Automated Input Data Management for Discrete Event Simulation Models of Emergency Departments

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Keywords: Emergency Department, Health Information System, Input Data Management, IDM, Discrete Event Simulation.

Abstract: Emergency Department (ED) overcrowding, that relates to congestion due to the high number of patients, has a negative effect on patient waiting time. The analysis of the flow of patients through Discrete Event Simulation (DES), that models the operation of a system through a sequence of events, is a relevant approach to find a solution to such problem. This technique relies on high-quality input data which needs to be previously managed in a complete process known as Input Data Management (IDM). The objective of this research is to propose a tool to automate the IDM process required for DES models of ED. To do so, we used a case with real data in order to contextualize the problem, evaluate required statistical methods, and gather specific requirements. Based on these results, a prototype was designed and developed by using web and cloud application development tools.

1 INTRODUCTION

One of the main problems in Emergency Departments (ED) is over-crowding, which is according to Duguay and Chetouane (2007), "the situation in which ED function is impeded primarily because of the excessive number of patients waiting to be seen, undergoing assessment and treatment, or waiting for departure comparing to the physical or staffing capacity of the ED". Overcrowding is thus recognized as a global problem, which has reached crisis proportions in some countries. It has direct implications for the well-being of patients and staff, mainly due to waiting times derived from process deficiencies, the inappropriate placement of physical and human resources, and budget restrictions. In addition, it can affect an institution's financial performance and reputation (Komashie & Mousavi, 2005).

One of the strategies to mitigate the adverse effects of overcrowding is using Discrete Event Simulation (DES) to provide analytical methods to assess and redesign processes and support data-driven decision-making. In the ED context, DES models aim to reproduce the flow of patients and their relationship with the different areas, personnel, and resources available to solve specific problems.

The success of DES applications depends on the prior preparation of high-quality input data. Some of the event data required in DES are represented in probability distributions. The parameters describing the underlying distributions are a key input for the simulation. The process that involves transforming raw data into a quality-assured representation of all parameters appropriate for simulation is known as Input Data Management (IDM) (Skoogh & Johansson, 2008).

Input data preparation is one of a DES project's most crucial and time-consuming tasks (Robertson & Perera, 2002). According to (Skoogh et al., 2012) the input data management process consumes about 10-40% of the total time of a DES project. In most cases, practitioners manually transform raw data from different sources into appropriate simulation input (Robertson & Perera, 2002) and separately from the software used for the simulation. Automating the data preparation phase can potentially increase efficiency in DES projects by integrating data resources (Skoogh et al., 2012). The IDM required to address the problem of Overcrowding in ED must consider automating the estimation of the probability distributions required to simulate patient flow. These statistics can be grouped into three categories: Arrival Patterns, Routing Probabilities, and Processing Times (Ghanes et al., 2015).

Mogollon, J., Goepp, V., Avila, O. and de Guio, R.
Automated Input Data Management for Discrete Event Simulation Models of Emergency Departments.
DOI: 10.5220/0011718600003467
In *Proceedings of the 25th International Conference on Enterprise Information Systems (ICEIS 2023) - Volume 2*, pages 31-42
ISBN: 978-989-758-648-4; ISSN: 2184-4992

While reviewing the literature, we found no commercial IDM automation tool. We identified only three open-source tools with such capabilities, namely, GDM-Tool (Skoogh et al., 2011), DESI (Rodriguez, 2015), and KE Tool (Barlas & Heavey, 2016). Although these tools have features for fitting some statistical distributions, they do not fit all the possibilities required for ED operation simulation, such as Markov chains modeling. Some other gaps we found when reviewing them include the fact that these tools do not offer features for sharing data and results, limiting the opportunities for collaboration by allowing other researchers to replicate the process to obtain similar outputs. Moreover, the reviewed tools do not have features for managing projects, generating data quality reports, handling large datasets, or running intensive workloads; only examples with small volumes of data on personal computers are presented.

To identify potential current challenges in the data preprocessing tasks in the case of a DES project studying ED crowding, we analyzed a sample of the patient flow data of the ED at the Hautepierre Hospital located in the city of Strasbourg, France. This analysis had two main objectives: (i) identify the statistical methods to generate the required inputs in a simulation of the patient pathway within an ED and (ii) determine the preparation and validation requirements that guarantee data quality. As a result, we identified limitations regarding the automation of the required processing.

In this context, the research problem addressed by our research is: how to automate the IDM process for DES models to address the overcrowding problem in ED? To deal with this question, this article presents the architecture of a cloud-based web application for IDM, in which we provide the statistical methods required to estimate the parameters needed to describe the patient flow in ED and the management features to handle the IDM tasks. Our approach focuses on the definition and development of the IDM software and not on the integration of enterprise data or the simulation itself, as illustrated in Figure 1.

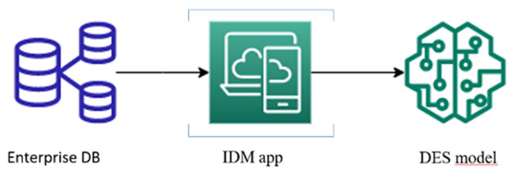


Figure 1: IDM Approach.

The article is organized as follows: section 2 presents related work in the domain. Section 3 presents the IDM requirements and evaluation of required statistical methods from the analysis of the real case. Section 4 introduces the IDM solution's architecture. Finally, section 5 presents conclusions and recommendations for future work.

