# IBBRB: Intelligent Blockchain-based Reputation Broker for Robot Selection

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under the supervision of
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# Certificate of Original Authorship

I, Wafa Matar A Alharbi declare that this thesis, is submitted in fulfilment of the requirements for the award of Doctor of Philosophy (Ph.D.), in the Faculty of Engineering and Information Technology at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise reference or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifcations at any other academic institution.

This research is supported by the Australian Government Research Training Program.

Signature:

Date:

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# ABSTRACT


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by

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Robot as a service (RAAS) is a cloud-based subscription service that enables robotic devices to be leased instead of purchased. RAAS has recently increased in popularity due to the numerous advantages that it offers to robotic service requesters such as flexibility and the lower cost of entry and maintenance compared to owning the equipment, and the ease of implementation. The concept of RAAS has contributed to the increased use of robots in different disciplines, such as industry, education, health and agriculture.

Robotic service requesters may face difficulties in searching for the most suitable robot for their required tasks based on their preferences. Robot selection has attracted the interest of many researchers and it has been widely discussed in the literature. Robot selection is based on ranking the available robotic alternatives after they have been assessed by robotic experts. The assessment process is based on customer requirements as well as the task's functional and non-functional requirements.

However, through a systematic literature review, it has been identified that selecting a robot based on its previous performance in similar tasks has not been discussed yet. Furthermore, all the proposed robot selection methods require robotic experts to determine the requirements and robotic alternatives.

To address these issues, this research aims to propose and develop an intelligent blockchain-based reputation broker for robot selection termed IBBRB. IBBRB is

an intelligent reputation system that allows robotic service requesters (customers) to rate the performance of robots after hiring them. To avoid data manipulation, which is a common issue with reputation systems, blockchain technology is used to store and secure all trust values in IBBRB.

IBBRB is built to provide novel and intelligent mechanisms to: (i) standardise robotic knowledge across all robotic service requesters, suppliers and manufacturers by encapsulating all the robotic attributes and their relationships into an ontological manifestation called Robotic Attribute Ontology (RAO), and then to propose a blockchain-based method for RAO evolution using a crowdsourcing approach, (ii) develop a comprehensive method to carry out robotic reputation computations termed Reliable Reputation Computation Method for Robotics (RRCM). RRCM incorporates building: (a) a reputation model that produces reputation values for robots based on previous customers' ratings, and (b) a prediction model that predicts reputation values for non-reviewed robots to bootstrap new robots and overcome the cold start issue, (iii) develop a method to infer reputation values for all non-reviewed contexts of multi-purpose robots based on their similarities to the reviewed contexts. Finally, this research uses software prototyping to validate the performance and accuracy of the aforementioned proposed methods.

# List of Publications

The following is a list of my research papers during my PhD study.

### Journal Papers

J-1. **Wafa Alharbi, and Farookh Khadeer Hussain**, "Blockchain-Based Reputation Systems for Internet-Based Robotics: A systematic Literature Review" , (under preparation).

J-2. **Wafa Alharbi, and Farookh Khadeer Hussain**, "Context-driven Inferencing of Reputation Values for Multi-purpose Robots," *Knowledge based System Journal*, (Submitted).

### Conference Papers

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# Abbreviation

| | | |
|---|---|---|
| AHP | - | Analytic Hierarchy Process |
| bcRAOe | - | Blockchain-Based Crowdsourcing RAO Evolution Method |
| CAMeOnto | - | Context Awareness Meta Ontology Modelling |
| CaRVInf | - | Context-Aware Reputation Value Inferencing Method |
| CAT | - | Context-aware Trust |
| CORA | - | Core Ontology for Robotics and Automation |
| CRSs | - | Centralized Reputation Systems |
| DLT | - | Distributed Ledger Technology |
| DSRM | - | Design Science Research Methodology |
| EFPI | - | Enhanced Fuzzy Prediction Interval |
| FAHP | - | Fuzzy Analytical Hierarchical Process |
| FDM | - | Fuzzy Delphi Method |
| FPI | - | Fuzzy Prediction Interval |
| GFNs | - | Generalised Fuzzy Numbers |
| IBBRB | - | An Intelligent Blockchain-Based Reputation Broker for Robot Selection |
| IC | - | Information Axiom Value |
| MAE | - | Mean Absolute Error |
| MAPE | - | Mean Absolute Percentage Error |
| MCDM | - | Multicriteria Decision Making Method |
| MVC | - | Model-View-Controller Design Pattern |
| NDR | - | Normal Distribution-based Reputation model |
| PCR | - | Principal Components Regression |
| PLSR | - | Partial Least Square Regression |
| QFD | - | Quality Function Development Method |

| | | |
|---|---|---|
| RAAS | - | Robot As A Service |
| RAO | - | Robotics Attributes Ontology |
| RMSE | - | Root Mean Squared Error |
| RRCM | - | Reliable Reputation Computation Method for Robotics |
| RS | - | Reputation Score |
| RV | - | Reputation Value |
| TV | - | Trust Value |
| SLR | - | Systematic Literature Review |

# Chapter 1

# Introduction

## 1.1 Introduction And Motivation

In recent times, and due to the advancement in the technology sector, the way of communication and service requesting between parties has been changed. People who have no prior real-world relationships can communicate and make transaction over the internet. So, the internet has remodelled the way of submitting business and commercial transactions since the e-commerce applications have emerged in people daily life. E-commerce applications are these where purchasing and selling products are done over the internet. People prefer to shop online due to the convenience, and simplicity that are offered in online shopping but not in the physical store shopping. According to Zhou et al. (2021), in 2018, 1.6 billion people shopped online using well-known retail platforms such as eBay and Amazon. However, issues related to trust have been arise as a consequences of using the internet as a medium to carry out online transactions in e-commerce environments (Jøsang et al., 2007). One of the issues affecting trust is that buyers or service requesters must make a decision to proceed with the transaction based on the product or service descriptions that are provided by the seller or service providers. In other words, the service requesters have no physical contact with the desired product, hence they are not able to test the quality of the service/ product before making the transaction.

In this interconnected world, the concept of the reputation system has been introduced to address trust issues. Reputation systems evaluate the trustworthiness of an entity based on previous feedback generated by other entities who have interacted with that entity. Reputation systems have been implemented mainly in a large number of online platforms in various areas such as e-commerce websites and file-sharing systems. Reputation systems are essential in domains where the expertise of service requesters is important in making a decision about the required service/product, such as hiring a robot for a specific task.

Robotics is an important technology that has improved life by providing enhanced levels of service. Undoubtedly, the need for robots in humans lives is increasing (IFR, 2020). The increasing demand for robots has contributed to the birth of robot as a service (RAAS) concepts (Kapitonov et al., 2021). RAAS is a business model that allows robotic service requesters to access services through a subscription based on cloud computing instead of buying a robot. For example, the Cobalt Robotics company offers robot-as-a-service solutions for security applications. They offer robots that are trained to identify potential security threats and enhance security operations through prebuilt artificial intelligence algorithms. Figure 1.1 shows the global growth in the use of service robots between 2018 and 2020. As it is obvious in the figure, robots have been used mainly in many situations where humans may be at risk, robots are more precise than humans, or in simpler situations, such as entertainment and doing chores tasks. Thus, the robotics service requesters range from industrial/ educational/ medical organisations to home users or children and many more. Hence, it is necessary to build a robotic reputation-based framework to help non-expert robotic service requesters find the most suitable robot for a specific task and increase the efficiency of the robotic selection process.

## 1.2 Problem Statement

As discussed, reputation systems are important in solving trust issues in online transactions. It is based on encouraging service requesters to evaluate the quality of a service/ product after finalising the transaction. Then the users' evaluations

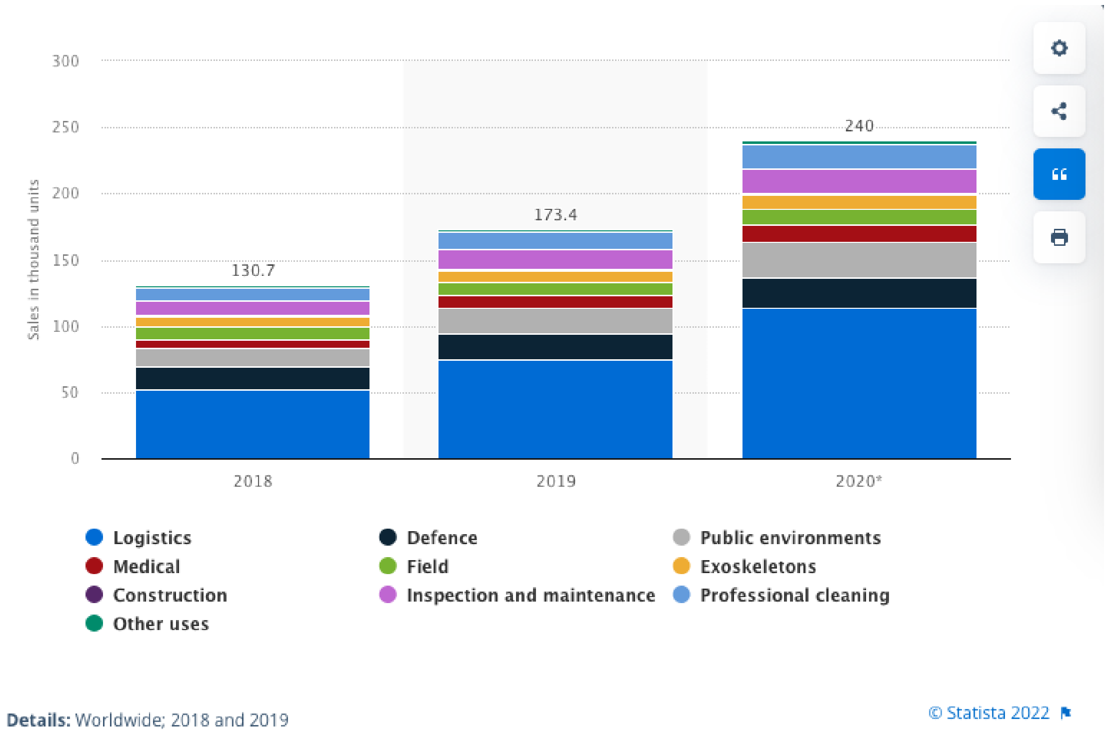


Figure 1.1 : Global sales of service robots between 2018 and 2020 (IFR, 2020).

are used to produce an overall trust value for the service/ product. These trust values are stored in storage mechanisms and are shown to future requesters to help them in their decision making. Most of the popular online retailing platforms such as Amazon and eBay have built centralized reputation systems (CRSs) to store the reputation scores centrally on their servers ( Zhou et al., 2021). This exposes reputation systems to security issues including the manipulation of trust values or the addition of fake ratings by malicious employees or attackers. Thus, building a tamper-proof reputation score is one of the goals of this research.

In addition, and as the capabilities and specifications of robots are rapidly growing and services are being provided to consumers with different levels of expertise in a wide range of applications, a robotics reputation system should be able to help all requesters during the decision-making process, ensure the integrity and reliability of the trust scores, build an effective score computation method, and provide a reliable method to boost the reputation of newly launched robots. In this research, we propose integrating blockchain technology with reputation systems to address the aforementioned issues. The process of carrying out the reputation computation is done using innovative intelligent-based algorithmics on the top of blockchain.

## 1.3 Robotics Technology

Robotics is a branch of science that studies the design, creation, and operation of robots. Robotics technology falls at the intersection between electrical engineering, mechanical engineering and computer science disciplines (Vrontis et al., 2022).

### 1.3.1 What is robot?

Although there is no consensus in the literature regarding to the definition of robots, there is a general agreement with the definition of a robot as any programmable machine that is used to perform a variety of tasks using intelligent sensors and actuators (Asada, 2003).

While there are many attempts to classify robots, we will highlight the most common. Robots can be classified based on the working environment or on the intended application area (Ben-Ari & Mondada, 2018).

The environment in which they operate may require a fixed or mobile robot (Figure 1.2, A). Fixed robots are those that work in a well-defined environment and are used to perform stationary tasks such as painting or soldering objects in manufacturing organisations. Industrial robot manipulators are a good example of a fixed robot. Mobile robots are those that are expected to move in uncertain environments to perform several tasks with the help of mapping and could computing. These robots collect information about the environment using their intelligent sensors to ensure their movements are safe. The motion mechanism of mobile robots differs for aquatic, terrestrial and airborne robots and each type requires different design principles. For example, the design of aquatic robots must integrate one or more underwater driving forces such as tails, fins, wings, etc., whereas terrestrial robots must be designed with legs or wheels, and aerial robots must have light-weight bodies. Moreover, robots can be categorised according to the application and tasks they perform (Figure 1.2, B). Industrial robots perform specific and repetitive tasks on behalf of human workers in pre-defined environments. In contrast, service robots assist humans to do some tasks in uncertain environments such as home chores, medical surgeries or driving cars.

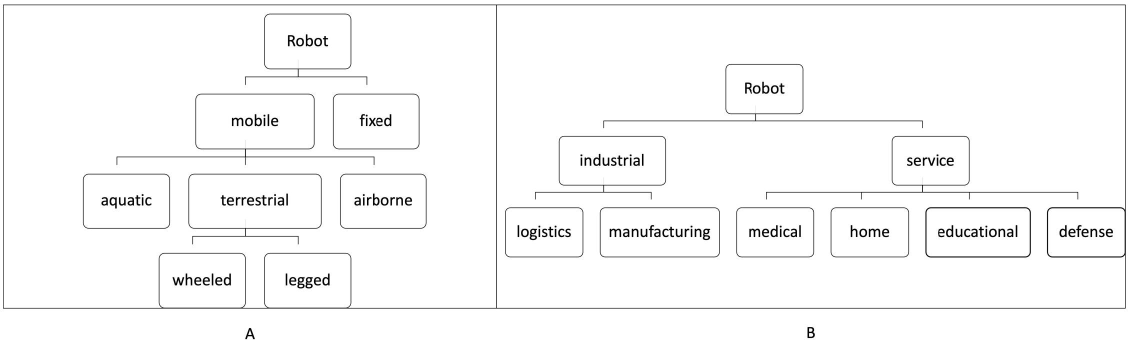


Figure 1.2 : Classification of robots according to A. the working environment, B. the application field 'taken from (Ben-Ari & Mondada, 2018)'.

### 1.3.2 Robot characteristics

Although there is no agreement on the definition of a robot, there are a number of characteristics that are common to all robots. These characteristics could help to decide what is a robot.

1. Sensing: Robot sensors are used to collect data from and evaluate the working environments and then send electronic signals to the robot to perform a conditioned behavior to complete a specific task. There are a large number of robotic sensors that differ according to their application. Some sensors are

used to capture the light, sound, temperature, humidity and pressure of the surrounding environment. Other sensors are used to detect if there is physical contact with other objects (Contact Sensors), or to detect the presence of other objects in the environment (Proximity Sensor). It is impossible to list all the available sensors in the robotics field since hundreds of sensors are being made and being involved in the design of robots.

2. Movement: Movement is the second main characteristic of all robots. Robots can move in a straight line, in a circular arc, from one point to another point, or on any pre-programmed path. In addition, robots can move in three dimensions, i.e., they can move forward/ backward, and/or upward/ downward. Robot movements could occur with the use of wheels or legs or a robot may only move a single part of its body, such as its arm.

3. Energy: Energy is required so that robots are able to move their wheels, raise the arm etc. The energy that powers robots could be solar, electric, oil, wind, battery or gas.

4. Intelligence: All robots need to have some sort of intelligence that allows them to process the environmental data and follow predefined rules to complete a task in changeable environments. Robots require software to receive the instructions programmed by programmers.

### 1.3.3 Robot specifications

There are two broad categories of robotics specifications: (a) subjective and (b) objective specifications. Subjective specifications refer to linguistic or qualitative specifications that cannot be measured while objective specifications are specifications that have quantitative or numerical values.

## 1.4 Blockchain Technology

Blockchain technology was introduced for the first time in 2008 as a distributed ledger for Bitcoin transactions. It can be defined as a distributed ledger technology (DLT) that utilises the P2P network protocol to secure data and transactions where there is no need for any centralised third party. It also integrates other key technologies such as smart contracts and asymmetric encryption which allows it to reach a consistent state between interacting parties and record any completed transaction in a secure, immutable and transparent manner in a public ledger (Lu, 2019).

Blockchain technology was initially used in the finance sector as a distributed ledger for crypto-currencies. Recently, the use of blockchain has increased and is being used in many sectors other than crypto-currencies, such as education, carbon credits, energy, supply chains and identity management (Alsobhi et al., 2021).

### 1.4.1 Blockchain structure

Blockchain is made of a sequence of blocks that are arranged chronologically. Each block consists of a header and a body (Figure 1.3). The body contains the actual transaction data and the header of a block contains metadata for the block, such as the timestamp, a hash for the previous block (parent block hash), the current block hash, Nonce and Merkle root. The parent block hash value is included in the current block hash. Storing the parent block hash of a block in its header creates a chain of blocks until the genesis block (the very first block in the chain). This design of blockchain ensures that there is no data manipulation. Any attempt to alter the data in a block in the blockchain will automatically create a different hash and break the chain (Strobel et al., 2018).

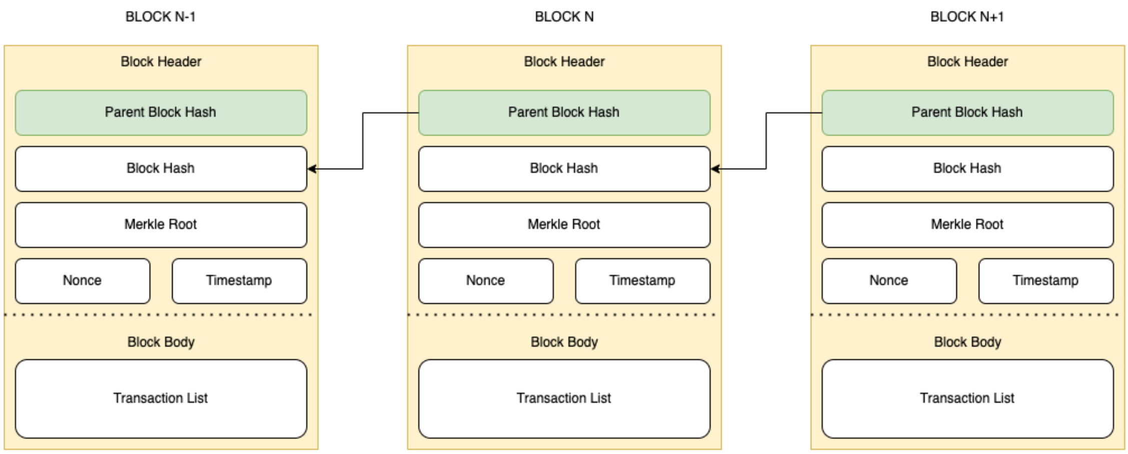


Figure 1.3 : Block structure in blockchain technology.

### 1.4.2 The main features of blockchain

- Decentralisation: In blockchain, control and decision making are transferred from a centralised authority to distributed nodes. Each node in the blockchain has the ability to verify, record and store all transactions in the form of a distributed ledger. Each node in the network has a copy of the same ledger. So, any attempt to alter a ledger of a member will be rejected by other members.

- Immutability: after the majority of network members have verified a transaction, it is timestamped and added to the chain as a new block. The new block is cryptographically secured by a hashing process that ensures the blockchain ledgers permanent and unalterable. Meta-data from the last block's hash output are included in the hashing process of the new block. This makes it very difficult to break the chain. Any attempt to alter a block will result in the creation of a different hash which is easily detected.

- Anonymity: The privacy and security of members are protected in the blockchain networks by integrating asymmetric encryption to generate a digital signature. Digital signatures are used to validate the sender of the transactions. Senders are represented as digital identities with a private key.

- Transparency: All transactions are made available to all members by storing them in distributed ledgers throughout the blockchain nodes. Also, all transactions are easy to trace since they are hash chained.
- Credibility: As a copy of the same transactions are stored in all nodes' ledgers, it is easy to detect malicious transactions. External attacks cannot be made on the network while no more that 51% of the nodes in the networks are controlled by hackers.

## 1.5 Reputation Systems

According to the Concise Oxford Dictionary, reputation can be defined as the general saying or believing about the character or standing of a person or a thing. Reputation and trust overlap and are closely related to each other. Some papers represent reputation as trust values (Jøsang et al., 2008) while other works assume that trust is based on the subjective opinion between two parties and reputation is not related to personal opinion but it represents global opinions (Bhuiyan et al., 2010; Wang & Vassileva, 2007). In this research, we assume that the reputation score is used to support trust of an entity. The trust in reputation systems is embedded in calculating a global reputation score for an entity considering the opinions of all other entities who have interacted with that entity before ( Zhou & Hwang, 2007). The entities in reputation systems could be any objects such as services, products, users, and webpages. So, the goal of reputation systems is to help buyers choose trustworthy services, products or sellers to interact with.

The main components of all reputation systems can be epitomised into three components. The first component is the users' feedback collection, where the users are given the ability to share their opinion on a service/ product after utilizing it.

The second component is the reputation computation engine, where the reputation system converts users' evaluations into a reputation score for the service/ product. The final component is the reputation score presentation, where the system shares the score with other users to help them make a decision based on that score. The most popular method that is used to present reputation scores is the five-score rating. Figure 1.4 illustrates the components of reputation systems.

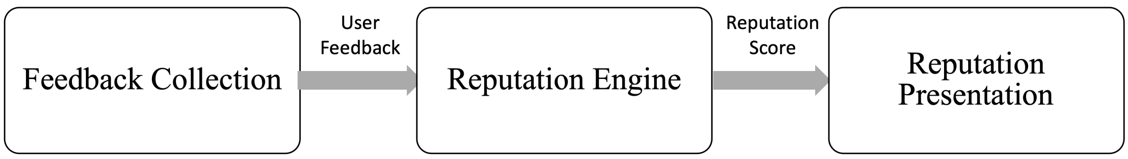


Figure 1.4 : Reputation system components 'taken from (Abdel-Hafez, 2016)'.

## 1.6 Research Contribution

This research aims to develop an intelligent blockchain-based reputation system for robotics to help select the most suitable robot for a specific task. This section discusses the contributions of this research.

### 1.6.1 Social contribution

- This research is the first to propose a (broker) platform for robotic selection based on blockchain technology.

- It contributes to the adaption of robots because IBBRB is intelligent, reliable and open source.

### 1.6.2 Scientific contribution

- This research presents a systematic review of the extant literature on robotic selection methods and discusses the limitations of these methods.
- This research is the first develop an intelligent algorithm to help service requesters carry out the selection based on bespoke parameters.
- This research is the first to use an ontology to semantically understand robotic attributes during the selection process
- This research is the first to use transfer learning to predict a reputation score for a newly launched robot to solve the cold start issue which occurs when a new product is added to the system.
- This research is the first to carry out context-based inferencing to enable robotic selection in new or previously unknown contexts.

## 1.7 Outline of Research Thesis

In this thesis, an intelligent reputation-based broker is proposed to help robot service requesters select robots. The proposed methodology incorporates developing various methods, models, and algorithms to achieve the main aim of this study. These methods and algorithms are discussed in different chapters in this thesis. Therefore, this thesis has been organized into nine chapters as shown in Figure 1.5. In this section, we give a brief summary of each chapter:

- Chapter 1 provides a brief introduction to the thesis topic, defines the main technologies that have been integrated to achieve the aim of this thesis, and outlines the research major contributions.

- Chapter 2 presents a systematic literature review of the existing literature on robotic selection approaches.
- Chapter 3 defines the main terms that have been used in this thesis. It also discusses the main research gaps that are addressed in this work, and then defines the research questions and objectives.
- Chapter 4 presents the selected research methodology and provides an overview of the solutions that are proposed to achieve the main aim of this thesis.
- Chapter 5 presents the solution developed to address research objective 2. A robotic ontological manifestation and ontology evolution method are proposed in this chapter.
- Chapter 6 presents the reputation computation method that includes developing reputation and prediction models. This chapter also validates the method by conducting experiments and presents the results. This is the solution to research objective 3.
- Chapter 7 presents the solution developed to address research objective 4. A context-aware inferencing of the reputation value for multi-purpose robots is provided in this chapter.
- Chapter 8 provides the system prototype developed to demonstrate the solution methods proposed in this thesis.
- Chapter 9 concludes the thesis by providing a summary of the main achievements in this study and discussing potential future work.

## 1.8 Conclusion

Robotics is a driving technology that has the potential to positively change human lives and work practices. The learning capabilities of robots allow them to

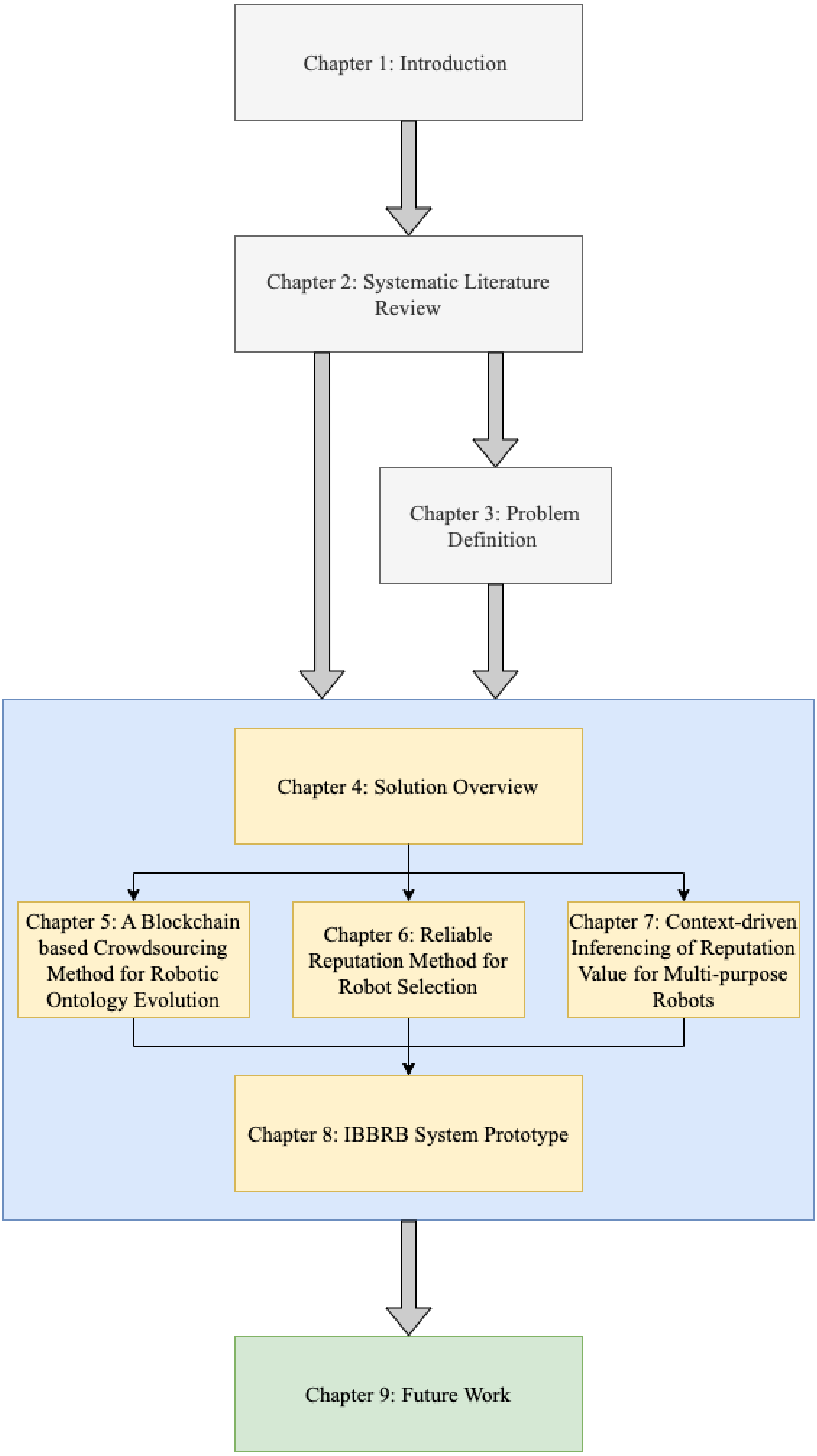


Figure 1.5 : Thesis structure.

interact with human beings and provide an advanced level of performance in manufacturing as well as non- manufacturing industries. However, the selection of the most suitable robot for a specific task is a critical issue due to the different capabilities of robots. This thesis develops a comprehensive solution for robot selection that addresses several shortcomings of the existing approaches in the literature. This chapter presented the problem statement of this study, introduced the main technologies that will be integrated in the proposed solution such as blockchain and reputation systems. This chapter also highlighted the significance of this research and provided an outline of this thesis.

The next chapter reports on the systematic literature review that analyses all the related approaches that have been discussed in the literature and formally identify the research gaps and shortcomings.

# Chapter 2

# A Systematic Literature Review

## 2.1 Introduction

This chapter analyses the existing literature by conducting a systematic literature review (SLR) in the area of robotics selection. The issues and shortcomings of the relevant research and the state-of-the-art approaches are discussed to identify the research gaps and formulate the research questions of this thesis.

This chapter is structured as follows: Section 2.2 discusses the key requirements that need to be considered for robotics selection. In Section 2.3 , the protocol that was followed in conducting this SLR is discussed. This includes identifying the sources of the research data, defining the search terms and setting the inclusion and exclusion criteria. Section 2.4 highlights the key findings from all the papers that have been included in the study. In section 2.5 , we evaluate the reviewed studies based on several criteria to identify the gaps and limitations of these studies. Section 2.6 concludes this chapter. The structure of this chapter is shown in Figure 2.1.

## 2.2 Key Requirements to Consider for Robotics Selection

Robot selection methods have been broadly discussed in the literature. However, the participation of expert decision makers is essential in most of the proposed methods to determine the exact requirements of a robot for a specific task. Here, we aim to help non-expert end-users in the decision-making process by providing recommendations based on their requirements. To achieve this goal, the following requirements need to be considered:

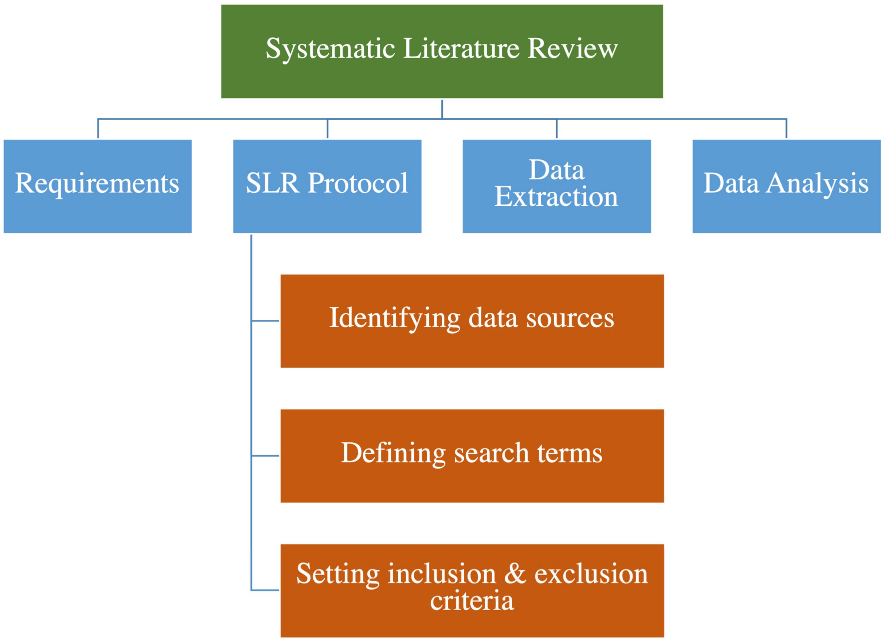


Figure 2.1 : Structure of the systematic literature review

- Req 1: Medium broker service: this works as an expert and carries out the process of comparing all robot alternatives and suggests the most suitable one based on the end-user's requirements and the previous robot performance scores (Figure 2.2).

- Req 2: Multi-criteria robot selection method: Some non-expert end-users may require a combination of requirements such as the lightest robot that has the longest battery lifetime, or the cheapest robot that has a thermometer and camera (as sensors). Hence, there is a need for a multi-criteria method that considers all the requirements in the selection process to ensure that the selected robot meets most/all of the end-user preferences.

- Req 3: Robotics performance evaluation: this allows end users to evaluate the performance of a robot after finishing their tasks in a reputation-like framework. This helps other end users to browse the alternatives and choose the most suitable robot for their needs, based on other users' experiments.

- Req 4: Bootstrapping new robots : as the robotics industry still in its infancy and there is potential to build more robots with expanded skills, there is a need to consider all newly produced robots in the comparison step. This can be achieved by predicting a performance score for not-yet-evaluated robots to ensure that they have been considered in the selection process.

- Req 5: Context-aware performance score evaluation method: with the innovations in robot capabilities, the concept of the multi-purpose robot was born (Hsu et al., 2017). A multi-purpose robot can be used to perform more than one task (or context). The performance score for one context may be exist however the score for the performance in other contexts is not known. This method can help in determining the performance score for robotic contexts based on its similarity to other contexts.

- Req 6: Trustworthy: to minimize the risk of manipulation which can occur in all reputation systems, we need to securely and reliably store the previous end-users' evaluations.

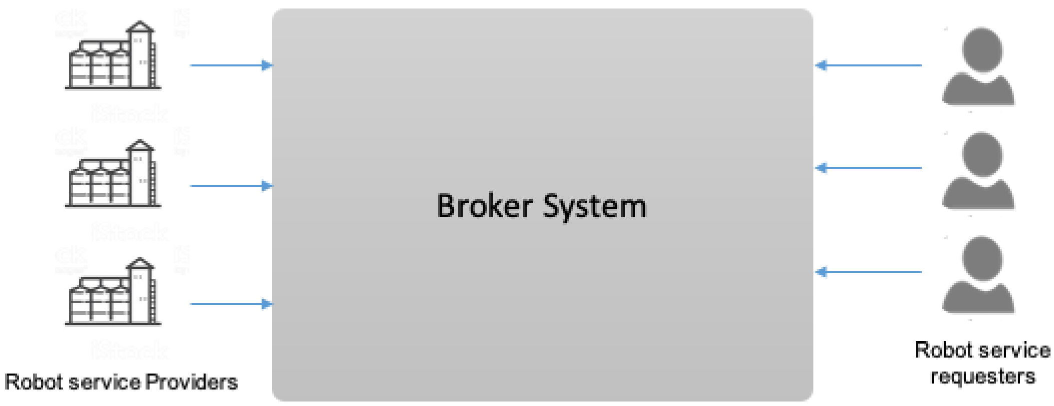


Figure 2.2 : Robotics broker system

## 2.3 Systematic Review Protocol

Based on the systematic review protocol proposed by Kitchenham and Charters (2007), this review has been conducted to increase the reproducibility of the research. The main aim of this review is to identify and evaluate all the available research that discusses the decision-making mechanisms used for selecting a particular service robot and the degree to which these mechanisms can be trusted.

The steps in this systematic review protocol are detailed in the following subsections:

- Step 1: Search protocol: In this step, the sources of the research data are identified and search terms are defined.
- Step 2: Inclusion and exclusion criteria: The inclusion and exclusion criteria are defined to set the search boundaries and extract the most relevant studies.
- Step 3: Study selection process: In this step, studies which satisfy the defined criteria in step 2 are selected for inclusion in the SLR.
- Step 4: Data extraction: Data is extracted from the included studies after they have been reviewed.

