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Additional Information

A Repository of Method Fragments for Agent-Oriented Development of Learn-Based Edge Computing Systems

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Abstract

The upcoming avenue of IoT with the massive generated data makes it really hard to train centralized systems with machine learning in real-time. This problem can be addressed with learn-based edge computing systems where the learning is performed in a distributed way on the nodes. In particular, this work focuses on developing multi-agent systems for implementing learn-based edge computing systems. The diversity of methodologies in agent-oriented software engineering reflects the complexity of developing multi-agent systems. The division of the development processes into method fragments facilitates the application of agent-oriented methodologies and their study. In this line of research, this work proposes a database for implementing a repository of method fragments considering the development of learn-based edge computing systems and the information recommended by the FIPA technical committee. This repository makes method fragments available from different methodologies and computerizes certain metrics and queries over the existing method fragments. This work has compared the performance of several combinations of dimensionality reduction methods and machine learning techniques (i.e. support vector regression, k-nearest neighbors and multi-layer perceptron neural networks) in a simulator of a learn-based edge computing system for estimating profits and customers.

Index Terms

Edge computing, machine learning, multi-agent system, method engineering, method fragment

1 INTRODUCTION

CENTRALIZED machine learning (ML) approaches are difficult to be applied in some Internet of Things (IoT) scenarios, given the rapid generation of data. In this context, learn-based edge computing systems (LBECSSs) emerge as a solution for this context, allowing a distributed manner of performing ML.

However, the programming and coordination of the edge in LBECSSs is not trivial and requires that programmers apply tailored solutions for applying and coordinating the different ML methods. This work proposes the adaptation of existing methodologies for multi-agent systems (MASs) with the existing ML methods for tailoring processes for developing LBECSSs as MASs with ML on their nodes. The agent-oriented approach allows developing LBECSSs with autonomous edge devices that can extract relevant information through ML techniques and share the relevant information concerning a required service. The agent-oriented approach also supports a distributed coordination based on different flexible configurations of IoT devices with different types of sensors and tolerable to failures of some devices [1].

Several methodologies are proposed for the creation of MASs, such as Adelfe, Passi and Ingenias. Their processes usually involve several steps, which can be described with several *method fragments* to facilitate the application of the processes and their further analysis.

The method fragments discussed in [2] allow designers to build their own processes by concatenating them. Thus, method fragments are the building units. As indicated in [3], method fragments need to be available for MAS designers in repositories. In this manner, designers can access them and build their processes.

The current work extends the repository of fragments [3] that regards the information proposed by the working group “Design Process Documentation and Fragmentation”, belonging to the *IEEE Foundation for Intelligent Physical Agents (FIPA) Methodology Technical Committee (TC)*.

Both the previous repository and the proposed extension are aimed at allowing designers to acquire a quick and easy retrieval of fragments but they use different definitions for fragments. The previous repository is based on the old definition of fragment (the FIPA one) and presents an easy and simple interface providing means only for selecting fragments on the base of their categorization, i.e. activity, process role, work product and *MAS Meta-Modeling Entities (MMMEs)* kinds.

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However, in the new application, designers can use the new definition of fragments that is indicated in [2] and is called *method fragment*.

Furthermore, this new repository extension computerizes the measurement of fragments *attitude* to specific features (e.g. autonomy and sociability). The attitude reflects the degree in which a fragment can imply that the work products (i.e. MASs) have a given feature.

Finally, the repository is tested by inserting not only PASSI method fragments but also INGENIAS method fragments. More concretely, as experimentation, we have developed a simulator of a LBECs called BigDataSim in order to illustrate the current approach. In this experimentation, we have compared the different dimensionality reduction methods and several ML techniques, and we have compared the errors.

The remainder of the paper is organized as follows. The next section discusses the related work. Section 3 introduces the background of this work. Section 4 describes the repository database for method fragments in the development of MASs. Section 5 presents the experimentation with the LBECs simulator and comparison of ML methods. Finally, section 6 mentions the conclusions and future work.

2 RELATED WORK

A recent work proposed an approach of model-driven development of agent-based cyber-physical systems [4]. Their approach used the Organization-based Multi-agent Software Engineering (O-MaSE) process framework using method frameworks. However, their approach was mainly focused on cloud computing rather than edge computing.

In addition, there is a repository for method fragments that are represented with the *Open Process Framework* (OPF). Furthermore, the work in [5] presents a *Situational Method Engineering* (SME) framework that contains a repository for reusing situational method fragments. That framework allows designers to combine fragments, and computerizes the retrieval of method fragments that have certain requirements.

Nevertheless, none of those works has computerized the measurement of metrics for further analysis of processes that contain certain process fragments as the current work has done.

Anya et al. [6] present an agent-based simulator (ABS) that simulates the discovery of big data. Their simulations show that cross-group knowledge exchange increases the discovery from data in comparison to collaboration only within each group. They provided an initial ABS approach for simulating the influence of organizational dynamics and social structures on the discovery and reuse of relevant data.

Some researches on simulation are now focusing on obtain high-performance frameworks for modeling and simulations for supporting big data applications [7]. In this line of research, the Care HPS (i.e. from high performance simulation) tool [8] supports agent-based modeling with parallel computing for increasing the performance of the simulations.

Big data have assisted enterprises in increasing their profits. For instance, the work in [9] proposed the metric profit per hour as an indicator for supporting the decision-making in business. Their approach was able to measure this metric thanks to big data analytics. Their approach was designed to be applicable to all manufacturing industries.

