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MIXED MACHINE LEARNING AND AGENT-BASED SIMULATION FOR RESPITE CARE EVALUATION

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ABSTRACT

Respite care is a new service to decrease burnout risk of caregivers. Hospitalization related to caregivers burnout are costly and should be avoided. Pre-identification of caregivers with severe burnout is crucial to better manage respite care services through smart admission policies and health resources management. In this article we propose a mixed machine learning and agent-based simulation for respite care evaluation taking into account smart admission policies. Results show that neural networks approach demonstrate best results for burnout prediction and allows a significant decrease of undesirable hospitalizations when used as decision aid for admission control.

1 INTRODUCTION

1.1 Context

New healthcare processes such as ambulatory care (Roure et al. 2015) or hospitalization at home (Rodríguez-Verjan et al. 2013) have proven effective to decrease hospital crowding and improve quality of care. A large part of care are given at home and relatives are solicited to assist the care recipient with his/her everyday treatment. However, caregivers have many commitments towards the patient and are vulnerable to severe burnout.

In France recent investigation entitled "Avenir Focus" related to caregivers revealed that eight million people are in charge of relatives who are sick. Respite of caregivers becomes a major priority. This is the challenge of the "France Répit" organization to promote and develop respite in France. Respite resources remain limited compared to the potential caregivers demand. Management of such services is complex regarding forward-looking caregivers demand and limited respite resources constraints. Respite services management must take into account emergent caregivers (extremely exhausted) who have the highest priority in the system. If undetected, they may not be admitted and will be taken into care in traditional hospitalization which should be avoided at all costs. To tackle this problem, future demand from emergent caregivers should be taken into account.

This research is supported by the "France Répit" organization and aims at developing respite care in France. In particular, a new dedicated respite care service will open late 2018 and will admit exhausted caregivers and/or care recipients.

1.2 Literature Review

In a previous work (Batata et al. 2017) a first agent-based model was proposed to evaluate respite services impact. Indeed, each entity of the system was considered as an agent (caregiver, respite service, hospital). This study allowed to validate the positive impact of respite care service over two dimensions (i) the caregiver's burnout and (ii) the total cost of respite care and hospitalization. However, the demand forecast from caregivers agents was not taken into account in the respite service management. To extend the previous agent-based model, we need to build a prediction model for caregiver's burnout. Little research was conducted on prediction of caregivers burnout. Most of existing studies focus on risk factors determination of caregiver's burnout. In (van Exel et al. 2004) authors aim to develop a diagnosis tool to detect a caregivers at risk. The study was conducted over 148 caregivers whose patient's disease was cancer. In the Netherlands over 212 caregivers of stroke patients (van den Heuvel et al. 2001) were solicited to determine risk factor of burnout. To the best of our knowledge, no study related to burnout prediction or emergent caregiver profiling could be found. Consequently, respite services management is difficult taking into account the stochastic demand of caregivers. Machine learning approaches have been widely used in numerous fields, particularly in healthcare with application of classification or regression (Yue et al. 2016). For burnout prediction supervised learning methods seem particularly interesting.

1.3 Scientific Contribution

The scientific challenge tackled in this paper is twofold: (i) Development of an effective supervised machine learning approach to predict caregiver burnout, and (ii) Performance evaluation of a smart admission policy using the aforementionned machine learning approach for respite services management through an agent-based simulation approach (Batata et al. 2017).

The remainder of the paper is organized as follows. Section 2 provides the problem description. Section 3 describes the machine learning approach and the collected data. The agent-based simulation implementation is described in Section 4. Numerical results are presented and discussed in Section 5. Conclusions and perspectives are given in Section 6.

2 PROBLEM SETTINGS

2.1 Dynamic Burnout Model

Definition 1 (State Model) The caregiver's burnout state is defined by a Markov chain having a set of states $S = \{Normal, Emergency\}$:

- state *Normal* means the caregiver can deliver care to his/her patient;
- state *Emergency* means the caregiver reached a severe burnout situation and cannot deliver care to his/her patient anymore.

