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PERFORMANCE EVALUATION OF RESPITE CARE SERVICES THROUGH MULTI-AGENT BASED SIMULATION

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ABSTRACT

Caregivers of patients with chronic diseases are undergoing a daily burnout in their lives. Although respite care seems a promising solution, no quantitative analysis has yet been provided to demonstrate its positive impact. In this article, we propose (i) a new model of caregivers' burnout evolution based on Markov chain and machine learning to model health state evolution, and (ii) a multi-agent based simulation approach to describe the burnout evolution of caregivers and the impact of respite structures on the system. Optimal capacity of respite structures is obtained through a design of experiment. Several management strategies are also tested (collaboration between structures, reservation of beds for emergent cases). Key performance indicators considered are quality of service and costs. Results show a positive impact of respite services on both quality of service and costs. The model also show a trade-off between quality of service and costs when bed reservation policies are used.

1 INTRODUCTION

Advances in medicine have made it possible for critically ill people to live longer and in better health. With demographic structures in continuous progression, hospital management evolves towards policies proposing shorter stays to the patients. At the same time, relatives of patients benefit a growing attention from health-care practitioners. In France, 8 million people are in charge of a sick relative. The role of the caregiver is a difficult and unpredictable experience. It requires effort and entails emotional and economic burdens (McCann et al. 2009).

The over-solicitation of caregivers leads to exhaustion situations. (Osaki et al. 2016) affirm that the burden on caregivers of people with dementia greatly affects their mental and physical health. (Gater et al. 2014) report that caregivers of patients with schizophrenia assume a great part of responsibility in caring for their patients. The burden of caregivers is reflected in their health and emotional well-being. Since late 1960, the concept of respite is in development. The primary purpose of respite care is to relieve caregiver stress, thereby enabling them to continue caring for the individual with a disability. Respite care is typically provided for individuals with disorders related to aging (dementia, frail health), terminal illnesses, chronic health issues, or developmental disabilities.

In this paper, a new approach is proposed to assess the added value of respite care services. The scientific contribution of this study is two-fold: **(1) A new model of caregivers' burnout evolution based on a Markov chain** to model the health state evolution of caregivers and a machine learning approach to design state transitions and better model burnout progression; **(2) A multi-agent based simulation**

(MABS) model integrating the Markov chain model to assess the performance of collaborative respite services against traditional hospitalization. The model can also be used to predict the burnout evolution of a cohort of caregivers. The entity at the center of the proposed approach is the couple Caregiver-Patient. The proposed model may be adapted to different types of chronic diseases. Various respite services are taken into account to quantify their impact on caregivers. This research has been supported by the French Respite Fundation (Fondation France Répit).

The article is organized as follows. A literary review on (i) burnout and caregivers and on (ii) modeling methods in health-care is presented in Section 2. A detailed description of the respite care problem is given in Section 3 as well as the formal model of caregivers' burnout evolution and its implementation using multi-agent based simulation. Simulation setup and scenarios are presented in Section 4. Results are discussed in Section 5. Finally, conclusions and perspectives are given in Section 6.

2 LITERATURE REVIEW

2.1 Burnout and Caregivers

Burnout is a type of prolonged response to chronic emotional and interpersonal stressors on the job (Maslach and Leiter 2016). During the 90's, Danish unions in the human service sector observed an important spike in the anticipated departure of their employees. The main reason for their departure was burnout. Despite the large number of employees in the health sector in Denmark, no studies on prediction of burnout have been conducted. In this context, National Institute of Occupational Health was motivated to conduct a study over five years on the various employees of organizations in the human service sector. Midwives and home care workers show a high level of burnout compared to other practitioners (Borritz et al. 2006).

Over the last decades, informal care giving is an indispensable part of most health-care systems. It is a low-cost alternative to expensive formal care. Moreover, patients prefer in-home and informal care. A report was performed from survey conducted in the United States in 1998 with 1,002 caregivers. Every year, nearly 23% of Americans provide informal help to ill persons (Donelan et al. 2002). Caregivers frequently experience stress in the forms of physical fatigue and psychological distress (resentment, frustration, anxiety, guilt, depression, etc.) (Osaki et al. 2016). In Turkey, a study was conducted on caregivers of patients with multiple sclerosis (Dayapolu and Tan 2016), concluding on the factors affecting the caregiver burden. A study was carried on caregivers of individuals with chronic mental illnesses. It concludes that not only the caregivers suffer physically and emotionally, but also they are angry about their situation.

