Surgery process - an approach based on case-based reasoning

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"Dedicated to the memory of my beloved grandmother, Maria Clotilde Araujo Faria Soares, who always cherished me and believed in my ability to be successful, no matter the challenges."

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Resumo

A cirurgia trata-se de uma das mais importantes funções a gerar receita e admissão ao hospital, assim sendo, melhorias na eficiência do processo poderia traduzir-se numa redução de gastos e aumento de benefícios tanto para o paciente quanto para o hospital. Os pacientes deveriam usufruir de uma experiência de alta qualidade, dignidade e segurança quando submetidos a uma cirurgia, contudo, a imprevisibilidade da cirurgia torna difícil que tal aconteça. Assim sendo, existe uma forte necessidade de melhoria de serviços, de forma a otimizar os recursos e maximizar o nível de satisfação por parte dos pacientes, sem para isso pôr em causa o existente nível de qualidade. Porém, para se obter tais melhorias, são necessários esforços de maneira a utilizar de forma inteligente a informação existente relativa a cirurgia.

O objetivo desta tese é fazer uso de tal informação com o recurso à criação de um sistema de suporte na decisão, de forma a avaliar o processo cirúrgico a que um paciente necessita ser submetido, construído em uma abordagem de *Programação Lógica* para *Representação do Conhecimento e Raciocínio*, completada com uma abordagem híbrida baseada em raciocínio baseado em casos e redes neuronais artificias para computação. A solução proposta é única em si mesma, uma vez que atende ao tratamento explícito de informação incompleta, desconhecida, ou até mesmo auto contraditória, seja em termos quantitativos ou qualitativos. Além disso, devido à imprevisibilidade que o processo cirúrgico exibe, uma configuração de tempo é apresentada de forma a se poder lidar com tais situações.

Palavras-Chave: Processo Cirúrgico; Raciocínio baseado em casos; Representação e raciocínio de conhecimento; Programação Lógica.

ABSTRACT

Surgery is one of the most important sectors that generate revenues and admission to the hospital, therefore improvements in the efficiency of the process could be translated into significant savings and benefits to the patient as well as the hospital. Patients deserve a high-quality, dignified, and safe experience when submitted to surgery, however, the unpredictably of the surgery makes it hard for it to happened. Thus, there is a strong necessity of improvement of the services in order to optimize the resources and maximize the patients level of satisfaction, without jeopardising the existing level of quality. However, in order to obtain such improvements, efforts need to be made in order to smartly make use of the existing information.

The goal of this thesis is to make use of such information with resource to the development of a decision support system to assess the surgery process that a patient needs to be submitted, built on top of a Logical *Programming approach* to *Knowledge Representation and Reasoning*, completed with a hybrid case-based reasoning and artificial neural networks approach to computing. The proposed solution is unique in itself, once it caters for the explicit treatment of incomplete, unknown, or even self-contradictory information, either in terms of quantitative or qualitative setting. Also, due to the unpredictability that the surgery process exhibit, a time setting is presented in order to deal with such situations.

KEYWORDS: Surgery process; Case-Based Reasoning; Knowledge Representation and Reasoning; Logic Programming.

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Acronyms

ACO – Ant Colony Optimization

AI – Artificial Intelligence

ANFIS – Adaptive Neuro Fuzzy Inference Systems

ANN – Artificial Neural Network

BMI – Body Mass Index

CBR – Case-Based Reasoning

CI – Contracted Infection

DSU – Day Surgery Unit

ETL – Extract, Transform and Load

LP – Logic Programming

ICU – Intensive Care Unit

ICUt – Intensive Care Unit Time

MRLA – Multiple Linear Regression Analysis

MT – Medical Team

OCASE – Objective Computer-Aided Skill Evaluation

OR – Operating Room

PACU – Post-Anaesthesia Care Unit

PACUt – Post-Anaesthesia Care Unit Time

PIS – Patient Intraoperative State

POA – Preoperative Assessments

PPA – Patient Postoperative Assessment

PPES – Patient Perioperative State

PPOS – Patient Postoperative State

PRFSP – Patient Risk Factors For Surgery Performance

QBE – Query-By-Example

SC – Surgery Complications

SP – Surgery Performance

SPR – Surgery Physical Resources

SS – Surgery Speciality

St – Surgery Time

TS – Type of Surgery

WBt	– Ward Bed Time

CHAPTER 1

INTRODUCTION

With the increasing interest by the healthcare services on providing a higher quality services to the patient, there is a strong necessity of improvement of the services in order to optimize the resources and maximize the patients' level of satisfaction, without jeopardising the quality. Nowadays, hospitals face multiple challenges due to cuts on the economic domain that puts in risk this quality. Between the multiple services provided on the hospital, the surgery department, being one of the services with the highest level of importance and economic impact on the hospital environment, presents a crucial task in terms of hospital organization. In case of delay or cancellation of a surgery this affects negatively the health care quality, harms the patient, and wastes resources (Talalwah & Mciltrot, 2018).

A special circumspection needs to be taken when the surgery process is considered, since the diversity of entities present through the process make it to be a complex and dynamic structure were both hospital and patient related information are taken into account, therefore multiple problems may arise from that instability. Thus, it is in everybody's interest that measures are taken into account in order to find the best solution for a better management of the situations encounter every time a new surgical case is presented.

Since healthcare systems include a high level of complexity and large amount of available information, data uncertainty is one of the major problems, since data reliability is crucial for the obtainment of a valid solution when it is applied to the real system. In healthcare, uncertainty may arise in different contexts and due to different causes, and in all cases, cannot be neglected, as it may have a significant impact on the solution and on the quality of service provided to patients (Addis et al., 2014).

With this thesis an efficient approach is presented, that is capable of leading with the uncertainty present on the information that has incomplete, self-contradictory, and even unknown data focusing on a Logic Programming (LP) based approach to knowledge representation and reasoning able to handle this type of data. This system will also have an approach capable of handling with the time where a simple logic interpreter allows an effective reasoning based on the manipulation of a sequence of snapshots. Moreover, the system will be capable of dealing with the high computational complexity presented due to the high quantity of data presented. Thus, it is intended the development of an intelligent decision support system capable of predicting a new successful case for a new surgery process of a patient needing surgical intervention, with resource to a hybrid Case-Based Reasoning (CBR) and Artificial Neural Network (ANN) soft computing approach to knowledge processing.

1.2 Motivation

In healthcare inconvenient problems occur frequently, namely cancelations, long time waiting, and resource overload (Meskens, Duvivier, & Hanset, 2012). In terms of health services, surgery is one of the most important functions that generate revenue and admissions to the hospitals, being one of the largest cost category were multiple resources are used. Between 187.2 million and 281.2 million surgeries are performed per year (Weiser et al., 2008). Therefore, improvements in the efficiency could translate into significant savings and benefits to the patient as well to the hospital (Min & Yih, 2010). Patients deserve a high-quality, dignified and safe experience when they're submit to surgery, however, the unpredictably of the surgery makes it hard to succeed in every case, since multiple factors are taken into account, not only the patient health condition but also the hospital services and resources provided. Consequently, new approaches that improve their service and handle this problem need to be implemented.

Despite the tremendous progress the use and implementation of data has been slow and difficult, mostly due to the lack of stored information, without data to provide an insight into actual practice, disparity in outcomes is an inevitable consequence (Maier-Hein et al., 2017). Therefore, new approaches need to be taking into account that is more capable of dealing with the presence of imprecise data.

Current approaches implemented to surgery tend to focus on the management of the hospital resources through mathematical optimization models but are not capable of leading with real data that present such imprecise information, so the application of the model to the real system becomes difficult, presenting little efficiency. Also their' models tend to be more focussed on the costs savings of the hospital through management, although this approaches are valid, they will lack in some aspect when implemented on the real world.

In this thesis the use of an intelligent decision support system is introduced to the process of surgery capable of leading with real world data, focusing the implementation of the process not on the resources of the hospital services but on the patient path through the process. In the moment the stable conditions for a successful case are presented, this will give the patient the minimal care that is needed in order to the process to succeed, but will also prevent the hospital from overuse the resources, since the prediction of the complete path of the process made by the system will give the hospital the information about the minimal expenses, in order to successfully save costs and time.

Concluding, both patient and hospitals will benefit from improvements on the quality and efficiency of the healthcare services provided.

1.3 Objectives

The objective of this thesis consist on the study of the surgery process in order to develop an intelligent decision support system to predict the most suitable surgical path for a new patient. With the implementation of such a system, a survey and analysis of the information that is relevant to the health unit regarding the surgical process will exist; the entire system present in the surgery process will improve benefiting both patient and hospital; the management of the resources will be more efficient; an improved capacity of respond regardless of the type of case encountered will be provided, allowing to deal with the situations where information is incomplete, self-contradictory, and even unknown; and an greater fidelity on the services provided to the patient will be created due to the reduction of anomalies.

1.4 Structural Document Organization

An organization of the thesis is presented.

Chapter 2. In this chapter, the state of the arte is presented, were an introduction to the surgery process is made by giving a background of the current problems on the surgery domains and the future perspectives. A review is presented about the essential aspects of the surgery process and the problems present on the surgery domains are discussed, describing the problem of cancelations and delays on surgery and the block that they create on the services. Also the uncertainty and variability is described and the consequences of such when present. Additionally, the future of the surgery process is described, namely the paths that are being created and what paths need to be taken in order to obtain the best surgery experience for the patients. In the end, a complete literature review of computational approaches proposed on surgery until now is presented.

Chapter 3. In this chapter, a review of the structure of the CBR approach is described in order to understand its operation and the advantages in using the CBR. Subsequently, a description of the way cases can be represented and indexed on the Case Base is presented. Further, the case retrieval performed by the CBR, the adaptation of a case, the learning of the Case Base and the Case Base maintenance is explained. Also, a hybrid system of CBR with recourse to ANNs is described, giving a review on the way that ANNs behave.

Chapter 4. In this chapter, a Knowledge Representation and Reasoning using the *Logic Programming* is presented in order to deal with the type of data present on the system, where background information and the use of the approach on the both quantitative knowledge and the qualitative knowledge are described.

Chapter 5. In this chapter, a handle of time approach for the surgery process is presented. A knowledge representation of time is described, where a basic system with the mechanism for defining and adding semantic knowledge to data base system is described. Also, the approach in order to deal with handle of time and negation is described. The data base operations performed on the data is described, where the retrieval of the desired data and the update of the data on the database is explained.

Chapter 6. In this chapter, the structure of the knowledge database used by the system for the surgery process is described and the treatment made on the data to be used is presented. Moreover, the structure of the scheme used on the knowledge database for the surgery process and the representation of the qualitative information on the time domain is explained. Furthermore, the knowledge database is presented in terms of the extensions of the relations and the procedure used on the data is exemplified.

Chapter 8. In this chapter, a logical programming approach to Case-Based Reasoning is described, where a new Case-Based reasoning approach base on logical programming is presented and the influence of the time knowledge representation on CBR is described.

Chapter 9. In this chapter, a computing approach for the surgery process of Artificial Neural Networks and Case-Based Reasoning is presented.

Chapter 10. In this chapter, the conclusions about the system created are discussed.

CHAPTER 2

STATE OF THE ART

Over the years' surgery has been growing and improving in order to give the best possible result to the patients in need of such, being a focal point on the health care system. In terms of health interventions, surgery's past presents a long historical record, dating from the third millennium B.C. from an old text that was found transcribed to the Egyptian papyrus Smith, where the author simply advised how wound edges had to be approximated by sutures or linen bandages strips (Van Hee, 2013). From the past to the present a lot have changed on the way surgery is seen and performed, now a day, surgery presents high standard procedures and technology that those from the past could not even imagine possible.

Although, all this progresses have been made, there is still a lot of issues that stagnate the process and need to be addressed. In order to improve, the use of the current existent technology need to happened, that way, the excellence of services provided on the surgery domain could increase and the obstacles that prevent un successful surgical process would diminish.

2.1 An introduction to the surgery process

As the growth, and sophistication of new treatments and technologies are being implemented, surgery becomes one of the fastest changing specialties. The capacity to perform surgery on patients with complex medical problems means that the tools required to provide competent and compassionate fundamental care, so far displayed for these patients must extend well beyond. It will not only be benefit to the patient but also to the hospital and all health professionals working in the many settings in which surgical care is delivered (Smith, Kisiel & Radford, 2016). Surgery as one of the most important functions that generates revenue and admissions to the hospitals, is economically one of the largest hospital cost category with it being approximately one-third of the total cost. That's why surgery is the area with the highest potential for cost savings, being approximately two-third of hospital incoming. Therefore, small improvements in efficiency could translate into significant savings and benefits to the patient as well as to the hospital. For these reasons, managing the surgical resources effectively in order to reduce costs and increase revenues has a considerable attention from the healthcare community (Min & Yih, 2010).

Statistically it was estimated that the global volume of major surgery in 2004 was between 187.2 million and 281.2 million cases per year, translated as one operation for every 25 human beings. In terms of death and complication rates after surgery, major morbidity complicates 3–16% of all inpatient surgical procedures in developed countries, with permanent disability or death rates of about 0.4–0.8%, being half of the adverse events identified as preventable and for the death for major surgery a rate 5–10%. Mortality from general anaesthesia, infections and other postoperative morbidities are a serious concern worldwide. With the assumption of a 3% perioperative adverse event rate and a 0.5% mortality rate globally, almost 7 million patients undergoing surgery have major complications, including 1 million that die during or immediately after surgery every year. Postoperative morbidity and mortality are probably far more common globally, but the fact that less than a third of countries can offer data for surgical volume is an indication of not only how difficult making an accurate global estimate of surgery is, but also how inadequate present health-care surveillance is. Surgery occurs at a tremendous volume worldwide and this growth calls for public-health efforts, improving the monitoring, safety and availability of surgical services, especially in view of their high risk and expense, that's why public-health strategy for surgical care is indispensable (Weiser et al, 2008).

Patients and their families deserve and expect a high-quality, dignified and safe experience when they have surgery. This requires competent resources that continue to enhance and develop better healthcare service. Since the physical treatment received by surgical patients are in the form of operative procedures, this means that, specific aspects of the care of these patients may differ from those of medical patients since they are at risk of complications following the surgical procedure (Smith et al., 2016).

Two major patient classes are considered in the literature namely the elective patients and non-elective patients. As for the first class it represents patients for whom the surgery can be planned in advance, whereas the latter class, groups patients for whom a surgery is unexpected and hence needs to be fitted into the schedule on short notice. A non-elective surgery is considered an emergency if it has to be performed immediately and an urgency if it can be postponed for a short time. Elective patients can be distinguished between inpatients and outpatients. Inpatients are hospitalized patients who have to stay overnight, whereas outpatients (ambulatory care) typically enter and leave the hospital on the same day. Moreover, since outpatients are not already present in a hospital ward before surgery, their actual arrival time is uncertain (Samudra et al., 2016).

Patient safety is at the centre of care provision, and requires quality and effective management of the surgical process, including a strong clinical staff. The surgical team embrace a range of healthcare professionals who are involved in the patient's care throughout the perioperative period. The wider members of the multidisciplinary team and the surgical team have an obligation to support each other while delivering patient care in wards, theatre, clinics, and community settings following discharge. It is imperative that there is effective communication between all team members with regard to the patient's care, in order to maintain high standards and reduce the risk of errors. The key members of the general intra-operative team include the surgeon, surgical care practitioner, anaesthetist, anaesthetic practitioner, advanced scrub practitioner, circulating practitioner and recovery practitioner (Smith et al., 2015). The surgeon is only present during the surgery act and requires a certain amount of time between interventions mainly for cleaning, change of clothes and rest, that depends on the duration of the previously performed surgery. During a surgery additional resources, human or physical are required and each resource unit assigned to a surgery must be available throughout the preparation and performance of the surgery with a fixed preparation time that depends on the resource type (Latorre-Núnez et al., 2016). Capacity shortage of downstream resources will keep patients from moving forward and it will significantly deteriorate de OR utilization (Min & Yih, 2010).

Once the surgery is finished, the patient must be transported to a bed of PACU and if the patients require special care it must be transported to an ICU (Latorre-Núnez et al., 2016).

With the increasing specialization of surgery, a radical shift in the organization of surgical care has resulted in fewer surgeons maintaining general skills and an increasing number having a more organ-specific focus. This shift has occurred during a period when perioperative pathways have changed due to the increasing use of technology, pharmacology, and refined techniques that result in reduced pre-operative and overall length of stay. Significantly, the intensity of care is higher, with greater throughput of patients in fewer hospital beds (Smith et al., 2016).

Hospitals provide many types of surgery delivery systems and are typically equipped with a broad range of capabilities, including an emergency department for handling cases resulting from unpredictable adverse events.

There are different degrees of urgency associated with patient care, depending on the patient case, the current classifications in use of interventions are respectively the immediate, urgent, expedited and elective surgery. Immediate surgery takes place within minutes of the decision to operate, in order to save life, an organ or a limb, therefore, it should take place in the next available operating theatre and can necessitate interrupting existing theatre lists. Urgent surgery normally takes place within hours of the decision to operate, in order to treat the acute onset or the clinical deterioration of a potentially life-threatening condition. It also includes the fixation of fractures, the relief of pain or other distressing symptoms. Additionally, patients who are to undergo this category of surgery should be added to the emergency theatre list. Expedited surgery takes place within days of the decision to operate, for a condition that requires early intervention but which does not pose an immediate threat to life, a limb, or an organ. The patient should either be added to an elective theatre list which has spare capacity or be included on a daytime emergency list. As for the elective surgery, is planned in advance of a routine admission, at a time to suit the patient and the hospital. It takes place on an elective theatre list, having been booked in advance (Denton, Rahman, Nelson & Bailey, 2006; Smith et al., 2016). Elective surgeries can be either conventional (inpatient surgeries) or ambulatory (outpatient surgeries). For an ambulatory surgery both the hospital admission and the discharge of the patient occur on the same day and, therefore, the patient is not in hospital overnight. According to Portuguese legislation, elective surgeries are classified in four levels of priority, defining the due date in which they must be performed, namely the deferred urgency surgeries must be completed in three days, high priority surgeries within 15 days, priority surgeries must be completed within two months and normal surgeries in one year (Marques, Captivo & Vaz Pato, 2013).

These classifications exist to ensure that patients receive surgery within the time frame necessary for their condition and also to ensure that medical staff only perform surgery out of hours when it is appropriate to do so. The classification should be assigned by the consultant caring for the patient, at the time when the decision to operate is taken. Specific conditions or types of surgery cannot be pre-assigned to these categories since, individual patient need will vary on a case-by-case basis (Smith et al., 2016).

All stages of surgery are encompassed by the perioperative period including the preoperative, intraoperative, and postoperative stages of patient care. The preoperative care begins with the patient's decision to have surgery, and ends with the transfer of the patient to the OR bed and it can include a variety of activities such as patient education, a patient visit to an anaesthesia outpatient clinic, preparation for the day of surgery, and arrival at the designated location for surgery. As for the intraoperative care it is defined as the time between when the patient reaches the OR bed, and the time when they are admitted to the recovery area which may be a PACU, ICU, or other post-procedure recovery area. The postoperative care covers the time between arrival in the recovery area and the time that the surgeon terminates follow-up care with the patient. Each of these stages are critical to the successful delivery of surgical services to the patient (Denton et al., 2006).

It is important to highlight, that in order to ensure that the patient is apt to go through surgery, prior to the elective surgical procedure, an pre-operative assessment is needed, to enhance issues that may complicate the surgery, so that the surgical or anaesthetic team be aware during the perioperative period, ensuring that way the safety of the patient and also avoiding unnecessary cancellations or complications due to an unsuitable surgery, benefiting that way, both patients and health services in terms of costs and quality.

During the perioperative period, the post-operative management of the elective surgical patients begins involving the surgical team, anaesthetic staff and all the associated health professionals. Requiring proper monitoring and repeated clinical evaluations, supporting all major organ systems, including cardiorespiratory function, renal function, fluid, electrolyte balance and awareness of signs of early surgical complications, such as bleeding and infection (Akhtar, MacFarlane, & Waseem, 2013).

In healthcare inconvenient problems are a frequent occurrence, namely cancelations, long time waiting and resource overload. Although, traditional approaches have been proposed to solve these problems, such as, hiring more personnel, purchasing more equipment or providing more beds and among others, this may offer solution to curtain degree but, the underlying problems have not been solved. Therefore, managers are increasingly looking for new approaches that improve their service or reform their organization (Meskens, Duvivier, & Hanset, 2012).

2.2 Surgery process Issues

Surgery is a very inconsistent field, recurrent problems occur, because there is intervention from multiple clinical systems, the troubling factor could be inconsistences in the hospital resources or circumstances of the patient, between many other reasons. As result unpredictability and variability are a constant present in surgery and may cause disruption, delays or even cancellation of the surgery.

2.2.1 Delays and Cancelations

Unexpected delay or cancellation of elective surgeries has a significant impact on hospital performance and causes undesired patient outcomes. When surgery is cancelled for any reason, efficiency is in jeopardy, waiting time increases, patient care may be compromised, resources are wasted, and the cost increases. Short notice cancellation has a negative psychological effect on patient satisfaction and causes significant disappointment and frustration for patients and their families.

The impact of cancellation result in the inability of performing surgery within a reasonable time, so the prolonged waiting time for surgery coupled with a prolonged hospital stay causes both pain and possible deterioration of the patient's medical condition, which might lead to an impaired recovery.

Cancellation of planned elective surgery is a significant problem that negatively affects health care quality, harms the patient, and wastes resources (Talalwah & Mciltrot, 2018).

The problem of last-minute changes in a surgical schedule is complex and involves multiple clinical systems such as the day surgery unit (DSU), Operating Room (OR), OR scheduling team, post-anaesthesia care unit (PACU), and Intensive Care Unit (ICU). When the surgical scheduling team fails to update the DSU about a surgical case sequence change, the patient waiting time for surgery becomes uncertain, nursing assignments change and workload increases. These consequences distress the DSU nurses, hindering their ability to prioritize patient needs and work as a team (Talalwah & Mciltrot, 2018).

In the event of cancellation, the OR workflow is interrupted, instrument kits previously prepared must be returned to central supply, resources are wasted and the use of the room is reduced. Limited health care resources and inefficient scheduling processes significantly affect the decision to perform the surgery. Only when resources become available, the patient will go to the OR and then to the PACU. Also, the unavailability of a bed in the ward or in the ICU leads to patient delay in the PACU for many hours. This delay increases safety risk, leads to poor continuity of care and increases stress for the patient, families and staff. The delay of surgery has a significant impact on the patient outcome as most surgical patients experience worry and uncertainty while waiting in the ambulatory surgery unit, since, if the waiting period becomes complicated, a cancellation or a postponement will occur. In most cases, a delay is identified as a work flow problem in the microsystem that requires specific consideration to improve patient experience, whereas a cancellation of surgery is a significant problem with far-reaching consequences. Thereupon, cancellation on the day of the surgery is widely recognized as a common dilemma with a negative impact not only on the organization, but also on patient outcome. Likewise, cancellation and rescheduling may harm patients, influence their quality of life, and increase the cost of conventional treatment (Talalwah & Mciltrot, 2018).

Evidence suggests that 86.5% of cancellations were preventable, whereas 13.5% were non-preventable. In addition, causes of cancellation are classified into three broad classes namely hospital related, patient related and surgeon or anaesthesia related causes (Talalwah & McItrot, 2018).

Most causes of surgical cancellation were related to hospital and administration, such as unavailable OR time, prioritizing emergency cases, failed or missing equipment, insufficient planning of surgery, lack of hospital beds and personnel. Being the unavailable OR time considered the highest cause of surgery cancellation (Talalwah & Mciltrot, 2018).

Cancellation related to patient factors occurred because of several reasons, such as absenteeism, self-cancellation, financial constraints, medical reasons and inadequate preoperative assessments (POA). The inadequate POA was associated with 10% to 20% of cancellations in 2011 (Talalwah & Mciltrot, 2018).

Unavailability of the surgeon, lack of anaesthesia staff, failure to administer anaesthesia and over booking are examples of physician related causes that may lead to cancellation. On one hand, surgeon unavailability is considered one of the cancellation reasons identified, providing a range of 2.6% to 41%, as well the overbooking was responsible for at least 77.4% of cancellations. Another cancellation reason was anaesthesia related matters like failure to administer anaesthesia, due to lack of anaesthesia facilities or due to an inadequate number of anaesthesiologists (Talalwah & Mciltrot, 2018).

Reasons for surgical cancellation can varied, however, a high incidence of cancellation is due to hospital and administrative causes. As mentioned above the leading cause of cancellation is due to lack of OR time, the second leading cause of cancellation is a patient related reason, with absenteeism on the day of surgery being the most frequent reason, followed by lack of POA before the surgery date. On the contrary, the unavailability of surgeons or anaesthesia service is the least likely cause of cancellation (Talalwah & Mciltrot, 2018).

Surgical cancellations are a significant quality issue in health care. These cancellations are associated with the undesired outcome of wasting resources, patient dissatisfaction and increased health care costs. It is essential to analyse the reasons for cancellation to reduce the rate. Most cancellation causes are preventable. However, special attention must be given to cancellation causes at one's individual hospital when implementing interventions. Every effort should be made to enhance cost-effectiveness and efficiency as well as to prevent unnecessary cancellations (Talalwah & Mciltrot, 2018).

2.2.2 Uncertainty

Features of healthcare systems include a high level of complexity and a large amount of available data, which have only recently begun to be stored digitally. Moreover, one of the major problems faced by people working in health care management is data uncertainty. Available data need to be properly analysed and processed in order to obtain reliable input parameters. In fact, data reliability is a key factor in guaranteeing the feasibility and efficiency of the obtained solution when it is applied to the real system. In healthcare, uncertainty may arise in different contexts and due to different causes, and in all cases, uncertainty cannot be neglected, as it may have a significant impact on the solution and on the quality of service provided to patients (Addis et al., 2014).

One of the major problems is the uncertainty inherent to surgical services, two types of uncertainty that seem to be well addressed in the stochastic literature are the arrival uncertainty and duration uncertainty. For instance, there is the unpredictable arrival of emergency patients or the lateness of surgeons at the beginning of the surgery session. Next to arrival and duration uncertainty, other types of uncertainty may be addressed, for instance, resource uncertainty, though, that resource uncertainty often coincides with arrival uncertainty. For example, the arrival of emergencies may result in a claim of both the surgeon who is needed to perform the emergent surgery and a specific OR. These claims actually result in resource breakdowns as the elective program cannot be continued and hence has to be delayed ((Cardoen, Demeulemeester, & Beliën, 2009).

The biggest problem associated with the development of accurate OR planning and scheduling strategies is the uncertainty inherent to surgical services. Surgery durations are difficult to predict because for some surgeries the magnitude of the procedure only becomes apparent once the surgery is already in progress. Additionally, the durations often depend on various complex factors, namely the characteristics of the patient, the surgeon and the surgical team (Samudra et al., 2016).

The decision of scheduling elective surgery patients is to determine whether an elective patient should be scheduled and, if so, when it should happen. There are two challenges with this, the capacity constraints of downstream resources such as surgical ICU beds or ward beds and the uncertainty in surgery operations. The elective surgery schedule will attempt to admit as many patients as possible while satisfying resource constraints, in order to maximize the quality of care. With regard to resource constraints for scheduling elective surgeries, the consideration of OR capacity alone does not mean good schedules. Capacity shortage of downstream resources will keep patients from moving forward and it will significantly deteriorate OR utilization. Scheduling surgery becomes challenging when considering the uncertainty in surgery operations. Surgery operations have case dependent durations and there is often a large variation between scheduled durations and actual durations. Also after surgery, there is a patient's length of stay on ICU uncertainty (Min & Yih, 2010).