### 2.3.1 Search protocol

Similar to any SLR, this study aims to review all the relevant papers in the literature. The following four scientific databases were used to conduct the search. These databases were selected because they are well known in the engineering research area and provide good coverage of the relevant literature.

1. Scopus (https://www.scopus.com/search/form.uri?display=basic)
2. IEEE Xplore (www.ieexplore.ieee.org/Xplore/)

3. SpringerLink (https://link-springer-com.ezproxy.lib.uts.edu.au/)

4. . ACM Digital Library (https://dl-acm-org.ezproxy.lib.uts.edu.au/)

Table 2.1 summarises the keywords used in this search to find the relevant literature. These search terms were extracted from the research questions. The search process was divided into three categories: the first relates to robot selection, the second is how to manage robot identity and the third is how to evaluate the behaviour of a robot.

To maximize the search results, we used Boolean operators "AND", "OR" and parentheses. The majority of the search statements contain two parts: the first is the union (linked by "OR") of similar terms (e.g Robot OR Robotics firm) to obtain maximum coverage. The second includes the union of terms that are primarily related to the three categories listed in Table 2.1.

Table 2.1 : Search categories and keywords used in this review.

| **Search Category** | **Keywords** |
|---|---|
| Robot's or Robotics firm's behaviour Selection | (robot OR robotic) AND (reputation OR "quality of service"),"Selecting robot" OR "selecting Robotics", "robot Selection" OR "Robotics Selection". |
| Identity management for things "Robots" | (robot OR robotics) AND ("Identity management"), (robot OR robotics) AND ("Identity trust"). |
| Robot Assessment | (robot OR robotic) AND (("task assessment" OR "behavior assessment")). |

### 2.3.2 Inclusion and exclusion criteria

The inclusion and exclusion criteria were applied to determine which articles should be included in the review. The inclusion and exclusion criteria are listed as follows:

- Inclusion criteria

  1. Does the article propose a solution to select a robot for a specific task "Decision making mechanism for selecting a robot OR a robotics firm"?
  2. Does the article propose a solution to identify trust values for robots?
  3. Was the article published between 2015 and 2022?
  4. Is the full text available and written in English?
  5. Is it a scholarly peer-reviewed article?
  6. Does the article propose a solution for task assessment for robots?

- Exclusion criteria

  1. Non- English papers.
  2. Papers whose full text is not available/published.
  3. Duplicate papers of the same study.

### 2.3.3 Study selection process

Based on the search terms defined in section 3.1, 180 papers were retrieved from the databases, of which 10 were excluded due to duplication. A second filtration process was conducted on the remaining 170 papers based on the titles of the papers. The studies that have irrelevant titles were excluded. At the third filtration stage, the abstract of the remaining 81 studies were reviewed to assess the eligibility of these papers. Only 36 studies remained from this filtration stage. The final filtration process was based on reviewing the introduction of the studies. Finally, 25 studies were accepted for this review, as shown in Figure 2.3. Figure 2.4 illustrates the number of accepted and rejected papers at each stage. In comparison to other databases, Scopus provided the most articles while IEEE Xplore did not provide any relevant papers, as illustrated in Figure 2.5(a) and Figure 2.5 (b).

## 2.4 Data Extraction

### 2.4.1 Robot selection related work

The final set of 25 papers was reviewed to extract how they addressed the problem of robot selection. Table 2.2 presents the included studies, how the studies contribute to the robot selection issue, and what tools are used in each study?

The included studies can be classified into two groups: the first group focuses on robotics behaviour validation while the second group tries to solve the robot service selection issue.

When reading through the existing literature on robot selection, it is observed that a fairly large number of studies have investigated fuzzy logic concepts to address robot selection issues. Deli (2020) introduced a TOPSIS multi-criteria decision-making method (MCDM) to rank robot alternatives based on their closeness to the best solution. The method proposed by Deli (2020) is based on converting an evaluation of alternatives with respect to selection criteria to generalized hesitant trapezoidal fuzzy (GTHF) numbers. Deli (2020) outlined the working of the GTHF-positive ideal and GTHF-negative ideal solutions. Subsequently, the author introduced a distance measure method called $\lambda$-generalized hybrid distance measure on GTHF-numbers to compute the distance between alternatives and ideal solutions. The best robot alternative is the nearest one to the positive ideal solution and the farthest one from the negative ideal solution. The main drawbacks of this study

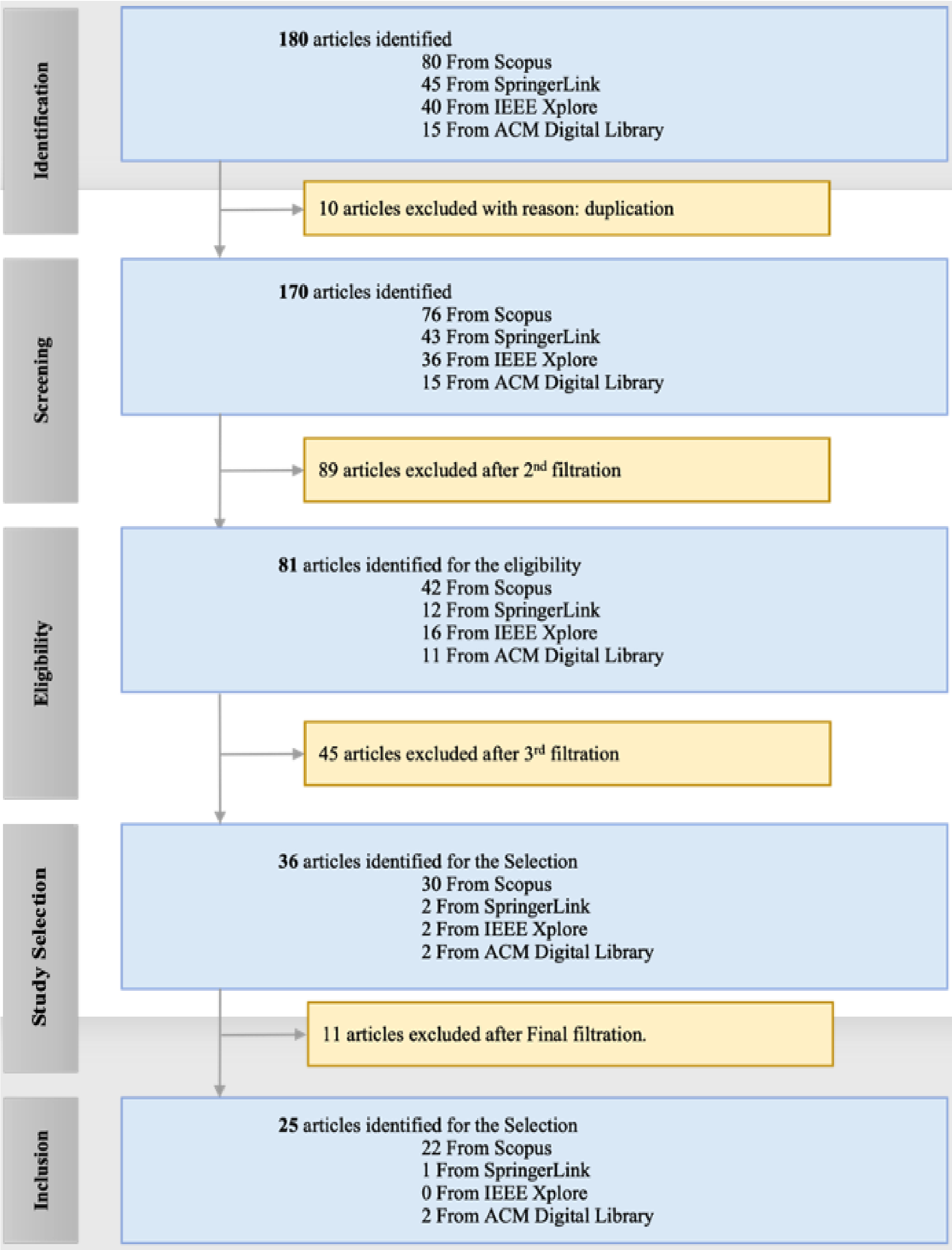


Figure 2.3 : Process of study selection.

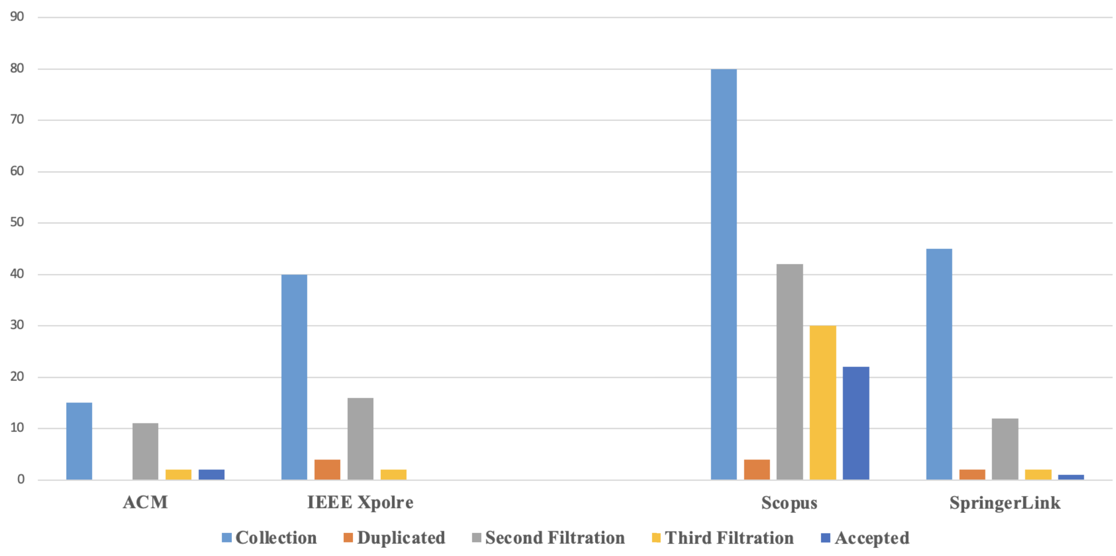


Figure 2.4 : Study filtration processes per search engine.

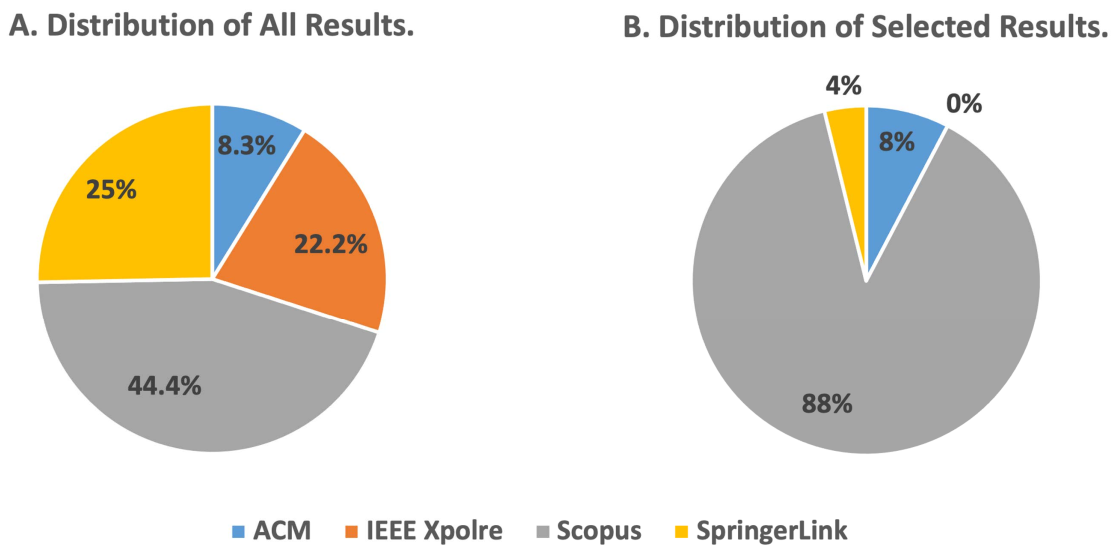


Figure 2.5 : Distribution of results across search engines.

are that the proposed selection algorithm is built to be used by an expert decision maker to set and weight the selection criteria, the performance and specifications of robots are taken from brochures and manufacturer data not from their performance on similar tasks and this method addresses the problem of selecting a robot based on subjective attributes only.

Similar to (Deli, 2020), Keshavarz Ghorabaee (2016) also developed a MCDM fuzzy logic method to select a robot according to the distance between the robot and an ideal solution. His method integrated the VIKOR method and type-2 fuzzy sets concepts. In the proposed method, each decision maker is required to evaluate the performance of all alternatives on all criteria and then an average matrix is conducted. Then the proposed method determines the ideal values for all criteria from the values in the average matrix. The trapezoidal interval type-2 fuzzy sets are calculated for all alternatives. Then the alternatives are ordered according to the best values of the interval type-2 fuzzy sets. However, similar to the method proposed by Deli (2020) , this method relies on expert decision makers to identify and weight the selection criteria and the robot alternatives data are collected statically from brochures and manufacturer websites which could be commercial data. Khandekar & Shankar (2015) applied fuzzy axiomatic design principles to solve the robot selection problem. Their method uses a five-point fuzzy scale to uniformly express all functional requirements (whether they are subjective or objective attributes) of all robot alternatives. Subsequently, they calculated total Information Axiom (IC) values for all alternatives using the triangular membership function to rank alternatives according to the IC values to identify the most appropriate robot. Similar to the previous studies by Deli (2020) and Keshavarz Ghorabaee (2016), their method relies on manufacturer websites to collect robot information.

Liu, Quan, et al. (2019) proposed a method where the decision-maker's evaluations are converted to interval-valued Pythagorean uncertain linguistic sets and then they applied an extended quality function development (QFD) method to weight the selection criteria based on customers' perspectives. The expert decision maker then determines the importance of the customer requirements. Their method identified the best alternative using a modified Qualiflex method which is based on the closeness degree to a positive-ideal solution. This method results in an accurate selection process as it allows customers to participate in requirements formulation. However, in this method, reliance on expert decision makers is essential and the number of robot alternatives and/or decision makers should be limited to obtain faster and more accurate results.

Liu, Zhao, et al. (2019) also proposed a modified Multimoora method in a fuzzy environment to solve the robot selection issue. Their proposed method comprises the following three steps:

a. Generating a matrix using hesitant fuzzy linguistic term sets to evaluate all alternatives.

b. Determining the importance of subjective and objective selection criteria.

c. Using the extended Multimoora method to rank alternatives.

Taking both objective and subjective attributes into account during the selection process makes this method more realistic and practical as, unlike the previously discussed approaches, it is not solely reliant on experts' judgements. However, this method has several limitations such as, it requires expert decision makers to identify and weight the selection criteria, and specifications of robot alternatives are statically collected from manufacturers' websites.

Parameshwaran et al. (2015) developed an approach for optimal robot selection that considers both subjective and objective criteria. Their method integrated the Fuzzy Delphi Method (FDM) to identify the selection criteria, the Fuzzy Analytical Hierarchical Process (FAHP) to weight each criterion, and Fuzzy TOPSIS or VIKOR to rank robot alternatives. The identification and weighting of the selection criteria in this approach relies on a committee of experts who select a robot based on its technical specifications, so this method cannot be used by non-expert users who need a recommendation from other users in the selection process.

Sen, Datta and Mahapatra (2016, 2017) made three attempts at solving the robot selection issue. In their first attempt, they applied the TODIM method to select an industrial robot to suit a particular application based on robot requester needs (Sen et al., 2016a). The main limitation of their method is that it assumes all criteria are objective or have numerical values in nature, and it collects robot information from manufacturers' brochures, not by observing the actual performance of robots.

Sen et al. (2016b) extended the Promethee method to select a robot by considering both objective and subjective criteria. The extended Promethee method analysed objective and subjective criteria separately and computed a composite score to combine the results and select the most appropriate robot. In 2017, they published a study that utilised TODIM and generalised fuzzy number (GFN) set theory to solve the robot selection decision-making problem (Sen et al., 2017). In this study, they defined a set of linguistic terms to rank robot alternatives and also selection criteria by the expert decision makers. Subsequently, the linguistic data is converted to fuzzy numbers to apply the TODIM approach. Although their last two attempts considered both subjective and objective criteria in the evaluation and selection processes, these methods require expert decision makers to set and evaluate alternatives as well as the selection criteria. These methods rely on the initial specifications provided by robot providers to collect robot information.

Sharaf (2018) used an ellipsoid algorithm to rank fuzzy numbers that were obtained from evaluating each robot alternative against each criterion by the decision makers. This method simplifies the selection process as it uses the linear membership function or its derivative. Similar to some of the existing proposed methods, unfortunately, this method too depends on expert decision makers' judgment in identifying a limited number of robot alternatives and selection criteria.

Wang et al. (2018) proposed a method that combines a cloud model which is applied to handle linguistic decision-making problems since it uses probability and fuzzy sets to remove fuzziness and the TODIM method to facilitate robot selection in fuzzy environments. Firstly, this method uses cloud model theory to describe the linguistic evaluation of decision makers. Secondly, it calculates the weight of subjective and objective criteria. Finally, the TODIM method was applied to rank robot alternatives. This method does not address the issue of evaluating robots according to the performance in the workspace as it collects selection criteria from robots' manufacturing data.

Xue et al. (2016) integrated an extended Qualiflex approach with hesitant 2-tuple linguistic term sets to address robot selection problems. Hesitant 2-tuple linguistic term sets were used to capture the ambiguity of the decision makers' assessment while the extended Qualiflex was used to calculate the concordance/discordance index of all possible permutations of robot alternatives. However, one limitation should be highlighted, namely this method becomes more complicated as the number of alternatives increase.

Moreover, machine learning concepts such as neural networks and regression models have also been used to address the robot selection problem. For example, Nayak et al. (2016) presented a new technique using the gradient descent momentum optimization algorithm and backpropagation neural network to select an industrial robot. This algorithm took robot specifications as inputs and then predicted a rank for the robot in respect to predefined minimum requirements. The main drawback of this algorithm is that it cannot consider more than ten parameters as inputs. Nayak et al. (2019) compared and evaluated the performance of three mathematical models in predicting a rank for a robot based on predefined requirements. The evaluated models were partial least squares regression (PLSR), principal component regression (PCR), and linear regression using a feedforward neural network. They found that PLSR provides better rank prediction with a minimum number of errors. This method considers a limited number of robot parameters and uses them as selection criteria.

Sahu et al. (2015) compared the performance of three fuzzy membership functions that have been used to measure the closeness of a robot to an ideal solution. The three functions are: triangular, trapezoidal and Gaussian membership functions. They found that the Gaussian membership function was the most effective as it satisfied the requirements. This method relies on the initial static specification provided by robot providers to collect robot information and relies on expertise from decision makers in reading technical terms.

Some papers in the literature discussed the selection of robots for specific tasks where all requirements and stakeholders are well known. For instance, Breaz et al. (2017) employed the use of the analytic hierarchy process (AHP) method to find a suitable industrial robot for milling applications. The AHP method has also been used in a method proposed by Piotrowski & Barylski (2016) to select a robot for lapping systems. The AHP method is based on pairwise comparisons between all the selection criteria of the robot candidates. In the healthcare sector, Zhou et al. (2018) presented a fuzzy extended VIKOR approach to select a mobile robot for a hospital pharmacy. They integrated AHP and VIKOR methods in a fuzzy environment. In addition, the selection of a robot for educational purposes was discussed by Papakostas et al.(2018). They applied the TOPSIS method to select a social robot to be used as an educator according to predefined criteria that were set by expert decision makers in the education sector. Despite the promising results of these methods in the aforementioned applications, they cannot be used to select a general-purpose robot as they rely on experts to specify the exact requirements and robot alternatives.

Another significant factor in the robot selection problem is capturing and recording robot behaviour in its working environment to detect malicious robots. In this regard, Benko et al. (2019) proposed an algorithm to detect malicious robots in a network using a Kalman filter to improve the security of the robotic network. This method helps in deciding when an agent can be trusted by measuring the deviation of the agent from its expected behaviour. Zikratov et al. (2016) also introduced a trust management framework for decentralised robotics multi-agent system networks to obtain the reputation of robots and dynamically update the reputation score over time. The access privileges are then controlled according to the reputation score of the robot.

Hafizoglu & Sen (2018) measured how human trust could be affected by the agent's reputation in human-agent teams by conducting experiments using a team game called the Game of Trust. The reputation of an agent was provided to a human-teammate and then they observed the impact of the agent reputation on human trust. Danilov et al. (2018) and Strobel et al. (2018) both used blockchain to securely store and validate the trust values of an agent. Danilov et al. (2018) proposed a method to validate agent-based service provider's delivered tasks using blockchain. In this method, the validation is obtained by a third member who is identified in the contract. The validator checks the correctness of the provided service based on a predefined behaviour model and then the validation result is stored in a blockchain platform. In contrast, Strobel et al.(2018) built a mechanism in the smart contract to identify and exclude byzantine robots from the swarm. The method showed the advantage of blockchain technology in excluding byzantine robots and reaching consensus among other robots even if a byzantine robot was present.

As trust is cumulative and methods that calculate trust must be cyclic, the need to securely store trust values is increasing. However, all the aforementioned studies (except the last two studies that used blockchain) suffered from this common and critical flaw. In the other approaches, this fundamental has not been discussed at all.

Table 2.2 : Relevant papers including publication information

| **ID** | **Study Title** | **Author(s)/ Year** | **Journal/ Conference Name** | **Contributions** | **Techniques/ tools used** |
|---|---|---|---|---|---|
| S1 | Security and Resiliency of Coordinated Autonomous Vehicles (Benko et al., 2019) | Benko, J. et al. (2019) | 2019 Systems and Information Engineering Design Symposium, SIEDS 2019 | Proposes an algorithm to detect malicious robot in a network | Kalman filter |
| S2 | Selecting industrial robots for milling applications using AHP (Breaz et al., 2017) | Breaz, R. E. et al. (2017) | 5th International Conference on Information Technology and Quantitative Management, ITQM 2017 | Proposes a general-purpose robot selection method for specific tasks (milling application) | Analytic Hierarchy Process (AHP) |
| S3 | Towards Blockchain-Based Robonomics: Autonomous Agents Behavior Validation (Danilov et al., 2018) | Danilov, K. et al. (2018) | 9th International Conference on Intelligent Systems, IS 2018 | Proposes a method to validate agent-based service provider's delivered tasks using blockchain | Model checking method |

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**Table 2.2 – continued from previous page**

| ID | Study Title | Author(s)/ Year | Journal/ Conference Name | Contributions | Techniques/ tools used |
|---|---|---|---|---|---|
| S4 | A TOPSIS method by using generalized trapezoidal hesitant fuzzy numbers and application to a robot selection problem (Deli, 2020) | Deli, I. (2020) | Journal of Intelligent and Fuzzy Systems | Proposes an algorithm to support decision makers in the robot selection problem | TOPSIS of GTHF-numbers |
| S5 | Developing an MCDM method for robot selection with interval type-2 fuzzy sets (Keshavarz Ghorabaee, 2016) | Keshavarz Ghorabaee, M (2016) | Robotics and Computer-Integrated Manufacturing | Proposes a method to address the fuzzy multi- criteria robot selection problem based on the number of objective and subjective criteria and when the decision maker is a group | VIKOR method and interval type-2 fuzzy numbers |
| S6 | Selection of industrial robot using axiomatic design principles in fuzzy environment (Khandekar & Shankar, 2015) | Khandekar, A. V. and Shankar, C. (2015) | Decision Science Letters | Uses FAD to evaluate the suitability of the number of robot alternatives for a task | Fuzzy axiomatic design |
| S7 | An integrated MCDM method for robot selection under interval-valued Pythagorean uncertain linguistic environment (Liu, Quan, et al., 2019) | Liu, H. C. et al (2019) | International Journal of Intelligent Systems | Proposes a model to help in selecting the most suitable robot based on a linguistic set of criteria | QFD and QUALIFLEX |

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**Table 2.2 – continued from previous page**

| ID | Study Title | Author(s)/ Year | Journal/ Conference Name | Contributions | Techniques/ tools used |
|---|---|---|---|---|---|
| S8 | Robot evaluation and selection using the hesitant fuzzy linguistic MULTIMOORA method (Liu, Zhao, et al., 2019) | Liu, H. C. et al (2019) | Journal of Testing and Evaluation | Introduces a method to assesses and select the best robot for a predefined industrial purpose | MULTIMOORA and hesitant fuzzy |
| S9 | Gradient descent with momentum-based backpropagation neural network for selection of industrial robot (Nayak et al., 2016) | Nayak, S. et al (2016) | International Conference on Information and Communication Technology for Intelligent Systems, ICTIS 2015 | Proposes a method to help expert decision makers with robot selection problems | Gradient descent momentum optimization algorithm and the backpropagation neural network prediction technique |
| S10 | Selection of commercial robots with anticipated cost and design specifications using regression models (Nayak et al., 2019) | Nayak, S. et al (2019) | International Journal of Recent Technology and Engineering | Uses a mathematical model to select the best robot according to certain criteria | Linear regression using a feedforward neural network |
| S11 | Social Robot Selection: A Case Study in Education (Papakostas et al., 2018) | Papakostas, G. A. et al (2018) | 26th International Conference on Software, Telecommunications and Computer Networks, SoftCOM 2018 | Selects the most suitable social robot for educational purposes | TOPSIS |

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**Table 2.2 – continued from previous page**

| ID | Study Title | Author(s)/ Year | Journal/ Conference Name | Contributions | Techniques/ tools used |
|---|---|---|---|---|---|
| S12 | An integrated fuzzy MCDM based approach for robot selection considering objective and subjective criteria (Parameshwaran et al., 2015) | Parameshwaran, R. er al. (2015) | Applied Soft Computing Journal | Integrates several MCDM methods to select the best robot based on certain objectives and subjective attributes | FDM, AHP, TOPSIS and VIKOR |
| S13 | Multi-criteria robot selection problem for an automated single-sided lapping system (Piotrowski & Barylski, 2016) | Piotrowski, N. and Barylski, A. (2016) | Advances in Intelligent Systems and Computing | Contributes to selecting the (best) robot for lapping processes | AHP |
| S14 | An Effective Selection of Mobile Robot Model Using Fuzzy Logic Approach (Sahu et al., 2015) | Sahu, J. et al. (2015) | Materials Today: Proceedings | Evaluates some fuzzy logic techniques to select a mobile robot based on weighted qualitative attributes | triangular, trapezoidal and Gaussian membership functions |

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**Table 2.2 – continued from previous page**

| ID | Study Title | Author(s)/ Year | Journal/ Conference Name | Contributions | Techniques/ tools used |
|---|---|---|---|---|---|
| S15 | Application of TODIM (Tomada de Decisión Inerativa Multicritero) for industrial robot selection (Sen et al., 2016a) | Sen, D. K. et al. (2016) | Benchmarking | Applies the TODIM approach to solve the industrial robot selection problem assuming that all criteria are numeric in nature and taking into consideration the conflict between benefit and adverse criteria. It fails to include subjective criteria into the decision-making process. | TODIM |
| S16 | Extension of PROMETHEE for robot selection decision making: Simultaneous exploration of objective data and subjective (fuzzy) data (Sen et al., 2016b) | Sen, D. K. et al. (2016) | Benchmarking | Analyses objective and subjective criteria separately, then a global scoring system is used to combine the results | extended PROMETHEE I and II |
| S17 | Extension of TODIM for decision making in fuzzy environment: A case empirical research on selection of industrial robot (Sen et al., 2017) | Sen, D. K. et al. (2017) | International Journal of Services and Operations Management | Selects the most preferable robot for a specific purpose based on its subjective and objective factors, taking into consideration the risk attitude/preferences of the decision maker | TODIM and generalised fuzzy numbers |

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**Table 2.2 – continued from previous page**

| ID | Study Title | Author(s)/ Year | Journal/ Conference Name | Contributions | Techniques/ tools used |
|---|---|---|---|---|---|
| S18 | A new approach for Robot selection in manufacturing using the ellipsoid algorithm (Sharaf, 2018) | Sharaf, I. M. (2018) | Journal of Industrial Engineering International | Selects a robot from alternatives based on decision makers' assessment | Ellipsoid algorithm |
| S19 | A comparative evaluation of three industrial robots using three reference measuring techniques (Slamani et al., 2015) | Slamani, M. et al. (2015) | Industrial Robot | Compares and assesses the static and dynamic performance of industrial robots by observing the robot's motion accuracy | Laser tracker and laser interferometer |
| S20 | Robot evaluation and selection with entropy-based combination weighting and cloud TODIM approach (J. J. Wang et al., 2018) | Wang, J. J. et al. (2018) | Entropy | Proposes a method to interpret hesitant linguistic information to handle the robot selection problem. | Cloud TODIM |
| S21 | An integrated linguistic MCDM approach for robot evaluation and selection with incomplete weight information (Xue et al., 2016) | Xue, Y. X. et al. (2016) | International Journal of Production Research | Proposes an approach to select the most appropriate robot after removing the ambiguity of decision makers' assessment. | Hesitant 2-tuple linguistic sets and extended QUALIFLEX |
| S22 | Fuzzy extended VIKOR-based mobile robot selection model for hospital pharmacy (F. Zhou et al., 2018) | Zhou, F. et al. (2018) | International Journal of Advanced Robotic Systems | Supports the health sector by identifying (the best) mobile robot to deliver the pharmaceutical product. | AHP and VIKOR |

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**Table 2.2 – continued from previous page**

| ID | Study Title | Author(s)/ Year | Journal/ Conference Name | Contributions | Techniques/ tools used |
|---|---|---|---|---|---|
| S23 | Dynamic trust management framework for robotic multi-agent systems (Zikratov et al., 2016) | Zikratov, I. et al. (2016) | 16th International Conference on Next Generation Teletraffic and Wired/Wireless Advanced Networks and Systems, NEW2AN 2016 and 9th conference on Internet of Things and Smart Spaces, ruSMART 2016 | Develops a trust management framework to control access and manage the agent's reputation. | - |
| S24 | Reputation Based Trust In Human-Agent Teamwork Without Explicit Coordination (Hafizoglu & Sen, 2018) | Hafizoglu, F.M. and Sen, S. (2018) | Proceedings of the 6th International Conference on Human-Agent Interaction | Explores how the agent's reputation could affect human trust | - |
| S25 | Managing Byzantine Robots via Blockchain Technology in a Swarm Robotics Collective Decision Making Scenario (Strobel et al., 2018) | Strobel, V. et al. (2018) | Proceedings of the 17th International Conference on Autonomous Agents and MultiAgent Systems | Establishing a secure swarm coordination mechanism using blockchain technology to isolate byzantine robots from the swarm. | Blockchain |

### 2.4.2 Ontology evolution related work

As previously mentioned, ontology evolution is necessary when an expert's perception of domain knowledge changes over time. Hence, there is a need for the corresponding domain ontology to evolve.

When reading through the existing literature on ontology evolution, it is observed that the studies in this field can be classified into three main groups: the first group proposes new approaches to ontology evolution, the second group focuses on storing and versioning the ontology changes without paying any attention to the ontology evolution methodologies, and the third group measures the impact of ontology evolution on dependent applications which is not in the scope of this study.

Many studies have proposed new methodologies for ontology evolution. One of the proposed methods to enable ontology evolution is Ontology Evolution Wiki which is based on the Wikipedia crowdsourcing technique, where different community users are involved in the evolution of ontologies by proposing changes/ updates and discussing them with domain experts until agreement is reached (Aseeri et al., 2008). In a similar vein, the method proposed by Wang et al. (2019) employed the use of a crowdsourcing technique to allow learners in an online learning environment to contribute to ontology generation and evolution. This approach has been tested on three learning activities: a semantic annotation activity, a knowledge graph activity, and a reverse quiz activity. In (Lin et al., 2010), the authors presented a semantic navigation support service and tool for ontology evolution called OntoAssist. It evolves a base ontology by aggregating knowledge from a large number of actual web users.

Other studies in the literature tried to solve the issue of ontology history access. Grandi (2016) proposed a method to manage and simplify the versioning of an ontology by storing all the evolved versions of an ontology in a rational database. This involves identifying all types of primitive operations that are used to evolve an ontology and identifying each version of the ontology with a unique timestamp. Then, any version of the ontology can be manipulated, reconstructed or retrieved using SQL queries. In a similar premise, Bayoudhi et al. (2017) proposed a hybrid approach which also used rational databases to store ontology versions. In their approach, they tried to build a space-efficient storage strategy that keeps a complete history of ontology evolution by capturing the semantics of a domain using a predefined reference version and the most recent version of the ontology. A formal framework was developed by Kozierkiewicz & Pietranik (2019) to track the changes in an ontology by assigning a timestamp to each version of the ontology. The framework then takes two states of an ontology as input and returns a description of the changes. The framework treats the ontology changes in four levels: concepts, concepts' relations, instances and their relations.

In the robotics domain, a number of ontologies have been built in the literature. Some of these works employ ontologies to support robot capabilities in the working environment by defining a conceptualization of all instructions and situations of the required task (Olivares-Alarcos et al., 2019), while other studies built ontologies for technical terminologies of robots and robot parts (Schlenoff et al., 2012). For instance, an IEEE standard ontology termed Core Ontology for Robotics and Automation (CORA) is developed in (Prestes et al., 2013). This ontology describes the physical design of robots and it is currently being used to build other robotic ontologies that cover other robotic sub-domains.

Umbrico et al. (2020) built a domain ontology that is designed to facilitate human-robot collaboration by considering three contexts: the environment, the behaviour and the production contexts. However, none of these works discussed how to evolve the proposed robotic ontologies. In the proposed bcRAOe method, we address the limitations of the current ontology evolution methods as follows:

1. All robotic ontologies in the literature are static. We aim to allow robotic ontology evolution to change the nature of robotic ontologies to be dynamic ontologies.

2. There is no automated method to recover the previous version of the ontology

before applying the changes (Khattak et al., 2013).

## 2.5 Data Analysis

We analysed all the reviewed studies along several criteria to accurately define gaps in the literature. The analysis criteria that were used in this study are listed in Table 2.3.

Table 2.3 : Analysis criteria used to evaluate the included 25 papers

| **Analysis Criteria** |
|---|
| 1. Did the study use tamper-proof databases to securely store robot trust values? |
| 2. Does the study propose an algorithm for selecting a robot? |
| 3. How does the study select a robot to complete a specific task? |
| 4. Did the study propose a method to evaluate the selected robot after it had completed the task? |
| 5. Did the study use an authentic method to identify robots? |

The selected studies were analysed according to the assessment criteria in Table 2.3. Each of these criteria were given a score of 1 or 0 where 1 indicates that the study has met the corresponding criteria while 0 indicates it has not. Table 2.4 shows that only two papers used tamper-proof databases to store robot trust values while no papers discussed robotic ID management. A few papers met the other three criteria as shown in Table 2.4.

