Wireless Communications and Mobile Computing for Ambient Assisted Living

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Research Article

Smart Nursing Homes: Self-Management Architecture Based on IoT and Machine Learning for Rural Areas

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The rate of world population aging is increasing. This situation directly affects all countries socially and economically, increasing their compromise and effort to improve the living conditions of this sector of society. In environments with large influxes of elderly people, such as nursing homes, the use of technology has shown promise in improving their quality of life. The use of smart devices allows people to automate everyday tasks and learn from them to predict future actions. Additionally, smartphones capture a wealth of information that allows to adapt to nearby actuators according to people's preferences and even detects anomalies in their behaviour. Current works are proposing new frameworks to detect these behaviours and act accordingly. However, these works are not focused on managing multidevice environments where sensor and smartphone data are considered to automate environments with elderly people or to learn from them. Also, most of these works require a permanent Internet connection, so the full benefit of smart devices is not completely achieved. In this work, we present an architecture that takes the data from sensors and smartphones in order to adapt the behaviour of the actuators of the environment. In addition, it uses this data to learn from the environment to predict actions or to extrapolate the actions that should be executed according to similar behaviours. The architecture is implemented through a use case based on a nursing home located in a rural area. Thanks to this work, the quality of life of the elderly is improved in a simple, affordable, and transparent way for them.

1. Introduction

The world is experiencing population aging, a trend that is both pronounced and historically unprecedented. Over the past six decades, countries had experienced only a slight increase in the share of people aged 65 years and older, from 8% to 10%. However, in the next four decades, this group is expected to rise to 22% of the total population, a jump from 800 million to 2 billion people [1].

Due to low population density and the migration of young people to richer regions, the elderly often live alone or in nursing homes where the elderly live there temporarily or continuously. These nursing homes are modernizing their facilities to provide better services and care to their residents. These improvements affect the quality of life of the elderly and the costs of nursing homes [2]. During the last few years, they are making use of technologies [3–5], to make life easier for their residents and help healthcare professionals to monitor their health and daily activities.

Over the past few years, both for aging populations and for the population at large, significant research efforts have been devoted to various aspects of health monitoring and active aging activities. One of the main objectives of the scientific community is to monitor and accurately identify the activity patterns of the elderly. Different studies have shown that the activity patterns of the elderly are a valid parameter to predict their quality of life [6]. There are approaches in this area to propose new algorithms, techniques, or systems to improve activity monitoring such as [7], focused on collecting different types of home surveillance technologies for monitoring behaviour of older people, or [8], where an architecture is developed that exploits the benefits of the Internet of Things (IoT) to capture location and other data to detect patterns of behaviour in older people in a nonintrusive way, or [7], where an IoT detection infrastructure for the city is presented that through REST and Linked Open Data application programming interfaces (APIs) collect and present data related to older people.

In this line, there are different reviews in the literature in which the different alternatives regarding the integration of Ambient Assisted Living (AAL) technology in residences are studied [9, 10]. Reviews in which network projects, middleware, sensors, communications, or actuators are proposed, although most of them with a very particular focus and for specific scenarios, mainly focused on ubiquitous sensor systems and telehealth devices.

An alternative to these residences is home care, automating and monitoring the daily activities of the elderly [11]. There are also reviews of studies and projects aimed at the elderly for the home as an alternative to nursing homes [12, 13]. But this alternative is not sufficient in rural and dispersed population environments due to infrastructure costs and the difficulty of arriving at these homes in a minimum time in case of emergency.

However, most of the current solutions provided by the research community and companies offer too closed solutions or address a very specific problem [14, 15]. Moreover, most of these solutions do not allow the integration of devices from different manufacturers or using different communication protocols [16]. Furthermore, collaboration between these types of devices remains a challenge, considering that the heterogeneity of devices and manufacturers makes this collaboration difficult. In most deployment environments, resources are limited as in rural environments or nursing homes. In this sense, the economic cost of implementation and deployment (mainly the cost of devices) of technological systems that improve monitoring is a major barrier. Moreover, due to the poor Internet connections that exist today in certain rural areas, it is necessary that the monitoring system does not depend on a permanent Internet connection to ensure its proper functioning. Therefore, it is necessary to integrate all these technologies under a common system that helps in the care and monitoring of the elderly, saving costs and giving the possibility to any nursing home to create their own smart ecosystem.

This paper presents an architecture that facilitates the integration and collaboration of IoT devices from different manufacturers. Also, this architecture makes use of machine learning (ML) techniques to improve the automation and detection of elderly people's activities in nursing homes located in rural and sparsely populated regions. In particular, this architecture can be applied to any nursing home that can conduct the monitoring of its patients through the use of the latest technologies in an affordable way and independent of the type of technology used. In addition, the architecture has been validated and promising results have been obtained in detecting people's behaviours.

The rest of the paper is structured as follows. In Motivations, the main motivations and some related literature for this paper are presented; then, in Architecture Proposal Based on IoT and ML, our proposal for rural environments is detailed, while in Use Case Description a use case is shown for a better understanding of the proposal. Next, in Results and Discussion, the obtained results and some discussions are described, and finally, in Conclusions and Future Works, the conclusions of this work are exposed.

2. Motivations

The high rate of population aging means that there are more and more elderly people in nursing homes, and as a consequence, more nursing homes are created to accommodate them. One of the main activities of these homes is to monitor the activities of the people who live there to detect behavioural routines or possible abnormalities. Current technology allows this monitoring to be carried out in a simple way through intelligent devices such as sensors and actuators [17]. These sensors and actuators are usually integrated through a central node or controller that manages the communication and the information exchange. However, in environments with limited resources such as less populated rural areas, the implementation and deployment of these IoT systems can be difficult to achieve.

The monitoring of elderly people's activities is possible thanks to the latest technologies we have today. Among these technologies, we can highlight the latest generation of sensors that can detect movement when people are walking, if a door is open or closed, if a tap leaks, if there is smoke in a room, or trigger an alarm in an emergency situation, for example. The use of sensors of this type allows nursing homes to monitor the daily activities of their inhabitants in order to detect behavioural routines or possible anomalies. There is a multitude of sensors of all types that are offered to the market by different suppliers. The choice of some sensors or others will depend on the needs that the residence has and the available budget and it will also depend on the rest of the devices to integrate into the ecosystem. Creating an intelligent ecosystem can be problematic when acquiring sensors or devices. This is due to the lack of compatibility that currently exists between devices from different manufacturers or those using different communication protocols [18]. Because of this, in environments with limited resources, alternative solutions are needed to address this problem of integration and connectivity, to provide nursing homes located in rural areas the ability to create their smart ecosystem in a simple and affordable way. In order to monitor the daily activities of elderly in nursing homes, different technology projects have been launched with the aim of establishing a comprehensive care plan in the community through the adoption of smart health and care in the area of geriatric care in nursing homes [19]. The main idea of the new smart nursing homes is the incorporation of technological devices for the monitoring of determined vital signs or specific actions of the elderly, to tackle specific aspects of health and care in these residences. On the one hand, there are solutions for personal care and integrity, such as bed-exit alarm systems [4] based on multiple sensing such as infrared, ultrasonic, and triaxial accelerometers on the route that patients pass by most often; facial recognition systems for emotion detection with smartphones to improve the quality of life of the elderly [20–22]; a smartwatch-based communication system for nursing homes [23], which improve communication between residents and caregivers, thus reducing staff response time and improving residents' safety; or an experimental smart diaper [24] as an indicator of saturation for diaper change in people with dementia living in nursing homes. On the other hand, there are rehabilitation assistance projects, such as a new electro-informatics assistive medical system [25] used for the communication with neuromotor disabled patients, which allows bidirectional communication through using an interface with a software application by using different types of sensors including switch-type sensors or eye tracking devices; a system for monitoring and rehabilitation services for elderly [26], based on mobile and wearable technologies ready to be used in residential long-term care facilities to reduce the risk of depression and social isolation; a telecare and telerehabilitation system using computer vision techniques [27]; or a software application for tablet device [3] to support social connections and reducing responsive behaviours of people with dementia while in a care setting, such as nursing homes. The use of touch screen tablets, such as an iPad, may offer the possibility of helping people in rehabilitation with dementia to remain in a care setting.

Also, other initiatives facilitate the work of caregivers and medical staff, such as devices that assist in the early intervention of diseases such as diabetes [5], dementia [28], or other diseases [29]. The authors of this paper are working on different lines to improve the life and health of the elderly; among the many works we can highlight are an extensible environment for monitoring and detecting symptoms of depression [30], different systems for food and beverage monitoring [31–33], or a voice assistant to remind the pharmacological treatment [34]. Although in this work we will only focus on the self-management architecture based on IoT and machine learning for rural areas, these approaches are interesting to be aware of the common diseases and how the caregivers can be supported.

