-Sarfo et al. 2016). From among simulation approaches, the study by (Davis et al. 2010) employed a micro-simulation approach to create a representative set of health histories by combining population census data and performing scenario analyses using MC random sampling. An MC simulation model was also created by (Cardoso et al. 2012) to predict long-term care service demands.

Our hybrid simulation model considered a few aspects that were not simultaneously included in other models. These included the effects of population ageing on regional hospital demands, geographic accessibility of health care providers (key information generated by the model), the integration of population dynamics with healthcare-demand forecasting, and an analysis of medical conditions based on widely variable ageing across diagnoses groups.

3 MODEL SPECIFICATION

3.1 Population Submodel

The hybrid simulation model consists of two submodels. These two sub-models exchange data using an Excel interface. The simulation begins in 2006 and lasts until 2030. Every year of the stochastic (DES) simulation is replicated 10 times. A simplified illustration is provided in Figure 1.

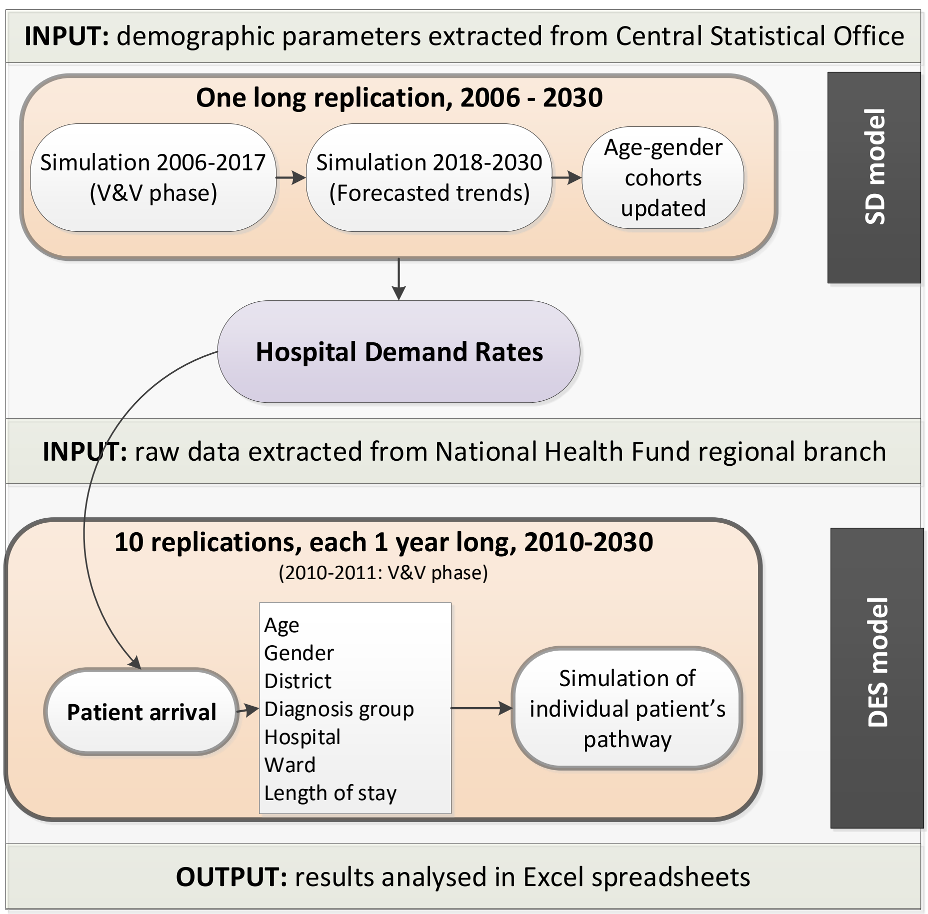

Figure 1: Overview of the population-demand hybrid model.

The population submodel was developed in ExtendSim using SD and the aging chain approach described by (Eberlein and Thompson 2013). The model simulates demographic changes in the WR. The detailed discussion on the methodology that enabled us to simulate demographic changes can be found in a previous study (Mielczarek and Zabawa 2018).

