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SIMULATION MODELLING FOR PREDICTING HOSPITAL ADMISSIONS AND BED UTILISATION

MARIA HAJŁASZ*, BOŻENA MIELCZAREK

Wroclaw University of Science and Technology,
Łukasiewicza 5, 50-371 Wrocław, Poland

Demographic research of the world population shows that societies are ageing. The ongoing changes in the population structure will require appropriate quantitative and qualitative adjustments in health services to meet the needs of society. Simulation methods turn out to be helpful in these kinds of analyses. In this paper, the authors present a case study on using discrete event simulation (DES) to support decision-making in the field of hospital bed management in the light of demographic changes. The case study was elaborated for one of the Polish district hospitals. A DES model was built to simulate admissions to two hospital wards: paediatric and geriatric. A series of experiments were carried out as based on real data extracted from the hospital database and forecasted demographic trends elaborated by the Central Statistical Office of Poland (CSO). The influence of demographic changes on hospital admissions in the chosen age-gender cohorts was explored, examining different variants of hospital bed availability. The results of the experiments show that demographic trends significantly influence healthcare admission and bed utilisation. The reduction in the number of admissions to the paediatric ward by about 6% results in a change in average bed utilisation from 57.90% to 54.06%. With about 12% more admissions to the geriatric ward, the change is from 68.88% to 75.59%.

Keywords: *simulation modelling, bed management, healthcare, ageing*

1. Introduction

Population ageing is intrinsically associated with the development of civilisation and changes in awareness of health and fitness issues. The average life expectancy for both men and women is being prolonged [20], and the development of diseases which once lead to death can be stopped, and even result in an outright cure. Moreover, main-

*Corresponding author, email address: maria.hajlasz@pwr.edu.pl

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taining a healthy lifestyle, free from drugs and destructive influences, is becoming increasingly visible, which can be considered preventive actions in the field of health [2]. Modern trends in taking care of both men and women health will lead to an increase in the number of elderly people. However, population ageing is connected with a higher probability of disabilities, which often involves other health complications [9]. That usually leads to an increase in demand, increasing healthcare expenditure. There is therefore a strong need to include credible demographic forecasts in shaping health policy booth at the micro and macro level. Analysis of demographic data and forecasts can lead to an adjustment of medical services to the real demand for particular services.

Simulation methods play an increasingly larger role in supporting the decision-making processes attributable to healthcare [13]. Associating these methods with research on demography enables us to obtain conclusions that are useful in resources planning. The authors here focus on discrete event simulation, an appropriate solution for observing stochastic changes taking place in a system at a specific time. Objects, in this case, patients, are relocating dynamically across the system. Each object can be characterized by various features, such as gender, age, diagnosis, the therapy used or time of treatment. Thus, DES can be used to examine a specific hospital with dynamic changes taking place at the time [15].

The case study was elaborated for one of the Polish district hospitals and regions of patients' origin. The data sets come from two sources: a hospital and the CSO. Data on patients is obtained for the years 2014 and 2015. Demographic data include the year 2015 and forecasts for the years 2016–2020. The objective of this research is to show the possibilities of the use of computer simulation to support decisions in the field of hospital bed management in light of demographic changes. To achieve the goal, the DES model is built and several experiments were conducted.

2. Bed management in literature

In the literature, we can find a lot of research about the decision-making problems associated with bed management. This undoubtedly indicates the universality of this issue as an object of research. Different aspects of bed management can be modelled using many available techniques such as simulation modelling, queuing theory, mathematical modelling, predictive modelling or lean Six Sigma [10].