Elderly monitoring provides valuable information to those responsible for nursing homes. Thanks to it, daily routines or possible anomalies in the behaviour of the elderly can be detected. These routines can be related to the time they get up, when they have breakfast, at what time and where they go for a walk, and even with whom they relate to most. Also, these routines can help detect abnormal behaviours such as a person spending too much time in their room, not relating to others, or performing actions outside of their routine on a regular basis [35]. All of this information is valuable to nursing homes and can be used to take action. The processing of this information must be carried out in an intelligent device through machine learning technologies. Today, there are a large number of devices that can perform this type of computing tasks, from small microcontrollers to servers specifically dedicated for such purposes. Most of the existing proposals are focused on capturing the information obtained from the cloud and processing it there [36]. In this sense, smartphones are the smart devices that are evolving the fastest and achieving more computing capacity. Thanks to this, the processing of the information that determines people's daily routines can be carried out on their own smartphone. In addition, smartphones have different types of sensors that can further enrich the information of the elderly and make their monitoring more effective. However, this processing does not allow us to obtain behaviours and anomalies from a group of people, which is essential in social environments such as nursing homes. Besides, this process should be performed in a central device that integrates the different sensors and actuators of the residence. In addition, in this paper, the authors propose to make use of these techniques in a balanced way between the central controller and the smartphones of the elderly that will allow to make better use of the available resources and avoid possible overloads.

All these proposals are a great step forward, but each of them involves the development and maintenance of a system independently. This situation complicates the development of smart ecosystems for nursing homes, as well as raising costs. For all these reasons, the main efforts should be directed towards the integration of all these proposals into a single system [37].

3. Architecture Proposal Based on IoT and ML

The proposal presented in this work is aimed at taking advantage of the benefits that the IoT offers in combination with machine learning algorithms to monitor people in order to detect pattern behaviours and to predict future actions in nursing homes with no or intermittent Internet connection. This is achieved by developing an architecture that integrates different sensors and actuators in nursing homes to improve the monitoring of elderly people and processing the gathered data by these devices. Furthermore, the correct behaviour of this architecture does not depend on the Internet connectivity as it is designed to work in rural areas with limited or no Internet connections.

Although the proposal is designed for environments with a limited Internet connection, it can be implemented in places where the connection is stable such as nursing homes located in smart cities, where there is a growing awareness of intelligent devices and they are being incorporated into people's daily lives. The proposed architecture consists of three main parts: inputs, a controller, and outputs (Figure 1). The following sections detail these three aspects of architecture.

3.1. Collecting Data: Inputs. The inputs represent those devices that can provide information about the environment, such as (1) sensors of temperature, humidity, movement or luminosity; also (2) people's smartphones that can be used to track their locations within the nursing home or frequent interactions with other devices and to provide contextual information about the person employing the different sensors they possess (accelerometer and gyroscope), such as whether they are moving, walking, and standing or any other detection that can be deduced from the smartphone's internal sensors; and (3) web services that provide additional information about the seniors' residence, such as virtual sensors to monitor weather conditions, to know the TV guide or upcoming events of interest.

In this sense, smartphones can process each person's personal information to detect patterns of behaviour through

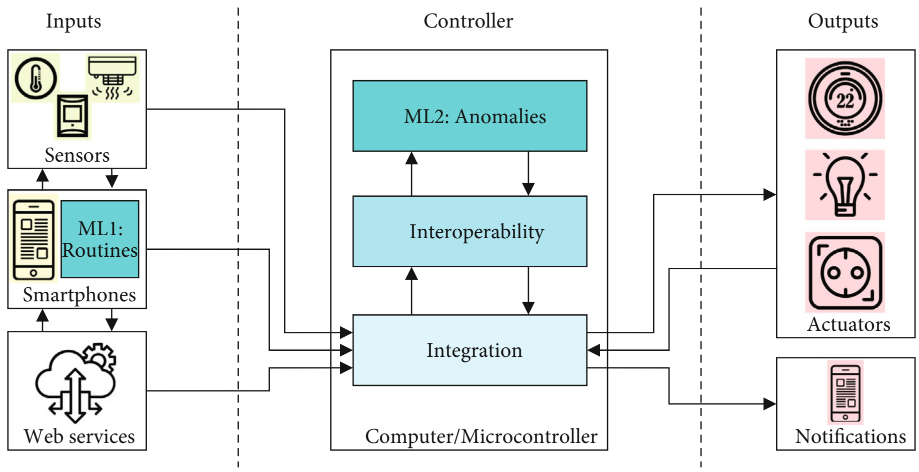

FIGURE 1: Architecture for the integration of sensors and actuators.

machine learning techniques. This information is related to location, interaction with other devices, data sensed by their sensors, or time invested in a room. The information is obtained through the different sensors that the smartphones have, but in addition, it can be combined with the data offered by the physical sensors placed in the residence to obtain a richer and more accurate prediction. Nowadays, mobile devices are increasingly powerful and capable. This allows increasingly expensive operations to be carried out, computationally speaking, and also at runtime, without the time delay of these processes being increased [38]. That is why the computation of the preferences of the elderly could be done directly on their mobile (ML1) devices and sent to the controller once processed, with the aim of offloading processes to the controller. In this line, many libraries offer this type of computing. TensorFlow (https://www.tensorflow.org) offers the TFLite library for running predictions on thin clients (such as Android) on models previously defined and trained with TensorFlow. Also, from the latest versions of Android (API 27), Google is working on the inclusion of an API for Neural Networks (https://developer.android.com/ndk/guides/neuralnetworks), which allows for definition, training, and prediction on the same device. Regarding this task, there are previous works [39] developed by the authors of this paper based on the use of neural networks to automate actions with IoT devices, where details of how to identify a person's behaviour and actions can be found. In that work, the detected actions depend on information from the context, such as the time, the day of the week, or the type of IoT device with which the user interact with. In addition, sensors' values and other inputs mentioned in Figure 1 are added to those input variables. Therefore, the sensors' values are considered together with the previously mentioned context variables, to determine which conditions cause an elderly to interact in one way or another with an actuator. For example, the ambient temperature captured by a temperature sensor can be decisive in how the elderly person acts with an air conditioner. The used neural network is a Multilayer Perceptron Neural Network (Figure 2), where there is an input layer of the size of the context variables that is used as an input, two intermediate layers of 45 neurons each, and a *bias* neuron in each layer, to reduce the bias of data, and an output layer of the number of actions that can be performed with the actuators. In this way, each neuron in the input layer has an associated context variable, taking its value as input to make predictions. In addition, each neuron in the output layer provides an associated action of a specific device, indicating the probability of performing that action with that device, based on the inputs specified in the input layer. The number of intermediate layers, as well as their number of neurons, is determined by adjusting the loss function and evaluating the percentage of under- and overfitting during training. This machine learning model provides the ability to discover people's pattern behaviour during the monitoring with the aim to predict actions over the actuators, but it does not provide the ability to detect behaviours that change over time (actions that stop being executed in favour of new actions). To detect these changes in elderly behaviour, it is necessary to make the neural network aware of time, to enable it to analyze not only the context variables that condition behaviour with an actuator but also the change in behaviour with the actuators (for the same or other context variable values) over time. In other words, it analyzes a time series with the changes in the way the actuators are used. For this, recurrent neural networks (RNNs) are used, which allow the neurons to be provided with memory. Specifically, Long Short-Term Memories (LSTMs) are usually used, a type of recurrent neural network that solves the short-term memory problem of classic RNNs, so long data sequences can be analyzed. An alternative to all this is to use the same neuronal network as now, creating a mechanism, like a system of weights, to evaluate positively the records of newer interactions against older ones. However, this solution is less appropriate and may give worse results than analyzing the time series of interactions with an actuator, using an LSTM. At this point, both the information processed by the smartphones and that produced by the different physical sensors are sent as output from ML1 device and as inputs to the controller, for identifying actions and social behaviours from a set of people and smart devices.