Big data has also been useful for discovering lifetime value of costumers. Chiang et al. [10] applied big data analytics to determine the relations of personality traits and country-of-origin of customers with their potential as lifetime customers. They found that customers with peacefulness and openness personality traits were the ones with the highest customer lifetime values. Thus, this information can be used for determining useful market strategies.

Big data can be applied to customize services for the customers. For example, the approach of [11] analyzes the customer behaviors by means of big data analytics. They proposed an implementation based on the Map Reduce model with the Hadoop technologies to analyze the data, and visualized the results through an HTML interface.

In the field of wearable technology, Chen et al. [12] proposed a LBECs that coordinated different wearable devices. Each wearable device applied deep analytics for performing ML on the edge and sharing their knowledge discovery with other devices, in order to propose complex services to the user. This work focuses on the challenges related to the integration of different types of edge wearable devices and its underlying architecture, but does not provide support for composing development processes.

Some of the aforementioned works proposed generic method engineering approaches, others present different ML contributions, and others focus on integration challenges in LBECs. Nevertheless, none of the aforementioned works proposed to use method engineering for improving the development processes of specifically LBECs.

3 BACKGROUND IN LEARN-BASED EDGE COMPUTING AND METHOD ENGINEERING

The LBECs are in the intersection of ML and edge computing. Some works have applied tailored solutions of applying ML in edge computing. In particular, Kozik et al. [13] presented a scalable ML approach for detecting attacks in edge computing. They proposed a LBECs as they performed the ML on the nodes to detect upcoming attacks. More concretely, they used a pre-built classification model, but they did not have enough processing and storage capabilities. Thus, they applied traffic classification using extreme learning machines for coordinating the ML across the different edge nodes. Nevertheless, they did not propose any software engineering methodology for developing LBECs as the current work does.

Method Engineering was defined as the engineering discipline to design, construct and adapt methods, techniques and tools for the development of information systems. Method engineering is related to: meta-modeling techniques that

describe modeling languages; tool interoperability, in which fragments are recommended to be available in repositories and to be combined; situational methods, for describing and particularizing the methods to specific development projects; and comparative review of methods and tools.

A *method fragment* is a discrete component of a method which can be used in one or more methods. The discreteness of method fragments makes it much easier to describe their strengths and weaknesses than is the case with methods, enabling designers to put together a customized method to suit a particular elicitation need.

The *Agent-Oriented Software Engineering* (AOSE) methodologies have been divided into method fragments, for their analysis, promotion and application. FIPA describes the transition from general method engineering to its specific application in AOSE methodologies. That work is promoted by the FIPA Methodology TC, and indicates the structure of documents for describing method fragments for AOSE methodologies. This document structure includes the definition of input and output *Work Products* (WPs) and the concepts to be designed in each fragment. Among other features, the structure also includes the relationships between the WPs and the *MAS Meta-Modeling Elements* (MMMEs), and a composition guideline for each fragment. The information of that structure is included in the presented repository.

Furthermore, it is worth mentioning that the method fragments of several AOSE methodologies are already described with the document structure promoted by the FIPA Methodology TC and presented in [2]. Specifically, an example of PASSI fragment is included in [2] and the description about PASSI fragmentation as another example. The ADELFE method fragments and the INGENIAS are already defined.

4 THE REPOSITORY FOR LEARN-BASED EDGE COMPUTING SYSTEMS

This repository stores method fragments for AOSE, and all the data involved with the method fragments. This repository is structured by taking the recommendations of the FIPA Methodology TC [2] into account, and the design of this repository is further described in sub-section 4.1.

The repository is implemented by means of a database. This database is complemented with menus and formularies in order to facilitate the human-interaction with the database, and these menus and formularies are presented in sub-section 4.2.

The analysis of AOSE methodologies can become crucial when selecting fragments for composing a development process. For this reason, this repository includes queries that computerize the measurement of certain metrics that facilitate the association of processes with attitudes, such as the autonomy and the sociability. Section 4.3 briefly introduces these metrics and the corresponding formularies that computerize their measurement.

4.1 Design

The Entity-relationship design of the repository database is presented in Figure 1. The repository includes all the information recommended by the FIPA Methodology TC: fragments, processes, input and output *Work Products* (WPs) of fragments, WP Kinds, activities, roles and glossary terms. Each WP is linked with MMMEs and *MAS Meta-Modeling Relationships* (MMMRs), with an operation mode that can be *Designed*, *Related* and *Quoted*.

Furthermore, MMMEs are related to certain features (like autonomy and sociability) with certain weights, in order to analyze the features of processes as described later in section 4.3.

Each agent using ML in each edge device has a purpose in providing each service. Depending on the service that is being provided, each agent plays a role for providing this service. This role is usually performed by several agent activities and assisted by other activities.

4.2 The running repository system

The repository system incorporates menus and formularies for facilitating its use. The database contains menus that organize all the existing operations. At the main menu, the *Process* and *Fragment* options concern the storage and management of method fragments, whereas the *Feature* and *Metrics* options regard the analysis and measurement of the existing method fragments.

Figure 2 presents an excerpt of the form for fragments. As one can observe, the form contains the information proposed by the FIPA Methodology TC. There is an introduction, in which the user can both write a text and link an external document containing a figure of the whole process that the fragment belongs. The form also contains the description, consisting of a text and a reference to an external document. In the form, users can also specify the workflow, a guideline, the composition guideline, the aspects, the dependency relationships, and the process that the fragment belongs to.