Little research was conducted for predictors of burnout in the context of caregivers. In (Truzzi et al. 2012), authors performed a study on familial caregivers of patients with dementia in the Center for Alzheimer's Disease in Rio de Janeiro using the Maslash survey. In our research, we try to adapt the predictor burnout on caregivers of patient with chronic disease in order to predict the needs of the population for respite services. We contribute to the literature by developing a simulation model specifically focused on prediction of state of caregivers.

2.2 Modeling Methods in Health-Care

Health-care delivery systems are intrinsically complex, consisting of several levels of interdependent subsystems and processes that adapt to changes in the environment and behave in a non-linear manner (Marshall et al. 2015). With increasingly complex systems, particularly in health, the use of dynamic modeling methods becomes indispensable for effective service planning. Common dynamic simulation modeling methods to evaluate system interventions for health care delivery are system dynamics, discrete event simulation, and agent-based modeling. As an example of complex health systems, the cardiovascular surgery department of the MAYO clinic in the US has been extensively studied. The number of recovery beds for cardiovascular surgical patients is costly and very difficult to manage for efficient service planning (Marmor et al. 2013). For this purpose, a discrete-event simulation model has been developed for the prediction of the number of beds required according to the planned surgeries and the recovery of the patient.

In (Silverman et al. 2015), authors report the benefit of models based on multi-agent systems, precisely their ability to capture the behavior of a system with generality and precision at the same time. Indeed, there are three types of agent models: (i) broad-shallow category of agents (for a general and comprehensive description of the problem); (ii) narrow-deep category of agents (for a deep and detailed interpretation of the system); and (iii) mixed modeling category of agents (combination of models (i) and (ii)). In this paper, we want to interpret a global behavior of our system to capture information about the approximate number of caregiver who are at a high level of burnout. At the same time, we want to ensure the caregiver's pathway during the simulation in a precise and detailed manner.

Finally, the planning of the services of certain health-care systems depends on the patient's recovery. (Kao 1972) optimized the coronary care systems, thanks to its semi-Markov model for predicting the recovery progress of coronary patients. Similarly, this time with model parameterized by burnout predictors (Maslach and Leiter 2016) of caregiver, we are trying to analyze and optimize respite home resources, for effective service planning.

2.3 Scientific Contribution

In this paper, we propose an innovative methodology in a context that has not received much attention in the literature. Our approach attempts to model the caregivers burnout on one hand, and to show the impact of respite structures on the caregiver on the other hand. In addition, we propose an analysis through a design of experiment to determine the number of respite resources needed for caregivers based on two aspects: (i) health status of the caregiver, and (ii) costs of care services (hospitalization/re-hospitalization and various respite care).

3 POSITION OF THE PROBLEM

3.1 Description of the System

The metropolis of Lyon counts 134,476 inhabitants (one of the most densely populated regions along with Paris and Marseilles). Our study will be carried out on this territory with a population of caregivers of patients suffering from various pathologies. The characteristics of caregivers in our population vary according to several parameters: age, gender, marital status, type and severity of the illness of the care recipient. Hence the population is heterogeneous.

A variety of respite structures exist in the metropolis of Lyon. These structures are dedicated to burnout people, in order to provide them with respite. A caregiver with a high level of burnout may solicit one of these services and leave the care recipient to them for a short period (several days to one week usually). The caregiver will benefit depending on the type of services provided and the availability of resources for this respite service. The respite services available on the Lyon metropolis vary according to different criteria. First, the type of service provided varies from service to another: long-term respite, short-term respite, home-based interventions, etc. Secondly, there is a diversity of respite center infrastructures, in terms of the number of resources, and the number of specialists involved in the service. And finally, the daily cost of a respite benefit varies depending on the service provided. In this study, we consider the following respite structures: respite home (a health-care structure dedicated to respite), respite services (home care, helpers...) and the hospital (which should be avoided for respite).