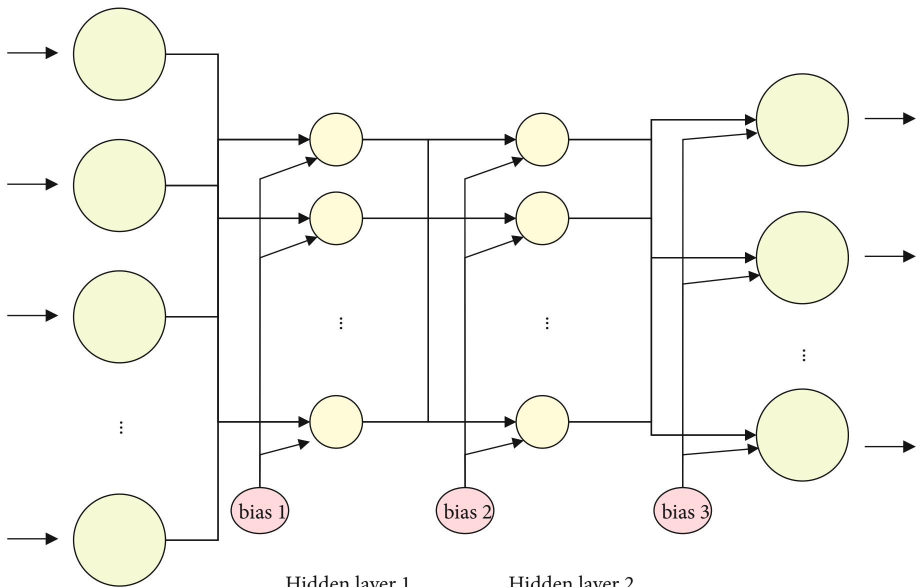

Figure 2: Neural network definition.

3.2. Processing Data: Controller. The controller, which can be from a simple Raspberry Pi to a dedicated server, processes the information coming from the different sensors and smartphones (inputs) to interpret it. The controller consists of three main components. The first component, *integration*, is responsible for ensuring proper integration among the different devices (sensors and actuators). To do this, one of the most popular assistants for the automation of smart environments is used: Home Assistant (HASS) (https://www.home-assistant.io). HASS is a system designed for the configuration and automation of many devices from different brands. It is developed in Python, which is a free and open-source software with a large community behind 216 and large support of brands (https://www.home-assistant.io/integrations) such as Amazon Alexa, Google Assistant, Ikea, Philips, Sonos, or Xiaomi. HASS allows the integration of devices (sensors, actuators, mobile phones, etc.) through a great number of different protocols like Bluetooth, BLE, WiFi, ZigBee, or MQTT, to be controlled or to make automation in a concrete environment, like a smart home, an office, or as in the case of this work, a nursing home. Also, this system allows triggering specific actions when an event occurs, such as turning on a lamp when motion is detected or sending a notification when an alarm is triggered. HASS also allows nearby devices to be detected through different mechanisms, such as those connected to the same network (NMAP), or within Bluetooth or BLE range. This is particularly interesting for finding out who is nearby, where they are by tracking devices such as smartphones, smartbands or smartwatches. The wide range of possibilities that HASS offers is an interesting option to perform the automation of the nursing home, allowing the responsible of the nursing home to purchase a wide range of smart devices. Once the devices are integrated, the *interoperability* component is responsible for ensuring the collaboration among the devices. To achieve this collaboration among smart devices, we must link elder's needs to the services that the devices offer. We define as *needs* the preferences that people have and that need to be covered in order to perform a certain task, such as for example, selecting a certain luminosity level. These needs can be manually specified by the person or be detected by another device, for example, selecting a specific luminosity level when a person is entering in a room. These needs will be covered by the *services* that the smart devices possess within the nursing home. To this end, ontologies are used to define the characteristics of the sensors, actuators, and smartphones, with the aim of creating logical relationships between them and facilitating their collaboration.

There are numerous ontologies that currently exist for healthcare in smart environments and that could be reused for the proposed architecture. In this sense, the authors of this paper developed in [40] a study of the most relevant ontologies mainly related with healthcare. Some of the ontologies included in the study are *HealthIoT*, *HOTMES*, or *FIESTA-IoT*. These ontologies can represent medical devices, provide information to perform personalized services to certain patients, represent smart environments dependent on certain conditions or parameters, or monitor different people's activities. However, none of them gathers all the information that is necessary to represent the correct communication and collaboration between inputs and outputs. A complete description of these ontologies is detailed in [40] as well as their main properties' pros and cons. The development of ontologies is usually done to solve a specific problem. It is for this reason that although the ontologies considered have classes and types of data that could solve our problem, they do not achieve it completely and do not allow us to represent the required information in the way

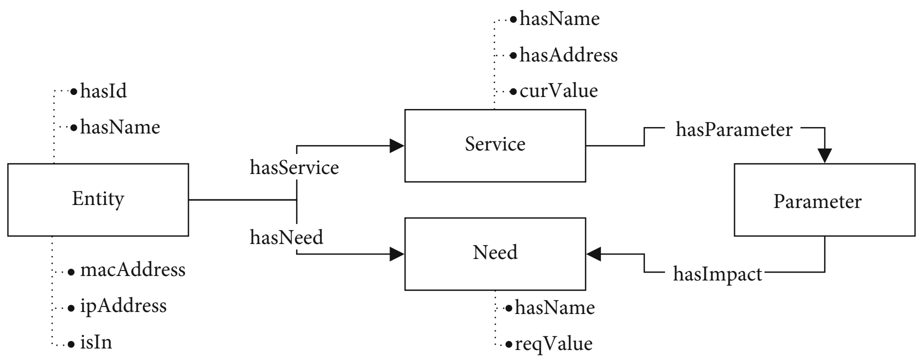

Figure 3: Proposed ontology to improve elderly monitoring in nursing homes—*Ont4SM*.

we intend to do it. This information is related to the identification of inputs and outputs, associated services such as turning on a light or triggering an alarm, parameters that indicate the operation of the services, such as the intensity of the lighting, specific preferences of people, and values of those preferences to suit the devices. For this reason, we propose an ontology to improve the interoperability among smart devices in nursing homes. The proposed ontology is defined as Ontology for Smart Monitoring (*Ont4SM*) (Figure 3). The aim of this ontology is to represent the information of smart devices belonging to different application domains and manufacturers as well as the information about people to achieve a semantic relationship.

Given the fact that both people and devices have services and needs, we use a single class (*Entity*) to represent people and the different sensors and actuators that we treat them equally. In addition, this class allows us to represent the entity's personal information so that it can be correctly identified and for the moment is not necessary to make a separation. Besides, this ontology is able to represent the services (*Service*) the entities have, as well as the needs (*Need*) that will be solved by the available services. We must bear in mind that the impact of services on needs will not always be the same and will depend on different parameters. For this reason, a class (*Parameter*) has been introduced that receives the necessary parameters to make the invocation and to adapt the service according to the characteristics of the need that it is going to solve. The following example shows how the ontology works and how the information represented in JSON format is treated. Let us suppose that a person, Bob, from the nursing home is in the living room. Through the information collected by his smartphone and contextual information, his needs (Need) are detected and interpreted by the controller and the nearby devices can adapt their services (Service) to this person as well as additional information to identify him in the nursing home (Figure 4). In this case, Bob would like a medium illumination (6/10). To solve this, the intelligent light bulb in the living room, a SmartBulb, receives the data from the person through the controller to adapt the lighting level to the detected need. In this case, the service that allows changing the lighting is invoked and receives the "illumination" parameter that acts directly on the detected need when it is solved (Figure 5). Also, the SmartBulb has an associated need to optimize energy consumption.


```
{
    "hasId":"135487",
    "hasName": "Bob",
    "macAddress":"4e:25:d5:f0:e4:4d",
    "ipAddress":"192.168.0.115",
    "isIn": "LivingRoom",
    "hasService":[],
    "hasNeed":[
        { "hasName":"Illumination",
          "reqValue": "6"

        }
    ]
}
```


Figure 4: Entity Bob.


```
{
    "hasId":"21547",
    "hasName": "SmartBulb",
    "macAddress":"db:93:09:a5:5c:69",
    "ipAddress":"192.168.0.140",
    "isIn": "LivingRoom",
    "hasService":[
        {
            "hasName":"Illumination",
            "hasAddress":"http://192.168.0.140/service?
                    illumination=value",
            "curValue":"0",
            "hasParameter": ["illumination"] }
    ],
    "hasNeed":[ {
            "hasName":"Consumption",
            "reqValue": "2"
        }
    ]
}
```


Figure 5: Entity SmartBulb.

If there is a nearby entity that can perform this optimization, for example, lifting a blind for natural light entering so that the bulb can be turned off temporarily, the process would be repeated so that this need would be resolved by the service of the nearby smart blind.