2 RELATED WORK

Skoogh and Johanson (2008), defined Input Data Management (IDM) as "the entire process of preparing quality assured, and simulation adapted, representations of all relevant input data parameters for simulation models. This includes identifying relevant input parameters, collecting all information required to represent the parameters as appropriate simulation input, converting raw data to a quality assured representation, and documenting data for future reference and re-use".

Data collection has multiple inherent difficulties (Bokrantz et al., 2018). Organizations can have multiple data sources and systems to collect the data from. Second, accuracy, reliability, and validity are the analyst's responsibility when extracting and preparing the data for the simulation; those procedures, in most cases, are made manually, which makes it prone to errors. In a survey presented in (Robertson & Perera, 2001), it was inquired about the most frequent issues in simulation projects, considering data collection issues: 60% of respondents indicated they manually input the data to the model; 40% reported they use connectors to an external system like spreadsheets, text files or databases.

In summary, as described in (Furian et al., 2018), the main challenges in this process are, in the first place, manual data collection and data entry, which increases the likelihood of data entry errors arising from human manipulation of data. The inherent difficulties of the manual process compromise the quality and integrity of the data. In addition, multiple manual files handling to maintain and process data makes it difficult to track errors and reproduce procedures. Finally, data preparation requires specific knowledge of techniques and algorithms, which could lead to misuse of statistical packages and lead to unexpected outcomes.

We identified only three of open-source specialized in IDM for DES, GDM-TOOL (Skoogh et al., 2011), DESI (Rodriguez, 2015) and KE tool (Barlas & Heavey, 2016). To the extent of our knowledge, no survey or study compares them, or use them in the ED context. We analyzed such tools in the following section by using criteria extracted from the requirements in the case of Hautepierre Hospital.

3 IDM FOR ED

This section focuses on analyzing the IDM tasks enabling to prepare statistical representations of the patient flow data of the ED of the Hautepierre Hospital in Strasbourg (France). In addition, we evaluate IDM tools that could be used for the analysis.

3.1 Emergency Department Description

To analyze the overcrowding problem, it is necessary to know in advance the configuration the ED, which depends on the needs, staff, capacities, and areas of the health institution. We sketch thus the main steps of the patient flow of the Hautepierre Hospital ED in Figure 2. In the diagram, the patient flow is represented linearly as patients perform each of the activities consecutively. However, it is worth mentioning that there are iterations between the stages, as patients may require a procedure to be repeated or an exam to be performed multiple times. In addition, patients may undergo many different paths and not necessarily goes through all the steps of the process. The number and types of diagnosis tests (blood analysis, RX or CT Scan) depend on the consultation and are not known as the outset, that is why we model the pathway using routing probabilities.

The data were provided in comma-separated values (CSV) files extracted from the ED databases. The files contained anonymized records of patients and the events during their stay in the ED. The collected data contains records from June 22nd, 2020, to June 28th, 2020, of the ED flow of 795 patients. The records include information on the following events of the patient flow: arrival, triage, blood analysis (BA) (Coagulation, Hematology, Biochemistry), Computer tomography (CT) Scan, and X-rays (RX). The average throughput time is 5,52 patients/h. We consulted the physicians to check the consistency of data, as we had to deal with multiple files from different data sources.

The ED uses a severity index for the assignment of degrees of emergency to decide the priority and the order of procedures. It considers three levels of severity identified by colors: red for immediate care, orange for cases that can be taken care of within the hour, and green for not urgent care. According to each severity level, the patients are assigned to one of three zones in the ED.

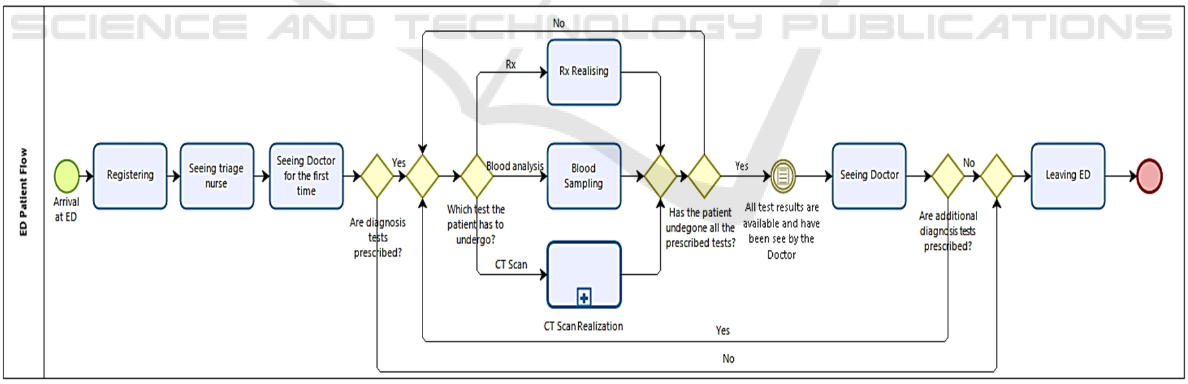


Figure 2: Hautepierre Hospital ED BPM.