Within the form for fragments, user can also include a picture of the MAS metamodel. Furthermore, the form of fragments includes a sub-form for managing its activities. This sub-form includes a button for opening the activity form in case the user needs to create a new activity.

The form of fragments also contains a sub-form for WPs, indicating the input and output WPs. The form also includes buttons for accessing the formularies that relate the WPs with their MMMEs and *MAS Meta-modeling Relationships* (MMMRs). In this manner, designers can change and observe the WP that they are adding to a given fragment. Moreover, the form for fragments also includes a sub-form for managing its glossary terms, as it is recommended for the FIPA methodology TC.

As a proof of concept, fragments are introduced in the repository for the INGENIAS [14] and PASSI [2] methodologies.

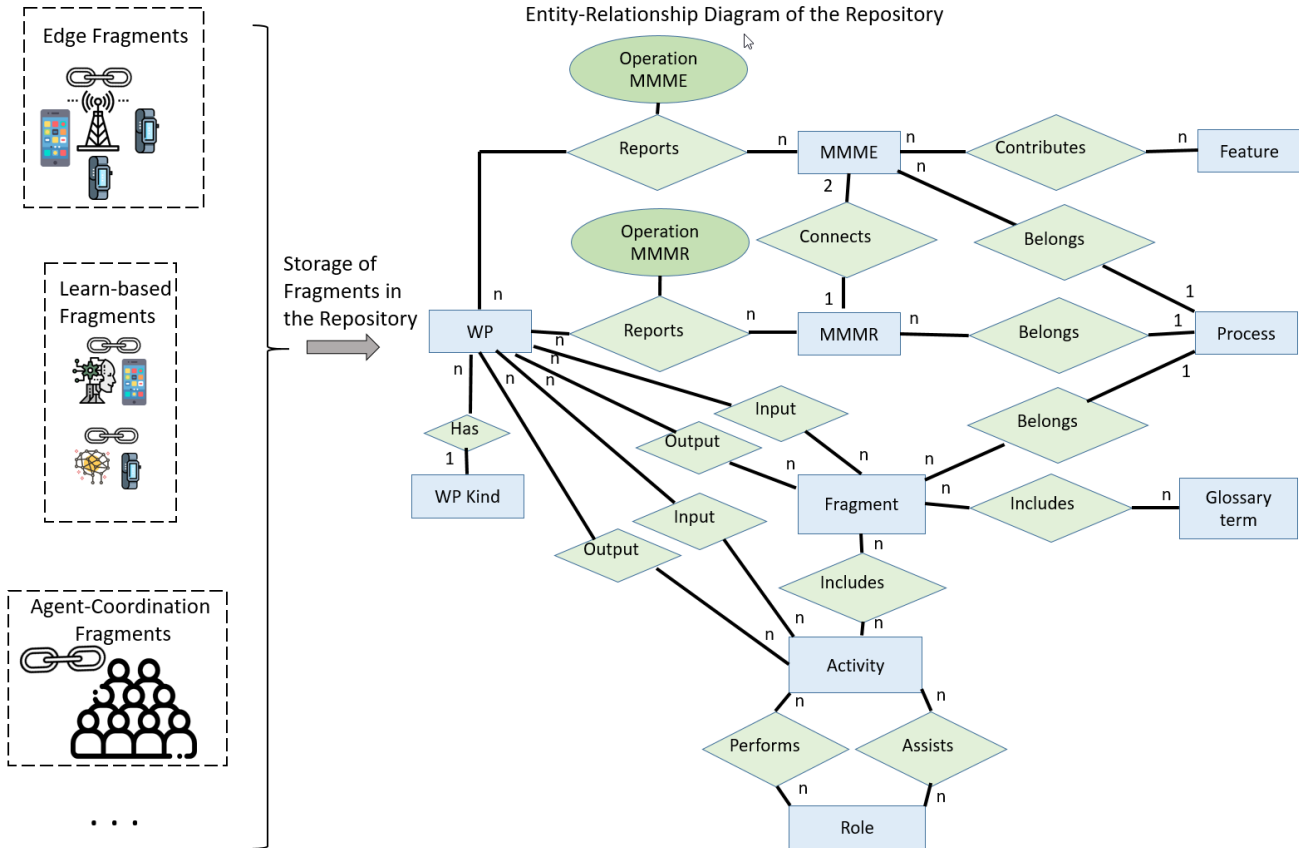


Fig. 1. The entity-relationship design of the repository database for LBECSS

4.3 Measurement and Analysis

A hypothesis of another of our ongoing works is that the importance of an element can be measured with the *Element Relevance Index* (ERI), which is calculated in Equation 1.

$$ERI(E) = NumRel(E) + NumFrag(E) + NumWP(E) \quad (1)$$

where:

- $NumRel(E)$ is number of MMMRs in which the E element is involved.
- $NumFrag(F)$ is the number of fragment that are related with the E element.
- $NumWP(F)$ is the number of work products that are related with the E element.

ERI is relevant for calculating the features of processes composed of certain method fragments, such as the sociability of agents from different devices, showing the kind of expected of communication. For instance, processes with intensive communications will probably need an appropriate communication infrastructure, while systems with computing-intensive ML techniques like deep learning will probably need devices with enough computation resources.

The query *MeasureERI* computerizes the measurement of ERI, in which the user just selects the MMME and the query returns its ERI. This query and other queries that facilitate obtaining partial results are summarized below:

- *MeasureERI*: It measures the ERI of a given MMME according to Equation 1.
- *ERI*: It provides a list of all the names of all the MMMRs, fragments and work products that are related with a given MMME.
- *NumRel* : It provides a list of all the names of all the MMMRs that are related with a given MMME.
- *NumFrag* : It provides a list of all the names of all the fragments that are related with a given MMME.
- *NumWP* : It provides a list of all the names of all the work products that are related with a given MMME.

The ERI measurement can be calculated with the presented repository by means of the form shown in Figure 3. This figure presents a brief practical example of the measurement of ERI over the 'InteractionUnit' entity. This entity

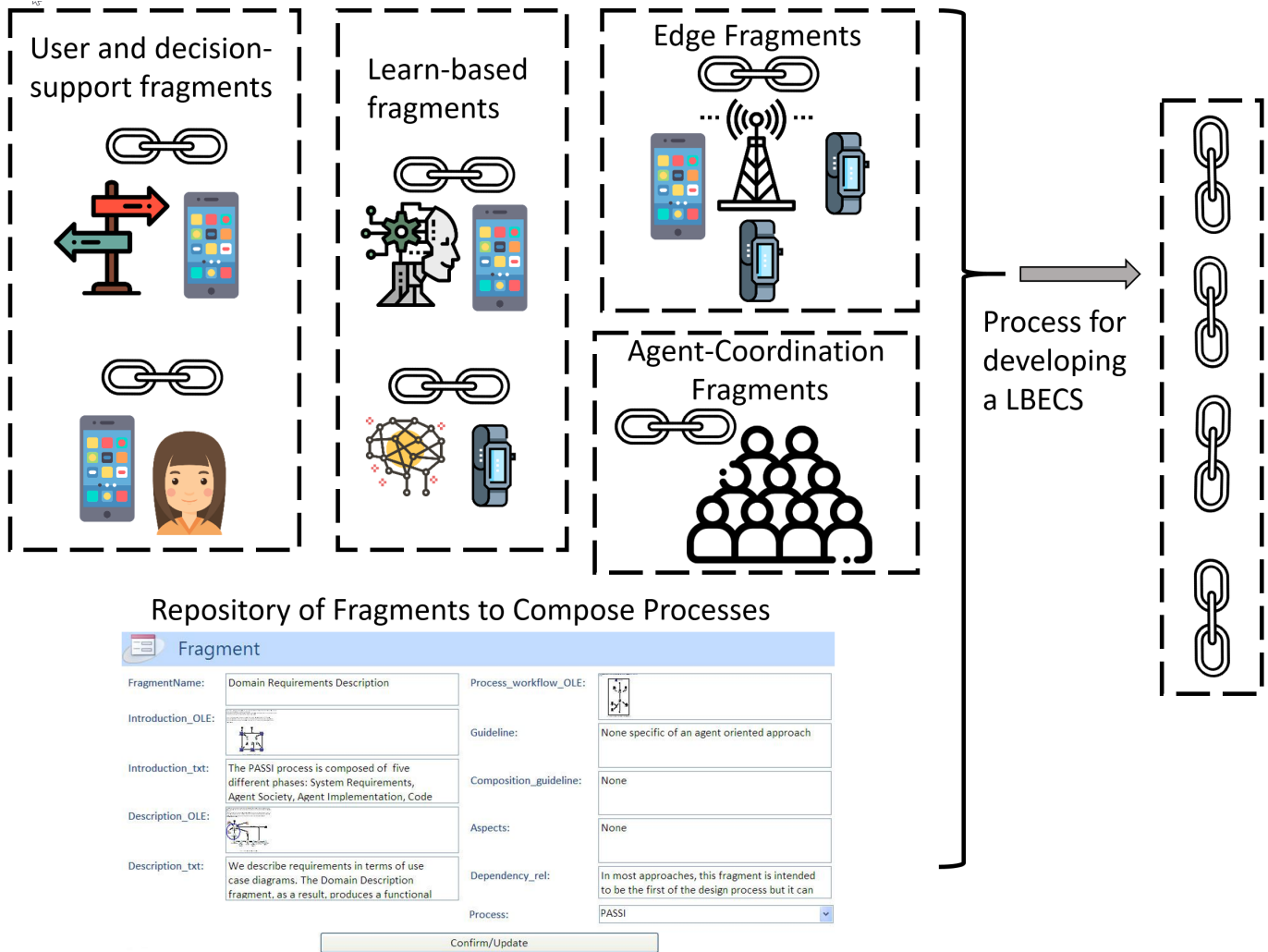


Fig. 2. Definition of fragments in the repository for composing processes to develop LBECSs

represented a message among two different devices. Its relevance (i.e. ERI = 5) showed the need of a proper communication infrastructure for the process designed for the development of health LBECSs in smart hospitals.

The *Methodology Attitude* (MA) metric calculates the degree in which a given methodology is related to a given feature, such as autonomy or sociability. For this reason, the MMEs are related with attitudes indicating weights. Then, the MA metric is calculated for a given process with a weighted sum of the ERI measurement values of the related MMEs. Figure 4 shows the form that calculates the MA metric.

5 EXPERIMENTATION WITH LEARN-BASED EDGE COMPUTING IN BIGDATASIM SIMULATOR

The objective of this use case was to use the repository to compose a process with method fragments for a tailored development of a LBECS in the field of business boosted by analysis of big data from IoT sensors. Functional requirements referred to the use of IoT sensors information in shops to extract relevant data that can help in shop organization to boost profits. Non-functional requirements (1) limited the amount of data transmitted over the network, making that most processing should be performed locally on the edge, and (2) established a minimum percentage of 10% for the increase of profits.