2.2.3 Variability

If it was to consider a healthcare system without variability, it would be supposed that all patients are homogeneous in disease process, they all appear for care at a uniform rate and all medical practitioners and healthcare systems have the same ability to deliver quality care, being possible to achieve 100% efficiency in healthcare delivery. There would be no waste, the cost would be minimal and quality maximal within the boundaries of knowledge and technology. It would be easy to satisfy the goal of managed care to provide the right care, to the right patient, at the right time.

In the real world, healthcare systems are expected to deliver quality care for patients with many different types of disease. Patients with the same disease exhibit significant differences in their degree of illness, choice of treatment alternatives and response creating clinical variability, usually appearing for care in randomly.

In addition, professional variability emerge since the medical practitioners and healthcare delivery systems are not uniform in their ability to provide the best treatment. The constant challenge to the healthcare system is to efficiently convert a naturally variable incoming group of sick patients into a homogeneous outgoing stream of healthy patients. The goal then is to optimally manage natural variabilities. However, dysfunctional management often leads to the creation of artificial variability that unnecessarily increases the very cost and inefficiency. For example, the extreme variation in daily bed occupancy. On days when occupancy is too high, quality of care decreases because it is too costly for staff to peak loads, in contrast, on days when occupancy is too low, there is waste. No staffing system can be flexible enough to optimally manage these daily fluctuations. It is reasonable to assume that these variations in occupancy are related to a combination of the natural clinical variability of the patients' response to therapy and the natural flow variability of their admission through physician offices or the emergency room. Surprisingly, this assumption is only partially correct. An additional source of admission and occupancy variability in many hospitals is through the ORs. Typically, 80% or more of this variability from the ORs is due to variations in the elective scheduled daily caseload. The variability is not related to unexpected changes in the OR day from unscheduled emergencies, cancellations, or additions. It is artificial variability introduced into the system by the advance elective surgical scheduling process. Not only are there significant variations in the elective caseload among each day of the week but as much as a 50% difference in caseload on the same day of the week. Compared with natural variability, artificial variability is non-random. Yet it also is unpredictable, driven by numerous competing demands on the surgeons' time that are usually unknown and therefore unaccounted for by the healthcare system. So, the predictability of the number of admissions to the hospital on any day from elective scheduled surgery may be worse than the purely random appearance of patients for emergent admission through the emergency room (Litvak & Long, 2000).

Has previously appreciated, this variability is an obstacle to efficient delivery of healthcare. However, analyse the types and amounts of variability present in healthcare delivery systems and then to eliminate or optimally manage them, gives us the potential to overcome it. Therefore, all system expense resulting from artificial variability in healthcare delivery should be eliminate, using operations research methods and optimally manage the remaining natural variabilities (Litvak & Long, 2000).

Applying variability methodology at the hospital unit or departmental level is necessary but not sufficient, it needs to conduct a system wide analysis. Supposing there is a traffic jam, and is proposed to avert future jams the widening of the road. If the true dynamics of the traffic flow are not apparent, and the problem is a constriction at a distant exit, it will only worsen the jam at the area. To achieve maximal effectiveness in healthcare, it is necessary to understand the complete dynamics of patient interaction with all components of the delivery system and their mutual interdependencies. Much of the artificial variability in healthcare that is costly and should be eliminated is caused by poorly understood interdependencies between different hospital identities, who are simultaneously contributing to the delivery of healthcare. Simulation tools for modelling such interdependencies can be developed for the healthcare industry using network structures (Litvak & Long, 2000).

Significant variability in healthcare delivery is inevitable because of the changing nature of disease, the availability of new therapies, the wide variety of patients' psychological and physical responses. Unless, healthcare delivery models that can respond to this variability are developed, hospitals will never be able to maximize operating efficiency and quality, so it's needed new tools to reassure the patients that their cares are efficiently manage in a way that delivers the highest possible quality (Litvak & Long, 2000).

2.3 Surgery process Future

Future advances in the surgical care demands a greater extent of a close partnership between caregivers, patients, technology and information systems. In order to obtain a personalized medicine, interventional care will increasingly transform from a craft based on the physicians' individual experiences, preferences and traditions into a discipline that relies on objective decision-making based on large scale data from heterogeneous sources (Maier-Hein et al., 2017).

Data science as an emerging interdisciplinary field that deals with the extraction of knowledge from data. Despite the tremendous progress, there has been a delay in introducing large-scale data science into interventional medicine like surgery, attributed to the fact that, only a fraction of patient related data and information is digitized and stored in a structured and standardized manner. Without data to provide an insight into actual practice, disparity in outcomes is an inevitable consequence. An increasing access to large amounts of complex data throughout the patient care process, complemented by advances in data science and machine learning techniques, has set the stage for a new generation of analytics that will support decision-making and quality improvement in interventional medicine (Maier-Hein et al., 2017).

Future advances in surgery will continue to be motivated by safety, effectiveness and efficiency of care. The next paradigm shift will be from implicit to explicit models, from subjective to objective decision-making and from qualitative to quantitative assessment. This will enable personalized treatment and ensure that future evolution is cantered around patients and caregivers. Surgical data will evolve to observe everything occurring within and around the treatment process. Also, providing the surgeon with quantitative support to aid decision-making, surgical actions and link decisions to patient outcomes. For the patient, this will mean, access to the best surgical care with less variability arising from unique patient characteristics rather than the choice of surgeon or care facility. Ultimately, surgical data will offer the opportunity to create exceptional surgery by moving beyond the data associations that individuals are able to perceive, detect and maintain, into the realm of vast data types and sizes that can only be exploited through modern computing solutions (Maier-Hein et al., 2017).

The quality of surgical care is affected by decisions made by caregivers and patients throughout the care pathway. Traditionally, surgeons relied upon their experience to play a major role in consequential decisions such as whether to operate and the type of surgery to be performed. This decision-making model has gradually evolved to be informed by predictive analytics based on systematic data capture and curation through patient registries. However, currently available registry-based analytics to support surgical decision-making rely upon cross-sectional measures of a subset of patient characteristics before surgery. Furthermore, registries rarely capture the full record of the patient care pathway and the amount of data that they are missing varies. A data science approach to decision support relies not only upon continuously updating predictive analytics throughout the patient care process but also upon more comprehensive and unconventional sources of data. In addition, surgical decisions may be optimized by modelling individual patients within the context of population level data and other multimodal data sources (Maier-Hein et al., 2017).

Surgical education and certification ensure that competent surgeons provide care, being a critical element in assuring quality of care. Poor surgical technical skill is associated with an increased risk of readmission, reoperation and death. Technical skills and errors are also associated with non-technical skills such as decision-making.

In addition, surgical data can be transformative for surgical training through objective computer-aided skill evaluation (OCASE), robot-assisted active learning of technical skills, patient and context specific simulation training and assessment, and surgical coaching. Additional data analytics such as surgical process modelling, detection of constituent activities, errors and skill deficits facilitate targeted feedback based on OCASE (Maier-Hein et al., 2017).

Surgical data science thus represents the new frontier for surgical training in a complex patient care environment with limited resources. In terms of challenges, data availability and analysis of highly heterogeneous multimodal data, relies upon access to high quality data on a large scale that documents both the patient care process and patient outcomes. While other communities share databases for advancing research and practice, such resourceful databases are lacking in documentation of surgery, despite it being inherent that quality improvement can be achieved through outcome measurement, for example, using patient registries. This paucity of databases may be attributed to a multitude of regulatory, technical and sociological factors. On the other hand, although large amounts of data are routinely available during interventional care, they are not captured and annotated using standardized protocols (Maier-Hein et al., 2017).

Analysis of data from interventions also introduces unique challenges. The surgical process varies significantly from case to case and is highly specific to procedure, patient and surgeon. The heterogeneity in the data is a great challenge to be overcome, not only for the development of data analysis methods but also for the validation of new methodology and systems. Finally, procedural data must be holistically analysed with other heterogeneous data, enabling us to move from eminence-based to knowledge-based and data-driven medicine (Maier-Hein et al., 2017).

Moreover, surgical data enables fundamental understanding of surgical procedures, their variability, crucial parameters, hidden structures, dependencies, optimal pathways, the importance of each parameter, keys to success and failure of methodologies, and the basic principles driving our surgical education, training and practice. In this sense, its dissemination will be manifold. As discussed above, surgical data could change the education and training of millions of physicians across the planet (Maier-Hein et al., 2017).

Towards next-generation surgery, surgical data will pave the way from artisanal to data-driven interventional healthcare with concomitant improvements in quality and efficiency of care. A key element will be to institutionalize a culture of continuous measurement, assessment and improvement using evidence from data as a core component (Maier-Hein et al., 2017).

2.4 Approaches made on the Surgery process

Surgery has a considerable importance on health services, therefore multiple researches have been made on the subject, particularly on the operating theatre due to the conflicting priorities and preferences of its stakeholders, but also due to the scarcity of costly resources. Consequently, solutions to the issues present on the OR management and development of adequate planning and scheduling procedures are the topics with greatest enhancement on literature.

Large quantity of literature on the management of operating theatres have been presented, so there are some reviews made of literature past released papers. Therefore, only the most recent papers on the subject released will be review. However, a detail and organized review of the previous literature can be consulted on Cardoen, Demeulemeester and Beliën (2009) where is provided an overview on OR planning and scheduling, that captures the developments made in this area until 2008. The literature reviewed is structured using seven descriptive fields, allowing the analyse of the papers from different perspectives, respectably patient characteristics, performance measures, decision level, type of analysis, solution technique, uncertainty and applicability of research. Each section consisting on a brief discussion of the specific field on a selection of appropriate papers. As for the released papers following the review made, the ones found with the closest analogies are presented below.

Tànfani and Testi (2010), proposed a holistic integrated approach that could be used as a decision support tool to compare alternative operative scenarios, by means of a complete set of performance indexes, regarding all the different sub-processes. An integrated framework for surgery department performance evaluation from the moment the patient enters the system to the moment it is discharged was developed, taking advantage of both simulation and optimization ability to support decision.

Min and Yih (2010), proposed a stochastic optimization model for elective surgery scheduling considering surgical ICU capacity constraints. A sample average approximation algorithm was employed to solve the problem, numerical experiments demonstrate the convergence of statistical bounds with moderate sample size for a given test problem and a simulation study was conducted to show that stochastic surgery scheduling problem outperforms the expected value problem. However, because each patient may have different initial condition, speed of disease progress and either be making a recovery from a disease or relapsing, it is very difficult to define an explicit structure.

Wang, Tang and Qu (2010), proposed an operation scheduling model with a genetic algorithm. It focused on partitioning patients into different priorities according to the state of illness, an optimization model with the aim of maximizing customer satisfaction established under the consideration of a three-dimensional parameter, constraint related patients, ORs and medical staffs. A Genetic algorithm was proposed with two-dimensional 0-1 encoding for solving the surgery scheduling problem with the data derived from an upper first-class hospital, the experimental results showed the efficiency of the model and algorithm.

Taneva, Plattner, Byer, Higgins and Easty (2010), proposed a breakdown detection method as a useful approach to the management of breakdowns in inter-team coordination, within the context of the daily operations of surgical units. By mapping information flow expectations for various information needs in clinical work, an analyst could derive a set of predictions that served as input to the algorithm for detecting the breakdowns. The method was verified over data from three sets of observational studies in two different hospitals. Performance analysis demonstrates excellent detection rate.

Atle and Burke (2010), presented a model for the admission planning problem, in which intervention assignment and scheduling is combined, including scheduling interventions for each surgeon. A meta-heuristic resolution method was presented, along with its underlying move operators and associated distance measures. It also presented computational results for a set of realistically sized benchmarks that were generated based on the characteristics of the admission planning problem in a Norwegian hospital.

Devi, Rao and Sangeetha (2010), focused on the scheduling of the operating theatre, such that there was no overload on any of the beds. It forecasted the surgery time by taking into account the surgical environment in an ophthalmology department. The estimation of surgery times was done using three techniques, such as the Adaptive Neuro Fuzzy Inference Systems (ANFIS), ANN, and Multiple Linear Regression Analysis (MRLA) and the results of estimation accuracy were compared. The framework was validated by using data obtained from a local hospital. The ANFIS model was found to out-perform the other two models. It was hypothesized that by accurately knowing the surgery times, one could schedule the operations optimally resulting in the efficient utilization of the ORs. The scheduling is done using $P||C_{max}$ algorithm. The increase in the efficiency was demonstrated through computer simulations of the operating theatre.

Ghazalbash, Sepehri, Shadpour and Atighehchian (2011), a novel mixed integer programming model was presented for minimizing completion time of the last patient's surgery and the operating room idle times in hospitals. The model was then used to determine the allocation of resources, including operating rooms, surgeons and assistant surgeons to surgeries, moreover the sequence of surgeries within operating rooms and the start time of them. The proposed model was then evaluated against some real-life problems, by comparing the schedule obtained from the model and the one currently developed by the hospital staff. Numerical results indicated the efficiency of the proposed model compared to the real-life hospital scheduling and the gap evaluations for the instances show that the results were generally satisfactory.

Kargar, Khanna and Sattar (2013), develop a prediction based methodology to drive optimal management of scheduling processes, with historic utilization data and current waiting list information to manage case mix distribution. A novel algorithm used current and past perioperative information to accurately predict surgery duration. A National Elective Surgery Target compliance guided optimization algorithm was then used to drive allocation of patients to the theatre schedule.

Marques, Captivo and Pato (2013), contributed with a population based approach to solve an elective surgery scheduling problem applied to real case instances and with the specifications of the Portuguese hospital under study. The problem combined simultaneously advance and allocation scheduling, and two optimization criteria were considered maximizing the surgical suite occupation and maximizing the number of surgeries scheduled. Instances with 508–2306 elective surgeries were successfully solved in 22–240 s using the genetic heuristic. It was better results than the authors previous approaches to the same problem.

Antonelli, Bruno and Taurino (2014), presented a thorough analysis of the patient flow in an elective surgery ward using data gathered in a large hospital in Italy. An engineering approach was used to provide a process parameterization in order to reach managerial objectives of beds utilization. A simulation of the new process was done to test proposed parameters. Simulation results showed that small variation on the average value of inter-arrival times caused significant variations on waiting times. So a solution to find a compromise between bed utilization and waiting times was provided and simulated.

Sperandio, Gomes, Borges, Brito and Almada-Lobo (2014), an intelligent decision support system was developed, allowing the centralization and standardization of planning processes, improving the efficiency of the operating theatre and tackling the waiting lists for surgery fragile situation. The intelligence of the system was derived from data mining and optimization techniques, which enhance surgery duration predictions and ORs surgery schedules. Experimental results show significant gains, reducing overtime, under time and better resource utilization.

Zhao and Li (2014), investigates the problem of scheduling elective surgeries to multiple ORs in an ambulatory surgical centre. It was build a Mixed Integer Nonlinear Programming model and a Constraint Programming model to provide support for the daily scheduling decision, with the objective of minimize the sum of the fixed costs and overtime costs of the ORs. The two models were tested on random instances, the results showed that the Constraint Programming model was more efficient on computational time and solution quality. However, they assumed that all patients to be scheduled were known in advance and the surgery durations were deterministic. Also, the patients were assumed to arrive punctually and all the resources needed for the surgeries were available.

Wang, Tang, Pan and Yan (2014), developed a heuristic and metaheuristic algorithms to solve the daily laminar scheduling problem. It was used real data from the hospital to evaluate and compare algorithms. Based on our numerical experimentation, it was found that the DPSO- TNSS algorithm works very well. Compared with CPLEX, the DPSO-TNSS algorithm provided a similar solution quality but required far less computation time. However, uncertainty that usually happens in surgery process, which includes the emergency arrival or uncertain service time is not considered.

Saadouli, Jerbi, Dammak, Masmoudi, and Bouaziz (2014), studies the problem of scheduling elective surgery patients in the orthopaedic surgery division of an hospital in Tunisia. The problem consisted in optimize the assignment of surgeries to ORs and planning the recoveries, in order to avoid them in the ORs when no bed is available in the recovery room. The proposed solution took into account the uncertainty in surgery, and recovery durations and the capacity of resources. A knapsack model was proposed to choose operations to be scheduled and were assigned to the different ORs using a mixed integer programming model. The suggested solution showed that a substantial amount of operations could be saved.

Aringhieri, Landa, Soriano, Tànfani and Testi (2014), presented a two level metaheuristic algorithm that solves the joint master surgical schedule and advance scheduling problem taking into account many resource and operative constraints, while minimizing the total social cost of the resulting surgery schedule. Results showed that the proposed method exhibited very good performances, both in terms of solution quality and computational times.

Xiang, Yin and Lim (2014), integrated the surgery scheduling problem with real-life nurse roster constraints. This article proposed a mathematical model and an ant colony optimization (ACO) approach to efficiently solve such surgery scheduling problems. A modified ACO algorithm with a two-level ant graph model was developed to solve such combinatorial optimization problems, because of its computational complexity. The outer ant graph represented surgeries, while the inner graph was a dynamic resource graph. Three types of pheromones, i.e. sequence-related, surgery-related and resource-related pheromone, fitting for a two-level model were defined. The performance of the proposed ACO algorithm was then evaluated using the test cases from published literature data with complete nurse roster constraints and real data collected from a hospital in China. The ACO approach proposed efficiently solved the surgery scheduling problem with daily nurse roster, while providing a shortened end time and relatively balanced resource allocations.

Duma and Aringhieri (2015), considered a generic surgical clinical pathway for elective patients in which were evaluated the introduction of an online optimization approach for the Real Time Management and some additional optimization modules to deal with the surgery process scheduling problem. An accurate computational analysis proved the effectiveness of the proposed approach. It was also demonstrated the capability and the flexibility of the approach by extending the hybrid model to deal with emergency surgeries and different trained surgery teams.

Dios, Molina-Pariente, Fernandez-Viagas, Andrade-Pineda and Framinan (2015), presented a Decision Support System for surgery scheduling which is currently in use in one of the largest hospitals in Spain. The system embeds several optimization procedures to help the responsible of each Surgical Unit in several related decisions. In addition, allows users to fine-tune the schedule by including a graphically-interactive user interface. The proposed system is currently in use in the Hospital and there are several research avenues for its extension.

Castro and Marques (2015), addressed the short-term scheduling problem involved in the selection of a subset of elective surgeries from a large waiting list. A decomposition algorithm was proposed that relies on two continuous-time Generalized Disjunctive Programming models. It showed that the new algorithm outperforms a full-space discrete-time formulation and a genetic algorithm, improving the total surgical time as well as the number of performed surgeries by 5%.

Molina-Parient, Hans, Framinan and Gomez-Cia (2015), tackled the OR planning problem of the Plastic Surgery and Major Burns Specialty of the University Hospital in Spain, in order to assign an intervention date and an OR to a set of surgeries on the waiting list, minimizing access time for patients with diverse clinical priority values. It was proposed a set of 83 heuristics (81 constructive heuristics, a composite heuristic and a meta-heuristic) based on a new solution encoding. The computational experiments show that the proposed meta-heuristic was the best for the problem under consideration. Also, the proposed heuristics were tested with data from the Plastic Surgery and Major Burns Specialty. The results show significant improvements on several key performance indicators and the hospital implemented the heuristic methods.

Neyshabouri and Berg (2016), proposed a formulation for surgery scheduling while considering the downstream units. It was applied two-stage robust optimization to address the inherent uncertainty in surgery duration and length-of-stay in the downstream unit. Extensive computational experiments show that the model had the potential of being employed to manage multi-stage care operations.

However, the proposed algorithm may not be efficient for cases with large number of patients, with large uncertainty sets.

Latorre-Núñez et al. (2016), addressed the surgery scheduling problem considering simultaneously, the operating rooms, the post anaesthesia recovery, the resources required by the surgery and the possible arrival of emergency surgeries. It was proposed an integer linear programming model that allowed finding optimal solutions for small size instances, it was transformed to use constraint programming, and developed a metaheuristic based on a genetic algorithm and a constructive heuristic, that solved larger size instances.

Molina-Parient, Hans and Framinan (2016), addressed a stochastic operating room scheduling problem which consists of assigning an intervention date and operating room to surgeries on the waiting list. To solve the problem, it was proposed a Monte Carlo optimization method based on the sample average approximation method, which combined an iterative greedy local search method and Monte Carlo simulation. The results show that the objective function value converged with exponential rates when the number of samples increases, obtaining an optimality index value around 1 % and concluded that an important cost reduction could be obtained by solving the stochastic problem rather than the deterministic one.

Guido and Conforti (2016), proposed a multi-objective integer linear programming model aiming at efficiently planning and managing hospital OR suites. By effectively exploiting a novel hybrid genetic solution approach, the devised optimization model was able to determine, in an integrated way, the OR time assigned to each surgical specialty, the OR time assigned to each surgical team, the surgery admission planning and the surgery scheduling. The resulting Pareto frontiers provided a set of "optimal" solutions able to support hospital managers in efficiently orchestrating the involved resources, and planning surgeons and surgeries.

Marques and Captivo (2017), work results from a close collaboration with a large and publicly funded Portuguese hospital. It was proposed a systematic approach to help the surgical planner in the scheduling of elective surgeries, in order to optimize the use of the available surgical resources, improve equity, and access to operated and waiting patients. Three versions were modelled in (mixed) integer linear programming and a robust approach was proposed to tackle the uncertain surgeries' duration. Practical and realized problems from the hospital were solved providing very good optimization gaps within a short time limit, both for the deterministic and robust approaches.

Jebali and Diabat (2017), the present work aimed the planning problem by accounting for the availability of the ORs and the ICU which are shared between elective and emergency patients. A featured Sample Average Approximation algorithm was developed to solve the model. The results demonstrate the superiority of the OR plans obtained by the proposed approach in terms of robustness. However, it was shown that this robustness was achieved at the expense of higher costs and lower OR utilization.

Feng et al. (2017), proposed an Intelligent Perioperative System, a real-time system that assesses the risk of postoperative complications and dynamically interacts with physicians to improve the predictive results. In order to process large volume patients' data in real-time, was design the system by integrating several big data computing and storage frameworks with the high through-output streaming data processing components. It was also implement a system prototype along with the visualization results to show the feasibility of system design.

Ebadi, Tighe, Zhang and Rashidi (2017), proposed a tool for facilitating decision making in surgical team selection based on considering history of the surgical team, as well as the specific characteristics of each patient. A decision support tool for surgical team selection, a metaheuristic framework for evaluation of surgical teams and finding the optimal team for a given patient, in terms of number of complications. It was also tested using intra-operative data from 6,065 unique orthopaedic surgery cases and results suggested high effectiveness of the proposed system in a health-care setting.

CHAPTER 3

CASE-BASED REASONING

Case-based reasoning is a problem solving paradigm that is fundamentally different from other major Artificial Intelligence (AI) approaches. Instead of relying solely on general knowledge of a problem domain, or making associations along generalized relationships between problem descriptors and conclusions, CBR is able to utilize the specific knowledge of previously experienced into concrete problem situations (cases). Therefore, a new problem is solved by finding a similar past case and reusing it in the new problem situation. It also is an approach to incremental sustained learning, since a new experience is retained each time a problem has been solved, making it immediately available for future problems (Aamodt & Plaza, 1994).

During the period 1977–1993, CBR research was highly regarded as a plausible high-level model for cognitive processing. It was focused on problems such as how people learn a new skill and how humans generate hypotheses about new situations based on their past experiences. The objectives of these cognitive-based researches were to construct decision support systems to help people learn (Pal & Shiu, 2004).

The roots of CBR in AI arose out of the research in cognitive science. The earliest contributions in this area were from Roger Schank and his colleagues at Yale University, on dynamic memory and the central role that a reminding of earlier situations (episodes, cases) and situation patterns (scripts, MOPs) has in problem solving and learning. Other trails into the CBR field has come from the study of analogical reasoning and from theories of concept formation, problem solving and experiential learning, within philosophy and psychology. The first system that might be called a case-based reasoner was the CYRUS system, developed by Janet Kolodner, at Yale University (Schank's group). CYRUS was based on Schank's dynamic memory model and MOP theory of problem solving and learning. It was basically a question-answering system with knowledge of the various travels and meetings of former US Secretary of State Cyrus Vance. The CBR field has grown rapidly over the last few years, as seen by its increased share of papers at major conferences, available commercial tools and successful applications in daily use (Aamodt & Plaza, 1994).

As mentioned, CBR solves new problems by adapting solutions used in older problems. Therefore, retains a memory of previous problems, their solutions and solves new problems by reference to that knowledge. Generally, it is presented with a problem, wither by a user, a program or system, then it searches for past cases in its memory and tries to find some case that presents the same problem characteristics as the new presented one. If the reasoner fails to find such case, it will try to get a case or multiple cases that present the most proximity in terms of characteristics (Pal & Shiu, 2004).

When a past case with identical structure is retrieved and the success on the solution is assumed, it can be presented as the solution to the new problem. But the most common situation is where the case retrieved is not identical to the case in analyse, as result there is the necessity of an adaptation phase. In this adaptation, the new case and the retrieved cases differences are identified and the solution of the retrieved case is altered by taking this differences into account. Then the proposed solution to the new problem can be tested in the appropriate domain (Pal & Shiu, 2004).

Most CBR systems have an internal structure divided into two major parts, namely the case retriever and the case reasoner. The function of the case retriever consists into find in the Case Base the most suitable cases, while the case reasoner tries to find a valid solution to the problem description given from the retrieved cases. This reasoning process generally involves the determination of the differences between the retrieved cases and the current one and the modification of the solution in order to efficiently reflect these differences. Also, this process may or may not involve retrieving some additional cases or portions of cases from the Case Base (Pal & Shiu, 2004).

CBR can be seen as a reflection of a particular type of reasoning performed by humans, in the equivalent way they solve problems, since once faced with a new situation or problem, the previous experiences of a similar problem experienced on a personal level, or from another person who faced the same situation can be used by adding it to the memory through either an oral or a written account of that experience. This gives the advantage on the use of CBR once it can be based on superficial knowledge not requiring significant effort in knowledge engineering when compared with other existing approaches. In general, CBR has been referred as a tool for problem solving, but it can also be used in other ways like arguing a point of view (Pal & Shiu, 2004).

Unlike other logical systems, CBR is capable of using knowledge that is incomplete or there is little evidence. Traditional AI systems tend to use certainty factors and other methods of inexact reasoning to solve this problems, requiring a considerable amount of effort from the computer. CBR uses another method in order to deal with incomplete knowledge, were a case-based reasoner makes assumptions in order to fill incomplete or missing knowledge out of what its own experience tells and starts from there. These generated solutions won't always be optimal, or even successful, but with a careful evaluating on the proposed answers from the reasoner, the case-based methodology gives it a way in order to generate answers easily (Kolodner, 1993).

Is worth mention that CBR also can provide advantage even if the old solution is far from what is needed. Either the features of the remembered case that must be ruled out in the new situation, can be added to its description and a new case recalled, or the recalled case can be used as a starting point for coming up with a new solution. When there is considerable interaction between the parts of a solution, then even if large amounts of adaptation are required to derive an acceptable solution, that may still be easier than generating a solution from scratch. The case provides something concrete to base reasoning on. In short, CBR reduces the cognitive load involved in interacting with a complex real-world environment (Kolodner, 1993).

In 1994, Aamodt and Plaza defined a well-received four step view on the process of CBR, described by the four steps retrieve, reuse, revise and retain, as showed in the Figure 1.