The processing of the ontology goes through several phases from the entities which are detected in the nursing home, until the information is processed to improve the elderly monitoring. This is a brief description of the ontology, so all the details about it and its processing is available in [40]. The last component of the controller, *ML2Anomalies*, is responsible for processing the information collected to detect possible anomalies in people's behaviour. In addition, this component allows us to discover social behaviour that can be identified within the nursing home, such us the frequency with the people interact between them, what are the most interesting topics they talk about or if they develop certain task together, such as play a game or go for a walk. This can be done by using machine learning techniques. Thanks to these algorithms it is possible to process the information gathered from the inputs and to make a decision that allows the adaptation of the actuators or to predict future actions in the environment. To do this, unsupervised algorithms are used for anomaly detections. Anomaly detection, in data mining, is the process of detecting, for a large dataset, observations from this dataset that differ significantly from the values taken by most other observations. Therefore, it is used in tasks such as fraud detection [41]. Due to the unsupervised algorithms work with unlabeled data, the previous data that was used as input (sensors) and output (actuators) is used as input for the anomaly detection algorithm. This allows certain areas to be identified where the elderly is interacting normally with the actuators, according to the input data from the sensors, for example. When unusually operating with the actuators according to the inputs, this interaction produces data that is outside any of the zones where most of the data is, assuming that the elderly are performing an action that differs from their usual behaviour. Also, it is important to indicate that, although the information of which elderly performs a certain interaction with the sensors/actuators is saved and it is considered as part of the model entries, the information will always be processed globally for the whole residence, so the models generated will be at the residence level (one model to automate actions and another to detect anomalies) and not models for each elderly. In this way, it will be possible to extrapolate the models from a residence to a similar residence, as will be seen in Results and Discussion.

3.3. Taking Actions: Outputs. Finally, the outputs represent the actuators that are in charge of triggering different actions depending on the information that has been previously processed. These actions will vary depending on the type of actuator, such as setting a certain illumination, regulating the temperature of a room, tuning to a specific channel on the television, and turning on/off a device connected to the electrical current. Additionally, push notifications, or any other type of notifications, could be sent to caregivers in case of emergency. One of the main advantages that this architecture has is that it does not require an Internet connection. Once the architecture is implemented, the sensors and actuators are connected through different communication protocols to the controller, which is in charge of performing all the information processing locally. The integration of these three parts of the architecture, inputs, a controller, and outputs, contributes to improving the elderly monitoring in a transparent way for them mainly in environments with limited or no Internet connection such as rural areas or small villages, isolated from the big cities.

4. Use Case Description

The proposed use case is based on a nursing home located in a rural area with limited resources. In this residence, it has been proposed to monitor the daily activity of the elderly living in the second floor to check what activities they do or when and even to detect strange behaviours. To do this, the nursing home's caregivers want to use the latest technologies that allow data to be collected and processed in the most efficient and easy way. Due to limited resources, such as Internet connectivity or a minimal budget, it required a solution that they can perform simply and affordably.

For the proposed use case, it has been decided to use three different communication protocols (WiFi, ZigBee, and Bluetooth) to take advantage of the benefits of each of them and to cover a wider range of different devices' specification. In addition, the use of different technologies serves as a complement to evaluate the integration, collaboration, and interoperability among different sensors and actuators. The selected sensors and actuators are shown in Table 1, as well as the different smartphones that the elderly living in the residence have.

In Figure 6, the floor plan of the second floor of the nursing home on which the current case study is conducted is shown. In this floor, there are four rooms for people, a living room, and the central corridor automated with sensors (*green*) and actuators (*red*). Each room is provided with a sensor to control when the windows are opened and closed, as well as a bulb to change the luminosity or color, and a socket to turn on/off any electronic device connected to it, for example, a TV or a radio. Besides, sensors to control the opening of windows and smoke detection, temperature, and movement sensors have also been installed in each living room. In addition, the living room has sockets that allow elderly to activate or deactivate any device connected to it, a smart button that allows elderly to interact with the light bulbs or other smart devices, a bulb that can change its intensity or color apart from being turned on/off, and a thermostat that allows to regulate the temperature of the room. Different devices have also been installed in the corridor to monitor the activities of the elderly. In the corridor, there are a movement sensor, a smoke detector, and a general alarm that allows for notification of possible incidents. On this second floor, four elderly people (*yellow*) are currently living, who move freely between the rooms and the living room to perform personal, social, or leisure tasks. Each person has its personal smartphone that collects information about their position, who is near them and even the most used applications, to recognize behaviour patterns in their daily routines. These smartphones are constantly gathering data from the different sensors they have with the aim to detect behaviour pattern about

Table 1: Selected controller, sensors, actuators, and smartphones for the use case.

Device	Supported protocol(s)	Description
	Controller	
(i) Raspberry Pi 3 Model B+	WiFi/Bluetooth/ZigBee	The controller to manage the environment
	Sensors	
(i) Motion sensor Xiaomi	ZigBee	To detect movement
(ii) Temperature/Humidity Xiaomi	Bluetooth	To control the temperature and humidity
(iii) Doors/Windows closed Xiaomi	ZigBee	To detect when a door or window is opened
(iv) CR Smart Home Smoke Xiaomi	ZigBee	To detect smoke/fire
	Actuators	
(i) Xiaomi Yeelight Color V2	WiFi	Bulbs to illuminate rooms/corridors
(ii) Smart Plug Zoozee	WiFi	Plugs to control electrical devices
(iii) Google Nest	WiFi	Thermostat to control the temperature
(iv) Smart Switch Xiaomi	ZigBee	Button to trigger different actions
(v) Xiaomi Aqara Gateway	WiFi/Bluetooth	Alarm to trigger notify emergencies
	Smartphones	
(i) Xiaomi Mi 9	WiFi/Bluetooth	Elder's daily data
(ii) Huawei Mate 20	WiFi/Bluetooth	Elder's daily data
(iii) Moto Z	WiFi/Bluetooth	Elder's daily data
(iv) Honor 9	WiFi/Bluetooth	Elder's daily data

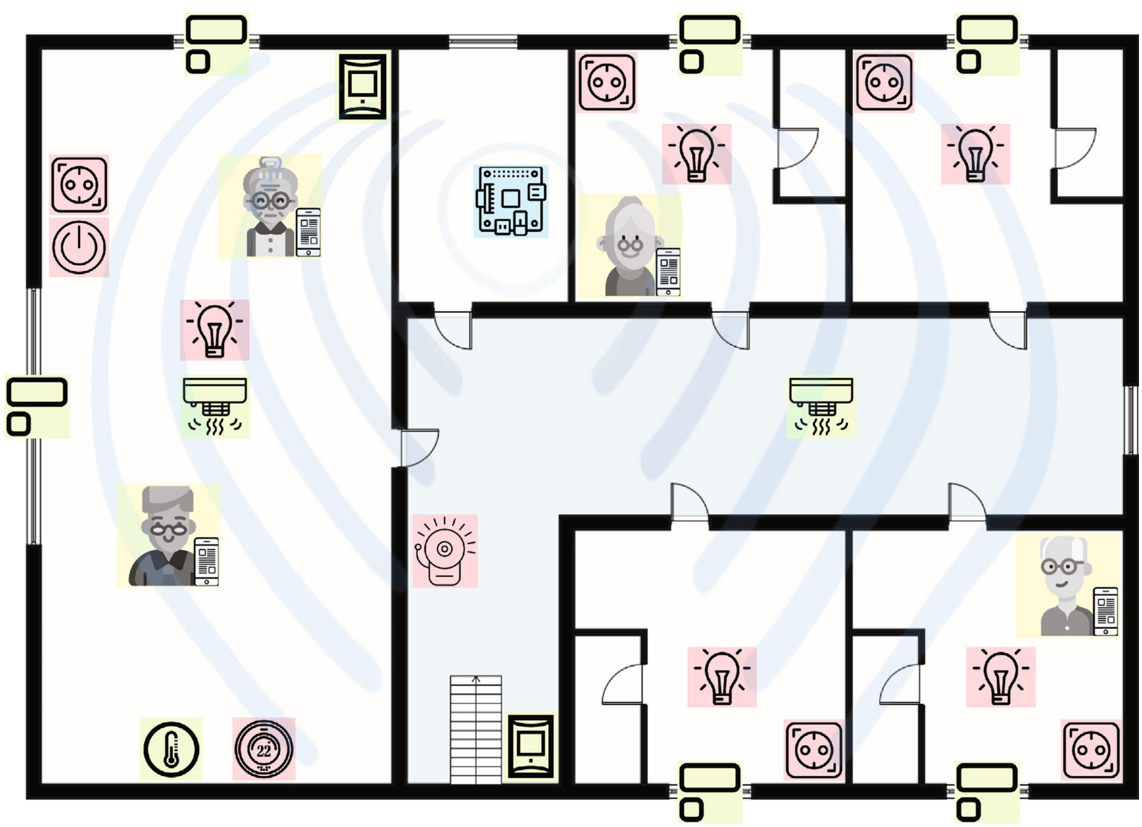

Figure 6: Nursing home floor plan (2nd floor) use case.

their owners by using the machine learning techniques previously explained. Also, in this second floor, a controller is located, a Raspberry Pi (*blue*), that receives and sends information from sensors, actuators, and elderly smartphones via WiFi, Bluetooth, and ZigBee, depending on the type of device. All these devices have been integrated through HASS to perform the appropriate automations as well as to adapt their behaviour to the environment. The information collected in this environment is processed through unsupervised algorithms previously detailed in the controller to detect anomalies in elderly behaviours.