Table 2.4 : Assessment of the selected 25 articles against the analysis criteria

| Study | TV Secure and tamper-proof? | Algorithms for Robot Selection | Algorithms to support task specific selection | Robot Task assessment | ID Management for Robots (authentication system for robots) | Total |
|---|---|---|---|---|---|---|
| S1 | 0 | 0 | 1 | 0 | 0 | 1 |
| S2 | 0 | 1 | 1 | 0 | 0 | 2 |
| S3 | 1 | 0 | 0 | 1 | 0 | 2 |
| S4 | 0 | 1 | 1 | 0 | 0 | 2 |
| S5 | 0 | 1 | 1 | 0 | 0 | 2 |
| S6 | 0 | 1 | 1 | 0 | 0 | 2 |
| S7 | 0 | 1 | 1 | 0 | 0 | 2 |
| S8 | 0 | 1 | 1 | 0 | 0 | 2 |
| S9 | 0 | 1 | 0 | 0 | 0 | 1 |
| S10 | 0 | 1 | 0 | 0 | 0 | 1 |
| S11 | 0 | 1 | 1 | 0 | 0 | 2 |
| S12 | 0 | 1 | 1 | 0 | 0 | 2 |
| S13 | 0 | 1 | 1 | 0 | 0 | 2 |
| S14 | 0 | 1 | 1 | 0 | 0 | 2 |
| S15 | 0 | 1 | 1 | 0 | 0 | 2 |
| S16 | 0 | 1 | 1 | 0 | 0 | 2 |
| S17 | 0 | 1 | 1 | 0 | 0 | 2 |
| S18 | 0 | 1 | 1 | 0 | 0 | 2 |
| S19 | 0 | 0 | 0 | 1 | 0 | 1 |

Continued on next page

**Table 2.4 – continued from previous page**

| Study | TV Secure and tamper-proof? | Algorithms for Robot Selection | Algorithms to support task specific selection | Robot Task assessment | ID Management for Robots (authentication system for robots) | Total |
|---|---|---|---|---|---|---|
| S20 | 0 | 1 | 1 | 0 | 0 | 2 |
| S21 | 0 | 1 | 1 | 0 | 0 | 2 |
| S22 | 0 | 1 | 1 | 0 | 0 | 2 |
| S23 | 0 | 0 | 0 | 1 | 0 | 1 |
| S24 | 0 | 0 | 0 | 1 | 0 | 1 |
| S25 | 1 | 0 | 0 | 0 | 0 | 1 |

Although several methods have been proposed in the literature to address the problem of robot selection, Table 2.4 highlights several limitations of these approaches that need to be addressed in order to build a comprehensive and efficient methodology for robot selection. Some of these shortcomings are: (a) building a reputation system for robotics has not been discussed yet in the literature, (b) there is no attempt in the literature to standardise the technical terminologies of the robotics domain among all robotic experts and non-expert end-users, (c) dynamically evaluating the performance of a robot in a specific task is still missing in the literature and (d) inferring a reputation value for the performance of a non-reviewed purpose of a multi-purpose robot based on its similarities to already evaluated purposes is not explored yet.

## 2.6 Conclusion

This chapter summarised some of the key requirements that should be considered to help non-expert end-users in the robotics selection process. The requirements included developing a tamper-proof storage platform to store the robotics reputation scores, deriving the reputation score of a robot based on its previous performance, boosting the reputation of new robots by predicting a reputation score based on its similarity to other robots, and developing a context-aware reputation method to evaluate robots in all contexts. It also discussed the protocol that was followed to conduct the SLR. A total number of 25 papers were reviewed and analysed in this SLR. In the next chapter, the research gaps and limitations are identified based on the systematic literature review discussed in this chapter.

# Chapter 3

# Problem Definition

## 3.1 Introduction

The aim of this chapter is to identify the research gaps and limitations that are addressed in this thesis. Moreover, it presents the research questions and main objectives of this thesis. This chapter is organized into six sections as follows: section 3.2 defines the key research terms and concepts that are used in this thesis. In section 3.3 , the research gaps are formally identified. Section 3.4 presents the research questions and section 3.5 defines the research objectives. In section 3.6 , this chapter is concluded.

## 3.2 Key Terms and Concepts

This section presents a formal definition of a set of keywords and concepts that are used in this thesis.

### 3.2.1 Robotics

Robotics is the science that studies the principle of robot design, fabrication, theory and application (Bajd, 2010).

### 3.2.2 Robot

A robot is defined as a programable machine that performs tasks and interacts with its environment using its intelligence, sensors and physical actuators (Tzafestas, 2013).

### 3.2.3 Multi-purpose robot

A multi-purpose robot is any robot that is designed to independently perform a number of functions. It is also known as a general purpose robot (Zaman et al., 2015).

### 3.2.4 Context

According to Dey (2001) "Context is defined as any information that can be used to characterise the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves". In this research, we will use the term contexts to refer to the different purposes of the multi-purpose robots.

### 3.2.5 Robot service requester/consumer

A robot service requester is any entity who employs robots to perform a set of tasks. The robot service requester could be a human user, business or another robot.

### 3.2.6 Robot service provider

We use the term robot service provider to refer to the manufacturer or the supplier who designs, builds and offers robotic services to the robot service requesters.

### 3.2.7 Robot service broker

A robot service broker is a middleware agent between the robot service requester and robot service provider. A robot service broker helps robot service requesters in the robot selection process by addressing their requests, ranking all alternatives and suggesting a robot that meet the requirements of the robot service requesters.

### 3.2.8 Blockchain

Blockchain is a tamper-resistant, distributed and decentralised digital ledger of all transactions that have been executed among the network parties. Each transaction is verified by a consensus protocol (Yaga et al., 2019).

### 3.2.9 Reputation systems

A reputation system is a system that is designed to manage trust between stranger entities who have not interacted before. It is a critical component of online marketplaces, file-sharing systems or any online platform that involves online transactions. A reputation system collects data about an entity from previous entities who have interacted with that entity, computes a reputation value for the entity and then displays the entity's reputation value to other entities to establish trust based on the previous experiences (Sänger & Pernul, 2018).

### 3.2.10 Reputation score (or trust value)

We define a reputation score as the value that indicates the trustworthiness degree of an entity. This score also can be used to predict the behaviour of the entity in future transactions.

## 3.3 Research Gaps in the Existing Literature

As discussed in the previous chapter, significant advances have been made in the robot selection approaches in the literature. However, the systematic literature review reported in chapter 2 raises some issues and highlights several limitations of the previous research that need to be addressed in order to build an *intelligent blockchain-based reputation broker for robot selection*. The following sub-section summarises the gaps that were identified from the SLR in the previous chapter.

### 3.3.1 Robotics trust values are not securely stored in a tamper-proof database

The selection of the most suitable robot for a specific task is a critical decision because of the large number of available robot alternatives and the variation in their attributes. Consequently, decision makers need to consider a number of attributes for every robot and then compare them to find the best robot for their purposes. This process requires long and complex calculations which could be an iterative process. In other words, these calculations give an initial vision into the performance of the robot in related tasks. So, the decision makers could reuse the same attributes to measure the suitability of a robot that has succeed in completing a task to another similar task. For this reason, storing and securing robot trust values is essential. Most of the reviewed robot selection algorithms in the literature do not introduce the idea of storing trust values at all while a few studies have suggested storing (plain, unencrypted) trust values in traditional databases (Benko et al., 2019).

Although, Danilov et al. (2018) and Hafizoglu & Sen (2018) did not address the robot selection problem, they have taken advantage of the immutability feature of blockchain to solve the security issues in a decentralized system such as swarm robots.

### 3.3.2 Expert decision maker/s are required to select robots

Once the need for a robot is received, there must be a process where candidate robots are measured against criteria extracted from the service requester's requirements. According to the existing literature, the robot selection process relies on an expert human or intelligent robot decision maker/s at different stages of the selection process. The majority of the selected studies, such as (Sahu et al., 2015) and (Sen et al., 2016b) proposed methods to select a robot after prioritising some criteria over others by an expert decision maker while (Breaz et al., 2017) and (Sen et al., 2017) presented methods that rely on the decision maker/s to determine which criteria should be considered to achieve a specific task. Moreover, the decision maker/s are responsible for extracting user requirements and mapping them to robots' attributes in some studies like (Papakostas et al., 2018).

Thus, the need for an algorithm that helps non-expert service requesters find the most suitable robot according to their requirements is increasing.

### 3.3.3 Lack of approaches for personalised robot selection

From a practical point of view, only certain types of robot attributes need to be examined during the selection process to successfully achieve a specific task. For example, the criteria to evaluate a mobile delivery robot is very different from the criteria to evaluate a medical surgical robot. However, due to differing user requirements, they may want to personalise the selection process depending on their needs. The ability to customise the robot selection process is missing in the extant literature.

An analytical reading of the literature studies clearly shows that:

- The evaluation of alternatives becomes complicated as the number of alternatives AND/ OR the number of criteria increase. Thus, most of the reviewed studies such as (Liu, Quan, et al., 2019) and (Breaz et al., 2017) tended to increase the effectiveness of the evaluation process by reducing the number of robot alternatives. These alternatives are either recommended by the expert decision maker or by the service requester who needs a robot to help complete their tasks.

- Some papers such as (Breaz et al., 2017), (Papakostas et al., 2018), (Piotrowski & Barylski, 2016) and (Xue et al., 2016) contributed to solve the robot selection problem for specific applications only, which allows them to predefine the evaluation criteria that are relevant to the desired applications.

- Few papers focus on one category of attributes. For example, (Sen et al., 2016a) introduced an algorithm to evaluate objective attributes only, while (Deli, 2020) used subjective attributes only as the evaluation criteria.

Thus, there is scant research that allows robot service requesters to compare the suitability of a large number of robots or to allow them to make their selection based on comparing a large set of attributes.

### 3.3.4 Selection process depends on (initial) manufacturers' specification report

None of the included studies proposed methods to select a robot based on the dynamic evaluation of its performance during similar tasks. This means all of the studies used the manufacturers' promises to evaluate the suitability of a robot for a specific task. Consequently, the selection process is very challenging for non-expert users who are not able to understand the technical specification. Moreover, most manufacturers' specification are often written for marketing purposes. Danilov et al. (2018), Zhou et al. (2018), Zikratov et al. (2016) and Strobel et al. (2018) dynamically evaluated robot reliability by observing the robot's behaviour to enhance the security of swarms or to manage trust in teams. However, a dynamic evaluation to address robot selection has not yet been discussed in the literature.

## 3.4 Research Questions

Based on the research gaps that are listed in section 3, this research aims to solve the following main research question:

**How can a robot consumer reliably select a robot from multiple alternatives to provide "Robot as a service"?** To address the main research question, we break it down into the following sub-questions:

### 3.4.1 Research sub-question 1

How do we develop a trustworthy platform to select a robot based on its previous performance?

### 3.4.2 Research sub-question 2

How can the robot attributes provided by manufacturers be standardized?

### 3.4.3 Research sub-question 3

How can we develop intelligent methods to compute a reputation value for all robots?

### 3.4.4 Research sub-question 4

How can each purpose of a multi-purpose robot be evaluated?

### 3.4.5 Research sub-question 5

How can the solutions developed for objectives 1-4 be evaluated?

## 3.5 Research Objectives

Based on the main research question and sub-questions, the research objectives are as follows:

### 3.5.1 Research objective 1: to develop a reliable robotics selection framework

This objective can be achieved by developing a robotic broker framework that integrates several technologies such as blockchain and reputation systems. Blockchain technology will be used to build an accurate and reliable framework to store robotics information and trust values that will be used in the robot selection process. The decentralization, immutability and transparency features of blockchain enable it to process robotic data in a reliable, secure, intelligent and efficient manner.

### 3.5.2 Research objective 2: to intelligently standardise the robotics attributes provided by the manufacturer among all requesters and providers

This objective will be addressed by using an ontology for representing and managing robotics attributes and also allowing ontology evolution overtime. A blockchain-based crowdsourcing ontology evolution method will be developed for this purpose.

### 3.5.3 Research objective 3: to develop a reliable and intelligent reputation-based mechanism for robot selection and ranking

This objective can be achieved by building a reputation method that produces a reputation value for all robots based on their previous performance and predicts a reputation value for other robots that have been recently added to the network but have not been used as yet.

### 3.5.4 Research objective 4: to develop an intelligent context-aware or purpose-aware method to infer the reputation value based on values known in other contexts

To address this objective, we will build an ontology-based method for modelling different contexts of robots and then the trust value of a non-reviewed context will be computed based on its similarity to other reviewed contexts.

### 3.5.5 Research objective 5: to validate and evaluate the accuracy of the proposed methods to address objectives 1-4

The working of the proposed blockchain-based reputation broker will be evaluated using the Ethereum Goerli network. The solutions developed for objectives 2, 3, and 4 will then be systematically evaluated to check whether they meet the defined requirements and perform as expected or not. This can be achieved by defining certain metrics to measure the agreement between the predicted and observed results of the conducted experiments.

## 3.6 Conclusion

This chapter provided formal definitions for the keywords and the concepts that will be used in the remainder of this thesis. It also identified the research gaps in the literature. Based on these gaps, the main research question and sub-questions were defined. In this chapter, brief descriptions of the research objectives also were provided.

In the next chapter, the research methodology that is followed to achieve the objectives of this thesis are presented. In addition, it will present an overview of the research solutions.

# Chapter 4

# Research Methodology and Solution Overview

## 4.1 Introduction

The previous chapter defined the main research keywords, identified the research gaps and detailed the research aims and objectives. This chapter discusses the min research methodology that is followed in this thesis to address the gaps and achieve the research objectives. In addition, it presents an overview of the proposed solution. This chapter is organised as follows: Section 4.2 introduces the selected research methodology that is used in this research. Section 4.3 - 4.7 presents an overview of the research objectives 1-5, respectively. Section 4.8 concludes this chapter.

## 4.2 Selected Research Methodology

In addressing the research gaps identified in the previous chapter, we need to follow a systematic scientific approach to propose solutions for each issue. This thesis follows the design science research methodology (DSRM) to achieve the research objectives (Peffers et al., 2007). DSRM is a popular method in engineering and architecture disciplines. For more details about this methodology, the reader can refer to (Geerts, 2011), (Hevner et al., 2004) and chapter 11 in (Williamson & Johanson, 2017). This method is chosen in this thesis because it helps to create a new prototype in attaining goals, and this research aims to build a new broker that helps the stakeholder community (robot service requesters) to select a robot. Figure 4.1 depicts an overview of this methodology.

The DSRM consists of the following six phases:

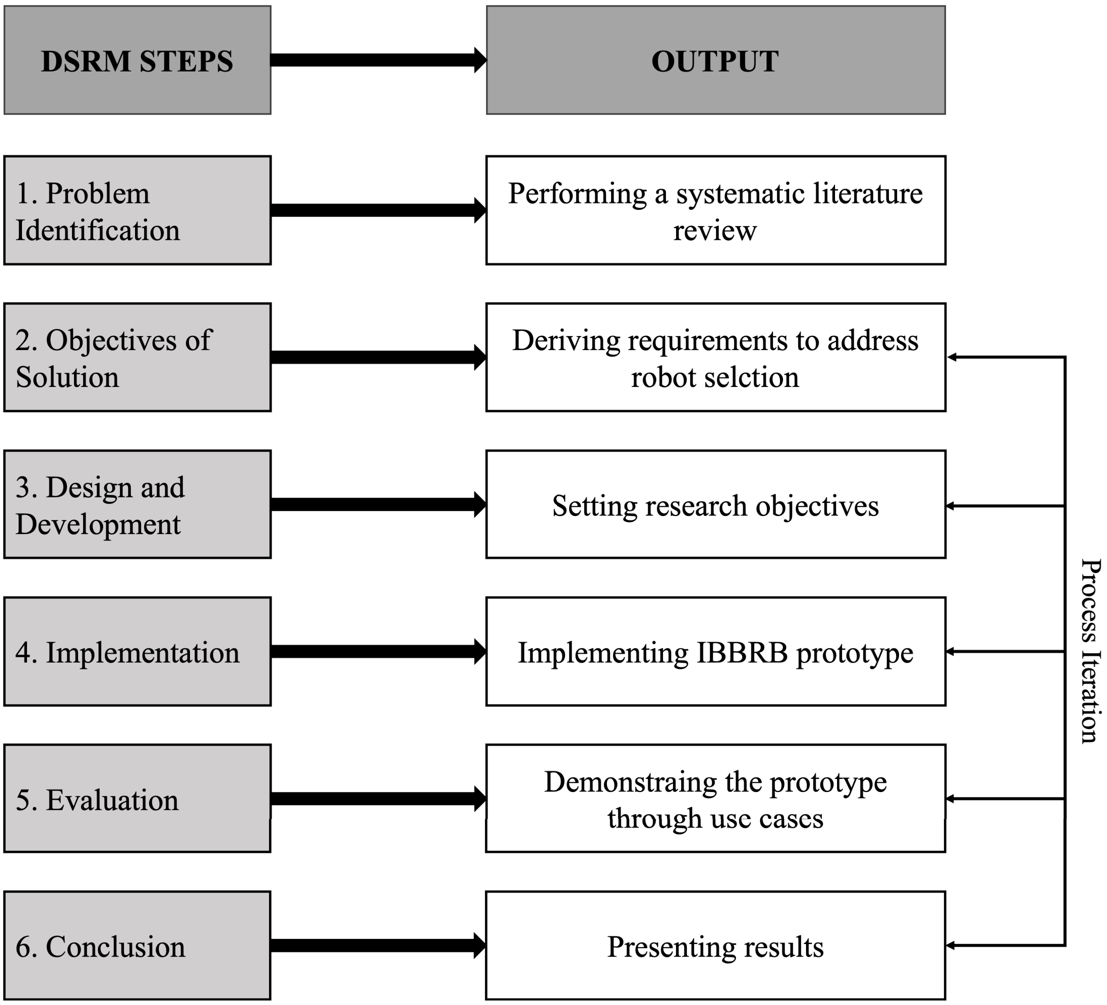


Figure 4.1 : Steps in the Design science research methodology process model 'adapted from (Peffers et al., 2007)'.

**Phase 1: Problem identification**

In this phase, we review the related works in the literature and analyse the weakness or limitations of each existing solution to identify the problems that need to be addressed in this area.

**Phase 2: Defining research objectives**

As a consequence of identifying research problems, the primary objective of this research has been recognised. This research develops an intelligent blockchain-based reputation broker to address the problem of robot selection.

**Phase 3: Design and development**

In this phase, a proof-of-concept software artifact is built using blockchain and different intelligent methods such as fuzzy logic, machine learning and context-aware inferencing approaches. The solutions to research sub-questions 2-4 are integrated into this artifact.

**Phase 4: Demonstration phase**

This phase applies the proposed algorithms and methods to related contexts to solve similar problems.

**Phase 5: Evaluation**

In this phase, a set of evaluation metrics, namely MAE, RMSE and MAPE are used to evaluate the results of the proposed solutions in comparison to the result of the existing approaches.

**Phase 6: Communication**

This phase shares the results with the research community by publishing the results in international journals and conferences.

## 4.3 Solution Overview

The main aim of this thesis is to build an intelligent blockchain-based reputation broker (IBBRB) for robot selection which is able to help robotic service requesters in the selection processes. IBBRB integrates reputation systems, blockchain and service-oriented computing. IBBRB has three main functionalities, as shown in Figure 4.2. In the following subsections, the proposed solutions for each objective of this thesis are discussed.

### 4.3.1 General framework architecture of the proposed blockchain-based reputation broker (IBBRB)

As previously mentioned, IBBRB works as a middleware layer to manage robotic information and to help robot service requesters in the robot selection processes. We use the Model-View-Controller (MVC) design pattern to develop the system architecture (Figure 4.3).

**The view layer:** is the presentation layer that presents data to the robot service requesters and providers. It allows robot service requesters to request, obtain the required results and/or evaluate a robot. The robot service providers are allowed to add robots, request ontology changes or vote on an ontology update request from other providers.

**The control layer:** is the layer where processing and computations of data take place. This layer acquires data from the model layer then processes it in embedded intelligent modules to update these data and sends it to the presentation layer. Some of the intelligent modules that are embedded in this layer are the reputation model and the prediction model.

**The model layer:** is the layer where the robotics data is stored in blocks in a blockchain network. The main characteristics of the blockchain network that are

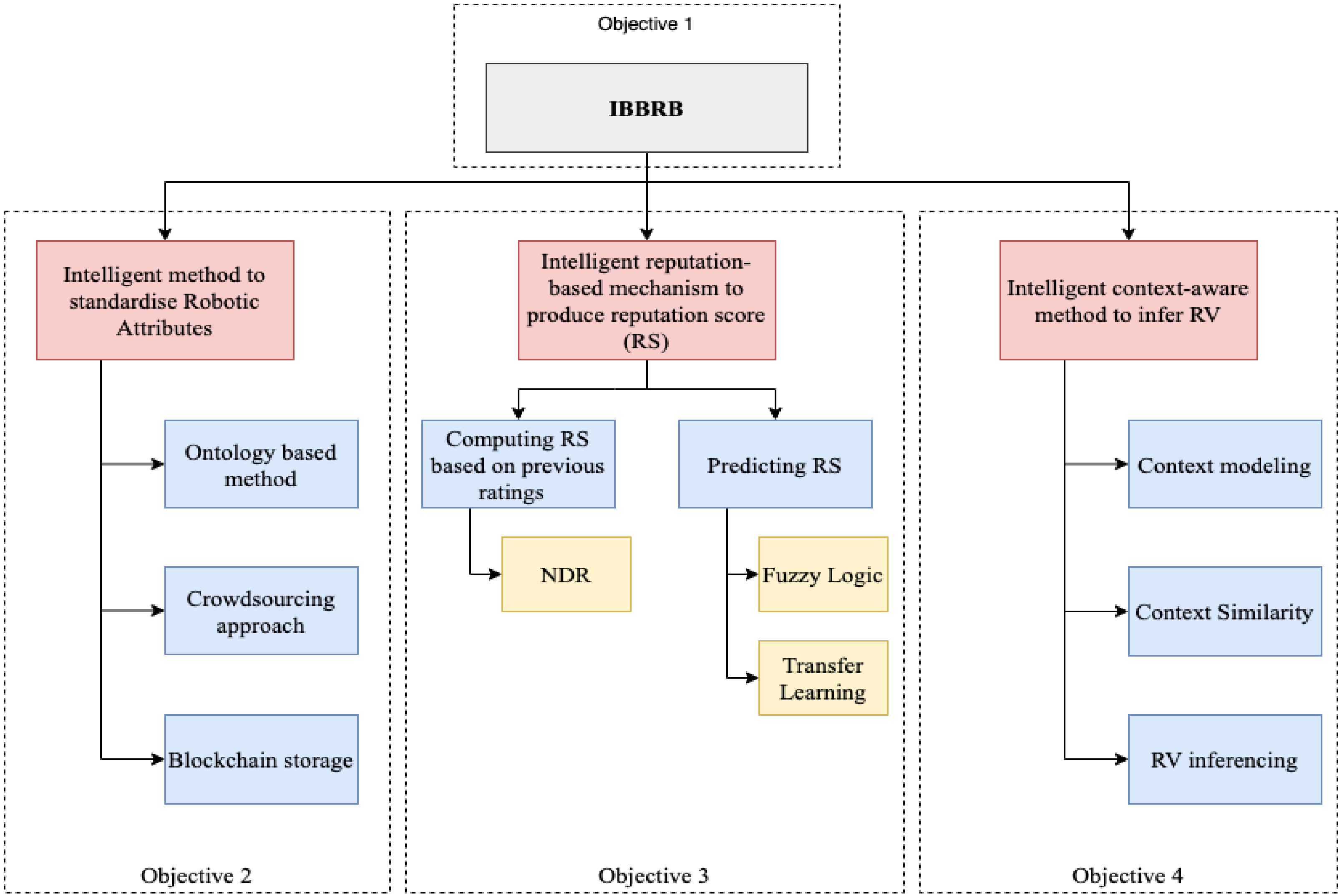


Figure 4.2 : Overview of the research objectives and proposed solutions.

used in the model layer of IBBRB are detailed in Table 4.1. There are two virtual sub-layers in the model layer namely: (a) robotics' static specification sub-layer and (b) robotics' dynamic reputation sub-layer. In the static layer, the service providers (manufacturers) are allowed to generate the genesis block for every robot while storing blocks in the dynamic reputation layer is done by the system after calculating a reputation score for the robot. More details of reputation score computations are given in chapter 6. Storing reputation scores in a blockchain network increases the security and minimises the risk of losing or manipulating this information.

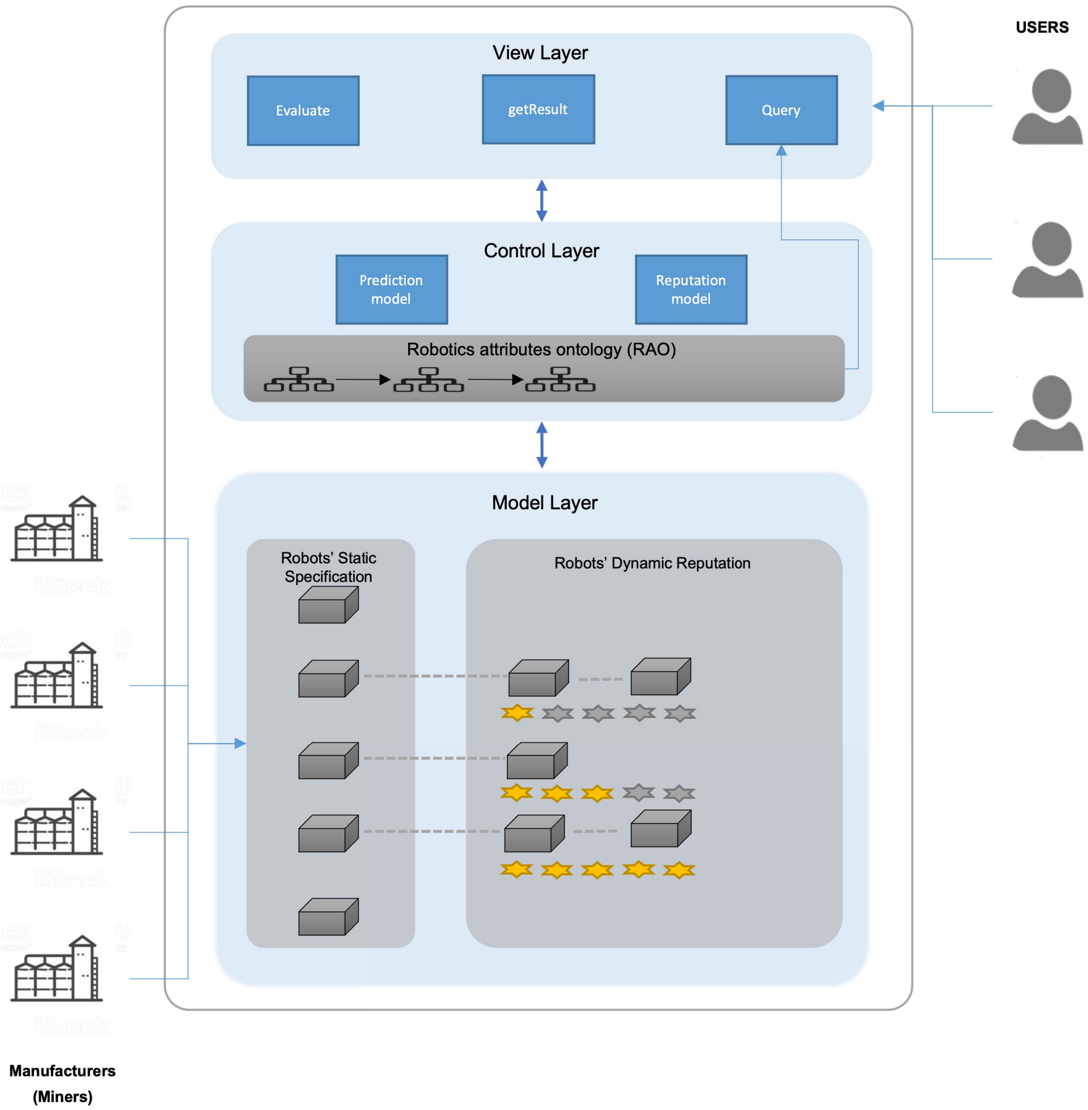


Figure 4.3 : Overview of the IBBRB system architecture.

Table 4.1 : Characteristics of blockchain in IBBRB.

| | | |
|---|---|---|
| **CATEGORY** | Consortium (hybrid) chain | **Why?**<br>• Service providers are known.<br>• Service provider nodes only can generate new blocks<br>• Service requesters are not allowed to participate in the consensus process. |
| **PLATFORM** | Ethereum 2.0 | **Why?**<br>• Open-source platform<br>• Most popular one<br>• Support consortium networks<br>• Support smart contract functionality |
| **PEERS** | Service provider (manufacturer) and service requesters (consumers) | |
| **CONSENSUS PROTOCOL** | Proof of stake | |

## 4.4 Overview of the Solution for Robotics Attributes Standardisation (Objective 2)

The robotics attributes are expressed differently depending on the manufacturers, the purpose of the robot, and the intended use of the robot. This variation in robotics terms makes building a global application/ platform which requires managing robotics knowledge infeasible unless we can standardise robotics knowledge terminologies across providers, users and systems to simplify gathering, managing, retrieving and presenting these data. So, IBBRB requires a common understanding and interpretation of robotics attributes. To address this issue, we use an ontology to represent and manage robotics attributes. We term the ontological manifestation that encapsulates the attributes of the robots and their relationship as the robotics attributes ontology (RAO). RAO is embedded in the control layer as shown in Figure 4.3. Robot service providers can use the existing RAO to add new robots to the network. As the robotics domain is evolving quickly, we also propose a blockchain-based crowdsourcing method for RAO evolution (bcRAOe). The robot service providers are involved in improving or updating RAO. The workflow of the proposed solution for robotic attribute standardisation is presented in Figure 4.4.

## 4.5 Overview of the Solution for Robot Reputation Computation (Objective 3)

To achieve this objective, we need to build a reputation model that can produce an overall reputation score for each robot in the network based on previous users' experiences to help future users in their decision making. In the literature, a significant number of reputation models have been proposed to aggregate and collect evaluations or assessments from users and subsequently compute the reputation score. One of the challenges that faces users of reputation systems is the cold start

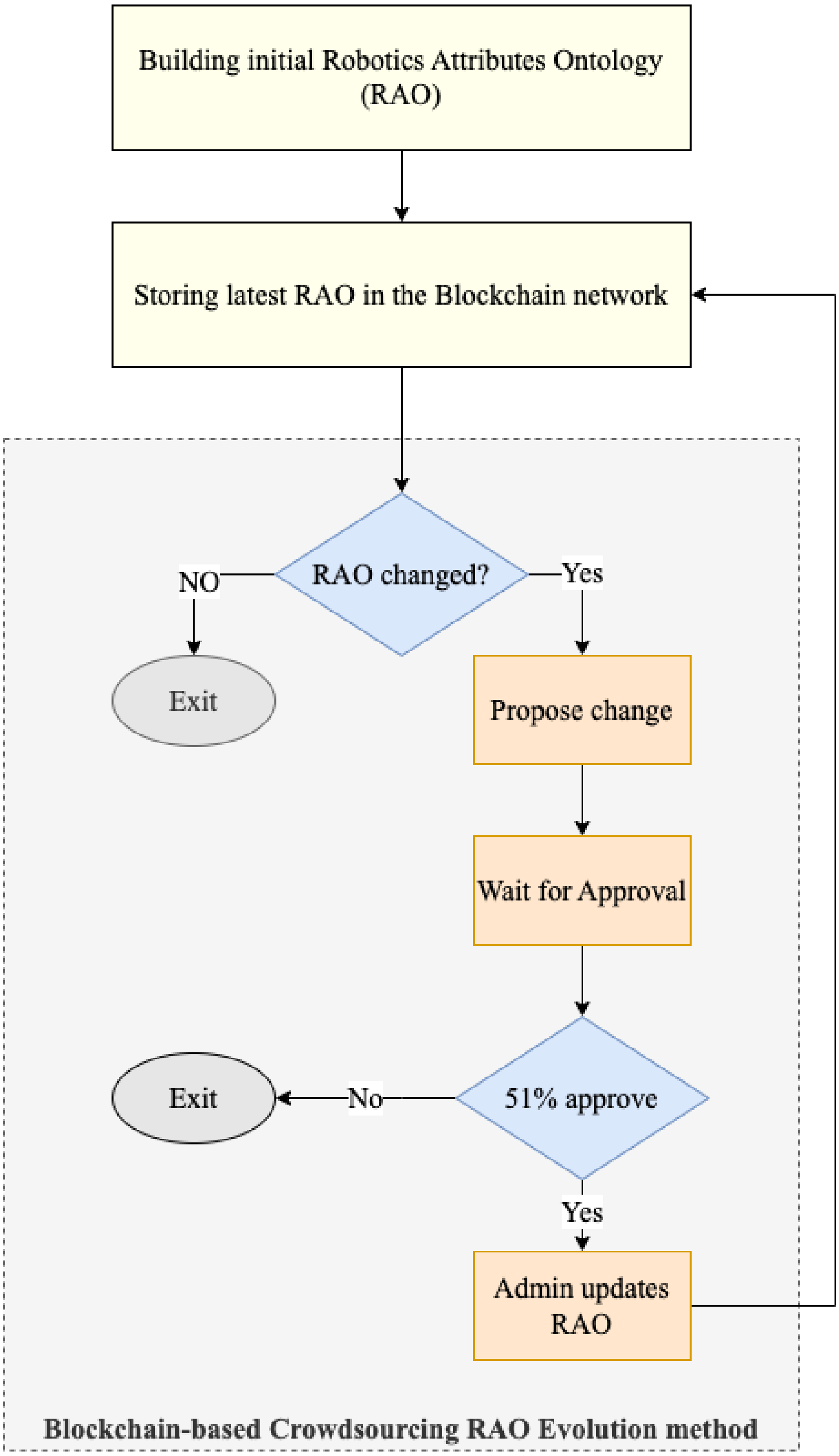


Figure 4.4 : Overview of the proposed solution for robotics attribute standardisation (objective 2).

problem. Cold start occurs when an entity in the system has no or few ratings. In this research, we propose a reputation computation method that addresses this issue by intelligently generating a reputation score for all robots in the network, even if that robot has not been reviewed by the users yet. The proposed method intelligently predicts a reputation score for a robot that has recently been added to the network but has not been used as yet and it also collects robot users' opinions and generates a reputation score for other robots, as shown in the workflow of Figure 4.5. The proposed reputation method is based on a five-star rating and comprises the following two models:

a. Rating model which is used to collect users' evaluations and generate reputation scores.

b. Prediction model which is used to predict a reputation score for a newly added robot to boost the reputation of the new robot.