Definition 2 (Caregiver Entity) A caregiver entity as described in Figure 1 is defined by the 4-uple $c = (A, P, r, s)$:

- $A = \{a_1, ..., a_n\}$, $n \in \mathbb{N}$, is the list of caregiver's attributes;
- $P = \{p_1, ..., p_m\}$, $m \in \mathbb{N}$, is the list of patient's attributes;
- $r \in \{0, 1\}$ is the respite status of caregiver, $r = 1$ if the caregiver is in respite, $r = 0$ otherwise;
- $s \in S$ is the caregiver's current burnout state in the Markov chain.

Definition 3 (Transition Matrix) The states defined previously in the Markov chain constitute a matrix whose transitions probabilities are characterized by the empiric distribution extracted from collected data. $M = [P_{NN}, P_{NE}, P_{EN}, P_{EE}]$ is a Markov chain transition matrix:

- P_{NN}: probability that caregiver stays in state *Normal*;
- P_{NE}: probability that caregiver transits from state *Normal* to state *Emergency*;
- P_{EN}: probability that caregiver transits from state *Emergency* to state *Normal*;
- P_{EE}: probability that caregiver stays in state *Emergency*.

The system dynamics is intrinsically linked to the caregivers pathway. Indeed, the pathway of each caregiver depends on (i) his/her burnout evolution and on (ii) the amount of respite care delivered to the caregiver. The main challenge of this study consists in demonstrating how respite care impacts caregivers pathways. Without respite care, the caregiver's pathway follows a natural burnout evolution which can be modeled using the transition matrix: a significant duration without respite care means the caregiver has a greater probability to move to an *Emergency* state (i.e. severe burnout).

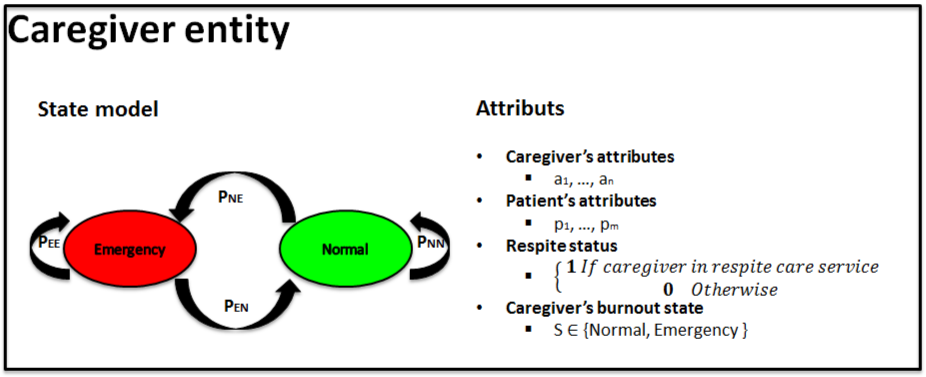

Figure 1: Caregiver Entity.

2.2 Respite Care Process

The pathway of each caregiver is influenced by provided respite care. When a caregiver benefits respite, he/she is considered in respite for a certain duration and goes back to the *Normal* state.

2.2.1 Respite Frequency

The need of respite care can be formally considered as respite frequency of caregiver. This frequency depends of his/her burnout level (*Normal* or *Emergency*) and the attributes of the couple (caregiver/patient). However, a caregiver whose state is *Emergency* needs more respite than a caregiver in *Normal* state.

Moreover, based on clinicians' expertise, respite care is prescribed to the caregiver in a regular way and according to its burnout level: once a week for a caregiver in normal state, and twice a week for a caregiver in emergency state.

2.2.2 Respite Duration

After accepting the request of a caregiver for respite care, a respite duration is calculated according to the state of the caregiver. A caregiver in *Emergency* state can benefit a longer duration than a caregiver in *Normal* state. During respite care, the caregiver's burnout evolution is shutdown according to the set of states S, and its status r is switch to 1 which means "In respite".

2.2.3 Respite Impact

At the end of respite care, respite impact depends on the caregiver's burnout level before he/she took respite. Caregivers in *Normal* state with respite care can be maintained more time in the normal state. Caregivers previously in *Emergency* state switch to the *Normal* state.