The queuing modelling method was used to meet the administrative expectations regarding the level of services by proper hospital bed allocation among wards [1]. In other research, the queuing system was integrated with a compartmental model and an evolutionary-based optimisation, to support decision-making in the field of patient management [4]. The queuing theory and compartmental flow models were used to check the influence on bed occupancy, emptiness and rejection, as well as such factors as changing admissions rate, length of stay and bed allocation in the department of geriatric medicine [8]. Patient flow can be modelled using the Markov chain, and optimise it using local search heuristics to solve the problem of insufficient beds in hospital wards [3]. Other systems to support decision-making can be used for the optimisation of bed occupancy as well as the cost of its utilisation. To that aim, a hybrid genetic algorithm-queuing multi-compartment model was suggested for patient flow in hospitals [5]. As it is shown, queuing modelling has a wide application in the context of healthcare management. He et al. indicate the ability to model time-dependent stochastic flows, the possibility of analysing a system's steady-state with limited data resources and suitability to simpler systems as strengths of queuing. Queuing models are a useful tool in modelling systems where queues are created. However, they contain a few limitations. One of them is the inability to present the system as a whole. Also, they contain a large number of simplified assumptions about uncertainty [10]. More about the use of queuing theory in healthcare can be found in a wide literature review [14].

Another approach used to support decision-making in bed management is the DES method. It is used, for example, in research on hospital discharges. Needless bed occupation can often be caused by a delay in the patient discharge and makes a new admission to this bed impossible. In that case, DES can be useful in modelling patient flow to examine the impact of discharge time on emergency department (ED) operations and the number of readmissions [6]. DES was also presented to examine ways to improve the efficiency of paediatric wards due to a better patient discharge policy [19]. Within the framework of the proposed actions, the cost influence of placing patients ready for discharge in a discharge holding area instead of waiting in hospital beds was examined. DES can also be used to minimise overcrowding, by, for instance, proper bed allocation among hospital wards [11]. The problem of overcrowding as a research problem is often taken concerning ED, and with the use of DES. The method enabled an examination of the influence of various operational strategies on improvements in patient flow from ED to other hospital wards without increasing capacities [15]. More about the use of DES in healthcare can be found in a literature review by Zhang [21]. The use of simulation modelling brings many benefits. Among other things, the ability to imitate real systems and implement different scenarios is a great advantage of the method over others. One of the challenges of using this method is to correctly perform model verification and validation.

In the field of supporting decisions in bed management, many other methods are available and used apart from those presented in this short literature review. The simulation comprises a large portion of them. The pros and cons of each approach make it possible to apply them in different contexts within one research problem. This diversity allows us to look at one issue from more than one perspective. In this case study, we present the issue of hospital bed management including the demographic aspect and using DES.

3. Assumptions of the case study

3.1. Justification

The facility under examination is one of the Polish district hospitals located in the south of Poland. There are 16 specialist wards. In this case, two were selected: paediatric, and geriatric, as particularly vulnerable to demographic changes, such as population ageing. Most of the patients came from 6 counties located nearest to the hospital. In Figure 1, historical data for these regions are shown. The population pyramid for ages 0–19 indicates that the population in that age group decreases by about 35% in 2018. On the other hand, the population over 60 years old increased by about 33% in 2018.

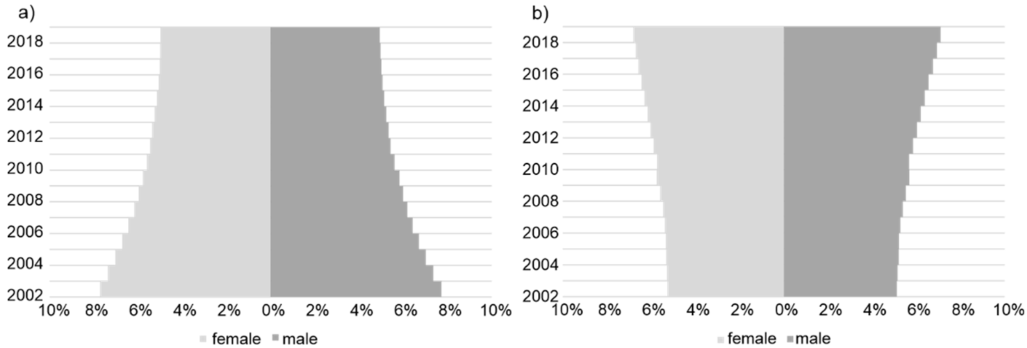

Fig 1. Population pyramid: the percentage share of each cohort in subsequent years for the analysed region from 2002 to 2018: a) ages 0–19, b) ages over 60. Source: the CSO