Thanks to the structure of the proposed architecture, as well as the technologies it uses for the integration of devices and information processing, the data collected in this use case are potentially usable for the detection of behaviour patterns and anomalies in residences with similar characteristics (number of people, arrangement of sensors and actuators, size of the building, location, etc.).

5. Results and Discussion

The need for mechanisms to facilitate the monitoring of older people is increasingly real. The increase in the average age of the population poses new challenges to societies and healthcare systems. Nonetheless, the emergence of the area of IoT research, wireless communications, and mobile computing is raising hopes for automated assisted environments. These environments combine the advances of sensor networks with those of run-time monitoring systems, to create intelligent nursing homes capable of monitoring the elderly. However, although various AAL systems have been proposed in the last years, the goal of realizing an effective support system for elderly is still far from reach. That is why, in this paper, we have presented a project aiming to reengineer a set of everyday life objects, equipping the nursing home with different types of sensors and actuators, thus monitoring the condition of older people in their nursing homes and providing security while preserving the autonomy and independence of the persons, in an environment with limited resources such as rural areas. This solution is based on an architecture capable of managing different types of devices, such as sensors, actuators, and smartphones with an algorithm to detect pattern and anomalies in elderly behaviour.

The developed algorithm to detect pattern behaviours has shown promising results. The following results are an extract of the main work developed by the authors of this work [39] where the neural network developed and evaluated in different scenarios for the detection of behavioural patterns in different scenarios of people is presented.

In this case, these results are related to the (*ML1: Routines*) component of the proposed architecture. The results shown correspond to the behaviour of an elder in the nursing home who performs different activities from Monday to Friday, on Saturday he/she goes for a walk, and on Sunday he/she goes to his/her children's house. The validation lasted three weeks. The two first weeks were used for training the model with information about the different actions that the users performed with the present devices for this scenario. And the last week was used for the testing phase in order to get prediction and evaluate them. Some predictions were also made during the two weeks of training, to check how much data were needed for the system to start learning new behaviours and how the predictions improved with new records. However, this depended a lot on how frequent the behaviour is. First, regarding the responsiveness, it is interesting to indicate that on average 11.05 seconds are required to refit the neural network with the inputs of each user every day and 1.35 milliseconds on average are required to make a prediction. As can be seen, the responsiveness is very good for almost any IoT application. Other similar proposals [42] are getting prediction times of 896.1 milliseconds (when the number of devices is small) and 1.21 seconds (when the number of devices is higher). Training times are not included in these proposals. Second, regarding the accuracy, the results obtained for the scenario can be seen in Table 2. In this table, the number of predictions, the correct and the incorrect ones, is detailed.

Table 2: Table of predictions.

Predictions	Correct	Failed	Accuracy
245	212	33	0.86

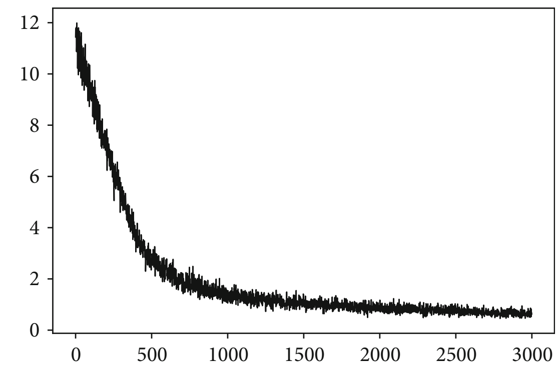

Figure 7: Loss function for the validation model.

By analyzing the joint results for that scenario, we have to notice that 33 predictions were not correct. According to this, we detected that 29 were produced by trying to predict actions that do not have a specific behaviour pattern, since there were records of different actions for the same device in the same context and for the same user. For example, imagine a person who sets a different television channel every day when arriving at the nursing home. If the system tries to predict which channel the person will choose, the probability of getting a correct prediction is low. For the other 4 incorrect predictions, the model was not able to learn the action. Therefore, it can be said that only 4 out of the 245 predictions were not correct.

In addition to analyzing the results offered by the model in terms of accuracy, it is important to analyze other functions measuring the quality of the developed model. For this purpose, the loss function has been used. The loss function for the model discussed in this section is shown in Figure 7. It can be seen how the function tends to the value zero (target value in this function), which allows us to know if the value of the learning rate or the value of the batch size is appropriate. To do this, the evolution of the loss function through the epochs is compared with the ideal evolution of the loss function [43]. Thanks to this analysis, it can be determined that the learning rate is good, although it could still be reduced a little. The noise that can be observed in the loss could be reduced by decreasing the batch size a little but is not significant.

Table 3: Table of measures over probabilities.

Measure	Correct predictions	Failed predictions
Min. value	0.3266	0.3266
Max. value	0.9923	0.9667
Average	0.7825	0.5898
Typical deviation	0.1800	0.1850

In addition, we also evaluated the probability of success for every prediction in order to identify a *threshold* that allows us to know when a predicted action should be performed or not. In Table 3 can be appreciated the average, the maximum, and the minimum value and standard deviation for the probability of the correct and failed actions.

Finally, to determine the *threshold*, a *univariate* distribution has been created with the value of the probability of success of the correct (Figure 8(a)) and failed (Figure 8(b)) predictions. Thanks to these data and reducing the number of false positives even if the accuracy is reduced, it can be determined that the best *threshold* is over 0.4 and 0.5. Besides, in Table 4, it can be observed that a *threshold* of 0.44 is better, because a lower *threshold* includes more false positives.

With the obtained results, it can be stated that the algorithm has been able to correctly predict 86% of the interactions, failing only in 1% of the predictions or when the performed actions do not follow a pattern.

Regarding the machine learning algorithm development, another way to implement them to detect pattern behaviours and anomalies can be by developing a single model using the neural network for both functions. Each time an elder performs an action manually, he/she employs the neural network to check the probability of execution of that action, according to the model trained with previous records and the context (inputs). By assigning a minimum probability threshold, if the action being executed by the elder does not exceed the threshold in the prediction model, it is considered an anomaly. This is because the elder is performing an action that has very little probability of being performed according to his/her usual behaviour. Also, it is necessary to verify that there are actions that the elder could perform at that moment that exceed the threshold. If not, the reason why the performed action did not exceed the probability threshold could be that the model is not sufficiently trained for that situation and not because of an anomaly. However, this method is more susceptible to errors, since there are already dedicated algorithms to do this. It could be useful in case we wanted to reduce to the maximum the amount of computation and complexity of the controller, using a machine learning model for everything. This may be a way to reduce the energy footprint on the controller.

Although the selected use case is based on a nursing home with specific characteristics, the proposed architecture can be implemented in another nursing home. This is especially beneficial. This work is part of a project on gerontechnology, in which one of the tasks is to define an architecture that can be used in all residences in the regions of Extremadura (Spain) and Alentejo (Portugal). This architecture and implementation allows to reduce the costs of the residences and be more efficient in caring for their residents. The benefits of the proposed architecture should be considered when implementing this as well as the requirements of the destination nursing home. These benefits include the wide variety of sensors and actuators that can be integrated, regardless of the manufacturer and technology used. More and more devices are compatible with systems like HASS, which allow users to create their own intelligent environment without having to rely on third-party applications or hardware to operate and communicate with each other. This allows the application to be used in rural environments, even if it has no Internet connection or is limited, because all information processing is done locally at the controller. To implement the architecture in any other scenario, it would be necessary to study the available resources and the available budget. Furthermore, it would be necessary to study the requirements, mainly the type of sensors or actuators to be used, depending on the type of monitoring and the performance to be achieved. For example, monitoring the movement of people or if the lights remain on for a long time. In addition, it must be decided what type of controller will be suitable for managing the environment, from a microcontroller to a dedicated server with more power and resources. This decision will vary depending on the size of the environment and the number of devices being managed. Once the sensors, actuators, and the controller have been identified, they must be integrated into the HASS installed in the controller so that the information from the sensors, actuators, and smartphones can be processed by the machine learning algorithm to detect behaviour patterns or predict certain actions. If the new scenario in which the architecture is to be implemented has the same number and type of sensors and actuators as any other previously known scenario, the machine learning models can be exported from the known scenario to the new one.