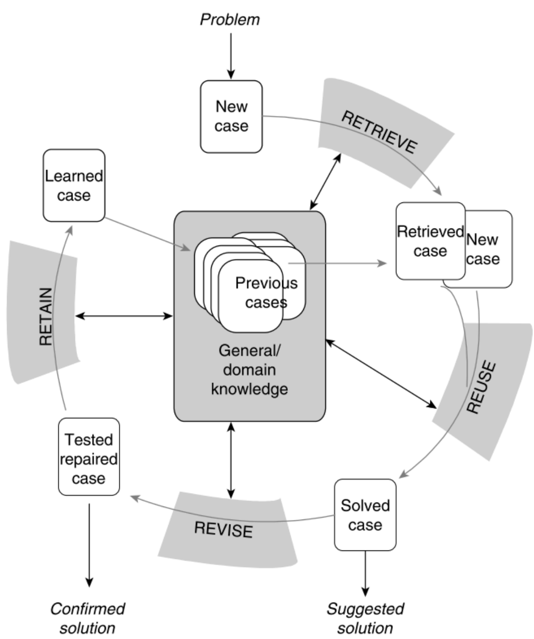


Figure 1— CBR Cycle (From Pal & Shiu, 2004).

1. ***Retrieving*** similar past experienced cases whose problem is judged to be similar;

2. ***Reusing*** the cases by copying or integrating the solutions used on the retrieved cases;

3. ***Revising*** or adapting the solution(s) retrieved in order to try to solve the new problem;

4. ***Retaining*** the new solution once it has been confirmed or validated

A new problem is solved by retrieving one, or more previously experienced cases, reusing the case in one way or another, revising the solution based on reusing a previous case and retaining the new experience by incorporating it into the existing knowledge-base (Case Base) (Aamodt & Plaza, 1994).

An initial description of a problem defines a new case and is used to ***retrieve*** a case from the collection of previous cases. The retrieved case is then combined with the new case through ***reuse*** into a solved case, i.e. a proposed solution to the initial problem. Through the ***revise*** process this solution is tested for success, e.g. by being applied to the real world environment or evaluated and repaired if failed. During ***retain***, useful experience is retained for future reuse and the Case Base is updated by a new learned case, or by modification of some existing cases (Aamodt & Plaza, 1994).

As indicated in the *figure 1*, general knowledge usually plays a part in this cycle, by supporting the CBR processes. This support may range from very weak (or none) to very strong, depending on the type of CBR method. By general knowledge, we here, mean general domain-dependent knowledge, as opposed to specific knowledge embodied by cases. For example, in diagnosing a patient by retrieving and reusing the case of a previous patient, a model of anatomy together with causal relationships between pathological states may constitute the general knowledge used by a CBR system (Aamodt & Plaza, 1994).

3.1 Case-Based Reasoning Advantages

Some of the main advantages of CBR to have in count are presented below:

1. ***Reducing the knowledge acquisition task.*** It does not need to extract

a model or a set of rules, the knowledge acquisition tasks of CBR consist primarily on the collection of relevant existing experiences/cases and their representation and storage;

2. ***Avoiding repeating mistakes made in the past.*** Information about the reason for the failures in the past can be used in order to predict potential failures in the future, since the systems record failures, successes and perhaps the reason for those failures;

3. ***Providing flexibility in knowledge modeling.*** In contrast with other model-based systems, case-based systems can use past experience as the domain knowledge in order to provide a reasonable solution, through appropriative adaptation, to situations where there is a problem with missing or incomplete data;

4. ***Reasoning in domains that have not been fully understood, defined, or modelled.*** In the presence of insufficient knowledge, in order to build a causal model of a domain or to derive a set of heuristics for it, a case-based reasoner can still be developed using only a small set of cases from the domain. For the case-based reasoner to function the underlying theory of domain knowledge does not have to be quantified or understood entirely;

5. ***Making predictions of the probable success of a proffered solution.*** With the information stored regarding the level of success of past solutions, the case-based can be capable of predicting the success of a suggested solution for a current problem. This happens thanks to the ability of referring to the stored solutions, the level of success of these and the differences between the previous and current contexts of applying these solutions;

6. ***Learning over time.*** With the increase of use of the CBR systems, more problem situations are inserted and more solutions are created. If this solutions cases are then tested in the real world, and the level of success is determined, these cases can be added to the Case Base and used to help in future problems. As the number of cases grow, the capacity of reasoning of the CBR system also increases, being able to solve a wider verity of situation with a higher degree of refinement and success;

7. ***Reasoning in a domain with a small body of knowledge.*** When the system is faced with only few cases, a case-based reasoner can start with these few known cases and build its knowledge incrementally as cases are added to the system, this addition will expand the system in directions determined by the solutions obtained by the cases encountered;

8. ***Reasoning with incomplete or imprecise data and concepts.*** Retrieved cases may not be identical to the current case, but even in the presence of any incompleteness and imprecision this can be dealt by a case-based reasoner. Although these factors affect the performance, due to the increased disparity between the current and the retrieved cases, reasoning is still possible;

9. ***Avoiding repeating all the steps that need to be taken to arrive at a solution.*** When it is required to create a solution from scratch, the alternative approach is to modify an earlier solution, reducing this processing requirement significantly. Also, reusing a previous solution allows the actual steps taken to reach that solution to be reused for solving other problems;

10. ***Providing a means of explanation.*** A CBR system can justify its proposed solution to a user, by supplying a previous case and its solution.

11. ***Extending to many different purposes.*** The implementations of the CBR system is almost unlimited. It can be used for many purposes, such as creating a plan, making a diagnosis and arguing a point of view. Therefore, the data dealt with by a CBR system are able to take many forms, and the retrieval and adaptation methods will also vary;

12. ***Extending to a broad range of domains.*** CBR can be applied to extremely diverse application domains, due to the limitless number of ways of representing, indexing, retrieving and adapting cases;

13. ***Reflecting human reasoning.*** Since the humans, use regularly a form of CBR, it is not difficult to convince implementers, users and managers of the validity of the paradigm (Pal & Shiu, 2004).

It is described in the next section, briefly, the four major tasks: case representation and indexing, case retrieval, case adaptation, and case learning and Case Base maintenance.

3.2 Case Representation and Indexing

A case can be said to be a record of a previous experience or problem and the information that is recorded will, by necessity, depend on the domain as well as the purpose for which this case will be used. Also the case presents a description of the solution that was used when presented with a similar situation, may include the facts that define a solution, or it may include information about additional steps or processes involved. It is also important to include a measure of success in the case description for situations where the solution (or cases) have achieved different levels of success or failure. Also the specific knowledge of a case-based system means that related knowledge is stored in close proximity. Thus, rather than drawing knowledge from a wider net, the knowledge needed to solve a specific problem can be found grouped together in a few or even one of the cases. The Case Base in the CBR system is the memory of all cases stored previously (Pal & Shiu, 2004).

3.2.1 Case Representation

Many different types of knowledge can be stored in many different representational formats represented by cases in a Case Base. The intended purpose of a CBR system will greatly influence what is stored. In many practical CBR applications, cases are usually represented as two unstructured sets of attribute–value pairs that represent the problem and solution features (Pal & Shiu, 2004).

In some situations, cases may need to be decomposed to their subcases. For example, a person’s medical history could include as subcases all patient’s visits to a doctor. Features have to be represented in some format, regardless of what a case actually represents as a whole. Depending on the types of features that have to be represented, an appropriate implementation platform can be chosen. This implementation platform ranges from simple boolean, numeric, and textual data to binary files, time-dependent data and relationships between data. Independently of how is stored, or the data format that is used, a case must store information that is both relevant to the purpose of the system and also will ensure the most appropriate case is retrieved to solve each new problem situation. Thus, the cases have to include those features that will ensure that a case will be retrieved in the most appropriate context. In many CBR systems, not all of the existing cases need to be stored, since there are specific criteria that decide which cases will be stored and which will be discarded. For example, when faced with two or more cases that are very similar, only one case may need to be stored. It also may be possible to create an artificial case that is a generalization of two or more cases that describe actual incidents or problems. By creating generalized cases, the most important aspects of a case need to be stored only once. When choosing a representation format for a case, there are many choices and many factors to consider. Some examples of representation formats that may be used include database formats, frames, objects, and semantic networks (Pal & Shiu, 2004).

In conclusion, cases are assumed to have two components: problem specification and solution. Normally, the problem specification consists of a set of attributes and values. The attributes of a case should define that case uniquely and should be sufficient to predict a solution for that case. The representation may be a simple flat data structure or a complex object hierarchy (Pal & Shiu, 2004).

3.2.2 Case Indexing

Case indexing refers to assigning indexes to cases for future retrieval and comparison. The choice of indexes is important to enable retrieval of the right case at the right time. This is because the indexes of a case will determine in which context it will be retrieved in the future. Indexes must be predictive in a useful manner. This means that indexes should reflect the important features of a case, and the attributes that influence the outcome and describe the circumstances in which a case is expected to be retrieved in the future. Indexes should be abstract enough to allow retrieval in all the circumstances in which a case will be useful, but not too abstract. When a case's indexes are too abstract, the case may be retrieved in too many situations or too much processing is required to match cases. Although assigning indexes is still largely a manual process and relies on human experts, various attempts at using automated methods have been proposed in the literature (Pal & Shiu, 2004).

3.3 Case Retrieval

Case retrieval consist in the process of finding, within a Case Base, those cases that are the similar to the current case. In order to carry out an effective case retrieval, it is needed selection criteria that determine how a case is judged and a mechanism to control how the Case Base is searched. The selection criteria, are necessary to determine which is the best case to retrieve, by determining how similar the current case is to the cases stored. The case selection criteria depend partly on what the case retriever is searching for in the Case Base (Pal & Shiu, 2004). When the case retriever is searching for the most suitable solution in order to solve a new problem, CBR relates the new problem to the problems in the cases of the Case Base in such a way that the notion of "most suitable" (i.e. similar) is reflected. The main difficulty present is that a similar problem may not be recorded in the Case Base since one cannot store all possible situations. Therefore, CBR has developed intelligent techniques to take advantage of the experiences even if they do not exactly match the new problem. This is done by comparing the new problem with the ones of the stored cases, with the purpose of finding a case that shows to be useful in a way that helps in solving the new problem. The goal is that the cases are analogous in such a way that their solutions can be reciprocally reused. Assessing similarity between two cases takes into account the similarity between attributes and the relative relevance of each attribute (Ritcher & Weber, 2013). However, when only a portion of a case is being sought because no full case exists and a solution is being synthesized by selecting portions of a number of cases. The actual processes involved in retrieving a case from a Case Base is highly dependent on the memory model and indexing procedures used. Retrieval methods employed by researchers and implementers are extremely diverse, ranging from a simple nearest-neighbour search to the use of intelligent agents (Pal & Shiu, 2004).

Retrieval is a major research area in CBR. The most commonly investigated retrieval techniques, by far, are the k-nearest neighbours (k-NN), decision trees, and their derivatives. These techniques involve developing a similarity metric that allows closeness among cases to be measured (Pal & Shiu, 2004).

3.4 Case Adaptation

Case adaptation is the process of transforming a solution retrieved into a solution appropriate for the current problem. It has been argued that adaptation may be the most important step of CBR since it adds intelligence to what would otherwise be simple pattern matchers (Pal & Shiu, 2004). The use of cases is a reuse of previous experiences in a new situation, if the case is exactly like a previous one than the reuse is simply done by copying the old solution. However, the use of a solution exactly as it is recorded is very rare. If the new problem situation is not too different in essential aspects from the nearest neighbour selected from the Case Base, then the recommendation is to adapt the recorded solution before reusing it to best suit the new problem. This can be done either manually or automatically (Richter & Weber, 2013).

Adaptation can be performed on different levels of granularity. One extreme case is reusing the solution strategy. Another extreme case is using the solution itself. Both are called solution adaptation. Suppose we have to design exercise plans for people who need to increase their endurance, the simplest way would be to create a weekly plan for running. Now suppose there is a person who is not allowed to run because of knee problems, the previous plan can still be used but running has to be replaced by swimming or bicycling (Richter & Weber, 2013).

The approximate nature of case-based reasoning has the consequence that there is no guarantee that the chosen case provides a good solution. For instance, the Case Base may not even contain a single good solution for the new problem. Sometimes, this can be easily seen as symmetric problems. Therefore, after adaptation, the adapted solution has to be tested in reality and possibly modified further. If the solution obtained in this way is satisfactory, then one may decide to add the case to the Case Base in order to improve it. This last step can be interpreted as a learning step (Richter & Weber, 2013).

Adaptation allows Case Bases to be smaller than if no adaptation could be done. Furthermore, adaptation can also be extended by reusing a strategy when the solution is given, because strategies can also be adapted (Richter & Weber, 2013).

3.5 Learning on Case-Based Reasoning Systems

In the presence of a valid solution generated and outputted by the system, it is expected that the solution will be properly teste in reality. In order to do so, both the way it may be tested and how the outcome of the test will be classified if a success or a failure, needs to be consider. Thus, some criteria need to be defined for the performance rating of the present solution. This information can be added to a system for two purposes, the more information is stored, more likely will be to found a match in the Case Base and with the increase of the information more successful will be the solution created by the system.

The learning phase can occur in many ways, a common method is the addition of a new problem, its solution and the outcome to the Case Base. As more cases are added to the Case Base, the range of situations covered by the stored cases will increase and reduce the average distance between an input vector and the closest stored vector. Other method of learning in a CBR system is using the solution's assessment to modify the indexes of the stored cases or to modify the criteria used for the case retrieval. When a case has indexes irrelevant to the specific contexts in which it should be retrieved, adjusting the indexes may increase the correlation between the occasions when a case is actually retrieved and the occasions when it should have been retrieved. Similarly, assessment of a solution's performance may lead to an improved understanding of the underlying causal model of the domain that can be used to improve adaptation processing. If better ways can be found to modify cases with respect to the distance between the current and retrieved cases, the output solution will probably be improved (Pal & Shiu, 2004).

3.6 Maintenance of Case-Based Reasoning Systems

With the application of the CBR system for solving a problem, there is always a trade-off between the number of cases to be stored in the case library and retrieval efficiency. The larger the case library, the greater the problem space covered, but it also downgrades system performance. Removing redundant or less useful cases to attain an acceptable error level is one of the most important tasks in maintaining CBR systems. Case Base maintenance consists in the implementation of policies for revising the organization or contents of a Case Base to facilitate future reasoning for a particular set of performance objectives. Some measures for case competence are developed, that are the range of problems that a CBR system can solve. Various properties may be useful, such as the size, distribution, and density of cases in the Case Base, the coverage of individual cases, the similarity and adaptation knowledge of a given system. Another reason for CBR maintenance is the possible existence of conflicting cases in the case library, due to changes in domain knowledge or specific environments for a given task. For example, more powerful cases may exist that can contain inconsistent information, either with other parts of the same case or with original cases that are more primitive. Furthermore, if two cases are considered equivalent (with identical feature values), or if one case subsumes another by having more feature criteria, a maintenance process may be required to remove the redundant cases (Pal & Shiu, 2004).

3.7 Hybrid Case-Based Reasoning with ANNs

Artificial neural networks (ANNs) are commonly used for learning, and the generalization of knowledge and patterns. They are not appropriate for expert reasoning and their abilities for explanation are extremely weak. Therefore, many applications of ANNs in CBR systems tend to employ a loosely integrated approach where the separate ANN components have specific objectives, such as classification and pattern matching. Neural networks offer benefits when used for retrieving cases, because case retrieval is essentially the matching of patterns. Neural networks are very good at matching patterns. They cope very well with incomplete data and imprecise inputs, which is of benefit in many domains, as some portion of the features is sometimes important for a new case, whereas other features are of little relevance. Domains that use case-based reasoning are usually complex, this means that the classification of cases at each level is normally nonlinear, and hence for each classification a single-layered network is not sufficient and a multi-layered network is required (Pal & Shiu, 2004).

Hybrid CBR and ANNs are a very common architecture for applications to solve complicated problems. Knowledge may first be extracted from the ANNs and represented by symbolic structures, for later use by other CBR components. Alternatively, ANNs could be used for retrieval of cases where each output neuron represents one case (Pal & Shiu, 2004).

3.7.1 Artificial Neural Networks

Artificial neural networks (ANNs) are inspired by the biological nervous systems, which consists of a large number of highly connected elements called neurons. The brain stores and processes the information by adjusting the linking patterns of the neurons. ANNs are signal processing systems that try to emulate the behaviour of and ways of processing information in the biological nervous systems, by providing a mathematical model of the combination of neurons connected in a network. In an artificial neural network, artificial neurons are linked with each other through connections, assigned with a weight that controls the flow of information among them. By adding the information into a neuron through the connections, it is summed up first and then, undergoes a transformation by an activation function $f(x,w)$ where x is the input and w the weight of the connection, that send outputs to other neurons or back to itself as input. In artificial neural networks, input information is processed in parallel in the neurons. This improves the processing speed and the reliability of the neural network (Pal & Shiu, 2004).

Some advantages of ANN are summarized below:

- *Adaptive*: Through some training algorithms or learning rules its connection weights can be modified and the ANN can optimize its connections to adapt to the changes in the environments;

- *Parallel*: As the ANN distribute the input information to different neurons for processing, neurons when activated by the inputs can work in parallel and synergetically if they are activated by the inputs. This way, the computing power of the neural network is fully utilized and the processing time is reduced;

- *Rugged*: If one of the neurons fails, the weights of the connections can be adjusted for preserving the performance of the ANN. While the connections to the failed neuron will be weakened, the working neurons will establish a stronger connection with each other. By doing so, the reliability of the ANN improves (Pal & Shiu, 2004).

The architectures of ANNs can be classified into two categories based on the connections and topology of neurons:

- *Feedforward networks*: The inputs travel in only one direction, from input to output layer, and no feedback is allowed as showed in Figure 2 with a three-layered feedforward ANN.

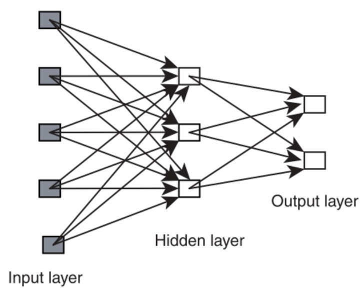


Figure 2 – Simple feedforward ANN (From Pal & Shiu, 2004).

- *Recurrent (or feedback) networks*: The inputs can travel in both directions and loop is allowed, as showed in Figure 3.

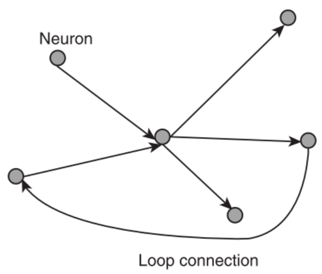


Figure 3 – Simple recurrent ANN (From Pal & Shiu, 2004).

Before using an ANN, it needs to be trained. In the training phase, the weights are adjusted using some gradient-based algorithms or predefined learning rules. After training the ANN successfully, it can be used for problem solving (Pal & Shiu, 2004).

There are principally three ways of training ANNs: supervised, unsupervised, and reinforcement. In supervised training, weight modification is carried out by minimizing the difference between the ANN outputs and the expected outputs. In unsupervised training, weight modification is driven by the inputs. The weights are trained with some predefined learning rules that determine how to modify the weights. Reinforcement training is similar to supervised training, except that the training samples are obtained through the use of outputs from the neural networks. If the feedback of the output is successful, the input–output pair is stored as a training sample, and no modification is performed on the weight vector. Otherwise, the output will be repaired using some domain knowledge (Pal & Shiu, 2004).

CHAPTER 4

KNOWLEDGE REPRESENTATION AND REASONING

As mentioned before, surgery is the most influent specialty present in hospitals, with the most generate revenue and admissions. Thus, improvement of the quality and efficiency of the surgery process will not only help in the performance of healthcare services provided to patient, but also give significant savings and benefits to the hospital as well.

Therefore, in this work, it will be presented a clinical decision support system in order to propose the surgery process that a patient will be submitted. Since, the patient is the reason for the surgery to be performed, it is to be expected that the system present should be focused on the patient and is course through all the perioperative period of the surgery process, including the preoperative, intraoperative and postoperative stages. This way, the patient needs will be assured and all the remain factors that influence the process will be improved as well, namely the available hospital resources or medical team, among many others. It will not only ensure a more secure surgery but also, provide a bigger confidence in the process. Moreover, the patients and the medical team will have a more precise vision of the situation when presented with a complete customized surgical route.

As previously mentioned, surgery is a very inconsistent field, unpredictability and variability are constantly present through all the surgery process. This is why, the system needs to be capable of leading with incomplete, self-contradictory and/or unknown data that will most certainly be present in majority of the cases presented.

In this chapter, will be described a Knowledge Representation and Reasoning approached capable of dealing with the data present on the used dataset for the system, that will be described further in the next chapter. It will also be present an approach to deal with time and negation present in this type of systems, since the surgery process will need to take into account the constant changes of the elements that influence the case of the patient.

4.1 Background

Many approaches to Knowledge Representation and Reasoning have been proposed using the *Logic Programming* epitome, namely in the area of *Model Theory* (Kakas, Kowalski and Toni

,1998; Pereira and Anh ,2009), and *Proof Theory* (Neves ,1984; Neves, machado, Analide, Abelha and Brito ,2007). In the present work the *Proof Theoretical* approach in terms of an extension to the *LP* language is followed. An *Extended Logic Program* is a finite set of clauses, given in the form:

$$
\begin{array}{l}
\{ \\
\quad \neg\, p \leftarrow not\ p, not\ exception_p \\
\quad p \leftarrow p_1, \cdots, p_n, not\ q_1, \cdots, not\ q_m \\
\quad ?\,(p_1, \cdots, p_n, not\ q_1, \cdots, not\ q_m)\ \ (n, m \geq 0) \\
\quad exception_{p_1} \\
\quad \cdots \\
\quad exception_{p_j}\ \ (0 \leq j \leq k), being\ k\ an\ integer\ number \\
\} :: scoring_{value}
\end{array}
$$

where the first clause stand for predicate's closure, "*,*" denotes "*logical and*", while "*?*" is a domain atom denoting "*falsity*", "::" stands for "where", the p_i, q_j, and p are "*classical ground literals*", i.e., either positive atoms or atoms preceded by the classical negation sign "¬" (Neves ,1984). Indeed, "¬" stands for a strong declaration that speaks for itself, and *not* denotes *negation-by-failure*, or in other words, a flop in proving a given statement, once it was not declared explicitly. Under symbols' theory, every program is associated with a set of "*abducibles*" (Kakas, Kowalski and Toni ,1998; Pereira and Anh ,2009), given here in the form of exceptions to the extensions of the predicates that make the program, i.e., clauses of the form:

$$exception_{p_1},\ \cdots\ , exception_{p_j}\ \ (0 \leq j \leq k),\quad being\ k\ an\ integer\ number$$

that stand for data, information or knowledge that cannot be ruled out. On the other hand, clauses of the type:

$$?\,(p_1, \cdots, p_n, not\ q_1, \cdots, not\ q_m)\ \ (n, m \geq 0)$$

also named *invariants*, allows one to set the context under which the universe of discourse has to be understood. The term $scoring_{value}$ stands for the relative weight of the extension of a specific *predicate* with respect to the extensions of peers ones that make the inclusive or global program.

4.1.1 Knowledge Representation and Reasoning – Quantitative Knowledge

In order to set one's approach to knowledge representation, two metrics will be set, namely the Quality-of-Information (*QoI)* of a logic program that will be understood as a mathematical function that will return a truth-value ranging between 0 and 1 (Lucas ,2003; Machado, Abelha, Novais and Neves ,2008), once it is fed with the extension of a given predicate. Indeed, $QoI_i = 1$ when the information is *known* (*positive*) or *false* (*negative*) and $QoI_i = 0$ if the information is *unknown*. For situations where the extensions of the predicates that make the program also include *abducible* sets, its terms (or clauses) present a $QoI_i \in]0, 1[$, in the form:

$$QoI_i = {}^{1}/_{Card} \qquad (5.1.1)$$

if the *abducible* set for *predicates i* and *j* satisfy the *invariant*:

$$?\left(\left(exception_{p_i};\ exception_{p_j}\right), \neg\left(exception_{p_i};\ exception_{p_j}\right)\right)$$

where "*;*" denotes " *logical or*" and "*Card"* stands for set cardinality, being $i \neq j$ and $i, j \geq 1$. A pictorial view of this process is given in Figure 4 (a), as a pie chart.

On the other hand, the clauses cardinality (*K*) will be given by $C_1^{Card} + \cdots + C_{Card}^{Card}$, if there is no constraint on the possible combinations among the abducible clauses, being the QoI acknowledged as:

$$QoI_{i_{1 \leq i \leq Card}} = {}^{1}/_{C_1^{Card}}, \cdots, {}^{1}/_{C_{Card}^{Card}} \qquad (5.1.2)$$

where C_{Card}^{Card} is a card-combination subset, with ***Card*** elements. A pictorial view of this process is given in Figure 4 (b), as a pie chart.

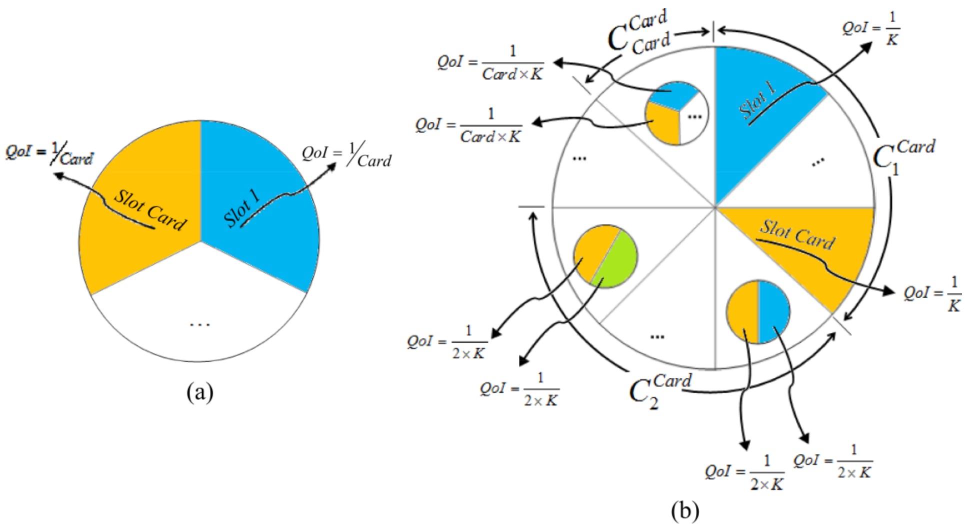


Figure 4 – QoI's values for the abducible set for predicate given in terms of an hatched area (a), i.e., considering only the abducibles clauses, or with a circle (b), i.e., considering the possible combinations among the abducible clauses.

However, a term's QoI also depends on their attribute's QoI_s. In order to evaluate this metric, look to Figure 5, where the segment with bounds 0 and 1 stands for every attribute domain, i.e., all the attributes range in the interval [0, 1]. [*A*, *B*] denotes the range where the unknown attributes values for a given predicate may occur (Figure 5):

Figure 5 – Setting the QoIs of each attribute's clause.

$$QoI_{attribute_i} = 1 - ||A - B|| \qquad (5.1.3)$$

where $||A–B||$ stands for the modulus of the arithmetic difference between *A* and *B*, i.e., taking the absolute value. It must be also stated that unsharp (e.g., fuzzy or probabilistic) or linguistic attribute values (e.g., good, bad, ...) may be transferred into an arithmetic difference as it is shown below (Figure 6 and subsection 5.1.2). Indeed, this generalized conception of observable enables a consistent notion of unsharp reality and with it an adequate concept of joint properties.

Under this setting, another metric has to be considered, which will be denoted as DoC

(*Degree-of-Confidence*), that stands for one's confidence that the argument values or attributes of the terms that make the extension of a given predicate, having into consideration their domains (which were set to the interval $[0, 1]$, are in a given interval (Fernandes, Vicente, Abelha, Machado and Neves ,2012). Therefore, the DoC is figured using $DoC = \sqrt{1 - \Delta l^2}$, where Δl stands for $||A–B||$ (Figure 7).

Thus, the universe of discourse is engendered according to the information presented in the extensions of such predicates, according to productions of the type:

$$predicate_i - \bigcup_{1 \leq j \leq m} clause_j \left(\left((A_{x_1}, B_{x_1})(QoI_{x_1}, DoC_{x_1})\right), \cdots, \right. \quad (5.1.4a)$$

$$\left. \left((A_{x_l}, B_{x_l})(QoI_{x_l}, DoC_{x_l})\right)\right) :: QoI_j :: DoC_j \quad (5.1.4b)$$

where *U*, *m* and *l* stand, respectively, for *set union*, the *cardinality* of the extension of $predicate_i$ and the number of attributes of each clause (Fernandes, Vicente, Abelha, Machado and Neves ,2012). On the other hand, either the subscripts of the QoI_s and the DoC_s, or those of the pairs (A_s, B_s), i.e., $x_1, \ldots, x_l$, stand for the attributes' values ranges.

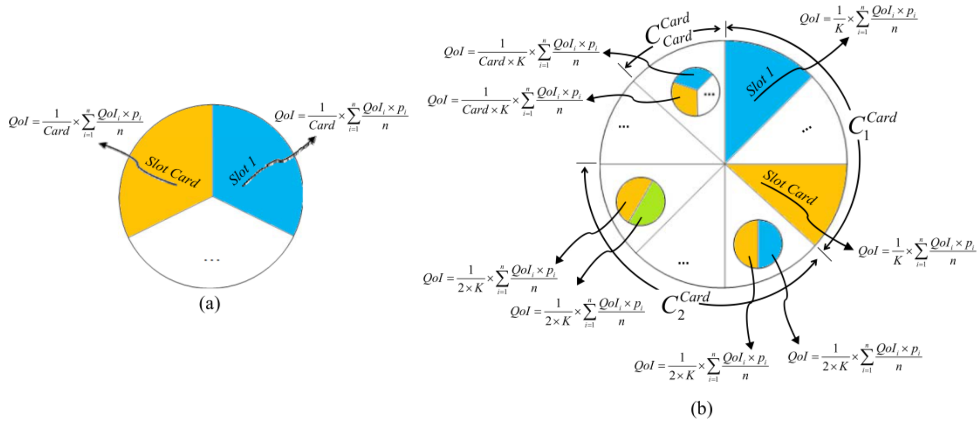


Figure 6— QoI's values for the abducible set for predicate$_i$ given in terms of an hatched area (a) considering only the abducible clauses, or with a circle (b), considering the possible combinations among the abducible clauses. $\sum_{i=1}^{n} (QoI_i \times p_i)/n$ denotes the QoI's average of the attributes of each clause that sets the extension of the predicate under analysis. n and p_i stand for, respectively, for the attribute's cardinality and the relative weight of attribute p_i with respect to its peers ($\sum_{i=1}^{n} p_i = 1$).

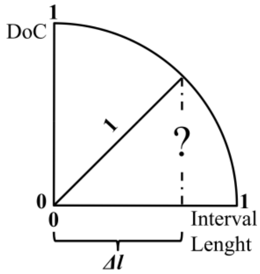


Figure 7 — Evaluation of the attributes' Degree of Confidence.

4.1.2 Knowledge Representation and Reasoning — Qualitative Knowledge

In present study both qualitative and quantitative data/knowledge are present. Aiming at the quantification of the qualitative part and in order to make easy the understanding of the process, it will be presented in a graphical form. Taking as an example, consider a set of *n* issues regarding a particular subject, where the values of the k criteria, understood as linguistic ones, are *none*, *low*, ..., *high* and *very high*. Now, enumerating a unitary area circle split into *n* slices (Figure 8), the marks in the axis resemble each of the possible criteria' values. If the answer to issue 1 is *high* the correspondent area is $\pi\times\left(\sqrt{(k-1)/k\times\pi}\right)^2/n$, i.e., $(k-1)/(k\times n)$ (Figure 8 (a)). Assuming that in the issue 2 are chosen the alternatives *high* and *very high*, the correspondent area ranges between $\left[\pi\times\left(\sqrt{(k-1)/k\times\pi}\right)^2/n,\ \pi\times\left(\sqrt{k/k\times\pi}\right)^2/n\right]$,i.e.,$\left[(k-1)/(k\times n),\ k/(k\times n)\right]$ (Figure 5(b)). Finally, in issue *n* if no alternative is ticked, all the hypotheses should be considered and the area varies in the interval $\left[0,\ \pi\times\left(\sqrt{k/k\times\pi}\right)^2/n\right]$, i.e., $\left[0,\ k/(k\times n)\right]$ (Figure 8 (c)). Thus, the total area is the sum of the partial ones (Figure 8 (d)), i.e., $\left[(2k-2)/(k\times n),\ (3k-1)/(k\times n)\right]$.

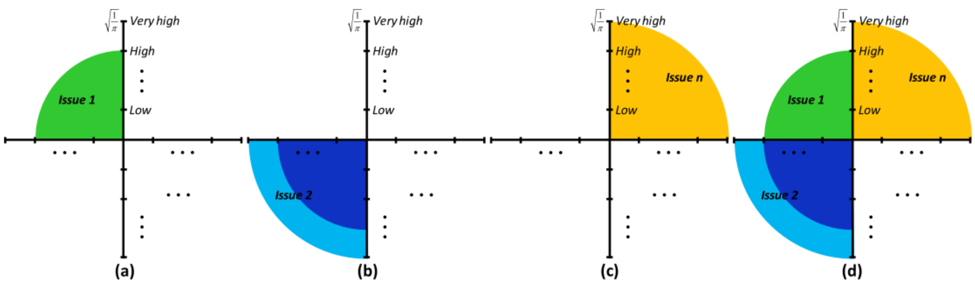


Figure 8 — A view of a qualitative data/knowledge processing.

Chapter 5

Handle of time on the Surgery process

As already mentioned, in surgery there is frequent inconsistency that comes with the unpredictability and variability present throughout the process. From the perioperative period, were the surgery is planned, to the postoperative stage where the patient is accompanied, until his discharge from the hospital, there is a strong time dependent unpredictability. Therefore, changes in the attributes related both to patient and hospital services, present in the knowledge base are an inevitable event.

With the use of time, a complete surgery process history record of the alteration of some attributes will be created, increasing the retrieval and reliability of the system model, with a more real assemble proximity to the process, improving the trustworthiness in the knowledge base. Moreover, one of the crucial parts of the process will be the motorization of the patient, this means that until his discharge from the hospital the system will need a time dependent analysis, in order to get a complete and reliable patient related performance. Another situation that also needs to be taken into account is the strong possibility of absence of elements from the knowledge base, for example, since some hospitals struggle to provide some recourses, some elements can be removed from the intervention, this means that the deleted attribute must be taken into account, since is absence could have a major impact in all case and lead to a delay, cancelation or even to a failed surgery.

Therefore, a temporal knowledge representation and reasoning approach proposed in Neves (1984), in order to deal with such circumstances, is presented in this section.

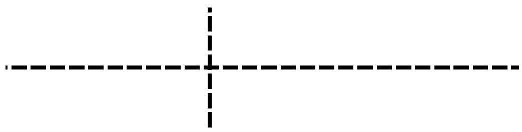
Most approaches to modeling information in data base ignore the problem of time and focus on the static properties of a world model. Outdated data is simply deleted from the data base. In the approach presented here a world model captures change by manipulating a sequence of snapshots. The interrelations of events in time are explicitly represented in the data base by marking the data base clauses with a form of time stamp (Williams and Neves, 1983).

Another of the problems which arises in data base theory is the way in which negative information is distinguished from absence of information. This problem is generally solved by adopting the “negation as failure” approach suggested by Clark (Clark, 1978). An alternative approach suggested here caters for explicit negation. It applies to logic data bases and allows for native information to be represented explicitly in the data base either using ground clauses or general rules.

5.1 Basic System

A mechanism for defining and adding semantic knowledge to data base system has been implemented in prolog and is described in Neves, Anderson and Williams, 1983. It makes use of an extended version of the query language Query-By-Example (QBE) (Zloof, 1977), a non-procedural data base language in which queries are expressed by filling in skeleton tables with examples of the result required. This system consists on the use of a skeleton of a table as show in table 1, where the user introduces a request by filling is quadrants with information about relations in the data base in the form of example elements, constants and operators.

Table 1 – Table skeleton.



Taking into account the present work, as an example, it's considered a surgery domain where a data base with relation "surgeries" and relation "patient", given by the set of ground clauses with the format:

surgery (patiente_number, surgeon_name, type_of_surgery , operating_room_number)

patient (patient_number, patient_name, condition_degree, pathology)

Supposing that the user would want to find the *surgeon name* and the *type of surgery* in surgeries being performed in the operating room 1 and the patients with the aneurysm as pathology. He may enter as showed on Table 2 (the user's contribution is underlined).

Table 2 — Tables skeleton of surgery and patient.

surgery	patn	surgn	types	oproom
	X	p.N	p.A	1

patient	patn	pname	cdegree	pathology
	X			aneurysm

This is translated by the system to yield the logic rule (i.e. theorem):

query ([N , A]) if [surgery (X, N, A, 1), patient (X, Y, C, aneurysm)].

Where "*[* " and "*]* " denotes a set. This is then applied to the data base. The results of queries are collected in lists enclosed in square brackets (i.g. [N, A]) rather than in new relations. More detail of the way in which QBE maps into Prolog are given in Neves (1983).

5.2 Time and Negation

One solution to the problem of negation that applies in the case of ground clause data bases was described by Reiter (1978) and Clarck (1978) following work by Nicolas and Syre (1974). A negative assertion is supposed to be implicitly present if its positive counterpart is not explicitly present (i.e. failure to find an instance of a tuple in a relation means that the negation of the tuple is true).

If a ground clause "p" is not a logical consequence of the data in the data base infer "not p".

Formally this is expressed as:

:– not :– p infer :– not p

Where the notation "*:– p*" is to be read as "*p* is deducible from the axioms in the data base". This is similar to the approach taken by *Cood (1972)* to allow for the use of negation in relational calculus, and it is referred to as the "negation as failure inference rule".

In a logic data base, it is desirable to think in terms of accumulating additional information without altering any existing information in the data base. If this were true, then the data base system would contain a complete record of every transaction which was occurred to date and the system would be responsible for deducing the information which is applicable at any particular point in time.

In order to model time changes each data base relation is extended to include an additional attribute value, denoting the state number. Tuples which are inserted into the data base have the same format as in the previous section, with the first field of each tuple set aside to contain the *state number* or *time stamp*. Thus, the equation 5.1.4 presented on the chapter 5 section 5.1.1, relative to the universe of discourse is engendered according to the information in $t_{k \geq 0}$,presented in the extensions of such predicates, were k stands for time and being k an integer number, according to productions of the type:

$$predicate_i - \bigcup_{1 \leq j \leq m} clause_j \left(t_{k \geq 0}, \left((A_{x_1}, B_{x_1}) (QoI_{x_1}, DoC_{x_1}) \right), \cdots, \right. \quad (6.1.1a)$$

$$\left. \left((A_{x_l}, B_{x_l}) (QoI_{x_l}, DoC_{x_l}) \right) \right) :: QoI_j :: DoC_j \quad (6.1.1b)$$

As an example, the relation "surgery" given in the previous section will be extended to the form:

*surgery (**state_number**, patiente_number, surgeon_name, type_of_surgery, operating_room_number)*

*patient (**state_number**, patient_number, patient_name, condition_degree, pathology)*

The additional field (*state*) contains the state number, a value which represents the point in the time the clause was created (a time stamp).

An example of data base of a set of clauses could be presented:

*patient (**0**, 29, blake, elective , glaucoma).*

*patient (**1**, 10, smith, urgent, aneurysm).*

*surgery (**0**, 29, charles, trabeculectomy, 1).*

*surgery (**0**, 7, jones, kidney_transplant, 1).*

*surgery (**1**, 10, andrea, brain_aneurysm_repair, 4).*

*surgery (**1**, 2, peter, brain_aneurysm_repair, 4).*

On deletion of a tuple, *p (t, a, b, ...)* the tuple concerned is left untouched in the data base and the tuple *not-p (t, a, b, ...)* is added to indicate that the original tuple has been deleted at time *t*. Returning to the example data base, supposing that the surgeon name of the surgery for kidney transplant is updated to Robert.

patient (0, 29, blake, elective , glaucoma).

patient (1, 10, smith, urgent, aneurysm).

surgery (0, 29, charles, trabeculectomy, 1).

surgery (1, 10, andrea, brain_aneurysm_repair, 4).

surgery (1, 2, peter, brain_aneurysm_repair, 4).

not-surgery (2, 7, jones, kidney_transplant, 1).

surgery (2, 7, robert, kidney_transplant, 1).

That is, whenever a new tuple is to be inserted into the relation "*p*" or an existing tuple in "*p*" is to be changed at some point in time *t'*, a new entry of the form:

p (t', a1, a2, ..., an).

or p (t', a1, a2, ..., an) if p1, p2, ..., pj.

will be created. If a tuple is to be deleted from relation "*p*" at time *t''*, as entry of the form:

not-p (t'', a1, a2, ..., an) .

or p (t', a1, a2, ..., an) if p1, p2, ..., pj.

is created. In order to access such a data base a simple rule of inference is required. The general search strategy corresponding to such an inference rule is:

search-tp (t, a1, a2, ..., an) if p(t, a1, a2, ..., an), fail;
not not-p (t, a1, a2, ..., an), fail;
search-tp (pred (t), a1, a2, ...,an).

where the semicolon ";" reads as "or" while "pred" stands for the predecessor relation. This steps systematically through each data base state, starting from t and moving backwards in time to the initial state looking for a tuple from the relation "p" which was either created at some point t' in time prior to t and not deleted before t. For relation "surgery" this becomes:

search-surgery (t, a, b, c, d) if surgery (t, a, b, c, d);
not not-surgery (t, a, b, c, d), fail;
search-surgery (pred (t) , a, b, c, d).

This asserts that a surgery exists during the interval *t'* to t if a surgery tuple can be found which was inserted ate some point *t'* in time prior to t and was not deleted (or updated) before *t*. To deal with the negative part of a relation, one has:

search-np (t, a1, a2, ..., an) if not-p (t, a1, a2, ..., an);
p (t, a1, a2, ..., an), fail;
search-np (pred (t), a1, a2, ..., an).

In the Appendix of Neves (1984), a simple logical interpreter which implements this strategy from dealing with time and explicit negation in the context of a logic data base is presented. Any query to the relation "*p*" must therefore be translated as a query to "*tp*", while any query to "*notp*" will be translated to "*np*" before being applied to the data base. The inference rules will then systematically search for the most recent clauses in the data base which either proves or refutes the query. Should the system fail to prove or disprove a given conjecture an answer of "*IT IS NOT KNOW IF THE STATEMENT IS TRUE OR FALSE*" is returned to the user. This is the case when neither a "*YES*" nor "*NO*" answer is possible from the axioms in the data base. If the answer is "*NO*" or "*IT IS NOT KNOW IF THE STATEMENT IS TRUE OR FALSE*" and analysis of the presuppositions made by the user in his query about the data present in the data might follow if requested (Neves and Williams (1983)).

5.3 Data Base Operations

It is possible to represent and answer user requests that make the distinction between a proposition always being true of the domain of discourse and one which is true at some particular point in time. It handles default reasoning of the type “If a surgery of a patient is to be performed at time t, and it was not delayed or canceled, the surgery should still be schedule to be performed now”. That is, it supports persistence.

5.3.1 Retrieval Operations

As an example, consider the user queries:

- Is there now a surgery to be performed on an urgent patient?
- Has there been surgeries to be performed on an immediate patient?
- Are there more surgeries to be performed on an immediate patient now than at any time in the past?

The first request can be answered by consulting the current state of the data base; the second by consulting all data base states. The third request can only be answered by evaluating two data base queries, one over the current state of the data base, another over every past situation and computing the answer from the values returned. As an example of the user dialogue to the system, consider the query “Has there ever been a surgery patient, at least one with high body temperature?”.

For this he may enter:

Table 3 — Tables skeleton of patient and patient-condition.

patient	state	patn	pname	cdegree	pathology
	L			X	

patient-condition	state	cdegree	pain	btemp	bloodp
any 1.	L	X		high	

This is translated by the system to yield the logic rule:

Query ([ ]) if [any 1(_, (patient (L, X, A, B, C), patient-condition (L, X, D, low, E)), _)].

where the predicate "any 1" returns as its value a list of no more than 1 data base entry in the relation "patient" that satisfy the predicate conjunction "patient (L, X, A, B, C), patient-condition (L, X, D, high, E)". Other queries that a user might want to ask include:

- Are there at least as many schedule surgeries now as there ever have been in the past?
- Has the number of performed surgeries by surgeon Foster risen?
- Has Clark ever had the same number of performed surgeries as Foster?
- When was Clark listed to perform a surgery to a patient with *aneurysm?*

Time dependent questions of this sort are not handle by existing data base systems, although the need for temporal semantics in data base systems has been discussed (Clifford and Warren (1983)).

5.3.2 Update Operations

Suppose that the user wishes to set to 5 the operating room to the patients with urgent surgery necessity. He may enter:

Table 4 — Tables skeleton of patient and surgery.

patient	state	patn	pname	cdegree	pathology
		X		urgent	

surgery	state	patn	surgn	types	oproom
u.		X			5

Where the entry "u." in the tuple-command-field of relation "surgery" refers to the relation to which the update operation applies. This request is mapped into the rule clauses:

not-surgery (3, X, Y, G, B) <— [patient (2, X, E, urgent, F) , surgery (2, X, Y, G, B)].

Surgery (3, X, Y, G, 5) <— [patient (2, X, E, urgent, F) , surgery (2, X, Y, G, B)].

which when applied to the data base yields the ground clauses:

surgery (3, 14, amber, liver_transplant, 5).
not-surgery (3, 14, amber, liver_transplant, 3).

These clauses are then added to the data base.

With this approach a system for reasoning about time and negation that is not too extravagant with respect to storage is presented. Changes to the data base are explicitly represented by time stamping the data base clauses, i.e. time is represented as a series of data bases describing the world in successive states. Both positive and negative information are represented explicitly in the data base, i.e. the components of a relation are now defined by positive and/or negative ground instances or general rules, or by a mixture of both. A first-order logic model is presented as a paradigm of a temporal data base model. This approach is referred to as the open world assumption and corresponds to the standard first-order interpretation of negation.

These ideas have been realized in an extension to the query language QBE, which has been implemented in Prolog and is currently running on VAXs, PDPs and an Eclipse machine.

CHAPTER 6

SURGERY PROCESS KNOWLEDGE DATABASE

A high level of complexity and large amount of available data is present throughout the surgery process. Therefore, in order to get the best panorama of the process as a whole, a large group of entities that play an influential role in the process needs to be taken into account and efficiently structured. Moreover, available data needs to be properly analysed and processed in order to obtain reliable input parameters, guaranteeing the feasibility and efficiency of the obtained solution, when applied to the real system. Also, the unpredictable state of the process demands that adverse situations that could risk a successful case to be avoided, by taken into account the presence of responsible entities on the data. Thus, everything occurring within and around the process will provide a successful intervention.

In order to develop a predictive model to estimate the surgery process a database was set. The data used was taken from the health records of patients at a major health care institution in the north of Portugal.

In this section the process of extraction, transformation and loading is briefly demonstrated. Likewise, it shows how the information is structured and how it is processed.

6.1 Extract, Transform and Load

In order to supply the CBR and ANN processes used, it was necessary to organize the information by gathering data from several sources and carry out with an Extract, Transform and Load (ETL) process. A star schema was used to organize the information, which consists of a collection of tables that are logically related to each other. To obtain a star schema a few steps were needed. The first stage was necessary to understand the problem in study and gather the parameter that have influence in the final outcome. Several variables that have a direct influence in the surgery process are taken into account and can be grouped in two categories. The ones directly related with the patient and the ones that have to do with the hospital environment during the inpatient care. The variables chosen and the structure applied are discussed in the next section (section 7.2). The following stage was related with the dimensions that would be needed to define these parameters on the facts tables. For the final stage, information from several sources was collected, transformed according the fact and dimension tables and loaded to the fact tables.

6.2 Data Processing

After studying the best way to delineate the surgery process in a way that includes the most focal points of the process as a whole, an example of how the structure would be created was set and an overview is presented in Figure 9. The schema focus on a chronological assessment of the surgery process encompassing the perioperative, intraoperative and postoperative periods. The process is initiated on the perioperative period by the patient admission to the hospital flowed by an evaluation about is health condition, in order to obtain the most fitted schedule for his surgery performance. As for the intraoperative period, the surgery is performed and through its execution the record of the patient state, medical team and physical resources is made. Ultimately, in the postoperative period, the state of the patient is supervised until is stabilization and discharge from the hospital, ending the surgery process.

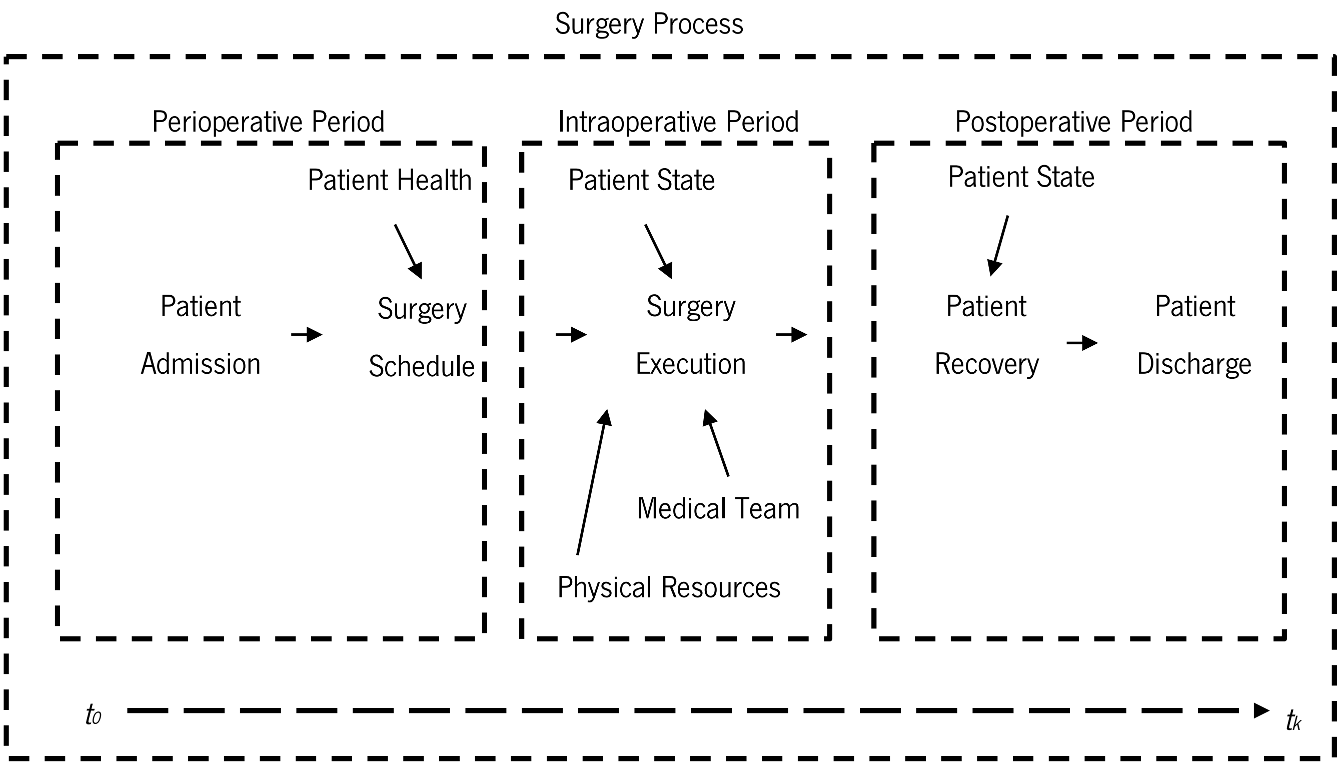


Figure 9 — Overview of the Surgery Process.

By following the schema delineated in Figure 9, after obtaining the star schema it is possible to build up a set of tables with the information that most influence the surgery process and construct the database knowledge structure presented on the Figure 11, that is described next.

The insertion of data begins with the patient admission to the hospital, where the patient related data relevant to the surgery process is added to the database into the *Patient Information* table.

- ***Patient Information***

  This table describes the characteristics of the patient when admitted in to the hospital, namely the variables *Age, Gender, Body Mass (kg), Height (m), Type of Patient and Admission Date (day/month/year)*. The variable *Age* is filled with the patient age; the *Gender* with patient sex either *male (M)* or *female (F)*; the *Body Mass* with the patient weight in *kilograms*; the *Height* with the patient height in meters; the *Type of Patient* with the type of patient either *elective* or *non-elective*.

Followed by the record of the patient information an assessment of the condition of the patient is performed and two tables will be filled with data, namely the *Symptoms* and the *Pathology* tables.

- ***Symptoms***

  This table describes the symptoms that a patient present when admitted to the hospital, namely the variables *Loss of Consciousness, Physical Pain, Body Temperature, Vision Disturbance, Nausea and Vomiting, Blood Pressure Disturbance and Breading Disturbance*. The variables are filled with qualitative information of the presence of a symptom that the patient may or may not have, where the scale is respectively *Non, Low, Moderate, High, Very High*.

- ***Pathology***

  This table is filled with the variable *Classification* where the designation of the pathology that the patient is diagnosed is present.

With data present in the three tables *Patient Information*, *Symptoms* and *Pathology* a new table is set, named *Pathology Incidence* in order to be used by the ANN process.

- ***Pathology Incidence***

  This table is filled with variables with data from other tables namely the variables *Age, Gender, Body Mass Index (BMI) (kg/m²), Pathology and Symptoms.* Where, the variable *Age* is filled with the patient age; the Gender with *0* (zero) or *1* (one) standing for male or female respectively; the *BMI* with the result of the body max index of the patient from the use of the equation $Body\ Mass\ /Hight^2$; the *Pathology* is populated with the number of the corresponding *Classification* presented on the *Pathology* table; the *Symptoms* variable is filled with ranges of the qualitative values present in the *Symptoms* table.

  The function of this table is to feed the ANN process with the variables that define the incidence of the pathology on the patient in order to obtain the urgency state.

After the information is processed by the ANN, the *Pathology Incidence* is obtained with the classification of the pathology degree and the *Surgery Scheduling* table is populated.

- ***Surgery Scheduling***

  This table is filled with the variables *Pathology Incidence, Surgery Date (day/month/year)* and *Surgery Hour (hrs/min)*. Where, the *Pathology Incidence* is populated with the degree of incidence that a pathology has in the patient in order to decide the urgency of the surgery execution, where, the higher the degree is, more urgent the patient case is, therefore the surgery needs to be performed earlier. Thus, the *Surgery Date* and the *Surgery Hour* is populated according with the degree obtained.

By filling the *Surgery Scheduling* table, the surgery is to be performed in the date and hour defined in the previous table.

The next tables to be taken into account are the *Patient Perioperative State* and *Patient Risk Factors For Surgery Performance*.

- ***Patient Perioperative State***

  This table describes the patient condition in order to be accepted to perform the surgery, since a low value of the interval range could mean that the surgery would need to be delayed or even cancelled until the patient is in condition to be operated and a rush on the execution of the surgery could put in risk the patient life or the success of the surgery. The patient condition variables taken into account are respectively the *Loss of Consciousness, Physical Pain, Hemodynamic Stability, Respiratory Stability, Oxygen Saturation Stability, Vital Signs, Pain Absence, Nausea and Vomiting Absence*. These variables are filled with qualitative information of conditions that the patient may or may not present, where the scale is respectively *Non, Low, Moderate, High, Very High*.

- ***Patient Risk Factors For Surgery Performance***

  This table describes risk factors that could put in risk the patient life and the surgery success, the table contemplates the variables *Allergies, Medication*, *Other Diseases.* Where the *Allergies* stands for the possibility of the patient undergoing surgery having some type of allergic reaction, for example to some anaesthetic drugs, natural latex rubber, antibiotics or analgesics that can induce life-threatening anaphylaxis reactions; the *Medication* the patient could have taken some risk medication, for example some anti-coagulants that would make the blood thinner and increase the risk of wound infections and postoperative Anemia; the *Other Diseases* stands for the possibility of the patient having some other diseases that could risk the surgery performance. All these variables are filled with boolean data respectively 1 (one) for *yes* or 0 (zero) for *no.*

After the patient conditions to perform surgery is addressed in the previous tables, multiple factors play a major role in order to obtain a successful surgery. Therefore, the following tables taken into account are respectively the *Medical Team*, *Surgery Physical Resources*, *Surgery Characteristics* and *Patient Intraoperative State*.

- ***Medical Team***

  This table describes the medical staff present in the operating room. The table variables are divided by speciality respectively *Surgeon*, *Surgical Care Practitioner*, *Anaesthetist*, *Anaesthetic Practitioner*, *Advanced Scrub Practitioner*, *Circulating Practitioner* and *Recovery Practitioner* and all are filled with the number of staff in each speciality available to perform the surgery.

- ***Surgery Physical Resources***

This table describes the surgery resources used in the operation. The table is divided into the variables *Operating Room*, *Surgery Equipment*, *Surgery materials*, *PACU Bed (min)*, *ICU Bed* (day) and *Ward Bed (day)*. Where, the *Operating Room* informs about the availability of an operating room, since for example in the case of an immediate surgery none of the operating rooms could be available, or in the case where the operating room was needed for an immediate surgery a less urgent patient needs to wait until there is one free; the *Surgery Equipment* and *Surgery Material* informs respectively about the availability of all equipment and material needed in order to operate; the *PACU Bed*, *ICU Bed* and *Ward Bed*, informs respectively about the availability of a Post-Anaesthesia Care Unit bed, an Intensive Care Unit bed if needed and Ward bed. All these variables are filled with boolean data respectively 1 (one) for *yes* or 0 (zero) for *no.*

- ***Surgery Characteristics***

This table describes the characteristics of the surgery to be performed. It is composed by the variables *Type of Surgery*, *Surgery Specialty* and the *Surgery Time*. Where, the *Type of Surgery* variable is filled with the options of the type of surgery to be perform, namely the *Elective, Expedited, Immediate and Urgent*; the *Surgery Speciality* is filled with the name of the specialization of the surgery, as for the *Surgery Time (min)* it gives the time in minutes of the duration of the performance of the surgery.

- ***Patient Intraoperative State***

This table describes the patient state during the surgery performance integrating the variables *Hemodynamic Stability*, *Respiration Stability*, *Oxygen Saturation Stability* and *Vital Signs* while performing the surgery. These variables are filled with the respectively qualitative information of the conditions that the patient may or may not present, where the scale is respectively *Non, Low, Moderate, High and Very High*.

With the data populating the previous tables, namely the *Medical Team*, *Surgery Physical Resources*, *Surgery Characteristics* and *Patient Intraoperative State* a new table is set with the name *Surgery Performance*, so that the contained information is used by the ANN process.

- ***Surgery Performance***

  This table is filled with variables with data from other tables, namely the variables *Medical Team (MT)*, *Patient Perioperative State (PPES)*, *Patient Intraoperative State (PIS)*, *Patient Risk Factors For Surgery Performance (PRFSP)*, *Type of Surgery (TS)*, *Surgery Speciality (SS)*, *Surgery Time (min) (St)* and *Surgery Physical Resources (SPR)*. Where, the *Medical Team* is filled with the total number of elements present in the performance of the surgery; the *Patient Perioperative State* with the qualitative values of the perioperative state of the patient; the *Patient Intraoperative State* with the qualitative values of the state of the patient during the intraoperative period; the *Patient Risk Factors For Surgery Performance* with the total number of risk factors that the patient performing the surgery has; the *Type of Surgery* is present with the value of the respective type presented on the *Surgery Characteristics* table namely 1 (one) for *Elective, 2 (two)* for *Expedited,* 3 (three) for *Immediate* and 4 (four) *for Urgent*; the *Surgery Speciality* is filled with the respective number of the speciality of the surgery; the *Surgery Time (min)* gives the duration of the performance of the surgery in minutes; the *Surgery Physical Resources* gives the number of the surgery related resources available, given by the quantity of 1 (one) present on the *Surgery Physical Resources* table.

The function of this table is to feed the ANN process through the gathered data with the variables that most influence the surgery performance in order to obtain the state of the surgery execution.

After the information is processed by the ANN, the *Surgery Performance* is obtained with the classification of the surgery is state and the *Surgery Assessment* table is populated.

- ***Surgery Assessment***

  This table is filled with the variables *Surgery Performance (SP)*, *Surgery Complications (SC)*, *ICU Time (ICUt) (day)* and *PACU Time (PACUt) (min)*. Where, the *Surgery Performance* is filled with the performance state of the surgery given by the ANN process resulting into the respectively possibilities of *Cancelled*, *Delayed*, *Operating* and *Performed*; the *Surgery Complications* gives information if some type of complications happened during the surgery procedure, it is filled with boolean data namely 1 (one) for *yes* and 0 (zero) for *no*; the *ICU Time* and *PACU Time* give respectively the time of days that a patient was in the Intensive Care Unit bed and the time of minutes that a patient was in the Post-Anaesthesia Care Unit bed.

After the surgery is performed and the patient is discharge from *PACU* or *ICU* bed, it is moved to the ward bed were an evaluation of is recuperation state is made in order to be discharge from the hospital. This evaluation made to the patient populates the table *Patient Postoperative State*.

- ***Patient Postoperative State***

  This table describes the patient condition in order to be discharge from the hospital. The patient condition variables taken into account are respectively the *Loss of Consciousness, Physical Pain, Hemodynamic Stability, Respiratory Stability, Oxygen Saturation Stability, Vital Signs, Pain Absence, Surgical Bleeding Absence, Nausea and Vomiting Absence*. All these variables are filled with qualitative information of conditions that the patient may or may not present, where the scale is respectively *Non, Low, Moderate, High* and *Very High.*

With data present in previous tables *Patient Postoperative State* and *Patient Information* a new table is set, named *Patient Postoperative Assessment* in order to the information be used by the ANN process.

- ***Patient Postoperative Assessment***

  This table is filled with the variables *Age, Gender, Body Mass Index (BMI) (kg/m²), Patient Postoperative State (PPOS).* Where, the variable *Age* is filled with the patient age; the Gender with *0* (zero) or *1* (one) standing for male or female respectively; the *BMI* with the result of the body max index of the patient from the use of the equation $Body\,Mass\;/Hight^2$; the *Patient Postoperative State* is filled with the qualitative values of the postoperative state of the patient.

  The function of this table is to feed the ANN process through the gathered data that give the state of the patient is health condition, in order to be discharge from the hospital.

After the information is processed by the ANN and the *Patient Postoperative Assessment* is obtained with the classification of the surgery is state, the *Surgery Postoperative Assessment* table is populated.

- ***Surgery Postoperative Assessment***

This table is filled with the variables *Patient Postoperative Assessment (PPA)*, *Ward Bed Time (day) (WBt), Contracted Infection (CI)*, *Discharge Date (day/month/year)*. Where, the *Patient Postoperative Assessment* variable is filled with the state of the patient healthy obtained by ANN process, namely *Unhealthy*, *Unstable, Stable* and *Healthy*, where, *Unhealthy* means that the patient health is still in a critical condition, therefore it needs special attention in order to regain is healthy state, the *Unstable* means the patient still needs constant observation of the health state, the *Stable* means that the patient is almost ready to be discharge but needs some minor observations and *Healthy* means that the patient is ready to be discharge from the hospital; the *Contracted Infection* is filled if a patient during is surgery process contracted an infection, in order to identify the risk of future patients contracting some type of infection when performing the same surgery process, this variable is filled with boolean values 1 (one) for *yes* and 0 (zero) for *no*; the Discharge Date is filled with the date of the patient discharge of the hospital ending the surgery process as a whole.

After populating all the previous tables with the respectively data the main table *Surgery process* is set with all the main variables from the surgery process in order to feed the CBR process.

- ***Surgery process***

This table is filled with all the main variables from the surgery process in order to be used by the CBR process, namely the variables *Age, Gender, Body Mass Index (BMI) (kg/m^2), Type of Patient (TP), Pathology, Pathology Incidence (PI) , Medical Team (MT), Patient Perioperative State (PPES), Patient Intraoperative State (PIS), Patient Risk Factors For Surgery Performance (PRFSP), Type of Surgery (TS), Surgery Specialty (SS), Surgery Time (St), Surgery Physical Resources (SPR), Surgery Performance (SP), Surgery Complications (SC), ICU Time (ICUt) (day), PACU Time (PACUt) (min), Patient Postoperative State (PPOS), Patient Postoperative Assessment (PPA), Ward Bed Time (WBt) (day), Contracted Infection (CI), Surgery Hours (hrs:min), Surgery Waiting Time (day), Patient Hospitalization Time (day), Surgery process Time (day) and Observations.* Where, the variable *Age* is filled with the patient age; the Gender with *0* (zero) or *1* (one) standing for male or female respectively; the *BMI* with the result of the body max index of the patient from the use of the equation $Body\ Mass\ /Hight^2$; the *Type of Patient* with the type of patient either 1 (one) for *elective* or 0 (zero) for *non-elective*; the *Pathology* is populated with the number of the corresponding *Classification* presented on the *Pathology* table; the *Pathology Incidence* is populated with the value of the degree of incidence that a pathology has in the patient, in order to decide the urgency of the surgery execution given by the ANN process being respectively 1 (one) for *Non*, 2 (two) for *Low*, 3 (three) for *Moderate*, 4 (four) for *High* and 5 (five) for *Very High*; the *Medical Team* is filled with the total number of elements present in the performance of the surgery; the *Patient Perioperative State* with the qualitative values of the perioperative state of the patient; the *Patient Intraoperative State* with the qualitative values of the state of the patient during the intraoperative period; the *Patient Risk Factors For Surgery Performance* with the total number of risk factors that the patient performing the surgery has; the *Type of Surgery* is present with the value of the respective type presented on the *Surgery Characteristics* table namely 1 (one) for *Elective, 2* (two) for *Expedited,* 3 (three) for *Immediate* and 4 (four) *for Urgent*; the *Surgery Speciality* is filled with the respective number of the speciality of the surgery; the *Surgery Time (min)* gives the duration of the performance of the surgery in minutes; the *Surgery Physical Resources* gives the number of the surgery related resources available; the *Surgery Performance* is filled with the performance state of the surgery given by the ANN process resulting into the respectively possibilities of 1 (one) if *Cancelled*, 2 (two) if *Delayed*, 3 (three) if *Operating* and 4 (four) if *Performed*; the *Surgery Complications* gives information if some type of complications happened during the surgery procedure, it is filled with boolean data namely 1 (one) for *yes* and 0 (zero) for *no*; the *ICU Time* give respectively the time of days that a patient was in the Intensive Care Unit bed ; the *PACU Time* give the time of minutes that a patient was in the Post-Anaesthesia Care Unit bed; the *Patient Postoperative State* is filled with the qualitative values of the postoperative state of the patient; the *Patient Postoperative Assessment* variable is filled with the state of the patient health obtained by ANN process namely 1 (one) for *Unhealthy*, 2 (two) for *Unstable* , 3 (three) for *Stable* and 4 (four) for *Healthy*; the *Ward Bed Time* with the days that the patient stayed on the ward bed; the *Contracted Infection* is filled if a patient during is surgery process contracted an infection, filled with boolean values 1 (one) for *yes* and 0 (zero) for *no*; the *Surgery Hour* provides the hour at which the surgery was performed; the *Surgery Waiting Time (day)* with the time in days that the patient had to wait until the surgery was performed; the *Patient Hospitalization Time (day)* with the time in days that a patient was admitted to the hospital from the admission to the discharge day; the *Surgery Process Time (day)* with the time in days that the surgery process has taken from the identification of the patient need of surgery to the day of discharge from the hospital; the *Observations* with an free text fields that allow for the registration of relevant events during the surgery process.

After the *Surgery Process* table if filled, the knowledge database representation is completed, and the information is processed by the CBR system in order to add the new information to the cases record base.

6.3 Knowledge Database Time Representation

As mentioned above, this knowledge database is time depend, this means, that all the variables presented in each table describe a complete historical record of all the changes made throughout the process from t_0 to t_k, by using an additional attribute value denoting the state number, as described on the Chapter 6. Therefore, the qualitative information present will also be affected by the presence of the state number since, changes to the qualitative data will be explicitly represented by time stamping, thus aiming at the quantification of the qualitative part and in order to make easy the understanding of the process, it will also be presented the time changes of the qualitative data in a three dimensional graphical form as presented on Figure 10. In it is possible to view a time lapse of the changes occurred to the information of a particular subject present on the knowledge base. This graphics follow the same concept as the representation of the Qualitative Knowledge, respecting the same characteristics presented on section 5.1.2 of Chapter 5, but taking into account the time changes occurred on the information of some issue regarding a particular subject, where in this case the information can vary from *Low* to *Very High* or other intermediate value that has taken place in a certain time state.

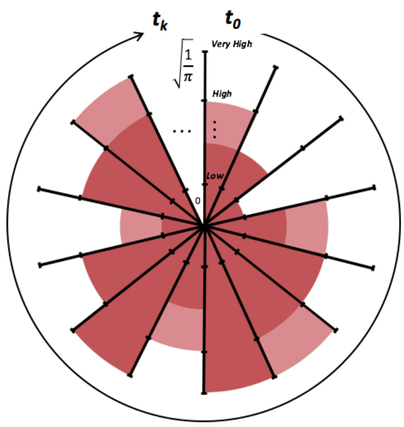


Figure 10 – A view of a qualitative data/knowledge processing changes on a time domain.

Subsequently, each patient surgery process will have the complete chronological history record of all the changes made in the surgery process, increasing the proximity of the model to the real surgery process, since changes, removal or updates in the data, are inevitable and extremely important to the trustworthiness off the database, allowing a more accurate use of the data by the CBR process.

More details about the benefits of the use of time on the system will be discussed in detail on the Chapter 8 section 8.2.

6.4 Logical Programming Approach to Data Processing

With the structured presented on the section 7.1, the knowledge database is given in terms of the extensions of the relations depicted in Figure 11, which stand for a situation where one has to manage information of a surgery process. Under this scenario some incomplete and/or unknown data is also present. For instance, in the *Surgery Process* table, the *PACU Time* (*PCAUt*) in case 1 is unknown, which is depicted by the symbol $\perp$, while the *Patient Intraoperative State (PIS)* range in the interval [0.71, 0.73].

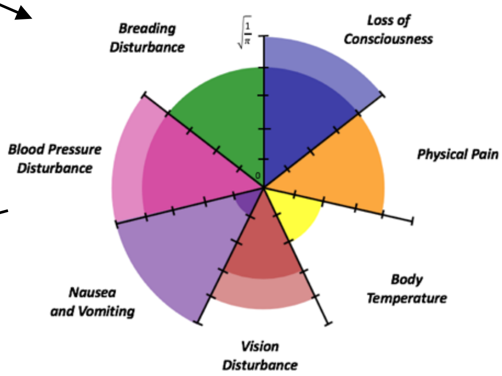
Patient Information

#	t	Age	Gender	Body Mass (kg)	Height (m)	Type of Patient (TP)	Admission Date (day/month)
1	0	53	M	83.6	1.81	elective	11/08/18
2	0	49	F	63.4	1.65	non-elective	29/09/18
3	0	66	M	79.2	1.71	elective	27/05/18
...	...	...	...	...	...	...	...
n	0	28	F	59.3	1.69	elective	26/08/18

Symptoms

#	t	Loss of Consciousness	Physical Pain	Body Temperature	Vision Disturbance	Nausea and Vomiting	Blood Pressure Disturbance	Breading Disturbance
1	2	High/Very High	High	Low	Moderate/High	$\perp$	High/Very High	High
2	2	Very High	Very High	$\perp$	Very High	High	Very High	Very High
3	0	None	Moderate	None	Very High	None	None	None
...	...	…	…	…	…	…	…	…
n	0	None	Moderate/High	High	None	Moderate	None	$\perp$

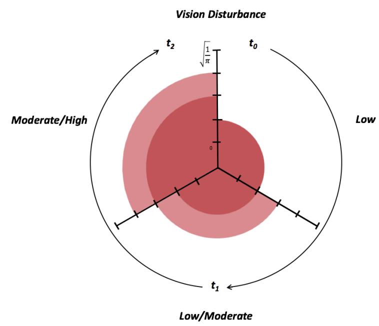
Case 1



Case 1

Pathology Incidence (PI)

#	t	Age	Gender	BMI (kg/m^2)	Pathology	Symptoms
1	2	53	1	25.52	1911	[0.60 , 0.74]
2	2	49	0	23.29	398	[0.68 , 0.80]
3	0	86	1	27.09	1122	0.21
...	...	...	...	...	…	...
n	0	28	0	20.76	55	[0.30 , 0.42]
		[0 , 120]	[0 , 1]	[12 , 42]	[0 , 100000]	[0 , 1]



ANN

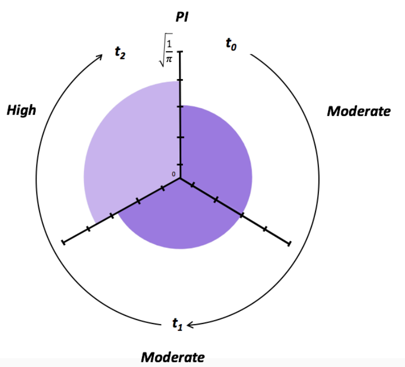
Pathology

#	t	Classification
1	0	Ischemia
2	0	Aneurysm
3	0	Cataract
...	...	…
n	0	Otitis media

Surgery Scheduling

#	t	PI	Surgery Date (day/month/year)	Surgery Hour (SH) (hrs.min)
1	2	High	11/08/18	9.00
2	4	Very High	29/09/18	16.50
3	0	Moderate	01/06/18	8.00
...	...	…	...	...
n	0	Low	14/09/18	10.00

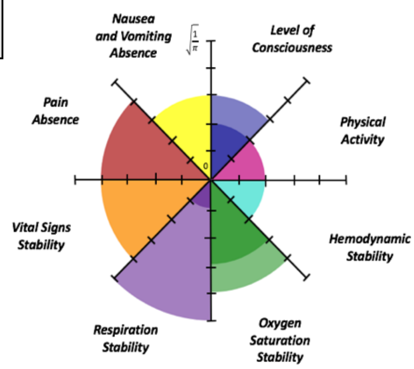
Case 1



Patient Perioperative State (PPES)

#	t	Level of Consciousness	Physical Activity	Hemodynamic Stability	Respiration Stability	Oxygen Saturation Stability	Vital Signs Stability	Pain Absence	Nausea and Vomiting
1	2	Low/Moderate	Low	Low	Moderate/High	$\perp$	High	High	Moderate
2	2	Low	Low	$\perp$	Low	Moderate	Moderate	Low	Low
3	0	Very High	Moderate	Moderate/High	Very High	Very High	Very High	Low	Moderate
…	…	…	…	…	…	…	…	…	…
n	0	Very High	Very High	Very High	Very High	Very High	Very High	Moderate	Low

Case 1



Medical Team (MT)

#	t	Surgeon	Surgical Care Practitioner	Anaesthetist	Anaesthetic Practitioner	Advanced Scrub Practitioner	Circulating Practitioner	Recovery Practitioner
1	4	1	1	1	1	1	1	0
2	5	1	1	1	1	1	0	0
3	0	1	2	1	1	2	1	1
…	…	…	…	…	…	…	…	…
n	0	1	1	1	1	1	1	1

Case 1

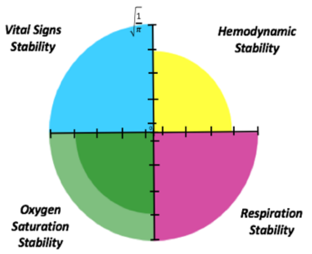
Surgery Performance (SP)

#	t	MT	PPES	PIS	PRFSP	TS	SS	St (min)	SPR
1	14	6	[0.54 , 0.67]	[0.71 , 0.73]	1	3	3	120	5
2	18	5	[0.48 , 0.58]	0.71	0	4	3	180	5
3	2	9	[0.71 , 0.72]	0.79	0	2	36	10	5
…	…	…	…	…	…	…	…	…	…
n	1	7	0.74	0.78	1	1	39	15	5
		[7 , 15]	[0 , 1]	[0 , 1]	[0 , 3]	[1 , 4]	[1 , 65]	[10 , 1920]	[0 , 6]

Surgery Physical Resources (SPR)

#	t	Operating Room	Surgery Equipment	Surgery Materials	PACU Bed	ICU Bed	Ward Bed
1	2	1	1	1	1	0	1
2	3	1	1	1	0	1	1
3	0	1	1	1	1	0	1
…	…	…	…	…	…	…	…
n	0	1	1	1	1	0	1

Case 1



Case 1

ANN

Surgery Characteristics

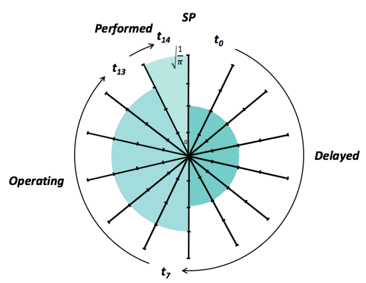
#	t	Type of Surgery (TS)	Surgery Specialty (SS)	Surgery Time (St) (min)
1	0	Urgent	Vascular Surgery	120
2	1	Immediate	Vascular Surgery	180
3	0	Expedited	Ophthalmology	10
…	…	…	…	…
n	0	Elective	Otorhinolaryngology	15

Patient Intraoperative State (PIS)

#	t	Hemodynamic Stability	Respiration Stability	Oxygen Saturation Stability	Vital Signs Stability
1	6	Moderate	High	Moderate/High	High
2	7	Moderate	Moderate	High	High
3	2	High	Very High	Very High	Very High
…	…	…	…	…	…
n	1	High	Very High	Very High	Very High

Patient Risk Factors For Surgery Performance (PRFSP)

#	t	Allergies	Medication	Other Diseases
1	0	0	1	0
2	0	0	0	0
3	0	0	0	0
…	…	…	…	…
n	0	1	0	0



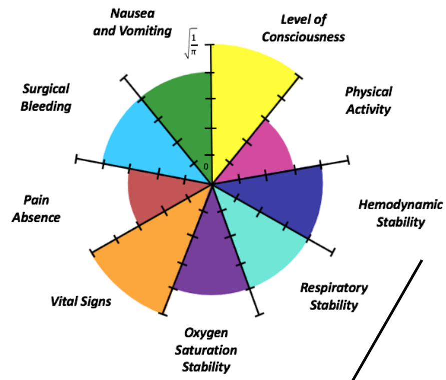
Case 1

Surgery Assessment

#	t	SP	Surgery Complications (SC)	ICU Time (ICUt) (day)	PACU Time (PACUt) (min)
1	14	Performed	0	0	$\perp$
2	18	Performed	0	480	120
3	2	Performed	0	0	10
…	…	…	…	…	…
n	1	Performed	0	0	2

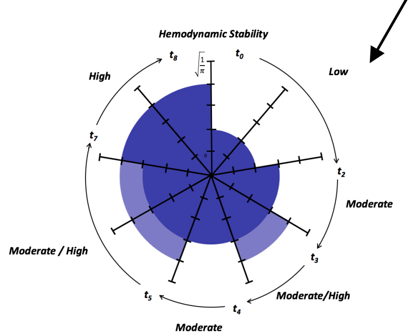
Patient Postoperative State (PPOS)										
#	t	Level of Consciousness	Physical Activity	Hemodynamic Stability	Respiratory Stability	Oxygen Saturation	Vital Signs	Pain Absence	Surgical Bleeding	Nausea and Vomiting
1	8	Very High	Moderate	High	High	High	Very High	Moderate	High	High
2	10	Very High	Moderate	Moderate/High	High	High	Very High	Low/Moderate	Moderate/High	High
3	4	Very High	High	Very High	Very High	Very High	Very High	High	Very High	Very High
...	...	…	…	…	…	…	…	…	…	…
n	3	Very High	Very High	Very High	Very High	Very High	Very High	High	Very High	Very High

Case 1

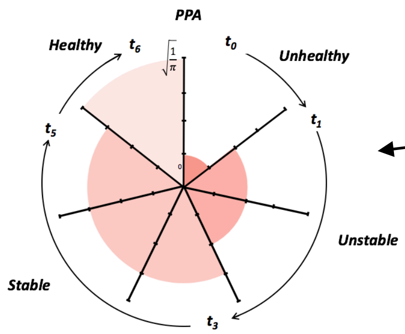


Case 1

Patient Postoperative Assessment (PPA)					
#	t	Age	Gender	BMI (kg/m^2)	PPOS
1	8	53	1	25.52	0.74
2	10	49	0	23.29	[0.71 , 0.75]
3	4	86	1	27.09	0.79
...	...	...	...	...	…
n	3	28	0	20.76	0.79
		[0 , 120]	[0 , 1]	[12 , 42]	[0 , 1]



ANN



Case 1

Surgery Postoperative Assesment					
#	t	PPA	Ward Bed Time (WBt) (day)	Contracted Infection (CI)	Discharge Date (day/month/year)
1	6	Healthy	2	0	16/08/2018
2	8	Healthy	8	0	9/10/2018
3	3	Healthy	⊥	1	02/06/18
...	...	…	…	…	…
n	1	Healthy	1	0	16/09/18

Surgery Process																												
#	t	Age	Gender	BMI (kg/m^2)	TP	Pathology	PI	MT	PPES	PIS	PRFSP	TS	SS	St (min)	SPR	SP	SC	ICUt (day)	PACUt (min)	PPOS	PPA	WBt (day)	CI	SH (hrs.min)	Surgery Waiting Time (day)	Patient Hospitalization Time (day)	Surgery Process Time (day)	Observations
1	42	53	1	83.6	1	1911	4	6	[0.54 , 0.67]	[0.71 , 0.73]	1	3	3	120	5	4	0	0	⊥	0.74	4	2	0	9.00	0	5	5	Observation 1
2	54	49	0	63.4	0	398	5	5	[0.48 , 0.58]	0.71	0	4	3	180	5	4	0	480	120	[0.71 , 0.75]	4	8	0	16.50	0	10	10	Observation 2
3	11	86	1	79.2	1	1122	3	9	[0.71 , 0.72]	0.79	0	2	36	10	5	4	0	0	10	0.79	4	⊥	1	8.00	5	1	6	Observation 3
...	...	...	...	...	...	…	…	...	...	...	…	...	...	…	...	…	…	…	…	…	…	…	…	...	…	…	…	…
n	6	28	0	59.3	1	55	2	7	0.74	0.78	1	1	39	15	5	4	0	0	2	0.79	4	1	0	10.00	19	2	21	Observation n
		[0 , 120]	[0 , 1]	[12 , 42]	[0 , 1]	[0 , 100000]	[1 , 5]	[7 , 15]	[0 , 1]	[0 , 1]	[0 , 3]	[1 , 4]	[1 , 65]	10 , 192(	[0, 6]	[1 , 4]	[0, 1]	[0 , 480]	[0 , 360]	[0 , 1]	[1 , 4]	[0 , 31]	[0 , 1]	[0 , 24]	[0 , 365]	[0 , 31]	[0 , 386]	

CBR

Figure 11– A fragment of the knowledge base for Surgery Process.

