A configurable agent-based simulation model for reducing patients’ waiting time in oncology departments

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Abstract: Nowadays, the increase of demand and the progressive decrease of resources are causing higher patients’ waiting time in many chemotherapy oncology departments. Therefore, enhancing the quality of health services is needed so as to avoid claims and disappointments. To this end, reducing the patients’ waiting times in the oncology units represents one of the main goals of any healthcare manager. Simulation models are considered an effective tool for identifying potential ways to improve the patient flow in an oncology unit. This paper presents a new agent-based simulation model properly designed to be configurable and adaptable to the needs of the oncology departments that have to interact with an external pharmacy. In these cases, a courier service is needed to deliver the therapies, collected in several batches, from the pharmacy to the oncology department. A real oncology unit located in (to be revealed after the paper acceptance in respect of the double-blind peer review policy of the journal) was studied through the agent-based simulation and alternative scenarios were compared with the aim of selecting the ward configuration capable of reducing the patients’ waiting time.

Keywords: Agent-based models; Healthcare; Oncology

1. Introduction

Recently, the oncology departments have to face new managerial challenges, due to the need of satisfying the increasing demands of patients and tackling the high costs with restricted budgets.

The ceaseless growth of healthcare requests is mainly due to the aging trend of the worldwide population. Healthcare systems are able to increase the population’s life
expectancy and, consequently, the mean age of the population. At the same time, ageing progression involves a decrease of immune defences and an enlarged predisposition to illness (Candore et al., 2006; Troen, 2003). In the opinion of Vasto et al. (2009), “the pro-inflammatory status of ageing might be one of the both convergent and divergent mechanisms which relate cancer to ageing”. Furthermore, epidemiological studies have shown causal associations between cancers and other several factors such as lifestyle or diet (Katzke et al., 2015), tobacco exposure (Montesano & Hall, 2001) and air pollution (Martoni, 2018).

Siegel et al. (2021) estimated 1,898,160 cases of cancer in 2021 in the United States. Due to these numbers, the demand for healthcare services in the oncology centres steadily grows, but often such increasing demand is not accompanied by an adequate improvement of the oncology department service levels. The outcomes of this dichotomy are a higher workload for people working in the oncology healthcare environment and, even more, a dramatic growth of the patients’ treatment waiting time.

The oncology facilities manage large volumes of patients under limited resources (e.g., pharmacists, nurses or treatment chairs) (Alvarado et al., 2018). Goldstein et al. (2008) stated that the balance of supply and demand of total annual oncology visits showed in 2005 become unstable in 2020. A few years later, the same forecast was confirmed by the estimation of an increase by 40% in thirteen years (from 2012 to 2025) of the overall market demand for this type of healthcare service (Yang et al., 2014).

Despite the mentioned outlooks and the new challenges, the oncology departments have to steadily maximize their service levels. To this end, the healthcare community looks for an improvement of the quality of service and positive experiences of the patients. The reduction of the patients’ waiting time is considered one of the top
priorities for the patients in cancer units (Gesell & Gregory, 2004). The main goals of the healthcare departments consist in providing cares to the highest number of patients in a given time period and, simultaneously, to reduce the patients’ waiting time also increasing the patients’ satisfaction (Ahmed & Alkhamis, 2009).

However, the oncology process involves several human and material resources and the cooperation with the pharmacy, which prepares the therapies, increases the complexity of the system. Therefore, the simulation modelling appears as an effective tool to support the decision-making policies as it also represents a risk-free and low budget method to assess the impact of potential changes on health systems before implementing any intervention (Cassidy et al., 2019).

A simulation technique acting at different abstraction levels relies on the Discrete Event Simulation (DES). In health care environment, DES is widely used for modelling and optimizing hospital workflows and other processes. According to this approach, variables and states change after a set of events happen at discrete time points and entities are just data objects influencing system’s decision processes, without an individual behaviour. In contrast, Agent-Based Simulation (ABS) modelling allows users to reproduce the reality at a detailed level in a straightforward manner. In health care contexts, persons (e.g., patients, doctors) can be represented by agents with an individual behaviour, but it is also possible to model rescue service vehicles and other resources using agents (Djanatliev & German, 2013)

Inspired by the studies performed on a real-life oncology unit located in (to be revealed after the paper acceptance), this paper presents a novel ABS model, which is configurable and adaptable to the needs of oncology departments cooperating with a pharmacy located far away. The ABS model, which is considered one of the most
promising tools for building simulation models of hospitals (Abar et al., 2017; Cassidy et al. 2019; Gunal, 2012; Sulis et al. 2020), has been developed using Netlogo® (Wilensky, 1999), a programmable multi-agent open-source platform that enables to realize user-friendly intuitive interfaces. In this regard, the presented model has been designed to allow healthcare managers to adequately reproduce their oncology unit in a virtual environment and to easily test new configurations of the oncology process with the goal of reducing patients’ waiting time.

The effectiveness of the proposed ABS model has been verified through a case study based on an existing oncology unit of a hospital. It is worth noting that, unlike similar scenarios described in the literature, our model also considers the case in which the pharmacy unit is detached from the oncology department and, therefore, therapies are gathered in batches by pharmacists and delivered through a courier. Once the proposed ABS model has been validated, it has been used to compare several ‘what-if’ scenarios so as to identify better ward configurations that minimize the patients’ waiting times.

The configurability and the free availability of the Netlogo ABS framework as well as the validation based on a real-life case study represent the strengths of the proposed research. The present paper provides several contributions to the scientific community as follows:

i) It represents the first attempt to use ABS to investigate outpatient flow in a multi-stage oncology department where the pharmacy is detached from the ward itself;

ii) It provides a configurable and adaptable tool that easily can be used by stakeholders for investigating alternative ward configurations and for optimizing the service level as well;
iii) A real-life scenario problem is presented with the aim of testing and validating the effectiveness of the proposed approach;

iv) A series of findings properly supported by an ANOVA analysis allows the readers to assess how some organizational aspects and/or certain system resources may affect the performance of oncology departments.

The paper is organized as follows. After a comprehensive literature review, the proposed ABS model is introduced and described in detail. Then, the application to the case study is presented and the model is validated by comparing the behaviour of the real oncology unit and the one simulated. Finally, a Design Of Experiments (DOE) has been carried out with the aim of identifying more effective configurations of the oncology unit under investigation. The best configuration in terms of patients’ waiting time reduction has been identified and the managerial implications resulting from the present study have been further explicated. Finally, the conclusion and future research directions have been summarized.

2. Background and related work

Simulation tools have been increasingly used in healthcare management, along with other Operational Research/Management Science (OR/MS) methods. Often, computer simulation is employed to virtually evaluate ‘what-if’ scenarios of health departments, so that healthcare managers can assess the impact of potential changes on health systems without implementing them in the real systems (Cassidy et al., 2019; Gunal, 2012; Salleh et al., 2017). In general, computer simulation can be distinguished based on three different methods: Discrete Event Simulation (DES), System Dynamics (SD) and Agent-Based Simulation (ABS).
DES methodology deals with real systems with a strong queue structure that can be modelled in discrete periods and where the process can be described stochastically. In this approach, patients are represented by ‘entities’ that go through different processes of the system. DES has been widely used to support healthcare decision-making. For example, Abo-Hamad and Arisha (2014) and Demir et al. (2017) merged the DES model with typical decision support tools (e.g., balanced scorecard) in an emergency department, while Luo et al. (2018) applied DES in a radiology department to properly study how to reserve capacity for emergency and non-emergency patients.

On the other hand, SD technique is typically adopted to model health systems at an aggregate level. Introduced by Forrester (1958), it is based on differential equations and is used to capture the macro-level dynamics of a complex system under study. In this respect, Rashwan et al. (2015) modelled the flow of elderly patients to study the impact of various system parameters on the issue of acute bed blockage in the Irish healthcare system, while Edaibat et al. (2017) used SD simulations to assess the impact of health information exchange (HIE) adoption policies in hospitals located in the State of Maryland.

Finally, a considerable attention has being focused on ABS modelling in the OR context (Abar et al., 2017; Siebers et al., 2010) and for health systems as well (Cassidy et al. 2019; Gunal, 2012; Sulis et al., 2020). ABS is capable of modelling the flows of people by ‘agents’ (Metzner, 2019), as it allows writing specific instructions that control the behaviour and the interaction between agents in the system (Gunal, 2012; Mustafee et al., 2010). Several contributions reveal that ABS modelling is used to enhance the performance of healthcare departments, as follows. Yousefi and Ferreira (2017) combined ABS with a group of decision-making techniques to re-allocate resources in an emergency department. Fragapane et al. (2019) developed an ABS model to enhance
internal hospital logistics by examining the status of the goods’ delivery system and evaluating potential improvements. Saeedian et al. (2019) and Ajmi et al. (2019) used the ABS approach to reduce indicators related to patients’ pathways, such as total waiting time or length of stay, in surgery and emergency departments, respectively.

A new trend in the field of simulation concerns an innovative paradigm denoted as hybrid simulation, which consists in combining different types of simulation techniques (Brailsford et al., 2019). In general, DES is used to represent work processes, ABS is used to model individual agents (e.g., workers and machines), and SD is used to represent complex variables in agents (Goh et al., 2016). Recently, Olave-Rojas and Nickel (2021) developed a hybrid simulation framework combining ABS and DES to address the problem complexity arising from Emergency Medical Services.

Another research stream focuses on the integration between simulation and optimization related techniques. For example, Vahdat et al. (2019) used a simulation-optimization approach to study a paediatric orthopaedic outpatient clinic. Ordu et al. (2020) used a forecasting-simulation-optimization (FSO) strategy to cope with the resource capacity needs of an entire hospital.

As far as oncology departments are concerned, Sepúlveda et al. (1999) and Baesler and Sepúlveda (2001) can be considered the pioneers of decision-making through simulation in oncology units. Nowadays, these studies still represent a source of inspiration for researchers that aim to investigate the patient flow in oncology departments. Some research works handle simulation to examine the performance of the ward by focusing only on the chemotherapy treatment administration. Ahmed et al. (2011) employ simulation to propose new appointment scheduling rules with the aim of increasing both throughput, (i.e., number of patients per day) and treatment chair utilization. Baril et al. (2016a) and Baril et al. (2017) studied the nurses’ tasks in an
oncology department with the goal to reduce their workload. Baril et al. (2020) examined the workload of nursing staff in relation to the administration of patients’ treatment, considering both physical and mental workload.

Other studies also included the activities of the pharmacy, which consists of preparing the therapies required by the oncology unit (Alvarado et al., 2018; Arafeh et al., 2018; Baril et al., 2016b; Liang et al., 2015; Woodall et al., 2013) and delivering the therapies to the oncology unit by a courier (Arafeh et al., 2018). Woodall et al. (2013) assessed the impact of nurses’ unavailability on patients’ waiting times. Interestingly, Liang et al. (2015) proposed a robust DOE so as to assist healthcare managers in decision-making by investigating the impact of various experimental factors (such as number of patients per day, the number of chairs, etc.). Baril et al. (2016b) combined simulations with a business game in a Kaizen event, i.e., a workshop whose goal is to encourage the continuous improvement of a specific area or process (Farris et al., 2009). The authors compared a series of alternative management scenarios and pointed out the need to include pharmacists in the Kaizen event. Alvarado et al. (2018) developed a simulation model to analyse operational strategies related to the management of patients’ appointments in an oncology clinic.

In brief, this paper presents an ABS model for assessing the patient flow of an oncology department, with the aim of identifying a series of actions that in turn are capable of reducing the patients’ waiting time. To the best of our knowledge, this is the first time an ABS-based approach is employed for investigating oncology chemotherapy departments. Differently from other simulation methods, in health care contexts as the one under investigation, patients, doctors, nurse and auxiliary resources can be simulated by agents that communicate with one another, adapt and change their behaviour based on the outcome of the interaction. Although, several agent-based simulation packages are
available both in the market and in the web, we deployed Netlogo® modelling software as it is considered a user-friendly tool that make unexperienced people able to simulate any complex physical system (Cabrera et al., 2012; Chiachio et al., 2014; Liu et al., 2017; Saeedian et al., 2019; Sulis et al. 2020; Taboada et al., 2011, 2012; Yousefi & Ferreira, 2017).

3. Model description

To describe the proposed model, the STRESS-ABS scheme according to the guidelines introduced by Monks et al. (2019) has been used. Two sub-sections are in the following, the former describing in detail the patient flow and the patient classification, the latter explaining the dynamics of the proposed ABS model.

3.1 Problem formulation

In a generic day-hospital oncology department, the patients $p_k (k = 1, \ldots, P)$ attend for treatment and discharge on the same day. The main resources involved in the care process are the oncologists $o_j (j = 1, \ldots, O)$, the nurses $n_l (l = 1, \ldots, N)$ and the therapy chairs $c_i (i = 1, \ldots, C)$. Furthermore, each oncology unit interacts with the pharmacy department, which in turns entails pharmacist technicians $d_z (z = 1, \ldots, D)$ for the drug preparation process.

The oncology process can be assimilated to a three-stage hybrid flow shop (Bouras et al., 2017; Hahn-Goldberg et al., 2014) with limited human resources, denoted in literature as $HFS/HR$ problem (Costa et al., 2020). As depicted in Figure 1, the $k$-th patient $p_k$ receives oncology services through the following three stages:

1) **Medical consultation:** Each patient arrives at the department and meets the nurse at reception for a quick registration. Then, he/she is assigned to the $j$-th
oncologist $o_j(p_k)$, which defines the treatment protocol and assures the continuity of care of the patient. The treatment protocol specifies all the necessary information for the care path of the patient, such as drugs to be used for the treatment, treatment days or frequency of appointments. Before starting the chemotherapy treatment, every patient has to meet the provided oncologist for a preliminary medical consultation. The duration of the medical consultation $Tc(p_k)$ depends on the health status of the patient. Indeed, the oncologist monitors the patient’s health and evaluates the blood exams that the patient preliminarily underwent in the same hospital or in an external laboratory. Finally, based on the patient’s health conditions, the oncologist sends the request to the pharmacy of both type and doses of the drugs to be injected;

2) **Drugs’ preparation:** When the pharmacy receives the request, the pharmacist technicians start the drug preparation process, whose preparation time $Tp(p_k)$ depends on the type of therapy. This process occurs after the medical consultation, rejecting any anticipatory drug preparation policy, since, in case of absence or of unsatisfactory health status of the patient, the risk of wasting expensive drugs increases (Hesaraki et al., 2019). When the therapy is ready, it is delivered to the oncology department with a drug delivering time $Td$, which strictly depends on the location of the pharmacy and, thus, on its distance from the oncology department. If the pharmacy is located far away from the oncology unit, a courier service is necessary and therapies will be carried by batches $b_w$ ($w = 1, \ldots, B$);

3) **Chemotherapy’s administration:** Once the therapy arrives in the oncology department, the chemotherapy treatment of patient $p_k$ may start if both a nurse and a treatment chair are available. In this case, the setup task can be
accomplished by a nurse, which prepares the patient for the chemotherapy treatment. Of course, every nurse can prepare only one patient at a time while, during the treatment time of patients \( Tt(p_k) \), any nurse is in charge to simultaneously monitor up to \( N_{\text{max}} \) patients, which in literature is usually set to four (Baesler & Sepúlveda, 2001; Baril et al., 2020). In addition, conforming to what experienced by Demir et al. (2021), a nurse can monitor the infusion process of multiple patients while performing the setup process of a patient. Finally, when the therapy process is completed, the patient discharges the oncology department.

It is worth specifying that some patients do not need to undergo all the aforementioned processes. Indeed, patients can be classified into three categories depending on their daily pathway (Liang et al., 2015):

- **Standard patients**, or ‘OC type’ patients \( p^{OC}_{k_1} \) (with \( k_1 = 1, \ldots, P^{OC} | P^{OC} < P \)), go through all the stage of the oncology unit, as described above;

- **Repetitive patients**, or ‘C type’ patients \( p^{C}_{k_2} \) (with \( k_2 = 1, \ldots, P^{C} | P^{C} < P \)), are allowed to skip the medical consultation, since they have already met the oncologist and have received the treatment the day before;

- **Control patients**, or ‘O type’ \( p^{O}_{k_3} \) (with \( k_3 = 1, \ldots, P^{O} | P^{O} < P \)), do not need any therapy since they have successfully completed the provided chemotherapy protocol and they only require a periodical medical consultation. Since the continuity of care is usually assured for all patients, even patients \( P^{O} \) have to be assigned to a specific oncologist \( o_j(p^{O}_{k_3}) \).
3.2 The agent-based simulation model

A healthcare facility can be considered as a complex system where the agents, which represent - for example - patients, oncologists and nurses, can interact with each other and with the surrounding environment. In this respect, the ABS simulations allow users to identify the factors that influence the patients’ waiting time and possible bottlenecks in the systems under investigation. Figure 2 depicts the graphic framework of the
proposed ABS model developed by Netlogo® (Wilensky, 1999), while the lower side of the same figure contains a general description of each agent. The main features are described in the next subsections.

3.2.1 Layout of the model

A general layout of the model has been defined to emulate the patient flow in the oncology departments. Considering that the patients’ waiting time does not depend on the location of the rooms in the ward, there is no need to import the exact layout of an oncology unit in the simulation model. To this end, two main assumptions can be considered in the model: i) the layout of the model is qualitative; ii) the time needed by each patient to move from one room to another is negligible. The layout of the model includes the following main rooms:

- The welcome room, where the patient meets the nurse at reception for the registration;
- The first waiting room, where the patient waits for the medical consultation;
- The oncologists’ room, where the patient meets the oncologist for the medical examination;
- The nurse room, where the courier delivers the batches of therapies;
- The second waiting room, where the patient waits for the treatment;
- The treatment room, where the patient undergoes the treatment monitored by the nurses.
The object situated in the top-right corner of the ABS framework represents the pharmacy. Finally, the simulation time clock, which considers every simulation time step in seconds, is visible on the top-right side of the ABS framework.

3.2.2 Dynamical rules

Each simulation run represents a single day in the oncology unit, which starts at 08:00 AM and ends when all the treatments are concluded, which is exactly the same happens in the real-life scenario. Patients and human resources of the oncology departments are represented by two types of agents: moving agents, i.e., agents that can freely move within the framework or fixed agents that occupy a specific location. Specifically, the patients
and the courier act as moving agents, while the other resources play as fixed agents. For each simulation run, every patient agent is created in accordance with a vector of patients’ arrival times, defined as *arrival_time_list*. The *k*-th patient *p_k* can move through the rooms previously described, following a path that depends on his/her classification, indicated by the agent’s colour. Red agents are the standard patients *P^{Oc}* , the brown ones are the repetitive patients *P^c* and the green ones are the control patients *P^o*. Each patient may interact with four types of resources: a nurse at reception, the oncologist for the medical consultation, the chair and the nurse for the treatment.

According to the problem formulation in Section 3.1, patients *P^{Oc}* follow the whole therapy pathway, patients *P^o* are discharged after the medical consultation and patients *P^c* are allowed to skip the medical consultation. All the patients start the medical consultation or the treatment based on the status of the resources involved in the related processes, which can be denoted as ‘busy’ or ‘available’. In the case of the medical consultation, a patient *p_k* is allowed to enter his/her oncologist’s room *o_j(p_k)* only if the latter is available. The First In First Out (FIFO) policy is adopted to decide the order of patients for the oncologist visit. Finally, a patient *p^{Oc}_{k_1}* or *p^c_{k_2}* goes to the treatment room if at least one chair *c_i* and one nurse *n_l* are ‘available’ and the courier has delivered the therapy as well. As described in the model description (see Section 3.1), the nurse can setup only one patient at a time and can simultaneously monitor up to *N_{max}* persons. In this regard, the nurse’s agent is characterized by a setup_status and a monitor_status that can be ‘busy’ or ‘available’. In fact, a patient starts the treatment if both setup_status and monitor_status of a nurse are simultaneously ‘available’. A vector called monitoring_patient_list is created to record the patients monitored by the nurse. If the length of monitoring_patient_list is lower than provided limit, i.e., *N_{max}* , then the
monitor_status is ‘available’.

As concerns the pharmacy’s resources, each pharmacist technician, which is handled as a fixed agent, can prepare only one therapy at a time and pre-emption is not allowed. In Figure 2 pharmacists are represented by three boxes, whose colour indicates when each of them is available/unavailable (i.e., green/red) to prepare any therapy. The behaviour of agents related to the pharmacy strictly depends on the specific list of therapy requests coming from the oncologists, named request_list. If the list is empty, the agents are ‘available’ and the related box of the simulation framework gets green, otherwise, they assume the ‘busy’ status and the box will be red coloured. In this case, the therapy under preparation is registered in a vector called wip_list. When the preparation of a therapy is completed, another vector named ready_list is updated with the information of the therapies to be delivered. Once the length of the ready_list equals the provided batch size, the courier picks up that batch and the travel from the pharmacy to the oncology department may start. Now, a new vector denoted as delivery_list is used to contain the information of the therapies that are being transported by the courier. At the same time, these therapies are removed from the ready_list and a new batch size is defined for the next therapies to be prepared and delivered.

As mentioned earlier, the courier for delivering the therapies is configured as a moving agent and is depicted in blue in Figure 2. It is assumed that the courier is engaged only to carry the batches of therapies to the oncology department and no other task is carried out. Also, the proposed agent-based simulation model handles the round-trip travel of the courier from the oncology unit to the pharmacy. The courier delivery time \( Td \) is a model descriptor, i.e., an input variable, to be set by the analyst. Interestingly, if \( Td \) is set to zero, an in-house pharmacy could be modelled. When the courier arrives to
the oncology department, a specific \textit{therapy\_flag} becomes ‘true’ to indicate that the patient’s treatment may start.

\subsection*{3.2.3 \textit{Communication between agents}}

The ABS model is characterized by multiple interactions between agents. When there exists a communication between agents, one agent sends an input to another agent, causing an output, \textit{i.e.}, a certain behaviour of the latter agent. The ABS includes three types of communication \cite{Yousefi2017}: \textit{i)} one-to-one; \textit{ii)} one-to-n; \textit{iii)} one-to-location. One-to-one communication happens when a single agent interacts with another agent, as in the case of the interaction between a patient and an oncologist. In this case, the arrival of the patient in the oncologist’s room (input) makes the status of the oncologist as ‘busy’ (output). One-to-n communication occurs when a single agent communicates with a group of agents. For example, the communication between the courier arriving in the department and the group of nurses to notify that the batch of therapies has been delivered. Finally, one-to-location communication exists between an agent and all the agents in a specific location, such as when an oncologist communicates with the pharmacist technicians in the pharmacy to request the preparation of the patient’s treatment. Table 1 shows the kinds of communications involved in the ABS model for oncology units.
| Input agent              | Output agent | Type of communication | Description                                                                                                                                                      |
|--------------------------|--------------|-----------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Nurse at reception       | Patient      | One-to-n              | The nurse at reception registers patients according to a FIFO rule.                                                                                              |
| Oncologist               | Patient      | One-to-n              | Each oncologist receives a patient on the basis of the FIFO rule.                                                                                                |
| Patient                  | Oncologist   | One-to-one            | The arrival of the patient in the oncologist’s room makes the assigned oncologist busy.                                                                         |
| Oncologist               | Pharmacy     | One-to-location       | The oncologist sends a request for a new treatment preparation to the pharmacy.                                                                                |
| Pharmacist technician     | Courier      | One-to-one            | A pharmacist technician notifies the courier that the batch is ready to be delivered.                                                                           |
| Courier                  | Nurse        | One-to-n              | The courier arrives at the department and notifies the group of nurses that the therapies have been delivered.                                                    |
| Nurse                    | Patient      | One-to-n              | Nurses allow patients to start the treatment once the therapy is at the ward and a chair is available. Again, the first patient arrived at the waiting room is the first served. |
| Patient                  | Nurse        | One-to-one            | The arrival of the patient in the treatment’s room makes the nurse busy.                                                                                       |

Table 1. Communication map between agent in the proposed ABS model.

4. Case study

The proposed ABS model has been applied to improve the quality of services provided by a real-world oncology unit located in (to be revealed after the paper acceptance). The goal of the project is to analyse the performance of the oncology unit in its current configuration and, subsequently, to find new configurations capable of reducing the patients’ waiting times.

The preliminary phases of the project were the following. First, some briefings with the clinic’s employees were scheduled to define both the features of the oncology unit and the key performance indicators. Then, during the next three working weeks, the project team, which includes clinicians, members of the oncology department and
developers of the simulation model, performed an intense time study on the tasks related to the different oncology processes earlier described. Once the data have been collected, a statistical analysis was performed with the aim of finding the stochastic distributions of the main input variables of the ABS model.

4.1 Key Performance Indicators (KPIs)

It is well known that cancer diseases dramatically affect the physical and emotional status of suffering individuals. In this context, reducing the patients’ waiting time appears as the leading objective for enhancing the quality level in the cancer treatment facilities (Gesell & Gregory, 2004) since it is recognized as the major source of patients’ dissatisfaction (Aboumatar et al., 2008; Edwards et al., 2017; Gourdji et al., 2003).

In light of the previous considerations, in this paper the total flowtime $F$ (i.e., the sum of the length of stay of patients) is adopted as key performance indicator (KPI). The length of stay consists of the total time a patient spends in the oncology unit, i.e., the time interval ranging from the time he/she is registered at the reception to the end of the chemotherapy treatment. Particularly, the mean flow time, hereinafter denoted $\bar{F}$, has been considered to measure the performance of any ward configuration in the successive analyses.

Furthermore, two additional indicators are engaged to compare the status-quo of the oncology department with the simulated configurations, namely the mean patients’ waiting time $\bar{WT}$ and the system efficiency $Eff$, calculated as follows:

$$Eff = \frac{F - \bar{WT}}{F} \cdot 100$$

(1)
4.2 Data collection and statistical distributions

A time study covering three working weeks has been carried out to collect the experimental data related to the ward status-quo. During that period, the health unit received 28 patients on average per day and consisted of 3 oncologists, 13 chairs, 1 nurse at reception and 3 nurses for the treatment, which can monitor four patients simultaneously. A single employer of the pharmacy is dedicated to the preparation of the oncology therapy and the pharmacy is located far away, in another building. Finally, as expected, a single auxiliary operator works as a courier for the batch therapy deliveries.

For the sake of transparency, Table 2 reports model parameters and stochastic distributions obtained by analysing the aforementioned status-quo related data. The number of patients per day is derived from a normal distribution with mean 28.07 and standard deviation 3.94. As stated above, usually these patients undergo two different processing stages: medical consultation and chemotherapy administration, which starts after the drug delivery. Among them, 22.32% needs only the medical consultation (control patients or patients \( P^O \)), while 6.18% attend only the chemotherapy’s administration monitored by the nurse (repetitive patients or patients \( P^C \)), while the rest are classified as standard patients \( P^{OC} \). The experimental analysis revealed that the arrival times for each type of patient can be discreetly handled by considering five time windows, each one related to a different occurrence probability. Therefore, once the time interval is selected, every patient arrival time is drawn from an uniform distribution \( U[0, 59] \) in minutes. A random criterion drives the patient-oncologist assignation while the duration of the medical consultation is derived from a uniform distribution \( U[5,35] \), in minutes, for both patients \( P^{OC} \) and \( P^O \). Regarding the drug’s preparation, the therapies can be classified into three typologies based on the preparation time (short, medium and long);
they are delivered in batches whose size may vary between 2 and 12 therapies, depending on the courier availability and on the pharmacy workload. So, a batch might contain any type of therapy and the batch size may vary at every pick up of the courier, who takes 10 minutes to deliver the therapies to the ward. However, a delay due to traffic congestion with a probability of 26.53% may happen. Finally, the experimental studies conducted on the ward showed that the treatments can be classified into five types, each one involving a different time duration. Notably, each treatment can be executed according to a specific occurrence probability and its duration implies the setup time.
### Descriptors of process | Values or probability distribution
--- | ---
**Patients**<br>Number of patients ($P$) | N(28.07,3.94)<br>Classification of patient<br>Standard patient ($P^{OC}$) | 71.50%<br>Repetitive patient ($P^{C}$) | 6.18%<br>Control patient ($P^{O}$) | 22.32%
**Arrival time**<br>08:30-09:30 | 56.58%<br>09:31-10:30 | 12.54%<br>10:31-11:30 | 5.81%<br>11:31-12:30 | 13.76%<br>12:31-13:30 | 11.31%
**Medical consultation**<br>Number of oncologists ($O$) | 3<br>Duration (min) of medical consultation ($Tc(p_k)$) | U(5,35)<br>Assignment of patient-oncologist ($o_j(p_k)$) | Random
**Pharmacy**<br>Number of pharmacist technician ($D$) | 1<br>Duration (min) of drug’s preparation ($Tp(p_k)$)<br>Short preparation | U(1,5)<br>Medium preparation | U(6,10)<br>Long preparation | U(11,27)<br>Probability of typology of drug’s preparation<br>Short preparation | 71.38%<br>Medium preparation | 20.34%<br>Long preparation | 8.28%
**Therapies’ delivery**<br>Number of couriers ($\alpha$) | 1<br>Batch size | U(2,12)<br>Duration (min) of delivery ($Td$)<br>Delivery without delay | 10<br>Delivery with delay | 10 + U(2,10)<br>Probability of delay in delivery<br>Delivery without delay | 73.47%<br>Delivery with delay | 26.53%
**Treatment administration**<br>Number of chairs ($C$) | 13<br>Number of nurses ($N$) | 3<br>Treatment duration (min) ($Tt(p_k)$)<br>Type 1 | U(15,60)<br>Type 2 | U(61,120)<br>Type 3 | U(121,180)<br>Type 4 | U(181,240)<br>Type 5 | U(241,300)<br>Probability of treatment occurrence<br>Type 1 | 30.13%<br>Type 2 | 38.91%<br>Type 3 | 14.23%<br>Type 4 | 12.13%<br>Type 5 | 4.60%

Table 2. Model descriptors.
5. Experimental results

The first step of the project development is the verification and validation process, which has been accomplished to verify if the simulation code is consistent and that the outcomes of the simulations adequately reproduce the status quo of a typical day of the oncology unit. Then, a proper DOE has been arranged so as to use the validated ABS model for testing different ward configurations and improving the performance of the unit. Due to the multitude of stochastic parameters as well as to assure the robustness of the proposed analysis, a stochastic simulation approach has been adopted for all the numerical investigations. Therefore, each KPI has been evaluated in terms of its expected value $E(KPI)$, i.e.:

$$E(KPI) = \frac{\sum_{\omega=1}^{\Omega} KPI(\omega)}{\Omega}$$

(2)

where $\omega$ is the replicate of a certain ward configuration and $\Omega$ is the whole set of replicates.

5.1 Verification and validation of the ABS model

A preliminary step of any simulation model, which should undergo before being employed in the study of a real phenomenon, consists in providing credible results without any errors (Balci, 2003; Roza et al., 2017). To this end, Verification and Validation (V&V) techniques are generally carried out to assure the effectiveness of a simulation model (Kleijnen, 1995). Specifically, the verification process assures that the conceptual model of the problem has been transformed into a computer simulation model with a sufficient accuracy (Robinson, 1997). The well-structured debug tool of NetLogo® and its model visualization allow performing a dynamic verification test of the simulation model, which is widely used in literature (Sargent, 2013). The validation is necessary to
demonstrate the efficacy of the model in reproducing the actual performance of the system under investigation with a satisfactory approximation. Sargent (2013) classified several validation techniques that can be applied to a given simulation model. In this paper the ‘Historical data validation’ technique is adopted, which compares the key performance indicators obtained by the presented ABS model with one obtained by analysing the status-quo related scenario, as shown in Table 3. Looking at the numerical outcomes, the actual performance of the oncology unit in terms of the aforementioned KPIs are as follows:

- the mean flowtime \( \bar{F} \) is equal to 265.46 minutes, with (243.00; 287.92) 95% confidence interval (CI);

- the mean patients’ waiting time \( \bar{WT} \) is equal to 138.28 minutes, with (123.14; 153.42) 95% CI;

- the efficiency \( Eff \) is equal to 47.97%, with (45.41; 50.53), with 95% CI;

For both the real and the simulation scenario, Table 3 reports the expected KPIs, the confidence intervals at 95% and the percentage deviation \( (Dev) \), the latter calculated as follows:

\[
Dev = \left| \frac{E(KPI_{sim}) - KPI_{real}}{KPI_{real}} \right| \cdot 100
\]  

where \( E(KPI_{sim}) \) is the expected KPI resulting from the simulation model, while \( KPI_{real} \) is the KPI’s value of the status-quo of the oncology unit. Interestingly, the percentage deviation values reported in the last column of Table 3 confirm the validity of the developed ABS procedure. To further strengthen this outcome, a paired t-test has been carried out for each KPI, in order to assess if there exists any statistically significant difference between the means of the real scenario and the simulated one; \( p \)-values greater
than 0.05 for each test pointed out the effectiveness of the proposed ABS model in simulating the dynamics of the oncology unit under investigation.

| KPIs                | Real    | 95% CI     | KPIs          | Simulated | 95% CI     | Dev  |
|---------------------|---------|------------|---------------|-----------|------------|------|
| Mean Flowtime [min] | 265.46  | (243.00;287.92) | $E(\bar{F})$ | 259.50    | (242.30;276.70) | 2.25% |
| Mean Waiting Time [min] | 138.28  | (123.14;153.42) | $E(\bar{WT})$ | 133.99    | (116.54;151.44) | 3.10% |
| Efficiency          | 47.91%  | (45.41;50.53) | $E(\bar{Eff})$ | 48.84%    | (45.21;52.47)  | 1.94% |

Table 3. Validation procedure (results from 15 working days of measurements).

5.2 Design of Experiments (DOE)

In order to explore alternative configurations of the oncology department, a full-factorial Design of Experiments (DOE), i.e., a statistical method enabling to identify the impact of a series of experimental factors on the performance of the ward, has been developed. The influence factors, shown in Table 4, have been properly suggested by the medical staff, also considering the low or negligible cost of implementation. Briefly, such factors can be described as follows:

1) **The number of couriers (α)**. It refers to the number of couriers employed to deliver the batches of therapies to the oncology unit. Since only one resource is currently available for this task (level $A$ in Table 4), the aim is to evaluate how an additional resource (level $B$) would affect the patients’ waiting time;

2) **The batch size (β)**. The second factor consists of the number of therapies that can be collected in a batch. Currently, the batch size is not fixed and the number of therapies can vary from two to twelve therapies. The objective is to assess if a fixed batch size can enhance the adopted KPIs and, at the same time, to evaluate if a smaller batch size is better than a larger one. To this end, three levels have been considered: (A) fixed batch sized with three therapies; (B) fixed batch size
with six therapies; (C) variable batch size (i.e., corresponding to the current scenario);

3) **The appointment distribution** (\(\gamma\)). The first level (A) provides three time-windows of one hour and thirty minutes, each one with the same probability of occurrence equal to 33%. Similarly, the second level (B) consists of five time-windows of one hour, each with a probability of 20%. Level C entails the current case according to which patients arrive at the oncology unit conforming to five time-windows characterized by different occurrence probability (see Table 2);

4) **The daily number of patients** (\(\delta\)). The last factor represents the average number of patients for each working day. Currently, every day the department takes care of about 28 patients (level A). The goal is to analyse how the performance changes considering a higher number of patients. To this aim, an additional level (B) with 31 individuals is considered, which corresponds to an increase of about 10% of patients per day. It is worth specifying that both levels refer to the mean of the *normal* distribution related to the number of patients per day (see Table 2), while the standard deviation is kept unchanged.

Notably, the current configuration of the oncology unit is \{A-C-C-A\}, considering a one-to-one correspondence with the set of experimental factors \{\(\alpha\)-\(\beta\)-\(\gamma\)-\(\delta\)\}, respectively. To infer about the influence of these factors on the performance of the ward, a full-factorial DOE involves \(3^2 \cdot 2^2 = 36\) different configurations (scenarios) of the oncology unit has been adopted. In addition, to make the statistical analysis robust enough, \(\Omega = 5,000\) different replicates at varying random seeds, each one simulating a different working day, have been executed, thus achieving a number of \(5,000 \cdot 36 = 180,000\) experiments. The DOE has been performed by means of five virtual machines installed on a workstation equipped with an INTEL i9-9900 3.6 GHz 10 core CPU, 32Gb DDR4 2,666MHz RAM
and Win 10 PRO OS. Since the computational time required to simulate each configuration is equal about to 5 seconds, two days were needed approximately to accomplish the whole DOE. Only the expected mean flowtime $E(\bar{F})$ has been assumed as KPI, since the expected mean waiting time $E(\bar{WT})$ and the expected efficiency $E(\text{Eff})$ are strictly related to the former. However, all of the provided KPIs will be used later to stress the difference of performance between the best configuration and the current one used in the ward.

| Factors | Levels |
|---------|--------|
| Symbols | Description | A | B | C |
| $\alpha$ | Number of couriers | 1 | 2 | - |
| $\beta$ | Batch size | 3 | 6 | U(2,12) |
| $\gamma$ | Appointment distribution | 3 | 5 | 5* |
| $\delta$ | Capacity of the department | 28 | 31 | - |

(*) time intervals with different occurrence probabilities as for the status quo scenario (see Table 2).

Table 4. Design of Experiments.

5.3 Analysis of results and managerial implications

An analysis of variance (ANOVA) at 95% level of confidence has been carried out in Minitab® 2017 commercial package to evaluate the statistical significance of each factor. The numerical outputs from the ANOVA (see Table 5) show the results concerning the main effects, whose related plots are in Figure 3. No relevant findings have been derived from the 2-way interactions analysis, so they are not reported in the table, but they are available upon request. Looking at the condensed ANOVA table, it is worth pointing out that the adjusted R-squared, i.e., the adjusted coefficient of determination, is larger than 95%, thus confirming the robustness and the consistency of the proposed analysis.
| Source | DF | F-value | p-value |
|--------|----|---------|---------|
| Model  | 19 | 40299.03| 0.000   |
| $\alpha$ | 1 | 42.99   | 0.000   |
| $\beta$  | 2 | 292158.50| 0.000   |
| $\gamma$ | 2 | 52500.10| 0.000   |
| $\delta$ | 1 | 73713.83| 0.000   |

Adjusted $R^2 > 95%$

Table 5. ANOVA Table.

As regards the experimental factors, the $p$-value below 0.05 implies that they are statistically significant for the expected mean flowtime $E(\bar{F})$ at 95% confidence level. The significance of the influencing factors on the mean flowtime is further exacerbated by related $F$-values. Indeed, the most important factors are usually identified by an $F$-value larger than 50 (Yu et al., 2018). The very low $F$-value associated to factor $\alpha$ reveals that the number of couriers might have a weak effect on the performance of the system, as confirmed by the related main effect plot in Figure 3. To this end, a paired $t$-test at 95% confidence has been performed and confirmed that the null hypothesis assuming that the mean difference between the paired samples is zero (i.e., $H_0: \mu_d = 0$) can be rejected. In words, that misleading finding can be denoted as a type II error, i.e., a false negative result (Smith et al., 2002). In conclusion, the mean flow time is statistically insensitive to factor $\alpha$.

Interestingly, the main effect plot related to factor $\beta$ shows that fixing the batch size at the lowest value (level $A$) would favour the mean flow time reduction, while the current strategy based on a random batch size (level $C$) negatively biases the mean waiting time of patients. As for $\gamma$, smoothing the arrival of patients by introducing new appointment distribution strategies (e.g., levels $A$ and $B$) allow improving the service level than the
actual one (level $C$). In particular, the strategy corresponding to the level $B$ allows reducing the patients’ waiting time of approximately 20 minutes on the average. Finally, as for factor $\delta$, an increment in the number of patients (level $B$) slightly increases the patients’ waiting time but, on the other hand, such detrimental effect can be adequately compensated by the large number of patients that can be daily accepted without worsening the current performance of the oncology unit.

![Figure 3. Main Effect Plots.](image)

Table 6 shows the expected mean flowtime $E(\bar{F})$ over the $\Omega = 5,000$ simulation replicates, performed for each combination of experimental factors. Notably, the performance of the *status quo* scenario is illustrated in the first row of the table, while the other configurations have been sorted in ascending order of expected mean flowtime. Also, the confidence intervals of the expected mean flowtime for each configuration are reported in the last column. Looking at the table, label 21 indicates the *best configuration* characterized by factors \{B-A-B-A\} and an expected mean flowtime $E(\bar{F}_{21})$ equal to 208.53. However, it is worth noting that the *status quo* configuration is one of the worst scenarios in terms of expected mean flowtime, along with the last four configurations in which the $\beta$ factor always is set to the $C$ level.
To sum up, the following managerial implications would arise from the proposed numerical analysis:

1) The oncology unit could save daily 40 minutes of the patients’ waiting time by passing from a random batch size to a fixed batch size with three therapies. It can be noticed that this improvement could be realized without investing additional funds;

2) Acting on the patients’ appointments would also enable to reduce the patients’ waiting time. A uniform distribution of patients’ arrival times through five time-windows of one hour emerges as a valid alternative to enhance the performance of the ward without investing additional funds;

3) Looking at the best configuration, an increase in the number of patients per day (scenario \{B-A-B-B\}) would involve a slight increment of the expected patients’ waiting time equal about to ten minutes on average. However, this outcome is still more successful that the status-quo related one, under the patients’ waiting time;

4) Since the number of couriers does not influence the expected mean flowtime, there would be no benefit from the addition of new resources dedicated to the therapy delivery.
| Configuration No. | α | β | γ | δ | E(\(\bar{F}\)) [min] | 95% CI [min] |
|------------------|---|---|---|---|----------------------|-------------|
| 17 (status-quo)  | A | C | C | A | 260.17 (259.22;261.12) | |
| 21               | B | A | B | A | 208.53 (207.83;209.23) | |
| 3                | A | A | B | A | 209.05 (208.34;209.75) | |
| 19               | B | A | A | A | 216.07 (215.34;216.80) | |
| 1                | A | A | A | A | 216.61 (215.88;217.34) | |
| 22               | B | A | B | B | 218.16 (217.42;218.91) | |
| 4                | A | A | B | B | 218.71 (217.97;219.46) | |
| 23               | B | A | C | A | 223.29 (222.41;224.17) | |
| 5                | A | A | C | A | 223.81 (222.93;224.69) | |
| 20               | B | A | A | B | 226.71 (225.94;227.48) | |
| 2                | A | A | A | B | 227.27 (226.50;228.04) | |
| 27               | B | B | B | A | 231.02 (230.30;231.74) | |
| 9                | A | B | B | A | 231.13 (230.41;231.84) | |
| 24               | B | A | C | B | 237.48 (236.53;238.43) | |
| 6                | A | A | C | B | 238.05 (237.11;239.00) | |
| 25               | B | B | A | A | 238.34 (237.61;239.08) | |
| 7                | A | B | A | A | 238.46 (237.73;239.20) | |
| 28               | B | B | B | B | 240.09 (239.35;240.83) | |
| 10               | A | B | B | B | 240.2 (239.46;240.94) | |
| 29               | B | B | C | A | 244.69 (243.80;245.58) | |
| 11               | A | B | C | A | 244.78 (243.89;245.67) | |
| 33               | B | C | B | A | 247.5 (246.67;248.33) | |
| 15               | A | C | B | A | 247.64 (246.81;248.47) | |
| 26               | B | B | A | B | 248.45 (247.68;249.22) | |
| 8                | A | B | A | B | 248.56 (247.79;249.34) | |
| 31               | B | C | A | A | 253.99 (253.14;254.84) | |
| 13               | A | C | A | A | 254.13 (253.28;254.98) | |
| 34               | B | C | B | B | 255.93 (255.07;256.78) | |
| 16               | A | C | B | B | 256.05 (255.20;256.91) | |
| 30               | B | B | C | B | 257.66 (256.70;258.62) | |
| 12               | A | B | C | B | 257.76 (256.80;258.72) | |
| 35               | B | C | C | A | 260.17 (259.21;261.12) | |
| 32               | B | C | A | B | 263.63 (262.74;264.52) | |
| 14               | A | C | A | B | 263.76 (262.88;264.65) | |
| 36               | B | C | C | B | 272.6 (271.54;273.59) | |
| 18               | A | C | C | B | 272.69 (271.67;273.71) | |

Table 6. Results of expected mean flowtime from the experimental campaign (5,000 replicates).
Finally, Table 7 compares the best simulated configuration and the simulated status quo in terms of expected mean flowtime $E(\bar{F})$, expected mean waiting time $E(\bar{WT})$ and expected efficiency $E(\text{Eff})$. Notably, confidence intervals and percentage deviations between the two scenarios are in the last column. The percentage deviation reveals that the best configuration improve expected flowtime $E(\bar{F})$, the expected mean waiting time $E(\bar{WT})$ and the expected efficiency $E(\text{Eff})$ of 19.85%, 37.73% and 24.77%, respectively.

| KPIs   | Simul. status quo | 95% CI        | Simul. best config. | 95% CI        | Dev   |
|--------|-------------------|---------------|---------------------|---------------|-------|
| $E(\bar{F})$ | 260.17 min       | (259.22;261.12) | 208.53 min         | (207.83;209.23) | 19.85%|
| $E(\bar{WT})$ | 136.87 min       | (136.01;137.73) | 85.23 min          | (84.66;85.80)  | 37.73%|
| $E(\text{Eff})$ | 47.39%           | (47.21;47.57)  | 59.13%             | (58.96;59.30)  | 24.77%|

Table 7. Simulation results: status quo Vs best configuration.

6. Conclusion

In this study, we developed an agent-based simulation framework explicitly designed to be configurable and adaptable to the needs of oncology departments. Although there exist alternative simulation methods, such as SD or DES, the ABS technique allows a more realistic approach to model health-care systems as agents adapt and change their behaviour by interacting with the other people (e.g., doctors, nurses, and so on) along the whole therapy path. Conversely, ABS is computationally expensive. Particularly, it is considered the case in which the pharmacy is detached from the oncology unit and, therefore, a courier service to deliver batches of therapies is needed. The validity of the proposed model has been demonstrated through a statistical analysis based on a set of experimental data obtained by studying an oncology unit located in (to revealed after the paper acceptance). Consequently, a series of alternative scenarios has been tested.
through a robust simulation campaign based on a full-factorial design of experiments. The results have been evaluated through an ANOVA analysis, revealing that a fixed batch size with a low number of therapies and an effective appointment strategy significantly decrease the patients’ waiting time. The best simulated scenario has been selected and compared with the status quo by means of three main key performance indicators. This comparison shows that the expected patients’ waiting time and the expected ward efficiency can be enhanced by 37.7% and 24.8% in percentage deviation, respectively. Finally, the ABS model has been delivered to the healthcare managers who implemented the “best configuration” to the chemotherapy unit at hand. Due to the COVID pandemic we are not allowed to visit the ward, but we have received positive feedbacks from the medical staff about a significantly improved service level. Hopefully, further data will be collected in the near future to support the validity of the proposed research.

Due to the complexity of the problem under investigation, future studies may be dispensed to expand the knowledge in this context. The present paper reports an experimental campaign specifically conducted for the oncology unit at hand. In fact, the proposed DOE has been defined jointly with the healthcare staff of the hospital, with the aim of identifying an improved service configuration, without investing additional funds (according to the lean principles). However, in accordance with the managing staff, further efforts will be dedicated to a future project for assessing the impact of additional resources (e.g., the number of pharmacist technicians or treatment chairs) on the performance of the oncology department.

To this end, future research can be oriented towards simulation-optimization approaches as well as hybrid simulation models, which combine different simulation techniques capable of adequately capturing macro- and micro-level dynamics of such complex healthcare systems.
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