Otherwise, if some of the inputs or outputs were different, it would be necessary to modify the inputs and outputs of the models, having to generate new models and train them from scratch. From this moment, it is possible to start with data collection and environment automation to perform the necessary tasks.

The system developed promises to be of great help to older people, especially in environments with reduced or no Internet connection such as rural areas. As mentioned above, the proposed architecture can also be applied in residences located in settings with good Internet connections. These environments can even enhance the characteristics of the proposal, allowing tasks to be performed remotely, such as controller management, using cloud services for more complex data processing or monitoring the status of people in the residence from other locations. In the case of remote management, HASS makes it easy to do so through the *Nabu Casa* (https://www.nabucasa.com) service, which allows access to the control panel from anywhere through the Internet browser. In this way, the HASS can be managed and the information of the sensors installed in the nursing home can be evaluated. For data processing in remote servers, the great versatility that the Raspberry Pi offers would allow one to easily cloudify these services, using Amazon Web Services

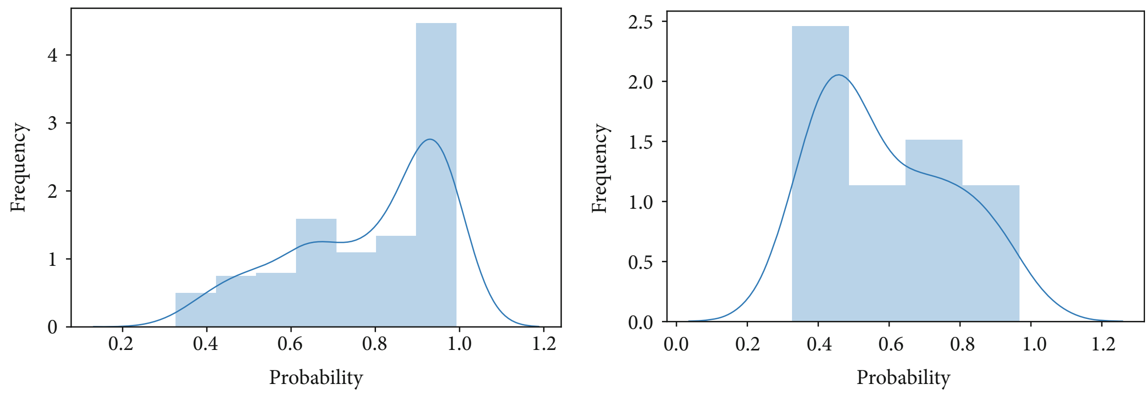

Figure 8: Univariate distribution of probabilities: (a) for correct predictions; (b) for failed predictions.

Table 4: Table of measures over threshold.

Threshold	False neg.	False pos.	Correct	% success
0.40	5	30	210	0.8571
0.42	10	26	209	0.8530
0.44	11	23	211	0.8612
0.46	13	22	210	0.8571
0.48	17	21	207	0.8449
0.50	21	19	205	0.8367

(AWS) (https://aws.amazon.com) or Microsoft Azure (https://azure.microsoft.com), to send the data and to be able to recover the results once processed. This feature could be added in the future to expand the possibilities of the architecture and support new features. Although the potential benefits of the proposed architecture have already been shown, further work is needed to overcome current limitations. Among these limitations is the amount of data required for the machine learning model to be able to act correctly. In this sense, machine learning models are more accurate when they have a large amount of data, so when used in small environments with few interactions with actuators, data collection can take a long time until the model begins to generate more reliable predictions. For the studied scenario, Figure 9 shows a line chart with the evolution of the accuracy of predictions with respect to the amount of data that has been collected. This chart shows the evolution of the accuracy in the 3 weeks that the validation lasted. However, only data for 15 days are shown, because the user did not use the system every day of these 3 weeks. When there were no interactions, the model was not retrained. These days are not represented in the chart in order to improve its readability. In this chart, it can be seen how, as the size of the datasets grows, the gap of the accuracy between the training and testing datasets (the overfitting) is reduced. It is important to mention that the training is done with data from real users. Then, the accuracy evolution depends on how they use the system. If a user always uses the system with a strongly determined behaviour, the amount of data needed to obtain good predictions will be low. If not, more data are needed and the algorithm will not be able to offer high accuracy predictions in all cases.

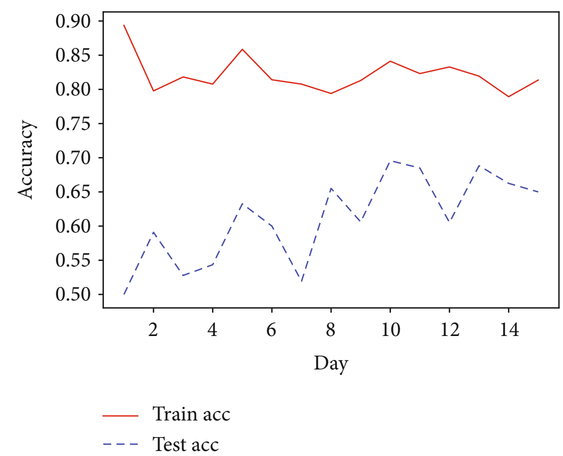

Figure 9: Evolution of accuracy along validation period.

During the training period, the model is trained with the actions performed in the different devices. Therefore, if the user has a random behaviour with any of them, the accuracy goes down, even if the probability of success of the model for the rest of the devices is high. To finish analyzing this figure, it is important to note that the accuracy values for the last measurements are not identical to those in Table 2. This is because the accuracy shown in Table 2 is obtained based on the number of actions that is automated by the user with the last trained model and the number of these actions that the user accepts or corrects immediately. The accuracy shown in this graph is the one obtained at the moment of training the model and testing it. Figure 10 shows, for the same period, the time needed for training (using CPU) and the space required to store the dataset. The training time is divided into two phases that are part of the training phase: *data cleansing* and *fit network*. In this way, the amount of training time dedicated to each of these tasks is shown. From the chart, it is possible to see how adding more data to the dataset does not considerably affect the time needed to train the model. This is because the amount of data that is collected in this timeframe is small, as can be seen in the *size dataset* (on the order of kilobytes). The number of inputs that the neural network model has for this scenario is small. If the

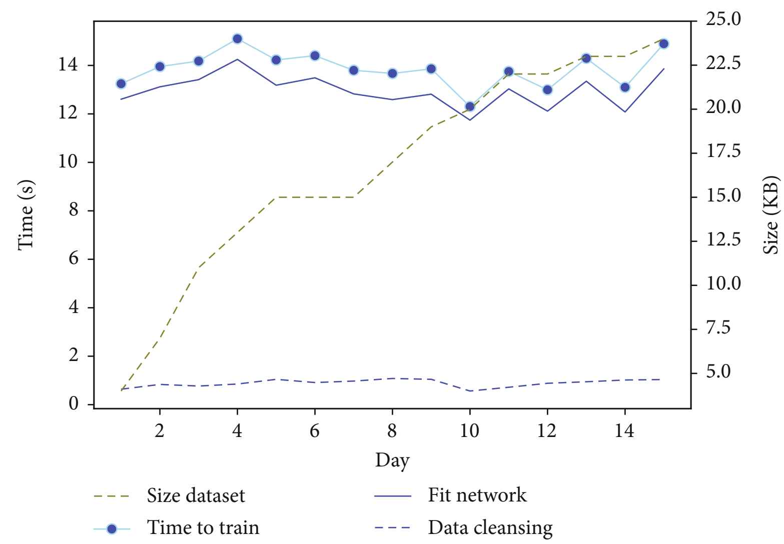

FIGURE 10: Evolution of time and space needed for training along validation period.

number of inputs in the model grows, the increment of the space occupied by the dataset with respect to the timeframe will be greater.

Another current limitation is that the information collected from smartphones is limited to space and time variables. To obtain other types of information, it would be necessary to install a mobile application that provides more detailed information.

