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MODELING HEALTHCARE DEMAND USING A HYBRID SIMULATION APPROACH

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ABSTRACT

This paper describes a hybrid simulation model that uses a system dynamics and discrete event simulation to study the influence of long-term population changes on the demand for healthcare services. A dynamic simulation model implements an aging chain approach to forecast the number of individuals who belong to their respective age-sex cohorts. The demographic parameters that were calculated from a Central Statistical Office Local Data Base were applied to the Wrocław Region population from 2002 to 2014, and the basic scenario for the projected trends was adopted for a time horizon from 2015 to 2035. The historical data on hospital admissions were obtained from the Regional Health Fund. A discrete event model generates batches of patients with cardiac diseases and modifies the demand according to the demographic changes that were forecasted by a population model. The results offer a well-defined starting point for future research in the health policy field.

1 INTRODUCTION

The effectiveness of the performance of a healthcare system depends largely on an appropriate level of financial and material resources. Although different countries are at different stages of economic development and can afford different packages of care, in the case of any public healthcare system, the number of provided services is permanently much lower than the growing demand, and the supply of services is usually insufficient to meet all of the associated needs. A population's health is therefore determined not only by the quantity of available resources but also by their appropriate distribution. The credible knowledge of a population's needs is the key determinant that can enable the optimal allocation of resources and provide the information that policy makers can use to improve people's access to health facilities.

In the application of quantitative modeling to support managerial decisions, healthcare needs are usually converted into indicators of demand. The terms that are used in this process include descriptors of the delivery of healthcare services such as volume, structure and dynamics. The most common methodological approach assumes that the *future demand* for healthcare services may be properly approximated by the *past supply* of the services that have been delivered to the patients; see, for example, (Bowers et al. 2009; Steins et al. 2010; Matta and Patterson 2007). However, this is not always the best solution that can be applied. According to Roberfroid et al. (2009), this approach is justified only when the current supply of healthcare services is appropriate and the population's demography changes according to currently observed trends. It is widely recognized that the population's needs for healthcare services are highly influenced by age-gender demographic profiles such as the proportion of elderly people, average expected length of life, birth and death rates, and the number of people of working age (Ansah et al. 2014). For example, Barber and Lopez-Valcarcel (2010) simulated a demographic pyramid to analyze the demand for medical specialties in Spain; Masnick and McDonnel (2010) modelled population evolution to link individuals with health conditions to clinical workload; Lagergren (2005) projected the population of older persons to estimate future needs for publicly financed long-term care. Furthermore, the *supply projection* approach does not consider the important uncertainties that could influence future demand, such as the uncertainty of future incidence rates of specific diseases. The random and uncertain factors that play a significant role in healthcare management issues and influence these types of external and internal factors on the overall demand for healthcare services should be considered (Cardoso et al. 2012).

The factors that are discussed above have an impact on the undesirable accumulation of demand, despite the fact that there is a satisfactory average supply level (calculated for the specific period). This in turn may lengthen the waiting time that is required for a particular service and generate additional costs. The overall goal of our project is to develop the general approach for predicting the demand for healthcare services. In an attempt to extend our previous studies (Mielczarek et al. 2014; Mielczarek 2013), we searched for new solutions that would enable the preservation of the unique and valuable features of the discrete simulation with the possibility of applying a holistic analysis of the problem. We decided to build a hybrid simulation model to capture different aspects of demand for healthcare services, in particular the effects of ongoing demographic changes, the uncertainty that surrounds the key determinants of future incidence rates and the healthcare indicators that vary geographically. The submodel, which was developed according to a continuous system dynamics (SD) paradigm, describes population evolution. The discrete event simulation (DES) submodel generates data that can facilitate an assessment of the demand for healthcare services on the regional level.

This paper presents the results of an experiment that was conducted to analyze the effects of long-term demographic changes on future demand for healthcare services. We outline the overall idea of the hybrid model and discuss the initial findings of the simulation of population projections. The remainder of the paper is organized as follows: section 2 provides background information about healthcare demand modeling and outlines the conceptual framework for using hybrid simulation. The methodology and the details of the model are presented in section 3. The features of the experiment and the analysis of the results are presented in section 4. Finally, section 5 ends the paper with discussion and conclusions.