Assessment of caregiver exhaustion should be monitored over time. The objective is to ensure the specific pathway of each caregiver in the population. The pathway of caregiver depends on these characteristics and their evolution over time. For example, a caregiver whose patient is a continuing loss of autonomy, will be made more effort, involving greater exhaustion. Then, consideration to the various respite services will have an impact on the evolution of the burnout of caregiver. As a result, the parameters for the use of respite services should be taken into account for a realistic estimate of caregiver depletion.

Finally, we consider an interaction between caregivers over time. Respite structures have very limited resources compared to the potential number of caregivers in the Lyon metropolis. With increasing demands for respite, respite services will often be comprehensive. At the same time other caregivers will solicit these services and will be forced to head to the hospital or wait. Thus, it is clear that the pathway of a caregiver over time is heavily dependent on other caregivers.

The definition of the various entities of the problem, as well as the environment in which they evolve and interact, allowed us to properly position our problem. In the following, we propose a formal model to analyze the system and evaluate its performance. The model must (i) take into account the characteristics of each entity (couple caregiver-patient), (ii) estimate its exhaustion, and (iii) ensure the prediction of future states. The prediction of depletion depends on several features of the caregiver-patient entity, current status of the caregiver, and state of the respite structures.

3.2 Agent Based Model

Agent based modeling and simulation (ABMS) is a relatively new approach to the modeling of complex systems composed of interactive and autonomous agents. It has been used in a wide variety of applications covering the physical, biological, social and management sciences(Tobergte and Curtis 2013). The typical structure of agent-based modeling is composed of three essential elements: (i) a set of agents, their attributes and behaviors; (ii) a set of agent relationships and methods of interaction; and (iii) the environment: agents interact with their environment in addition to other agents.

3.2.1 Agents definition

In our system, 3 types of behavioral agents are designated: (i) a population of caregivers, (ii) a set of care facilities, and (iii) the hospital. Each agent has its own characteristics, and can influence the environment.

Caregivers. The population of caregivers is a population of agents. In our model, each caregiver is specified by different parameters. These parameters also include features of the patient. To simplify, we consider the caregiver-patient agent as the caregiver agent. The behavior of agents is defined using states. Such states have been specified after discussion with various health practitioners.

- **Normal state:** caregiver is in normal health situation, mentally and physically. She/he is not affected by burnout.
- **Burden state:** certain situations result in caregiver burnout. The agent in a stressful situation and it is better for him/her to take a break.
- **Emergency state:** severe burden situation, a caregiver in emergency has to take a break as soon as possible. Emergency state leads to the admission of the patient in the hospital through emergency service, which should be avoided.

Respite structures. Each respite structure is also considered as a behavioral agent in our model with its own parameters: the number of beds available and the daily cost within the institution. Each request from a caregiver to a respite service may be accepted or rejected. For the respite home, the decision is taken based on the bed load. At first, the service accepts all caregivers. From a certain threshold, the respite home only accepts caregivers with a severe level of exhaustion. Finally, when the total number of beds occupied, the respite home refuses any request. Such behavioral model is modeled by 3 states:

- **Accept all:** if the bed-load is below a certain threshold, all requests are accepted.
- **Accept urgent requests only:** if the bed-load is above a certain threshold, only severe cases are accepted (caregivers in an emergency state).
- **Reject all:** if all beds are occupied, all requests are rejected.

Hospital. Each caregiver according to his/her stage of exhaustion may solicit the respite home or a respite service. However, in some cases, the caregiver can directly send his/her patient to the hospital. Some caregivers are unaware of respite structures, which implies direct referral to emergency services in hospitals. Such solution is costly and should be avoided.

3.2.2 Agent relationships

One of the fundamental concepts of agent-based modeling is the relationship between agents in their environment. Interactions occur between the different caregivers, which will make the behavior of a caregiver dependent on other caregivers. In our model, this interaction is defined as a relationship between caregivers, the respite home, the various respite services and the hospital.

Interaction between caregivers, respite services and hospital. Each caregiver can solicit respite according to his/her level of exhaustion. The demand for respite in our model is defined by a probability distribution. This request can affect the behavior and status of respite structures first, and then of hospital. At the time of the request, if the respite structure has enough resources it can accept it; the number of occupied beds will increase and its condition may change. If the service is saturated and the caregiver is in an advanced stage of exhaustion (emergency state), he/she will be sent to the hospital and the number of occupied beds will increase.