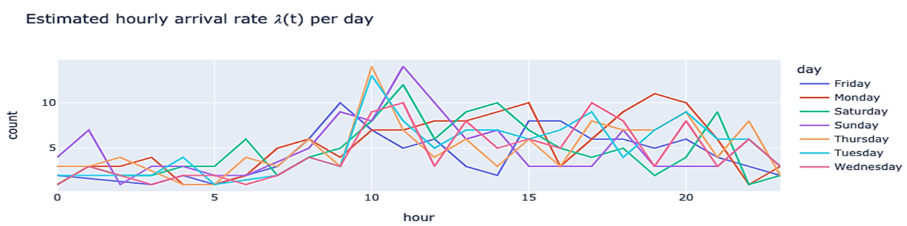


Figure 3: Estimate hourly arrival rate.

3.2 Statistical Analysis

3.2.1 Analysis Description

Different types of metrics are required to simulate an ED, which can be grouped into three categories: Arrival Patterns, Routing Probabilities, and Processing Times (Ghanes et al., 2015).

Arrival patterns. The arrival patterns refer to the measurements made to the patients at the time of entering the emergency room. The metric used in this case is the arrival rate per hour/day.

For the modeling we consider $N(t)$ the number of patients arriving at the emergency room at a particular time t. It is assumed that patients arrive randomly and independently. In that case, it is possible to model the patient count as a Poisson process of parameter λ. However, when considering the temporal dependence of the counts, it can be considered as a Non-Homogeneous Poisson process with rate $\lambda(t)$. For the estimation it is assumed that the rate is piecewise constant on a set of time independent intervals. Given that $N(t)$ is a Poisson process with rate $\lambda(t)$ the distribution of the interarrival time follows an exponential distribution of parameter $\lambda(t)$.

Routing probabilities. For the estimation of routing probabilities, we consider the sequence of events observed in the data as a Markov Process (Baum & Petrie, 1966), in which each state represents one event in the process, such as triage, or blood test, among others. The transition probabilities associated with the Markov Chain are in consequence, the routing probabilities. For the verification of this model, the following hypothesis tests on thproperties of the chain are considered: Markov property, order, and stationarity of the transition probabilities, and sample size (Anderson & Goodman, 1957).

Processing times. In the case, three elements can be distinguished in the processing times. The waiting times from the prescription of the exams to the moment they are performed, the time it takes to complete the exam and the additional waiting time to get the results. Once the data were adequately arranged, we iterate over a set of continuous distributions to identify the one with the best fit for each variable. To test the goodness of fit, we used the Kolmogorov- Smirnoff test (Massey, 1951) in which the null hypothesis evaluates that the data follow some specific distribution

3.2.2 Results Analysis

Arrival Patterns. Firstly, the non-homogeneous Poisson process was estimated and the parameter λ was determined for all the one-hour intervals. Figure 3 shows the behavior of the parameter for all the days of the week, which can be evidenced by the bands of greater congestion and the peaks of patient arrivals during the day. The x-axis indicates the hours of the day, and the y-axis is the number of patients. The curves represent the behavior of the intensity parameter for each day of the week. From these arrival patterns it is possible to construct the distribution of arrivals and inter-arrivals per hour, following the deduction mentioned above.

Routing Probabilities. The chain states are represented as the nodes of the Figure 4, which describes the transition matrix that indicates the probability of moving from one state to another. We can see that after triage, for example, the probability that a patient undergoes a blood test is 0.48, while not going through any stage is 0.44. Patients do not usually go directly from Triage to RX or MRI CT Scan; generally, to obtain these tests, a blood test is performed beforehand, where 70% are referred to one of these two tests. For Markov property, the Q statistic is 4535.63 and the p-value is: 1.0. Taking alpha = 0.05 there is statistical evidence to not reject H_0, there is no evidence to reject the hypothesis that the process satisfies the Markov property.

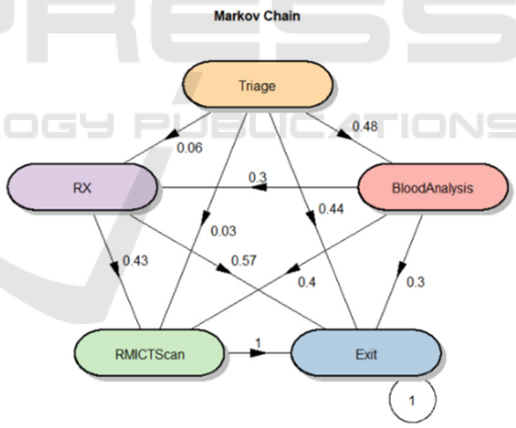


Figure 4: General routing probabilities.

Processing Time. After triage, the subsequent most frequent examination is a blood test. The collected samples are used for three evaluations, Biochemistry, Hematology, and Coagulation. For the Biochemistry blood analysis, we consider the distinction by severity index, and plot the histogram and the fitted distributions as seen in Figure 5.

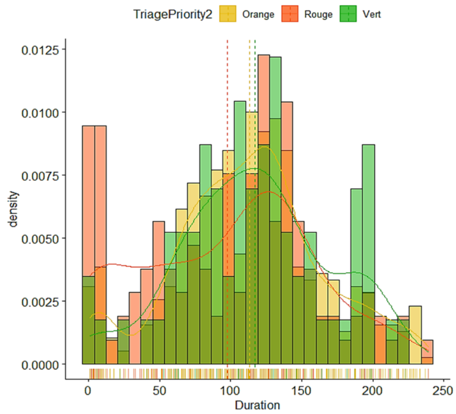


Figure 5: Biochemistry BT duration.