Now, applying the procedure presented in Fernandes et al. (2015) to the tables or relation's fields that make the knowledge base for *Surgery Process* (Figure 11), excluding at this stage such a process the Observation one, and looking to the DoC_s values obtained, it is possible to set the arguments of the set of predicates ***p**athology **i**ncidence* (*pi*) , ***s**urgery **p**erformance* (*sp*) , ***p**atient **p**ostoperative **a**ssessment* (*ppa*) and ***surg**ery **proc**ess* (*surgproc*), whose extensions also denotes the objective functions with respect to the problem under analyse, in the from:

$$pi: t_{ime}, Age, Gen_{der}, BMI, Path_{ology}, Sym_{ptoms} \rightarrow \{0,1\}$$

$$sp: t_{ime}, MT, PPES, PIS, PRFSP, TS, SS, SE, SPR \rightarrow \{0,1\}$$

$$ppa: t_{ime}, Age, Gen_{der}, BMI, PPOS \rightarrow \{0,1\}$$

$$surgproc: t_{ime}, Age, Gen_{der}, BMI, TP, Path_{ology}, PI, MT, PPES, PIS, PRFSP, TS, SS, St, SPR, SP, SC, ICUt, PACUt, PPOS, PPA, WBt, CI, SH, S_{urgery}W_{aiting}t_{ime}, P_{atient}H_{ospitalization}t_{ime}, S_{urgery}P_{rocess}t_{ime} \rightarrow \{0,1\}$$

where 0 (zero) and 1 (one) denote, respectively, the truth values *false* and *true*.

The application of the algorithm presented in Fernandes et al. (2015) comprises several phases. In the former one the clauses or terms that make extension of the predicate under study are established. In the next stage the boundaries of the attributes intervals are set in the interval [0,1] according to a normalization process in terms of the expression $(Y - Y_{min})/(Y_{max} - Y_{min})$, where the Y_s stand for themselves. Finally, the DoC is evaluated as described in the previous Chapter 5.

It is now possible to exemplify the application of the procedure referred to above and given in Fernandes et al. (2015), in relation to the term or clause that presents the feature vector in terms of the extension of each predicate.

In terms of the extension of predicate pi, with the feature vector *time = 0*, *Age = 35, Gender = 0, BMI = 22.13 , Pathology = 470, Symptoms = [0.24 , 0.37]* , one may have:

Begin

%The predicate's extension that sets the Universe-of-Discourse for the term under observation is fixed%

$$\{ \quad \neg\, pi\ \Big(t, \big((A_{Age}, B_{Age})(QoI_{Age}, DoC_{Age})\big),\ ((A_{Gen}, B_{Gen})(QoI_{Gen}, DoC_{Gen})),$$

$$((A_{BMI}, B_{BMI})(QoI_{BMI}, DoC_{BMI})), ((A_{Path}, B_{Path})(QoI_{Path}, DoC_{Path})), \big((A_{Sym}, B_{Sym})(QoI_{Sym}, DoC_{Sym})\big)\Big)$$

$$\leftarrow not\ pi\ \Big(t, \big((A_{Age}, B_{Age})(QoI_{Age}, DoC_{Age})\big),\ ((A_{Gen}, B_{Gen})(QoI_{Gen}, DoC_{Gen})),$$

$$((A_{BMI}, B_{BMI})(QoI_{BMI}, DoC_{BMI})), ((A_{Path}, B_{Path})(QoI_{Path}, DoC_{Path})), \big((A_{Sym}, B_{Sym})(QoI_{Sym}, DoC_{Sym})\big)\Big)$$

$$pi\ \begin{matrix} \Big(0, \big((35\ , 35)(1_{[35,35]},\ DoC_{[35,35]})\big), \big((0,0)(1_{[0,0]},\ DoC_{[0,0]})\big)\ , \big((22.13,\ \ 22.13)(1_{[22.13,22.13]},\ DoC_{[22.13,22.13]})\big), \\ \big((470\ , 470)(1_{[470,470]},\ DoC_{[470,470]})\big),\ \big((0.24,\ 0.37)(1_{[0.24,0.37]},\ DoC_{[0.24,0.37]})\big)\Big) \\ ::1::DoC \end{matrix}$$

$$\underbrace{[0,1] \qquad\qquad [0,1] \qquad\qquad [0,1] \qquad\qquad [0,1] \qquad\qquad [0,1]}_{\text{attribute`s domains once normalized}}$$

$$\}::1$$

%The attribute's boundaries are set to the interval [0, 1], according to a normalization process that uses the expression $(Y - Y_{min})/(Y_{max} - Y_{min})$ *%*

$$\{ \quad \neg\, pi\ \Big(t, \big((A_{Age}, B_{Age})(QoI_{Age}, DoC_{Age})\big),\ ((A_{Gen}, B_{Gen})(QoI_{Gen}, DoC_{Gen})),$$

$$((A_{BMI}, B_{BMI})(QoI_{BMI}, DoC_{BMI})), ((A_{Path}, B_{Path})(QoI_{Path}, DoC_{Path})), \big((A_{Sym}, B_{Sym})(QoI_{Sym}, DoC_{Sym})\big)\Big)$$

$$\leftarrow not\ pi\ \Big(t, \big((A_{Age}, B_{Age})(QoI_{Age}, DoC_{Age})\big),\ ((A_{Gen}, B_{Gen})(QoI_{Gen}, DoC_{Gen})),$$

$$((A_{BMI}, B_{BMI})(QoI_{BMI}, DoC_{BMI})), ((A_{Path}, B_{Path})(QoI_{Path}, DoC_{Path})), \big((A_{Sym}, B_{Sym})(QoI_{Sym}, DoC_{Sym})\big)\Big)$$

$$pi\ \begin{matrix} \Big(0, \big((0.29\ , 0.29)(1_{[0.29,0.29]},\ DoC_{[0.29,0.29]})\big), \big((0,0)(1_{[0,0]},\ DoC_{[0,0]})\big)\ , \big((0.34,\ \ 20.34)(1_{[0.34,0.34]},\ DoC_{[0.34,0.34]})\big), \\ \big((0.0047\ , 0.0047)(1_{[0.0047,0.0047]},\ DoC_{[0.0047,0.0047]})\big),\ \big((0.24,\ 0.37)(1_{[0.24,0.37]},\ DoC_{[0.24,0.37]})\big)\Big) \\ ::1::DoC \end{matrix}$$

$$\underbrace{[0,1] \qquad\qquad [0,1] \qquad\qquad [0,1] \qquad\qquad [0,1] \qquad\qquad [0,1]}_{\text{attribute`s domains once normalized}}$$

$\}:: 1$

%The DoC's values are evaluated %

$$\{ \quad \neg\, pi\ \Big(t, \big((A_{Age}, B_{Age})(QoI_{Age}, DoC_{Age})\big),\ ((A_{Gen}, B_{Gen})(QoI_{Gen}, DoC_{Gen})),$$

$$((A_{BMI}, B_{BMI})(QoI_{BMI}, DoC_{BMI})), ((A_{Path}, B_{Path})(QoI_{Path}, DoC_{Path})), \big((A_{Sym}, B_{Sym})(QoI_{Sym}, DoC_{Sym})\big)\Big)$$

$$\leftarrow not\ pi\ \Big(t, \big((A_{Age}, B_{Age})(QoI_{Age}, DoC_{Age})\big),\ ((A_{Gen}, B_{Gen})(QoI_{Gen}, DoC_{Gen})),$$

$$((A_{BMI}, B_{BMI})(QoI_{BMI}, DoC_{BMI})), ((A_{Path}, B_{Path})(QoI_{Path}, DoC_{Path})), \big((A_{Sym}, B_{Sym})(QoI_{Sym}, DoC_{Sym})\big)\Big)$$

$$\mathrm{pi}\underbrace{\Big(0, \big((0.29\,, 0.29)(1,\ 1)\big), \big((0, 0)(1,\ 1)\big)\ , \big((0.34\,, 0.34)(1,\ 1)\big), \big((0.0047\,, 0.0047)(1,\ 1)\big),\ \big((0.24,\ 0.37)(1,\ 0.99)\big)\Big)}_{\text{attribute`s values ranges once normalized and respective QoI and DoC values}}$$

$$:: 1 :: 0.99$$

$$\underbrace{[0, 1] \qquad\qquad [0, 1] \qquad\qquad [0, 1] \qquad\qquad\qquad [0, 1] \qquad\qquad\qquad [0, 1]}_{\text{attribute`s domains once normalized}}$$

$\}:: 1$

End

In terms of the extension of predicate *sp*, with the feature vector *time = 1, MT = 7, PPES = 0.77, PIS = 0.80 , PRFSP = 0, TS = 1, SS=* $\perp$*, St = 13, SPR = 5*, one may have:

Begin

%The predicate's extension that sets the Universe-of-Discourse for the term under observation is fixed%

$\{$

$$\neg\, sp\ \big(t, ((A_{MT}, B_{MT})(QoI_{MT}, DoC_{MT})),\ ((A_{PPES}, B_{PPES})(QoI_{PPES}, DoC_{PPES})), ((A_{PIS}, B_{PIS})(QoI_{PIS}, DoC_{PIS})),$$

$$((A_{PRFSP}, B_{PRFSP})(QoI_{PRFSP}, DoC_{PRFSP})), ((A_{TS}\ B_{TS})(QoI_{TS}, DoC_{TS})), ((A_{SS}\ B_{SS})(QoI_{SS}, DoC_{SS})),$$

$$((A_{St}, B_{St})(QoI_{St}, DoC_{St})), ((A_{SPR}, B_{SPR})(QoI_{SPR}, DoC_{SPR}))\big)$$

$$\leftarrow not\ sp\ \ \big(t, ((A_{MT}, B_{MT})(QoI_{MT}, DoC_{MT})),\ ((A_{PPES}, B_{PPES})(QoI_{PPES}, DoC_{PPES})), ((A_{PIS}, B_{PIS})(QoI_{PIS}, DoC_{PIS})),$$

$$((A_{PRFSP}, B_{PRFSP})(QoI_{PRFSP}, DoC_{PRFSP})), ((A_{TS}\ B_{TS})(QoI_{TS}, DoC_{TS})), ((A_{SS}\ B_{SS})(QoI_{SS}, DoC_{SS})),$$

$$\left((A_{St}, B_{St})(QoI_{St}, DoC_{St})\right), \left((A_{SPR}, B_{SPR})(QoI_{SPR}, DoC_{SPR})\right)\Big)$$

$$\mathrm{sp}\ \Big(t, \big((7\ ,7)(1_{[7,7]},\ DoC_{[7,7]})\big), \big((0.77, 0.77)(1_{[0.77,0.77]},\ DoC_{[0.77,0.77]})\big), \big((0.80\ , 0.80)(1_{[0.8,0.8]},\ DoC_{[0.8,0.8]})\big), \big(1, (0,0)(1_{[0,0]},\ DoC_{[0,0]}\ )\big), \big((1,\ 1)(1_{[1,1]},\ DoC_{[1,1]})\big), \big((0,1)(1_{[0,1]},\ DoC_{[0,1]})\big), \big((13,\ 13)(1_{[13,13]},\ DoC_{[13,13]})\big), \big((5,\ 5)(1_{[5,5]},\ DoC_{[5,5]})\big)\Big)$$

$$:: 1 :: DoC$$

$$\underbrace{[0,3]\quad [7,15]\quad [1,4]\quad [0,1]\quad [0,6]\quad [1,65]\quad [0,1]\quad [10,1920]}_{\text{attribute`s domains}}$$

$\}$ :: 1

%The attribute’s boundaries are set to the interval [0, 1], according to a normalization process that uses the expression $(Y - Y_{min})/(Y_{max} - Y_{min})$ *%*

$\{$

$$\neg\, sp\ \Big(t, \left((A_{MT}, B_{MT})(QoI_{MT}, DoC_{MT})\right),\ \left((A_{PPES}, B_{PPES})(QoI_{PPES}, DoC_{PPES})\right), \left((A_{PIS}, B_{PIS})(QoI_{PIS}, DoC_{PIS})\right), \left((A_{PRFSP}, B_{PRFSP})(QoI_{PRFSP}, DoC_{PRFSP})\right), \left((A_{TS}\ B_{TS})(QoI_{TS}, DoC_{TS})\right), \left((A_{SS}\ B_{SS})(QoI_{SS}, DoC_{SS})\right), \left((A_{St}, B_{St})(QoI_{St}, DoC_{St})\right), \left((A_{SPR}, B_{SPR})(QoI_{SPR}, DoC_{SPR})\right)\Big)$$

$$\leftarrow not\ sp\ \ \Big(t, \left((A_{MT}, B_{MT})(QoI_{MT}, DoC_{MT})\right),\ \left((A_{PPES}, B_{PPES})(QoI_{PPES}, DoC_{PPES})\right), \left((A_{PIS}, B_{PIS})(QoI_{PIS}, DoC_{PIS})\right), \left((A_{PRFSP}, B_{PRFSP})(QoI_{PRFSP}, DoC_{PRFSP})\right), \left((A_{TS}\ B_{TS})(QoI_{TS}, DoC_{TS})\right), \left((A_{SS}\ B_{SS})(QoI_{SS}, DoC_{SS})\right), \left((A_{St}, B_{St})(QoI_{St}, DoC_{St})\right), \left((A_{SPR}, B_{SPR})(QoI_{SPR}, DoC_{SPR})\right)\Big)$$

$$\mathrm{sp}\ \Big(1, \big((0\ ,0)(1_{[0,0]},\ DoC_{[0,0]})\big), \big((0.77, 0.77)(1_{[0.77,0.77]},\ DoC_{[0.77,0.77]})\big), \big((0.80\ , 0.80)(1_{[0.8,0.8]},\ DoC_{[0.8,0.8]})\big), \big((0,0)(1_{[0,0]},\ DoC_{[0,0]}\ )\big), \big((0,\ 0)(1_{[0,0]},\ DoC_{[0,0]})\big), \big((0,1)(1_{[0,1]},\ DoC_{[0,1]})\big), \big((0.00157,\ 0.00157)(1_{[0.00157,0.00157]},\ DoC_{[0.00157,0.00157]})\big), \big((0.833,\ 0.833)(1_{[0.833,0.833]},\ DoC_{[0.833,0.833]})\big)\Big)$$

$$:: 1 :: DoC$$

$$\underbrace{[0,1]\quad [0,1]\quad [0,1]\quad [0,1]\quad [0,1]\quad [0,1]\quad [0,1]\quad [0,1]}_{\text{attribute`s domains once normalized}}$$

$\}$ :: 1

%The DoC’s values are evaluated %

$$\{\ \neg\ \mathrm{sp}\ \Big(t, \left((A_{MT}, B_{MT})(QoI_{MT}, DoC_{MT})\right),\ \left((A_{PPES}, B_{PPES})(QoI_{PPES}, DoC_{PPES})\right), \left((A_{PIS}, B_{PIS})(QoI_{PIS}, DoC_{PIS})\right),$$

$$((A_{PRFSP}, B_{PRFSP})(QoI_{PRFSP}, DoC_{PRFSP})), ((A_{TS}\ B_{TS})(QoI_{TS}, DoC_{TS})), ((A_{SS}\ B_{SS})(QoI_{SS}, DoC_{SS})),$$

$$((A_{St}, B_{St})(QoI_{St}, DoC_{St})), ((A_{SPR}, B_{SPR})(QoI_{SPR}, DoC_{SPR})))$$

$$\leftarrow not\ sp\ \ (t, ((A_{MT}, B_{MT})(QoI_{MT}, DoC_{MT})),\ ((A_{PPES}, B_{PPES})(QoI_{PPES}, DoC_{PPES})), ((A_{PIS}, B_{PIS})(QoI_{PIS}, DoC_{PIS})),$$

$$((A_{PRFSP}, B_{PRFSP})(QoI_{PRFSP}, DoC_{PRFSP})), ((A_{TS}\ B_{TS})(QoI_{TS}, DoC_{TS})), ((A_{SS}\ B_{SS})(QoI_{SS}, DoC_{SS})),$$

$$((A_{St}, B_{St})(QoI_{St}, DoC_{St})), ((A_{SPR}, B_{SPR})(QoI_{SPR}, DoC_{SPR})))$$

$$\underbrace{sp \begin{array}{c}\big(1, ((0\ ,0)(1,\ 1)),\ \ ((0.70, 0.70)(1,\ 1)),\ \ ((0.80\ ,0.80)(1,\ 1)),\ \ ((0, 0)(1,\ 1)),\ ((0,\ 0)(1,\ 1)), \\ ((0, 1)(1, 0)),\ \ ((0.0016,\ 0.0016)(1, 1)),\ \ ((0.833,\ 0.833)(1,\ 1))\big)\end{array}}_{\text{attribute`s values ranges once normalized and respective QoI and DoC values}} :: 1$$

$$:: 0.88$$

$$\underbrace{\begin{array}{ccccccccc}[0, 1] & & [0, 1] & & [0, 1] & & [0, 1] & & [0, 1] \\ & [0, 1] & & [0, 1] & & & & [0, 1] & \end{array}}_{\text{attribute`s domains once normalized}}$$

$\}$ :: 1

End

In terms of the extension of predicate *ppa*, with the feature vector *time = 3, Age = 35, Gender = 0, BMI = 22.13 , PPOS = [0.78 , 0.79]*, one may have:

Begin

%The predicate's extension that sets the Universe-of-Discourse for the term under observation is fixed%

$$\{ \qquad \neg\, \mathrm{ppa}\ \big(t, ((\mathrm{A}_{Age}, \mathrm{B}_{Age})(\mathrm{QoI}_{Age}, \mathrm{DoC}_{Age})),\ ((\mathrm{A}_{Gen}, \mathrm{B}_{Gen})(\mathrm{QoI}_{Gen}, \mathrm{DoC}_{Gen})),$$

$$((\mathrm{A}_{BMI}, \mathrm{B}_{BMI})(\mathrm{QoI}_{BMI}, \mathrm{DoC}_{BMI})), ((\mathrm{A}_{PPOS}, \mathrm{B}_{PPOS})(\mathrm{QoI}_{PPOS}, \mathrm{DoC}_{PPOS})), \big)$$

$$\leftarrow \mathrm{not\ ppa}\ \ \big(t, ((\mathrm{A}_{Age}, \mathrm{B}_{Age})(\mathrm{QoI}_{Age}, \mathrm{DoC}_{Age})),\ ((\mathrm{A}_{Gen}, \mathrm{B}_{Gen})(\mathrm{QoI}_{Gen}, \mathrm{DoC}_{Gen})),$$

$$((\mathrm{A}_{BMI}, \mathrm{B}_{BMI})(\mathrm{QoI}_{BMI}, \mathrm{DoC}_{BMI})), ((\mathrm{A}_{PPOS}, \mathrm{B}_{PPOS})(\mathrm{QoI}_{PPOS}, \mathrm{DoC}_{PPOS})), \big)$$

$$\mathrm{ppa} \begin{array}{c}\big(3, ((35\ ,35)(1_{[35,35]},\ DoC_{[35,35]})),\ \ ((0, 0)(1_{[0,0]},\ DoC_{[0,0]})),\ \ ((22.13\ , 22.13)(1_{[22.13,22.13]},\ DoC_{[22.13,22.13]})), \\ ((0.78\ , 0.79)(1_{[0.78,0.79]},\ DoC_{[0.78,0.79]}))\big)\end{array}$$

$$:: 1 :: DoC$$

$$\underbrace{\begin{array}{ccc}[0, 120] & [0, 1] & [12, 42] \\ & [0, 1] & \end{array}}_{\text{attribute`s domains}}$$

} :: 1

%The attribute's boundaries are set to the interval [0, 1], according to a normalization process that uses the expression $(Y - Y_{min})/(Y_{max} - Y_{min})$ *%*

$$\{ \quad \neg\, ppa\left(t, \left((A_{Age}, B_{Age})(QoI_{Age}, DoC_{Age})\right), ((A_{Gen}, B_{Gen})(QoI_{Gen}, DoC_{Gen})), ((A_{BMI}, B_{BMI})(QoI_{BMI}, DoC_{BMI})), ((A_{PPOS}, B_{PPOS})(QoI_{PPOS}, DoC_{PPOS})),\right)$$

$$\leftarrow not\ ppa\left(t, \left((A_{Age}, B_{Age})(QoI_{Age}, DoC_{Age})\right), ((A_{Gen}, B_{Gen})(QoI_{Gen}, DoC_{Gen})), ((A_{BMI}, B_{BMI})(QoI_{BMI}, DoC_{BMI})), ((A_{PPOS}, B_{PPOS})(QoI_{PPOS}, DoC_{PPOS})),\right)$$

$$ppa\underbrace{\left(3, \left((0.29, 0.29)\left(1_{[0.29,0.29]}, DoC_{[0.29,0.29]}\right)\right), \left((0,0)\left(1_{[0,0]}, DoC_{[0,0]}\right)\right), \left((0.34, 0.34)\left(1_{[0.34,0.34]}, DoC_{[0.34,0.34]}\right)\right), \left((0.78, 0.79)\left(1_{[0.78,0.79]}, DoC_{[0.78,0.79]}\right)\right)\right)}_{\underbrace{[0,1] \qquad [0,1] \qquad [0,1] \qquad [0,1]}_{\text{attribute`s domains once normalized}}} :: 1 :: DoC$$

} :: 1

%The DoC's values are evaluated %

$$\{ \quad \neg\, ppa\left(t, \left((A_{Age}, B_{Age})(QoI_{Age}, DoC_{Age})\right), ((A_{Gen}, B_{Gen})(QoI_{Gen}, DoC_{Gen})), ((A_{BMI}, B_{BMI})(QoI_{BMI}, DoC_{BMI})), ((A_{PPOS}, B_{PPOS})(QoI_{PPOS}, DoC_{PPOS})),\right)$$

$$\leftarrow not\ ppa\left(t, \left((A_{Age}, B_{Age})(QoI_{Age}, DoC_{Age})\right), ((A_{Gen}, B_{Gen})(QoI_{Gen}, DoC_{Gen})), ((A_{BMI}, B_{BMI})(QoI_{BMI}, DoC_{BMI})), ((A_{PPOS}, B_{PPOS})(QoI_{PPOS}, DoC_{PPOS}))\right)$$

$$ppa\underbrace{\left(3, \left((0.29, 0.29)(1, 1)\right), \left((0,0)(1, 1)\right), \left((0.34, 0.34)(1, 1)\right), \left((0.78, 0.79)(1, 1)\right)\right)}_{\text{attribute`s values ranges once normalized and respective QoI and DoC values}} :: 1 :: 0.99$$

$$\underbrace{[0,1] \qquad [0,1] \qquad [0,1] \qquad [0,1]}_{\text{attribute`s domains once normalized}}$$

} :: 1

End

In terms of the extension of predicate *surgproc*, with the feature vector *time = 1, Age = 35, Gender = 0, BMI = 22.13 , TP = 1, Pathology = 470, PI= 2, MT = 7, PPES = 0.77, PIS= 0.80 , PRFSP= 0, TS=1, SS=* $\perp$*, St= 16, SPR= 5, SP = 4, SC= 0, ICUt= 0, PACUt= 4, PPOS= [0.78 , 0.79], PPA= 4, WBt= 1, CI= 0, SH= 9.00, Surgery Waiting Time = 7, Patient Hospitalization Time = 3, Surgery Process Time= 10*, one may have:

Begin

%The predicate's extension that sets the Universe-of-Discourse for the term under observation is fixed%

$$\{ \qquad \neg\, surgproc\ \Big(t, \big((A_{Age}, B_{Age})(QoI_{Age}, DoC_{Age})\big),\ ((A_{Gender}, B_{Gender})(QoI_{Gender}, DoC_{Gender})),$$
$$\big((A_{BMI}, B_{BMI})(QoI_{BMI}, DoC_{BMI})\big), \big((A_{TP}, B_{TP})(QoI_{TP}, DoC_{TP})\big), \big((A_{Path}\ B_{Path})(QoI_{Path}, DoC_{Path})\big),$$
$$\big((A_{PI}, B_{PI})(QoI_{PI}, DoC_{PI})\big), \big((A_{MT}, B_{MT})(QoI_{PPES}, DoC_{PPES})\big), \big((A_{PIS}\ B_{PIS})(QoI_{PIS}, DoC_{PIS})\big),$$
$$\big((A_{PRFSP}, B_{PRFSP})(QoI_{PRFSP}, DoC_{PRFSP})\big), \big((A_{TS}, B_{TS})(QoI_{TS}, DoC_{TS})\big), \big((A_{SS}\ B_{SS})(QoI_{SS}, DoC_{SS})\big),$$
$$\big((A_{St}, B_{St})(QoI_{SPR}, DoC_{SPR})\big), \big((A_{SP}, B_{SP})(QoI_{SP}, DoC_{SP})\big), \big((A_{SC}\ B_{SC})(QoI_{SC}, DoC_{SC})\big), \big((A_{ICUt}\ B_{ICUt})(QoI_{ICUt}, DoC_{ICUt})\big),$$
$$\big((A_{PACUt}, B_{PACUt})(QoI_{PACUt}, DoC_{PACUt})\big), \big((A_{PPOS}, B_{PPOS})(QoI_{PPOS}, DoC_{PPOS})\big), \big((A_{PPA}\ B_{PPA})(QoI_{PPA}, DoC_{PPA})\big),$$
$$\big((A_{WBt}, B_{WBt})(QoI_{WBt}, DoC_{WBt})\big), \big((A_{CI}, B_{CI})(QoI_{CI}, DoC_{CI})\big), \big((A_{SH}\ B_{SH})(QoI_{SH}, DoC_{SH})\big),$$
$$\big((A_{SWt}\ B_{SWt})(QoI_{SWt}, DoC_{SWt})\big), \big((A_{PHt}, B_{PHt})(QoI_{PHt}, DoC_{PHt})\big), \big((A_{SPt}\ B_{SPt})(QoI_{SPt}, DoC_{SPt})\big)\Big)$$
$$\leftarrow not\ surgproc\ \ \Big(t, \big((A_{Age}, B_{Age})(QoI_{Age}, DoC_{Age}),\ ((A_{Gender}, B_{Gender})(QoI_{Gender}, DoC_{Gender})),$$
$$\big((A_{BMI}, B_{BMI})(QoI_{BMI}, DoC_{BMI})\big), \big((A_{TP}, B_{TP})(QoI_{TP}, DoC_{TP})\big), \big((A_{Path}\ B_{Path})(QoI_{Path}, DoC_{Path})\big),$$
$$\big((A_{PI}, B_{PI})(QoI_{PI}, DoC_{PI})\big), \big((A_{MT}, B_{MT})(QoI_{PPES}, DoC_{PPES})\big), \big((A_{PIS}\ B_{PIS})(QoI_{PIS}, DoC_{PIS})\big),$$
$$\big((A_{PRFSP}, B_{PRFSP})(QoI_{PRFSP}, DoC_{PRFSP})\big), \big((A_{TS}, B_{TS})(QoI_{TS}, DoC_{TS})\big), \big((A_{SS}\ B_{SS})(QoI_{SS}, DoC_{SS})\big),$$
$$\big((A_{St}, B_{St})(QoI_{SPR}, DoC_{SPR})\big), \big((A_{SP}, B_{SP})(QoI_{SP}, DoC_{SP})\big), \big((A_{SC}\ B_{SC})(QoI_{SC}, DoC_{SC})\big), \big((A_{ICUt}\ B_{ICUt})(QoI_{ICUt}, DoC_{ICUt})\big),$$
$$\big((A_{PACUt}, B_{PACUt})(QoI_{PACUt}, DoC_{PACUt})\big), \big((A_{PPOS}, B_{PPOS})(QoI_{PPOS}, DoC_{PPOS})\big), \big((A_{PPA}\ B_{PPA})(QoI_{PPA}, DoC_{PPA})\big),$$
$$\big((A_{WBt}, B_{WBt})(QoI_{WBt}, DoC_{WBt})\big), \big((A_{CI}, B_{CI})(QoI_{CI}, DoC_{CI})\big), \big((A_{SH}\ B_{SH})(QoI_{SH}, DoC_{SH})\big),$$
$$\big((A_{SWt}\ B_{SWt})(QoI_{SWt}, DoC_{SWt})\big), \big((A_{PHt}, B_{PHt})(QoI_{PHt}, DoC_{PHt})\big), \big((A_{SPt}\ B_{SPt})(QoI_{SPt}, DoC_{SPt})\big)\Big)$$

$$\text{surgproc}\quad \Big(4,\big((35,35)(1_{[35,35]},DoC_{[35,35]})\big),\big((0,0)(1_{[0,0]},DoC_{[0,0]})\big),\big((22.13,22.13)(1_{[22.13,22.13]},DoC_{[22.13,22.13]})\big), \big((1,1)(1_{[1,1]},DoC_{[1,1]})\big),\big((470,470)(1_{[470,470]},DoC_{[470,470]})\big), , \big((2,2)(1_{[2,2]},DoC_{[2,2]})\big), \big((7,7)(1_{[7,7]},DoC_{[7,7]})\big)\big((0.77,0.77)(1_{[0.77,0.77]},DoC_{[0.77,0.77]})\big),, \big((0.80,0.80)(1_{[0.80,0.80]},DoC_{[0.80,0.80]})\big), \big((0,0)(1_{[0,0]},DoC_{[0,0]})\big),\big((1,1)(1_{[1,1]},DoC_{[1,1]})\big), \big((1,65)(1_{[1,65]},DoC_{[1,65]})\big), \big((16,16)(1_{[16,16]},DoC_{[16,16]})\big),\big((5,5)(1_{[5,5]},DoC_{[5,5]})\big), \big((4,4)(1_{[4,4]},DoC_{[4,4]})\big), \big((0,0)(1_{[0,0]},DoC_{[0,0]})\big), \big((0,0)(1_{[0,0]},DoC_{[0,0]})\big) \big((4,4)(1_{[4,4]},DoC_{[4,4]})\big), \big((0.78,0.79)(1_{[0.78,0.79]},DoC_{[0.78,0.79]})\big),\big((4,4)(1_{[4,4]},DoC_{[4,4]})\big), \big((1,1)(1_{[1,1]},DoC_{[1,1]})\big), \big((0,0)(1_{[0,0]},DoC_{[0,0]})\big) \big((9.00,9.00)(1_{[9.00,9.00]},DoC_{[9.00,9.00]})\big), \big((7,7)(1_{[7,7]},DoC_{[7,7]})\big),\big((3,3)(1_{[3,3]},DoC_{[3,3]})\big),\big((10,10)(1_{[10,10]},DoC_{[10,10]})\big)\Big) :: 1 :: DoC$$

$$\underbrace{\begin{array}{ccccc} [0,120] & & [0,1] & & [12,42] \\ & [0,1] & & [0,100000] & \\ [1,5] & & [7,15] & & [0,1] \\ [1,65] & & [10,1920] & & [0,6] \\ [1,4] & & [0,1] & & [0,480] \\ [0,360] & & [0,1] & & [1,4] \\ [0,31] & & [0,1] & & [0,24] \\ [0,365] & & [0,31] & & [0,386] \end{array}}_{\text{attribute`s domains}}$$

$\} :: 1$

%The attribute's boundaries are set to the interval [0, 1], according to a normalization process that uses the expression $(Y - Y_{min})/(Y_{max} - Y_{min})$ *%*

$$\{ \quad \neg\, surgproc\ \Big(\big((A_{Age},B_{Age})(QoI_{Age},DoC_{Age})\big),\ ((A_{Gender},B_{Gender})(QoI_{Gender},DoC_{Gender})),$$

$$((A_{BMI},B_{BMI})(QoI_{BMI},DoC_{BMI})),((A_{TP},B_{TP})(QoI_{TP},DoC_{TP})),((A_{Path}\ B_{Path})(QoI_{Path},DoC_{Path})),$$

$$((A_{PI},B_{PI})(QoI_{PI},DoC_{PI})),((A_{MT},B_{MT})(QoI_{PPES},DoC_{PPES})),((A_{PIS}\ B_{PIS})(QoI_{PIS},DoC_{PIS})),$$

$$((A_{PRFSP},B_{PRFSP})(QoI_{PRFSP},DoC_{PRFSP})),((A_{TS},B_{TS})(QoI_{TS},DoC_{TS})),((A_{SS}\ B_{SS})(QoI_{SS},DoC_{SS})),$$

$$((A_{St},B_{St})(QoI_{SPR},DoC_{SPR})),((A_{SP},B_{SP})(QoI_{SP},DoC_{SP})),((A_{SC}\ B_{SC})(QoI_{SC},DoC_{SC})),((A_{ICUt}\ B_{ICUt})(QoI_{ICUt},DoC_{ICUt})),$$

$$((A_{PACUt},B_{PACUt})(QoI_{PACUt},DoC_{PACUt})),((A_{PPOS},B_{PPOS})(QoI_{PPOS},DoC_{PPOS})),((A_{PPA}\ B_{PPA})(QoI_{PPA},DoC_{PPA})),$$

$$((A_{WBt},B_{WBt})(QoI_{WBt},DoC_{WBt})),((A_{CI},B_{CI})(QoI_{CI},DoC_{CI})),((A_{SH}\ B_{SH})(QoI_{SH},DoC_{SH})),$$

$$((A_{SWt}\ B_{SWt})(QoI_{SWt},DoC_{SWt})),((A_{PHt},B_{PHt})(QoI_{PHt},DoC_{PHt})),((A_{SPt}\ B_{SPt})(QoI_{SPt},DoC_{SPt}))\Big)$$

$$\leftarrow not\ surgproc\ \Big(\Big(\big((A_{Age},B_{Age})(QoI_{Age},DoC_{Age})\big),\ ((A_{Gender},B_{Gender})(QoI_{Gender},DoC_{Gender})),$$

$$((A_{BMI},B_{BMI})(QoI_{BMI},DoC_{BMI})),((A_{TP},B_{TP})(QoI_{TP},DoC_{TP})),((A_{Path}\ B_{Path})(QoI_{Path},DoC_{Path})),$$

$$\big((A_{PI}, B_{PI})(QoI_{PI}, DoC_{PI})\big), \big((A_{MT}, B_{MT})(QoI_{PPES}, DoC_{PPES})\big), \big((A_{PIS}\ B_{PIS})(QoI_{PIS}, DoC_{PIS})\big),$$

$$\big((A_{PRFSP}, B_{PRFSP})(QoI_{PRFSP}, DoC_{PRFSP})\big), \big((A_{TS}, B_{TS})(QoI_{TS}, DoC_{TS})\big), \big((A_{SS}\ B_{SS})(QoI_{SS}, DoC_{SS})\big),$$

$$\big((A_{St}, B_{St})(QoI_{SPR}, DoC_{SPR})\big), \big((A_{SP}, B_{SP})(QoI_{SP}, DoC_{SP})\big), \big((A_{SC}\ B_{SC})(QoI_{SC}, DoC_{SC})\big), \big((A_{ICUt}\ B_{ICUt})(QoI_{ICUt}, DoC_{ICUt})\big),$$

$$\big((A_{PACUt}, B_{PACUt})(QoI_{PACUt}, DoC_{PACUt})\big), \big((A_{PPOS}, B_{PPOS})(QoI_{PPOS}, DoC_{PPOS})\big), \big((A_{PPA}\ B_{PPA})(QoI_{PPA}, DoC_{PPA})\big),$$

$$\big((A_{WBt}, B_{WBt})(QoI_{WBt}, DoC_{WBt})\big), \big((A_{CI}, B_{CI})(QoI_{CI}, DoC_{CI})\big), \big((A_{SH}\ B_{SH})(QoI_{SH}, DoC_{SH})\big),$$

$$\big((A_{SWt}\ B_{SWt})(QoI_{SWt}, DoC_{SWt})\big), \big((A_{PHt}, B_{PHt})(QoI_{PHt}, DoC_{PHt})\big), \big((A_{SPt}\ B_{SPt})(QoI_{SPt}, DoC_{SPt})\big)\Big)$$

$$\Big(\big((0.29\ ,0.29)\big(1_{[0.29\ ,0.29]},\ DoC_{[0.29,0.29]}\big)\big), \big((0,0)\big(1_{[0,0]},\ DoC_{[0,0]}\big)\big)\ , \big((0.34\ ,0.34)\big(1_{[0.34,0.34]},\ DoC_{[0.34,0.34]}\big)\big),$$

$$\big((1\ ,1)\big(1_{[1,\ \ 1]},\ DoC_{[1,1]}\big)\big), \big((0.0047,0.0047)\big(1_{[0.0047,0.0047]},\ DoC_{[0.0047,0.0047]}\big)\big),\ \ ,$$

$$\big((0.25, 0.25)\big(1_{[0.25,0.25]},\ DoC_{[0.25,0.25]}\big)\big)\ , \big((0\ ,0)\big(1_{[0,0]},\ DoC_{[0,0]}\big)\big)\ \big((0.77\ ,0.77)\big(1_{[0.77,0.77]},\ DoC_{[0.77,0.77]}\big)\big),,$$

$$\big((0.80, 0.80)\big(1_{[0.80,0.80]},\ DoC_{[0.80,0.80]}\big)\big)\ ,\ \ \big((0\ ,0)\big(1_{[0,0]},\ DoC_{[0,0]}\big)\big), \big((0\ ,0)\big(1_{[0,0]},\ DoC_{[0,0]}\big)\big),$$

$$\big((0, 1)\big(1_{[0,1]},\ DoC_{[0,1]}\big)\big)\ , \big((0.0031\ ,0.0031)\big(1_{[0.0031,0.0031]},\ DoC_{[0.0031,0.0031]}\big)\big),$$

surgproc

$$\big(4, (0.83,0.83)\big(1_{[0.83\ 0.83]},\ DoC_{[0.830.83]}\big)\big), \big((1\ ,1)\big(1_{[1,1]},\ DoC_{[1,1]}\big)\big)\ , \big((0\ ,0)\big(1_{[0,0]},\ DoC_{[0,0]}\big)\big),$$

$$\big((0\ ,0)\big(1_{[0,0]},\ DoC_{[0,0]}\big)\big), \big((0.011, 0.011)\big(1_{[0.011,0.011]},\ DoC_{[0.011,0.011]}\big)\big)\ ,$$

$$\big((\ 0.78,0.79)\big(1_{[0.78,0.79]},\ DoC_{[0.78,0.79]}\big)\big), \big((1\ ,1)\big(1_{[1,\ \ 1]},\ DoC_{[1,1]}\big)\big),$$

$$\big((0.032, 0.032)\big(1_{[0.032\ \ \ 0.032]},\ DoC_{[0.032,0.032]}\big)\big), \big((0\ ,0)\big(1_{[0,0]},\ DoC_{[0,0]}\big)\big),$$

$$\big((\ 0.375, 0.375)\big(1_{[0.375,0.375]},\ DoC_{[0.375,0.375]}\big)\big), \big((0.019\ ,0.019)\big(1_{[0.019,0.019]},\ DoC_{[0.019,0.019]}\big)\big)$$

$$\big((0.097\ ,0.097)\big(1_{[0.097,0.097]},\ DoC_{[0.097,0.097]}\big)\big), \big((0.026\ ,0.026)\big(1_{[0.026,0.026]},\ DoC_{[0.049,0.026]}\big)\big)\Big)$$

$:: 1 :: DoC$

$$\underbrace{\begin{array}{ccccc}
[0,1] & & [0,1] & & [0,1] \\
& [0,1] & & [0,1] & \\
[0,1] & & [0,1] & & [0,1] \\
[0,1] & & [0,1] & & [0,1] \\
& [0,1] & & [0,1] & \\
[0,1] & & [0,1] & & [0,1] \\
& [0,1] & & [0,1] & \\
& [0,1] & & [0,1] & \\
& [0,1] & & [0,1] & \\
& [0,1] & & [0,1] & \\
& [0,1] & & [0,1] &
\end{array}}_{\text{attribute`s domains once normalized}}$$

$\} :: 1$

%The DoC's values are evaluated %

$$\{\qquad \neg\, surgproc\ \Big(t, \big((A_{Age}, B_{Age})(QoI_{Age}, DoC_{Age})\big),\ \big((A_{Gender}, B_{Gender})(QoI_{Gender}, DoC_{Gender})\big),$$

$$\big((A_{BMI}, B_{BMI})(QoI_{BMI}, DoC_{BMI})\big), \big((A_{TP}, B_{TP})(QoI_{TP}, DoC_{TP})\big), \big((A_{Path}\ B_{Path})(QoI_{Path}, DoC_{Path})\big),$$

$$\big((A_{PI}, B_{PI})(QoI_{PI}, DoC_{PI})\big), \big((A_{MT}, B_{MT})(QoI_{PPES}, DoC_{PPES})\big), \big((A_{PIS}\ B_{PIS})(QoI_{PIS}, DoC_{PIS})\big),$$

$$\big((A_{PRFSP}, B_{PRFSP})(QoI_{PRFSP}, DoC_{PRFSP})\big), \big((A_{TS}, B_{TS})(QoI_{TS}, DoC_{TS})\big), \big((A_{SS}\ B_{SS})(QoI_{SS}, DoC_{SS})\big),$$

$$\big((A_{St}, B_{St})(QoI_{SPR}, DoC_{SPR})\big), \big((A_{SP}, B_{SP})(QoI_{SP}, DoC_{SP})\big), \big((A_{SC}\ B_{SC})(QoI_{SC}, DoC_{SC})\big), \big((A_{ICUt}\ B_{ICUt})(QoI_{ICUt}, DoC_{ICUt})\big),$$

$$\big((A_{PACUt}, B_{PACUt})(QoI_{PACUt}, DoC_{PACUt})\big), \big((A_{PPOS}, B_{PPOS})(QoI_{PPOS}, DoC_{PPOS})\big), \big((A_{PPA}\ B_{PPA})(QoI_{PPA}, DoC_{PPA})\big),$$

$$\big((A_{WBt}, B_{WBt})(QoI_{WBt}, DoC_{WBt})\big), \big((A_{CI}, B_{CI})(QoI_{CI}, DoC_{CI})\big), \big((A_{SH}\ B_{SH})(QoI_{SH}, DoC_{SH})\big),$$

$$\big((A_{SWt}\ B_{SWt})(QoI_{SWt}, DoC_{SWt})\big), \big((A_{PHt}, B_{PHt})(QoI_{PHt}, DoC_{PHt})\big), \big((A_{SPt}\ B_{SPt})(QoI_{SPt}, DoC_{SPt})\big)\Big)$$

$$\leftarrow not\ surgproc\ \ \Big(t, \big((A_{Age}, B_{Age})(QoI_{Age}, DoC_{Age}\big),\ \big((A_{Gender}, B_{Gender})(QoI_{Gender}, DoC_{Gender})\big),$$

$$\big((A_{BMI}, B_{BMI})(QoI_{BMI}, DoC_{BMI})\big), \big((A_{TP}, B_{TP})(QoI_{TP}, DoC_{TP})\big), \big((A_{Path}\ B_{Path})(QoI_{Path}, DoC_{Path})\big),$$

$$\big((A_{PI}, B_{PI})(QoI_{PI}, DoC_{PI})\big), \big((A_{MT}, B_{MT})(QoI_{PPES}, DoC_{PPES})\big), \big((A_{PIS}\ B_{PIS})(QoI_{PIS}, DoC_{PIS})\big),$$

$$\big((A_{PRFSP}, B_{PRFSP})(QoI_{PRFSP}, DoC_{PRFSP})\big), \big((A_{TS}, B_{TS})(QoI_{TS}, DoC_{TS})\big), \big((A_{SS}\ B_{SS})(QoI_{SS}, DoC_{SS})\big),$$

$$\big((A_{St}, B_{St})(QoI_{SPR}, DoC_{SPR})\big), \big((A_{SP}, B_{SP})(QoI_{SP}, DoC_{SP})\big), \big((A_{SC}\ B_{SC})(QoI_{SC}, DoC_{SC})\big), \big((A_{ICUt}\ B_{ICUt})(QoI_{ICUt}, DoC_{ICUt})\big),$$

$$\big((A_{PACUt}, B_{PACUt})(QoI_{PACUt}, DoC_{PACUt})\big), \big((A_{PPOS}, B_{PPOS})(QoI_{PPOS}, DoC_{PPOS})\big), \big((A_{PPA}\ B_{PPA})(QoI_{PPA}, DoC_{PPA})\big),$$

$$\big((A_{WBt}, B_{WBt})(QoI_{WBt}, DoC_{WBt})\big), \big((A_{CI}, B_{CI})(QoI_{CI}, DoC_{CI})\big), \big((A_{SH}\ B_{SH})(QoI_{SH}, DoC_{SH})\big),$$

$$\big((A_{SWt}\ B_{SWt})(QoI_{SWt}, DoC_{SWt})\big), \big((A_{PHt}, B_{PHt})(QoI_{PHt}, DoC_{PHt})\big), \big((A_{SPt}\ B_{SPt})(QoI_{SPt}, DoC_{SPt})\big)\Big)$$

$$\text{surgproc}\ \underbrace{\begin{gathered}\Big(4, \big((0.29\,, 0.29)(1,\ 1)\big), \big((0, 0)(1,\ 1)\big)\,, \big((0.34\,, 0.34)(1,\ 1)\big), \big((1, 1)(1,\ 1)\big),\ \big((0.0047,\ 0.0047)(1, 1)\big),\\ \big((0.25, 0.25)(1, 1)\big),\ \big((0, 0)(1, 1)\big), \big((0.77,\ 0.77)(1,\ 1)\big), \big((0.80,\ 0.80)(1,\ 1)\big), \big((0,\ 0)(1,\ 1)\big), \big((0, 0)(1, 1)\big),\\ \big((0, 1)(1, 0)\big), \big((0.0031,\ 0.0031)(1,\ 1)\big), \big((0.83,\ 0.83)(1,\ 1)\big), \big((1,\ 1)(1,\ 1)\big), \big((0, 0)(1, 1)\big),\\ \big((0, 0)(1, 1)\big), \big((0.011,\ 0.011)(1,\ 1)\big), \big((0.78,\ 0.79)(1,\ 0.99)\big), \big((1,\ 1)(1,\ 1)\big), \big((0.032, 0.032)(1, 1)\big),\\ \big((0, 0)(1, 1)\big), \big((0.375,\ 0.375)(1,\ 1)\big), \big((0.019,\ 0.019)(1,\ 1)\big), \big((0.097,\ 0.097)(1,\ 1)\big),\\ \big((0.026,\ 0.026)(1,\ 1)\big)\Big)\end{gathered}}_{\text{attribute`s values ranges once normalized and respective QoI and DoC values}}$$

$$::\ 1\ ::\ 0.99$$

$$\underbrace{\begin{gathered}[0, 1]\quad [0, 1]\quad [0, 1]\quad [0, 1]\quad [0, 1]\\ [0, 1]\quad [0, 1]\quad [0, 1]\quad [0, 1]\quad [0, 1]\quad [0, 1]\\ [0, 1]\quad [0, 1]\quad [0, 1]\quad [0, 1]\quad [0, 1]\\ [0, 1]\quad [0, 1]\quad [0, 1]\quad [0, 1]\quad [0, 1]\\ [0, 1]\quad [0, 1]\quad [0, 1]\quad [0, 1]\\ [0, 1]\end{gathered}}_{\text{attribute`s domains once normalized}}$$

$$\}::\ 1$$

End

CHAPTER 7

LOGICAL PROGRAMMING APPROACH TO CASE-BASED REASONING

As previously mentioned, the surgery process is composed by multiple sources of complex and important information that needs to be taken into account in order to obtain an efficient model. Therefore, the computing approach applied to the existing data needs to be capable of processing all the information in an efficient and reliable way, in order to obtain a successful case. Thus, the most suitable main approach to use in the case of the surgery process was the CBR, since it provides the capability of solving a new case of patients that are in need of a surgical intervention, by using or adapting past similar successful surgery processes with the similar historical data organization. However, since the surgery process is composed by multiple sources of data, unknown and incomplete information is a constant on the data obtained, consequently, the actual CBR systems cannot be efficiently applied to the process, that would result in an inaccurate solution that could cost a successful case of surgery performed.

In this chapter a new approach is described where there is a junction of LP with the same structure presented on Chapter 5, using the CBR approach and presenting a new and more precise cycle to the process.

7.1 Case-Based Reasoning approach to Computing

As described on chapter 4, the CBR approach to computing has the ability to search and justify a valid solution to a given problem by reusing knowledge acquired from past experiences (i.e. solves new problems based on similar past solutions) (Aamodt & Plaza, 1994). The CBR process takes advantage of the cases' terms and solutions similarities, in order to find in its repository of cases a past case with the most suitable solution for a new one, even if the backgrounds differ. This means that the knowledge acquired when solving some situation can be used as a first approach to solve new ones (Balke et al, 2009).

In the current days, CBR has a tremendous potential of use in several areas, like Law, Medicine, among many others. But it faces a great obstacle of implementation, since the availability of data is scarce and the cost of obtaining such is high (Stahl and Gabel, 2006).

As it was already explained in chapter 4, the typical CBR cycle (Figure 1) has a consistent model, that is composed by the next phases. First with the description of the problem with knowledge that is used to *Retrieve* one or more cases from the *repository*, by retrieving the cases with the higher degree of similar characteristics with the new case. Then, a solution for the new problem is proposed on the *Reuse* phase, where the solution is reused, tested and adapted to the new case in order to obtain the solution (Aamodt & Plaza, 1994). Next, there is the *Revise* stage, were the suggested solution is tested by the user that creates the Test Repaired Case, which sets the solution of the new problem by correcting, adapting or changing the suggested solution. This feedback from the user is essential, since automatic adaptation in existing systems is almost impossible. It also implies an iterative process, since the solution proposed by the user must be tested and adapted while the result of applying that solution is unsatisfying. As for the Retain (or learning) phase the case is learned and the repository is updated with the new one.

The existent CBR systems are neither complete nor adaptable enough for all domains. In some cases, the user is required to follow the similarity method defined by the system, even if it does not fit user's needs. The current CBR system face an incapacity of dealing with unknown and incomplete information. Contrasting, this new approach presented, will be completely generic and it will have the capacity of dealing with those type of information.

The existing CBR tools follow different approaches to problem solving, i.e., looking at same patterns from different perspectives. However, they all look too complex and the effort to adapt them to a specific problem domain is comparable to develop a full new CBR. Also, an important feature that often is discarded is the ability to compare strings. In some problem domains, strings are important to describe a situation, the problem in itself or even an event. If the CBR is only prepared to work with number, then this gap will prove to be fatal. Therefore, this approach will use several of the most popular string similarity algorithms, namely the Dice Coefficient (Dice, 1945), Jaro Winkler (Winkler, 1990) and the Levenshtein Distance (Levenshtein, 1966), and have the possibility of set the weight of a particular attribute along the attributes that make a case's argument. With this new approach a new perception of this methodology for problem solving will be potentiated, going in depth in aspects like the case's *Quality-of-Information* (QoI) or the *Degree-of-Confidence* (DoC), a measure of one's confidence that the value of a particular attribute is the expect one. With this approach it will be possible to handle unknown, incomplete or even contradictory data. It will also change the typical CBR cycle presented on the Figure 1 of chapter 4. This new cycle will have into consideration a normalization phase, with the attributes values of the case argument being set in the interval $[0,\ 1]$, therefore making easier their DoCs evaluation. It will also improve performance and reliability of the similarity strategy. The Case Base will be given in terms of triples that follow the pattern:

Case= {<*Raw-case*, *Normalized-case*, *Description-case*>} where *Raw-case* and *Normalized-case* stand for themselves, and *Description-case* is made on a set of strings or even in free text, which may be analysed with specific string similarity algorithms.

This CBR cycle also contemplates a cases optimization process present in the *Case Base*, whenever they do not comply with the terms under which a given problem as to be addressed (e.g., the expected DoC on a predication was not attained). In this process may be used Artificial Neural Networks (Haykin, 2009; Vicente et al.,2012), Particle Swarm Optimization (Mendes Kennedy, & Neves, 2003) or Genetic Algorithms (Neves et al. 2007), just to name a few. Indeed, the optimization process generates a set of new cases which must be in conformity with the invariant:

$$\bigcap_{i=1}^{n} (\boldsymbol{B_i}, \boldsymbol{E_i}) \neq \emptyset \tag{8.1.1}$$

that states that the intersection of the attribute's values ranges for the cases' set that make the *Case Base* or their optimized counterparts (B_i) (being *n* its cardinality), and the ones that were object of a process of optimization (E_i), cannot be empty.

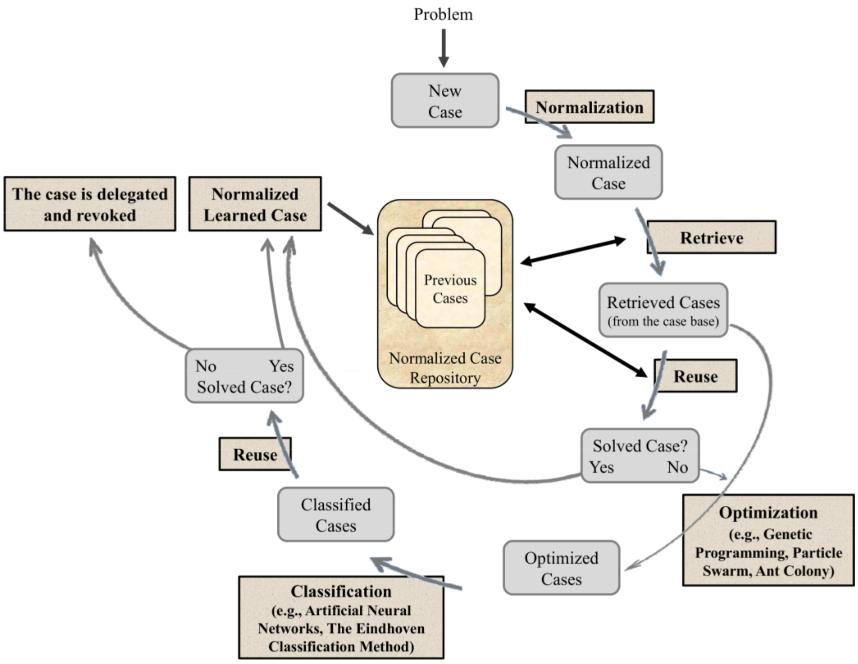


Figure 12 – The extended view of the CBR cycle.