Caregivers interactions. A caregiver, depending on his/her condition (level of exhaustion), may solicit one of the agents modeling a respite service. Then the respite service agent, depending on its state (occupation rate) and the caregiver status, accepts or refuses the request. A relationship between the caregivers exists through their interaction with respite services agents.

Respite services and hospital interactions. The respite home with its particular functioning can affect the behavior of other respite services and of the hospital. If the respite home is saturated, it may redirect requests to other respite services. If all services are saturated, emergency caregivers are sent directly to the hospital.

3.3 Next State Probability Generation using Machine Learning

In order to define the behavioral model of caregivers agents, it is necessary to define the probabilities to stay in one state or to go to another state. A formal description of the burnout monitoring for each caregiver is provided. The parameters related to each caregiver are important to predict the burnout, as well as the history of the caregiver (previous respite episodes). A dynamic generation of state change probabilities is proposed using a machine learning approach. Machine learning is a set of computer and automatic procedures based on logical and binary operations, which try to learn a task from a series of examples (Michie et al. 1994). In our context, we are interested in supervised learning, precisely in the methods of prediction and classification based on decision trees.

3.3.1 Decision tree modeling

The decision tree procedure is a non-parametric method that creates a classification model based on the tree (Alpaydin 2013). There is a traditional approach to building a decision tree. This approach is based on a set of training data with their different parameters. After a series of successive refinements on the input parameters we result at a model based on the decision tree (Andrews et al. 2002). The decision tree-based model, in addition to its ability to classify, can predict values of a target variable based on predictive variable values. (Andrews et al. 2002) confirmed and questioned some results analyzed by logistic regressions through decision tree models. (Tayefi et al. 2016) developed two models based on decision trees to identify risk factors for hypertension on a population of individuals. In our study, we propose a prediction of the values of parameters related to the burnout level of each caregiver in our population.

3.3.2 Decision tree implementation

The provided dynamic model aims at determining the state or the next burnout level for each caregiver. Each caregiver in our ABMS is defined by several parameters. The change from one state to another is explained by two sets of parameters: (i) the first set describes the stay duration in the current state of the caregiver; (ii) the second set describes the transition probabilities between the current state and the other states. The prediction of each group of parameters is characterized by a decision tree. The first decision tree takes as input the current status of the caregiver to predict the stay duration before going towards the next state. In this case, the quality of life is the main determining factor, followed by the social level and the type of relationship between the caregiver and the patient. The second decision tree determines the probability of passing to each state from different parameters:

- x_n: probability of going to a Normal state
- x_b: probability of going to a Burden state
- x_e: probability of going to a Emergency state

In that case, the most important parameter is the age of the caregiver, followed by the the quality of life and the type of relationship between the caregiver and the patient.

Generation of stay duration in the current state. Stays durations are dynamically estimated taking into account attributes of the caregiver. At each time slot, a classification method uses the attributes of the caregiver to predict stay duration before transiting to another state. Thus, at each time slot, if the caregiver's attributes (relationship with the caregiver, quality of life or social status) changes, this will influence the stay duration in the current stay and will update it.

Moreover, probabilities of transiting to each state that have been computed at the time step (i-1) will be taken into account in our decision tree at a time slot (i) to predict The stay duration. Figure 1 shows the overall scheme of the method of our classification method. From the fictitiously generated data, we train our decision tree to predict the stay duration from the various attributes of the caregiver on 70% of the data (training set). Remaining data (test set) is used to test our decision tree.

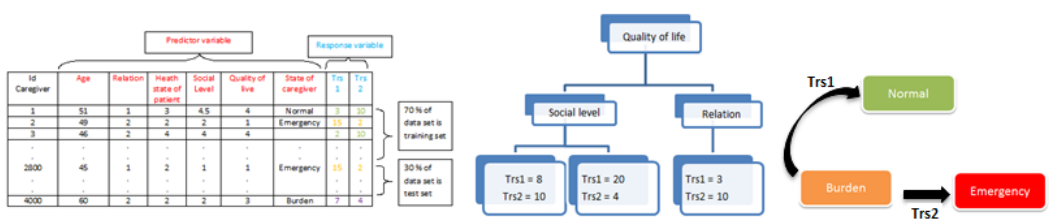

Figure 1: Generating the first decision tree.