In addition to these limitations, a procedure to evaluate the architecture has been performed using the ATAM (Architecture Tradeoff Analysis Method) methodology [44]. ATAM allows the evaluation of software architectures through nine steps grouped into four phases (presentation, research and analysis, testing, and reporting) to mitigate risks related to quality, performance, availability, security, and modifiability. One of the benefits of ATAM is that it can be used during different parts of the architecture's life cycle, either at the beginning when the architecture is being designed, throughout its life cycle, when the architecture is defined but barely developed, and even for a fully defined architecture. In this sense, the evaluation of the architecture proposed in this paper is made in a preliminary way to know the most important risks that it may contain.

(i) In terms of the quality of the architecture, the proposal advocates offering nursing homes the latest technologies for the domotization of smart environments. Among these technologies, the use of machine learning algorithms (TensorFlow) for data processing, or Home Assistant for the integration of intelligent devices, stand out. Also, these technologies have wide support from the scientific community, which allows the quick identification and solution of problems and a more than acceptable capacity of expansion. The risks associated with the quality of the architecture reside in the degradation of the physical devices over time and with the conditions of the environment, where interference with other devices or the physical layout of the walls of the residence could affect the architecture behaviour

(ii) The performance of the architecture depends on the type of devices selected for monitoring the nursing home. The architecture is designed to accept any type of device and taking into account that this implies a cost for the nursing home's managers. Moreover, since the controller is the main device, it can be more or less powerful depending on which ones are chosen. In the example proposed, we have chosen to use a low consumption microcomputer (Raspberry Pi) whose characteristics are sufficient for a small-medium size environment. However, the capacity of this device can be reduced depending on the number of devices that are integrated and the size of the nursing home. This is why this device can be replaced by higher performance elements such as a dedicated server to carry out all the required processing

(iii) In an intelligent environment, the availability is a key property. However, this feature often depends on the network infrastructure. In this case, the nursing home does not have to offer an Internet connection, but it must have at least one gateway (a router) enabling a local network with intelligent devices. Furthermore, although only one controller has been proposed to be installed, this could be replicated in another area of the nursing home to make the architecture fault-tolerant in case errors are triggered by a controller. For environments where there is an Internet connection and where the characteristics of the architecture can be extended, again there must be a backup system that allows the output to the Internet in case of an error

(iv) Also, the security supposes a fundamental aspect in software architecture. On the one hand, the architecture contemplates that the devices can be connected through secure P2P protocols against the controller, using WiFi, Bluetooth, or ZigBee technologies. This means that once configured, the devices only communicate with the controller to send and receive data. On the other hand, the privacy of people's data is a crucial aspect. This is since sensitive personal data is handled. Therefore, the authors of this paper are firmly committed to data privacy and have been working for some time to guarantee this privacy. In this sense, the authors of this paper are working on a framework that allows people to decide what information to share and with whom [45]. This allows residents to decide what information will be shared from their mobile devices with the rest of the devices and the controller. Therefore, data privacy is guaranteed and only the data that people want is shared. Another important point is that taking into account that no Internet connection is required and that the processing is done locally, the data does not travel to remote servers, thus reducing the chances of eavesdropping by third parties

(v) Finally, the characteristics of the architecture allow it to be easily adapted or modified, improving the system scalability. Both the integration of new devices and the configuration of existing ones are done intuitively from the controller by using the GUI provided by Home Assistant. However, it must be taken into account that the evolution of smart devices advances at great speed and that the communication protocols are constantly updated. This means that the controller must have its libraries updated to ensure the greatest possible compatibility with new devices. Also, Home Assistant is such a versatile software that any type of script can be incorporated to modify the behaviour of the controller or to add new functionalities easily. As for data processing, the machine learning algorithms used to allow them to be retrained with new data to detect new patterns or anomalies in patients easily. The previous paragraphs largely summarize the most important risks detected through ATAM. Although this is a preliminary report, the authors of this work plan to continue with this methodology during the architecture's life cycle to detect new risks that may arise to offer a solution with the highest possible quality

6. Conclusions and Future Works

This paper deals with the problem of automating environments to make everyday tasks easier for the elderly, through the use of smart IoT devices and machine learning techniques. To this end, an architecture has been proposed that, through a controller, allows data to be collected from multiple types of sensors and smartphones, to modify the behaviour of the available actuators under people's preferences. To favour multidevice environments and give users the freedom to use different types of sensors and actuators, the architecture is capable of working with WiFi, ZigBee, and Bluetooth (among others) communication protocols. Also, a neural network model has been developed that, from the data collected, allows the controller to be able to learn about the habits and routines of older people, predict future behaviour, and detect anomalies. This information analysis is also valuable for informing family members or health experts of the habits or routines that older people normally follow, reporting abnormalities or notifying in emergencies.

To validate the proposed architecture, the implementation has been done in a daily environment where many elderly people live: a nursing home. Thanks to the conducted automation, it is possible to detect when one or several people enter a room and turn on the TV, to turn off the lights when they leave, or to turn on the heating at the time they normally go to the living room. These interactions are also valuable in improving the model more and more. When data from a longer period becomes available, the use of the mentioned LSTM networks will be evaluated if it is necessary to allow the system to learn to identify changes in the way elderly interacts with the actuators. As future work, the implementation for the detection of anomalies (*ML: Anomalies*) by means of unsupervised algorithms will be performed. Besides, the conducted machine learning model will be extrapolated to an environment with similar characteristics to evaluate its operation and to be able to adjust those parameters that are necessary.

Thanks to this proposal, better monitoring of elderly people in nursing homes is achieved through the use of all kinds of intelligent devices, thus improving their quality of life and the effectiveness of their caregivers. Also, the flexibility and scalability that the presented architecture offers allow nursing homes to implement the system with a wide range of devices and without the need for an Internet connection.

Data Availability

The data used were obtained from tests conducted with real users. They are available upon request.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Acknowledgments

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Research Article

OPPNets and Rural Areas: An Opportunistic Solution for Remote Communications

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Many rural areas along Spain do not have access to the Internet. Despite the huge spread of technology that has taken place during recent years, some rural districts and isolated villages have a lack of proper communication infrastructures. Moreover, these areas and the connected regions are notably experiencing a technological gap. As a consequence of this, the implementation of technological health solutions becomes impracticable in these zones where demographic conditions are especially particular. Thus, inhabitants over 65 suppose a large portion of such population, and many elderly people live alone at their homes. These circumstances also impact on local businesses which are widely related to the agricultural and livestock industry. Taking into account this situation, this paper proposes a solution based on an opportunistic network algorithm which enables the deployment of technological communication solutions for both elderly healthcare and livestock industrial activities in rural areas. This way, two applications are proposed: a presence detection platform for elderly people who live alone and an analytic performance measurement system for livestock. The algorithm is evaluated considering several simulations under multiple conditions, comparing the delivery probability, latency, and overhead outcomes with other well-known opportunistic routing algorithms. As a result, the proposed solution quadruples the delivery probability of Prophet, which presents the best results among the benchmark solutions and greatly reduces the overhead regarding other solutions such as Epidemic or Prophet. This way, the proposed approach provides a reliable mechanism for the data transmission in these scenarios.

1. Introduction

Communication technologies have experienced an exponential spread in the last years. The increasing interest of users on the Internet has unleashed a big competition between Internet Service Providers (ISPs) to provide coverage to as many areas as possible. Furthermore, the lowering prices of broadband access have allowed small businesses and homes to have access to the Internet. Nowadays, the percentage of the population in Spain with access to high-speed Internet connectivity has extraordinarily increased up to values of 81% in 2019 [1]. In Figure 1, the evolution of the percentage of homes with FTTH (Fiber To The Home) coverage in Spain is shown for recent years. These numbers highlight an average increase of 12.98% per year, which is expected to continue growing in the next decade. The constant expansion of technology has promoted the improvement of infrastructures and the rise of connected places. Nevertheless, these encouraging statistics are not the same in all regions. Territories like Madrid, Barcelona, or the Basque Country possess the highest numbers of connected homes. However, regions like Extremadura, Castile and León, or Galicia constitute the lowest rates and the biggest "shadow surfaces" [1]. These districts, where Internet infrastructures are minimal, are normally rural and isolated areas in which network operators are not interested in deploying their solutions due to the low benefits they acquire. These circumstances aggravate the problem. Furthermore, along the technology gap, rural areas face additional challenges like healthcare.