7.2 Time Knowldge Representation on Case-Based Reasoning

As it was presented on Chapter 6, time will be considered on this approach, this mean that a chronological record of the arguments changes through the surgery process will be taken into account. Changes on the cases structure, will also update the way that the CBR retrieves past cases. With the presence of a time historical record of each argument present on a case, the similarity of a single argument will not only take into account the characteristics of the argument, but will also implements a similarity analyse to the time record of the argument, this means, that similarity of certain arguments will increase and others decrease. Some cases that were thought to be successful, but present low time similarity in the arguments, will decrees is similarity. However, some cases that were thought to be unsuccessful, but present high time similarity in the arguments, will be taken into account optimizing the process of *Retrieval* of the CBR process.

Other advantage is that the predictability of a certain event will be increased, meaning that, when the process is use on real time prediction, the time arguments will be changing through the process. Due to the constant adaptation of the knowledge present in the case, the prediction of the success of the new case will be changing, resulting in a view changer for some situations, since the path of a successful case will be traced. This can serve as an alert indicator to the user or to the system about the changes on the success of the new case. When a problem occurs and some arguments are changed, the state time path will alert about the changes on the success, by optimizing and proposing a more efficient case that has more time resembles to the present one. Likewise, it can also be an alert to the user that outside changes need to be made in order to not jeopardize the success of the current case, decreasing the uncertainty present through the process.

When the expectation for the case fail during the process, understanding and reminding prior explanation may be useful to help resolve the anomalies present in the input. Therefore, in the presence of a fail case, the historical record can help to understand the cause of such outcome, improving the efficiency of the optimization for a new case, changing it into a successful outcome.

Consequently, with the use of such approach it will improve not only the experience of the patient when submitted to a surgical intervention, but also the health services reliability.

CHAPTER 8

COMPUTING APPROACH FOR THE SURGERY PROCESS

As mentioned, multiple sources of complex and important information needs to be taken into account, in order to obtain an efficient model. The computing approach applied to the existing data needs to be capable of processing all the information in an efficient and reliable way, in order to obtain a successful case. As showed on the chapter 7, the surgery process is composed by multiple stages that complete the surgery process as a whole, therefore the computing approach presented in this chapter will be composed by a hybrid *CBR* and *ANN* approach, composed by three *ANN* processes that will be used as classification for some data, that will create new important parameters which will be taken into account when using the CBR process as the final stage.

The framework presented previously, shows how the information comes together and how it is processed. In this chapter, soft computing approaches were set to mode the universe of discourse, where the computational part is based on a hybrid *CBR* and *ANN* approach to computing.

8.1 Artificial Neural Netwroks approach to computing

In this section, a data mining approach to deal with the processed information is considered. It is set a soft computing approach to model the universe of discourse, where the computational part is based on *ANNs* which are used not only to structured data but also to capture objective function's nature (i.e., the relationships between inputs and outputs).

Considering the approach capacity of dealing with incomplete information and the necessity of an efficient classifier with the capacity of the obtainment of the *DoC* associated to the result. The most appropriated choice fell on ANNs, due to their dynamics characteristics like adaptability, robustness and flexibility, simulating the structure of the human brain and being populated by multiple layers of neurons with valuable set of activation functions.

In the surgery process model, the *ANNs* process will be used as an classifier for three different extensions of predicates, namely ***p****athology* ***i****ncidence* (*pi*), ***s****urgery* ***p****erformance* (*sp*) and ***p****atient* ***p****ostoperative* ***a****ssessment* (*ppa*).

In each extension of predicate, the normalized values of the interval boundaries and their *DoCs* and *QoIs* values (i.e., the tuple minimum, maximum, *DoC*, *QoI*) work as inputs to the ANNs. Also the time tuple is excluded from the input values since the use isn't needed for the process.

In terms of the extension of predicate *pi*, in the Figure14, a case can be seen being submitted for a pathology incidence assessment, where the output is given in terms of a pathology incidence value and the degree of confidence that one has on such a happening. Exemplifying with the arguments *Age, Gender, BMI, Pathology* and *Symptoms*, one may have (0.29, 0.29, 1, 1); (0, 0, 1, 1); (0.34, 0.34, 1, 1); (0.0047, 0.0047, 1, 1) and (0.24, 0.37, 1, 0.99). The output depicts the pathology incidence value of the degree of incidence that a pathology has in the patient being respectively 1 (one) for *Non*, 2 (two) for Low, 3 (three) for Moderate, 4 (four) for High and 5 (five) for Very High, plus the confidence that one has on such happening.

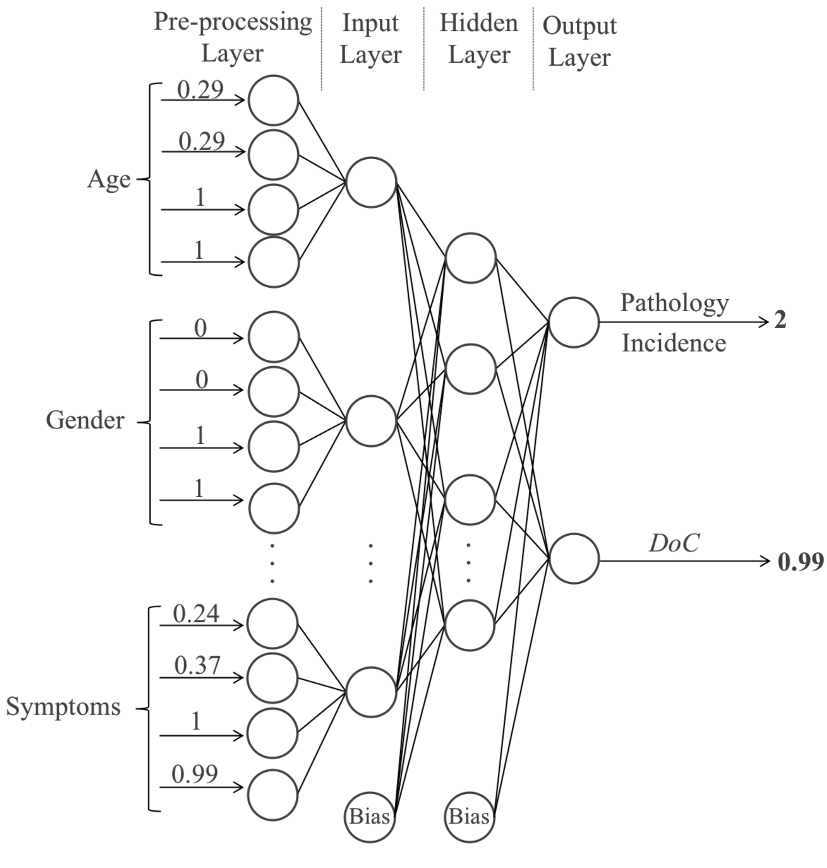


Figure 13– The Artificial Neural Network Topology for the Pathology Incidence.

In terms of the extension of predicate sp, in the Figure 15, a case can be seen being submitted for a surgery performance assessment, where the output is given in terms of performance state of the surgery value and the degree of confidence that one has on such a happening. Exemplifying with the arguments *MT, PPES, PIS, PRFSP, TS, SS, St* and *SPR*, one may have (0, 0, 1, 1); (0.70, 0.70, 1, 1); (0.80, 0.80, 1, 1); (0, 0, 1, 1); (0, 0, 1, 1); (0, 1, 1, 0); (0.0016, 0.0016, 1, 1) and (0.833, 0.833, 1, 1). The output depicts the surgery performance value degree of the performance state of the surgery, resulting into the respectively possibilities of 1 (one) if *Cancelled*, 2 (two) if *Delayed*, 3 (three) if *Operating* and 4 (four) if *Performed*, plus the confidence that one has on such happening.

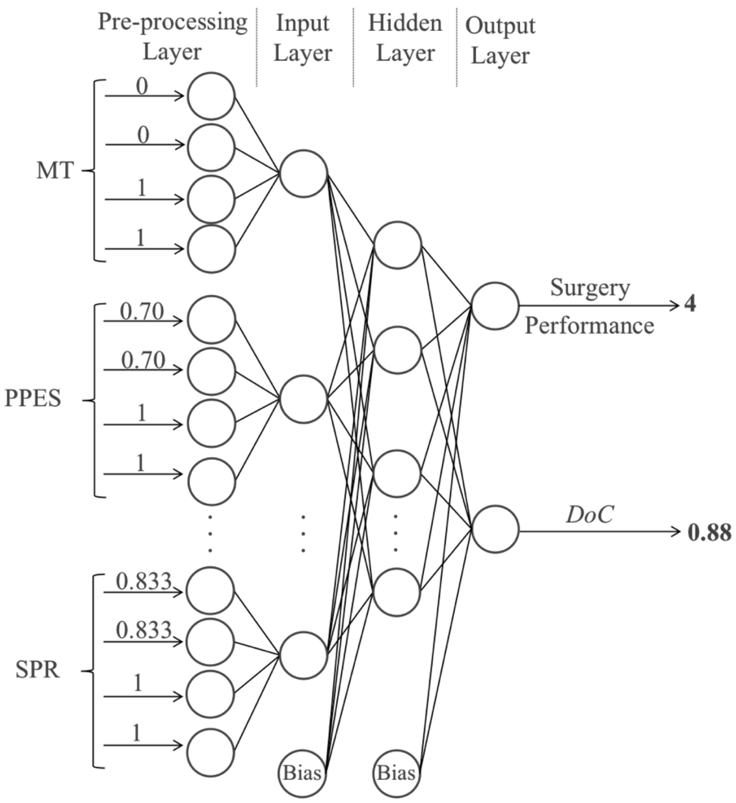


Figure 14 – The Artificial Neural Network Topology for the Surgery Performance.

In terms of the extension of predicate ppa, in the Figure 16, a case is being submitted for a patient postoperative assessment, where the output is given in terms of a pathology incidence value and the degree of confidence that one has on such a happening. Exemplifying with the arguments *Age, Gender, BMI, PPOS,* one may have (0.29, 0.29, 1, 1); (0, 0, 1, 1); (0.34, 0.34, 1, 1) and (0.78, 0.79, 1, 0.99). The output depicts the *Patient Postoperative*

Assessment value of the degree of the state of the patient health being respectively 1 (one) for *Unhealthy*, 2 (two) for *Unstable*, 3 (three) for *Stable* and 4 (four) for *Healthy*, plus the confidence that one has on such happening.

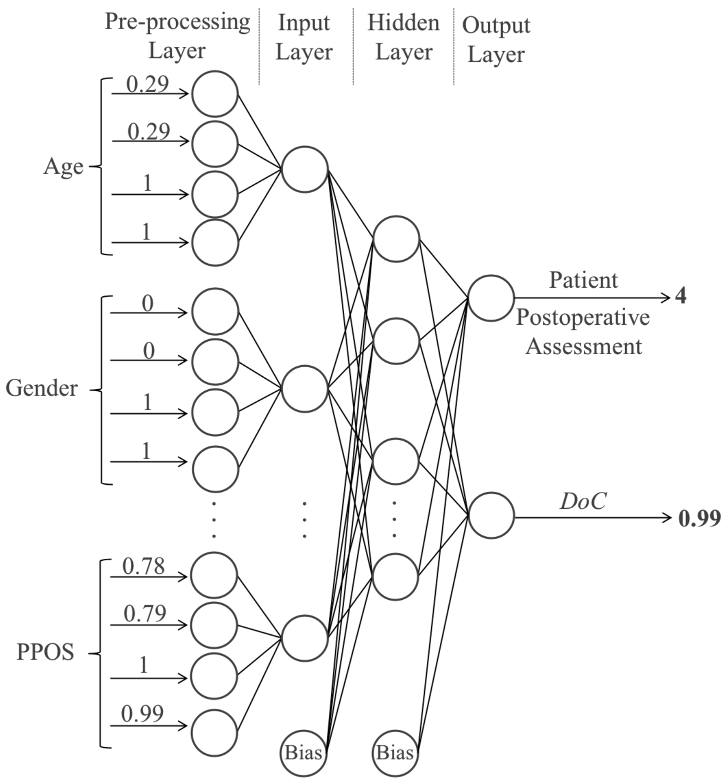


Figure 15 – The Artificial Neural Network Topology for the Patient Postoperative Assessment.

8.2 Case-Based Approach to Computing

In this section is set the formal model of the universe of discourse, where the computational part is based on a *CBR* approach to computing. Contrasting with other problem solving tools (e.g., those that use in almost all the situations the work is performed at query time. The main difference between this approach and the typical *Case-Based* one relies on the fact that, not only all the cases have their arguments set in the interval [0, 1], but also a situation that is complemented with the prospect of handling incomplete, unknown, or even self-contradictory data, information or knowledge (Figure 12).

When confronted with a new case, the system is able to retrieve all cases that meet such a structure and optimize, when necessary, such a population, i.e., it considers the attributes *DoC's* value of each case or of their optimized counterparts when analyzing similarities among them. Thus, under the occurrence of a new case, the goal is to find similar cases in the *Case Base*.

Having this in mind, the algorithm described above is applied to a new case, that presents the feature vector (*Age = 45, Gender = 1, BMI = 30,09 , TP = 1, Pathology = 36610, PI= 2, MT = 7, PPES = 0.75, PIS= 0.80 , PRFSP= 0, TS=1, SS= 36, St= 15, SPR= 5, SP = 4, SC= 0, ICUt= 0, PACUt= 4, PPOS= [0.68 , 0.70], PPA= 4, WBt= 1, CI= 0, SH= 10.00, Surgery Waiting Time = 10, Patient Hospitalization Time = 1, Surgery Process Time= 11*), having in consideration that the cases being retrieved from the *Case Base* satisfy the invariant of the equation 5 on section 8.1, which denotes that the intersection of the attributes range in the cases that makes the *Case Base* repository or their optimized counterparts (***B****i*), and the equals in the new case (***E****i*), and the equals in the new case (***E****i*), cannot be empty. Then, the computational process may be continued. With the outcome (once applying the algotithm presented in Fernandes et al. (2015):

$$\underbrace{surgproc_{new} \begin{array}{c} \left(\left((0.38, 0.38)(1, 1)\right), \left((1,1)(1, 1)\right), \left((0.60, 0.60)(1, 1)\right), \left((1,1)(1, 1)\right), \left((0.3661, 0.3661)(1,1)\right), \right. \\ ((0.25, 0.25)(1,1)), ((0,0)(1,1)), \left((0.75, 0.75)(1, 1)\right), \left((0.79, 0.79)(1, 1)\right), \left((0, 0)(1, 1)\right), ((0,0)(1,1)), \\ ((0.55, 0.55)(1,1)), \left((0.0026, 0.0026)(1, 1)\right), \left((0.83, 0.83)(1, 1)\right), \left((1, 1)(1, 1)\right), ((0,0)(1,1)), \\ ((0,0)(1,1)), \left((0.011, 0.011)(1, 1)\right), \left((0.68, 0.70)(1, 0.99)\right), \left((1, 1)(1, 1)\right), ((0.032, 0.032)(1,1)), \\ ((0,0)(1,1)), \left((0.42, 0.42)(1, 1)\right), \left((0.027, 0.027)(1, 1)\right), \left((0.032, 0.032)(1, 1)\right), \\ \left. \left((0.029, 0.029)(1, 1)\right)\right) \end{array} :: 1 :: 0.99}_{new\ case}$$

Now, the *new case* may be portrayed on the *Cartesian* plane in terms of its QoI and DoC, and by using clustering methods (Figueiredo, Esteves, Neves & Vicente, 2016) it is feasible to identify the cluster(s) that intermingle with the *new one* (epitomized as a square in Figure 16). The *new case* is compared with every retrieved case from the clusters using a similarity function sim, given in terms of the average of the modulus of the arithmetic difference between the arguments of each case of the selected cluster and those of the *new case,* which is crucial when different clustering methods are examined. Thus, one may have:

$$
\underbrace{
\begin{array}{lcr}
surgproc_1 & \begin{array}{c}
\big(\big((0.50, 0.50)(1, 1)\big), \big((1,1)(1, 1)\big), \big((0.90, 0.90)(1, 1)\big), \big((1,1)(1, 1)\big), ((0,1)(1,0)), \\
((0.25, 0.25)(1,1)), ((0,0)(1,1)), \big((0.64, 0.84)(1, 0.97)\big), \big((0.64, 0.80)(1, 0.99)\big), \big((0, 0)(1, 1)\big), ((0,0)(1,1)), \\
((0.55, 0.55)(1,1)), \big((0.0031, 0.0031)(1, 1)\big), \big((0.83, 0.83)(1, 1)\big), \big((1, 1)(1, 1)\big), ((0,0)(1,1)), \\
((0,0)(1,1)), \big((0.014, 0.014)(1, 1)\big), \big((0.43, 0.88)(1, 0.89)\big), \big((1, 1)(1, 1)\big), ((0,1)(1,0)), \\
((0,0)(1,1)), \big((0.46, 0.46)(1, 1)\big), \big((0.025, 0.025)(1, 1)\big), \big((0, 1)(1, 0)\big), \\
\big((0.034, 0.034)(1, 1)\big)\big)
\end{array} & :: 1 :: 0.87 \\
surgproc_2 & \begin{array}{c}
\big(\big((0.38, 0.38)(1, 1)\big), \big((1,1)(1, 1)\big), \big((0.97, 0.97)(1, 1)\big), \big((1,1)(1, 1)\big), \big((0.3661, 0.3661)(1,1)\big), \\
((0.25, 0.25)(1,1)), ((0,0)(1,1)), \big((0.70, 0.70)(1, 1)\big), \big((0.78, 0.78)(1, 1)\big), \big((0, 0)(1, 1)\big), ((0,0)(1,1)), \\
((0.55, 0.55)(1,1)), \big((0.0026, 0.0026)(1, 1)\big), \big((0.83, 0.83)(1, 1)\big), \big((1, 1)(1, 1)\big), ((0,0)(1,1)), \\
((0,0)(1,1)), \big((0.014, 0.014)(1, 1)\big), \big((0.67, 0.70)(1, 0.99)\big), \big((1, 1)(1, 1)\big), ((0.032, 0.032)(1,1)), \\
((0,0)(1,1)), \big((0.42, 0.42)(1, 1)\big), \big((0.022, 0.022)(1, 1)\big), \big((0.032, 0.032)(1, 1)\big), \\
\big((0.023, 0.023)(1, 1)\big)\big)
\end{array} & :: 1 :: 0.99 \\
 & \vdots & \\
surgproc_j & \begin{array}{c}
\big(\big((0.39, 0.39)(1, 1)\big), \big((1,1)(1, 1)\big), \big((0.53, 0.53)(1, 1)\big), \big((1,1)(1, 1)\big), \big((0.3661, 0.3661)(1,1)\big), \\
((0.25, 0.25)(1,1)), ((0,0)(1,1)), \big((0.73, 0.73)(1, 1)\big), \big((0.78, 0.78)(1, 1)\big), \big((0, 0)(1, 1)\big), ((0,0)(1,1)), \\
((0.55, 0.55)(1,1)), \big((0.0016, 0.0016)(1, 1)\big), \big((0.83, 0.83)(1, 1)\big), \big((1, 1)(1, 1)\big), ((0,0)(1,1)), \\
((0,0)(1,1)), \big((0.0111, 0.0111)(1, 1)\big), \big((0.68, 0.70)(1, 0.99)\big), \big((1, 1)(1, 1)\big), ((0.032, 0.032)(1,1)), \\
((0,0)(1,1)), \big((0.43, 0.43)(1, 1)\big), \big((0.033, 0.033)(1, 1)\big), \big((0.032, 0.032)(1, 1)\big), \\
\big((0.033, 0.033)(1, 1)\big)\big)
\end{array} & :: 1 :: 0.99
\end{array}
}_{normalized\ cases\ from\ retrieved\ cluster}
$$

Assuming that every attribute has equal weight, for the sake of presentation, the dissimilarity between $surgproc_{new}$ and the $surgproc_1$, i.e., $surgproc_{new \rightarrow 1}$, may be computed as follows:

$$
surgproc_{new \rightarrow 1}^{DoC} = \frac{\begin{array}{c}
\|1-1\| + \|1-1\| + \|1-1\| + \|1-1\| + \|1-0\| + \|1-1\| + \|1-1\| \\
+\|1-0.97\| + \|1-0.99\| + \|1-1\| + \|1-1\| + \|1-1\| + \|1-1\| + \|1-1\| + \|1-1\| \\
+\|1-1\| + \|1-1\| + \|1-1\| + \|0.99-0.89\| + \|1-1\| + \|1-0\| + \|1-1\| + \|1-1\| \\
+\|1-1\| + \|1-0\| + \|1-1\|
\end{array}}{26} = 0.12
$$

Thus, the similarity for $surgproc_{new\rightarrow 1}^{DoC}$ is set as *1 – 0.12 = 0.88.* Regarding the QoI the procedure is similar, returning $surgproc_{new\rightarrow 1}^{QoI} = 1$. Thus, one may have:

$$surgproc_{new\rightarrow 1}^{QoI,\,DoC} = 1 \times 0.88 = \ 0.88$$

As for the Descriptions (i.e. the surgery process observations), it will be compared using String Similarity Algorithms, as stated before, in order to get a similarity measure between them.

These procedures should be applied to the remaining cases of the retrieved clusters in order to obtain the most similar ones, which may stand for the possible solutions to the problem.

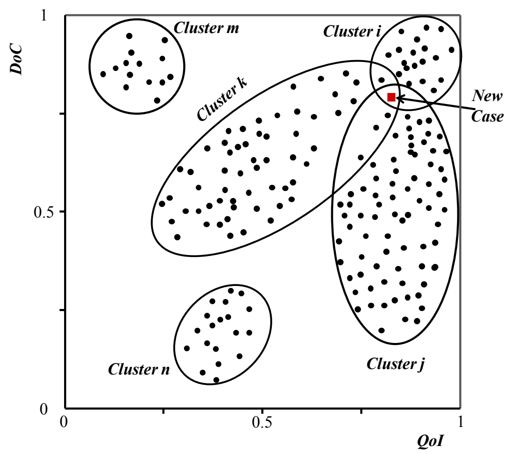


Figure 16 — A case's set clusters.

The present model, beyond to consider the surgery process, enables the integration of surgery process related data with other factors, such as patient and hospital related data, being assertive in the prediction of a successful surgery process. Thus, it can be claimed that the proposed model is able to evaluate the surgery process for each patient needing some type of surgical intervention, being a major contribution to achieve high standards concerning health services efficiency and patient health improvement.

CHAPTER 9

CONCLUSION

In this thesis, it was discussed a Case-Based Reasoning approach to the surgery process. To this end, multiple factors were needed to be taken into account, since the complexity of the surgical process requires great efforts from several hospital services in order to obtain a successful procedure. From the moment the patient is presented with a pathology that needs a surgical procedure to the end of the process where it is discharged from the hospital, several efforts are made, resources are used, unpredictability's happened and changes are constantly made. It is undeniable that the complete process has a constant presence of uncertainty and variability that could cost the success of a surgical procedure, therefore an efficient model needs to be used in order to deal with this issues, which will maximize the surgical efficiency and quality of service provided to the patient.

Thus, the proposed methodology solves the problem with the development of an intelligent support system that is able to give an adequate response to predict a successful surgery process, that takes into account all the data present through the process related to the hospital and patient. The system takes into account the three periods of hospital intervention on the patient respectively, the perioperative, intraoperative and postoperative. Beginning on the perioperative period, with the admission of the patient were is health state data is taken into account and processed by an ANN that classifies the degree of urgency for surgery execution in order to help with the scheduling of the operation. Then in the intraoperative period all the data related to the patient and to the hospital resources, in order to perform the surgery, will be processed by other ANN that will classify the success of the performance. As for the postoperative period, the system will take into account all the data related to the recovery of the patient by processing the patient health condition through the ANN process to classify the health state degree of the patient in order to be discharged. Finally, the complete process is taken by the CBR system in order to be used on future similar cases, which could result on a successful surgery process when presented with a new case of a patient with the same characteristics.

The CBR approach was the best choice in this situation, since it has the capacity of providing a solution for the complete process based on the past experience of other processes with the same characteristics.

An important aspect of the work is the capacity to handle incomplete, self-contradictory, and even unknown data present on the different variables and/or conditions with complex relations entwined among them. In order to overcome these difficulties, the methodology followed was centred on a formal framework based on *LP* for knowledge representation and reasoning, complemented with a CBR approach to computing. Furthermore, under this line of thinking the cases' retrieval and optimization phases were heightened, when compared with existing tactics or methods. It allows one to normalize all cases present in the knowledge base, improving the performance of the similarity analysis, that is made when retrieving cases. It is also able to analyse free text attributes using several String Similarities Algorithms, which fulfil a gap that is present in almost all CBR Software Tools.

The capacity of optimization from the system is a very useful feature on the surgery process, since the presence of a failed case is very likely to happen due to the multiple entities that are taken into account. With the optimization phase of the cycle, the DoC assumed when the solution of the problem is presented, has also into account the past solution, this way a new case is created with more probabilities to succeed. Also, due to the complexity presented by the process, observations are needed to be taken into account, since the comparisons can be crucial on the retrieval phase. For example, although a case can be seen as successful, errors may have occurred during the process that could risk such outcome, so an observation of such error, needs to be taken into account in order to prevent.

Additionally, under this approach the users may define the cases weights attributes on-the-fly, letting them to choose the appropriate strategies to address the problem (i.e., it gives the user the possibility to narrow the search space for similar cases at runtime). A possible limitation on its use is not on the model in itself, but on the unavailability of data, information or knowledge, since in health services data ethic regulations are very restrict when related to the patient information and some necessary specific data related to the hospital resources can be neglected by the medical staff and not be inserted on the data base. However, even in these situations, once it has the capacity to handle incomplete information, either in its qualitative or quantitative form, its usefulness is assured.

Other important characteristic added to the approach was the fact that the time was taken into account. A simple system for reasoning about time and negation was presented, where changes to the database are explicitly represented by time stamping the data clauses and both positive and negative information are represented explicitly in the database. With this, a time record (successive data states) is created every time there is a change on the data, improving the efficiency and accuracy of the process. When there is a fail on the expectations, the retrieve of prior data may be useful to help resolve the anomalies present in the process. Therefore, past data from some variable can be the answer to a wrong assessment, since the presence of this chronological data record the system can retrieve better solutions for the case. Moreover, the presence of a chronological record, represents a structural path that can lead to a more efficient prediction of the final outcome, this means, that with the use of the time a better prediction can be made ensuring a greater security for all the entities involved on the process.

In fact, with the approach presented on this thesis, the capacity of predicting surgery processes will not only benefit the patient experience, but also the hospital in terms of management, efficiency and security. Also, with a prediction of the complete path of the patient through the surgery process will save the hospital resources and time, which will induce an increase on the costs savings. Likewise, the patient will be presented with a more customized treatment, with greater guaranties of security and success in the procedure, improving the system of health, saving more lives and providing great help to the medical staff.

Future developments of the model, where more entities are included and the system is adapted to a real surgery department, according to the conditions that is presented on that hospital, should be taken into account. It is undeniable that the application of a system like this have numerous benefits, in terms of management of resources, the system would give the best solution for a successful case with the most suitable use of the hospital resources, that would also be translated into costs reduction. As well, the medical staff would have a support system that would help them to predict possible problems that may occur and therefore, prevent them and have more security on the decisions made.

Nevertheless, the system could be capable of increasing the number of successful cases of surgery, also improving the patients' trust in the health care services. For this reason, the implementation of such system would be a revolution on the way the surgery process is perceived by the health care system.

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