Generation of transition probabilities between the current state to another state. After assigning the stay duration for each caregiver, our model predicts the probabilities of transitions to each state from the current state using the same strategy. Attributes of the caregiver are taken as predictive variables to determine probabilities to transit to each state.

The whole procedure is described in Algorithm 1, which takes as an input a population of agents A and a time horizon H. All agents are randomly assigned to an initial state using knowledge about the case study. The procedure generate stay durations and transition probabilities.

Algorithm 1 State update procedure of agents.

INPUT:
$A = \{1, \ldots, a, \ldots |A|\}$: population of agents
$H = \{1, \ldots t, \ldots |H|\}$: simulation horizon
INITIALIZATION:
for all $a \in A$ **do**
  Randomly assign a state to a among $\{N, B, E\}$
$t \leftarrow 0$
PROCEDURE
for all $t \in H$ **do**
  for all $a \in A$ **do**
    Generate $trs1$, $trs2$
    Generate x_n^a, x_b^a, x_e^a
    if State of a is unchanged **then**
      Update time spent in current state
    else
      Update current state of a

4 NUMERICAL EXPERIMENTS

4.1 Data Collection

The main purpose of this study consists in the description and control of a population of caregivers and their pathway over time. Different respite and care structures influence the pathway of caregivers. Our model also includes the decision to accept or reject a caregiver in a respite structure. Indeed, a respite structure has limited resources.

In this model we consider 4 structures: the respite home, two respite services and the hospital. The respite home can accept up to 100 caregivers. The daily cost of a respite home is charged at 360 euros for each patient. In case of saturation of the structure the caregiver is sent to the hospital. The resources of the hospital are much larger and are considered unlimited. The daily cost of a hospital is 1036 euros for each patient. In addition to the respite home, our model takes into account two respite services. These respite services have a few resources than the respite home. The number of beds in each service is set to 50 beds. The quality of service of these respite structures is less efficient than the respite house, involving a daily cost of 18 euros.

As input to our model we will have the monthly data set of 4000 caregivers over a year. The caregivers were randomly generated on the basis of their static characteristics. The dynamic characteristics that influence burnout caregiver were also generated fictitiously. Thus, we will have a monthly history of 400 caregivers over a year on: the health status of the patient of caregiver, the caregiver's burden and quality of life. Data related to the various respite and care structures was collected from existing establishments in the metropolis of Lyon. The simulation of our model was carried out with AnyLogic 7.

4.2 Scenarios

4.2.1 Capacity of the respite home

The number of beds in the respite home is an influential resource on the burnout of caregivers. Different scenarios are set according to the number of beds in the respite home. In Scenario 1, the respite home is closed, whereas in Scenario 5 we consider an unrealistic scenario with infinite number of beds available. So that the scenarios 2,3,4 are respectively the capacities 50, 100, 200

4.2.2 Collaboration management policy

In addition to these scenarios, we consider two management policies for all respite structures: (i) the first policy assumes that each respite structure is independent of the others, whereas (ii) the second policy which assumes that respite structures collaborate and communicate for caregiver care (i.e. if a structure is full, the patient is referred to another respite service before being sent to the hospital). Each management policy is analyzed in our simulation of the 5 scenarios. The objective is to conclude on the best policy to choose for the management of respite structures.

4.2.3 Ratio of emergency beds

The respite home is a special respite structure. Its particularity lies in its quality of service and its large capacity compared to other respite structures. Moreover, it has a specific functioning which is adapted to the extreme case of exhaustion of caregivers. A number of beds is dedicated to caregivers in an advanced state of burnout. For example, out of 100 beds, the respite house may reserve 20% of these resources (20 beds) for caregivers in distress (i.e. in the state Emergency). Once the capacity of the respite home has been fixed and the management rule chosen, we propose a design of experiment to determine the best ratio of emergency beds in the respite home. We consider five other scenarios to analyze our system. We have scenarios 6, 7, 8, 9, 10 which designate the following emergency ratios, respectively; 10%, 20%, 30%, 40%, 50%. The objective is to find the best resource ratio dedicated to emergencies.