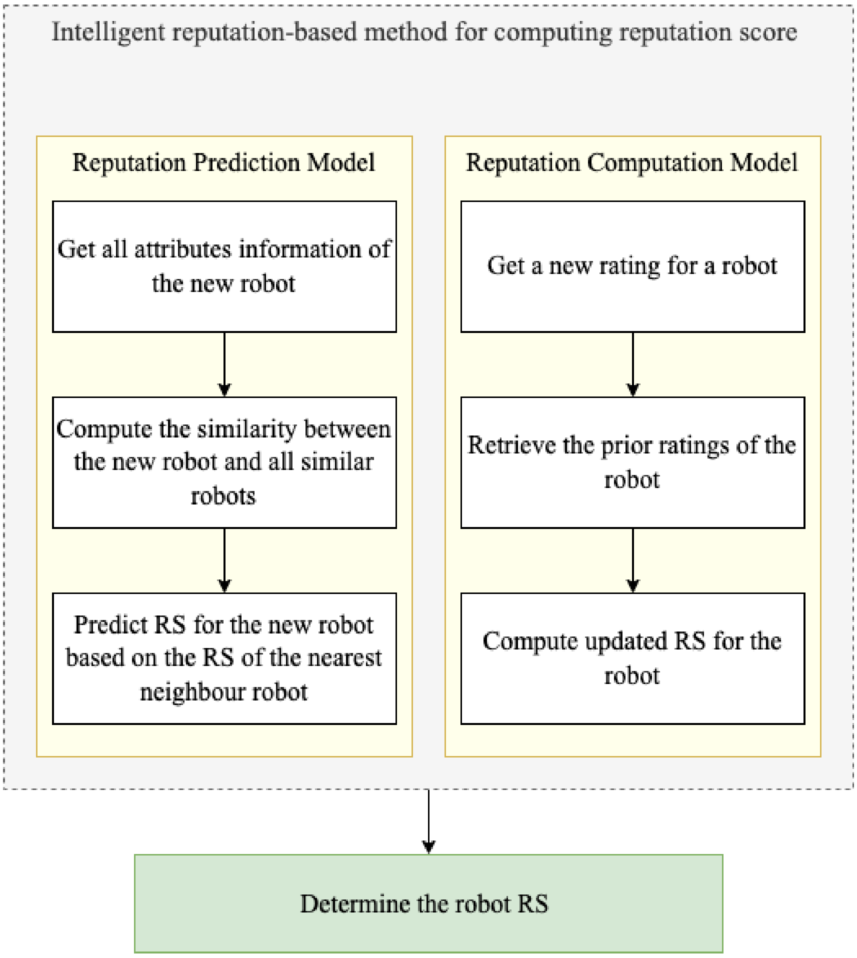


Figure 4.5 : Overview of the proposed solution for robot reputation (objective 3).

## 4.6 Overview of the Solution to Infer the Context-aware Reputation Value (Objective 4)

Multi-purpose robots are usually used to perform related tasks that require similar technical specifications and capabilities. However, the performance of a multi-purpose robot could vary according to the assigned task. In other words, the ability to complete a task does not indicate that the robot is the most efficient one to perform the task. The final research contribution of this thesis is to intelligently infer a reputation value for all the contexts of a robot. For this purpose, we propose a method termed *Context-aware reputation value inferencing for multi-purpose robot*

*(CaRVInf)*. CaRVInf is used to produce a contextual reputation value for different purposes of a multi-purpose robot, the working process of which is (i) context modelling , (ii) context similarity computation and (iii) context score inference. The proposed method begins by representing different contexts of a robot based on the ontology classes proposed in CAMeOnto (Aguilar et al., 2018), then measuring the semantic similarity between contexts, and finally predicting a fuzzy interval within which the reputation score of a context falls. The workflow of the proposed solution for contextual reputation value inferencing is presented in Figure 4.6.

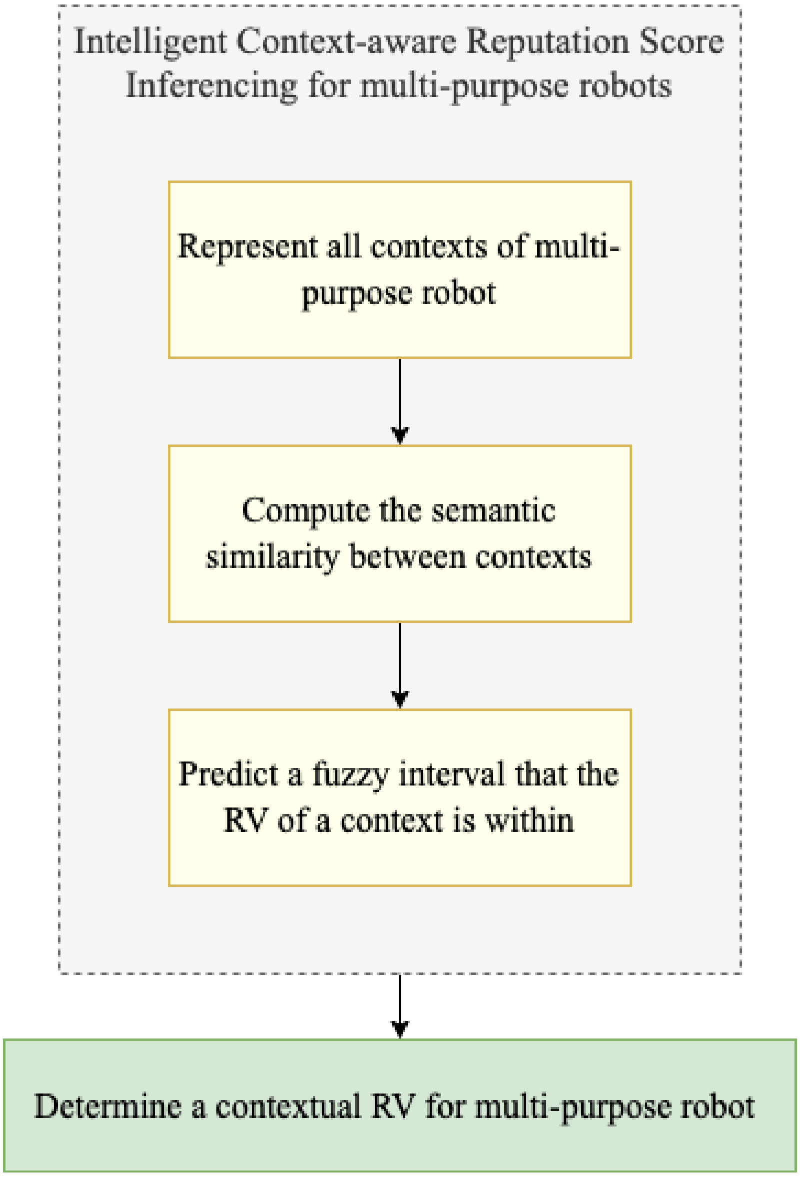


Figure 4.6 : Overview of the solution for context-aware reputation value inferencing (objective 4).

## 4.7 Validate and Evaluate the Accuracy of the Proposed Methods to Address Objectives 1-4 (Objective 5)

The developed solutions are then systematically evaluated to check whether they meet the defined requirements and perform as expected or not. This can be done using the most common metrics for machine learning. As all the proposed solutions incorporate building regression models to predict reputation values, we use the most common evaluation metrics to evaluate regression models, namely, mean absolute error (MAE), root mean squared error (RMSE) and mean absolute percentage error (MAPE). In this section, we provide an overview of the selected evaluation metrics.

1. MAE: MAE is a popular model evaluation metric used to evaluate the performance of regression models. MAE measures the average of absolute differences between predicted and actual values (Ali et al., 2020).

$$\mathrm{MAE}(y, \hat{y}) = \frac{\sum_{i=1}^{n} |y_i - \hat{y}_i|}{n} \tag{4.1}$$

2. RMSE: RMSE is another frequently used performance evaluation metric in regression. It presents the square root of the mean squared error between predicted and actual values (Chai & Draxler, 2014).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \tag{4.2}$$

3. MAPE: MAPE presents the error values in percentages. It is used to measure the average percentage difference between predicted and actual values (de Myttenaere et al., 2016).

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i - \hat{y}_i|}{y_i} \tag{4.3}$$

where:

- $n$ is the total number of observations
- $y_i$ is the actual value of the $i^{th}$ observation
- $\hat{y}_i$ is the predicted value of the $i^{th}$ observation

## 4.8 Conclusion

This chapter discussed the methodological approach that is selected to address the research gaps. The Design Science Research methodology (DSRM) was the approach selected in this thesis. We also presented an overview of IBBRB framework that was proposed to achieve our main objective in this thesis which was helping robot service requesters in the robot selection process. IBBRB will integrate reputation systems, blockchain and service-oriented computing. Furthermore, an overview of the solution that is proposed to achieve each objective of this thesis was discussed in this chapter.

In the next chapter, we describe the building of a robotic attribute ontology and we propose a method called blockchain-based crowdsourcing Robotic Attribute Ontology evolution (bcRAOe) which aims to evolve robotic ontologies.

# Chapter 5

# Blockchain-based Crowdsourcing Method for Robotic Ontology Evolution

## 5.1 Introduction

The robotics attributes and technical specifications are expressed differently depending on the manufacturers, the purpose of the robot, and the robot's intended users. This variation in robotics terms makes building a global application/ platform which requires managing robotics knowledge infeasible unless we can standardise robotics knowledge terminologies across providers, users and systems to simplify the gathering, management, retrieval and presentation of these data. Ontology addresses similar issues by harmonizing the terminology of any domain. For this purpose, an ontological manifestation that encapsulates the attributes of the robots and their relationship is proposed in this chapter. This ontology is termed the Robotics Attributes Ontology (RAO). As the robotics domain is still in its infancy, there is a high probability that robotic knowledge may change over time due to the addition or updating of new concepts, rules or requirements. Hence, there is a need to evolve the corresponding ontologies. In this chapter, we also propose a new blockchain-based crowdsourcing Robotic Attribute Ontology evolution (bcRAOe) method. The proposed method integrates the use of a crowdsourcing approach to allow a crowd of robotic experts to evolve the ontology and then use blockchain as a storage mechanism to store and manage different versions of the ontology. Major parts of this chapter have been accepted to be published as an article in CISIS-2023 conference. The conference paper is titled: "Towards a Blockchain-based Crowdsourcing Method for Robotic Ontology Evolution".

The structure of this chapter is as follows: an overview of the ontology and ontology evolution is provided in section 5.2 . Section 5.3 discusses the development of (RAO). In section 5.4 , the proposed method for RAO evolution is presented. Section 5.5 concludes this chapter.

## 5.2 Ontology and Ontology Evolution

An ontology is a knowledge representation that is used to share a common understanding of domain information among different users (Kim et al., 2012). It is a data model that is used to reduce conceptual and terminological ambiguity, merge all relevant data from heterogeneous databases, enable knowledge sharing and much more (Ahmad et al., 2011). It represents the knowledge of a domain as classes which describe the concepts and relationships between these classes.

A key issue with ontology is the evolution of ontologies (Khattak et al., 2013). As domain knowledge changes overtime, it necessitates a change in the corresponding domain ontology. Unfortunately, a number of ontologies are static in nature, in the sense that once engineered, they are unable to evolve or change over time to accommodate the new (or in some instances changed) knowledge. This has given rise to the notion of 'ontology evolution'.

Ontology evolution can be defined as the process of adapting the source ontology to a change in the domain by applying a set of change operators (Flouris et al., 2008). There exist several methods and techniques for ontology evolution in the literature (For a more detailed overview of the proposed ontology evolution methods, see section 2.4.2).

## 5.3 Robotic Attribute Ontology (RAO) Development

To develop the required ontology, we followed the ontology development life cycle which is illustrated in Figure 5.1. The ontology development lifecycle consists of the following 7 steps:

**Step 1: Determine the domain and scope of the ontology:**

In this study, we develop an ontology that represents robotic specifications and attributes to facilitate the management of these data. We collected and analysed all attributes/selection criteria used in the literature and found that:

- there are two broad categories of robotics attributes: (a) subjective, and (b) objective attributes. Subjective attributes refer to linguistic or qualitative attributes while objectives attributes are the attributes that have quantitative or numerical values.
- Some studies have categorised robots' attributes to other classes such as general, physical, performance and structure attributes.

An overview of all robotic attributes is provided in Table 5.1.

**Step 2: Consider reusing existing ontology:**

There are a number of developed ontologies in the robotic domain. Some of them capsulate all potential instructions and cases of tasks that are required to be done by robots while others represent the robots physical design terminologies. However, there is no existing ontology that provides a common understanding of the robotic technical attributes proposed in the literature as yet.

**Step 3: Enumerate important terms in the ontology:**

All the attributes and selection criteria that have been used to address robot selection are determined in this step.

**Step 4: Define the classes and classes hierarchy:**

As mentioned in Step 1, there are six categories of robotic attributes, namely subjective, objective, general, physical, performance and structure attributes.

**Step 5: Define the properties or slots of classes:**

In this step, we define the properties by which the classes are connected. For example: the objective and subjective classes should be disjoint.

**Step 6: Define facets of the slots:**

In this step, the domain and range for object properties are defined. For instance: the numeric class is defined to be *equal_to* the objective class. Also, the domain of the data properties is defined such as all subclasses of the general class can be *assigned_to* numerical or linguistic data.

**Step 7: Create instances:**

Once the ontology is developed, we can then integrate it into IBBRB to capture the different attributes of robots added by robotic service suppliers.

Table 5.1 : Overview of the robotic attributes and specifications.

| **Attribute** | **Relevant Terminologies** | **Class** | **Data Type** |
|---|---|---|---|
| Degree of freedom | Number of axes | Objective / Physical / Structure | numerical |
| Memory Capacity | - | Objective/ General | numerical |
| Speed of travel | Velocity ratio | Objective | numerical |
| Warranty Period | - | Objective | numerical |
| Manipulator reach | - | Objective | numerical |

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**Table 5.1 – continued from previous page**

| **Attribute** | **Relevant Terminologies** | **Class** | **Data Type** |
|---|---|---|---|
| Ambient temperature | - | Objective | numerical |
| Manipulator velocity | - | Objective / Performance | numerical |
| Gripper Payload | - | Objective / Performance | numerical |
| Run time | Battery Life | Objective | numerical |
| Repeatability error | - | Objective / Performance | numerical |
| Cost | Price / Purchase cost | Objective / General | numerical |
| Delivery Time | - | Objective | numerical |
| Reaction speed | - | Objective | numerical |
| Type of joints | - | Structure | linguistic |
| Actuators | - | Physical | linguistic |
| Dimensions | - | Objective / Physical | numerical |
| Processor | - | General | linguistic |
| Type of robot | - | General | linguistic |
| Man-machine interface | - | Subjective | linguistic |
| Programming flexibility | - | Subjective | linguistic |
| Vendor's service contract | - | Subjective | linguistic |

Continued on next page

**Table 5.1 – continued from previous page**

| **Attribute** | **Relevant Terminologies** | **Class** | **Data Type** |
|---|---|---|---|
| Simulation software | - | Subjective | linguistic |
| Stability | - | Subjective | linguistic |
| Compliance | - | Subjective | linguistic |
| Vendor's training | - | Subjective | linguistic |
| Reliability | - | Subjective | linguistic |
| Sensitivity | - | Subjective | linguistic |
| Accuracy | - | Subjective / Performance | linguistic |

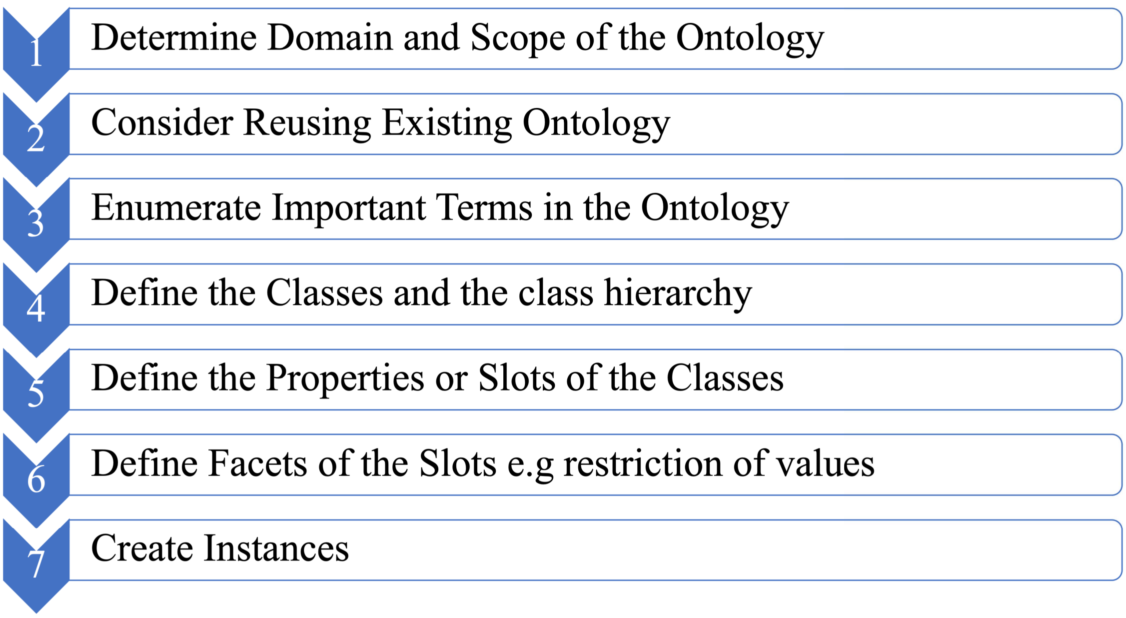


Figure 5.1 : Ontology Development Lifecycle 'taken from (Lalingkar et al., 2015)'.

Based on our analysis of the extant literature, we draft our initial version of the

RAO ontology including all the different concepts, classes, and subclasses of robots that we have collected from the literature. Figure 5.2 overviews the developed RAO draft. The draft RAO ontology will be built and saved in the control layer of the IBBRB platform. RAO will be linked to the robotics static specification layer which is responsible for the collection of manufacturer specifications from the providers. The providers can add new robots based on the existing version of the ontology or they can participate in ontology evolution. Ontology evolution is discussed in detail in section 5.4.


Figure 5.2 : Robot attributes ontology (RAO) draft.

## 5.4 Blockchain-based Crowdsourcing Robotic Attribute Ontology Evolution Method (bcRAOe)

The blockchain-based crowdsourcing robotic ontology evolution method is one solution to address some of the challenging issues facing the proposed ontology evolution methods in the literature. It is based on the crowdsourcing method proposed in (Aseeri et al., 2008) which allows the crowd to collaborate to evolve ontologies by sending change requests to domain experts who are required to approve the ontology change requests through a majority vote. We propose the use of blockchain as a platform for proposing ontology evolution requests and seeking the approval of the domain experts via a consensus vote on blockchain.

An overview of the bcRAOe framework is shown in Figure 5.3. The crowd of people who participate in ontology evolution in this method include any community member (robotic user in our case) or robotic expert who uses the robotic ontology, however, the robotic ontology can only be changed/updated after obtaining approval from the robotic expert community.

As shown in Figure 5.3, the robotic expert and the robotic user community can access and use the ontology, and they can also submit a change proposal to the robotic expert community who are asked to vote on the proposal. Once the change proposal is validated and approved by the majority of robotic experts, the robotic ontology is refined, updated and recorded in the blockchain ledger as a new block. Then, the robotic experts/ robotic user community members are able to access and use the evolved ontology again. The flow diagram of proposing changes in bcRAOe is illustrated in Figure 5.4.

Using blockchain allows us to capture and control the crowdsourcing method and track changes in ontologies. The consensus protocols of blockchain assist in the process of reaching consensus between different people in the crowd. Moreover, blockchain's key property of transparency makes it an excellent option for this method since all previous versions of ontologies are stored and secured in the blockchain which enables a specific version to be recovered when needed.

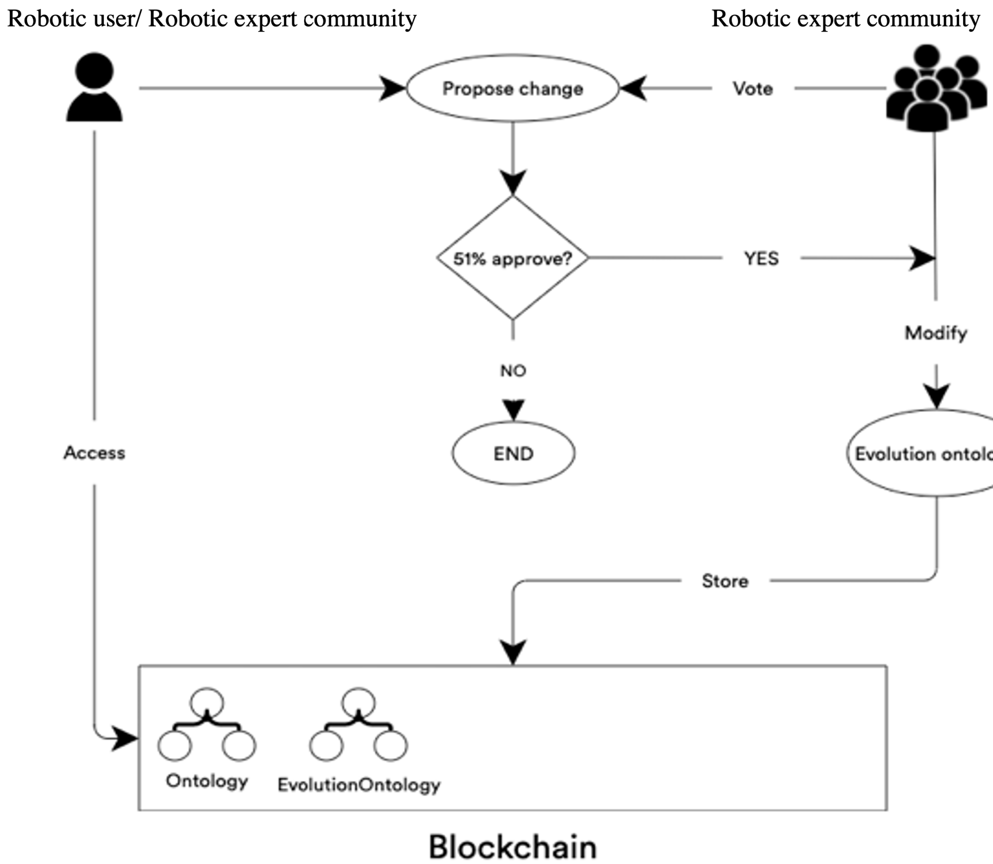


Figure 5.3 : Overview of bcRAOe framework.

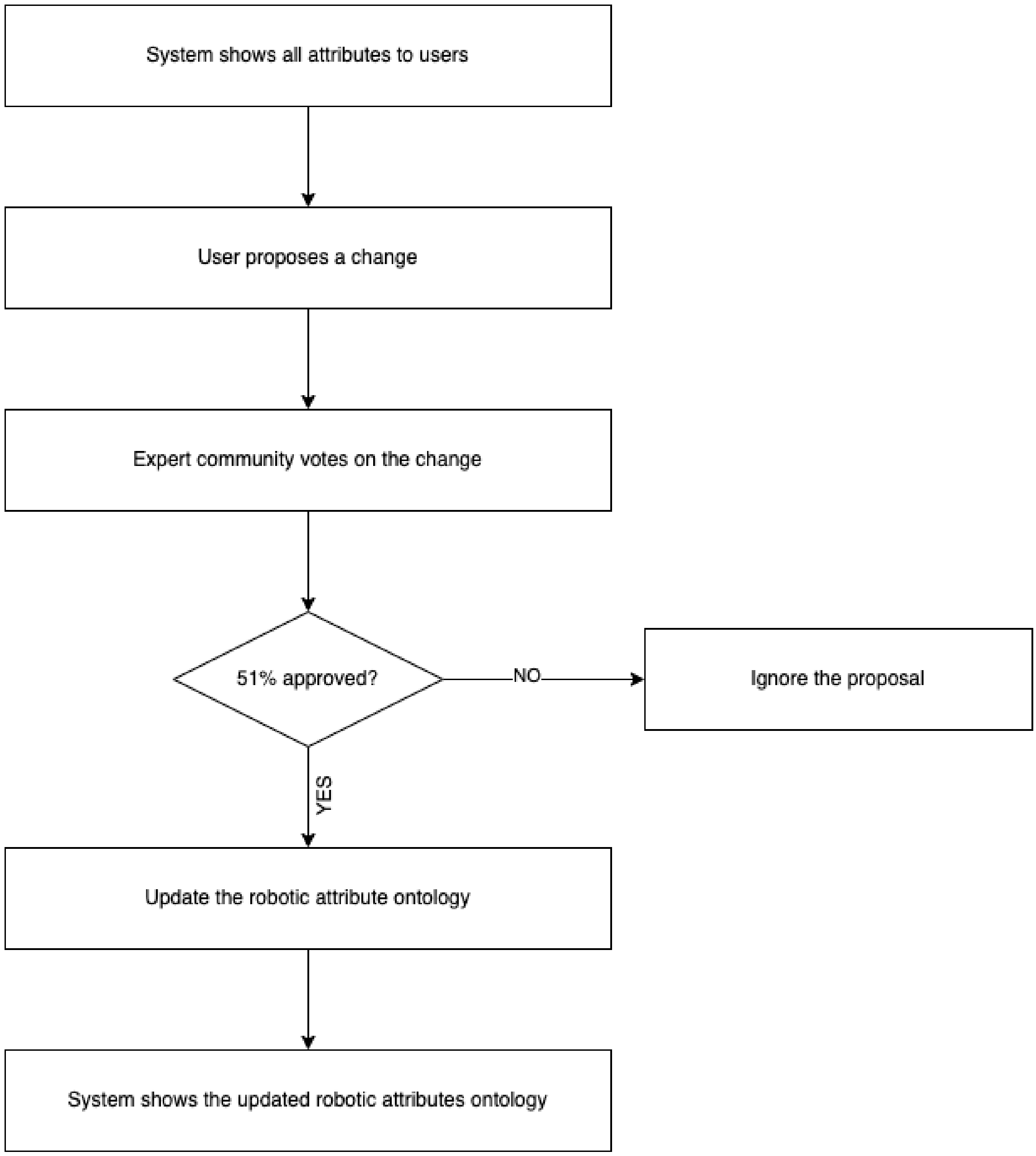


Figure 5.4 : The flow diagram of proposing changes in bcRAOe.

## 5.5 Conclusion

In this chapter, we solved some of the issues emanating from the methods proposed in the literature, such as preventing manipulation in ontologies, accessing different versions of ontologies, and involving a good number of domain experts in proposing changes and seeking their approval. We developed a robotic attribute ontology termed RAO. Furthermore, we proposed a new method for robotic ontology evolution. The proposed method is based on using the crowdsourcing method that engages a community of robotic experts and robotic users to participate in proposing changes in the ontology. It also integrates the use of blockchain as the platform for proposing changes and seeking approval (via a consensus vote) from the robotic expert community. The approved changed will then be manually made to the ontology by the robotic experts. The robotic experts participate in the voting process for each proposed change. Once a community member makes a change to the ontology, this change will not be added to the chain until it has been approved by the majority of experts, then it will be added as a block at the end of the ontology chain. Using blockchain as a storage mechanism has numerous benefits: the immutability feature of blockchain ensures the stored ontologies are secure and the transparency of blockchain allows reliable and trusted old versions of ontologies to be accessed.

In the next chapter, we propose a method termed *Reliable Reputation Computation Method for Robotics (RRCM)* which produces a reliable reputation score for all robots in the network.

# Chapter 6

# Reliable Robotic Reputation Method for Robot Selection and Ranking

## 6.1 Introduction

This chapter presents a novel method for carrying out robotic reputation computations termed *Reliable Reputation Computation Method for Robotics (RRCM)*. This method addresses research objective 3. In this method, we build a reputation model that produces a reputation score for all robots stored in the blockchain based on prior existing ratings to help robot requesters in the selection process before hiring a robot. However, one of the challenging issues in building such a model is the cold start issue. The cold start problem occurs when there are very few ratings for an item (Ahmadian et al., 2019). Therefore, the RRCM method also incorporates building a prediction model that is used to intelligently bootstrap new robots by predicting their reputation scores. So, the novelty of the RRCM can be summarised as follows:

A. Building a robotic reputation computation model that can generate an accurate reputation scores for robots based on users' opinions.

B. Building a robotic reputation prediction model that can be used intelligently to boost the reputation of new robots by predicting the reputation scores for these new robots based on their similarity to already evaluated robots.

This chapter is structured as follows: Section 6.2 outlines the algorithm that is used to carry out the robotic reputation score computation in the reputation model based on user evaluations. In section 6.3 , we explain the mechanism we employ for bootstrapping new robots with no prior evaluations in the prediction model. In section 6.4 , the proposed method is evaluated and discussed in detail. We conclude this chapter in section 6.5.

## 6.2 Robotic Reputation Computation Model

In Chapter 1, we reviewed the design, components and operation of reputation systems. As previously mentioned, all reputation models should employ a rating aggregation method to generate a global reputation score for each product/ service. The existing rating aggregation methods that are used for this purpose include average, weighted average, Bayesian and fuzzy models.

However, the weighted average method is currently the most commonly used for ratings aggregation. Initially, the weight of each rating is considered to be $\frac{1}{n}$ , where $n$ is the total number of item's ratings. Several studies in the literature proposed considering other factors such as user credibility, time of the rating and the frequency of each rating score for weighting ratings (Malik & Bouguettaya, 2009), (S. Wang et al., 2011).

To achieve our purpose in this chapter and build an accurate robotic reputation model and we adopt *the Normal Distribution-based Reputation model (NDR)* that is proposed by Abdel-Hafez (2016). The NDR model considers the popularity of users' opinions towards an item by calculating the rating weights based on the rating distribution and the frequency of each rating level. He assumes that the normal distribution represents most of the natural phenomena including rating distribution. So, in his model, he assumes that if a user (m) has to produce a single overall score for a product (p) then the overall reputation score of the product (p) is calculated using Equation 6.1.

$$Rep_p = \sum_{i=1}^{k} (l * LW_p^l) \tag{6.1}$$

where,

- $Rep_p$ is the total reputation score of a product $p$,
- $k$ is the number of rating system levels ($k = 5$ in this system),
- $LW_p^l$ represents the weight of every level which can be calculated as a summation of all rating's weight in one level.

The rating weight is calculated using the normal distribution probability density function of the normal distribution (Equation 6.2).

$$a_i = \frac{e^{-(x_i - \mu)^2} / 2\sigma^2}{\sigma\sqrt{2\pi}} \tag{6.2}$$

$$x_i = \frac{(k-1) * i}{n-1} + 1 \tag{6.3}$$

where,

- $a_i$ is the weight for the rating at index $i, i \in [0, n-1]$,
- $\mu$ is the mean of ratings which is fixed at 3,
- $\sigma$ is the standard deviation of ratings,
- $k$ is the number of levels in the rating system, $k \in [1, 5]$,
- and $x_i$ is supposed to be the value at index $i$, Equation (6.3) deploys the values of $x_i$ in $[1, k]$ where $x_0 = 1$ and $x_{n-1} = 5$.

Deploying this model in our method allows us to combine other factors that could easily affect the final reputation scores in the future. This can be done by considering the factors' coefficients when calculating the rating weight in Equation 6.1.

### 6.2.1 Illustrated example and discussion

We suppose that three robots (Robot A, Robot B, Robot C) receive a set of ratings from 10 users listed in Table 6.1. As shown in Table 6.1, Robot A, B and C tend to get neutral, positive and negative opinions (respectively). The NDR method that is proposed by Abdel-Hafez (2016) and the traditional weighted average method are applied to calculate the reputation scores for Robots A, B and C as shown in Table 6.2, Table 6.3, and Table 6.4 (respectively). We apply the NDR method that is proposed by Abdel-Hafez (2016) and then we discuss and compare the results from the traditional weighted average method (i.e., when the weight is considered to be $1/n$) and the NDR methods.

Table 6.1 : Users' evaluations for robot A, robot B and robot C.

| **Users' Ratings** | **Robot A** | **Robot B** | **Robot C** |
|---|---|---|---|
| User 1 | 1 | 1 | 1 |
| User 2 | 2 | 1 | 1 |
| User 3 | 3 | 1 | 1 |
| User 4 | 3 | 3 | 1 |
| User 5 | 3 | 4 | 1 |
| User 6 | 3 | 4 | 2 |
| User 7 | 3 | 4 | 2 |
| User 8 | 3 | 4 | 3 |
| User 9 | 3 | 4 | 3 |
| User 10 | 5 | 4 | 5 |

Figure 6.1 shows the results obtained by calculating the reputation scores for Robots A, B and C using NDR and weighted average methods. The figure shows

Table 6.2 : Reputation score for robot A using NDR and traditional average methods.

| $i$ | $x_i$ | Robot A | | | |
|---|---|---|---|---|---|
| | | **Ratings** | **Rating weight** $a_i$ | **Normalised Rating weight** $w_i$ | **Level weight** $lw^l$ |
| 0 | 1 | 1 | 0.046 | 0.021 | 0.021 |
| 1 | 1.44 | 2 | 0.11 | 0.05 | 0.05 |
| 2 | 1.89 | 3 | 0.21 | 0.096 | 0.91 |
| 3 | 2.33 | 3 | 0.33 | 0.15 | |
| 4 | 2.78 | 3 | 0.41 | 0.19 | |
| 5 | 3.22 | 3 | 0.41 | 0.19 | |
| 6 | 3.67 | 3 | 0.33 | 0.15 | |
| 7 | 4.11 | 3 | 0.21 | 0.096 | |
| 8 | 4.56 | 3 | 0.11 | 0.05 | |
| 9 | 5 | 5 | 0.046 | 0.021 | 0.021 |
| $\sum a = 2.21$ | | | | | |
| $Rep_{robotA} = \sum_{l=1}^{5} l * LW^{l}_{robotA} = 2.95$<br>Traditional weighted average $= \frac{1+2+3+3+3+3+3+3+3+5}{10} = 2.9$ | | | | | |

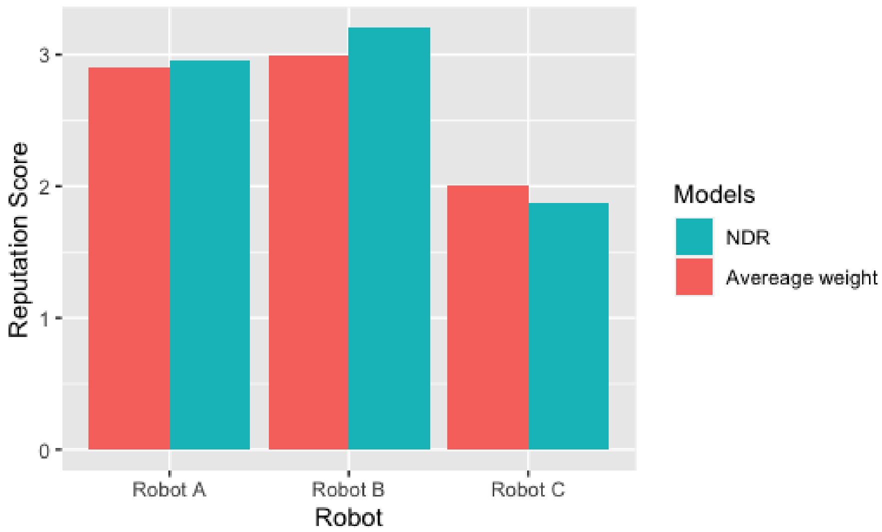


Figure 6.1 : Reputation scores using NDR vs weighted average methods.

Table 6.3 : Reputation score for robot B using NDR and traditional average methods.

<table>
<tr><th rowspan="2">$i$</th><th rowspan="2">$x_i$</th><th colspan="4">Robot B</th></tr>
<tr><th>Ratings</th><th>Rating weight $a_i$</th><th>Normalised Rating weight $w_i$</th><th>Level weight $lw^l$</th></tr>
<tr><td>0</td><td>1</td><td>1</td><td>0.1</td><td>0.05</td><td rowspan="3">0.23</td></tr>
<tr><td>1</td><td>1.44</td><td>1</td><td>0.15</td><td>0.08</td></tr>
<tr><td>2</td><td>1.89</td><td>1</td><td>0.21</td><td>0.1</td></tr>
<tr><td>3</td><td>2.33</td><td>3</td><td>0.26</td><td>0.13</td><td>0.13</td></tr>
<tr><td>4</td><td>2.78</td><td>4</td><td>0.29</td><td>0.14</td><td rowspan="6">0.64</td></tr>
<tr><td>5</td><td>3.22</td><td>4</td><td>0.29</td><td>0.14</td></tr>
<tr><td>6</td><td>3.67</td><td>4</td><td>0.26</td><td>0.13</td></tr>
<tr><td>7</td><td>4.11</td><td>4</td><td>0.21</td><td>0.1</td></tr>
<tr><td>8</td><td>4.56</td><td>4</td><td>0.15</td><td>0.08</td></tr>
<tr><td>9</td><td>5</td><td>4</td><td>0.1</td><td>0.05</td></tr>
<tr><td colspan="6">$\sum a = 2.03$</td></tr>
<tr><td colspan="6">$Rep_{robotB} = \sum_{l=1}^{5} l * LW^{l}_{robotB} = 3.2$<br>Traditional weighted average $= \frac{1+1+1+3+4+4+4+4+4+4}{10} = 3$</td></tr>
</table>

Table 6.4 : Reputation score for robot C using NDR and traditional average methods.

<table>
<tr><th rowspan="2">$i$</th><th rowspan="2">$x_i$</th><th colspan="5">Robot C</th></tr>
<tr><th>Ratings</th><th>Rating weight $a_i$</th><th>Normalised Rating weight $w_i$</th><th>Level weight $lw^l$</th></tr>
<tr><td>0</td><td>1</td><td>1</td><td>0.11</td><td>0.06</td><td rowspan="5">0.5</td></tr>
<tr><td>1</td><td>1.44</td><td>1</td><td>0.16</td><td>0.08</td></tr>
<tr><td>2</td><td>1.89</td><td>1</td><td>0.2</td><td>0.1</td></tr>
<tr><td>3</td><td>2.33</td><td>1</td><td>0.23</td><td>0.12</td></tr>
<tr><td>4</td><td>2.78</td><td>1</td><td>0.25</td><td>0.13</td></tr>
<tr><td>5</td><td>3.22</td><td>2</td><td>0.25</td><td>0.13</td><td rowspan="2">0.25</td></tr>
<tr><td>6</td><td>3.67</td><td>2</td><td>0.23</td><td>0.12</td></tr>
<tr><td>7</td><td>4.11</td><td>3</td><td>0.2</td><td>0.1</td><td rowspan="2">0.19</td></tr>
<tr><td>8</td><td>4.56</td><td>3</td><td>0.16</td><td>0.08</td></tr>
<tr><td>9</td><td>5</td><td>5</td><td>0.11</td><td>0.06</td><td>0.06</td></tr>
<tr><td colspan="6">$\sum a = 1.87$</td></tr>
<tr><td colspan="6">$Rep_{robotC} = \sum_{l=1}^{5} l * LW^{l}_{robotC} = 1.87$<br>Traditional weighted average $= \frac{1+1+1+1+1+2+2+3+3+5}{10} = 2$</td></tr>
</table>

that NDR method gives a result which is closer to our expectation. From Table 6.1, we observed that Robot A receives neutral opinions because of the high frequency of 3s in its ratings. So, its reputation score is reasonably close to 3, whereas the reputation score for Robot B is greater than 3 as it has a rating of 4 most of the time. Robot C receives negative scores that are very close to 1 since it receives ratings of 1 most of the time.

## 6.3 Robotic Reputation Prediction model

The reputation model in section 6.2 is used to aggregate user ratings and calculate the reputation scores for robots that have already been rated by users. Now, we build a prediction model that intelligently produces a reputation score for newly added robots which have no ratings. The aim of this prediction model is to boost the reputation of new robots and overcome the cold start issue. The proposed prediction model utilises the k-nearest neighbours algorithm (KNN) to compare the specifications (feature profile) of the new robot with the specifications of all robots with the same purpose and then predict a score for the new robot based on the reputation score of the nearest neighbour robot as shown in Figure 6.2.

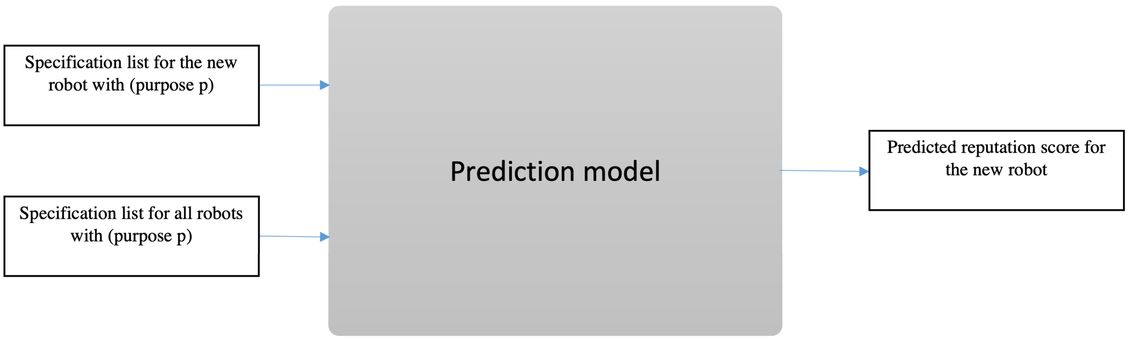


Figure 6.2 : Utilising existing labelled data in the prediction model.

As discussed in Chapter 5, robot specifications are classified into subjective and objective attributes. The subjective attributes include Man-Machine Interface, Programming Flexibility, Stability, Simulation Software, Compliance and any other attributes that have qualitative definitions while the objective attributes include Load capacity, Repeatability, Purchase Cost, Memory Capacity, Degree of Freedom, Vertical And Horizontal Manipulator Reach, Warranty Period and any other attributes that can be represented in quantitative values.

To measure the similarities between robots, we firstly measure the similarities between the subjective and objective attributes of these robots separately and then combine the results to produce an overall similarity degree. The proposed prediction model combines fuzzy modelling and transfer learning approaches to achieve this goal. In the following subsections, we discuss the process of measuring the similarities between the subjective and objective attributes:

### 6.3.1 Quantitative (objective) attributes

Data pre-processing or cleaning the data and making it suitable for the machine learning model increases the accuracy and efficiency of the model (Huang et al., 2015). So, to build the proposed prediction model, it is extremely important to standardise the input data into the same scale so that we can produce an overall similarity degree.

As the objective attributes of robots fall in different ranges, we propose using fuzzy modelling to convert the values of the objective attributes to a 0 to 1 scale. The values in this scale represent the closeness to the attributes of the target robot ($r$). We use the Gaussian fuzzy membership function for this purpose to compute the membership degree of each objective attribute of all robots to the attributes of the target robot ($r$) and then accumulate the results to represent the overall similarity degrees. The systematic procedure for finding the most similar (nearest neighbour) robot to the target robot $r$ based on the similarity of objective attributes is illustrated in Figure 6.3. It incorporates the following six steps:

Step I. Computing the standard deviations of all objective attributes. Assume that there are $o$ objective attributes and $m$ robots which have the same purpose ($p$) as the target robot $r$. In this step, the standard deviations of all ($o$) objective attributes for all ($m$) robots are computed as $sd_1, sd_2, \ldots, sd_o$.

Step II. Creating a vector of objective attributes for the target robot $r$ which has no reputation value as shown in Equation 6.4

$$v_r = (att_{1r}, att_{2r}, ...., att_{or}) \tag{6.4}$$

Step III. Creating a vector of objective attributes for each robot in the dataset which has a reputation value as shown in Equation 6.5.

$$v_a = (att_{1a}, att_{2a}, ...., att_{oa}) \ where \ a \in [1, m] \tag{6.5}$$

Step IV. Applying the Gaussian fuzzy membership function to compute the membership degree of each objective attribute using Equation 6.6.

$$MD_{ia}(att_{ia}, att_{ir}, sd_i) = e^{\frac{-1}{2}((\frac{att_{ia}-att_{ir}}{sd_i})^2)} \tag{6.6}$$

where $MD_{ia}(att_{ia}, att_{ir}, sd_i)$ is the membership degree of the objective attribute $i$ of the robot $a$, such that $MD_{ia} \in [0, 1]$ and $i \in [1, o]$.

Step V. Accumulating the results in Step IV to produce an overall membership value for each robot $a$ using Equation 6.7.

$$MD_a = \frac{\sum_{i=1}^{o} MD_{ia}}{o} \tag{6.7}$$

Step VI. Identifying the nearest neighbour robot ($nnr$) to the target robot $r$ considering the objective attributes, such that ($nnr$) has the highest membership value $MD$.

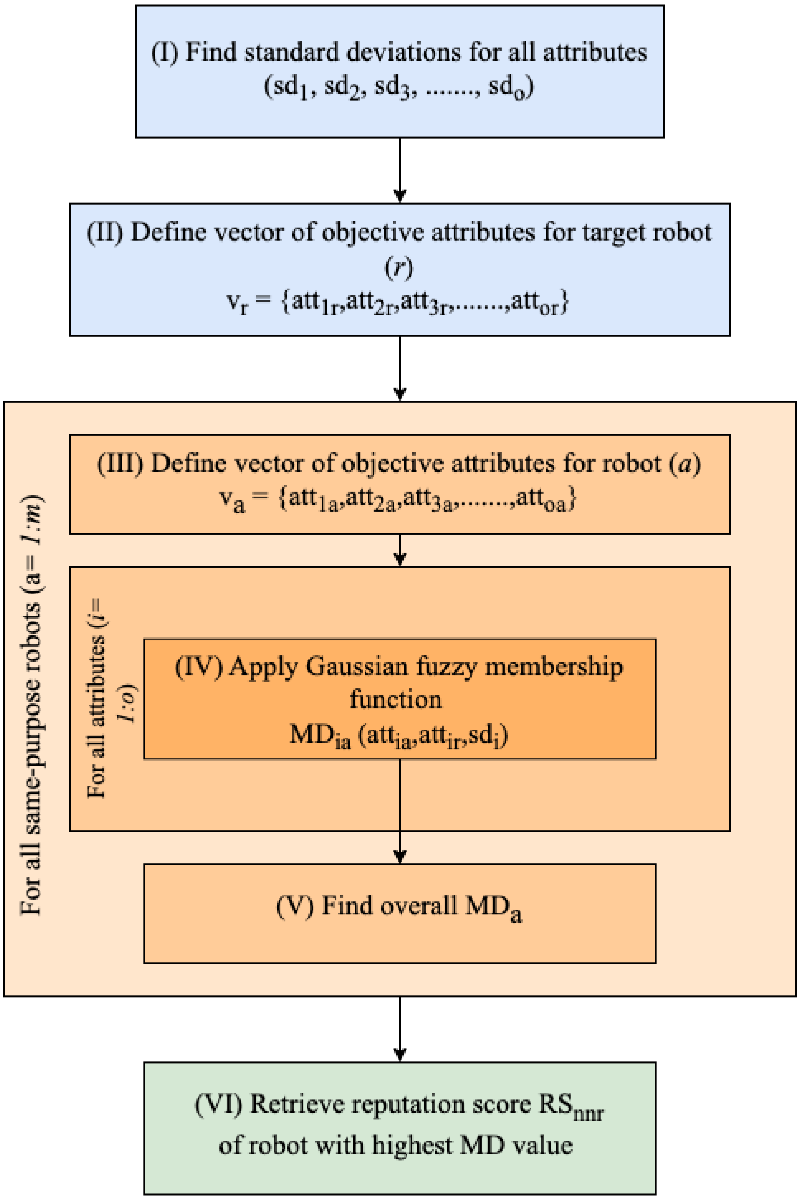


Figure 6.3 : The procedure for finding the nearest neighbour robot based on objective attributes.

### 6.3.2 Qualitative (subjective) attributes

As qualitative or subjective attributes cannot be measured, we propose building a transfer learning prediction model that studies and analyses the relations between subjective attributes and reputation scores of already-evaluated robots and then transfer the knowledge gained from this study to predict a reputation score for a target robot $r$. Figure 6.4 shows an overview of the knowledge transfer process to build the proposed prediction model. The knowledge gained from the analysis is stored so it can be applied during the score prediction process. So, the required prediction model will utilise the existing labelled data to predict a score for a newly added robot that has not been rated yet, as illustrated in Figure 6.2. In other words, suppose we want to predict a score for a specific purpose robot $r$ (with purpose $p$), the proposed prediction model will predict a score for the robot $r$ based on the stored knowledge that encapsulates the relations between each subjective attribute and the corresponding reputation score of other similar robots.

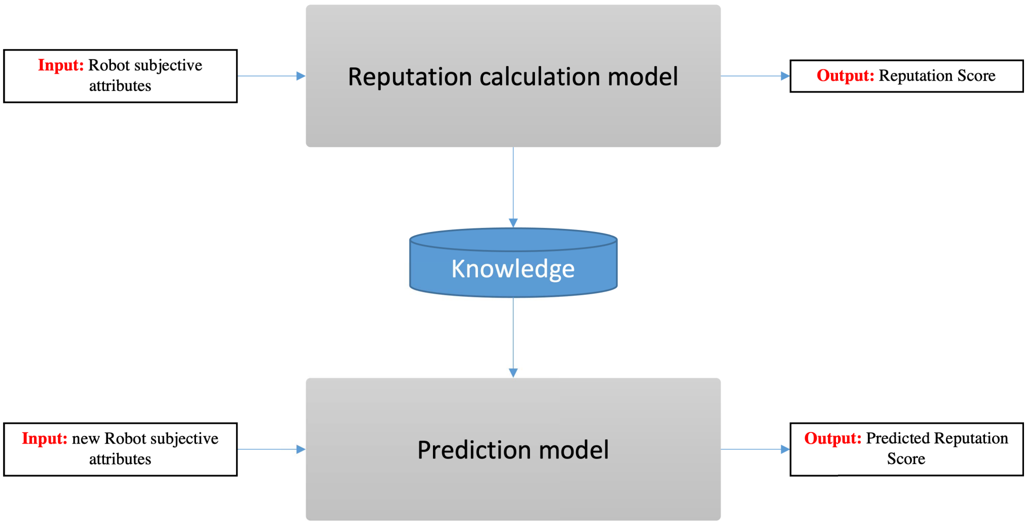


Figure 6.4 : Transferring knowledge to build the proposed prediction model.

In principle, the proposed transfer learning prediction model can be characterised into the following four steps:

Step I. Step I. Analysing the relation between the subjective attributes of all robots and the reputation scores.

Assume that there are $s$ subjective attributes and $m$ robots which have the same purpose $(p)$ as the target robot $r$. In this step, we study the relations between all subjective attributes and reputation scores of all $m$ robots. We construct s matrices that exhibit all possible reputation scores of values $\{v_1, v_2, \dots\}$ of attribute $j$ where $j \in [1, s]$, as in Equation 6.8.

$$\begin{aligned} RS_{att_1} &= (RS_{att_1}(v_1) \quad RS_{att_1}(v_2) \quad RS_{att_1}(v_3) \; ....) \\ RS_{att_2} &= (RS_{att_2}(v_1) \quad RS_{att_2}(v_2) \quad RS_{att_2}(v_3) \; ....) \\ &\vdots \\ RS_{att_j} &= (RS_{att_j}(v_1) \quad RS_{att_j}(v_2) \quad RS_{att_j}(v_3) \; ....) \\ &\vdots \\ RS_{att_s} &= (RS_{att_s}(v_1) \quad RS_{att_s}(v_2) \quad RS_{att_s}(v_3) \; ....) \end{aligned} \tag{6.8}$$

where $RS_{att_j}(v)$ is the mean of the reputation scores for all robot that have the value of $att_j = v$, as shown in Equation 6.9.

$$RS_{att_j}(v) = \frac{\sum RS \; for \; all \; robots \; that \; have \; att_j = v}{number \; of \; all \; robots \; that \; have \; att_j = v} \tag{6.9}$$

Step II. Fuzzification of all reputation scores into five intervals as follows:

a. Identifying $min_j, max_j$ values of reputation scores of attribute $j$ form the $j^{th}$ matrix in Step I.

b. Identifying interval length for each matrix as shown in Equation 6.10.

$$l_j = \frac{max_j - min_j}{5} \tag{6.10}$$

c. Defining five fuzzy intervals in the form of $[LB, UB]$, where $LB, UB$ are the lower and the upper boundaries of the interval, for each attribute

$j \in [1, s]$ according to Equation 6.11.

$$fuzzy\ intervals(j) = \{[min_j, l_j + min_j], [l_j + min_j, 2l_j + min_j], [2l_j + min_j, 3l_j + min_j], [3l_j + min_j, 4l_j + min_j], [4l_j + min_j, 5l_j + min_j]\} \tag{6.11}$$

d. Mapping all reputation scores in matrices ($1\ to\ s$) into the fuzzy intervals defined in Equation 6.11 such that the value of the reputation score lies within the assigned interval. For example, assume $RS_{att_j}(v) = 3.2l_j + min_j$; then $RS_{att_j}(v) \in [3l_j + min_j, 4l_j + min_j]$ as illustrated in Figure 6.5.

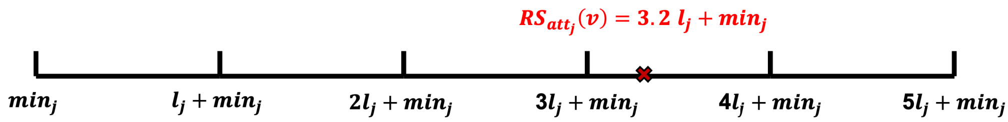


Figure 6.5 : Illustrated example for fuzzification of a reputation score.

Equation 6.12 is used to find the lower and upper boundaries of any reputation score.

$$\begin{aligned} LB(RS_{att_j}) &= Floor(\frac{RS_{att_j} - min_j}{l_j}) * l_j + min_j \\ UB(RS_{att_j}) &= Ceiling(\frac{RS_{att_j} - min_j}{l_j}) * l_j + min_j \end{aligned} \tag{6.12}$$

where,

- $Floor(\frac{RS-min}{l})$ is the greatest integer that is less than or equal to $(\frac{RS-min}{l})$.

- $Ceiling(\frac{RS-min}{l})$ is the smallest integer that is greater than or equal to $(\frac{RS-min}{l})$.

Step III. Computing the semantic similarity between the $j^{th}$ subjective attribute of the target robot $r$ and the corresponding subjective attribute of all robots that are included in the analysis in Step I using Jaccard index in Equation 6.13.

$$sim(att_{j,r}, att_{j,c}) = \frac{v_{j,r} \cap v_{j,c}}{v_{j,r} \cup v_{j,c}} \tag{6.13}$$

where,

- $sim(att_{j,r}, att_{j,c})$ is the semantic similarity between attribute $j$ of target robot $r$ and robot $c$, such that $c \in [1, m]$ and $j \in [1, s]$.
- $v_{j,r}, v_{j,c}$ are the values of attribute $j$ of robot $r$ and robot $c$ respectively.

Then each subjective attribute of the robot $r$ is assigned to the fuzzy reputation interval of the most similar subjective attribute as in Equation 6.14.

$$fuzzy\ RS(r)_{att_j} = [LB_{att_j}, UB_{att_j}] \tag{6.14}$$

Step IV. Finding the intersection between all reputation score intervals of all subjective attributes of the robot $r$ using equation 6.15.

$$fuzzy\ RS(r) = [LB_{att_1}, UB_{att_1}] \cap [LB_{att_2}, UB_{att_2}] \cap \ldots \cap [LB_{att_s}, UB_{att_s}] \tag{6.15}$$

Step V. Computing the mean of the interval that is the result from Step IV to obtain a crisp value that is considered a predicted reputation score for robot $r$ in respect to the subjective attributes, as in equation 6.16.

$$Predicted\ subjective\ RS(r) = \frac{UB + LB}{2} \tag{6.16}$$

Figure 6.6 shows the procedural diagram of the proposed transfer learning prediction model.

### 6.3.3 Overall reputation score

After identifying the nearest neighbour robot ($nnr$) to the target robot $r$ considering the objective attributes, and predicting a reputation score for the target robot $r$ considering the subjective attributes, the overall predicted reputation score considering both subjective and objective attributes is computed using equation 6.17.

$$Predicted\ RS(r) = \frac{RS_{nnr} * MD_{nnr} * length(o) + Predicted\ subjective\ RS(r) * length(s)}{length(o) + length(s)} \tag{6.17}$$

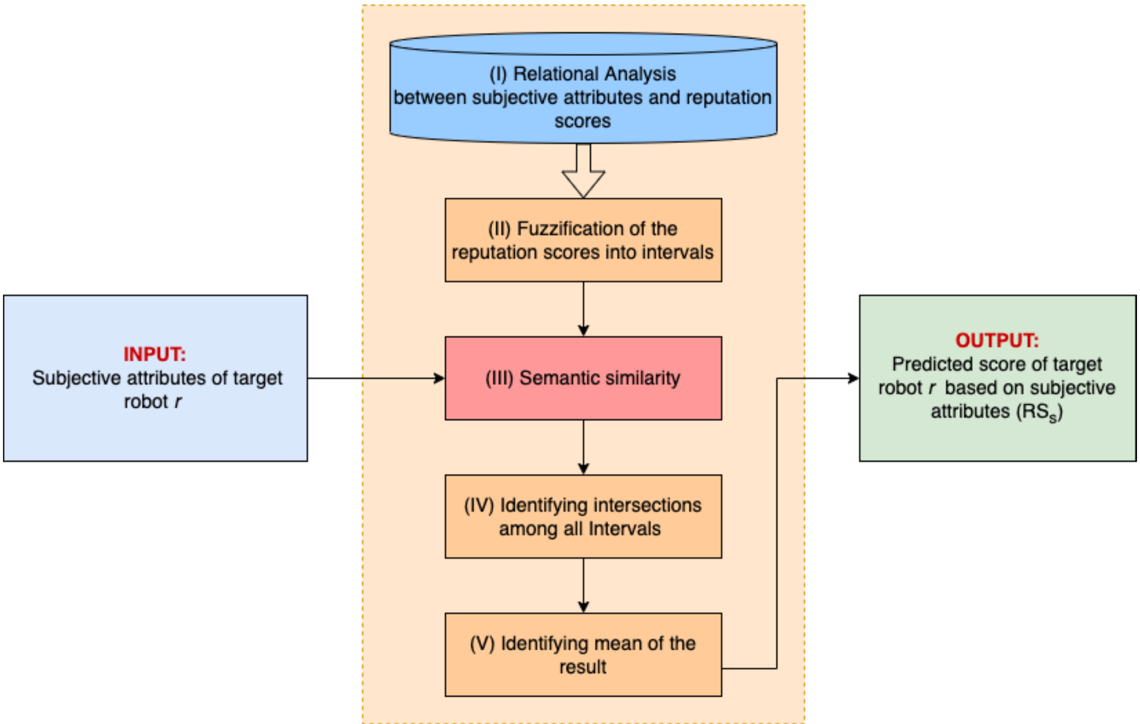


Figure 6.6 : General overview of the proposed transfer learning prediction model.

## 6.4 Evaluation Results and Discussion

To measure the accuracy of the proposed model, we use three well-known evaluation metrics for regression models, namely mean absolute error (MAE), root mean squared error (RMSE) and mean absolute percentage error (MAPE) that are defined in equations 4.1, 4.2 and 4.3 respectively. We validated the proposed methodology on a publicly available dataset. We used the Amazon mobile dataset revolving around ratings (and reviews) provided by customers. The data is real and commercial and was therefore anonymized. This dataset was taken from Kaggle (Tripathi, 2021), a platform that offers a huge repository of community published data. Figure 6.7 shows how the actual and predicted values are close to the regressed diagonal line.

As Figure 6.8 shows:

- MAE $\approx 0.38$, which means the average error between the predicted and actual values is around 0.38, which is likely a good value considering the average actual reputation score is 3.
- RMSE is 0.54, meaning the weighted average error between the predicted and actual values is 0.54, which is likely a good value given that the average actual reputation score is 3.
- MAPE is 9% which means our predictions are on average 9% away from the actual values.

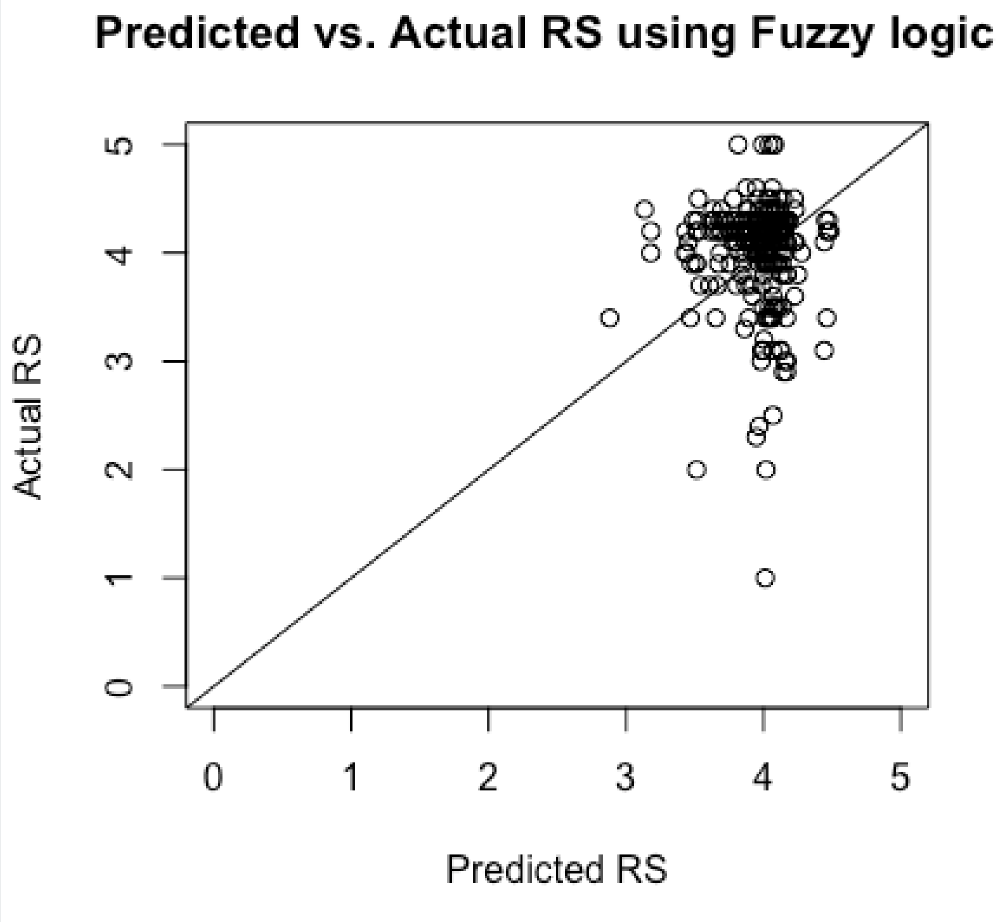


Figure 6.7 : Predicted VS actual reputation scores using the fuzzy-based transfer learning prediction model.

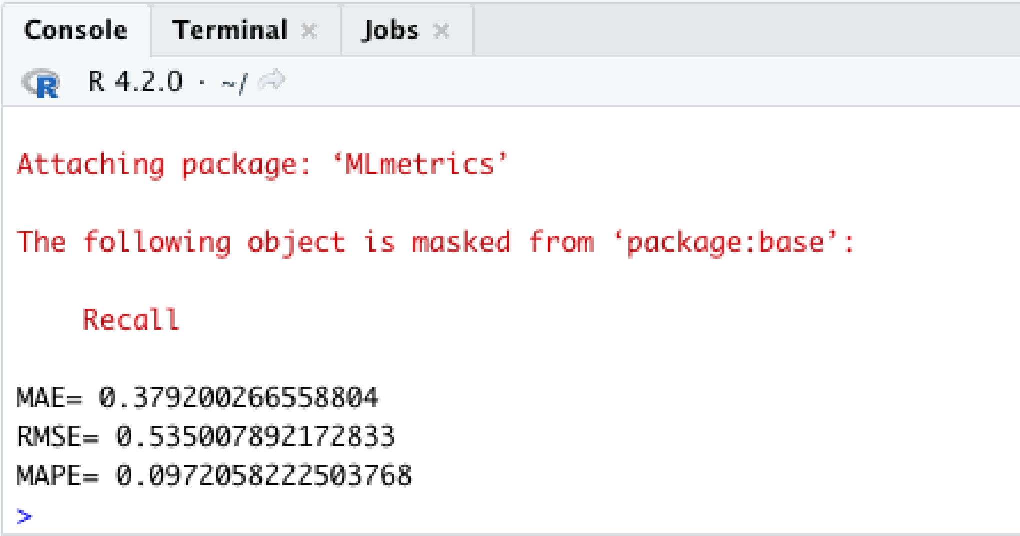


Figure 6.8 : Evaluation metrics results.

## 6.5 Conclusion

This chapter discussed the development of a method called the Reliable Reputation Computation Method for Robotics (RRCM). RRCM integrated the use of fuzzy modelling and transfer learning to produce a reputation score for all robots based on prior users' opinions to predict a reputation score for new robots based on robotic attribute similarities.

In the next chapter, we present a novel method for inferencing a contextual reputation score for multi-purpose robots.

# Chapter 7

# Context-driven Inferencing of Reputation Values for Multi-purposes Robots

## 7.1 Introduction

A multi-purpose robot, also known as a general purpose robot, has the capability to be adapted to automate a set of applications. The physical design of a multi-purpose robot should take into consideration that the robot has to be flexible in operation using a multi-axis configuration. Since this is a dynamic design feature for multi-purpose capabilities, multi-purpose robots can be redeployed over time by programming them to perform different tasks or a sequence of identical tasks. So, these robots are engineered to provide similar services (contexts) that overlap with each other (Mason, 2018). For example, FANUC M20ia is a multi-purpose industrial robot that is designed to move, perform repetitive tasks and hold different types of materials. It is used in various industries to move raw materials and to load parts made of different materials to computer numerical control machines. However, the performance of a multi-purpose robot can vary depending on the assigned task. In other words, the ability of a robot to accomplish a task does not indicate that this robot is the most efficient one for the task.

Despite the shortage of robotic reputation systems, the majority of popular reputation systems produce a global reputation value for a product/service (Abdel-Hafez, 2016), including robots. Therefore, there is no study in the literature that discusses building a reputation system that considers contextual reputation values for multi-purpose robots (Alsobhi et al., 2021).

In this chapter, we use the term *contexts* to refer to the different purposes of robots.

This chapter introduces an intelligent method to produce a contextual reputation value for different purposes of a multi-purpose robot, the working process of which is (i) context modelling, (ii) context similarity computation, and (iii) context score inference. Two fuzzy interval models, namely, the fuzzy prediction interval (FPI) and the enhanced fuzzy prediction interval (EFPI) are discussed in this chapter to predict an interval within which the reputation value of a context is predicted.

This chapter is organised as follows: Section 7.2 presents the proposed method and its various steps are discussed. Section 7.3 presents our experiment to validate the efficiency of our proposed method. In section 7.4, we conclude the chapter.

## 7.2 Algorithm for Context-aware Reputation Value Inferencing for Multi-purpose Robots

In this work, we introduce a novel method termed *Context-aware Reputation Value Inferencing for Multi-purpose Robots (CaRVInf).* The proposed method incorporates different methods, such as context modelling and context similarity computation, to infer a reputation value for a given context. Figure 7.1 overviews the proposed method. In the following sub-sections, the steps of the proposed method are discussed:

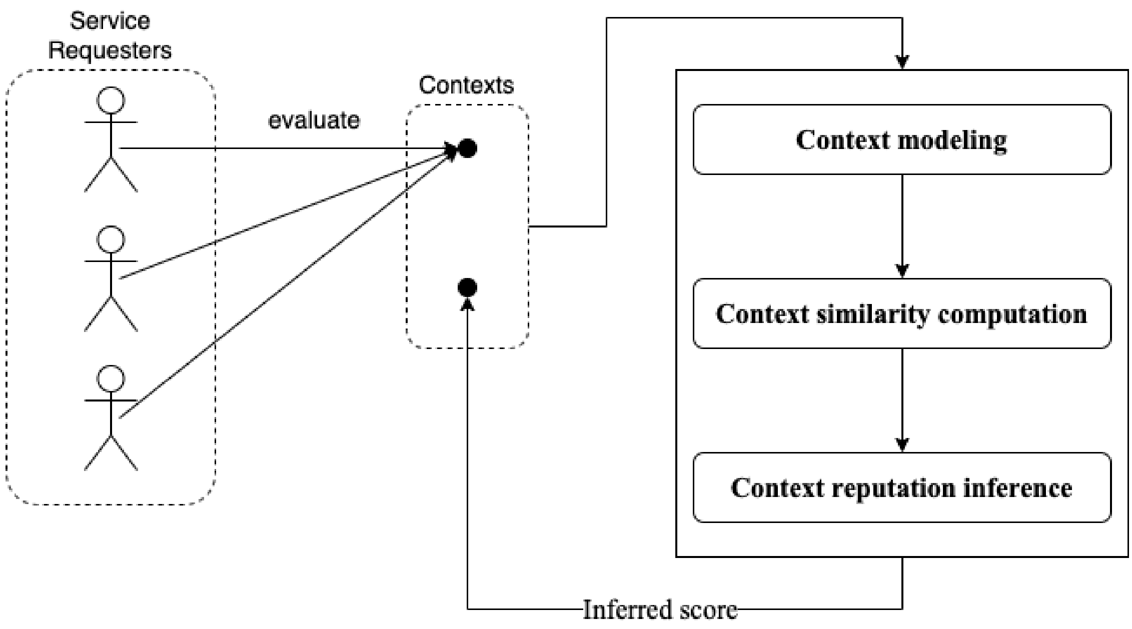


Figure 7.1 : Overview of context-aware trust value inference method.

### 7.2.1 Context modelling

The proposed solution for context modelling is built on two existing approaches, context awareness meta ontology modelling (CAMeOnto) proposed by Aguilar et al. (2018) and the context-aware trust (CAT) model (Uddin et al., 2008). We use a combination of these two approaches to model the contexts of a multi-purpose robot and then the semantic similarity between these two contexts is computed.

#### *7.2.1.1 Context awareness meta ontology modelling (CAMeOnto)*

The hierarchy of CAMeOnto is shown in Figure 7.2. We instantiate the CAMeOnto to present the relationship between multi-purpose robots and service requesters and then capture the required data to model the different contexts of the robot. Table 7.1 lists the data that should be considered during the robot context modelling process. The main classes of multi-purpose robot services are shown in Figure 7.3, following CAMeOnto.