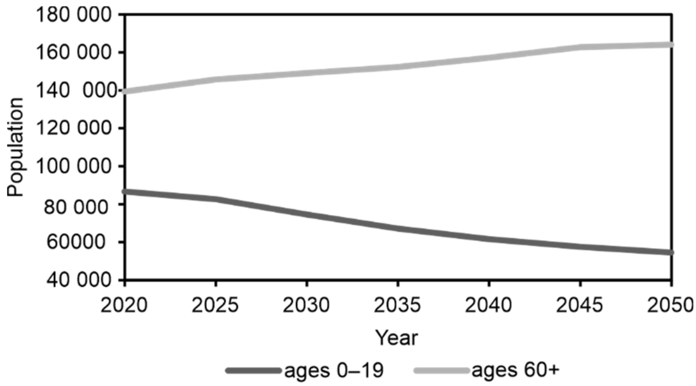

Fig. 2. Population forecast for the examined cohorts in Poland for 2020–2050. Source: the CSO

Figure 2 presents the population forecast for Poland from the CSO [9]. Forecasts for the population over 60 increase by ca. 18% in 2050, and for those under 18 decrease by ca. 37% in 2050. Changes in the population structure make it necessary to plan the number of beds associated with this.

3.2. Model design and validation

The simulation model was built according to the DES approach [16] using Arena software, version 15.00.00000 from the Rockwell Automation. We modelled the process beginning at the moment of admission and ending with discharge. In Figure 3, a flowchart of the DES model is presented.

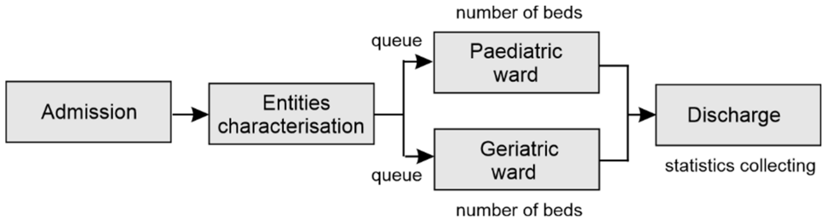

Fig. 3. Flowchart of the DES model

According to the DES methodology, the patient in the model is presented as an entity. After admission, features such as length of stay, origin, etc., are defined for each entity. Next, the entities move to a proper ward and, if a bed is unavailable, they wait in queues. The process ends at the moment when the patient is discharged, which means that the entity leaves the system, and statistics are collected. The output measures analysed are the number of admitted patients, hospital bed utilisation and waiting time in queue. It should be mentioned that in our model, queues for hospital wards are artificial constructions. Patients do not wait to occupy their beds. The analysis of these hypothetical indicators can be used to determine the insufficient number of beds concerning demand.

To elaborate on the input data, we used patients' data files from 2015, which contained 73 952 rows, each row representing the history of one admitted patient for one of sixteen hospital wards. We focused on two hospital wards, so it was necessary to filter out all the data which did not correspond to patients admitted to the paediatric or geriatric wards. As a result, we obtained 1942 rows containing patients' characteristics, such as patient number, date of birth, gender, admission date, discharge date, ward name, and county territorial code.

Based on this filtered data, we carried out an extensive and comprehensive analysis of some data connected to demographic data and other to patients' characteristics. We analysed historic and prognostic demographic data for 6 counties, chosen based on patients' origin of admission. We focused on population figures for ages 0–19 and 60+, fertility rates, mortality rates, and life expectancy, and all of the historic demographic analysis was conducted for 2002–2015. We also analysed prognostic data from the CSO for 2016–2020, which confirmed that the population is ageing.

Other analyses were related directly to admissions and patients' stay in a particular ward. We analysed various patient frequency inflow scenarios, revealing the Poisson distribution to be the best option, which is a discrete distribution used to model the number of random events occurring in a fixed time [12]. Function estimators λ for each day of the week were calculated by dividing the number of patients admitted on a given day of the week by the number of hours on those days. In this way, an average inflow of patients to the hospital was obtained, depending on the day of the week. Those calculations served as a basis to prepare the data for the experiments. We had real admission data for 2015 and 2014 (for verification and validation), so we assumed that admission in each different year constituted the same portion of the population as in 2015.

The admission rate for each age-gender group in 2015 was calculated according to:

$$\text{Admission rate} = \frac{n}{N}\left[\frac{\text{patients}}{\text{population} \times \text{year}}\right]$$

n – number of admitted patients in a particular age-gender group in year x, N – number of populations in a particular age-gender group from a specific region at the end of the year x.

To specify daily admission, the percentage structure of patients admitted to the hospital on a specific day of the week in 2015 in specific age-gender groups was determined.

Table 1. Admission rates for each age-gender cohort $\left[\frac{\text{patients}}{\text{population} \times \text{year}}\right]$

Age-gender cohort	$\frac{n}{N}$
Women under 18	0.011
Men under 18	0.011
Women over 60	0.009
Men over 60	0.005

After the calculation, we were able to determine the admissions for 2016–2020 on the grounds of demographic prognostic data from the CSO. The indicators calculated for 2015 within each age-gender group in the analysed period were assumed to be constant. For example, within women under 18, for every 1000 people, we can expect 11 admissions per year. The same applies to men under 18. In the case of women and men over 60, the values are 9 and 5 for every 1000, respectively (Table 1). In the case of the daily rate of admissions, it was assumed that if there was the same or a similar number of admissions on a given day within a particular age-gender group, then one rate valid on these days was counted for them (Table 2).

Table 2. Percentage distribution of daily admission for each age-gender cohort

Cohort	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Women under 18	0.36		0.15	0.18	0.14	0.08	0.10
Men under 18	0.30		0.34		0.16	0.20	
Women over 60	0.25	0.19	0.16	0.21	0.11	0.06	0.02
Men over 60	0.26	0.20	0.46			0.08	

The admissions on each day of the week took place with different intensity. A much larger number of patients was admitted at the beginning of the week and a smaller number during the weekend. As based on these rates, hospital admissions were developed and used in the model as a schedule of arrivals.

The length of patients' stay was analysed in details and the best solution was implemented in the model. The tool built into the Arena, called Input Analyzer, was used. We attempted to match only one mathematical distribution for each of the age-gender groups. It was possible to accept distribution for men over 60. Other hypothetical distributions had a p-value below a 0.05 significance level in χ^2 tests. So, for women, men under 18, and women over 60 we grouped data to fit distributions to the largest gathering of data (keeping the division into groups). As a result, we got few distributions and constant values then used empirical discrete probability distributions to present patients' stays in the hospital.

3.3. Model verification and validation

Verification and validation of the model were carried out based on the Naylor methodology [18]. According to the first step, the conceptual model and the final results were discussed with healthcare professionals. The model and assumptions were accepted. Even though analysis and results were obtained only for two wards, the model was considered as important and useful.

The second stage related to statistical analysis. Among other things, we checked the equality between simulated and historical data for the number of patients in specific age-gender groups from different counties. To do that, we made use of data from 2014 which was also obtained from the hospital database. The results are consistent with historical data. There are very small differences between the historical and simulation data when comparing the total number of patients arriving from different counties (Table 3). We also counted mean absolute percentage errors (MAPEs) for the relevant county (Table 4).

Table 3. Historical validation. The total annual number of patients' origin according to the division from 2014 and 2015

Historical data: division into counties based on data from 2014				
County	Men 0–19	Women 0–19	Men 60+	Women 60+
1	8	6	2	5
2	491	422	196	445
3	19	21	7	8
4	11	12	4	11
5	18	5	3	4
6	–	–	9	23
Simulation data: division into counties based on data from 2015				
County	Men 0–19	Women 0–19	Men 60+	Women 60+
1	8	7	5	5
2	498	425	185	412
3	20	25	12	20
4	14	4	4	18
5	11	5	3	10
6	–	–	11	24
Simulation data: division into counties based on data from 2014				
County	Men 0–19	Women 0–19	Men 60+	Women 60+
1	8	6	2	6
2	497	417	199	436
3	18	21	6	8
4	11	13	4	10
5	19	5	3	4
6	–	–	8	23

Table 4. MAPE counted for county 2 according to division from 2014 and 2015 [%]

Year	Men 0–19	Women 0–19	Men 60+	Women 60+
2014	1.23	1.21	1.28	2.00
2015	1.43	0.71	5.61	7.42

Table 5. The number of patients admitted and discharged from the hospital

Age-gender cohort	Admitted patients		Discharged patients	
	Average number	Half width on average	Average number	Half width on average
Women under 18	506.35	6.15	506.50	6.37
Men under 18	522.60	10.64	522.40	10.82
Women over 60	642.90	11.41	637.65	11.12
Men over 60	260.85	5.76	258.60	5.83

As part of the third stage, the forecasting capabilities based on the model were tested. We checked the compatibility between historical data from 2014 and simulation data from both 2014 and 2015. Both turned out to be satisfactory. Within the next test, the equality between the number of entities flowing into and out of the system was checked. This test finished positively and expectations were achieved (Table 5).

The results of verification and validation are sufficient to suggest that the model is well-aligned with reality and works correctly.

3.4. Simulation experiments

The baseline experiment was premised on data from 2015 and forecast from 2016 to 2020. The case study was conducted within the framework of the realities falling in 2015, thus the known present and the forecasted future. The general plan of other experiments was based on the changes in the number of admitted patients, according to demographic trends. A detailed plan of the experiments is shown in Table 6.

Table 6. Assumptions of the simulation experiments

No.	Changes
1	Baseline experiment – patient inflow according to the forecasted demographic trends
2	Differentiation in the number of available beds
3	Patient inflow according to the increased forecasted demographic trends for population over 60 (an assumption for an extreme situation such as, for example, an epidemic)

One simulation included 20 replications, 365 days each. For each year from 2015 to 2020, the individual simulation run was performed. The system works without any breaks, so the setting warm-up period was necessary. The seven-day warm-up period was established based on testing and observation of various solutions. After that time the model was filled, and statistics were collected.

In experiment 1, the following output measures were calculated: admitted patients, bed utilisation and waiting times. Admitted patients were presented as the number of entities flowing into the model. Bed utilisation was understood as the proportion of bed usage to simulation length. Waiting time (an artificial indicator) did not focus on the time which patients had to wait for the admission to the hospital. It can be used to determine the insufficient number of resources.

In experiment 2, we observed how bed utilisation was changing in response to the changes in the number of available resources in hospital wards. Changing this number was contingent on the forecasted demographic changes counted in experiment 1.

In experiment 3, we checked if resources on the geriatric ward are sufficient to meet a critical situation, for example, an epidemic among older people. The double forecasted demographic trends were considered. Output measures were the same as in experiment 1.

4. Results

4.1. Experiment 1

In 2015, 1925 patients were admitted to the hospital: 1030 patients to the paediatric ward, and 904 patients to the geriatric ward. Most of the admitted patients were women (643) over 60, followed by men (523) and women (507) under 18, and finally, men (261) over 60. Most patients came from county 2, and the fewest from county 1, 1620 and 24, respectively.