4.3 Key Performance Indicators

The evaluation of respite care will be carried out using the following key performance indicators (KPI): (i) Quality of service KPI: the average number of caregivers in an urgent state of burnout per month is recorded; (ii) Cost KPI: the total monthly cost of care and respite for caregivers is calculated to estimate the global cost related to respite. We consider the cost for the society, assuming such care is funded by the French social security.

5 RESULTS

The results of our simulation have been validated statistically, by comparing our results with the input data. For each scenario we set a 95% confidence interval. This interval must be ensured with a consistent replication number. The number replication was set at 100 replications per scenario to ensure a comparison without bias.

This section is organized in three parts. In parts 1 and 2, according to the two respite management policies as defined in Section 3, we analyze the scenarios related to the number of beds (Scenarios 1–5). In the results of our simulation, policy 1 refers to the management policy where each respite structure is independent and interacts only with the hospital whereas policy 2 means that the management is collaborative between respite structures and interact at the same time with the hospital. In the last part, we analyze our system according to the reserved beds of emergency (Scenarios 6–10). After the choose of the appropriate policy and number of beds, we conduct our experiments on the same KPI described in the previous section.

5.1 Quality of Service Analysis

In this section, we analyze our system on the basis of the recorded ratio of emergency cases per month (lower is better). The interval around the results of each policy are described, The statistical validity of our results is presented by the confidence interval of the scenarios for each policy. Table 1 designates the independent policy and the collaborative policy is explained in the Table 2.
The results of the simulation are presented in Figure 2. For each experiment, we reported the result with collaboration (red curve) and without collaboration (blue curve).

The results are coherent and demonstrate the impact of respite structures on the state of caregiver: when the capacity of the respite home increases, the monthly rate of emergency decreases significantly. Notice that the quality of service is not improved anymore with more than 200 beds. When the system reaches a stationary level, we notice that the collaboration policy between the respite structures is the best. Policy 1 (no collaboration, blue curve) converges towards 20.7% of cases of emergency whereas Policy 2 (collaboration, red curve) reaches 19.4% (that is a difference 51 emergent situations avoided).

Table 1: Confidence interval on the results of the first policy.

	1	2	3	4	5
Average	26,13%	20,75%	20,77%	20,75%	20,73%
Lower bound	26,07	20,67	20,68	20,66	20,64
Upper bound	26,18	20,83	20,856	20,84	20,81

Table 2: Confidence interval on the results of the second policy.

	1	2	3	4	5
Average	27,43%	20,92%	20,42%	19,41%	19,39%
Lower bound	27,37	20,84	20,34	19,33	19,25
Upper bound	27,48	21,00	20,50	19,48	19,42

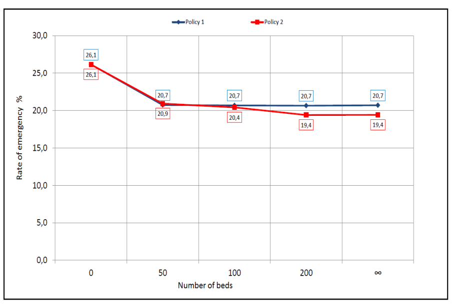

Figure 2: Emergency rate for different capacity of respite home.

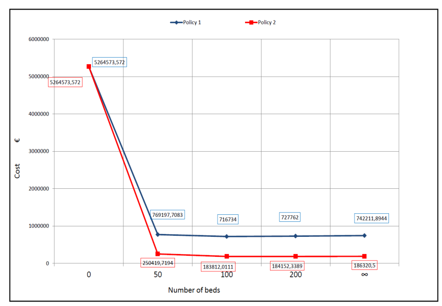

Figure 3: Cost for different capacity of respite home.

5.2 Cost Analysis

The statistical validity of our results is presented by the confidence interval of the scenarios for each policy. Table 3 reports the confidence interval of the independent policy scenarios. Then, Table 4 shows those of the collaborative policy.