Table 7.1 : Required data for robot context modelling.

| **CAMeOnto** | **Multi-purpose robot** |
|---|---|
| User | Type of robotic service requester (industrial / educational/ medical) organisation, home user, . . . .etc. |
| Service | Context $C_i$ of the robot's services |
| Location | Indoor or outdoor location |
| Environment | Description of the service location |
| Time | Instant or interval service |

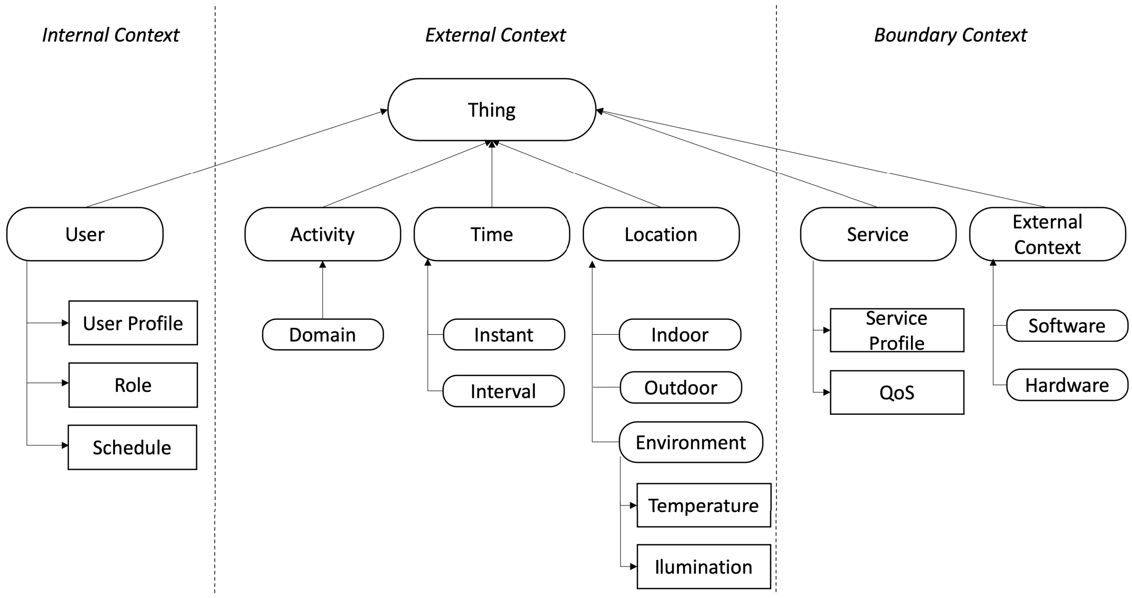


Figure 7.2 : Hierarchy of CAMeOnto 'taken from (Aguilar et al., 2018)'.

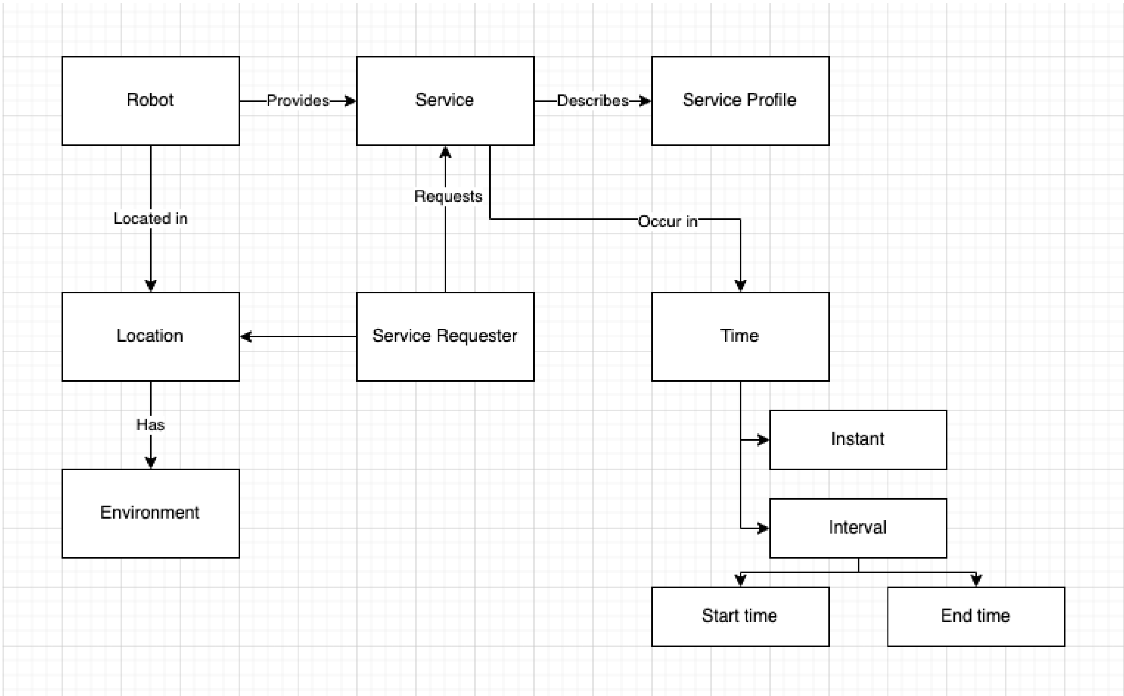


Figure 7.3 : Robotic service requesting process using CAMeOnto classes.

#### *7.2.1.2 Context-aware trust (CAT) model*

The keyword-based modelling method proposed by Uddin et al. (2008) is used to represent every context of a multi-purpose robot based on the data acquired from CAMeOnto. The proposed method assumes that each context has a set of keywords that describe it. In our method, the instances of the main classes described in Table 7.1 are included in the set of keywords that describe the contexts.

Suppose we have a multi-purpose robot $r$ which has two contexts $(C_x, C_y)$, and each context is represented by a set of keywords as follows:

$$K(C_x) = \{k_1, k_2, k_3, \ldots, k_n\} \tag{7.1}$$

$$K(C_y) = \{k_1, k_2, k_3, \ldots, k_m\} \tag{7.2}$$

where,

- $n, m$ denote the total number of keywords describing contexts $C_x$ and $C_y$ respectively.
- $\{CAMeOnto\ classes\ instances\ for\ C_x\} \subset k_1, k_2, k_3, \ldots, k_n$.
- $\{CAMeOnto\ classes\ instances\ for\ C_y\} \subset k_1, k_2, k_3, \ldots, k_m$.

### 7.2.2 Context similarity computation

After modelling the contexts in section 7.2.1 , the next step is to measure the semantic similarity between the two modelled contexts using the Jaccard similarity index (Equation 7.3). The Jaccard index measures the percentage of overlap between sets of keywords that represent each context.

$$sim(C_x, C_y) = \frac{K(C_x) \cap K(C_y)}{K(C_x) \cup K(C_y)} \tag{7.3}$$

where,

- $K(C_x), K(C_y)$ represent the set of all keywords describing contexts $C_x$ and $C_y$ respectively.
- $sim(C_x, C_y) \in [0, 1]$.

In our experiments, we note that the sizes of the predicted intervals become smaller when the similarity degrees between two contexts become larger. For this reason, we propose using 80% as the benchmark value that should be met by the semantic similarity degrees to predict more accurate intervals.

### 7.2.3 Context reputation value inference

The similarity degree obtained from Equation 7.3 indicates to what extent context $C_x$ is close to context$C_y$. It is expressed as a number between 0 and 1, where 0 means low similarity (the contexts are dissimilar) and 1 means high similarity (the contexts are identical).

We assume that the reputation value of target context $C_y$ is similar to the reputation value of source context $C_x$ by the degree of similarity ($sim$). However, the degree of similarity does not indicate which context has a higher value. In other words, the similarity degree only specifies how close they are to each other without indicating the direction of similarity. To address this, the fuzzy prediction interval model (FPI) is used to determine the predicted interval of the context reputation value (Marín et al., 2019). The boundaries of the fuzzy prediction interval are determined by the distance between the two contexts. Here, the distance between the two contexts is calculated by finding the complement of *the degree of similarity* in Equation 7.3, as shown in Figure 7.4 and calculated by Equation 7.4 (Raeesi et al., 2014).

$$distance(d) = 1 - sim(C_x, C_y) \tag{7.4}$$

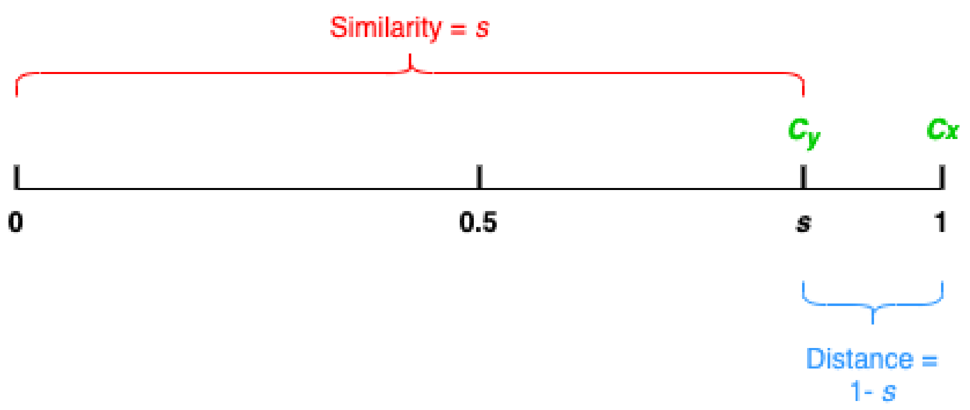


Figure 7.4 : The relationship between context similarity and distance.

Then the upper and the lower boundary equations are formulated based on our earlier assumption that the reputation systems have a normal distribution. The points above and below the reputation value of source context $C_x$ by $distance(d)$ are the upper and the lower boundaries of the fuzzy prediction interval of the predicted value of target context $C_y$, calculated using Equations 7.5, 7.6 and 7.7.

$$UB = RS(C_x) + \{(5 - RS(C_x)) * distance(d)\} \tag{7.5}$$

$$LB = RS(C_x) - \{(RS(C_x) - 1) * distance(d)\} \tag{7.6}$$

$$inferred\ RS(C_y) \in \{FPI | FPI = [LB, UB]\} \tag{7.7}$$

where,

- $UB, LB$: are the upper and the lower boundaries of the fuzzy prediction interval,
- $RS(C_x), RS(C_y)$ are the reputation values of source context $C_x$ and target context $C_y$ respectively.

The proposed algorithm to infer the context-based reputation fuzzy interval is shown in Figure 7.5. In the algorithm, there are two inputs, namely the reputation score of the source context $RS(C_x)$ and the degree of the similarity $sim(C_x, C_y)$. The output of this algorithm is $RV(C_y)$; the inferred reputation value of context $y$.

**Algorithm 1:** Fuzzy Prediction Interval model

**Input:** $RS(C_x)$, $sim(C_x, C_y)$
**Output:** $RV(C_y)$
BEGIN
distance(d) = 1 - $sim(C_x, C_y)$
$UB = RS(C_x) + ((5 - RS(C_x)) * distance(d))$
$LB = RS(C_x) - ((RS(C_x) - 1) * distance(d))$
$RV(C_y) \in [LB, UB]$
END

Figure 7.5 : Pseudocode for context-based value inference algorithm.

#### *7.2.3.1 Enhanced fuzzy prediction interval model (EFPI)*

To narrow the interval length and increase the precision of the results, the overall reputation value of robot $RS(r)$ is considered as an indicator to specify the direction of similarity. We assume that if the overall reputation value $RS(r)$ is greater than the source context value $RS(C_x)$, then the reputation value of the target context $RV(C_y)$ should be in the interval $[RS(C_x), UB]$ and if the overall reputation value $RS(r)$ is less than the source context value $RS(C_x)$, then $RV(C_y) \in [LB, RS(C_x)]$, as $RS(r)$ is the weighted average of the values of the two contexts.

In Figure 7.6, the context-based reputation fuzzy interval inference algorithm is modified to consider the enhancement of EFIP.

**Algorithm 2:** Enhanced Fuzzy Prediction Interval model

**Input:** $RS(r)$, $RS(C_x)$, $sim(C_x, C_y)$
**Output:** $RV(C_y)$
BEGIN
distance(d) = 1 - $sim(C_x, C_y)$
**if** $RS(r) \geq RS(C_x)$ **then**
  $UB = RS(C_x) + ((5 - RS(C_x)) * distance(d))$
  $RV(C_y) \in [RS(C_x), UB]$
**else**
  $LB = RS(C_x) - ((RS(C_x) - 1) * distance(d))$
  $RV(C_y) \in [LB, RS(C_x)]$
**end**
END

Figure 7.6 : Pseudocode for the modified context-based value inference algorithm using EFIP.

## 7.3 Results

The proposed method is validated on a publicly available dataset that was taken from Kaggle, a platform that offers a huge repository of community published data. The dataset revolves around the technical specifications of fitness tracker devices and their ratings provided by consumers (Madhugiri, 2022). The devices are either fitness bands or smart watches.

Figure 7.7 shows the actual values (scattered points) and the upper and lower boundaries of the predicted intervals in the proposed two models FPI and EFPI. As shown in the figure, the interval sizes are narrower in the EFPI model.

We used three evaluation metrices, namely precision, root square mean error (RMSE) and the size of the predicted range to evaluate the accuracy of the predicted intervals.

1. Precision:

   Precision is used to measure the ratio of the correctly predicted intervals to the total number of predicted intervals (Gama et al., 2009). The correctly predicted intervals are those intervals in which the actual reputation values of a context lie, calculated using Equation 7.8.

   $$Precision = \frac{correctly\ predicted\ intervals}{total\ number\ of\ predicted\ intervals} \tag{7.8}$$

   As shown in Table 7.2, the precision of the proposed two models is equal. This means the number of actual reputation values that lie outside the predicted intervals is the same in both models.

2. Root mean square error (RMSE):

   RMSE is a statistical accuracy metric used to measure the average distance between the predicted values and the actual values (Chai & Draxler, 2014).


Figure 7.7 : Actual values and predicted intervals using (A) FPI model, (B) EFPI model.

As the outputs of our proposed models are predicted intervals not crisp values, we use RMSE to measure how far the actual reputation value of context X ($RS(C_x)$) which does not lie within our predicted interval, is from the upper and lower boundaries $(UB), (LB)$ of the predicted interval, calculated using Equations 7.9.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\frac{(RS(C_i) - UB_i)^2 + (RS(C_i) - LB_i)^2}{2}} \tag{7.9}$$

Table 7.2 indicates that the RMSE of the FPI model is 0.8 while the RMSE of the EFPI model is 0.49, which means that the EFPI model produces better results than FPI since the weighted average error between the predicted intervals and the actual values is smaller in the EFPI.

3. The size of the predicted range:

We calculated the percentage of the predicted intervals compared to the whole domain to determine the size of the predicted range. The domain of the reputation values is within $[1, 5]$ which represents 100%.

$$Range\ percentage = \frac{1}{n}\sum_{i=1}^{n}\frac{UB_i - LB_i}{5} * 100 \tag{7.10}$$

We computed the sizes of the predicted intervals for all similarity degrees and when the similarity degrees are greater than or equal to 50% and greater than or equal to 80%.

Table 7.2 : Evaluation metrics results.

| **Metrics** | **FPI** | **EFPI** |
|---|---|---|
| Precision | 0.804 | 0.804 |
| RMSE | 0.803 | 0.49 |
| Range percentage ($sim \in [0, 1]$) | 24.7% | 11.1% |
| Range percentage ($sim \in [0.5, 1]$) | 22.7% | 9.9% |
| Range percentage ($sim \in [0.8, 1]$) | 11.9% | 4.6% |

## 7.4 Conclusion

In this work, we proposed a comprehensive methodology, called *context-aware reputation value inferencing for multi-purpose robots (CaRVInf)*, to infer the reputation value of a multi-purpose robot in a specific context based on existing trust values in other contexts. This methodology comprises three steps: context modelling, context semantic similarity computation and context value inference. Context modelling is based on the keyword-based modelling approach. We used the Jaccard similarity index to compute the semantic similarity of contexts. Then, we introduced two models (FPI and EFPI) to predict the interval in which the reputation value of a context lies. We examine our proposed method on a publicly available dataset to evaluate its accuracy.

Our experiment results prove that the proposed benchmark that the similarity degrees should meet narrows the size of the prediction intervals which ultimately improves the accuracy of the proposed method. In future, this research can further be extended by examining various contextual modelling approaches to observe how different modelling methods affect the accuracy of the predicted intervals.

# Chapter 8

# Prototype Working and Demonstration

## 8.1 Introduction

In the previous chapters, we introduced and discussed our proposed solution, the IBBRB framework, which incorporates proposing solutions for robotic reputation computation, robotic reputation prediction and contextual reputation inferencing for multi-purpose robots. In this chapter, the system prototype of IBBRB is presented. IBBRB is a blockchain-based reputation broker for robot selection. We demonstrate the prototype setup and the blockchain setup in a step-by-step manner using screenshots in this chapter. This includes demonstrating the working of the proposed solutions for our research objectives that are discussed in chapters 5, 6, and 7.

## 8.2 System Users and Roles

There are three user groups in the IBBRB framework, namely robotic service requesters, robotic service suppliers and system admins. Figure 8.1 summarises the different user groups, roles and tasks.

- Robotic service requesters are customers who previously used any robot in the IBBRB network and intend to rate the robot or rate a specific purpose of multi-purpose robots. Figure 8.2 shows the customer homepage.

- Robotic service suppliers are allowed to add new (single purpose/ multi-purpose) robots to the IBBRB network, proposing a change in the current RAO, and voting on RAO change proposals. The supplier's homepage is shown in Figure 8.3.

- The system admins are responsible for reviewing RAO change proposals, setting timeframes for proposal voting, broadcasting the RAO change proposal to the supplier community and applying the change proposal to the RAO based on the voting results. The admin's home page is shown in Figure 8.4.

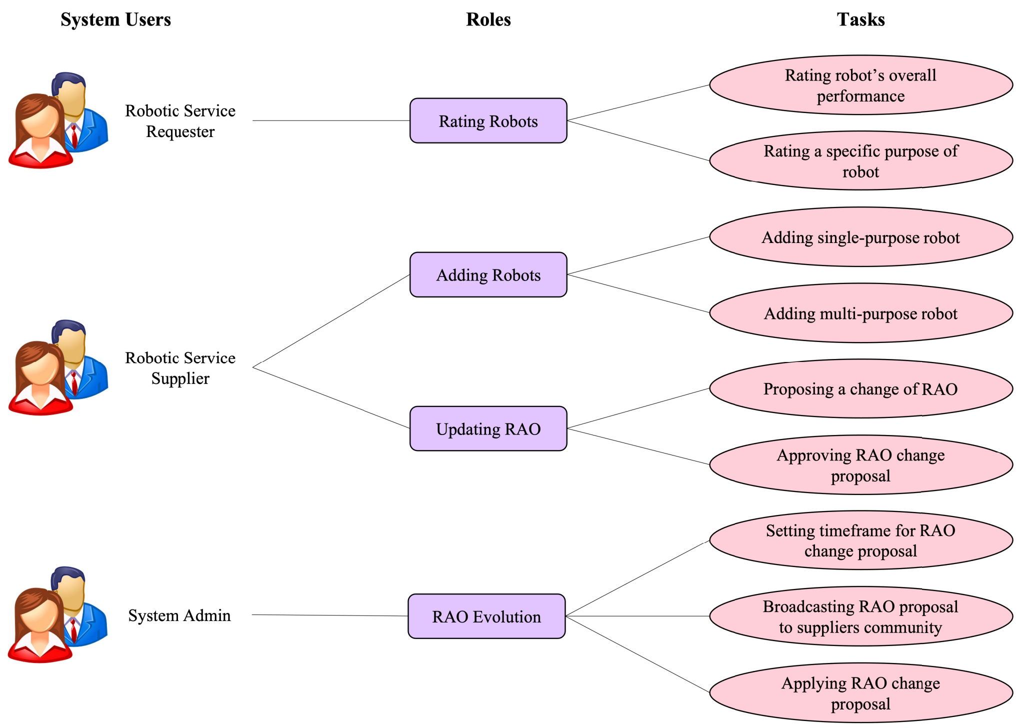


Figure 8.1 : IBBRB user groups, roles and tasks.

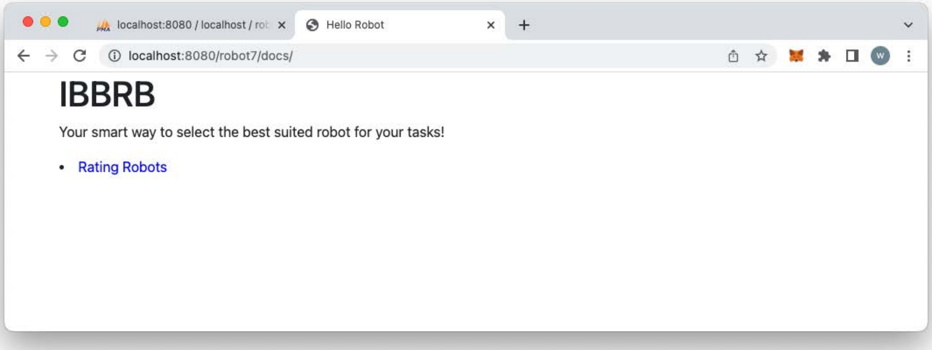


Figure 8.2 : Robotic service requester homepage.

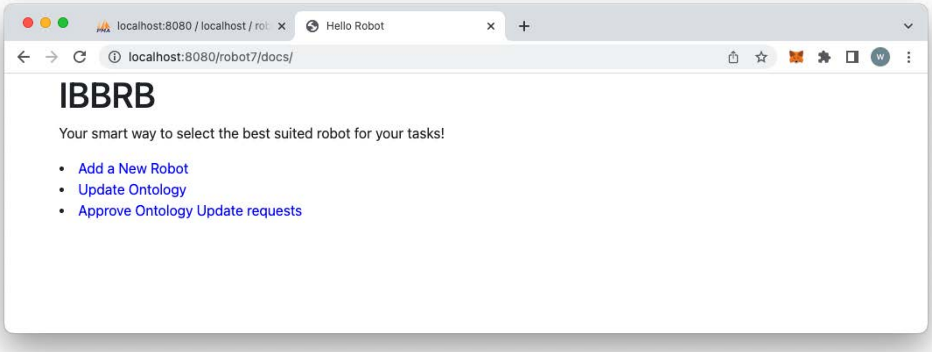


Figure 8.3 : Robotic service supplier homepage.

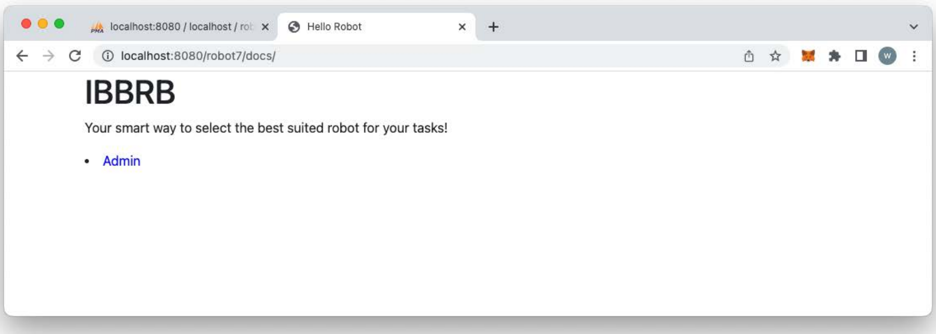


Figure 8.4 : Admin homepage.

## 8.3 Prototype Setup

Our proposed methods require intermediate computations such as rating aggregation, similarity computations, score prediction and then reputation computation. For this reason, we built our proposed IBBRB framework to carry out robotic reputation computation at two levels: the local level and the blockchain level. All the intermediate computations are stored at the local level while the final reputation scores are stored and retrieved in the blockchain. The physical system architecture is shown in Figure 8.5. The steps for the local level and blockchain level computation are discussed in the following subsections.

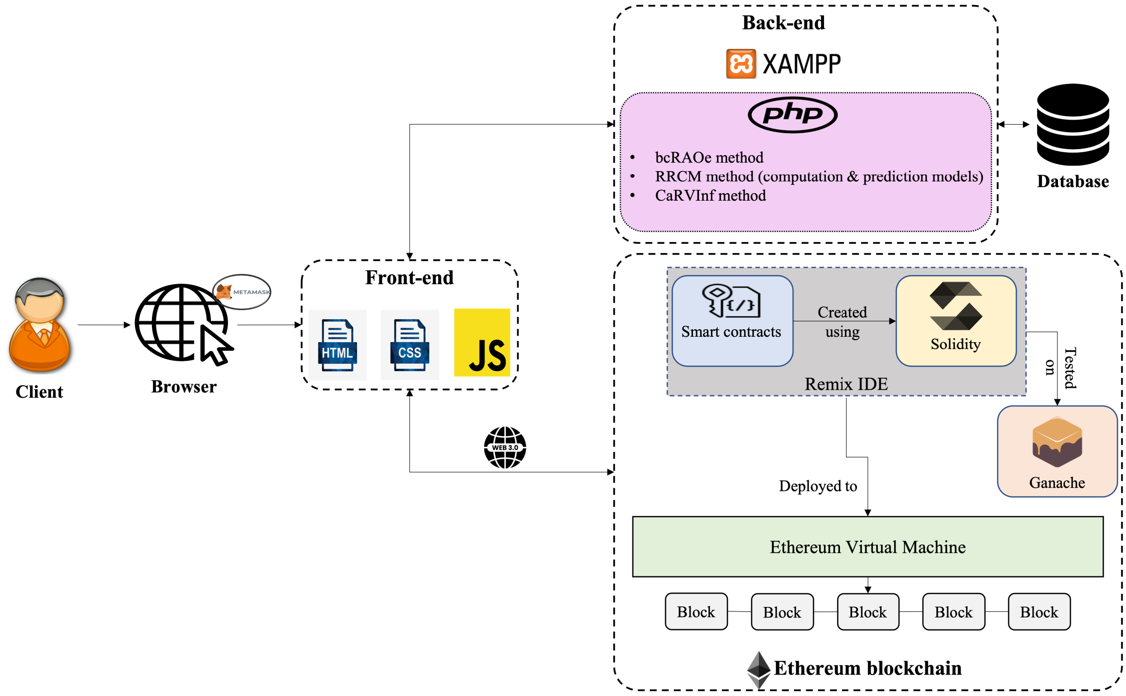


Figure 8.5 : IBBRB physical system architecture.

### 8.3.1 Local Machine Setup

XAMPP software is used to run the machine as a local server. XAMPP consists of an Apache web server and a MySQL database server (Figure 8.6). The Apache server is used as a local server for our prototype while the MySQL database server is used to run our local MySQL database and handle the storage of intermediate computation data.

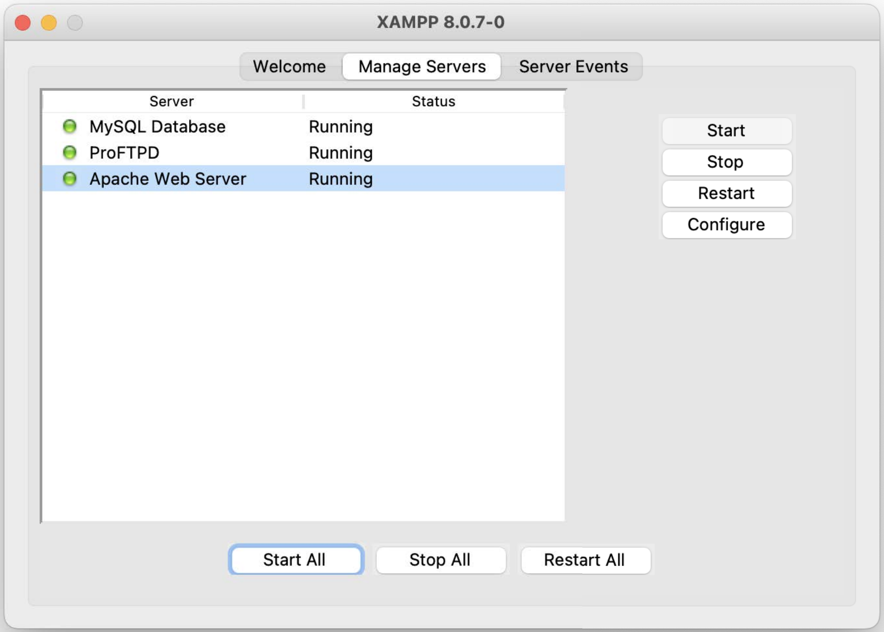


Figure 8.6 : XAMPP software components.

After running the servers, we opened the localhost home page in the browser to ensure that the server is working (Figure 8.7).

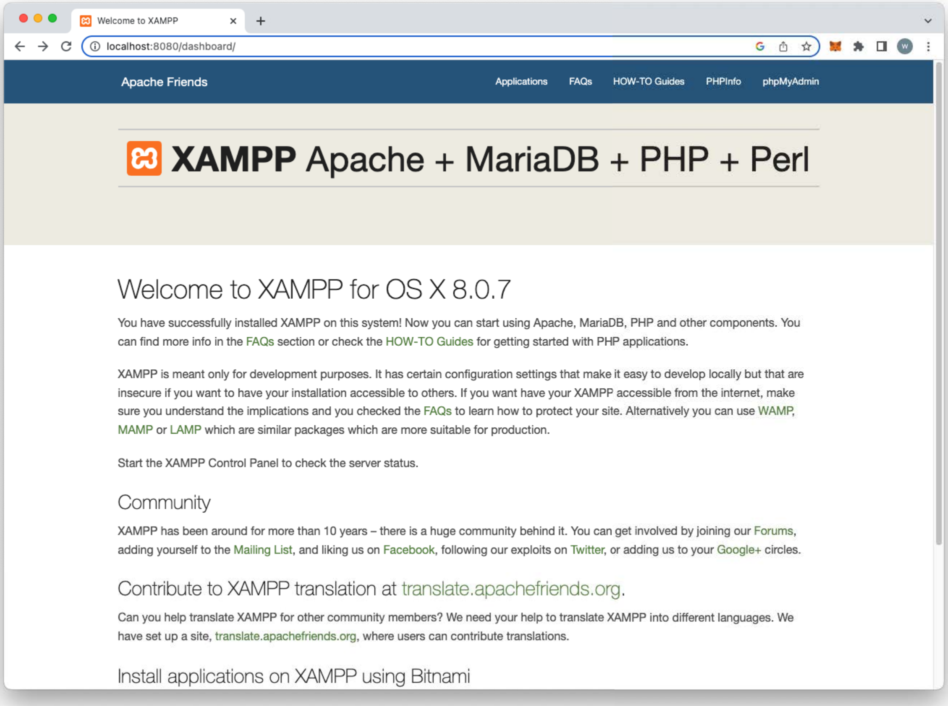


Figure 8.7 : Machine is successfully running localhost.

Then we built our local database using phpMyAdmin (Figure 8.8). We termed the database robodb and we created a table named rating. In this database, we store all the users' ratings that will be used to produce the overall reputation values for all robots and then these values will be sent to and stored in the blockchain. The structure of the rating table is shown in Figure 8.9. The rating table consists of the following 12 columns:

- ID: the id of the robot.
- Roboname: the name of the robot.
- Robopurpose: multipurpose robot or single purpose robot.

- robotSeller: seller's blockchain address.
- Customer : customer's blockchain address.
- Rating: overall rating given to the robot by the customer.
- Purpose1: name of purpose 1.
- Purpose2: name of purpose 2 if the robot is a multipurpose robot.
- Keyword1: description of purpose 1.
- Keyword2: description of purpose 2 if the robot is a multipurpose robot.
- Purpose1_rating: the rating of the first purpose given by the customer.
- Purpose2_rating: the rating of the second purpose given by the customer if the robot is a multipurpose robot.

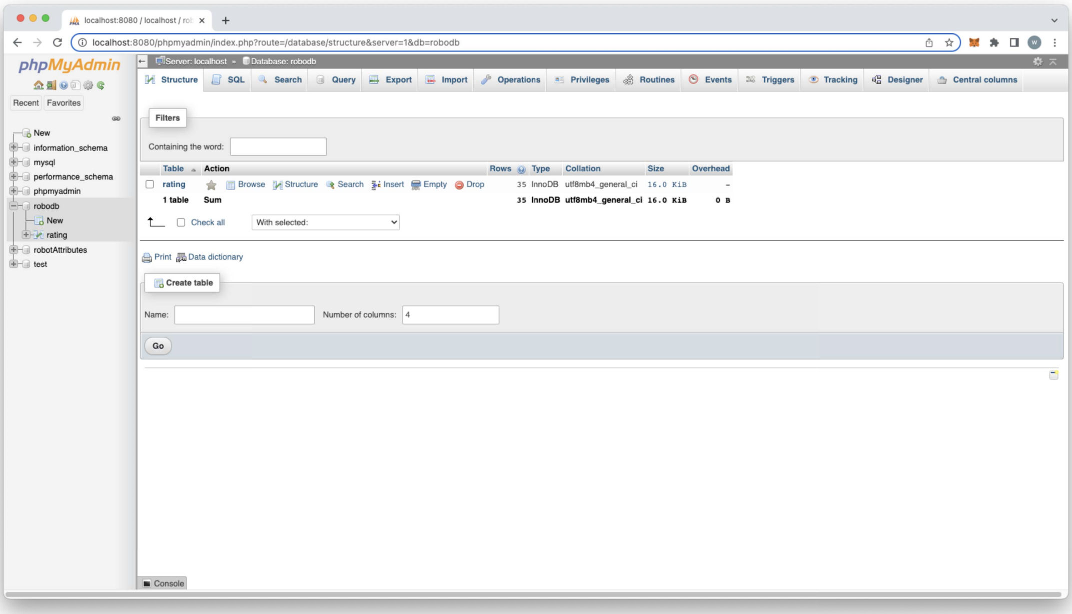


Figure 8.8 : Local Database using phpMyAdmin.

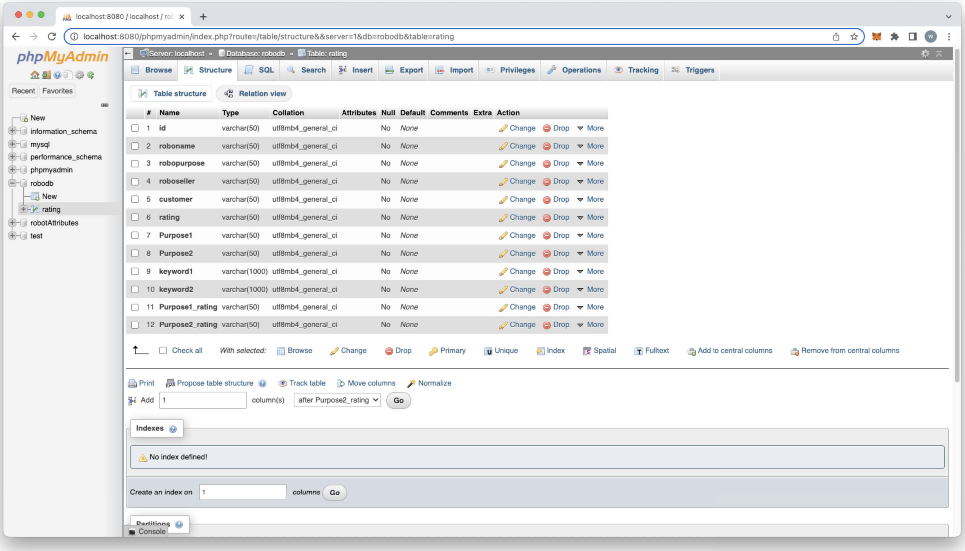


Figure 8.9 : Structure of the rating table.

We built a simulated blockchain-based reputation system using PHP for the system and using MySQL for the database. All these files are stored into the localhost directory (Figure 8.10).

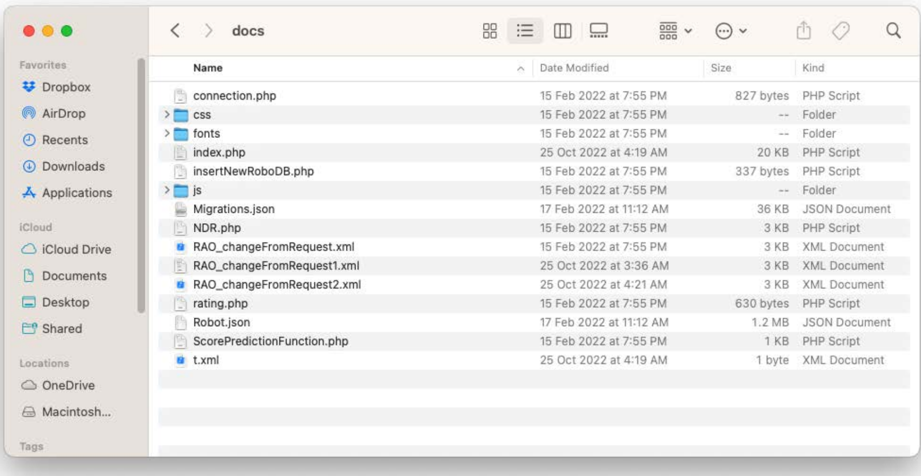


Figure 8.10 : IBBRB files.

### 8.3.2 Blockchain Setup

To set up the blockchain network, we firstly installed MetaMask and created an account. MetaMask is a browser extension that allows users to interact with the Ethereum network. Then we selected the Goerli test network to start deploying our smart contract, as shown in Figure 8.11.

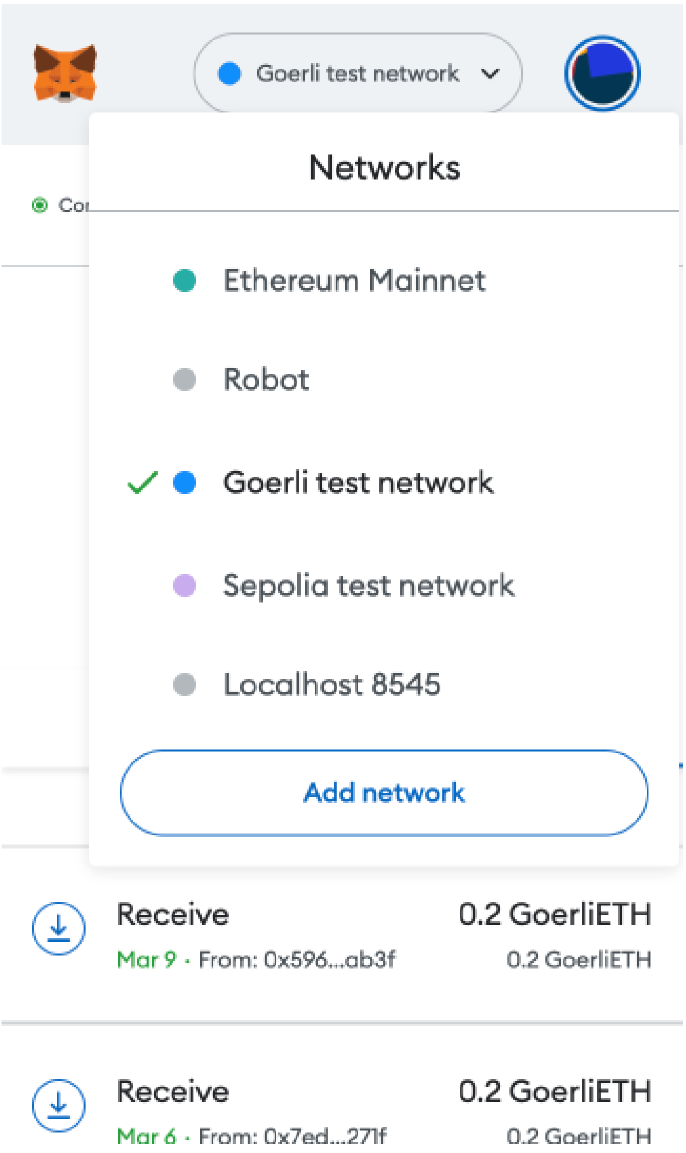


Figure 8.11 : Connecting MetaMask account to the Goerli test network.

To deploy the smart contract, we need to have test ether in the created account wallet to pay the gas fee for the transactions. Figure 8.12 shows the process of depositing test ethers from goerliFaucet.

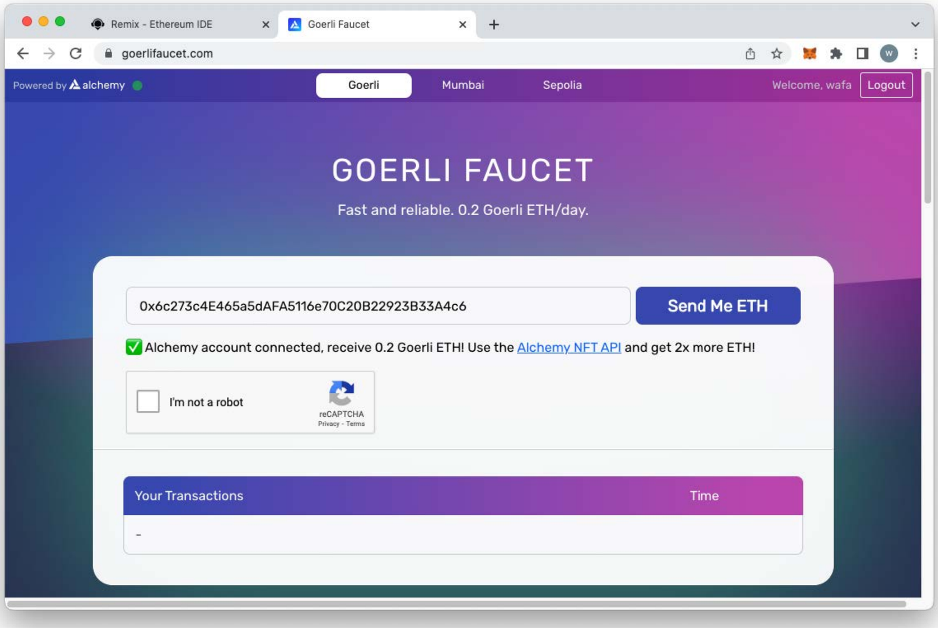


Figure 8.12 : Depositing Ether from goerliFaucet.

Then, Remix IDE is used to write the smart contract using the Solidity language. Remix is a web-based integrated development environment (IDE) for building, compiling, debugging and deploying smart contracts on the Ethereum virtual machine (EVM).

After successfully developing and compiling the blockchain smart contract on Remix IDE, we deployed it using the MetaMask wallet on the Goerli Test Network (refer to Figure 8.13 for more detail). Figure 8.14 shows the detail of our smart contract deployment on the EVM.

## 8.4 System Functionalities

There are three major functionalities of the IBBRB framework: RAO evolution, robotic reputation computation and robotic reputation inference. These functions represent the proposed solutions for objectives 2, 3, and 4 respectively. In the following subsections, we detail the working of the proposed functions using screenshots and pictures.

### 8.4.1 Prototype working for robotic attribute ontology evolution

Chapter 5 detailed the building of an initial robotic attribute ontology (RAO). We also introduced a new blockchain-based crowdsourcing Robotic Attribute Ontology evolution method (bcRAOe) to enable a crowd of robotic experts to be involved in the ontology evolution process.

The robotic service suppliers and the system admins are the interacting parties in the bcRAOe method in the IBBRB prototype. The sequence diagram in Figure 8.15 models the logic of the bcRAOe method.

Any robotic service supplier in the network is allowed to propose an update in the current RAO and send it to the admin address, as shown in Figure 8.16 and Figure 8.17. Then the proposal request, its justification and the sender address are reviewed by the system admin (Figure 8.18). The system admin has the option to ignore the proposal or set a timeframe for voting on the proposal and send it to the supplier community except the proposal sender. Figure 8.19 shows the voting page that is displayed to the supplier community.

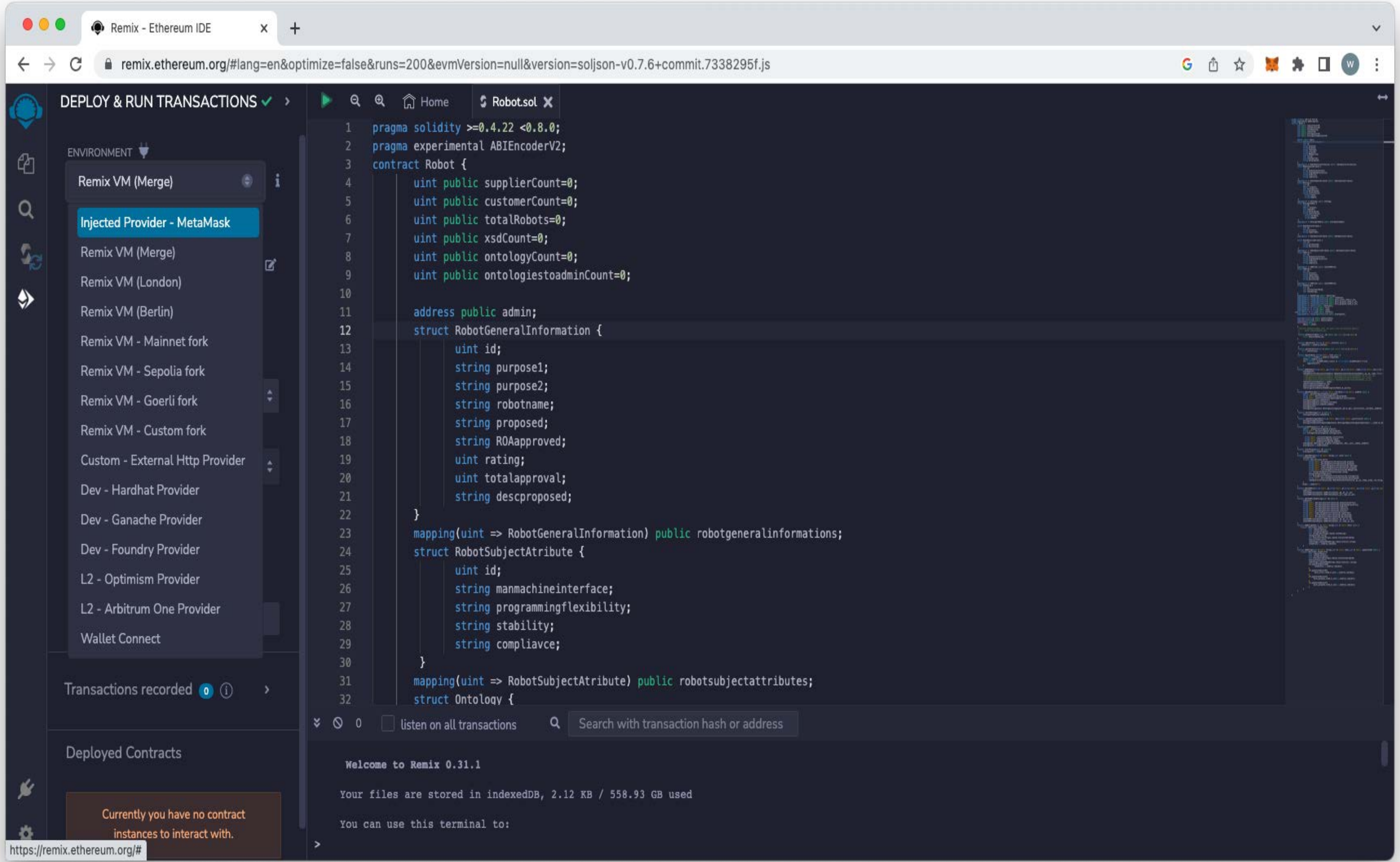


Figure 8.13 : Smart contract deployment.

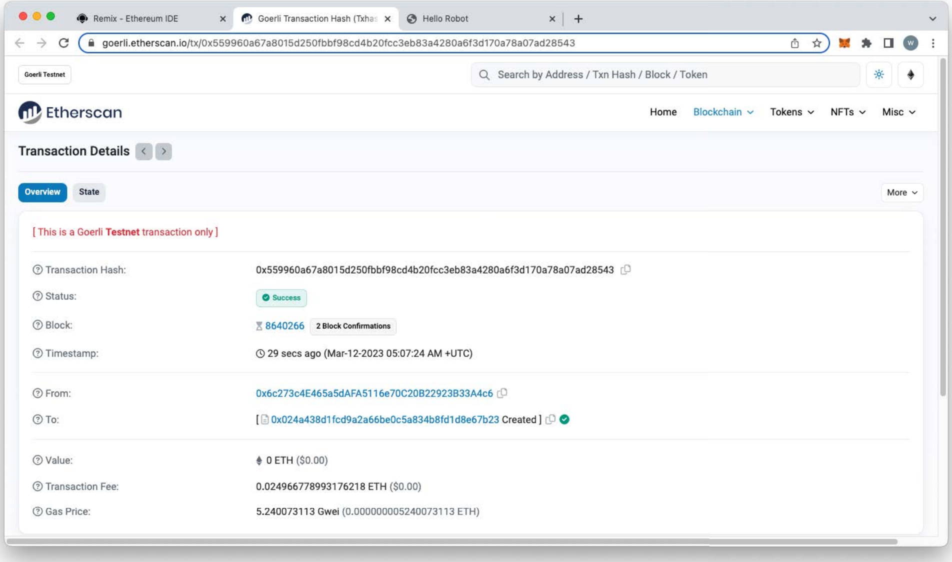


Figure 8.14 : Status of the smart contract deployment in Etherscan.

Once the polling time is over, the results can be reviewed by the system admin as shown in Figure 8.20. The system admin updates the current RAO if more than 50% of the suppliers accept the proposal, or the proposal will be ignored otherwise.

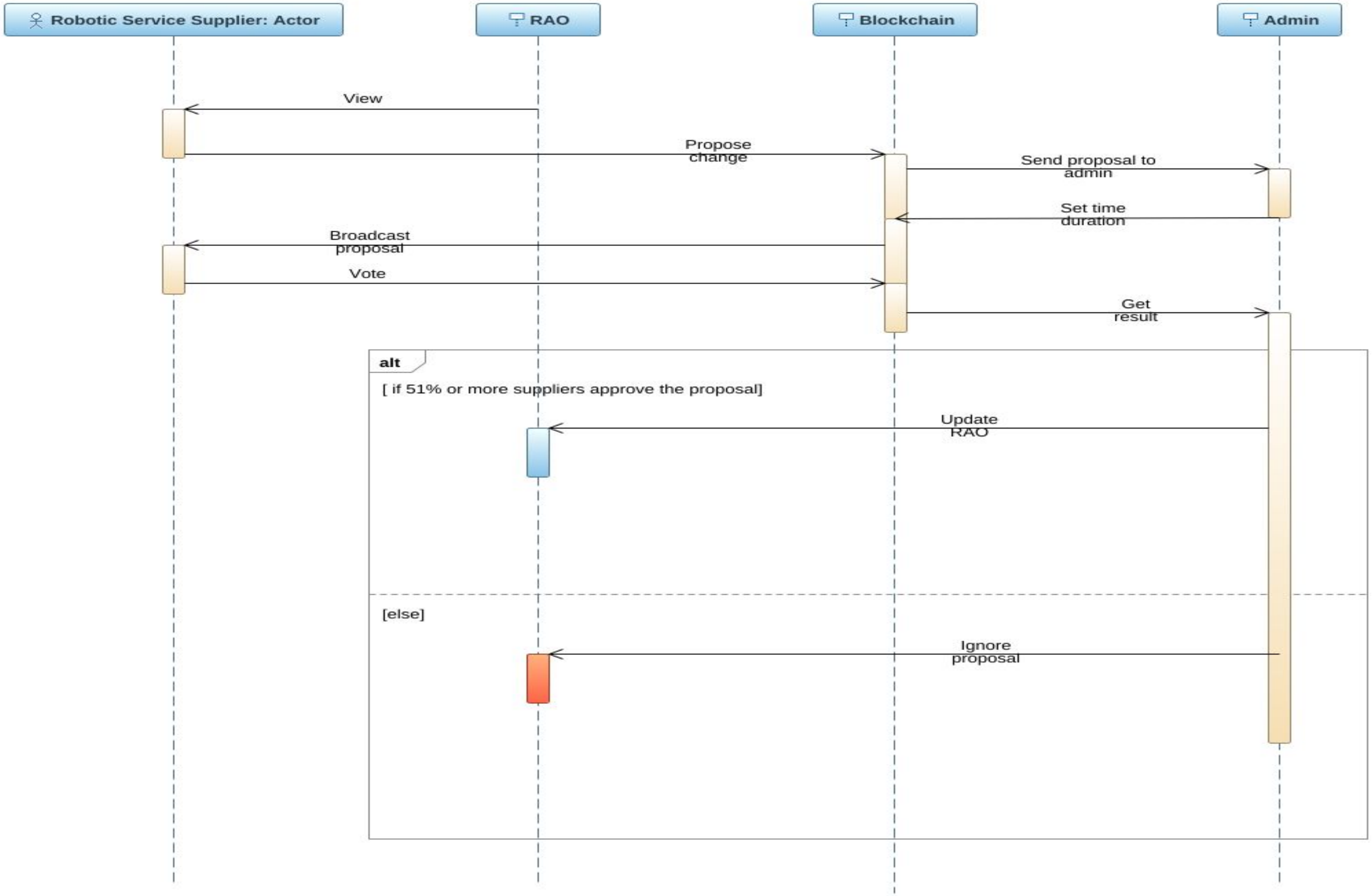


Figure 8.15 : Sequence diagram of bcRAOe method.

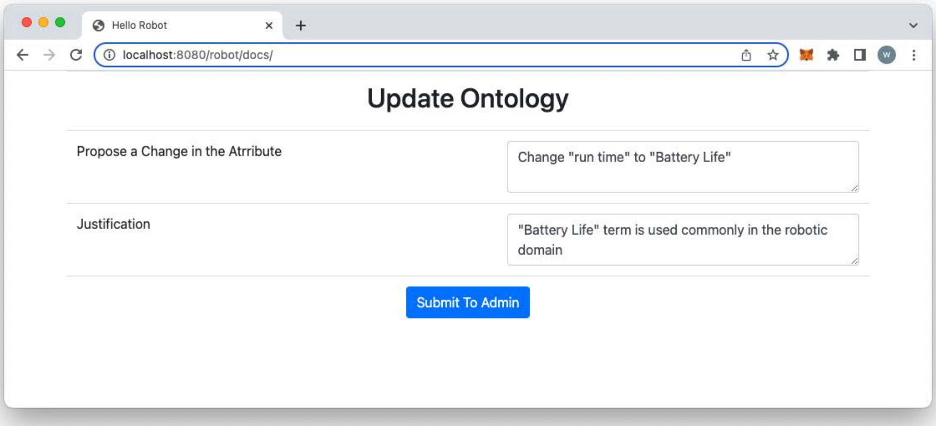


Figure 8.16 : Proposing an update in RAO by the robotic service supplier.

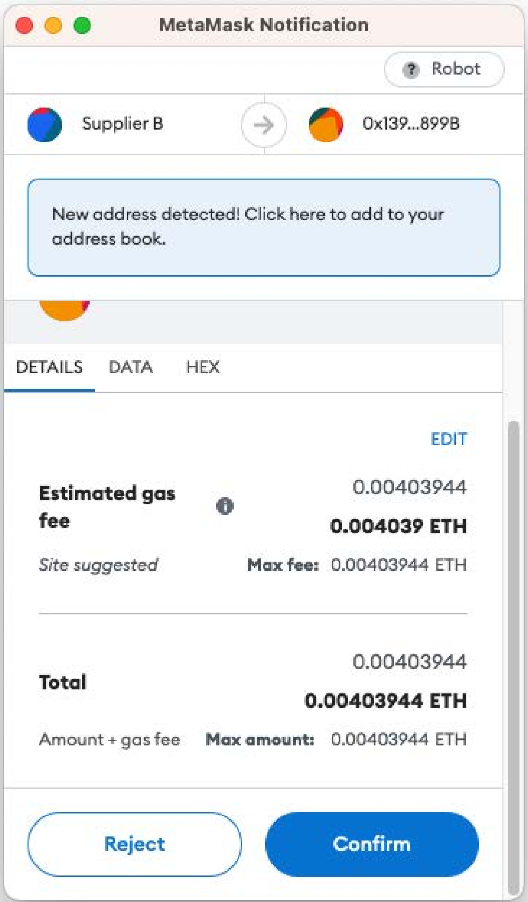


Figure 8.17 : Sending the RAO change proposal to the admin address.

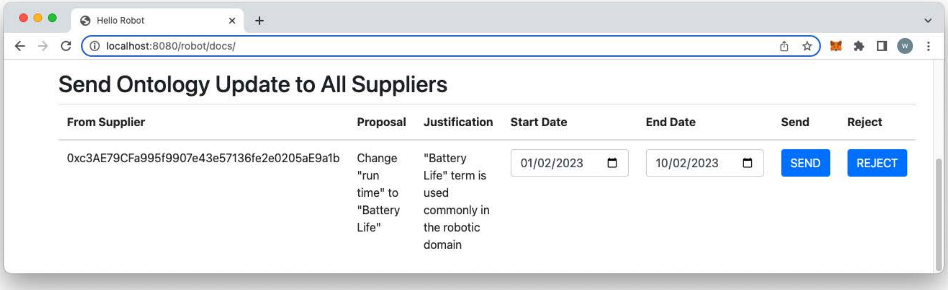


Figure 8.18 : Reviewing the RAO change proposal by the admin.

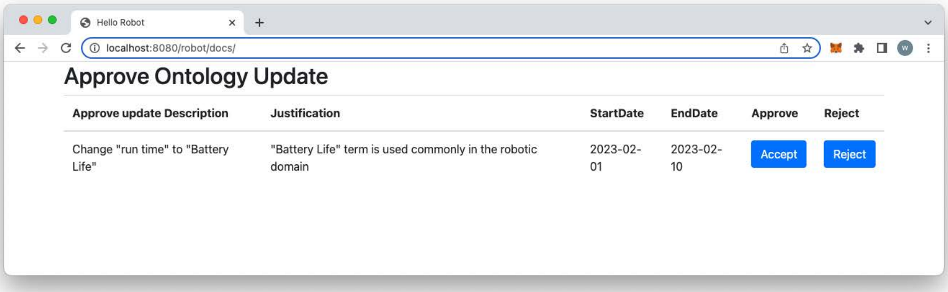


Figure 8.19 : Robotic service suppliers' voting page.

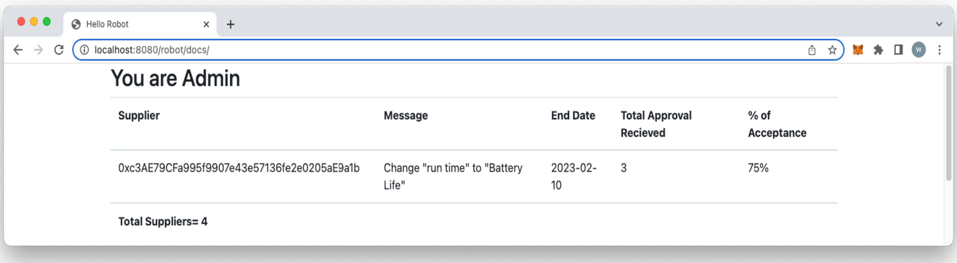


Figure 8.20 : Voting results.

### 8.4.2 Prototype working for the robotic reputation computation

In this section, we show the working of the RRCM method that was proposed in Chapter 6 using screenshots. RRCM includes building two models, namely the robotic reputation computation model to carry out robotic reputation computation based on prior existing ratings and the robotic reputation prediction model to intelligently predict reputation scores for new robots based on their similarities to already evaluated robots.

#### *8.4.2.1 Robotic reputation computation*

The IBBRB prototype produces a reputation score for a robot based on accumulating prior ratings. Once a new rating is received, all previous ratings are retrieved to calculate the overall reputation score and then the score is updated in the blockchain as indicated in the sequence diagram in Figure 8.21.

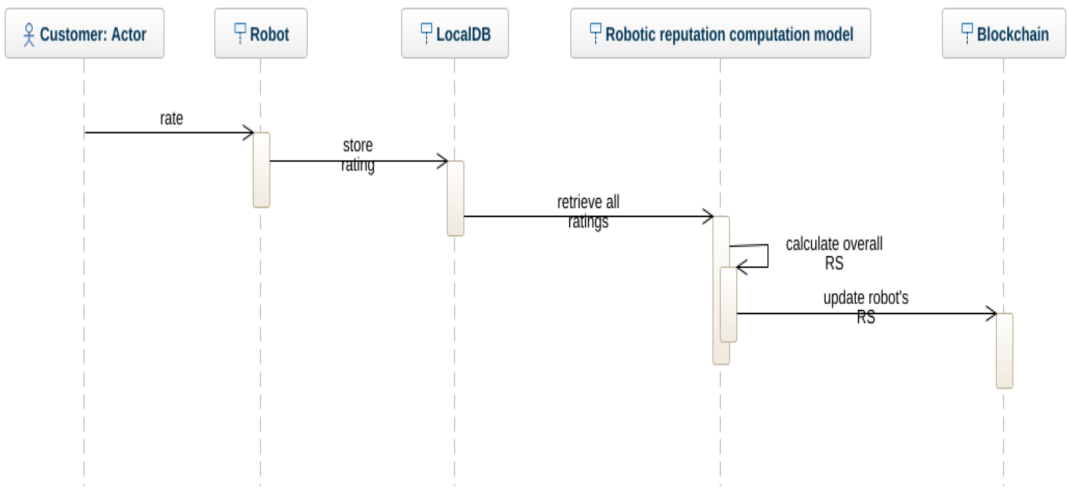


Figure 8.21 : Sequence diagram for robotic reputation computation model.

Figure 8.22 shows a robot named AIRROBO P10 that has not being rated yet. Figure 8.23 shows the rating process. The customers are allowed to give the robot rating scores between 1 and 5, where 1 means ‘extremely dissatisfied’ and 5 means ’extremely satisfied’. Using three customer accounts, we rate the robot as 2, 2, and 5 respectively. After the first customer rating, the reputation score of the robot is equal to the customer rating as illustrated in Figure 8.24. After the robot has been rated by more customers, the reputation score is calculated using the NDR function that was discussed in Chapter 6 and then the reputation score of the robot is updated in the blockchain, as shown in Figure 8.25.

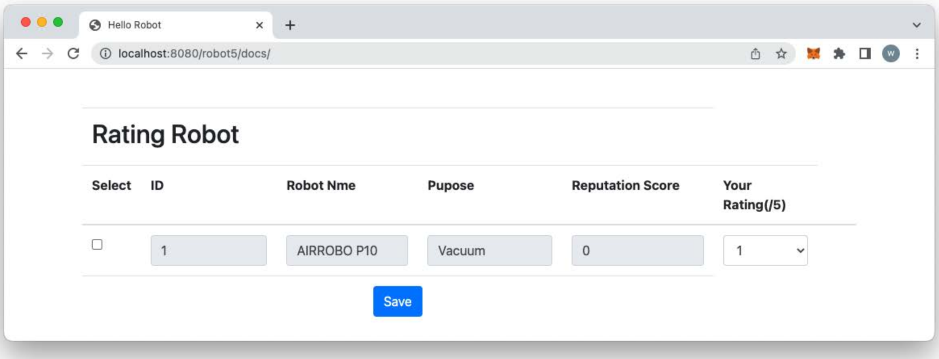


Figure 8.22 : AIRROBO P10 robot with no ratings.

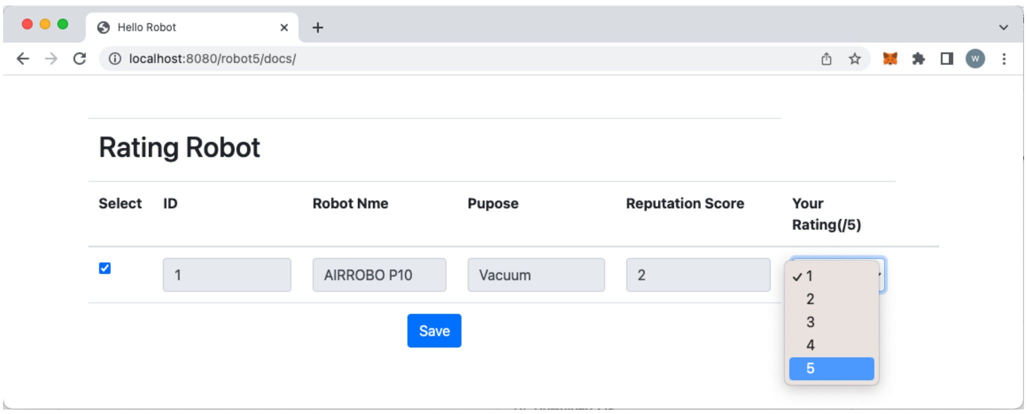


Figure 8.23 : AIRROBO P10 robot rating process.

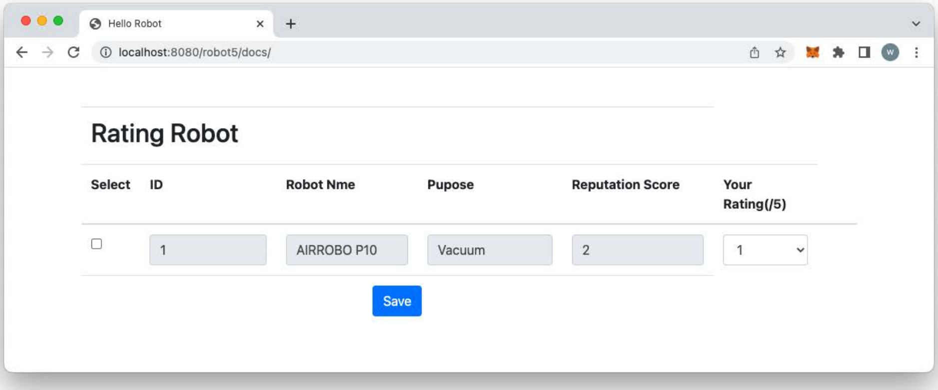


Figure 8.24 : AIRROBO P10 robot after being rated by one customer.

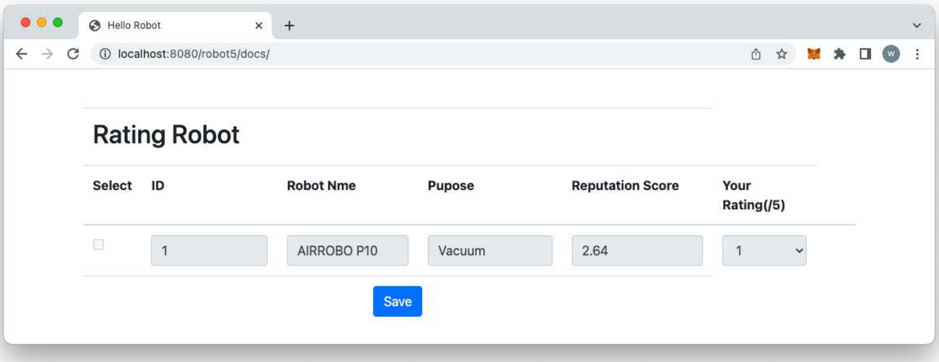


Figure 8.25 : AIRROBO P10 robot after receiving three ratings (2,2,5).

#### *8.4.2.2 Robotic reputation prediction*

The prediction function is invoked when a supplier account adds a new robot to the blockchain. The IBBRB prototype retrieves all the stored robots with the same purpose as the newly added robot, measures the similarities between robots, finds the most similar (nearest neighbour) robot to the new robot, and then predicts a reputation score for the new robot based on the reputation score of the nearest neighbour robot (refer to Section 6.3 for more details). Figure 8.26 shows the sequence of the robotic reputation prediction model events.

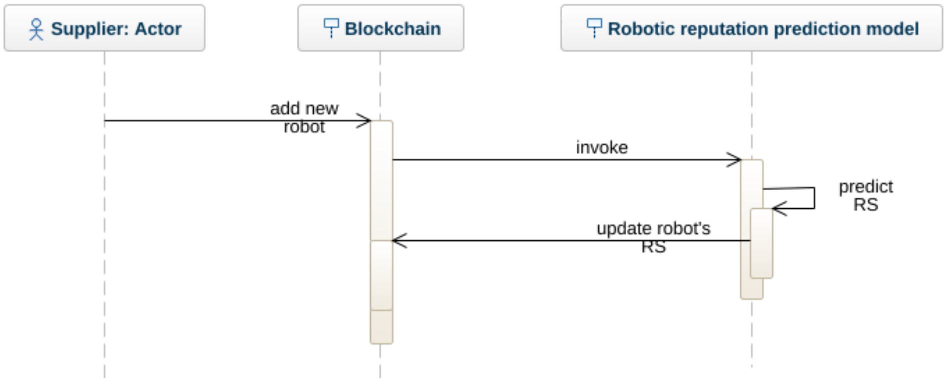


Figure 8.26 : Sequence diagram for the robotic reputation prediction model.

In Figure 8.27, we add a new robot with the 'vacuum' purpose (same as AIR-ROBO P10 robot). After storing the new robot in the blockchain, the prediction function is invoked, as shown in Figure 8.28. The predicted reputation score then is displayed in the customer accounts, as shown in Figure 8.29.

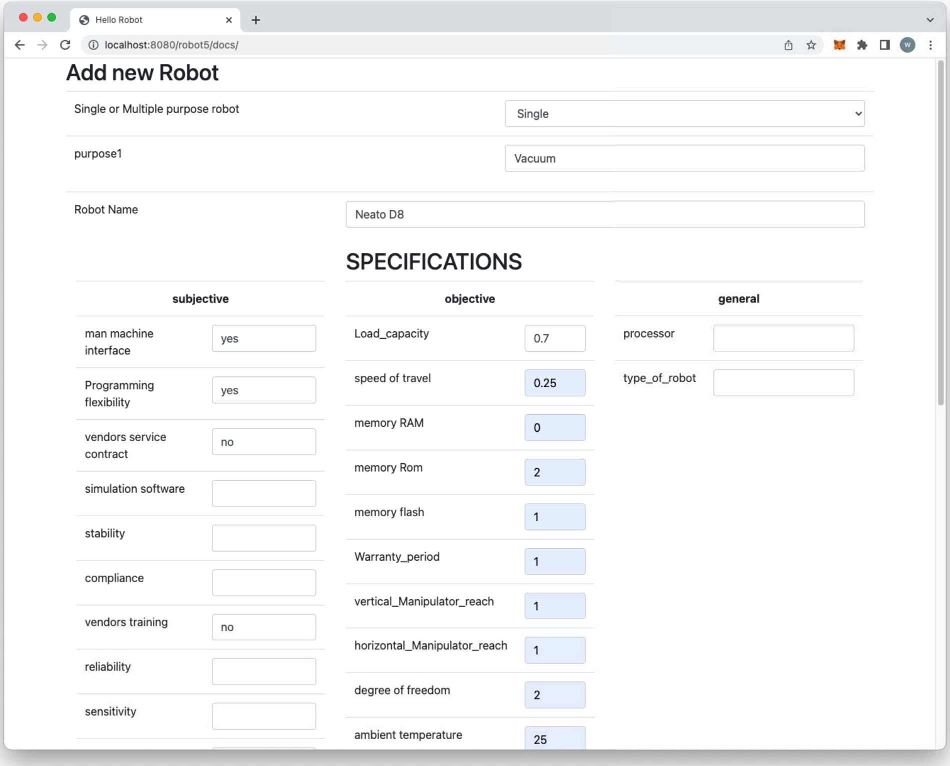


Figure 8.27 : Adding new robot with the same purpose as a previously stored one.