3.3 Requirements

We gathered requirements in terms of user stories through manual process analysis and interviews with an expert doctor and two DES researchers. *Functional:*

(1) *Manage Input Data*: As a user, I want to manage my datasets so I can analyze it on the platform. Acceptance criteria: Upload resource, encrypt and version files.

(2) Check Data Quality: As a user, I want to check the quality of my dataset so I can make sure my dataset is appropriate for simulation. Acceptance criteria: Perform data quality checks, generate data quality reports.

(3) Process Data: As a practitioner user, I want to process my input data and obtain statistical representations of my variables in a compatible format for the simulation software. Acceptance criteria: Display variables, fit distribution, display results, export results.

(4) Reproducibility: As a user, I want to replicate the analysis and results of my projects so I can make research reproducible. Acceptance criteria: Public repository, share data, share results.

Non-functional:

(5) *Availability*: As a user, I want the site to be available 99.9 percent of the time I try to access it so that I can trust the application and need another and do not need another app.

(6) Scalability: As a user, I want the application to support traffic spikes and several simultaneous processing requests so that no delays in the results should happen.

(7) Security: As a user, I want the application to ensure encryption for all my data so that is no risk associated with the exposure of confidential information.

3.3.1 Existing IDM Tools

The analysis of existing IDM tools is made through criteria extracted from the requirements identified before. We identified only three tools: GDM-TOOL DESI (Skoogh et al., 2011), KE tool (Barlas & Heavey, 2016) and DESI (Rodriguez, 2015). The specific gap between the tools' characteristics and the requirements are presented in Table 1.

Table 1: Evaluation of IDM tools.

Category	Criteria	GDM	KE	DESI
Manage input data	Manage projects	No	Yes	Yes
	Load data	Yes	No	No
	Encrypt files	No	No	No
	Version files	No	No	No
	Data storage	No	No	Yes
	Data collection	Yes	No	Yes
Check data quality	Check data quality	No	Yes	No
	Reports	No	No	No
Process data	User interface	Yes	No	Yes
	Visualization	No	Yes	Yes
	Fit distributions	Yes	Yes	Yes
	Fit Markov chain	No	No	No
	Hypotesis testing	No	No	No
	Display results	Yes	Yes	Yes
	Export results	Yes	Yes	Yes
Reproducibility	Public repository	No	Yes	No
	Cloud available	No	No	No
	Share data	No	No	No
	Share results	No	No	No
Non-functional	Availability	No	No	No
	Scalability	No	No	No
	Security	No	No	No

Manage Input Data: All the tools have data loading features, GDM-Tool (Skoogh et al., 2011), and DESI (Rodriguez, 2015), have features for data collection and use a database for storage. None of the tools has encryption, and versioning features.

Check Data Quality: The comparison of the tools in this criterion showed that only KE Tool (Barlas & Heavey, 2016) has methods for evaluating the input data. None of the tools has features to generate reports on the quality of the input data.

Process Data: it was found that all the tools have features for exporting data, displaying results, and adjusting statistical distributions. GDM-Tool (Skoogh et al., 2011), and DESI (Rodriguez, 2015) have a user interface. KE Tool (Barlas & Heavey, 2016) and DESI (Rodriguez, 2015) show graphs of the obtained distributions. Although the KE Tool (Barlas & Heavey, 2016) does not have a user interface, it is possible to generate graphs from the code in the development environment. None of the tools adjust specific distributions such as Markov Chain or evaluate the hypothesis of their properties.

Reproducibility: KE Tool (Barlas & Heavey, 2016), is available in a public repository. However, none of the tools is available in the cloud, and they do not have features for sharing data and results obtained.

Non-Functional: The evaluated applications are desktop apps, where availability, security, and scalability are not concerned.

4 ARCHITECTURE

We present our architectural decisions through different diagrams (reference, context, deployment, application layers, deployment in AWS) to provide a top-level view of a software's structure representing the principal design and understanding of the problem. We propose adopting cloud infrastructure instead of on-premises infrastructure by considering three characteristics of the former model: manageability, scalability, and cost. In the first place, there is an intrinsic responsibility for managing the entire hardware and software stack on the on-premises setting, which implies the ownership and administration of servers, databases, networks, and containers, among others. The cloud services take away the burden of managing the required infrastructure, the provisioning, and maintenance of software (Narasayya & Chaudhuri, 2021). In a cloud environment, provisioning instances to meet the desired response time is easily configurable. In an on-premises setup, scalable architecture is possible but is limited to implemented resources and budget. In addition, in cloud setup, there can be a reduction in the total cost of ownership (TCO) mainly regarding capital expenditure (Capex) (Qian et al., 2009).

The software architecture described in the following subsections will adopt a fully decoupled microservice pattern to cover two main non-functional concerns: availability and scalability. Each element can be scaled independently in a cost and time-effective manner in this architecture, which is essential when handling several simultaneous processing requests and large datasets. In addition, it is also more manageable to maintain due to its relatively smaller size.