The demographic forecasting model divides the population into two chains (females and males) and 210 elementary cohorts (105 cohorts per each chain). Each cohort simulates one year of ageing. In order to speed up the simulation experiments, we grouped 210 elementary cohorts into 36 main cohorts (18 per each chain). There are 36 main cohorts (0–4, 5–9, 10–14, 15–19, 20–24, 25–29, 30–34, 35–39, 40–44, 45–49, 50–54, 55–59, 60–64, 65–69, 70–74, 75–79, 80–84, 85–105): 18 female and 18 male cohorts. Each main cohort encapsulates five elementary cohorts. *Stocks*, basic constructs of SD approach, represent main age-gender cohorts. *Flows*, another basic SD constructs, are used to represent birth, maturation, immigration, and death. When an individual is born, she/he immediately becomes a member of the youngest cohort. After five years, a person grows up and is transferred to the older cohort. A person leaves the cohort when she/he dies, is old enough to be moved to the older cohort, or emigrates. The process continues along the aging chain. The marginal right cohorts (85–105) contain 20 elementary cohorts representing the entire population of the oldest people. All cohorts are placed inside positive or negative feedbacks loops that drive the changes observed in the whole population.

3.2 Healthcare Demand Submodel

The healthcare demand model was created using Arena. We applied the extended version of our model as described in a previous research (Mielczarek et al. 2018).

Patients belonging to every main age-gender cohort of the WR population are generated on an hourly basis, separately for every calendar month, with the non-stationary Poisson process. On arrival, a patient acquires a number of attributes, including age, gender, place of residence, servicing hospital, diagnosis (patient category). The attributes are interrelated and mutually dependent. For example, patient's category depends on the hospital selected by a patient and the diagnosis formulated on arrival. Individual patients are followed as they pass through a system, and their progress depends on uncertainties associated with admission and the length of delays in internal processes. A simulation replication starts from an empty and idle state and lasts 365 days.

4 DATA AND METHODS

4.1 Model Data Collection: Population

The population sub-model operated on demographic descriptive parameters collected from the Polish Central Statistical Office (GUS 2019) and demographic forecasts prepared by the Polish Government Population Council for 2014-2050 (Waligórska et al. 2014), and updated in (Potyra and Waligórska 2017). Data for the years 2006-2017 (Figure 2) were separately collected for two aging chains of the female and male populations. The initial values of every cohort matched historical conditions at the beginning of 2006 and equaled the number of individuals in each of the 36 main cohorts.

The following parameters were then applied to simulate evolution of the WR population from 2006 to 2017:

- Fertility rates: Number of infants (boys and girls) born by mothers from the following cohorts: 10-14, 15–19, 20–24, 25–29, 30–34, 35–39, 40–44, 45–49, and 50–54.
- Death rates: The number of deaths per year for a given cohort.
- Migration: The resulting balance in consideration of immigrations and emigrations for a given cohort. These parameters are given as absolute values.
- Fertility and death rates were given as relative values to the number of individuals in a given cohort.

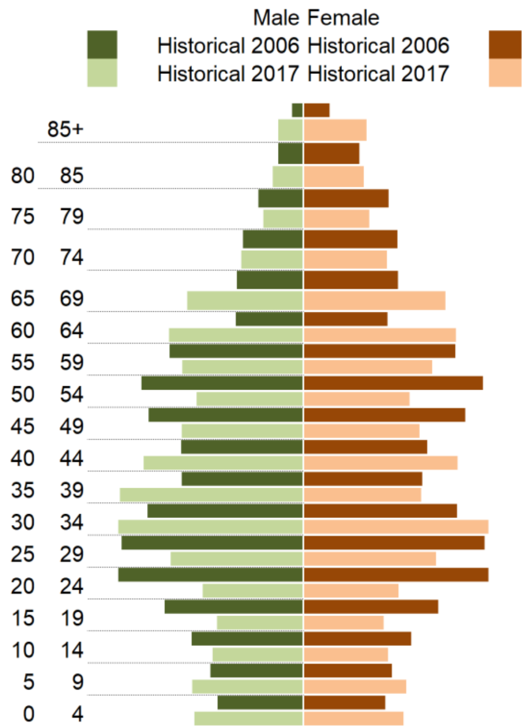

Figure 2: Comparison (age pyramids) of the WR population using historical data from 2006 (dark colors) and 2017 (light colors). The length of horizontal bars corresponds to the number of individuals in cohorts.

Historical data show that the number and share of women of childbearing age decreased from 65.9% in 2006 to 58.0% in 2017, while the number and participation rates of seniors (i.e., citizens older than 65) in the regional population grew from 13.9% in 2006 to 17.4% in 2017.

Beyond the year 2017, historical data were replaced by projections describing the probable trends involving WR population evolutions. We then applied four main scenarios suggested by Potyra and Waligórska (2017) from among a set of official forecasts described in a previous study by Waligórska et al. (2014) (Table 1). Scenario 2 is assumed to be "the most probable scenario" (basic scenario) and therefore the paper presents results of this scenario.

Table 1: Main scenarios involving possible demographic changes in the WR population. Migration was unchanged. Scenarios 2 is considered as "basic scenario".

Scenario	**Description**
Scenario 1	Medium fertility rate values, Medium mortality rate values
Scenario 2	High fertility rate values, Medium mortality rate values
Scenario 3	High fertility rate values, Low mortality rate values
Scenario 4	Very high fertility rate values, High mortality rate values

4.2 Model Data Collection: Demand

The input parameters for the DES sub-model required age-specific hospital utilization rates for a particular year. We used 2010 data collected from a regional branch of the National Health Fund to fit parametric distributions based on 183,517 admissions registered in 2010 among 17 WR hospitals. If unable to fit a parametric distribution, an empirical distribution was created instead. Table 2 summarizes the basic input distributions.

Table 2: Healthcare-demand input data.

Input parameter	Description
Arrival rates [no of patients per hour]	Non-stationary Poisson distributions defined for every cohort and each calendar month. There were 216 distributions for 18 age female cohorts (18 cohorts x 12 months), 216 distributions for 18 male cohorts (18 cohorts x 12 months), and 24 distributions for patients living outside WR (2 regions* x 12 months). * The first external region describes another area in the same administrative district and the second external region relates to the rest of the country.
Age [value]	Age was uniformly distributed between Min and Max values describing every cohort* *This assumption has been recently modified to enable the more realistic distributions of age inside cohorts.
District [code]	Empirical distribution dependent on gender
Diagnosis [ICD]	Empirical distribution dependent on gender and age (cohort)
Hospital [code]	Empirical distribution dependent on diagnosis
Ward [code]	Empirical distribution dependent on hospital, diagnosis, and age
Ward LOS [days]	Empirical distribution dependent on ward and diagnosis

4.3 Basic Assumptions

The following assumptions were made in the simulation model:

- Age-specific demand rates were calculated for each-gender cohort. Similar to a study by (Strunk et al. 2006), we assumed that inpatient hospital demand was dependent on age-gender cohort and remained stable in the short time horizon. Age-specific demand rates were used to predict the number of patients generated by a specific cohort. For example (Figure 3), the age-specific demand rate calculated for females 85+ (equals to 0.368; Figure 3) indicated that 368 of every 1,000 women aged 85+ living in WR would be admitted to hospitals located in WR during one calendar year. We were only interested in the number of visits: the number ‘368’ calculated for female patients/1,000 female population 85+ referred to visits and not persons.
- Age-specific demand rates were held constant throughout the simulation.
- The monthly distribution of patients’ arrivals remained constant throughout the simulation and corresponded with the observed demand intensity for particular calendar months (Figure 4).
- The number and location of hospitals were held constant throughout the simulation.
- The internal structure of WR hospitals (i.e., number and type of hospital wards) did not change throughout the simulation.
- Except for the demographic, no factors influenced the evolution of the WR population. Fertility and death rates were not modified by epidemic or other phenomena.
- Members of the WR population did not change places of residence. This assumption was important when considering demands directed to particular hospitals.
- The impact of emerging new medical treatments was included in the model through extrapolation of earlier trends in mortality.

4.4 Simulation Algorithm

The challenge was to create a credible framework that would enable us to link the demographic evolutions of the WR population with future hospital demands. We elaborated the three-phase algorithm described below (Figure 5).

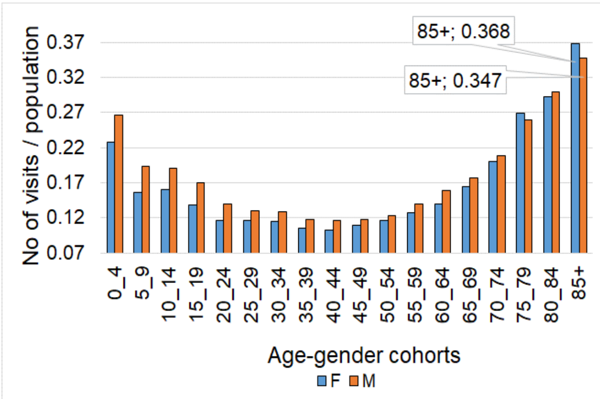

Figure 3: Age-specific demand rates calculated for each age-gender cohort (patients/population), separately for male and female cohorts.

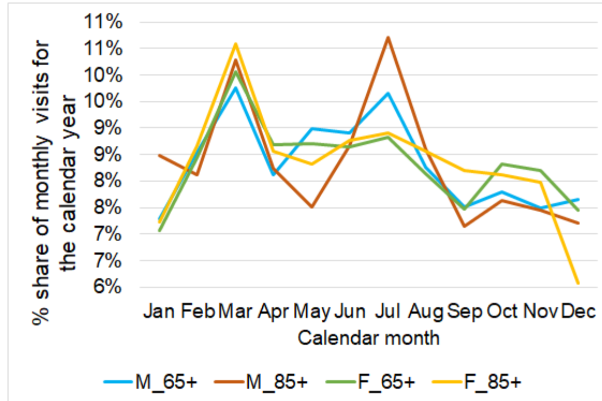

Figure 4: Monthly arrivals-per-day trends separately for the oldest male and female cohorts.

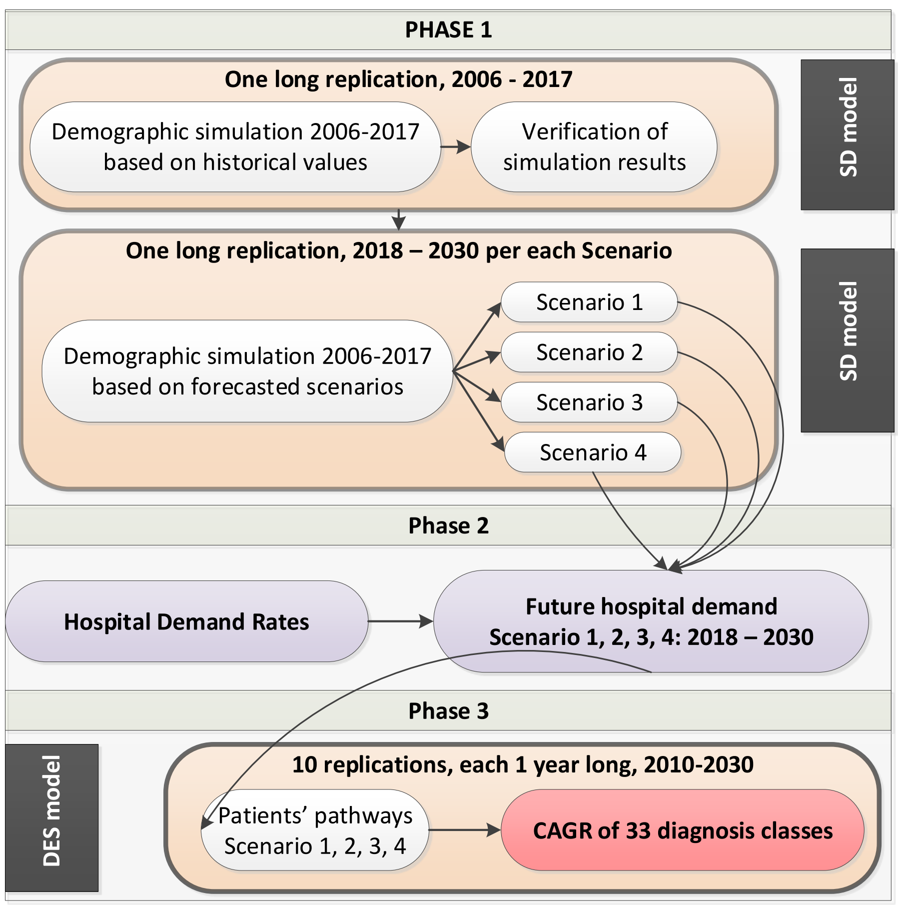

Figure 5: Three-phase simulation algorithm. CAGR: Compound Annual Growth Rates.

In Phase 1, we performed a demographic simulation for the years 2006-2017 and used the output data to verify the population model. The results were consistent with historical data; that is, the differences between the simulation and historical data were very small and the Mean Absolute Percentage Errors (MAPEs) values indicated that the population model provided very good predictions for WR population evolutions (Table 3). The highest MAPE value is as small as 1.13%.

Starting with the year 2017, we exchanged historical ratios with extrapolated values that were calculated based on official governmental forecasts. Results clearly indicated that the population would become much older. For instance, the share of post-working age (65+) population would rise from 17.4% in 2017 to 19.9% in 2030, while the share of the oldest population (85+) would reach 2.35% (compared to 2.19% in 2017). At the same time, the share of working age population from 25 to 54 years of age would fall from 45.4% to 42.7%.

Phase 2 enabled us to estimate future hospital demands. We used the population projections from Phase 1 and age-specific demand rates to calculate the number of patient arrivals for each age-gender group. For each cohort, we multiplied our age-specific demand rates by the total number of people of that age and gender in a given year (as simulated by the SD model). This annual total projection of patient visits to WR hospitals was distributed over 12 calendar months according to the percentage shares that characterized the annual trends in patient arrivals (Figure 4). The non-stationary Poisson process was used to represent time-varying arrival rates. We assumed that events occurred singly and independently and that the number of arriving patients during a given time interval was described by a random Poisson variable.

In Phase 3, individual patient pathways were simulated so that every patient received an ICD code used to place them into a medical specialty for direction to a corresponding hospital ward. The compound annual growth rates (CAGR, see par. 4.1) were calculated to better visualize the predicted changes in demand.

Table 3: Validation of the population model. Mean Absolute Percentage Errors (MAPEs) calculate the differences between simulation and historical data for male and female population of WR.

Year	MAPE M	MAPE F		Year	MAPE M	MAPE F
2006	0.09%	0.05%		2012	1.06%	0.72%
2007	0.05%	0.11%		2013	1.05%	0.73%
2008	0.04%	0.12%		2014	1.07%	0.78%
2009	0.05%	0.13%		2015	1.07%	0.73%
2010	1.12%	0.69%		2016	0.99%	0.67%
2011	1.13%	0.72%		2017	0.98%	0.61%

5 STUDY FINDINGS

5.1 Ageing Effects on Total Hospital Admissions

The ageing population trend will influence hospital demands based on two interconnecting factors (i.e., population shift toward older cohorts and high demand rates that characterize the senior population). Following a previous study (Aboagye-Sarfo et al. 2016), we calculated the compound annual growth rate (CAGR) to aid in visualizing predicted demand changes (Table 4), as follows (1):

$$CAGR = \left(\frac{V_{2017}}{V_{2030}}\right)^{\left(\frac{1}{13}\right)} - 1 \qquad (1)$$

where V_{2017} and V_{2030} are the demand values in 2017 and 2030, respectively, and 13 is the number of years from 2017 and 2030.

From the year 2017 to 2030, our simulations indicated that the projected population would increase by an average of 0.23% per year while healthcare demands would increase by an average of 0.44% per year. However, the CAGR values calculated for the oldest cohorts (the highlighted rows in Table 4) indicated a much more radical increase in demand among the elderly. This increase was much higher than that of the overall healthcare demand due to decreasing demands from younger cohorts. Knowing that older patients require more complex and more costly treatments, these predictions show that ageing will have a significant economic effect on total healthcare system expenditures.

Table 4: Compound Annual Growth Rates (CAGR) calculated for population and demand between 2017 and 2030 (based on the simulation results).

Cohorts	**Female**	**Male**	**Total**	**Female**	**Male**	**Total**
	CAGR [%] WR population			CAGR [%] WR demand		
0–4	-0.44	-0.54	-0.49	-0.42	-0.59	-0.51
5–9	0.50	0.42	0.46	0.46	0.45	0.46
10–14	1.61	1.60	1.61	1.64	1.56	1.59
15–19	1.38	1.42	1.40	1.40	1.39	1.39
20–24	-0.29	-0.22	-0.25	-0.27	-0.12	-0.18
25–29	-2.14	-2.12	-2.13	-2.23	-2.13	-2.18
30–34	-3.10	-3.15	-3.12	-3.19	-3.15	-3.17
35–39	-2.15	-2.37	-2.26	-2.18	-2.38	-2.28
40–44	0.35	0.00	0.17	0.38	0.06	0.21
45–49	2.81	2.50	2.66	2.81	2.47	2.63
50–54	3.05	3.07	3.06	3.03	3.11	3.07
55–59	0.64	1.08	0.85	0.63	1.05	0.84
60–64	-1.51	-0.87	-1.21	-1.50	-0.85	-1.17
65–69	-1.15	-0.74	-0.97	-1.13	-0.70	-0.93
70–74	1.71	1.87	1.78	1.68	2.02	1.82
75–79	3.49	4.13	3.73	3.48	4.22	3.75
80–84	2.20	3.23	2.56	2.13	3.23	2.51
85+	0.57	1.34	0.79	0.58	1.34	0.79
All	0.24	0.23	0.23	0.46	0.43	0.44

5.2 Ageing Effects on Demand According to Medical Condition

Ageing effects vary widely across medical conditions as classified by diagnosis categories. We again calculated CAGR values to predict changes in demand according to these categories as defined by the International Statistical Classification of Diseases (ICD) and Related Health Problems 10th Revision (ICD-10) WHO Version for 2016 (Table 5).

Average annual demand growth showed different distributions for the overall and elderly populations. The highest annual average increase in healthcare demands for male and female populations was predicted for neoplasms (malignant and *in situ*), diseases of blood system, and diseases of the circulatory system. However, older male cohorts will generate increased annual demands for diseases of the eye and ear, diseases of the digestive system, diseases of the blood, and *in situ* neoplasms. On the other hand, the oldest female cohorts will generate the highest annual demand growth for infectious and parasitic diseases, malignant neoplasms, and diseases of the blood.

5.3 Ageing Effects on Admission to WR Hospitals

Ageing had a significant effect not only on overall demand, but also on the demands directed to particular hospitals. This study's simulation enabled us to observe changes in patient flows within the WR administrative area (Table 6). Results clearly showed that demographic trends were diversified throughout the region. Some hospitals will face rapid demand increases (e.g., Hospital nos. 2 and 14), while others will only experience modest growth (e.g., Hospital no. 15).

Table 5: Compound Annual Growth Rates (CAGR) calculated for diagnosis categories (separately for all patients and older cohorts for the years 2017 and 2030 as based on simulation results).

	Female	**Male**	**Total**	**Female**	**Male**	**Total**
	CAGR [%] All cohorts			CAGR [%] Cohorts 65+		
Certain infectious and parasitic diseases	0.07	0.06	0.06	1.57	1.33	1.49
Malignant Neoplasms	0.78	1.21	1.02	1.55	1.57	1.56
In situ neoplasms	0.81	1.26	1.06	1.38	1.86	1.66
Diseases of the blood	0.91	0.65	0.77	1.57	1.95	1.73
Endocrine, nutritional, and metabolic diseases	0.53	0.88	0.67	0.85	1.79	1.14
Mental and behavioral disorders	0.23	0.25	0.24	1.20	1.76	1.39
Diseases of the nervous system	0.37	0.28	0.33	1.09	1.74	1.33
Diseases of the eye and adnexa. Diseases of the ear and mastoid process	0.45	0.45	0.45	1.35	1.86	1.54
Diseases of the circulatory system	1.08	1.09	1.09	1.44	1.77	1.56
Diseases of the respiratory system	0.14	0.10	0.12	1.31	1.69	1.48
Diseases of the digestive system	0.50	0.55	0.53	1.34	1.91	1.57
Diseases of the skin	0.27	0.19	0.23	1.34	1.14	1.27
Diseases of the musculoskeletal system and connective tissue	0.48	0.35	0.41	1.32	1.51	1.39
Diseases of the genitourinary system	0.01	0.49	0.24	1.16	1.47	1.32
Pregnancy	-1.61		-1.61			
Symptoms not elsewhere classified	0.45	0.59	0.51	1.32	1.90	1.56
Injury and poisoning	0.45	0.15	0.27	1.18	1.61	1.33
Certain infectious and parasitic diseases	0.07	0.06	0.06	1.57	1.33	1.49

Table 6: Compound Annual Growth Rates (CAGR) calculated for the 17 WR hospitals between 2017 and 2030 (based on simulation results).

Hospital	**2017**	**2030**	**CAGR**	**Hospital**	**2017**	**2030**	**CAGR**
	Annual no. of patients		[%]		Annual no. of patients		[%]
H_1	11295.1	11984.4	0.46	H_9	6797.4	7139.2	0.38
H_2	3050.1	3325.8	0.67	H_10	20660.2	21673.2	0.37
H_3	31132	32380.1	0.30	H_11	13478.6	14302.8	0.46
H_4	18777.5	19791.6	0.41	H_12	2833.8	2990.6	0.42
H_5	34573.8	36535.6	0.43	H_13	28398.1	30108.8	0.45
H_6	6209.4	6454.5	0.30	H_14	4463.7	4789.8	0.54
H_7	2292.5	2418.4	0.41	H_15	1230	1245.9	0.10
H_8	12380.6	12960.5	0.35	H_16	5258.7	5468.7	0.30
H_9	6797.4	7139.2	0.38	H_17	3960.6	4143.3	0.35

6 DISCUSSION AND IMPLICATIONS

Recent studies have shown that coming changes in age distribution will significantly affect the delivery of healthcare services. Our research provided guidance relevant to formulating healthcare strategies over the next 5-15 years. The effects of population ageing will clearly be noticeable through a global increase in healthcare demands as well as in the use of inpatient services for certain medical conditions.

The study notably revealed that these changes in demand will not fully correlate with population changes; that is, the direction and scale related to the increase/decrease in the number of patients could differ within particular cohorts. This paper presented the results of the most probable and moderate population change scenario. Although the related demographic changes are slow and seemingly easy to predict, continual corrections made to official governmental forecasts show that the dynamics of population evolutions are characterized by high uncertainty. The initial results of simulation experiments performed among the more radical demographic scenarios suggested there was no single correct answer for the amount of supplies needed to cover future demands.

Our results hold value in the hybrid simulation field. We attempted to demonstrate both the usefulness and wide possibilities offered through the combined usage of different simulation techniques. The hybrid model enabled us to connect a stochastic simulation that focuses on uncertain trends describing the demand for hospital services with a deterministic experiment that offers a holistic, long-term insight into the demographic tendencies. The benefit of the combined usage of these two simulation techniques is additionally strengthened by the possibility of including data extracted from different sources and characterized by divergent aggregation levels. DES makes it possible to simulate and register the detailed history of thousands of individuals, whereas the SD model is run using aggregated data that relate to the whole population. Stochastic models require a large amount of input data to be collected and processed, usually in the form of probabilistic distributions while SD models are much less demanding on that front. The unique benefit of using inter-connected models as opposed to each of them individually is the mixture of management levels the simulation output is directed to. DES usually supports operational level of healthcare decision making. The strategic level requires a wider and more general perspective and is more appropriate for macro decision processes. Therefore, models built using the SD approach are more often applied here. We managed to address these two management levels using a hybrid simulation model.

The presented methodology can be applied to individual hospitals as well as more general healthcare systems that deliver services to populations in larger areas. The combination of two simulation models enabled analysis at not only the regional level, but also at specific hospital and ward levels. The changes observed in the demographic trends describing the whole regional population can easily be translated into the demand directed to a given hospital by a specific cohort while distinguishing divisions into ICD categories.

This study's approach may be useful for regional policymakers in planning scenarios. Based on the estimated level of service demands as classified by ICD codes, it is possible to calculate number of beds needed to keep the ward utilization coefficients at the desired level. For example, we expect a sharp increase in the number of neurological patients. This is mainly because neurologic diseases are the major causes of death and disability in elderly patients. Our approach can credibly estimate the number of neurological beds needed in a given region or hospital to cover increased demands.

Nonetheless, we are fully aware that, although stable and worth consideration, population changes are weaker incentives than technological developments. For some conditions (e.g., cardiac diseases), technological advancements are stronger influencing factors than population aging and will certainly increase the use of services delivered to older populations. The effects of these factors on future demands should also be included in the model.

Next, there is a clear feedback loop between the healthcare system's ability to cover hospital demand and demographic trends. Therefore, we plan to consider this interaction more deeply in our future research.

ACKNOWLEDGMENTS

This project was financed by a grant from the National Science Centre, Poland titled *Simulation modeling of the demand for healthcare services.* It was awarded based on decision 2015/17/B/HS4/00306.

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