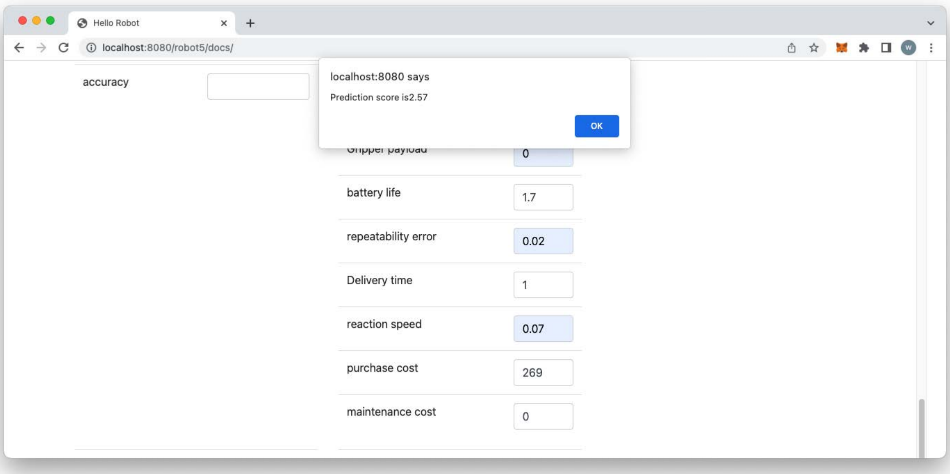


Figure 8.28 : Prediction function invoked.

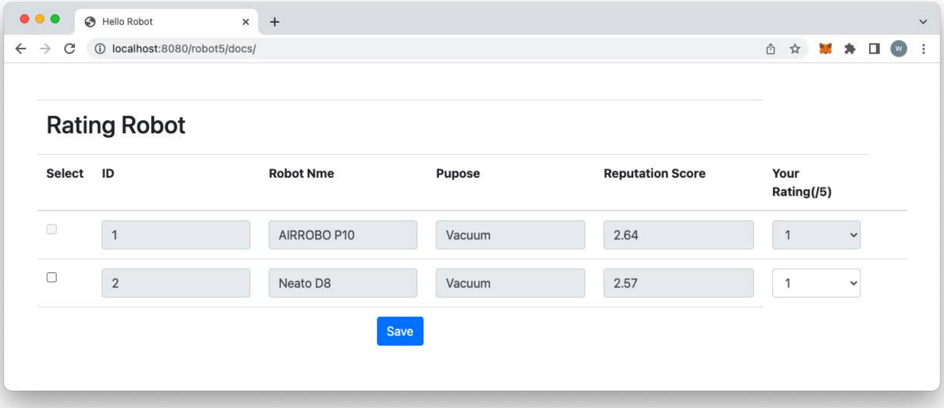


Figure 8.29 : Predicted reputation score is shown.

### 8.4.3 Prototype working for robotic reputation inference

The proposed method (CaRVInf) which is introduced in Chapter 7 of this thesis infers a reputation value for a non-reviewed purpose of a multi-purpose robot based on its similarity to other reviewed purposes. As discussed in Chapter 7, the CaRVInf method also assumes that the overall reputation of a multi-purpose robot (if it does not exist) is the average of all other purposes' reputation values. CaRVInf predicts the reputation value of non-reviewed purpose as a fuzzy interval in the form of $[LB, UB]$ until it has been rated by a customer, then the method will update the reputation value to a crisp value.

To explain the working of IBBRB prototype for the CaRVInf method, we have listed two multi-purpose robots in the IBBRB prototype using a supplier account, as shown in Table 8.1:

The sequence diagram of the CaRVInf method is illustrated in Figure 8.30. Table 8.2 and Figure 8.31 - Figure 8.43 explains the different cases of rating multi-purpose robots using the CaRVInf method.

Table 8.1 : Multi-purpose details inserted in the prototype.

| **Robot Name** | **Robot Type** | **Robot Purpose 1** | **Robot Purpose 2** |
|---|---|---|---|
| FANUC M20ia | Industrial robot | Automated material handling: moving materials for short distances. This task is a repetitive process. | Automate robotic assembly: forming or joining multiple parts of an equipment together. This task is a tedious job since it requires precision, speed and involves a repetitive process. |
| Bissell SpinWave | Domestic robot | Vacuuming: cleaning on different floor types - includes carpets, rugs, tiles, laminate and wood through a rotating brush roll and side bristles. | Mopping: mop all hard floors using a wet cleaning tank and the agitation of mop pads. |

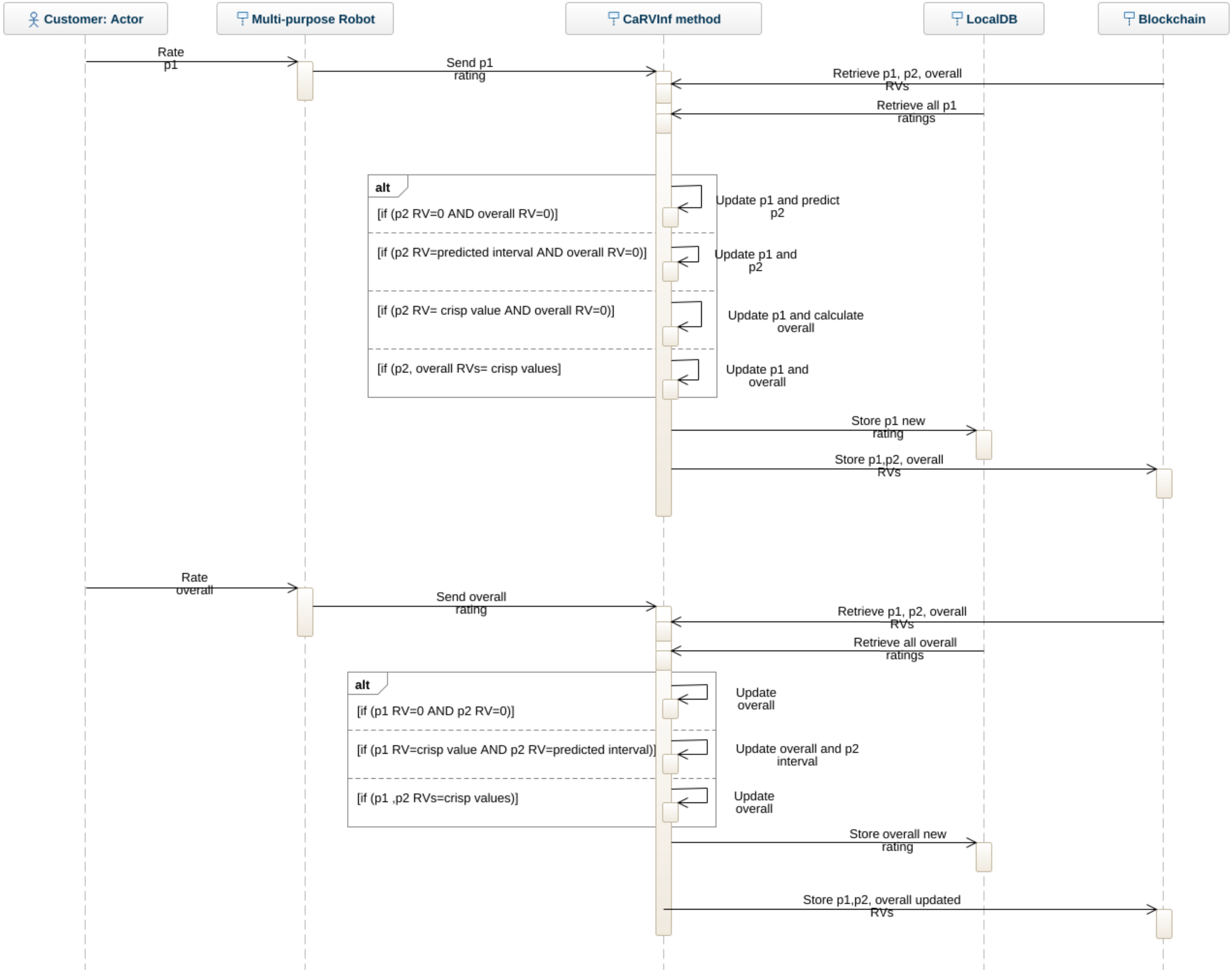


Figure 8.30 : Sequence diagram for the CaRVInf method.

Table 8.2 : Different cases of reputation value inferencing using the CaRVInf method.

| **Cases** | **A. When the overall performance of the multi-purpose robot is being rated ($r_o$)** | **B. When the first purpose of the multi-purpose robot is being rated ($r_{p1}$)** | **C. When the second purpose of the multi-purpose robot is being rated ($r_{p2}$)** |
|---|---|---|---|
| **Case 1: No ratings at all; (Overall RV=0, purpose1 RV=0 and purpose2 RV=0)** | Update the overall RV ($RV_o = r_o$). | 1. Update purpose1 RV ($RV_{p1} = r_{p1}$).<br>2. Predict purpose2 RV as a fuzzy interval $[LB, UB]$. | 1. Update purpose2 RV ($RV_{p2} = r_{p2}$).<br>2. Predict purpose1 RV as a fuzzy interval $[LB, UB]$. |
| **Case 2: Overall is rated; (Overall RV=crisp value, purpose1 RV=0 and purpose2 RV=0)** | Update the overall RV using NDR method. | 1. Update purpose1 RV ($RV_{p1} = r_{p1}$).<br>2. Predict purpose2 RV as a fuzzy interval $[LB, UB]$. | 1. Update purpose2 RV ($RV_{p2} = r_{p2}$).<br>2. Predict purpose1 RV as a fuzzy interval $[LB, UB]$. |
| **Case 3: One purpose is rated; (Overall RV=0, purpose1 RV= crisp value and purpose2 RV=$[LB, UB]$)** | Update the overall RV ($RV_o = r_o$). | 1. Update purpose1 RV using NDR method.<br>2. Predict purpose2 RV as a fuzzy interval $[LB, UB]$. | 1. Update purpose2 RV ($RV_{p2} = r_{p2}$).<br>2. Calculate overall RV as the average value. |

Continued on next page

**Table 8.2 – continued from previous page**

| Cases | A. When the overall performance of the multi-purpose robot is being rated ($r_o$) | B. When the first purpose of the multi-purpose robot is being rated ($r_{p1}$) | C. When the second purpose of the multi-purpose robot is being rated ($r_{p2}$) |
|---|---|---|---|
| **Case 4: Overall and one purpose are rated; (Overall and purpose1 RVs=crisp values, purpose2 RV=$[LB, UB]$)** | Update the overall RV using NDR method. | 1. Update purpose1 RV using NDR method.<br>2. Predict purpose2 RV as a fuzzy interval $[LB, UB]$. | 1. Update purpose2 RV ($RV_{p2} = r_{p2}$).<br>2. Calculate overall RV as the average value. |
| **Case 5: Overall and all purposes are rated; (Overall, purpose1 and purpose2 RVs= crisp values)** | Update the overall RV using NDR method. | 1. Update purpose1 RV using NDR method.<br>2. update overall RV as the average value. | 1. Update purpose2 RV using NDR method.<br>2. update overall RV as the average value. |

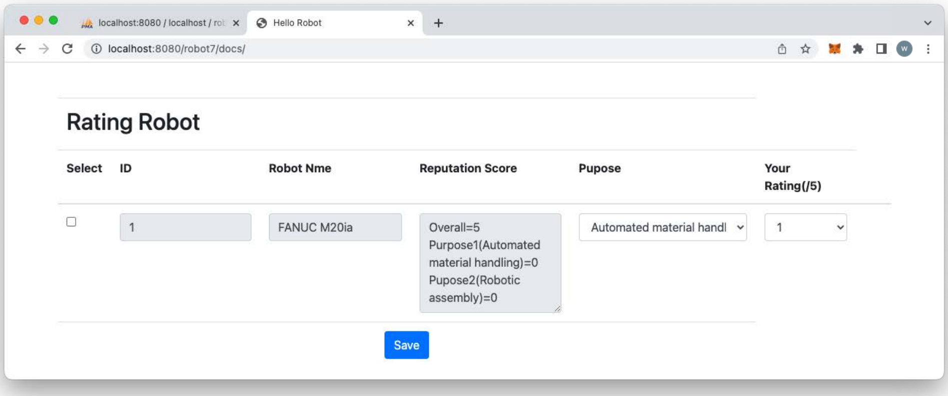


Figure 8.31 : Rating overall performance of a multi-purpose robot with (5) (Case 1A).

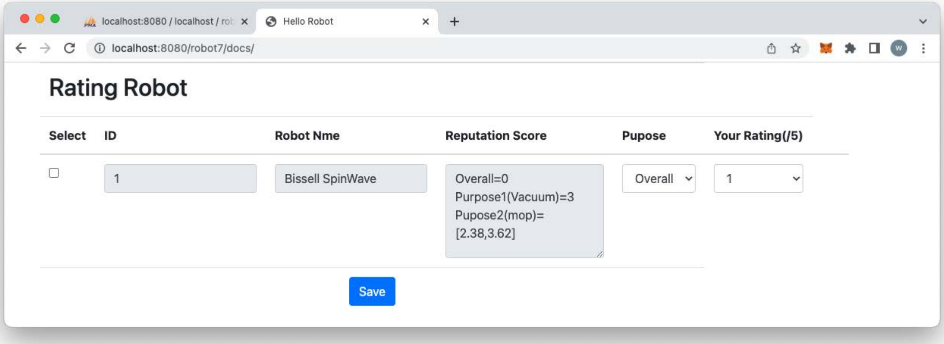


Figure 8.32 : Rating one purpose of a multi-purpose robot with (3) and predicting RV of the second purpose (Cases 1B and 1C).

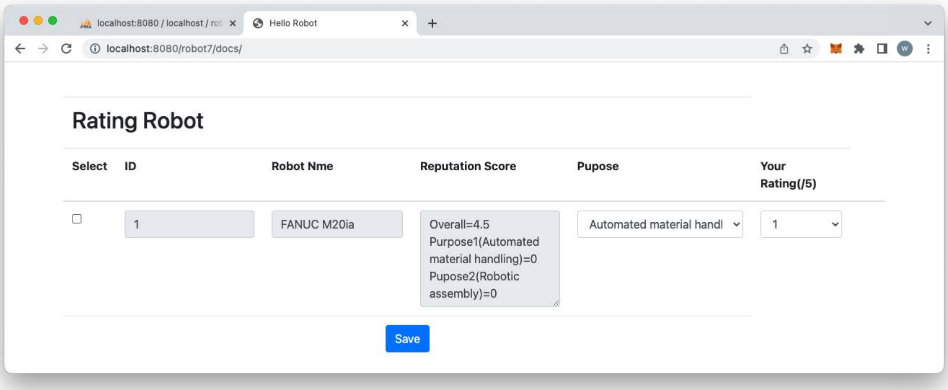


Figure 8.33 : Updating the overall RV using NDR method after receiving two ratings (5,4) (Case 2A).

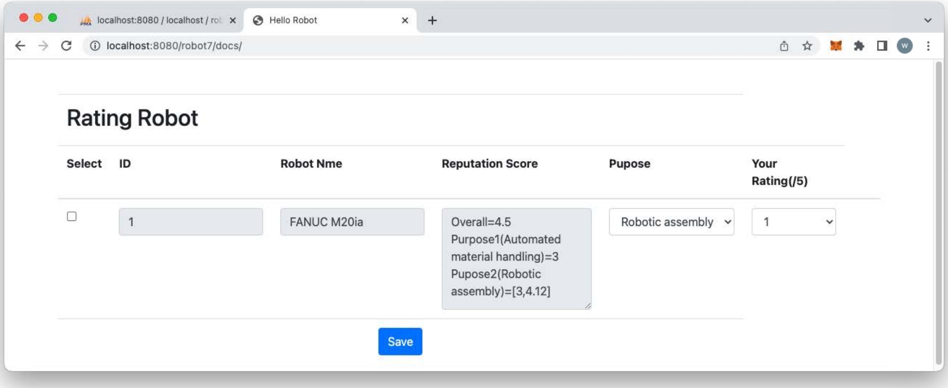


Figure 8.34 : Inferencing RV for purpose2 of a multi-purpose robot after rating purpose1 with (3) (Cases 2B and 2C).

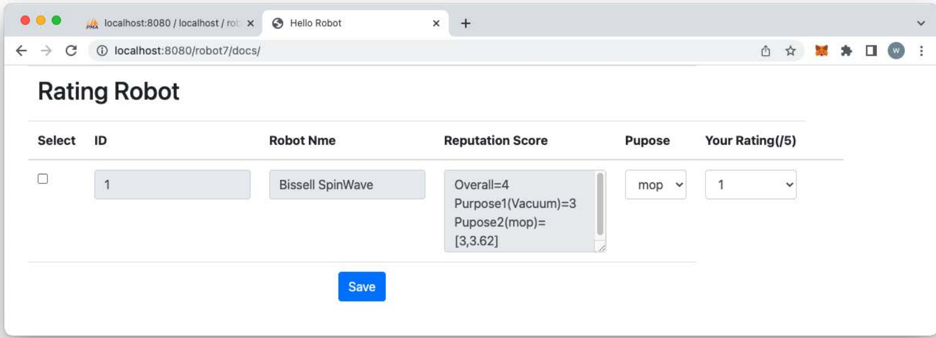


Figure 8.35 : Rating the overall performance of a robot with (4) will update the predicted RV of the non-reviewed purpose (Case 3A).

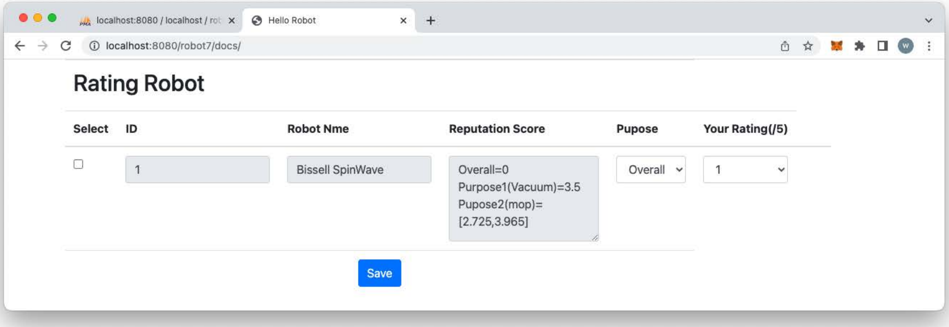


Figure 8.36 : Updating the first purpose RV using the NDR method after receiving two ratings (3,4), and updating the predicted RV of the second purpose (Case 3B).

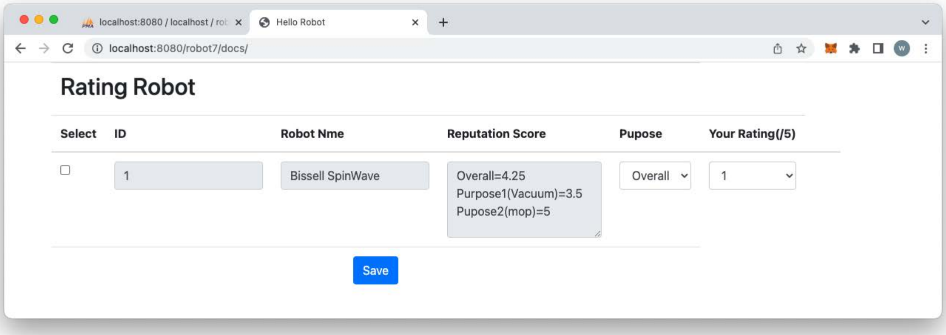


Figure 8.37 : Rating the second purpose of a multi-purpose robot with (5) and updating the overall RV as the average of the two purposes RVs (Case 3C).

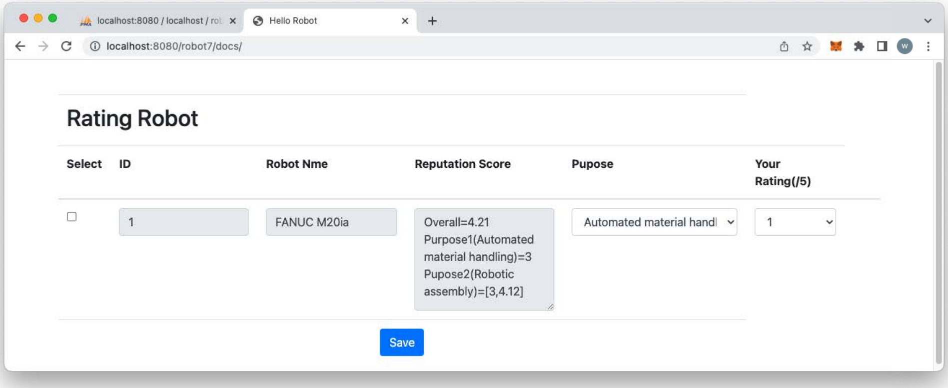


Figure 8.38 : Updating overall rating of the multi-purpose robot using the NDR method after receiving three ratings (5,4,4) (Case 4A).

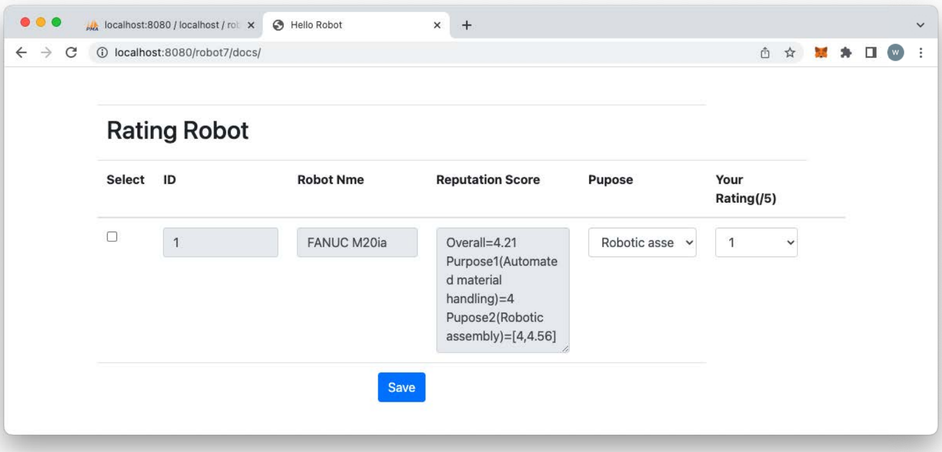


Figure 8.39 : Updating purpose1 RV using the NDR method after receiving three ratings (3,5,4), and updating the predicted range for purpose2 RV (Case 4B).

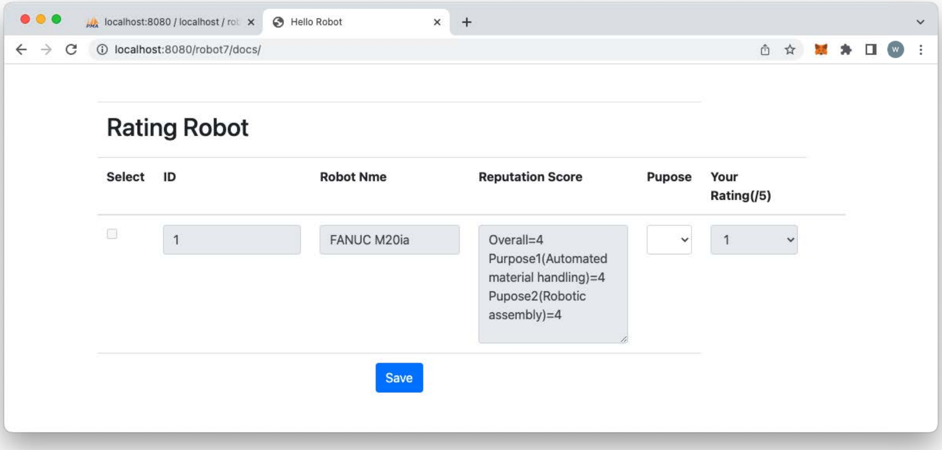


Figure 8.40 : Updating the overall and purpose2 RVs after rating purpose2 with (4) (Case 4C).

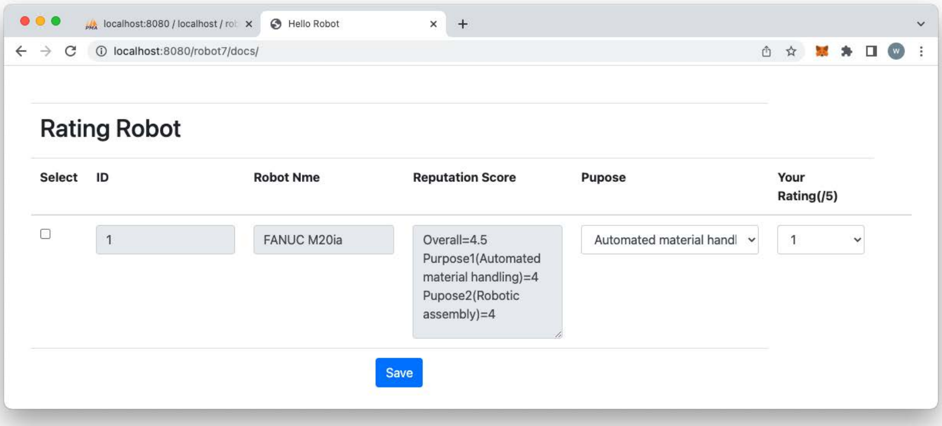


Figure 8.41 : Updating the overall rating of the multi-purpose robot using the NDR method after receiving four ratings (5,4,4,5) (Case 5A).

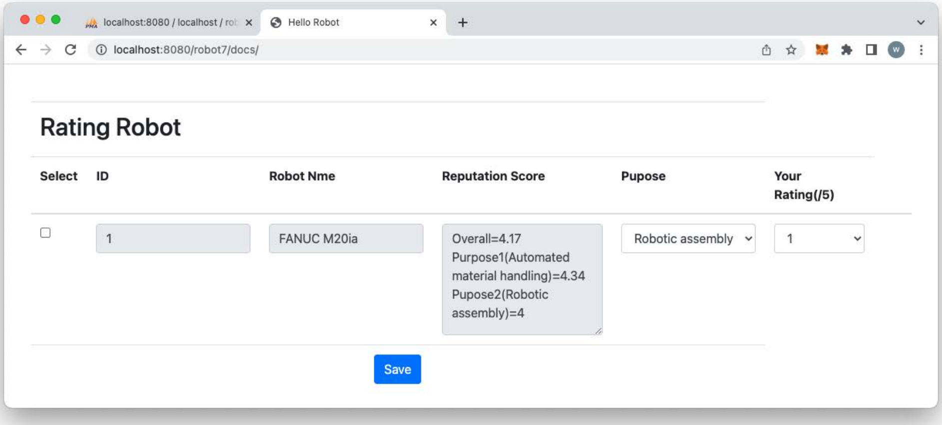


Figure 8.42 : Updating purpose1 RV using the NDR method after receiving four ratings (3,5,4,5), and updating the overall RV (Case 5B).

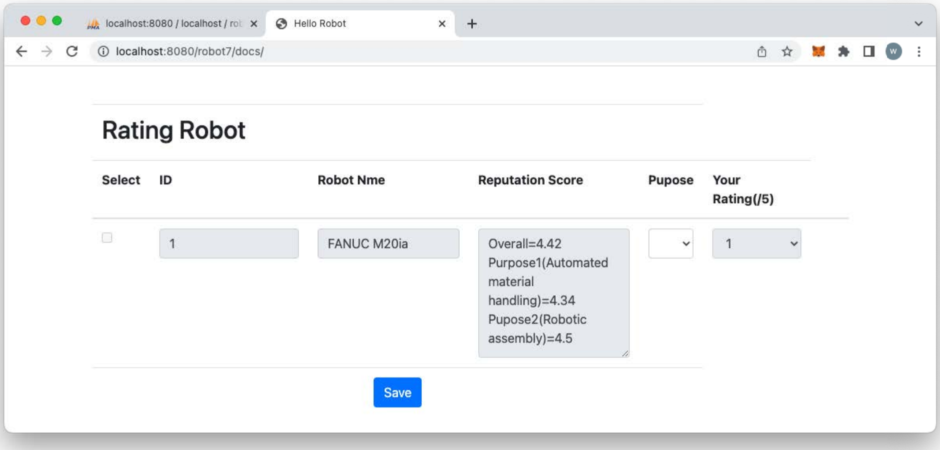


Figure 8.43 : Updating purpose 2 RV using the NDR method after receiving two ratings (4,5), and updating the overall RV (Case 5C).

## 8.5 Conclusion

This chapter demonstrated the working prototype of the IBBRB framework using screenshots and pictures. In this chapter, we presented the prototype setup which included the local and blockchain setup. Furthermore, we presented the main functionalities of the IBBRB prototype which represented the objectives of this thesis.

In the next chapter, we conclude this thesis, summarise the addressed shortcomings and make suggestions for future research work.

# Chapter 9

# Conclusion and Future Work

## 9.1 Introduction

This chapter concludes the thesis by summarising the research contributions and outcomes and then delineates the suggested future work. The main aim of this thesis is to develop a mechanism to help non-expert robotic service requesters in robot selection based on the robot's reputation. For this purpose, this thesis conducted a systematic literature review to study all the relevant works in the literature, then identified the research gaps, and defined research objectives. After this, a novel solution called the IBBRB framework was created to address the limitations of the state-of-the-art studies.

## 9.2 Problems Addressed in this Thesis

This thesis aims to address the critical shortcomings related to robot selection in the existing body of literature. Based on the systematic literature review that was conducted in Chapter 2, the research gaps were identified and listed in Chapter 3. These gaps are summarised as follows:

1. There is no attempt in the literature to solve robot selection based on a robot reputation value that reflects the robot's performance in similar tasks. In addition, storing and securing robotic trust values has not been discussed as yet in the literature.

2. There is no method to reach agreement on robotic terminologies that ensures a

common and an updated understanding of robotic knowledge across all robotic manufacturers, suppliers and end-users.

3. There is no mechanism that produces a reliable reputation score for robots based on prior users' opinions. Furthermore, there is no mechanism to bootstrap a new robot by predicting its reputation score based on its similarity to already evaluated robots.

4. There is no method to intelligently infer a contextual reputation value for a non-reviewed purpose of multi-purpose robots based on existing reputation scores of other reviewed purposes.

## 9.3 Contributions of the Thesis

The main contribution of this thesis to the literature is that it proposes a framework termed IBBRB to work as a reputation-based broker and facilitates the robot selection process. An overview of the research contributions of this thesis is presented in the following sections.

### 9.3.1 Contribution 1: Systematic literature review in the area of AI-driven Robot Selection

An extensive and systematic state-of-the-art review of the existing literature in the areas of blockchain, reputation systems and robot selection was conducted in this thesis. This review is presented in Chapter 2 of this thesis. The SLR followed the protocol that is proposed by Kitchenham and Charters in (Kitchenham & Charters, 2007). The main search terms were formalised and then inputted into the four well-known scientific databases (Scopus, IEEE Xplore, SpringerLink and ACM Digital Library) to provide good coverage of the relevant literature. Then the papers retrieved by the search process were filtered using a set of predefined inclusion and exclusion criteria. Finally, a set of 25 relevant papers were systematically reviewed to extract the methods that they proposed to address the problem of robot selection. Based on this, the research gaps were defined.

### 9.3.2 Contribution 2: Development of a novel solution: The IBBRB framework

An intelligent framework termed IBBRB was proposed and developed in this thesis. The IBBRB framework is a blockchain-based reputation system that computes reputation values for robots based on users' evaluations, predicts reputation values for robots that have not been evaluated yet based on their similarities to other robots and infers contextual reputation values for a specific context of multi-purpose robots. In developing the system architecture of the IBBRB framework, we followed the Model-View-Controller (MVC) design pattern (Figure 4.3). The blockchain network represents the model layer where all robotic reputation values are stored, the view layer is the layer that allows the end-users to interact with the system and evaluate robots, the controller layer involves all intelligent methods that are developed to compute, predict and infer robotic reputation values.

### 9.3.3 Contribution 3: Creation of a robotic attribute ontology and a robotic ontology evolution method

In Chapter 5, a robotic attribute ontology (RAO) is proposed. RAO encapsulates the robotic attributes and their relationships and is built with the aim of sharing a common understanding of robotic terminologies among all robotic service providers, requesters and manufacturers. Standardising robotic attributes is essential in the IBBRB framework to simplify the management and presentation of these data. In addition, an ontology evolution method for RAO has been proposed, termed a blockchain-based crowdsourcing method for RAO evolution (bcRAOe). The bcRAOe method enables the robotic expert community to be involved in the ontology evolution and it uses blockchain as a storage mechanism for storing and securing all versions of the RAO.

### 9.3.4 Contribution 4: Production of a reputation value for all robots stored in the blockchain

In Chapter 6, a novel method termed the Reliable Reputation Computation Method for Robotics (RRCM) is proposed for carrying out robotic reputation computation for all robots in the blockchain. RRCM incorporates building two models namely, the Robotic Reputation Computation model and the Robotic Reputation Prediction model. Robotic Reputation Computation model aims to produce a reputation value for robots stored in the blockchain based on prior users' ratings while the Robotic Reputation Prediction model aims to intelligently predict reputation values for robots with no prior rating data based on their similarities to already evaluated robots. The Robotic Reputation Prediction model helps in boosting the reputation of new robots and overcomes the cold start issue.

### 9.3.5 Contribution 5: Inferring a contextual reputation value for unrated purposes of multi-purpose robots

In Chapter 7, we propose a method called Context-aware reputation value inferencing for multi-purpose robots (CaRVInf). CaRVInf is an intelligent method to infer the trust value of a non-reviewed context of a multi-purpose robot based on its similarity to other reviewed contexts. It incorporates modelling all contexts of a multi-purpose robot using a combination of CAMeOnto and CAT approaches, then computing the semantic similarity between the modelled contexts. When the semantic similarity between the unrated context and other contexts is greater than a certain threshold, the reputation value is inferred.

### 9.3.6 Contribution 6: Development of a system prototype to evaluate and demonstrate the proposed solution

Software prototyping is used to validate the performance and accuracy of the IBBRB framework. The working of the IBBRB prototype, both for robotic reputation computation, robotic reputation prediction and contextual robotic reputation inferencing are demonstrated in Chapter 8 of this thesis.

## 9.4 Conclusion and Future Work

Although extensive research on the impact of using blockchain-based reputation systems to address robot selection problems was carried out in this thesis, there are still many potential directions that can be explored. Our future plan is to keep working on this topic, mainly along the following dimensions:

a) Studying, analysing and investigating other factors such as time and user credibility that could affect the weight of users' ratings.

b) Although our proposed fuzzy models achieve high performance, other fuzzy models can be investigated to compare the results.

c) Building a comprehensive dataset that includes robotic specifications and reputation values, which will open the door for further research.

d) Implementing the IBBRB framework in a real marketplace: In this research, we developed the IBBRB framework, conceptualized it and built a prototype for it. In future, this can be made into a commercial reality by building a commercial system that uses the IBBRB framework.

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