The maximum bed utilisation in both paediatric and geriatric wards equalled the maximum available number of beds, in succession 22 and 30. On the other hand, the minimum values were diverse. In the paediatric ward, the values were in the range of 2–4 for twelve months, and in the geriatric ward, of 6–11. The real data concerning the number of patients queuing was not available. According to the model, the queues are not supposed to exist, or they should be very short. The queues, during the simulation for 2015, barely exist. The maximum number waiting for the paediatric ward was in the range of 0–8, whereas for the geriatric ward, from 2 to 9.

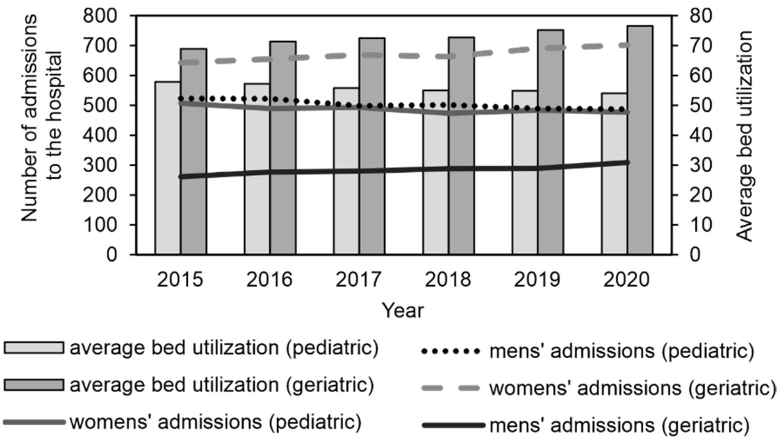

Fig. 4. Admissions and bed utilisation in the paediatric ward and the geriatric ward (experiment 1)

According to the demographic forecast elaborated by the CSO, we can observe a declining trend of people under 18 and increase of people over 60. The number of admissions to the hospital reflects these trends (Fig. 4). It is simulated that the number of admitted women to the paediatric ward in 2020 will be 30 fewer than in 2015 and men will be 36 fewer. The number of admitted women to the geriatric ward in 2020 will be 59 more than in 2015, and men will be 48 more. According to changes in the number of admitted patients, without changing the number of beds, we can observe other changes in the system parameters, such as bed utilisation. In the paediatric ward it falls from

57.90 to 54.06%, in the geriatric ward, grows from 68.88 to 76.59%. The results show that population forecasts are reflected in hospital admissions and change the demand for hospital beds.

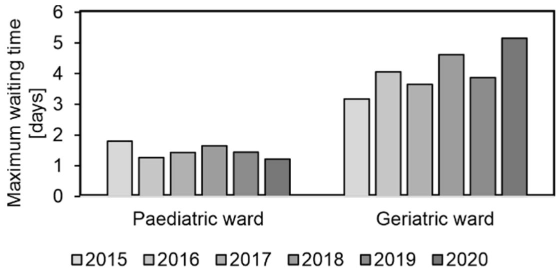

Fig. 5. The maximum waiting time for a free bed in each ward (experiment 1)

The maximum waiting time for a free bed was no longer than 2 days in the paediatric ward (Fig. 5). In the geriatric ward, however, the waiting time grew over time from around 3 in 2015 to around 5 in 2020. We do not observe any trends in waiting times over this period. So, despite a decreasing trend in admissions to the paediatric ward, the maximum waiting time does not necessarily decrease in the same way. The same trend can be observed in the geriatric ward. The length of queues has a connection with the number of admitted patients, but admissions could be spread over the year in a way which does not cause queues to lengthen. As previously written, these queues existed due to underestimations of the number of beds in each ward.

4.2. Experiment 2

In this experiment, the number of resources was modified. The number of beds in the paediatric ward was gradually reduced by 1, while in the geriatric ward, increased gradually by 1. The modification was done in model 1 including the forecast from the CSO (see Table 6).

The reduction in the number of beds in the paediatric ward increased the average bed utilisation. However, Fig. 6 shows that for each subsequent year, the increase was smaller. In Fig. 7, the opposite can be observed for the geriatric ward. Increasing the number of beds resulted in a decrease in the average bed utilisation, but in each subsequent year, the decrease was smaller.