Caregiver's state *Emergency* means respite care cannot be avoided. If respite services are saturated, such request cannot be satisfied; in that case, the patient is hospitalized to allow the caregiver to get some rest. This situation should be avoided: from a patient point of view, hospital is highly unadapted and the caregiver will not be able to benefit respite in good conditions. Finally, cost of hospitalization if high.

2.3 Respite Services Management

2.3.1 Classical Respite Services Management

The classical respite services management is based on the requests of the caregivers and their burnout states. Formally, according to the respite frequency, each caregiver has a certain probability to be accepted or rejected in the respite service. We can categorize two situation according to the caregiver's burnout state:

- **Caregiver in** *Normal* **state**: According to the respite service frequency, then the request of the caregiver can be accepted or rejected. If the request is accepted, admission of the caregiver depends on the availability of respite resources. If respite resources are available, respite care can occur. Otherwise, the caregiver will be in standby and will have to wait.
- **Caregiver in** *Emergency* **state**: The caregiver whose state is *Emergency* also depends to the respite frequency of the service and respite resources. However, if the respite request is rejected for any reason, the caregiver will be sent to the hospital. Cost of hospitalization is higher than respite care and should be avoided as much as possible.

Finally, According to the available resources of the respite service, the caregiver will be accepted or rejected. If the respite service is full, then the caregivers request will be rejected. However, if the caregiver rejected is in emergency he/she go to hospitalize his/her patient, else, the caregiver will be in waiting to the respite care.

2.3.2 Smart Respite Services Management Using Machine Learning

The respite service admission control policy can be significantly improved thanks to machine learning. Precisely, by accepting several requests from caregivers with *Normal* state, available respite resources will be reduced. As a result subsequent requests from *Emergency* caregivers will be rejected, leading to several patients hospitalizations.

Using machine learning, requests from caregivers in *Normal* states can be managed differently to optimize respite resources. Indeed, the machine learning can predict the next burnout state of caregiver from the current state and parameters (attributes of caregiver and patient). In the case the next state is still *Normal*, the caregiver does not need respite care urgently and can wait. If the output of machine learning is the *Emergency* for the next time period it is preferable to accept the caregiver's request to avoid a potential hospitalization in the future.

Figure 2 describes management strategies depending on caregiver state. For all requests from caregivers in an emergency state (process in the middle), admission in a respite service is done if possible, otherwise admission in made in a hospital. For all requests from caregivers in a normal state, two management strategies are possible: (i) for classical management (top process in the figure), caregivers are admitted if enough respite resources are available; (ii) for smart management (bottom process in the figure), machine learning approach is used to admit only caregivers that will change state in the future. In the latter, respite resources are reserved for caregivers that may quickly evolve to an emergency state.

3 MACHINE LEARNING FOR BURNOUT PREDICTION

3.1 Data Description

The "France Répit" organization collected data during six months through an online survey involving 2,000 caregivers. Predictive variables are divided into **referential data** which were collected only once (Age, Gender, Social Status, Salary...) and **varying data** which were collected each month (Patient's health state, Quality of life of caregiver, Exhaustion of Caregiver, Duration of informal care per night...). Finally, the caregiver's burnout (binary target variable) was also collected over six months (Normal state/Emergency state).