Results are reported in Figure 3. When the number of beds in the respite home increases, the total costs incurred by hospitalization and the respite decreases. Unlike the previous KPI (monthly emergency cases) the difference between the two policies is remarkable. From Scenario 2 (50 beds in respite home), we observe a significant gain for Policy 2 (collaboration, red curve) compared to Policy 1 (no collaboration, blue curve). With Policy 1 the average cost of respite is 769,197 euro against 250,419 euro for Policy 2. Collaborative policy based on communication and interaction of respite structures demonstrates a high financial impact. Policy 1 is almost three times more expensive than Policy 2.

Table 3: Confidence interval on the results of the first policy.

	1	2	3	4	5
Average	5264573,57 €	769197,70 €	716734,30 €	727762,27 €	742211,89 €
Lower bound	5262114,46	768446,96	715801,11	727537,08	742017,44
Upper bound	5267032,68	769948,45	717667,48	727987,45	742406,34

Table 4: Confidence interval on the results of the second policy.

	1	2	3	4	5
Average	5264572,30 €	250419,72 €	183812,09 1€	184152,43 €	186320,51 €
Lower bound	5262113,20	5262113,16	183045,82	183660,09	186003,56
Upper bound	5267031,38	251174,26	184578,35	184644,78	186637,47

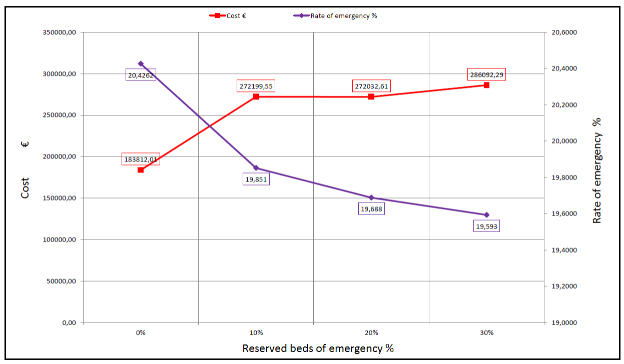

Figure 4: Cost and emergency rate for different ratios of beds reserved for emergency caregivers.

5.3 Emergency Beds Ratio Analysis

The results of previous experiments allowed us to conclude on the appropriate policy for the management of respite structures: we evaluate the impact of the ratio of reserved beds for emergency caregivers considering a respite home structure with 50 beds.

The results of the simulation are reported in Figure 4, where the two KPIs are presented according to Scenarios 6–10. While the rate of emergencies decreases when reserving more beds for emergent cases, the cost is also rising rapidly.

At the strategic level, the decision-maker of the respite home has to make a choice between maximizing the quality of service and minimizing the costs. Using the proposed model and the simulation, we are able to translate this compromise to the numerical graphics. In other words, the decision maker will have the choice to reduce the monthly emergency ratio by 0.833% (33 caregivers/month) in exchange of an increased cost of 102,280.28 euros/month.

6 CONCLUSIONS AND PERSPECTIVCES

In our study, we proposed an innovative approach in a original context. We were able to assess the burnout of caregivers and evaluate the impact of respite structures on quality of service and on health-care costs. To carry out our study we used an agent-based modeling approach. We have implemented machine learning methods to predict the burnout level of each caregiver over time. The originality of our method lies in the machine learning methods incorporated in our simulation model.

Numerical experiments show the positive impact of respite care structures on both quality of service and costs. The opening of new structures such as a respite home allows to decrease costs while increasing quality of service, even for a low number of beds. Collaborative policy demonstrates better results than the non-collaborative one. Finally, there is a tradeoff between quality of service and costs when considering bed reservation strategies for emergent cases. The decision-maker must arbitrate between different criteria. In our context, the results of the simulation report a compromise between the number of emergencies per month and the monthly cost incurred on the caregivers.

The model is generic can be setup for more experiments. For future work, we try to extend the performance indicator of costs incurred by caregivers to a budget impact analysis study. This study will be carried out in collaboration with experts in the field of medical economics in order to judge the pertinence of the simulation results. Moreover, one of the performance indicators to be considered in our future experiments is the quality of life of the caregiver. Such KPI is very interrelated to the caregiver's burnout, which should be carefully evaluated. Finally, we plan to compare our approach to a system dynamics model.

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