The reduction in the number of beds from 21 to 17 in the paediatric ward in 2020 will result in about 70% utilisation of beds, instead of about 55%. On the other hand, increasing the number of beds in the geriatric ward from 31 to 35, instead of about 75%, will be about 65% utilisation. Taking into account the demographic trends and the recommended use of beds in the paediatric and geriatric wards, it is possible to determine the optimal number of beds in subsequent years.

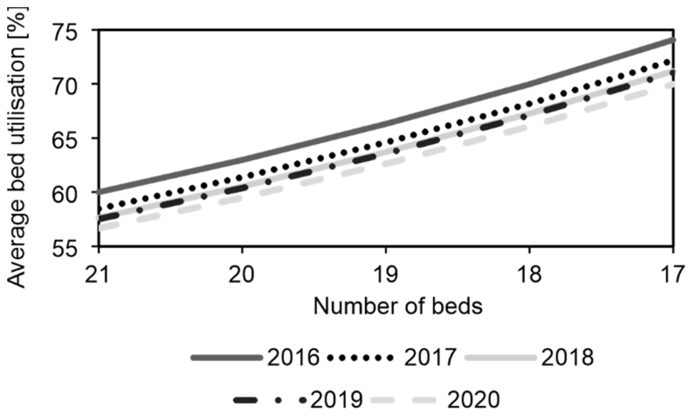

Fig. 6. Average hospital bed utilisation in paediatric ward based on 20 replications (experiment 2)

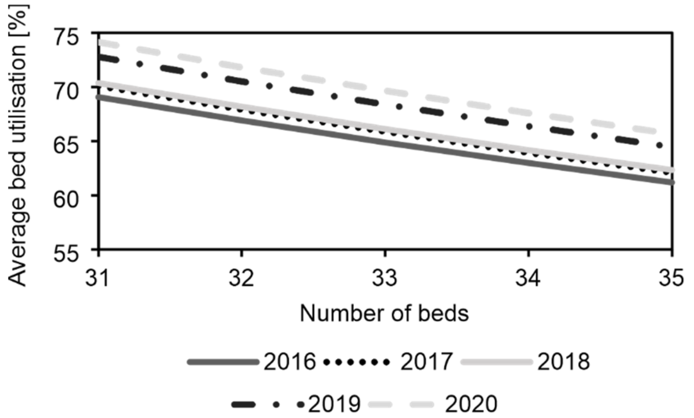

Fig. 7. Average hospital bed utilisation in geriatric ward based on 20 replications (experiment 2)

4.3. Experiment 3

According to the assumption for an extreme situation among people over 60, we can observe a significant increase in admission to the hospital (Fig. 8). The number of admitted women to the geriatric ward in 2020 will be 341 more than in 2015, and men will be 198 more. With an increase in admission, the average bed utilisation also grows, for 2015–2019 concerns the available number of beds, which was set as 30. But in 2020, 30 beds were not sufficient, and the system became overcrowded. Thus, attempts were made to increase the number of beds by one at a time. While the number of beds was 33, the overcrowding stopped showing. From 2015 to 2019, the average bed utilisation grows by about 27%. When comparing 2020 with 2015, with a changed number of resources, the average bed utilisation grows from 68.88 to 98.05%. The results of experiment 3 showed that the hospital is not prepared for those extreme situations, including for example an epidemic and admitting so many people for the geriatric ward.

In the geriatric ward, the maximum waiting time was bigger by almost 24 days (Fig. 9). Extending the number of beds in 2020 caused a slight decrease as compared to 2019, which was about 4 days. Nonetheless, the maximum waiting time in 2020, with an available number of resources of 33, concerning 2015 when the number of beds was 30, increases by around 20 days.