This experimentation has developed an ABS of a LBECS called BigDataSim to illustrate the proposed approach, using the process created from the repository. BigDataSim was designed to fulfill both aforementioned functional and non-functional requirements. It simulated the sales of different shop organizations, incorporating shop-organization improvements based on the learning from user behaviors detected with IoT sensors. It was trained with different techniques of ML and dimensionality reduction on several simulated edge nodes, for estimating the number of customers and profits, based on IoT devices that track people entering and sales. For example, curtain sensors can measure the number of customers that go through the doors of a shop to count the number of customers that visit a shop. The cash registers can track the number of customers actually buying items. In this way, the LBECS can calculate the ratio of customers that left the shop without buying anything. Presence sensors can also estimate in which section customers are looking for items to estimate which

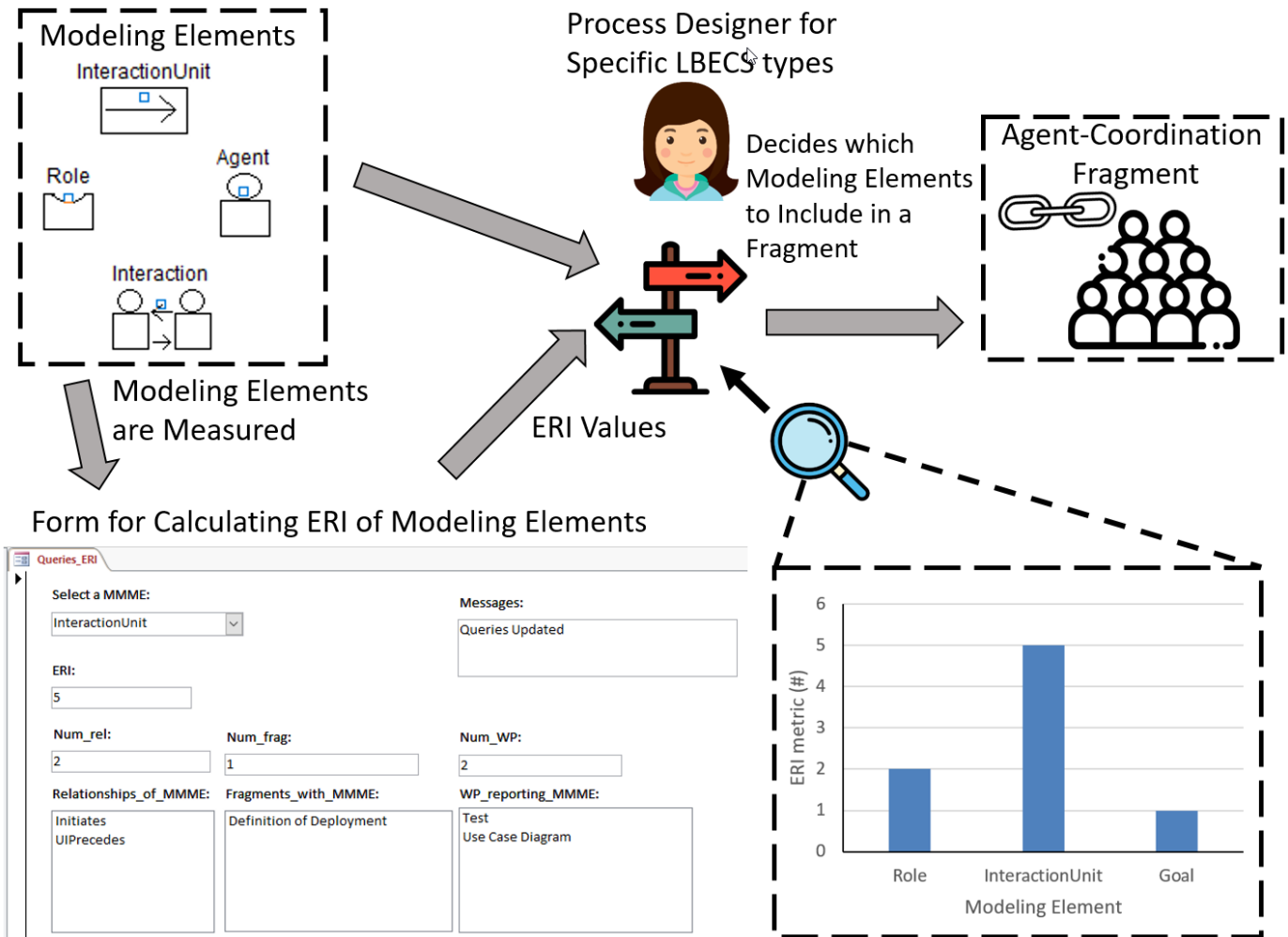


Fig. 3. Calculation of ERI for selecting modeling elements for each method fragment for LBECSS

products customers may be missing and could be more profitable to include, with most of the data processing on the edge. Then, the ML models were shared in the different nodes to improve their accuracy. This LBECSS has been developed using the proposed method engineering approach for applying the combination of different well-known AOSE methodologies.

The presented ABS provides a mechanism to estimate the profitability of including big data analytics in a firm. The user introduces certain input parameters about the potential customers, possible repercussions of marketing strategies, estimated costs and durations of the simulation. The ABS simulates different kinds of customers, and the repercussion the marketing campaigns of two different firms.