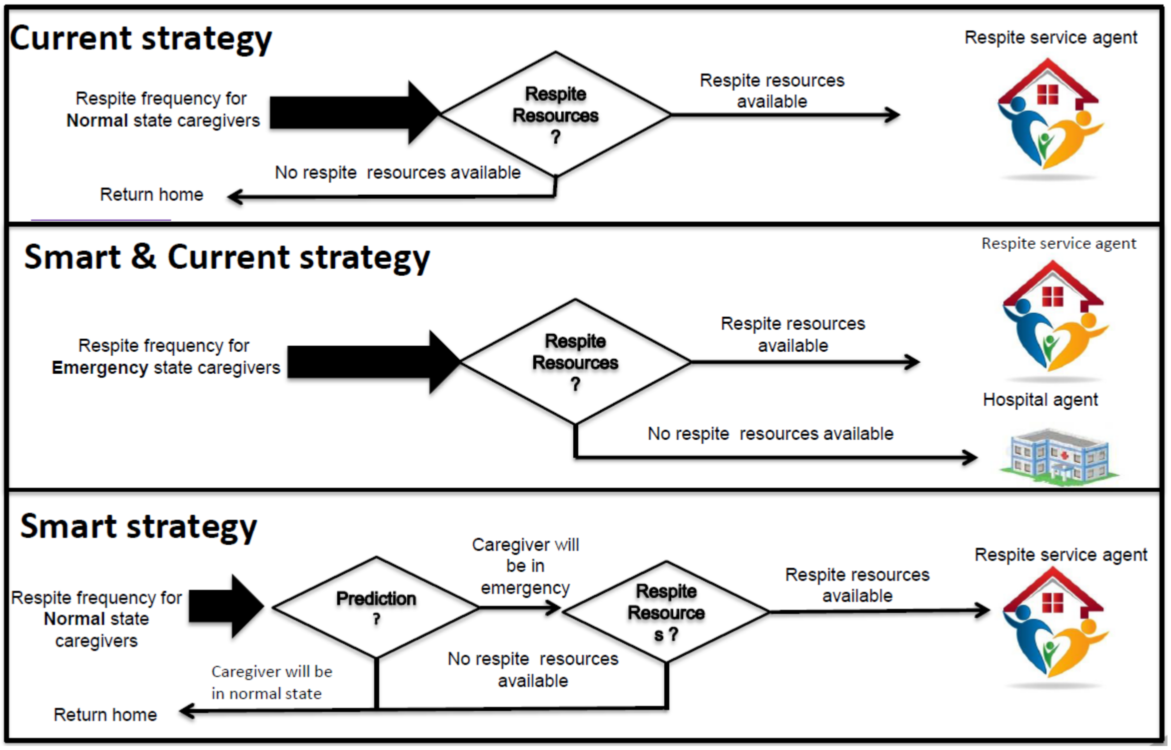

Figure 2: Respite management.

Since the target variable (burnout of caregiver) was evaluated 6 times during the survey (one time per month), it is possible to use the state of the caregiver/patient couple at each period to predict the burnout of caregiver for the next period. The learning set is made of predictive variables for each caregiver/patient couple and for each period: for n surveyed caregiver/patient couple, we then have $6 \times n$ predictive variables data set for learning.

3.2 Formal Machine Learning Modeling

In our problem, the caregiver's entity was introduced with several parameters, some parameters are static as the patient's age or pathology, and some others are dynamic as health state of caregiver. In the following, the caregiver's burnout is defined by two states *Emergency* and *Normal*. To perform the respite services management, we need an effectiveness prediction of the caregiver's burnout state. In machine learning, the output prediction categorizes the machine learning problem. In our problem, the prediction challenge is binary *Emergency* or *Normal*, formally, we have binary classification problem.

The machine learning method takes as input the attributes of the caregiver and her/his patient (dynamic and static parameters), and its current burnout level as input data. After the classification process, the machine learning method returns the caregivers burnout state for the next period.

To formalize the machine learning method, we introduce data of the caregiver/patient couple as follows: let $D = \{X, Y\}$ be a data set, X is a matrix $(n * m)$, n is the sample size (number of caregivers) and m is the number of predictive features. Then, Y is a vector with size n containing the target data to predict (caregiver's burnout state).

Definition 4 (Binary classifier) The binary-classifier can be defined as a function f that takes as argument the predictive data noted X and returns one of the possibles class of the target data $Y = \{0, 1\}$, where 0 means caregiver with "Normal" state and 1 for emergency caregiver.

$$\forall i \in [1,n], f : X_i \rightarrow f(X_i) = y_i \quad \text{with} \quad y_i \in \{0,1\}$$

3.3 Burnout Prediction Benchmark

Several classical machine learning methods were trained and tested using caregivers/patients collected data. Classifier evaluation is a crucial step before incorporation in the control process admission of the respite service. We considered four popular measures (Sokolova and Lapalme 2009) to evaluate each classifier: Accuracy, Precision, Recall, and F1-score. The data set noted D defined in Definition 4 was partitioned in K-fold with $K = 5$ (Rodriguez et al. 2010). Table 2 shows the cross-validation with defined measures for the following classifiers: Decision Tree (DT), Gradient Boosting Classifier (GBC), K-Nearest Neighbors (KNN), and Neural Networks (NN), The setting parameters of each machine learning model was described in the Table 1. Results will be further discussed in Section 5.

Table 1: Hyperparameters of machine learning.

Machine learning models	Hyperparamerts	Values
GBC	loss	“deviance”
	criterion	“friedman_mse”
	n_estimators	100
	max_depth	3
	min_samples_split	2
	min_samples_leaf	1
KNN	n_neighbors	5
	metric	“minkowski”
DT	criterion	“gini”
	min_samples_split	2
	min_samples_leaf	1
NN	hidden_layer_sizes	100
	activation	“tanh”
	alpha	0.0001
	max_iter	200
	solver	“adam”

Table 2: Machine Learning benchmark.

	Measures			
Classifier	Accuracy	Precision	Recall	F1score
GBC	0.55	0.43	0.67	0.52
KNN	0.55	0.76	0.67	0.52
DT	0.55	0.76	0.67	0.52
NN	0.65	0.65	1.00	0.78

4 PERFORMANCE EVALUATION THROUGH AGENT-BASED SIMULATION

4.1 Data Used for Simulation

The data provided from online survey also used for our simulation model. Indeed, the simulation model focus about caregiver agent whose the burnout state is modeled by Markov chain. To build the transition matrix we need all data over 6 months of burnout state.

From the caregivers distribution over burnout states (Normal, Emergency), based on the formula of (Baum, Petrie, Soules, and Weiss 1970) we can extract the transitions probabilities between the states; Normal and emergency for each period during the 6 month of the survey.

4.2 Agent Based Simulation (ABS)

In a previous study (Batata et al. 2017) an ABS was used for respite services performance evaluation. The current work proposes a simulation based on the same set of agents. Each entity of the system is considered as autonomous agent. We note the set of agents Ag, where, $Ag = \{Caregiver_1, \ldots, Caregiver_n, RespiteService, Hospital\}$. To describe each agent of a simulation, we consider the simulation's time horizon H is decomposed into elementary time periods, such as: $H = \{1, ..., t, ..., |H|\}$.

4.2.1 Agent Caregiver

The behavior of each caregiver agent can be described by the transition matrix introduced in Section 3: for any time period $t \in H$, according to the transition matrix the caregiver transit from current burnout state to the next state. Then without interaction with respite service agent the caregiver can trace its pathway based on the transition matrix.

4.2.2 Agent Respite Service

The respite service agent manages the requests coming from the caregivers agents. The possible action for respite service is to "accept a caregiver's request" or "reject caregiver's request". Their action are influenced by its resources in one hand, and the caregiver's burnout state in the other hand.

4.2.3 Agent Hospital

The hospital agent accepts all request of caregivers since it has unlimited resources. Generally, the caregiver agent whose state in "Emergency" address their request to the hospital in the case of rejection from respite service agent.

4.3 Smart Respite Service Agent

Using the burnout prediction approach described in the previous Section, the respite management of respite service agent becomes smart and preventive. Indeed, for each request from a caregiver agent whose state is "Normal", the respite service agent uses the binary classifier f defined in Definition 4. According to the output of classifier f the request will be accepted or not. The procedure is detailed in Algorithm 1.

5 NUMERICAL EXPERIMENT

5.1 Simulation Scenarios and Key Performance Indicators (KPI)

ABS is used to evaluate respite service impact. We propose two respite service management scenarios: (i) a smart respite services management based on machine learning method, and (ii) a classical respite service management without machine learning. The appropriate key performance indicator is the **number of patients hospitalizations**. Indeed, the objective of smart respite service management is preventive: we

Algorithm 1 Smart respite service management procedure.

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 $\{Normal, Emergency\}$
$t \leftarrow 0$
PROCEDURE
for all $t \in H$ **do**
  for all $a \in A$ **do**
    Update current state of a
    The agent a presents respite request
    if State of a is Emergency **then**
      Respite request of a is accepted
    else if State of a in the time t+1 is Emergency **then**
      Respite request of a is accepted
    else
      Respite request of a is rejected

try to avoid the emergency situation by accepting the requests from caregiver whose state in the next time period will be "Emergency" leading to the patient hospitalization.

5.2 Simulation Parameters

Our ABS has the following population of agents: (i) 2,000 agents caregivers; (ii) 1 agent respite service whose resources is set to 100 beds; and (iii) 1 agent hospital with unlimited resources.

Replication length is 6 months, by considering the day as time slot. After discussion with various health practitioners, we fixed respite frequency in respite service once a week for a caregivers whose state is "Normal", and twice a week for emergency caregivers. In our simulation the respite frequency is introduced as uniform distribution set once or twice a week for each caregiver, formally the uniform distribution is between 0 and 1, for each day if the probability is less than 1/7 (one a week for caregivers in normal state) or 2/7 (twice a week for emergency caregivers) then the caregiver's request will be accepted according to the respite service resources. Respite duration varies uniformly between 1 and 7 day(s) for all caregivers and hospitalization duration varies uniformly between 2 and 4 weeks.

To compare both scenarios (with or without machine learning for admission control policy), we need to ensure a statistical validity over the ABS results. For each respite service management we replicate 500 simulations to ensure a confidence interval at 95%. Then, with consistent replication number, we can compare both strategies and highlight machine learning impact without bias.

5.3 Numerical Results

For each classifiers (DT, GBC, KNN, NN) we propose simulation experiments with both scenarios (with or without machine learning for admission control policy). Then, we evaluate and compare scenarios according to our KPI **"Number of hospitalizations"**.

5.3.1 Gradient Boosting Classifier (GBC) and K-Nearest Neighbors (KNN) Experiments

The confidence interval of of each scenario is reported in Figure 3 for GBC and in Figure 4 for KNN. In Table 2, GBC seems to be the least relevant of the four classifier, particularly over recall measure (0.43).

Experiments results in Figure 3 confirms that GBC is inefficient to improve the control policy: the red curve (with GBC incorporation) for most time periods does not demonstrate any positive impact, and for some time periods (weeks 7 and 8) the classical respite service management (without machine learning) is better. Similar results are obtained for KNN in Figure 4 for which Scenario 2 is not significantly better than Scenario 1.

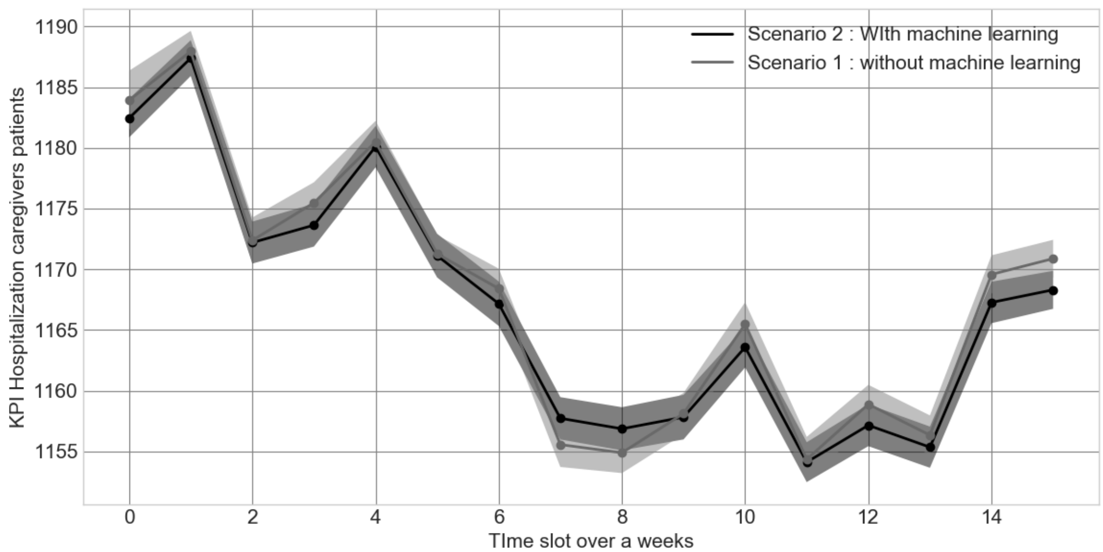

Figure 3: Experiments results with GBC incorporated.