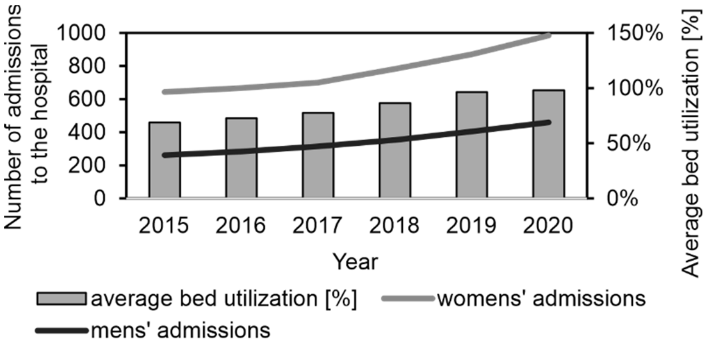

Fig. 8. Admissions and bed utilisation in the geriatric ward (experiment 3)

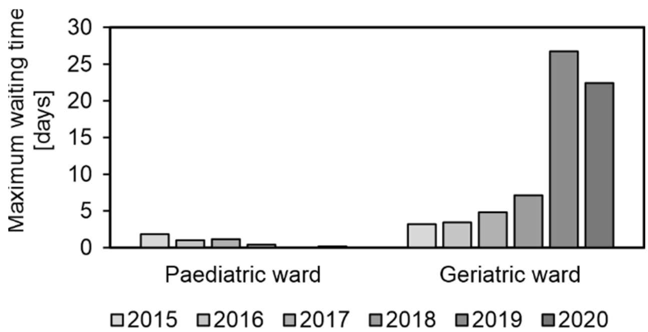

Fig. 9. The maximum waiting time for a free bed in the geriatric ward (experiment 3)

5. Conclusions

The aim of the research was achieved, and the case study results confirmed that computer simulation is a useful tool for decision-making support and offers a range of analytic possibilities. To decide on the number of hospital beds, many aspects should be considered. It is often impossible to check various scenarios and their real consequences without computer help. The simulation method is useful to do it. To build a simulation model and carry out experiments, we can take into account random changes, and freely control the number of available resources or parameters to check what will happen after the change.

The results of experiment 1 showed that in 2020, about 6% fewer admissions to the paediatric ward and about 12% more to the geriatric ward can be expected. This will result in a change in average bed utilisation from 57.90 to 54.06% in the paediatric ward and from 68.88 to 76.59% in the geriatric ward. The maximum waiting time was no longer than 2 days in the paediatric ward and from 3 to 5 days in the geriatric ward. The results of the second experiment are consistent with those of experiment 1, except that the observed changes are greater. The results of experiment 3 showed that a reduction in the number of beds in the paediatric ward changes the average bed utilisation from about 55 to about 70%. Increasing the number of beds in the geriatric ward change their average utilisation from about 75 to about 65%. According to those changes, simulation modelling can be a means to avoid negative effects, defined as the failure to provide appropriate services to patients, such as hospital beds. Depending on the assumed levels of the average hospital bed utilisation in specific wards, the number of beds in the model can be modified and set at a level that meets the requirements of society. The tool can therefore support decision-making processes regarding the number of beds in the paediatric and geriatric wards.

For this research and given the available sources of data, the focus has been on actual admissions directly to the wards. The process of patient admission to and discharge from specific wards is much more complicated. Among other things, it is possible to move patients between wards, and admission to the ward may be preceded by waiting in the emergency room. Therefore, there are many possible directions of development of the presented model, which may depend on the individual objectives of specific studies and the availability of the necessary data.

The research also suggests that the model has several limitations. Namely, the stay of patients in the hospital was determined only by the probability of the length of stay of one patient for a specific number of days. Moreover, there was no analysis of patient admission modes: the total number was examined during the year and for each day separately. Therefore, the lack of access to detailed data forced the adoption of certain simplifications, which, unfortunately, may lead to the distortion of certain parameters. However, this does not mean that the model is incorrect, but only that we should be aware of this when analysing and interpreting the results.

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