4.1 Software Architecture

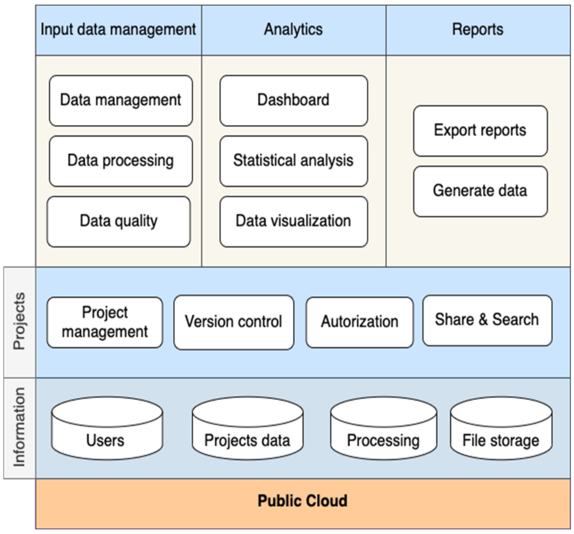


Figure 6: Software architecture.

This section describes each area of the software architecture that we propose in Figure 6, namely, IDM, analytics, reports, projects, and information.

Input Data Management: Data management: The system should provide a mean to ingest high volumes of data, persist it and store it securely. Data quality: The service must outline data quality issues and provide visualizations and reports to the user. Data processing: The platform must process all the data according to the user configuration and apply convenient transformation for analytical purposes.

Analytics: Dashboards allow the user to quickly gain insights into the critical metrics and information relevant to him. It also provides means for identifying potential issues that require imminent action. Statistical analysis: It provides summary statistics of variables, fits statistical distributions, estimates parameters, and test goodness of fit hypothesis. Data visualization: Visualization techniques provide the user with a clear representation of information to get quick data insights.

Reports: Export report: It enables the user to have a portable version of the results of the data quality inspection, data processing, and the statistical analysis in html format. Generate data: The platform has to provide the user a mechanism to generate synthetic data that mimic the system's original data according to the statistical distributions of the processes.

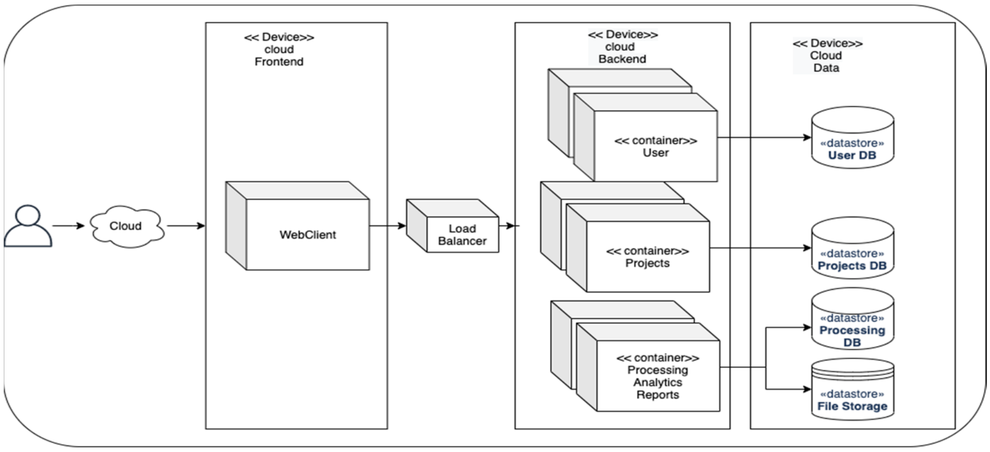


Figure 8: Deployment diagram.

Project: Project management: Projects allow the user to organize and centralize the resources, and arrange data, analysis, and reports. Version control: it keeps track of versions of the projects and their resources in an organized manner. Authorization: It allows the administrator to manage roles and permissions over the project's context. It provides a good way to secure files. Share and search: Provide mechanisms for indexing and cataloging data sources and analysis objects in order to facilitate the searching and sharing of files.

Information: Users: The database dedicated to centralizing the user's data, roles, and authorizations. Projects data: A dedicated database for project data management. Processing: All the data allocated in memory during the processing. File storage: The excepted contents of the system are the original data sources, transformed data, metadata, parameters, results, reports.

4.2 Context of the Application

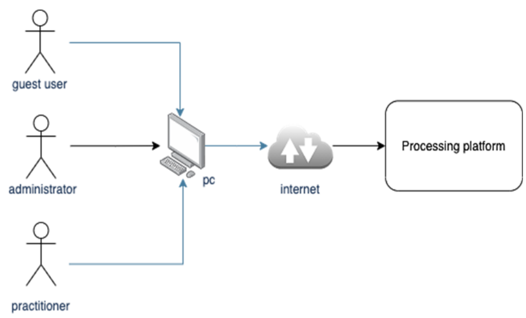


Figure 7: Context diagram.

The intended users are researchers and practitioners involved in the DES field. It considers three types of users: administrators, practitioners, and guest users as seen in Figure 7. The administrator and practitioners can login, create projects, manage input data, version resources, share resources, analyse data, generate reports, generate data quality reports. Practitioners require an invitation from an administrator for creating an account. Guest do not need an account but require an invitation from an administrator to see a project and generate reports.

4.3 Deployment of the Application

Figure 8 shows the system structure, the current understanding of the artifacts and how they will be deployed. First, the user accesses the application through a web client hosted in the cloud, specifically in a front-end component of the application. A load balancer act as a firewall and manage application loads, then a there is a back-end component based on three microservices: User, Projects, and Processing, analytics, and reports. All of them have a dedicated database, and the last one has also an object storage.