One firm (referred as control firm hereafter) performs marketing campaign towards some particular people from potential customers offering very special bargains. These potential customers are selected for a particular age and with certain features. The selection of the specific people from potential customers is random as the firm only has general information.

The other firm includes big data analytics and has a method to estimate the customer lifetime value (CLV). This values is an estimated probability of the customers to become lifetime users. This firm is assumed to be able to follow particularized marketing strategies for gaining the same customers than the other user per month. The difference is that it selects the customers with high CLV. However, this company has a cost for including big data analytics.

The ABS shows the comparative results of the evolution of profits and customers. In this way, firm owners can have an estimation of which might be the most profitable option between whether or not to include big data analytics.

The main kinds of agents are "customer" agents and "firm" agents. In the case of firm agents, there is an extension for simulating firms with the use of big data analytics called "firm-big-data" agents. Firm agents were able to apply common ML methods such as support vector regression (SVR) and neural networks. Firm-big-data agents not only used ML methods but also incorporated the possibility of applying dimensionality-reduction techniques. These facilitate reducing the information of big datasets for efficiently applying ML methods. We considered this separation for properly separating ML methods from big data techniques so that the former could be reused separately in the future.

The ABS is designed in a generic way for being applicable to most kinds of markets. However, the ABS simulates only

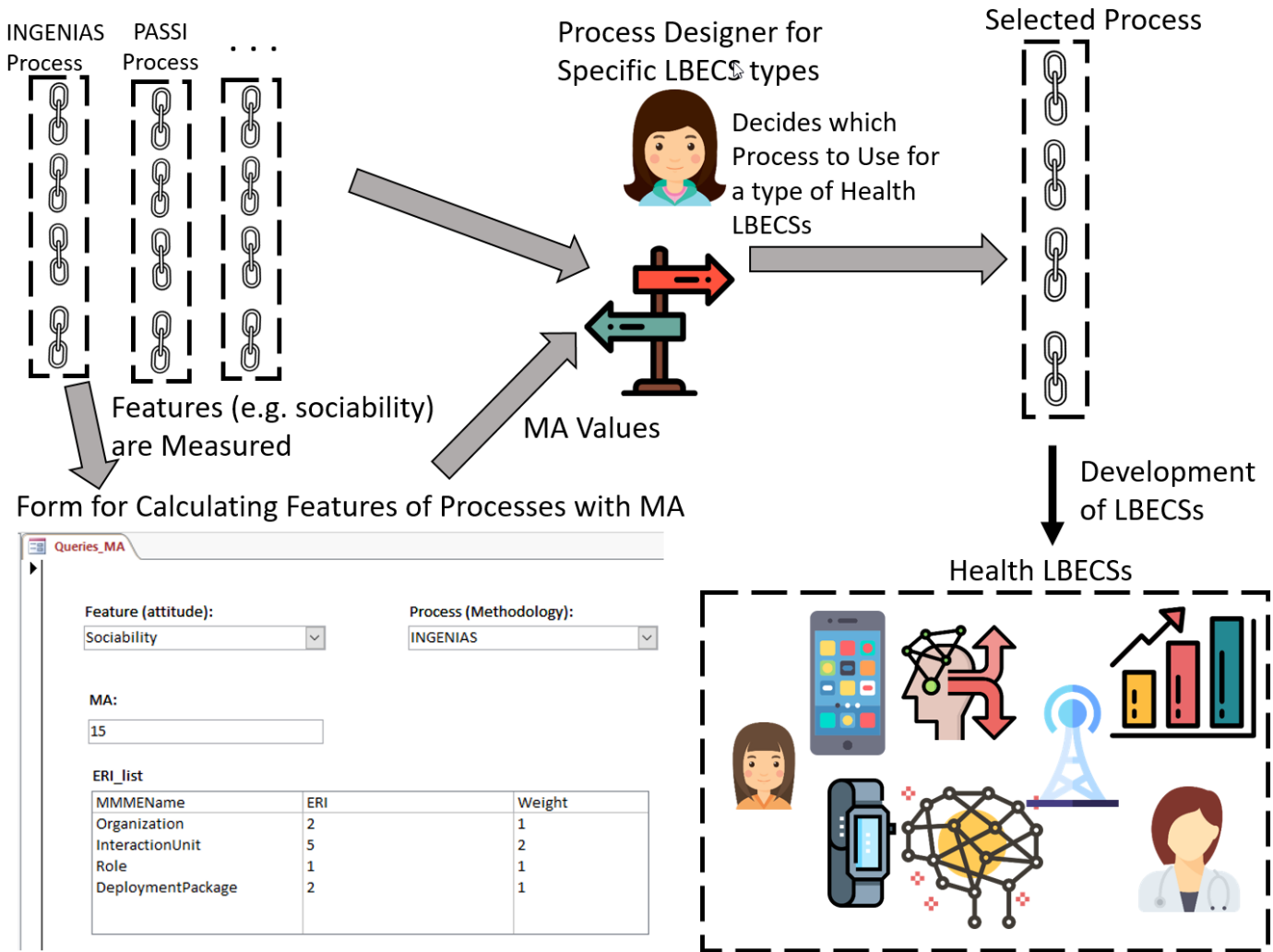


Fig. 4. Calculation of MA for selecting a process for a type of health LBECSs

one market kind in each simulations. For this reason, customers are modeled to simulate their relation with only one kind of markets.