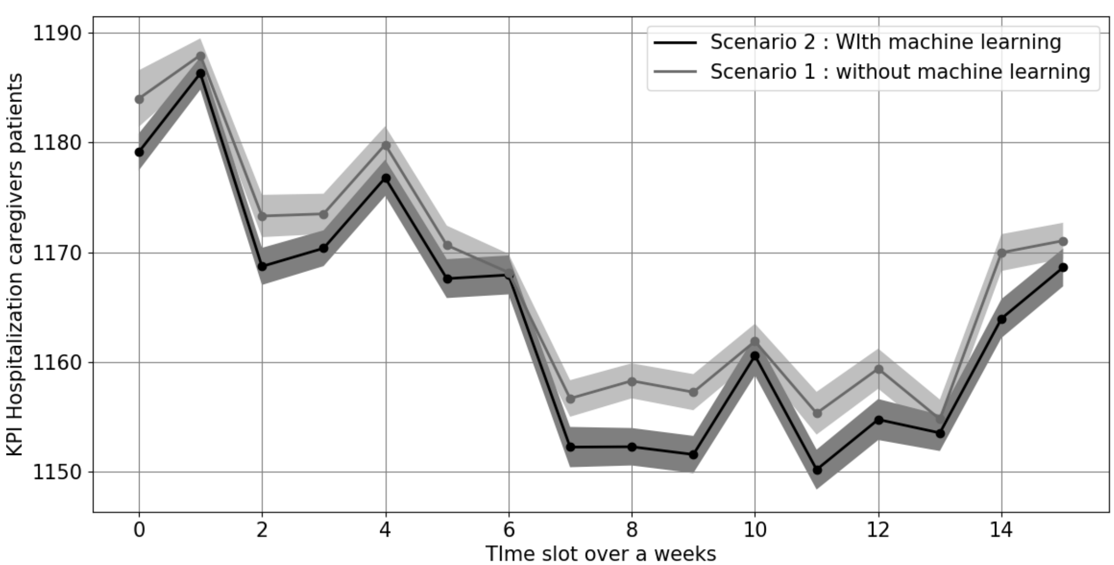

Figure 4: Experiments results with KNN incorporated.

5.3.2 Decision Tree (DT) Experiments

The statistical validity of the results for each scenario can be observed in Figure 5. Scenario 2 with smart respite service agent based on DT classifier achieves significantly better results than Scenario 1. Indeed, for some time slots, the scenario 2 with DT classifier allows to avoid up to 10 hospitalization. In Table 2 the performance of DT and KNN is the same, but DT demonstrated better adaptation with respite service agent and requests of caregivers.

5.3.3 Neural Network (NN) Experiments

The last experiment considers the NN classifier which demonstrates good results: in Table 2 the recall measure reaches 1. The recall measure aims to reduce false negatives (the caregiver will be in “Emergency” state but the classifier predicts “Normal” state). In our case study, ensuring prediction with minimum false negative is important. Best results for admission control policy are confirmed in Figure 6, with a significant number of avoided hospitalizations. For example, in week 10 NN allowed to avoid 15 hospitalizations.

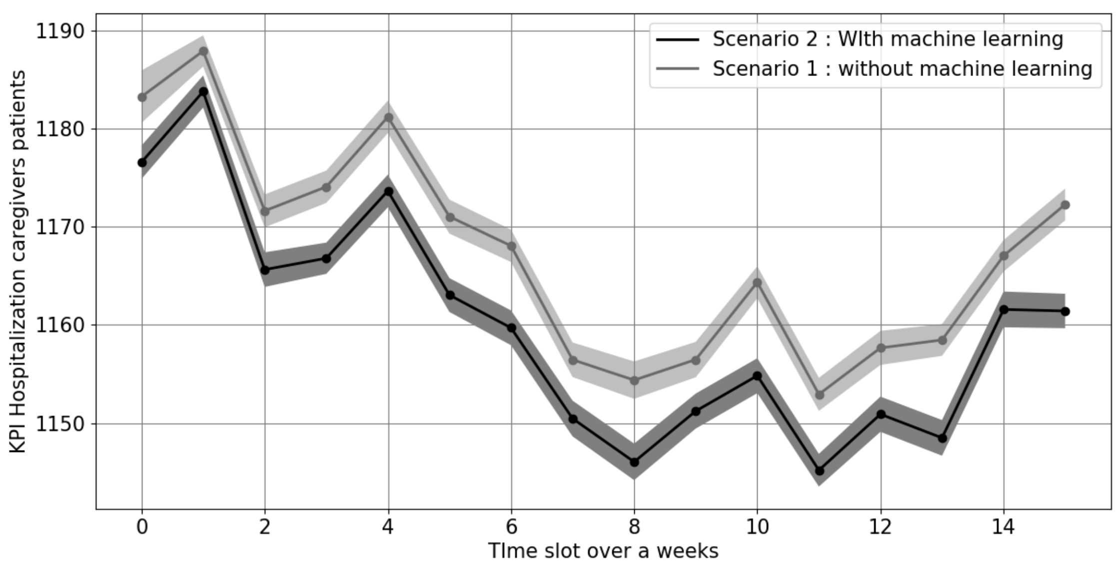

Figure 5: Experiments results with DT incorporated.

6 CONCLUSION AND FUTURE RESEARCH

In this paper, we proposed an original simulation approach including smart admission control policy based on machine learning to evaluate impact of respite services. Neural Networks demonstrate the best results both for burnout prediction and for admission control policy. The mixed machine learning and agent based simulation allowed to describe and evaluate realistic respite service management using a burnout diagnostic tool. Results obtained by the Neural Networks incorporation encourage the perspective to optimize machine learning to get better prediction.

The performance of agent based simulation mixed with machine learning depends on caregiver’s state model (Markov chain) and prediction provided by classifier. Indeed, the Markov chain was build empirically with only burnout data without considering attributes. Then, the machine learning model based its prediction over all attributes of couple (caregiver/patient).

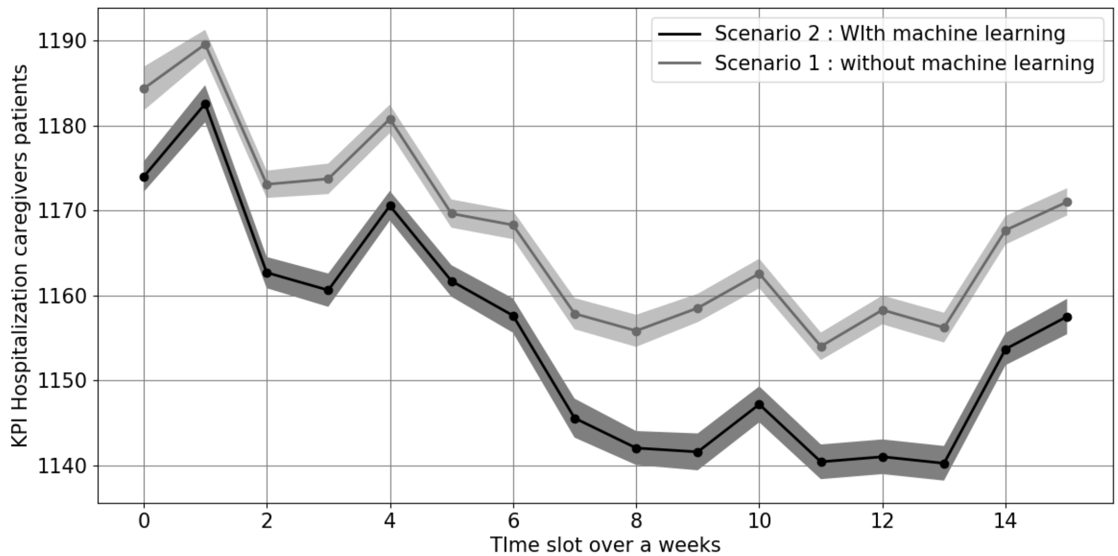

Figure 6: Experiments results with NN incorporated.

Future works of the the present paper are the following. First, the caregiver's state model based on Markov chain will be improved, the transitions probabilities should consider all attributes of couple (caregiver/patient). Also, the benchmark shall be extend to other machine learning and mix them with agent based simulation. We plan discussions and meeting with health-care practitioners to elaborate more complex scenarios scenarios and other Keys Performance Indicators (such as the size of queues in respite services, caregiver's quality of live).

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