4.4 Prototype

The application prototype was built using two lightweight software development frameworks, FastAPI (backend) and React.js (frontend). These are appropriate for this type of application as it is a small application with simple logic.

Microservices. The application has three microservices containerized using Docker, which hosts a REST-API created using the FastAPI python framework that exposes the service methods. Each of these microservices can access the storage services on one side to the Postgres database hosted in AWS RDS.

Elements of the User Interface (UI). It includes basic elements, such as input controls, navigation and information components and containers, to offer a simple interactive experience in which IDM is presented through a series of steps that do not require further configuration by the user to obtain the data reports (see Figure 9).

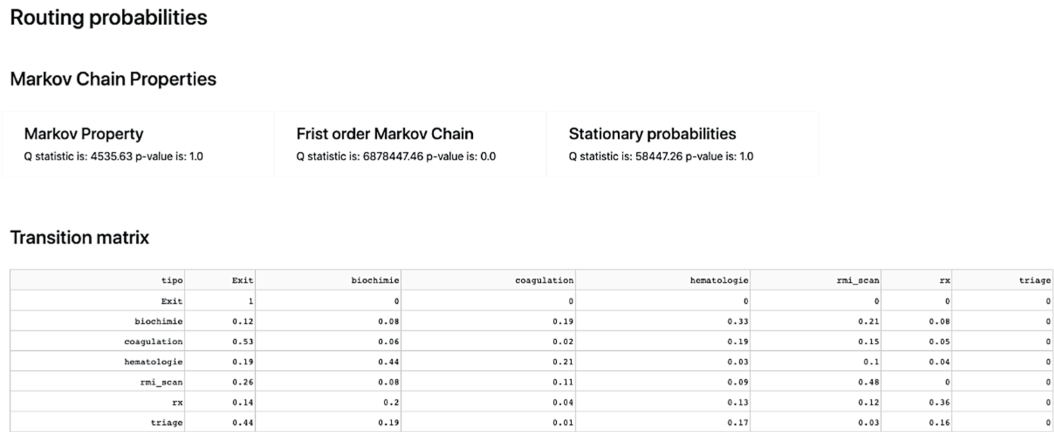
Figure 9: Data processing steps.

The first step is the creation of a project, in which the user must enter a name and description of the project and a label to reference. Then the user can load the files required to be processed following the template provided for this purpose. Once the file is loaded, if it corresponds to the structure required, the corresponding validations on the data will be executed. The next step is the data processing where the statistics are estimated. The last step corresponds to the menu where the user can share private links to the resources or download the reports. Regarding the data processing functionality, estimated parameters of the arrival process, the inter-arrival, the routing probabilities, waiting and processing times distributions are generated online under demand. The results are presented in a dashboard containing three pages, one for each analysis category.

Figure 10 shows an example of the dashboard with the properties of the Markov chain. It shows the results of evaluating the properties of the Markov chain and the transition matrix associated with the process. Two buttons allow the user to go to the other sections for navigation within the dashboard. Clicking on the routing probabilities option displays the dashboard with three main elements. First, some information cards are shown with the results of the hypothesis tests that verify the properties of the Markov chain, as are the Markov property, order, and stationarity. The processing microservices perform the calculations, and the results are presented to the user in cards as seen in Figure 10. The third page of the dashboard presents a drop-down list from which it is possible to choose the activities that are used as the starting point of an activity, process or waiting time. Then a graph is displayed with the histogram of the data, the kernel density, and the fitted density.

4.5 Deployment in AWS

The web application proposed in this article uses some of the tools available in Amazon Web Services, which follow the usual deployment patterns for the proposed architecture. Route53 is used to register the website domain and to redirect traffic. In addition, we use Elastic Load Balancing (ELB), the service managed by Amazon, for load balancing between applications, in order to distribute the application traffic, determine the scaling of resources on demand, and keep hidden the IPs of the microservices where the user information is hosted. To manage the containers where the microservices of the application are hosted, Elastic Container Registry is used to register and store the images of the containers, which facilitates the deployment using Fargate. The processing microservice has access to the data hosted in a RDS database instance, which can scale horizontally under demand. For Front-End content delivery we use CloudFront, the low-latency, highly available and secure content delivery network service that does not depend on a particular region. The Simple Storage Service (S3) is used to store the files that users import into the application, as well as the reports that are generated on data quality and statistics processed by the application.



tipo	Exit	biochimie	coagulation	hematologie	rmi_scan	rx	triage
Exit	1	0	0	0	0	0	0
biochimie	0.12	0.08	0.19	0.33	0.21	0.08	0
coagulation	0.53	0.06	0.02	0.19	0.15	0.05	0
hematologie	0.19	0.44	0.21	0.03	0.1	0.04	0
rmi_scan	0.26	0.08	0.11	0.09	0.48	0	0
rx	0.14	0.2	0.04	0.13	0.12	0.36	0
triage	0.44	0.19	0.01	0.17	0.03	0.16	0

Figure 10: Dashboard elements: Markov chain properties and routing probabilities.

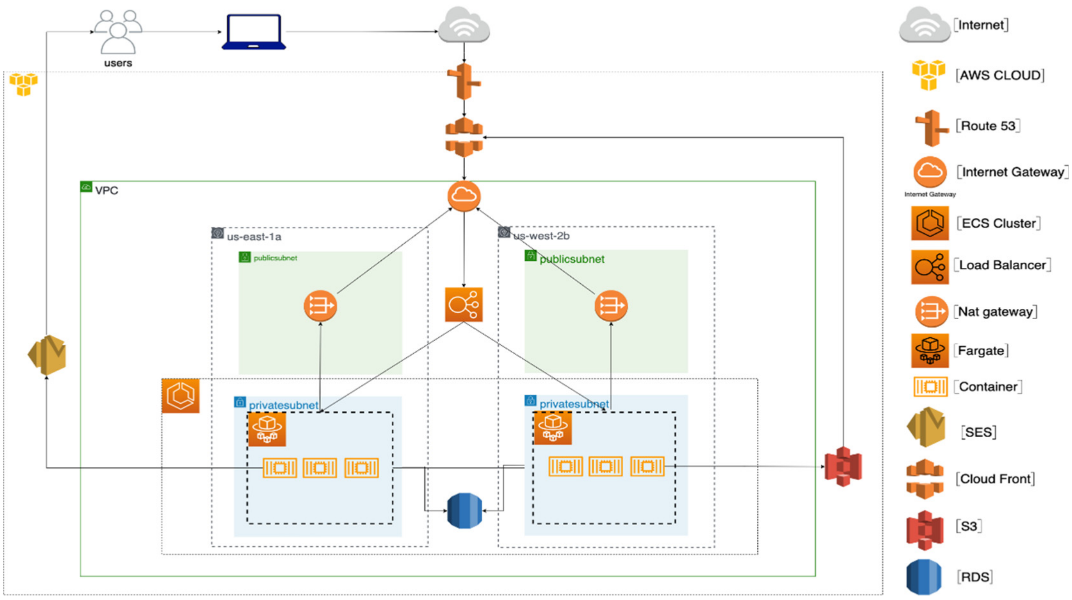


Figure 11: Deployment diagram in AWS.

Several security measures were considered to secure and protect user data. First of all, the application uses Virtual Private Cloud (VPC) to group the computing resources and database of the project securely. The output to the Internet of the VPC resources is through internet Gateway only. Also, the object storage S3 encrypts all original user data. On the other hand, the load balancer acts as a firewall so that the APIs that expose the microservices cannot be accessed directly. In addition, the proposed architecture considers the use of public and private subnets so that the response data of the microservices does not go directly to the Internet but through a Nat-Gateway that routes the response. Last but not least, the credentials, API keys, and database access data were stored encrypted in AWS Secrets Manager. Furthermore, to promote service availability, it was planned to deploy the application in two availability zones: us-east-1a and us-west-2b. Moreover, to ensure that the application responds to intensive workloads, an autoscaling group was defined to increase the number of processing instances if needed.

Regarding the client-side design, all requests made from the client side are handled by FastAPI. Within the application, design React handles two types of users: administrators who are in charge of creating projects and guests. For the verification and authorization of administrators, both client-side and server-side, an access token creation system, JWT, was used. React is responsible for the user interface and for making the corresponding HTTP requests to the application server.

For the server-side design, the model presented in Figure 11 shows all the elements involved on the server-side. The boxes group together: the AWS cloud represented by the AWS cloud logo, the Virtual Private Cloud (VPC), the availability regions identified by the texts "us-east-1a", "us-east-1b". The green background distinguishes the private subnets by the blue background, and finally, the Elastic Container Service (ECS) cluster is distinguished by the ECS logo.

Users access the application via internet through the website whose domain is registered with Route53. Once accessed, the site content is delivered by Cloud Front, which queries the static Front- End files stored in S3. In AWS, the application has a VPC to isolate the compute resources, storage, and subnets securely. The point of contact of the VPC with the Internet is the Internet Gateway. Requests received through this point are directed to the load balancer responsible for redirecting the request to the containers hosted in Fargate. The containers host the application's microservices and access the RDS database, S3 object storage, and SES mail delivery services.

The microservices are hosted on a private subnet, which means they cannot be accessed directly and cannot deliver request responses directly to the Internet. It is necessary to use the Nat gateway available on the public subnet. The proposed architecture complies with several elements to secure servers and user data, such as using a VPC, private and public subnets, a load balancer that serves as a firewall and encrypting the data in S3 in the RDS. Likewise, the multi-region deployment favors the availability of the application. In terms of scalability, the ECS cluster configuration has an auto-scaling policy to increase the number of instances required for processing in case of traffic spikes.

4.6 Validation

The application's validation consisted of verifying requirements with end-users. Table 2 shows the result of reviewing the requirements, the microservices, and the AWS components used to satisfy each requirement. Validation involved expert input from two simulation specialists and hands-on involvement from two students working with real data. End-user feedback was gathered through periodic validation sessions during prototype development. As we can see in Table 2, all requirements were satisfied through the application. In addition, the end-users transferred knowledge about ED processes and data, proposed and evaluated data analysis strategies, and requested features for visual components, navigation, and data results.

Table 2: Mapping of requirements and architecture's areas and components.

Feature	Container	AWS Service
Registry	Users	Fargate
Login	Users	Cognito, SES
Delete account	Users	Fargate
Create project	Projects	Fargate
Invite User	Projects	Fargate
Search project	Projects	Fargate, RDS
Delete project	Projects	Fargate
Manage data	Processing	Fargate
Download Data	Processing	Fargate, S3
Data quality	Processing	Fargate
Dashboard	Processing	Fargate. CloudFront
Process Data	Processing	Fargate, RDS, S3
Security		Subnets, Load Balancer, Autoscaling Group
Scalability		Load Balancer Autoscaling
Availability		Multi AZ

Functional Test. Benchmark against KE-Tool. One of the tests performed to validate the reliability of the results was to process and obtain the probability distributions using another IDM tool. The test consisted only of estimating the probability distributions of the data, as the other characteristics of the applications are not directly comparable. We compared the results of the statistical distributions generated by the application against those generated using the KE tool, the only tool we found in a public repository. The comparison was performed in terms of the KL divergence, the observed values were close to zero so we can affirm that there is no divergence, which means that the information distributions found in both programs are similar.

Non-Functional Requirements: As mentioned earlier, we considered non-functional scalability, availability, and security requirements. The proposed architecture facilitates storing and processing files and scaling on-demand. The application achieves this through the use and configuration of amazon's processing and storage services appropriate for this application, such as the object storage service and the configuration of the auto-scaling groups. On the other hand, optimized libraries were used for distributed data processing, thus reducing processing times. The availability and security of the application is achieved by implementing AWS services, such as RDS multi-AZ, availability zones, VPC, subnets, and load balancer. The availability is assured using two availability zones, and the security requirements are covered with object storage encryption.

Load Test. To assess the non-functional scalability requirement, we tested the processing microservice's ability to handle a certain number of HTTP requests per minute. We assume the system is completely degraded when a failure rate greater than 99% occurs. The web service https://loader.io/ was used to send the requests to the necessary endpoints. The auto-scaling configuration enabled up to 5 ECS tasks. We observed the system completely degrade when receiving 1500 requests in 15 seconds. And also if more than 6000 requests are received in two seconds. We found evidence of using the maximum number of enabled instances, thus satisfying the requirement.

5 DISCUSSION

This section discusses the advances that the proposed application brings concerning the previous propositions in the literature as well as our contributions to meet the needs identified from data analyzed.

Qualitative features comparison. The proposed solution has storage services such as databases for microservices. It uses s3 object storage to store all user information. The results obtained can be reproduced on-demand and facilitate the sharing of the original files, unlike DESI (Rodriguez, 2015), which has a temporary storage of the processed records. Additionally, the prototype integrates a feature for checking data quality that performs unit tests on the input data, unlike the KE Tool (Barlas & Heavey, 2016) that performs unit tests only on the methods of the classes that perform the processing.

Unlike KE Tool (Barlas & Heavey, 2016) and DESI (Rodriguez, 2015), the prototype has a more robust user interface with navigation, information, and visualization elements, that facilitates visualization of distributions, particularly the Markov Chain analysis results. Decisions are presented using the usual agile architecture diagrams such as context, deployment, components, classes, and soon unlike KE Tool (Barlas & Heavey, 2016), which illustrates a single high-level diagram of the system elements

The way in which the components fulfill the requirements is described below.

Manage Projects: The project microservice has methods for creating projects. Once a project has been created, the user can invite other users to view the content of the dashboards through a private link, which is generated in the project microservice. When a user wants to invite another user to the application, a record of the guest's email address is saved in the database, then an email invitation to the project is sent to the user.

Fit Distribution: In the dashboard, in the section of the adjustment of probability distributions, once the user selects a particular activity, the microservice is responsible for identifying the best distribution.

Check Data Quality: Rules were generated to validate the data at a stage before processing. It is worth mentioning that these rules do not limit the user to continue with the statistics generation process but serve to alert the user to avoid compromising the results of the estimations due to errors in the data.

User Interface: The processing microservice has a dashboard developed in Dash and Plotly that has three pages where all the statistics generated are displayed. This microservice is a python module in which each page of the dashboard is an independent module, which facilitates the maintenance and editing of the visual components. The data is presented in graphs and tables, making it easy for the user to quickly learn about the data distributions.

Markov Chains Validation: We implemented features for fitting Markov Chains and performing hypothesis testing to verify Markov chain properties.

6 CONCLUSION

By reviewing the literature and examining the real data, we defined the basic requirements that an IDM solution for DES should fulfil such as: managing the input data, verifying the quality of the data, processing and presenting process statistics in dashboards. We also analyzed probability distributions to be implemented in such application by using a real case. The proposed solution introduces therefore a cloud architecture that satisfies the requirements based on a microservices pattern that will enable high performance, availability, scalability, and security.

The novelty of this paper is the integration of Markov chain modeling to IDM, the proposed cloud architecture, the design, development and testing of the software, and the implementation with real data in the context of ED. The built application has elements that had not been previously used in similar tools, such as cloud computing services, containers, unit testing on data and interactive visualization. Additionally, the application implements straightforward and intuitive navigation tools in order to benefit user experience.

As future work, the results obtained in the evaluation of the properties of Markov chains rise to the question on how to approach the preparation of data for simulation models that consider routing probabilities for the problem of overcrowding in ED. Last, it would be desirable to adjust the code so that the processing is generic for data of similar data sources where IDM is required, such as manufacturing.

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