Each customer agent can be associated with a firm or not. Each customer agent has a reference to the firm from which it is buying some service or goods, if any. Normally, the customer agent can register in a firm. However, the customer agent hires the service for a certain period. Then, it can become a lifetime customer or leave the firm. This is simulated with an agent-based nondeterministic decision as proposed by TABSAOND (the technique for developing agent-based simulation apps and online tools with nondeterministic decisions) [15]. This decision is simulated by the generation of random number and its comparison to certain probability. The CLV of the customer agent determines this probability.

A decision $d = 1$ determines that the agent becomes a lifetime consumer of its actual firm, while $d = 0$ determines that the consumer unsubscribes from the firm agent once the common duration of non-lifetime consumer is expired.

If the customer does not become a lifetime user, it unsubscribes from the firm's service and becomes available again in the market. The customer can have a high CLV and a low CLV. The ABS user can determine the number of potential customers with respectively low and high CLVs with some input parameters.

The firm agent simulates the management of the corresponding company. It manages the profits of the firm starting this variable as zero at the beginning of the simulation. Then, it adds the profits per month proportionally distributed in the iterations of the month, considering the multiplication of the number of current customers and the profits per customer. Thus, the profits earned in each iteration (referred as p_i) are calculated with the corresponding ratio, with a given, number of customers, the profits earned from each customer per month, and the number of iterations per month.

The calculation of the accumulated profits (p) is performed by summing the profits per iteration. The firm big data agents also calculate their profits per iteration in the same way. However, these also calculate the costs of big data per iteration (denoted as c_i). The update of the profits per month in firm big data agents also takes these big data costs into account, with the sum of all these values.

Users can interact with BigDataSim through its user interface (UI). The user can introduce the input parameters. The

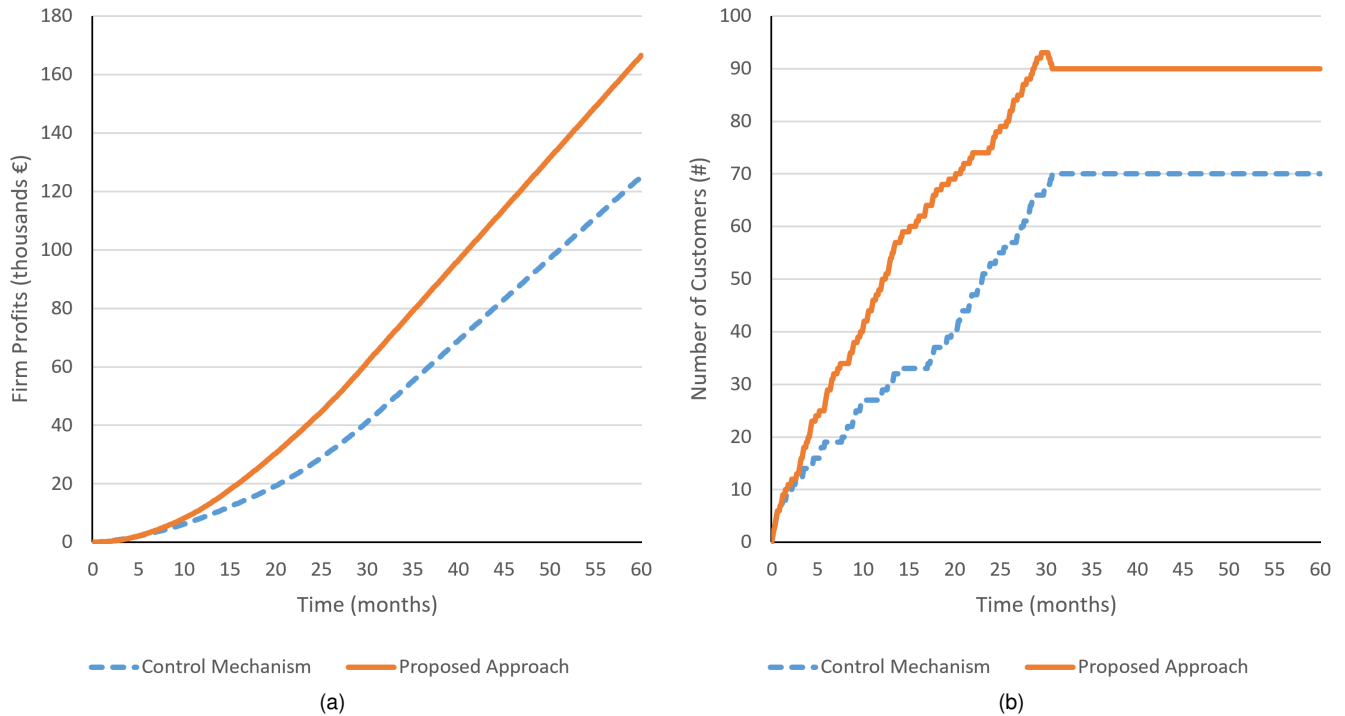


Fig. 5. Charts of simulation evolutions in BigDataSim for (a) profits and (b) customers

user indicates an estimated amount of the number of potential customers with a low CLV, and the estimated number of the ones with a high CLV. Regarding the market and the previous experience, the user introduces an estimated amount of the number of customers that the firm can gain per month using particularized marketing strategies. The user also determines the estimated profits from each customer per month.

The user is normally thinking about hiring a person for performing the big data analytics or hiring the service of a third party. Then, the user must introduce the cost of applying big data per month. In addition, the user indicates the common duration of non-lifetime customers regarding the simulated market. Finally, the user introduces the time of the simulation expressed as the number of months. The user can press the “Run simulation” button to start the simulation.

The UI of BigDataSim shows the simulation evolution. In particular, there are two bottom buttons that allow users to switch between two different views. The first view shows the evolution of profits in thousands of euros in a chart like the one shown in Figure 5a. It shows respectively the evolutions of (a) the firm without using big data analytics, and (b) the firm when using this analytics. In this way, the user can compare the estimated profits depending on whether or not the big data analytics are used. Figure 5b shows the second view about the evolutions of the numbers of customers in another chart. This chart also simulates the two possibilities about whether or not to use big data analytics.

In order to fully experience this approach, we have compared the average errors of the different combinations of dimensionality reduction methods and ML methods. Among the existing dimensionality reduction methods, we used recursive feature elimination (RFE), non-negative matrix factorization (NMF), and feature selection (FS) with a variance threshold. Among existing ML techniques we applied support vector regression (SVR), the k-nearest neighbors (KNN) and a multi-layer perceptron (MLP) neural network. We also used linear regression as a basis comparison. Figure 6 shows the boxplots of these errors. In this way, readers can check the average and the different quartiles, as well as observing the outliers. Notice that the combination of SVR and FS obtained the lowest average errors among the combinations of ML methods and dimensionality-reduction techniques. This combination improves the performance of the edge-learning process, almost without increasing the error over applying SVR without dimensionality reduction, so this combination is appropriate for developing efficient and accurate LBECs in this context. By contrast, the highest increase of error was obtained when applying MLPs with NMF, so this combination is not recommended in this context.

6 CONCLUSIONS AND FUTURE WORK

This paper has presented a new repository for AOSE method fragments in order to build LBECs including ML methods in the development of edge-computing software. Their main achievements are, first, to technically support the storage and share of the fragments and, second, to computerize the measurement of metrics for analyzing the features of processes composed of some given fragments.

To illustrate this approach, we have developed the BigDataSim simulator for testing different ML configurations in edge-computing applications. This simulator has been applied in the context of estimation of profits and number of customer in

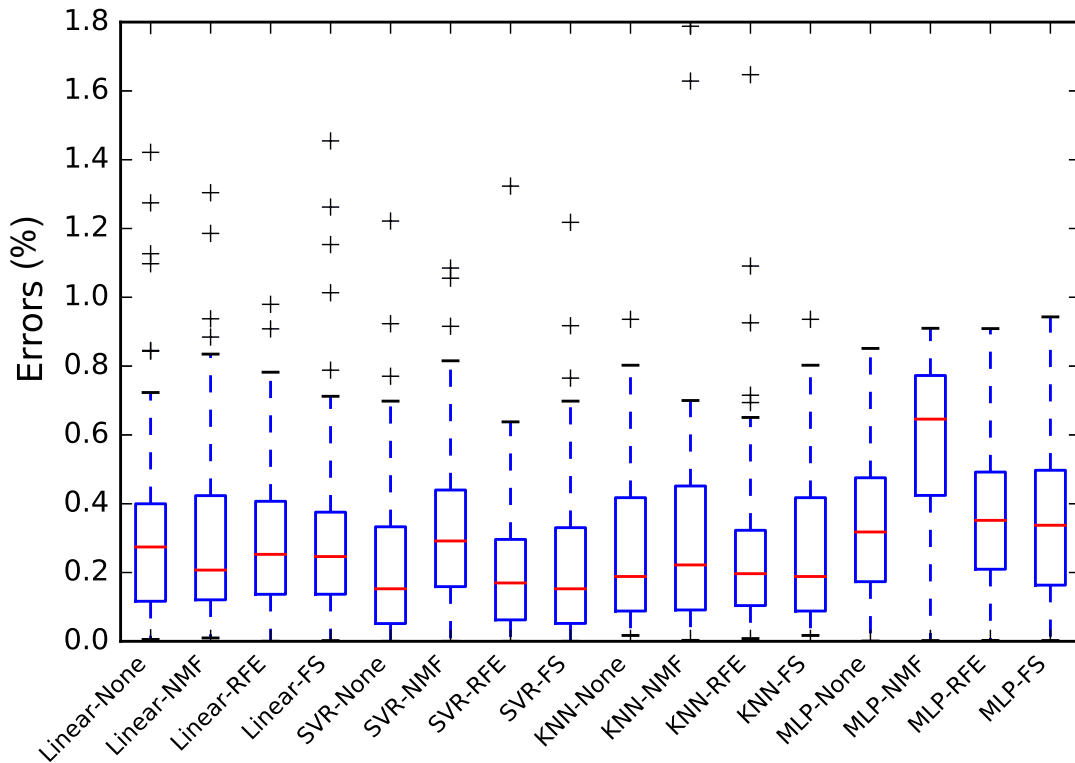


Fig. 6. Boxplot of errors of the different dimensionality reduction and ML methods in edge computing

supermarkets based on the received data from IoT sensors. We simulated this LBECS with different combinations of ML methods and dimensionality reductions, and provided a comparison of their resulting errors.

As future work, we plan to apply the proposed approach for developing a LBECS for managing smart cupboards for measuring memory of people, identifying their emotions and provide dietary suggestions, in an intelligent and supervised way. In this way, the smart cupboards will learn from their common users with the proposed approach. We plan to compare the proposed approach with alternative methodologies by comparing their efficacy in developing the smart cupboard system, to further assess the improvement of the proposed approach over the alternatives.

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