2 BACKGROUND

Simulation plays a vital role in healthcare decision making, and healthcare systems have benefited greatly from the use of simulation (Gul and Guneri 2015, Katsaliaki and Mustafee 2011). Simulation methods that are applied to the healthcare sector are categorized in various ways, but they are most commonly classified (Brailsford et al. 2009; Sobolev et al. 2011; Mielczarek and Uziałko-Mydlikowska 2012; Marshall et al. 2015) into four categories: Monte Carlo (MC), discrete-event simulation (DES), system dynamics (SD) and agent-based simulation (ABS). In the selection of a simulation method, the most central consideration is the type of the problem that is being investigated. For example, when modelling emergency departments, discrete-event simulation is definitely the preferred technique (Gul and Guneri 2015). In contrast, models of epidemics and disease prevention are usually built using the system dynamics approach (Homer and Hirsch 2006). ABS is used to study systems for which the consequences on the collective level are not predictable although the modeler is able to describe the behavior of individuals (Kasaie et al. 2010).

The estimation of the future demand for healthcare services is crucial in addressing the majority of the decision support management problems in healthcare systems. Mielczarek (2014) demonstrated that the issue of modeling and forecasting healthcare demand is present: in diagnosing and improving the performance of a healthcare system; in studying the cost-effectiveness and/or the clinical effectiveness of medical procedures, in connection with medical treatments that are associated with clinical pathways, and in the development of prevention strategies or contemporary health trends; and as support for decision makers who are engaged in the capacity planning process at the regional or national level.

In the projection of the demand for healthcare services, population demography and epidemiological estimates of prevalence are usually considered. For example, long-term care (Ansah et al. 2014) or highly age-related conditions such as dementia (Jagger et al. 2009) require that population projections with demand modeling are linked. So-called *cohort modeling* enables the representation of chronological ageing, i.e., the process that describes the dynamic movement of people from one population group to another over time. However, there is also a need to include more individual-specific components in the model, such as a region's socio-economic profiles, temporal factors (i.e., time of day, day of the week, season, and calendar year) or geographical characteristics (i.e., the location of healthcare providers, patients' place of residence) and other factors. The influence of different types of uncertainty and randomness should also be considered (Cardoso et al. 2012). The neglect of this type information can lead to forecasts that are constructed without links to the specifics of the observed changes in demographics, as well as the epidemiological, geographical and health related structures of the population. An incorrectly estimated demand could lead to the erroneous assumptions and could significantly lower the explanatory power of demand projections. Consequently, this may result in accepting a solution for which the planned supply of services far from meets the current demand.

Demand modeling is performed using system dynamics (Desai et al. 2008), discrete-event (Vissers et al. 2007) or agent-based simulation (Taboada et al. 2011). We assumed that the quantitative and qualitative factors as well as the deterministic and stochastic variability should all be present in the model. Such a possibility is offered by the *hybrid structure* that has already proven to be successful in many fields and has obtained benefits that were unattainable with the use of only one of the components alone. In hybrid modeling, different elements of a system are modelled by different simulation and/or analytical paradigms (Viana 2014). Balaban (2014) used a multi-method simulation approach to model the return-to-work behavior of people with disabilities. Gao et al. (2014) developed a hybrid simulation model to project the cost and health impacts of diabetic end stage renal disease. Crowe et al. (2015) used simulation and analytical modeling to study certain aspects of a pediatric heart transplantation program. According to Djanatliev and German (2015), the separate use of simulation techniques is not sufficiently powerful to solve large-scaled problems. The authors also suggest the use of a *hybrid simulation* term if a clear distinction between continuous and discrete methods is of particular importance.

Healthcare demand modeling requires the integration of two opposite perspectives in the simulation model. The projections of long-term population evolutions are performed with the aggregated data and focus on pre-specified age-sex cohorts. These groups are described using such demographic parameters as birth and death rates, life expectancy, and migration descriptors. The common approach to the study of demographic trends is system dynamics (SD), which is a method that focuses on the dynamic analysis of complex phenomena. SD uses a holistic perspective to describe a system by means of a set of *stocks* and *flows*, unique theoretical constructions that are capable of accumulating objects (i.e., individuals from a specific age-sex group) and pushing them from one reservoir to another during a specified time period (as individuals age during the natural passage of time). The opposite perspective, which is based on discrete modeling, concentrates on individuals, i.e., patients entering the healthcare system. The model keeps track of the patients' movements, tries to capture their individual choices, and attempts to incorporate the dynamic and uncertain factors that influence the time and place of admission and the type of services that are provided to patients.

3 METHODS

3.1 Overview of the Model

The initial population for the model was the 2002 Wrocław Region (WR), and the revised population estimates were extracted from the data that were published by the Polish Central Statistical Office (GUS, 2015). The WR belongs to Lower Silesia, which is the fourth largest region in Poland. From among the five subregions that make up the Lower Silesia voivodship, the central area, which consists of the capital (i.e., the city of Wrocław) and another subregion that encompasses the administrative districts and which are located near the capital, were selected for our study.

The general concept of the hybrid SD–DES model is shown in Figure 1. The main objective is to estimate the level and the structure of the exposed and unexposed demand for healthcare services. The key element is the inclusion of the factors for which the incidence, intensity and consequences are uncertain in relation to demography, human behavior, time and prevalence. The SD model uses an aging chain approach to forecast the demographic changes that will be observed within the WR population over next 20 years. The DES model generates batches of patients with a certain disease (e.g., patients with suspected cardiovascular disease) who will arrive at the WR hospitals. The model takes into account temporal (month, year), spatial (place of residence, location of the healthcare unit) and epidemiological (incidence rates) factors. The final volume of the demand is determined by integrating the outputs of the two submodels.

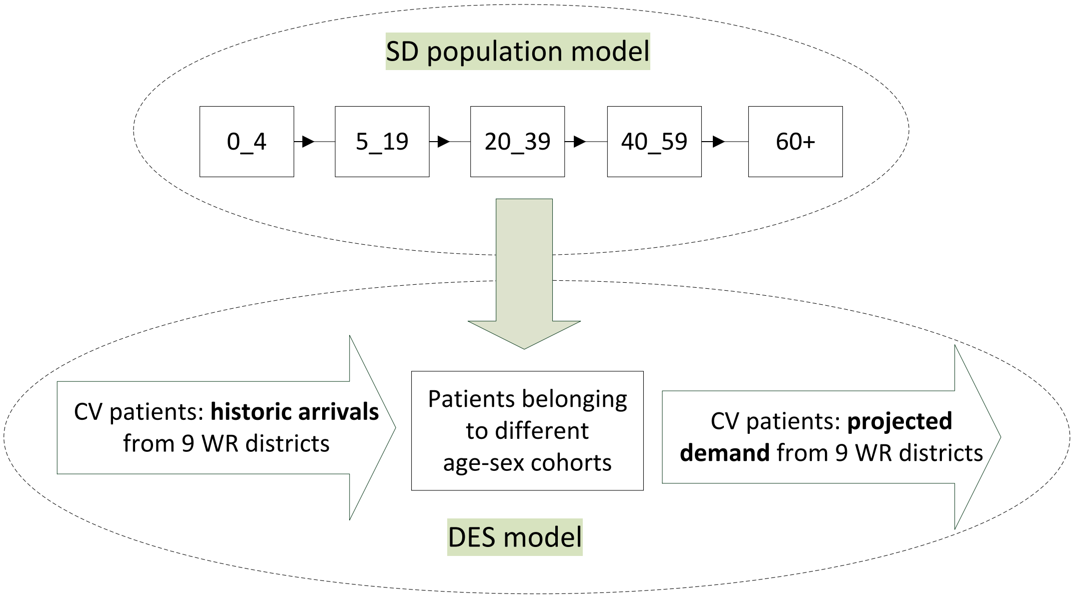

Figure 1: The general concept of the hybrid simulation model.

3.2 Population Submodel

The SD population submodel consists of two aging chains, with five age-sex cohorts in every chain. A detailed description may be found in (Mielczarek and Zabawa 2016). The stocks represent individuals who belong to a certain age-sex group, while the flows are responsible for the dynamic behavior of the population. Input flows, i.e., *births* and *immigrations*, increase the number of individuals inside the cohort; and output flows, such as *deaths* and *emigrations*, decrease this number. There are five cohorts inside each aging chain: F0_4; F5_19; F20_39; F40_59; F60+ and M0_4; M5_19; M20_39; M40_59; M60+. For example, the cohort F20_39 describes women at the ages between 20 and 39 years old. The cohorts are connected by the *maturation* input-output flows (see Figure 2). The movement between cohorts may be described by the *time in cohort*, i.e., the time that each individual needs to "live" from the moment at which she enters the younger cohort until the moment at which she moves to the older one.

The demographic variables are assumed to be exogenous. There are four main demographic variables: fertility, mortality, net migration and life expectancy. The last variable applies only to cohorts F60+ and

M60+, and it measures the average time that an individual at age 60 is expected to live based on sex and current age.

The members of each age cohort are updated on every computational interval so that the changes inside the cohorts are registered not once a year but on a continuous basis within a year. The time-step mechanism, which operates at discrete moments, aggregates all of the input and output flows that move to and from a particular cohort into one dynamic object. The singular resultant flow instantly increases or decreases the number of individuals in the cohort.

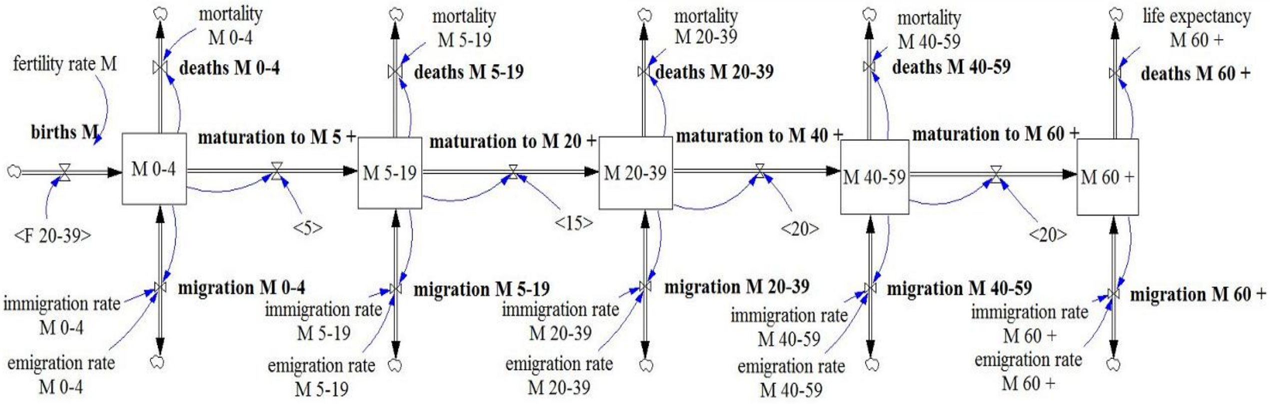

Figure 2: Female aging chain: five stocks (cohorts) with input (births), output (deaths) and input-output flows (migrations).

3.3 Arrivals Submodel

We used dynamic random Poisson processes to model patient arrivals to the WR healthcare facilities. There were nine input patient flows (see Figure 3) describing cardiovascular (CV) patients incoming from nine WR districts.

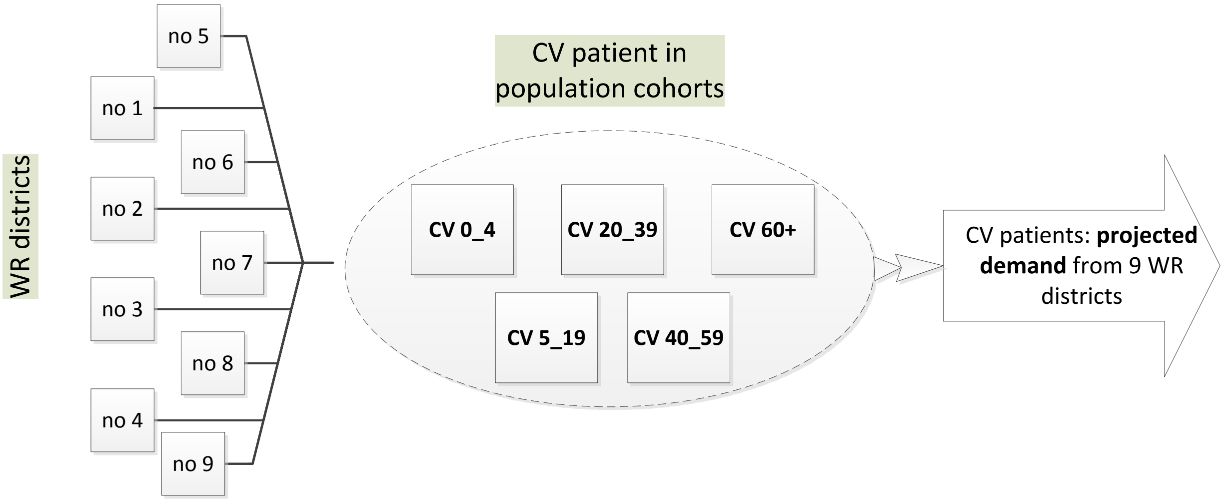

Figure 3: Patients with CV health problems arriving at the WR healthcare facilities.

The parameters for the exponential distributions with time-varying parameters were defined according to the results of the historical data analysis. All input parameters were based on the data sample from the Lower Silesian Health Fund branch registry. The flows of CV patients fluctuate considerably depending on the calendar month, and their intensity is highly dependent on the number of older people who live in particular districts. The output of the model predicted the number of CV patients who live in nine WR districts and will create the demand for healthcare services in the next few years.

3.4 Data

The simulation begins in 2002 and runs through 2014 according to parameters that were estimated on the basis of CSO (GUS, 2015) data. Beyond 2015, the input values were estimated based on the different scenarios according to (Waligórska et al. 2014). The goal of the simulation was to explore the past and future structure of the WR population and to generate numerical forecasts that can be used by the DES model. Table 1 presents the basic set of parameters calculated based on the historical data. The incidence rates that describe the number of WR patients with CV disease are based on the statistics from the Lower Silesia Health Fund (NFZ) branch registry from 2010 and 2011. The arriving patients were defined by two descriptive characteristics: age-sex group and place of residence (district code).

Table 1: Historical population parameters calculated based on (GUS, 2015) for the WR.

Parameter	2002	2008	2014
Total female population	606158	613093	633074
Population of children F0_4	23974	26924	30527
The oldest population F60+	124988	136798	165694
Fertility rates (F)	2.31%	2.99%	2.85%
Death rates (F0_4; F40_59)	0.23%; 0.32%	0.32%; 0.38%	0.07%; 0.29%
Migration rates (F20_39)	0.21%	0.28%	0.43%
Life expectancy (F60+)	22.15	23.18	24.40
Total male population	558302	559861	579707
Population of children M0_4	25452	28093	32560
The oldest population M60+	78835	87899	113164
Fertility rates (M)	2.55%	3.09%	3.08%
Death rates (M0_4; M40_59)	0.22%; 0.84%	0.17%; 1.00%	0.11%; 0.73%
Migration rates (M20_29)	0.14%	0.20%	0.39%
Life expectancy (M60+)	17.19	18.05	19.49

3.5 SD Model Testing

The model was calibrated to determine the optimal values of *times in cohorts* (so-called *maturation lengths*). The values of the *maturation lengths* were adjusted using the ExtendSim optimizer. The primary optimization function was to minimize the total differences between the number of females (and, respectively, males) from historical and simulation data in cohorts 0_4, 5_19, 20_39 and 40_59. The second optimization function was to minimize the total differences between the total number of women (and men, respectively) from the historical and simulation data in 60+ cohorts (Figure 4). The results of the calibration were acceptable. The total number of the WR population was simulated with a high level of accuracy. The Mean Percentage Error (MPE) differs from -1.49% to 1.96%. The discrepancies in the MPE values for particular cohorts were at an acceptable level: from -4.87% to 9.88% for the female cohorts and from -5.72% to 10.93% for the male cohorts.

It should be emphasized that the optimization of *maturation lengths* was necessary because the model must consider the diverse ages of the individuals within the same cohort. In addition, the time ranges that were defined for the particular cohorts differed from 5 to 20 years and this differentiation in the sizes of the cohorts adversely affects the correctness of the chronological aging. Another problem is caused by the intermediate inflows and outflows that dynamically increase or decrease the quantity within the stocks and disrupt the flow between the age cohorts. This blending problem lead to the differences between the theoretical values of the parameters *time in cohort* and the adopted values of *maturation length.* The time that is needed to move from one cohort to another takes on average longer than the *time in cohort* variable would indicate (see Table 2). The *life expectancy* parameter was also adjusted. The last two cohorts (F60+ and M60+) describe individuals who are older than 60 years. Life expectancy, as defined for a certain point of time, differs for a woman at age 61 and a woman at age 81. Therefore, during the optimization process, the values of numerical multipliers were found and applied.

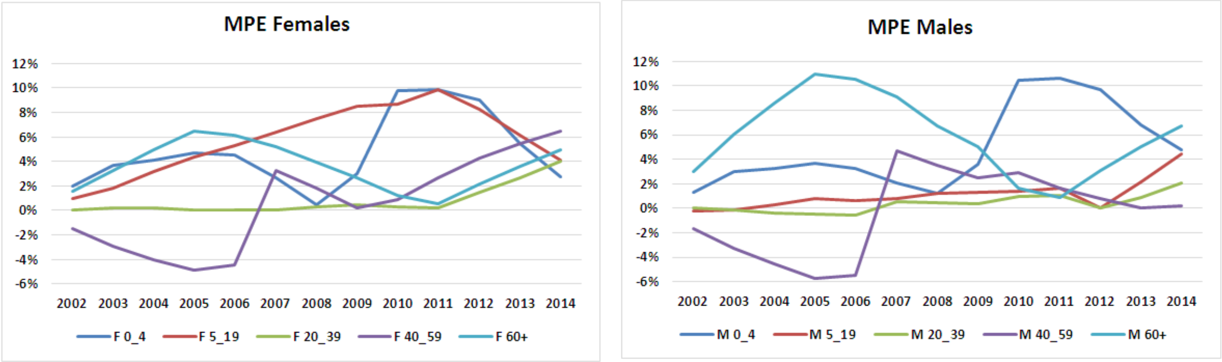

Figure 4: Mean Percentage Errors (MPE) calculated between historical and simulation data for the particular age-sex cohorts of the WR population.

Table 2: The comparison of the parameters describing the delays in the movement of individuals between cohorts. Values extracted from the data and calculated through the optimization process.

Cohort	data [years]		model [years]	
	F	M	F	M
	Time in cohort		*Maturation length*	
0_4	5	5	6.1	6
5_19	15	15	13.5	12
20_39	20	20	37	30
40_59	20	20	32	27
		Life expectancy		
60+	*n*	*m*	*n* x 1.9	*m* x 1.3

3.6 Simulation Scenario

We used the population projections for the period from 2015 to 2035 as published by the Polish Government. According to (Waligórska et al. 2014) four alternative scenarios forecast the demographic changes for Poland over the next 20 years. The scenarios assume different values of four basic parameters: births, deaths, migrations and life expectancy. We formulated the demographic assumptions for the WR according to the most likely scenario that was predicted for the whole country. It should be emphasized, however, that the governmental forecasts are published for the larger administrative regions (voivodships), such as, for example, the Lower Silesia. Our simulation study focused on two small regions (out of five) that belong to the Lower Silesia voivodship. These two regions are classified as an urban area, and the global population parameters are highly differentiated for rural and urban regions.

There are four parameters that are used in the simulation models that reflect possible future population changes: fertility rates, which are calculated as the percentage of the number of births in relation to the F20_39 cohort; death rates, which are calculated as the number of deaths in relation to a particular cohort; migration balance, which is calculated as the resulting balance of immigrations over emigrations in relation to a particular cohort, and average life expectancy, which is linked to the last two cohorts. The basic scenario makes the following assumptions for the period from 2014 to 2035:

- The fertility rates will first slightly decrease and then gradually increase by approximately 15.55% (females) and 13.50% (males).
- Death rates will increase gradually; however, the number of deaths in the middle-aged cohorts (F40-59 and M40-59) will slightly decline. The growth rates of deaths will be higher in urban areas compared to rural regions.
- The difference between the international and internal net migrations will decrease to almost zero; however, the total number of immigrating and emigrating populations will decrease by approximately 20%.
- Women and men will live longer; however, the differences in life expectancy between Poland and European countries will remain at the same levels. In 2035, a woman age 60 will live on average for 27.75 years, and a man at the same age will live on average for 24.27 more years.

Under the basic scenario, it was assumed that the age-specific prevalence of CV disease remains the same during the forecasted time horizon. However, we plan to explore other trends during the next phase of the study.

4 RESULTS

The simulation begins in 2002 and continues through to 2014 and runs according to the parameters that were calculated based on the historical data. Next, from 2015 on, the values of the parameters are projected according to the population scenario that is described in section 3.6. The simulation reveals the important demographic trends for the WR population for the next 20 years. The total number of individuals from the 60+ cohort, both women and men, will systematically rise (Figure 5); however, the difference between the volume of the oldest men's population in relation to the oldest women's population will slowly decrease. For example, in 2002 the M60+ cohort consisted of 63.34% of the F60+ age-sex group, and in 2035, this ratio will rise to 69.08%.

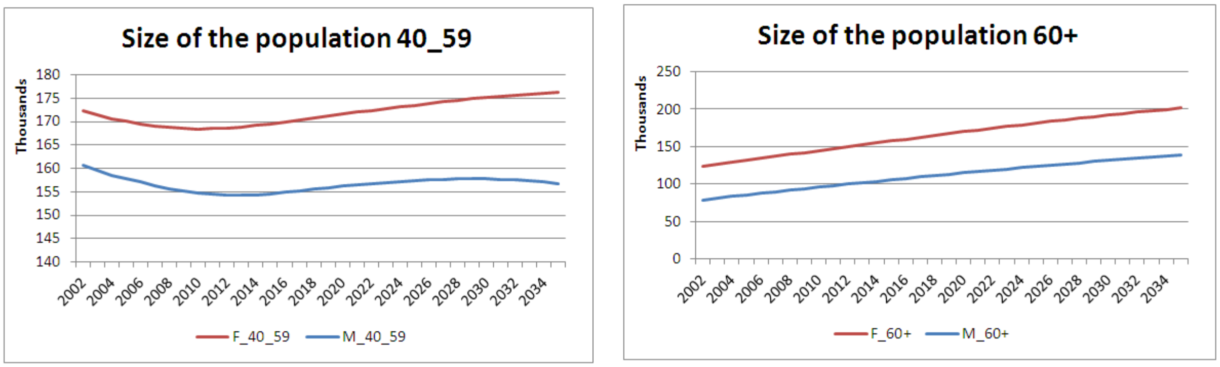

Figure 5: Forecasted trend of the WR population within two age groups: the middle-aged and the oldest, separately for women and men (simulation data).

The simulation shows that population aging will result in a 23.2% (women) and 25.6% (men) increase in the number of people aged 60+ over the next 20 years. The youngest cohorts, i.e., small children and adolescents from 5 to 19 years old, will systematically decrease from 2002 to 2020; however, in 2020, this drop will stop, and a small but continuous increase is observed (Figure 6). The number of the population between 40 and 59 years old (Figure 5) will fluctuate: a clear upward trend is observed for the female cohort F40_59; however, in the case of the male cohort M40_59, the falling trend will start in 2029. The forecasted changes in the structure of the WR population, both for women and men age-sex groups, are presented in Figure 6.

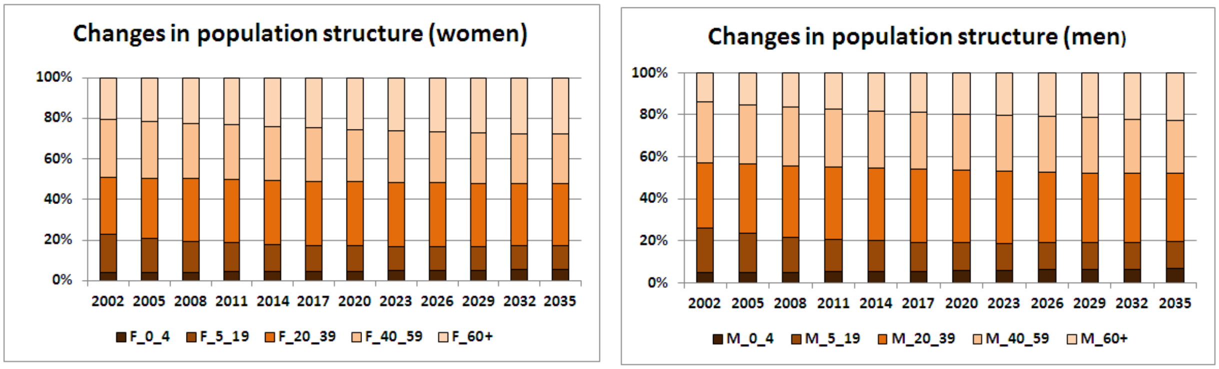

Figure 6: Changes of structure of the WR population by age cohorts, separately for women and men (simulation data).

Under the assumption that the proportion of CV patients per age group remains unchanged during the forecasted time horizon, the global trends for the population are well reflected in the decreases and increases of the prevalence of CV patients. It can be seen from Figure 7 that the trend in the prevalence of CV patients is upwards except for the M40_59 cohort. The older population (F60+ and M60+) will generate increasing demands, and the growth of CV patients between 2014 and 2035 will be more intense among the male population 60+ than the female 60+ (34.4% and 30.15%, respectively). The middle aged cohorts (F40_59 and M40_59) will produce a slightly increased demand; however, this growth will not be extensive, and the number of CV patients will remain at a stable level.

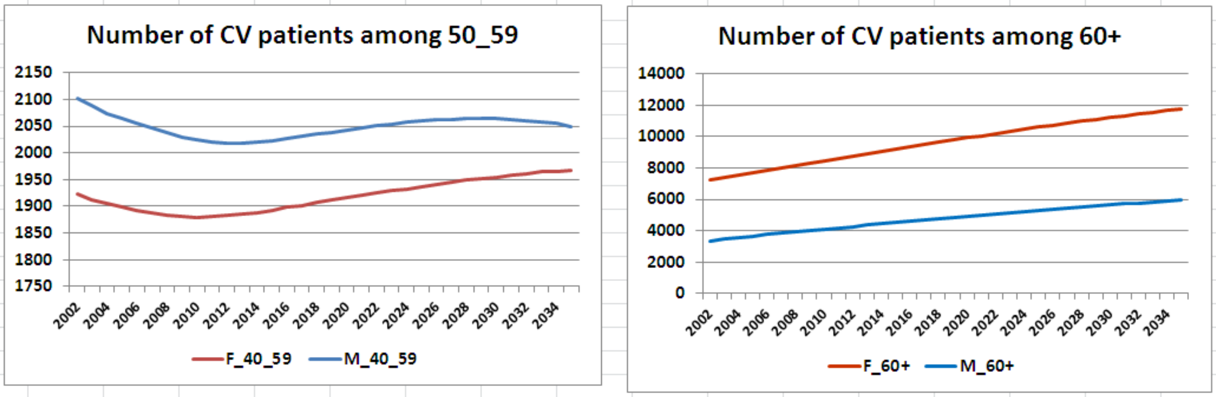

Figure 7: Forecasted trend of CV patients in the WR population within two age groups: the middle-aged and the oldest, separately for women and men (simulation data).

5 DISCUSSION AND CONCLUSIONS

The population model that is presented in this paper represents a step towards a hybrid simulation with the overall goal to forecast future volume of healthcare demands within different groups of patients. The valid prediction of the demand for healthcare services may contribute to the improvement of the quality of the decisions that are made to properly distribute the available resources and implement policies that aim to improve people's health. However, in Poland, no data have been collected on the regional level that show how services are provided in relation to certain measures of needs-for-service. There are also no published studies that show how the care is allocated within the region and the grounds for long-term plans that have been prepared to cover the forecasted population demand.

The basic concept of a computer simulation model assumes that it is possible to estimate future demand by taking into account the past supply of services and the projected trends of population demography. We believe that both types of healthcare needs, i.e. the demands exposed and recorded in healthcare system, as well as the demands that was not revealed and therefore cannot be found in NHF registries, may be estimated with the acceptable accuracy.

This study is an attempt to link the demographic trends with the regional volume of the demand for healthcare services. The major strength of our approach lies in the ability to integrate different simulation approaches and data from different sources. A dynamic simulation model implements an aging chain approach to forecast the number of individuals who belong to age-sex cohorts. A discrete event model generates batches of patients with cardiac diseases based on the historical data from the Regional Health Fund and modifies the demand according to demographic changes that have been forecasted by a population model. To the best of our knowledge, only a few studies have been conducted to quantify the relationship between expected patient volume and demographic, environmental, socio-economic and geographical variables. The issues of random and uncertain factors, such as the needs that originate in different geographical regions or forecasted changes in the future morbidity rates, have not been extensively studied in relation to long-term care planning.

The model described in the paper has its limitations. For example, it assumes a given and stable level of the proportion of CV patients per age group and the absence of technological progress effect. Further research is needed to more deeply examine the relationship between WR demographic parameters and CV prevalence indicators. It is clear that these trend extrapolations should be modified according to different scenarios.

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