Demography in rural areas is commonly characterized by a significant percentage of people who are over 65. In this manner, rural regions face the challenge of providing

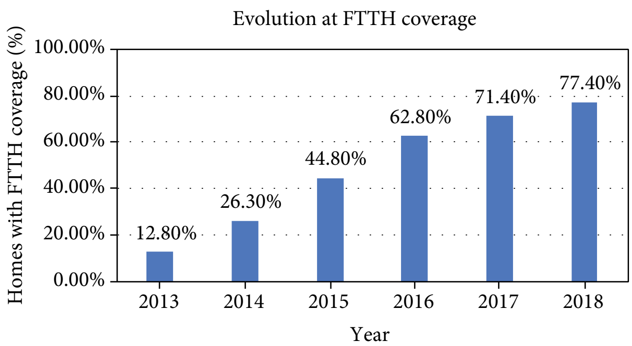

Figure 1: Evolution of FTTH coverage in Spain.

solutions to enhance the lives of elders in this challenging context. Loneliness is one of the main features in elderly people since a meaningful portion of them live alone in their homes. These circumstances can become a severe problem for health, especially in elderly people who are under clinical treatments. As a consequence of the lack of Internet infrastructures, technological solutions to help elderly people in their day-to-day routines cannot be applied, since monitoring systems and telemedicine platforms, which actively depend on the Internet, cannot be deployed. This way, these situations impact on the life of elderly people in rural areas.

On the other hand, technological constraints affect not only the elderly people but the local businesses too. Rural areas are filled with business activities like livestock or agriculture, and they are especially impacted by the conditions of the zone. Technological solutions for industry performance have become disruptive tools in production improvement. These systems provide mechanisms for monitoring and analyzing production processes, being implemented consistently in daily operation. Many of these systems provide a set of tools for production monitoring. In this manner, data processing becomes a relevant feature which requires specific communication infrastructures. In remote rural areas, where there is no Internet access, these procedures cannot be easily deployed.

Taking this context into account, rural areas that lack communication infrastructures face difficult challenges. The specific needs and the technological isolation motivate the spreading of alternative technologies which explore mechanisms for information transmission and system communication. Based on this idea, this paper proposes a DTN-based communication system for healthcare monitorization and livestock data transmission. The proposed platform brings a solution for elderly monitorization without an Internet connection. Thus, presence information about the elderly is transmitted to detect possible dangerous situations derivated from the physical inactivity. As a consequence, mortality rates in elderly people who live alone may decrease, taking into account that emergency detection becomes a crucial factor in healthcare. Moreover, since the platform provides a communication mechanism for isolated areas, local livestock businesses can transmit performance and production data. As a result, the technological gap is addressed while the system provides a healthcare solution for elderly people. The proposed approach exploits the use of SACAR OCVN [2], a routing algorithm based on the cooperation among nodes with different interests. In particular, this algorithm provides the mechanism to forward the information by adapting it depending on the type of data and on the interests of the receiver.

This article proposes the solution structuring the content as follows: firstly, Section 2 consists of a brief study of technological approaches to the communication challenges and rural areas. Section 3 describes our proposal, as well as the system model with the elements composing it. Section 4 shows the experimental results and the algorithm performance, by comparing the obtained results with the outcomes of other well-known opportunistic routing algorithms. Finally, Section 5 draws some conclusions and the next steps in this research line.

2. Related Work

During the last years, the research community has been actively working on solutions for communication in isolated areas. These ideas propose an alternative behaviour regarding the classical network operation, using the close proximity between devices and the movement between places. The most popular network technologies based on this idea are Delay Tolerant Networks (DTN). DTN technology is a communication paradigm based on the physical proximity of devices to reach information transmission [3]. This way, low energy interfaces are used to provide communication and broadcast information between the network components or gateways.

DTN are notably deployed in isolated and concrete areas where the Internet connection is not possible. However, the possibilities of DTN are numerous. Hostile-communication contexts like subaquatic communications, spatial transmission, or intermittent connections are some of these opportunities. Moreover, some communication applications do not require a constant information flow like wildlife tracking [4] or low-priority information traffic [5]. This way, DTN provides a suitable option for the deployment of applications and data exchange. Nevertheless, one of the most relevant applications of DTN is the reaction and deployment in natural disaster scenarios. Since the communication architecture is usually critically damaged, DTN provides a useful solution for simple data transmission. The application of DTN in isolated rural areas has led to multiple works in this field. In the early 2000s, many proposals based on DTN brought the connection to remote areas. Projects like Zhang et al. [6] or Pentland et al. [7] are good examples of technology applied in these isolated areas.

In Zhang et al. [6], the authors propose a communication system based on DTN which allows the population at Swedish Lapland to be connected to the Internet. This project addresses the requirement of providing a solution which adapts to the nomadic living conditions of the inhabitants. Following the same line, Pentland et al. [7] brought a low-cost communication infrastructure to remote areas using wireless communications and public transport mobility. Besides, the article includes the successful results of the deployment in isolated parts of India and Cambodia. Both proposals are mainly oriented to provide inhabitants with communication services like email or access to documents.

As DTN is improving, recent works explore new prospects. Some projects like Berrocal et al. [8] bring new paradigms like the hybrid model conformed by SDN [9] and DTN, using the movement of the cars and intermediate nodes to relay information to gateways. Other ideas like Galán-Jiménez et al. [10] focus on providing Internet coverage to rural and low-income areas based on 5G architectures, using Unmanned Aerial Vehicles (UAVs) in remote zones, and exploring optimal energy consumption [11].

Of course, the purpose of these systems is significantly varied. Technological healthcare is especially relevant in rural areas but is arduous to match with the possibilities of DTN. Usually, the healthcare system requires constant communication and Internet connection, factors which are hard to provide using DTN. However, several projects already proposed eHealth solutions using this network paradigm. Works like Galán-Jiménez et al. [12] proposes the use of the DTN model to monitor patients. This specific scheme provides opportunistic communication between the patient and the doctor, using body sensors and smartphones. Moreover, Galán-Jiménez et al. [13] keeps a similar behaviour but benefiting from intermittent connections. As a result, this architecture brings viable ideas which propose a solution for isolation and healthcare in rural areas.

The work presented in this paper is different from the ones introduced above in the sense that technological healthcare is addressed through the integration of SACAR OCVN [2], an opportunistic routing algorithm based on the interests of the nodes and that it is applied in rural areas to provide health monitoring and communication infrastructure for local businesses. Therefore, the proposed model forwards two kinds of information: health info from the ageing inhabitants and production data from smart livestock. Thus, the solution faces the problem of healthcare monitoring through the presence detection of the elderly at home and provides a mechanism to deal with the technological gap in rural industries. In the next section, the behaviour of our proposed algorithm is explained.

3. OPPNets and Rural Areas

As previously introduced, this work proposes a solution for healthcare monitoring and data transmission in rural isolated areas. The possibilities of DTN enable the deployment of schemes which allow communication in places where the Internet is not available. Therefore, the provided network scheme benefits from vehicular traffic and physical encounters to transmit two kinds of information: presence data from elderly people's homes and sensor records from livestock. These two types of variables are quite relevant in the proposed scenario.

Presence detection in homes of the elderly is critically relevant. A large number of elderly people live alone at home in isolated rural areas, which becomes a severe health issue in the case of an emergency. This way, the detection of a dangerous situation becomes arduous without human supervision. Nevertheless, there are some relevant clues for possible health risks like interaction within the home environment. Taking this into account, the proposed scheme is based on obtaining data from sensors distributed around the house. These devices provide information about actions like door opening or lights operation. Hence, this presence information is transmitted through the network.

On the other hand, the gateways receive additional information: livestock analytic reports. The usual isolation of many areas of agricultural exploitation and many livestock farms becomes a significant technological gap compared with those businesses which can access the Internet. These industry holdings are especially suitable for the deployment of sensors and production analytics. Nevertheless, the lack of communication infrastructures affects these technological approaches. Thus, using the communication capability of the proposed network, reports from sensors are transmitted into the platform to end gateways.

The network behaviour follows the scheme provided in Figure 2, which identifies several components: (i) sender nodes, (ii) intermediate nodes, and (iii) gateways.

(i) Sender nodes refer to the homes of the elderly people and the smart livestock. These elements generate and transmit new information toward gateway nodes which are connected to the Internet. Thus, the messages are sent into the network in specified intervals of time. This way, the nodes send the messages to reachable intermediate nodes, which serve as data mules

(ii) Intermediate nodes are in charge of forwarding messages to the gateway. Therefore, cars and pedestrians receive, carry, and deliver the information as they move through the streets and roads. These nodes decide the information which they prefer to obtain and broadcast: presence info or livestock performance data. Additionally, there is another fundamental element in the scenario: *throwboxes*. These devices are placed on the main points of the road path and can store messages from any other intermediate node. