Simulation of Patient Flow in Multiple Healthcare Units using Process and Data Mining Techniques for Model Identification

Sergey V. Kovalchuk¹, Anastasia A. Funkner¹, Oleg G. Metsker¹, Aleksey N. Yakovlev¹,²

¹ITMO University, Saint Petersburg, Russia
²Federal Almazov North-west Medical Research Centre, Saint Petersburg, Russia

kovalchuk@mail.ifmo.ru, funkner.anastasia@gmail.com, olegmetsker@gmail.com, yakovlev_an@almazovcentre.ru

Abstract. Introduction: An approach to building a holistic simulation of patients flow is introduced with a combination of data-driven methods for automation of model identification. The approach is described with a conceptual framework and basic methods for combination of different techniques. The implementation of the proposed approach for simulation of acute coronary syndrome (ACS) was developed and used within an experimental study. Methods: Combination of data, text, and process mining techniques and machine learning approaches for analysis of electronic health records (EHRs) with discrete-event simulation (DES) and queuing theory for simulation of patient flow was proposed. The performed analysis of EHRs for ACS patients enable identification of several classes of clinical pathways (CPs) which were used to implement a more realistic simulation of the patient flow. The developed solution was implemented using Python libraries (SimPy, SciPy, and others). Results: The proposed approach enables more realistic and detailed simulation of the patient flow within a group of related departments. Experimental study shows that the improved simulation of patients length of stay for ACS patient flow obtained from EHRs in Federal Almazov North-west Medical Research Centre in Saint Petersburg, Russia. Conclusion: The proposed approach, methods, and solutions provide a conceptual, methodological, and programming framework for implementation of simulation of complex and diverse scenarios within a flow of patients for different purposes: decision making, training, management optimization, and others.

Keywords. clinical pathways, discrete-event simulation, process mining, data mining, acute coronary syndrome, electronic health records, classification.

1. Introduction

Detailed simulation of patients' care provided in healthcare units requires analysis of this process from multiple points of view. The process involves multiple departments, many types of activities, different actors with particular roles, expertise level, knowledge, etc. Moreover, multiple scopes and aspects of the healthcare process can be considered (department’s resources load, accounting in a hospital, patient’s personalized experience during the care process, and many others). One of the key reason of growing interest to this subject is the latest attention to patient-centered healthcare, including personalized medicine [1], value-based healthcare [2]. In contrast to 'traditional' well-grounded evidence-based medicine dealing with typical patients, these areas consider the diversity of patients with more attention taking care of personal combination of factors specific to the particular patient. This leads to certain interest to comprehensive simulation approaches (see e.g. survey on multi-department simulation [3], or multiple publications on technologies and applications of simulation in healthcare [4-6]), as well as automatic or semi-automatic ways to analysis of medical records using machine learning [7], data mining [8], process mining [9] techniques, interaction with patients [10], and other approaches). E.g. certain
interest is attracted recently to automatic identification of clinical pathways (CP) [11] with various automatic approaches [12-14]. Still, there are multiple problems that reveal multiple sources of uncertainty in complex simulation tasks: lack of consistency, completeness, and correctness of medical data to be analyzed [15], low coverage of rare cases with CPs [16], weak formalization and high uncertainty in core medical knowledge [17]. To overcome these issues we developed a holistic approach introduced in the present work where a combination of techniques from data, process and text mining is proposed to support computer-aided simulation. The presented approach is aimed towards automation of comprehensive model and scenarios identification, classification of patient-centered CPs, and management of simulation applications.

The remaining of the paper is as follows. Section 2 discusses the key requirements for the developed approach. Section 3 introduce the basics of the conceptual framework developed to support simulation models building using EHR and other information sources. Section 4 uncovers the details of the proposed approach showing the way of different methods are combined within a solution. Section 5 demonstrates an example of the proposed approach’s application within a task of simulation of key departments involved in acute coronary syndrome (ACS) treatment procedures performed in Federal Almazov North-west Medical Research Center1 (Saint Petersburg, Russia), one of the leading cardiological centers in Russia. Finally, the last section presents concluding remarks and future development of the proposed ideas.

2. General requirements

Simulation of patients flow is tightly connected with consideration of several aspects to providing valid and realistic simulation.

1) Usually, patient flow simulation is focused on the specific category of patients defined by nosology(-ies), particular hospital structure(s), patient’s characteristics, etc. Still, the key problem is the diversity of the patients flow in the real world. Often, even within a small group with single nosology multiple classes and variations can be identified.

2) Activities simulated within patients flow should follow certain scenarios to arrange the events within the natural development of the disease. Typically the events are arranged within CPs [11], but to simulate the diversity of patients flow conditional branching, loops and interrelated events should be considered explicitly.

3) Decisions and activities of various actors and decision makers should be considered with respect to conditions and events in clinical pathways. The key attention of the simulation is around personal activities and experience of either patient or doctor. Nevertheless, to make a comprehensive simulation a multitude of actors and decision makers should be considered: patients, doctors, nurses, service workers of hospitals, visitors (depending on the simulation scenario).

4) Multiple classes of resources are involved into patient’s care process including human resources, hospital facilities, wards with defined capacity, drugs, etc. To make a simulation applicable in various ways a range of the resources should be considered during simulation both in terms of availability for patient care process (queueing, scheduling, capacity, etc.) and in terms of resource management (providing, renewing, cost, etc.).

1 http://www.almazovcentre.ru/?lang=en
5) To provide a proper simulation *multiple data and knowledge sources* can be integrated and analyzed to identify models and support simulation within different approaches (including data assimilation, model identification, and calibration, verification, etc.). The key data sources for simulation of patients flow is EHR, but multiple data sources can be involved: censuses, surveys, recommendations, data from sensors, and many others.

### 3. Conceptual framework

Taking into account the mentioned aspects and issues a conceptual framework was developed to bring broader but systematic view to the process of building solutions for simulation of patient flow. The developed conceptual framework is presented in Fig. 1 (the figure represents relationships between key concepts which can be directly obtained from sources (blocks with solid borders) or inferred using additional knowledge sources or intelligent technologies (blocks with dashed borders)). It covers the building of the simulation solutions focusing on patient flow within a hospital or set of departments in it. With this consideration, the framework is limited to the corresponding class of solutions. Nevertheless, it was done without loosing of generality and the framework can be easily extended to many other classes of problems and scales. Selected key data sources include EHR, pharmacy and accounting information, schedules of hospital operations which present the major part of information about treatment process and activity within the hospital.

![Figure 1 - Conceptual framework for holistic simulation](image)

The first step considered within the framework is cleaning and *systematization of available data* within a scope of patient treatment (EHR details) and resources utilization (moving from level I to level II of the proposed conceptual framework). These concepts enable checking and correcting of data consistency, detection of missing and contradictory data, obtaining events and attributes inferred with extended knowledge sources and additional intelligence technologies (e.g. retrieving parameters through text and data mining, rule-based inference, etc.).
Next step transform this data sets into model-oriented concepts arranged around patient care and activity of departments (from level II to level III). Patient-centered concepts include states of a patient, transfer between these states with relationship to certain departments of a hospital, high-order events (changing of attributes, knowledge-based detected events, typical sequences of events, and others), critical events with higher significance. Department-centered concepts include flow of patients (which can be divided into the flow of patients from selected groups and flow of “background” (other) patients) and resource management (resources of most types usually can be considered as “coming” from external sources and “spent” at the request of the system).

Finally, the concepts directly related to simulation of patients can be introduced (from level III to level IV). This set of concepts include a) data-driven models which enable to analyze and discover the structure in model-oriented concepts; b) models for simulation of patient flow using the discovered structures and relationships. The combination of those two conceptual levels enables detection and incorporation into simulation the diversity of patient flow to capture rare events and emerging phenomena through the simulation.

The developed conceptual framework can be easily extended to consider different tasks and solution. Still, the key issue is the implementation of the simulation solution which enables answering the proposed requirements through the proposed concepts.

4. Holistic methods combination

To implement the simulation solution on the basis of proposed conceptual framework multiple approaches and tools can be used. Within this section, a toolbox for building simulation solutions is proposed as a variant for such implementation with a combination of multiple methods.

![Toolbox for building holistic simulation models with EHRs](image)

Figure 2 - Toolbox for building holistic simulation models with EHRs

Fig. 2 shows the main tools within the proposed toolbox and their interconnection. A key role within the toolbox is played by knowledge formalized in a knowledge base using various approaches: rules, ontologies, and others. The first step of the implementation includes data cleaning, which is aimed at structuring, filtering, reconstruction of key datasets from available data sources. The second stage includes implementation of data and text mining algorithms as well as rule-based processing to construct unified extended event log which includes events reflecting key processes and attributes arranged around patients and hospital departments. On the next stage, the
extended event log is used to identify and analyze key processes and corresponding CPs. Here the approach enables identification of events, structure, and attributes even within partly known or (sometimes) unknown processes. The process mining technique provides complete and rapid methods for analysis processes such as conformance checking, process discovery and identification of bottlenecks. Indisputably, these methods with using process mining software allow understanding the diversity and complexity of the analyzed process as well as the general relationship of process components. Additionally, analysis of identified CPs enables knowledge discovery a) to extend knowledge base with classification and predictive models, rules, etc. and b) to build models which can be used during the simulation to represents relationships between pathways, events, and attributes. The later includes the development of data-driven models generated to simulate hidden and unknown processes as well as more complex process structures (conditional branches, loops, etc.).

Finally, simulation models are implemented as a combination of the following models (the list can be extended): a) patient flow simulation to reconstruct diverse patients at the entrance of model; b) CPs simulation (e.g. by the use of discrete events simulation); c) random events generators; d) control models to capture interrelationships between events and attributes. The patterns and knowledge discovered previously by data and process mining are used to interconnect and control simulation models. This enables more realistic simulation, capturing rare events and variation in patient flow, simulation of flow dynamics identified in an automatic way, etc. Additionally, high-level control of the simulation enables an intelligent combination of clinical pathways with a variation of the events and attributes. Simulation models can be verified using available event log and used in applications within different areas (decision support, training, research, etc.) with a realistic and comprehensive simulation of patient flow.

5. Simulation of patients with acute coronary syndrome

Acute coronary syndrome (ACS) is one of the major causes of death in the world. It is related to more than 2.5 million hospitalizations worldwide every year [18]. Usually, ACS is caused either by myocardial infarctions (MI) or by unstable angina (UA). One of the important aspects of ACS treatment is early therapy, which usually includes urgent (within 60-120 minutes) or delayed (within 24-72 hours) coronary angiography with possible percutaneous coronary intervention (PCI, i.e., angioplasty, stent placement). One of the key problem regarding ACS treatment is the organization of the required resources within a hospital. The resources include surgery facilities, beds in intensive and regular care wards, human resources, medications, and materials, etc. Having highly non-stationary flow of patients with multiscale periodic patterns (day, week, year) a simulation-based solution can serve for various purposes: a) estimation of departments load with different scenarios and dynamics of patient flow; b) analysis of risks of lack or queueing for different types of the resources; c) integration into training solutions or DSS for treatment process optimization.

Within our research, we used a set of 3434 EHRs collected for patients with ACS served in Federal Almazov North-west Medical Research Centre (FANWMRC) during 2010-2015. To consider patient flow we considered three types of medical departments involved into ACS patients care. Namely, surgery, intensive care and regular care wards with cardiological specialization which form a group of key departments (GKD) considered for simulation furtherly. FANWMRC has
several departments operating in each of these roles and providing care for the patients with ACS 24/7. Analysis of the patient flow in GKD reveals diverse and complex patterns. Moreover, to analyze and simulate a flow of patients with ACS within a scope of both patients and departments a full flow of patients through the GKD should be considered with division into two parts: the flow of patients with ACS and the flow of other patients (furtherly, “background flow”). Fig. 3 depicts dynamics of the ACS patient flow and background flow for three months in different departments.

![Figure 3 - Flow of patients in selected departments with different roles in FANWMRC during three months](image1.png)

Figure 3 - Flow of patients in selected departments with different roles in FANWMRC during three months a) regular care department; b) surgery room; c) intensive care department

Further analysis shows that multiple complex and diverse patterns can be discovered with a flow of patients. E.g. Fig. 4 shows the major transfers between the departments (transfer probability higher than 5% are shown, green lines depict inter-departments transfers with the probability higher than 20%, orange lines shows transfers from and to external sources) for background flow (two most popular departments of each role is shown). The complexity of the patterns are defined by the urgency of the cases, presented complications, and implicit interactions between departments and hospitals (e.g. this can lead to the immediate transfer of patients from another hospital or department).

![Figure 4 - patient flow within a group of key departments (background flow)](image2.png)

Figure 4 - patient flow within a group of key departments (background flow)

To analyze the complex patterns of the patient flow in more details the approach proposed earlier in Sections 3-4 was applied to identify and simulate the patient's behavior and the load of the GKD within ACS treatment.

5.1 Identification of complex processes

FANWMRC uses medical information system qMS which support exporting EHRs into XML documents. Each EHR consists of multiple events such as an entrance, tests, check-ups by physicians, surgeries, discharge, etc. An event is described by a date, time, a place, a title and staff
who executed it. Event data can include extended information on anamnesis and diagnosis, test results, description of procedures, etc. Still, EHRs often suffer lack consistency, completeness and correctness due to the weak structure (including plain text), missing data (hand-written paper documents are still in practice), technical problems (synchronization, consistency checking, etc.) and many other problems [19]. We perform basic heuristics including sorting of EHR events (applied to 89.3% of records) and reconstruction of missing events (applied to 11% of records) to clean the data and improve its consistency. The next step include structuring and encoding (so the sequence of states is represented by a string of letters of length in a range 1..59 characters) patient's CPs with respect to the departments and sub-departments (facilities with particular specialization within a department) related to the current state of the patient as well as cyclic patterns repeated in multiple pathways. The encoded sequences can be clustered to identify sustainable groups of patients. Using K-means method with the Levenshtein distance we got 13 clusters which were identified as the best number of clusters according to cluster coefficients of variation [20].

Figure 5 – Reduced decision tree to identify clusters of patients
Among the clusters, three of them include less than five sequences and these clusters were discarded. For a deeper analysis of clustering structure a decision tree was built (Fig. 5) which shows the distinction between clusters and helps for further simulation of CPs. Internal nodes test one of three possible attributes of patient’s moving sequence (LoS – a length of the sequence, NoC – a number of coronary catheterization, NoS – a number of surgeries). The branches represent the outcome of the tests (a left branch means an attribute is tested positively and a right branch means the opposite). Leaf nodes represent the probabilities for possible clusters according to this classification path in the tree.

After dividing patients into groups, it needs to match a template for alignment of events sequences within a cluster. To match better template for a cluster its structure should be analyzed: most common number of surgeries for this cluster; the last department before the discharge (cardiological department or other departments) and etc. To identify more peculiarities for cluster it is possible to use multiple alignment algorithms from bioinformatics which usually used to align three or more biological sequences [21]. We used an alignment algorithm which identifies a location of a state in a patient flow comparing with a template. The last step of identification of typical pathways for detected clusters is to form a flow with alignment sequences.

![Decision Tree](image)

**Figure 6 – Patients’ typical pathways for top-3 popular clusters**

Fig. 6 depicts typical pathways which are represented by directed graphs with edges weighted according to flow (number of patients moved this edge within the detected path in a graph) for top-3 clusters (clusters #1, 2, 4) which covers 58% of all cases. The edges assigned a flow for 70% of cluster’s patients are shown in bold to depict the most common pathways in the cluster. Fig. 7 shows length of stay in each state for selected clusters. Here AD is an admission department to cardiological departments, AD OD – an admission department to other departments, CD – a cardiological department, IC – an intensive care department, OR – an operating room with surgery, CC – an operating room with coronary catheterization.
Figure 7 – Length of stay for different states in typical pathways for top-4 popular clusters

Presented information obtained in an automatic and semi-automatic way can be effectively used to reconstruct patient flow within a simulation solution which is described in the next section.

5.2 Simulation implementation

To simulate identified patient flow a solution was developed on the basis of discrete event simulation (DES) approach and queuing theory (release of the developed solution [22] was published at Zenodo [23]). To implement the solution we used SimPy\(^2\) library for Python which implements basic concepts and enables easy development of DES solutions. The basic architecture of implemented DES solution is presented in Fig. 8. The processes within the solution include two generators for background/target patient flows and set of patients (each represented by a single process).

Flow generators produce a sequence of incoming patients in initial states with defined class and arrival time. To generate those sequences empirical distributions obtained from data are used. For instance, Fig.9 presents PDFs for simulation of daily ACS patient flow (Fig. 9a,b) and random selection of patients class according (Fig. 9c). To generate random sequences SciPy\(^3\) library classes were used.

\(^2\) [http://simpy.readthedocs.org/](http://simpy.readthedocs.org/)

\(^3\) [http://scipy.org/](http://scipy.org/)
Each generated patient is presented by a process instance which control the transfer of the patients between states in accordance with transition probabilities and LoS distributions associated with selected cluster (see Section 5.1).Selected states related to usage of limited resources with possible queueing (e.g. surgery facilities).Simulation of switching to such states is implemented within requesting and waiting for access to a predefined set of resource instances. For instance, within the detected pathways CC and OR states are related to queue simulation (as it requires access to angiography equipment).

5.3 Simulation results
To test implemented approaches flows of ACS and background patients with the detected classes of CPs were simulated. The analysis of the simulation results shows that the proposed approach (implemented as a combination of CPs classification and DES simulation) enable improvement of simulation to generate more realistic patient flow. Fig. 10a shows QQ-plot for LoS obtained with the proposed approach (for all classes and top-3 classes) in comparison to the simulation of the similar scenario but without classification (‘No classes’). More accurate control of patient flow provides better fitting for patients with a longer period of stay (more than 20 days) which is important to simulate rare but complicated cases.
For further analysis, we perform a simulation with for a period of 60 days with a different number of angiography equipment available and scaling of patient flows (each simulation was performed 100 times to analyze the stochastic behavior of the model). Examples of the tasks where the simulation can be applied are decision support and policy making to improve patients serving within different conditions (available surgery facilities, different patient flow) with estimation of the percentage of patients which experience waiting in a queue (Fig. 10b) and queueing time (Fig. 10c).

6. Conclusion and future works

The proposed approach is aimed towards the extension of simulation solutions with a combination of detailed data analysis for identification of CPs and further discrete-event simulation of patient flow. To perform data analysis a combination of data, text, and process mining techniques are used to detect and assess diversity in patient flow, structure, and classes of CPs, etc. As a result, the approach enables automatic identification of patients dynamics on micro-level to perform more realistic simulation and obtaining macro-level characteristics as department load, queueing parameters, patients experience, etc. The demonstrated example shows an implementation of the proposed approach to improve the simulation of ACS patient flow using automatic identification and classification of CPs.

Further development of the proposed approach includes additional systematization an extension of the conceptual framework for consideration of place complexity [23], integration with predictive models [24] to simulate the behavioral and clinical evolution of cases, integration with quality of life metrics [25] to enable detailed analysis of patients experience, and others. On the other hand future works on the developed implementation of the proposed approach include generalization of the solution (to build a framework for holistic simulation of patient flow) with detailed usage of CPs with multiple level of events and attributes detected with process mining approaches, implementation of surrogate models which can be identified and used to make the simulation more detailed and realistic, and others.

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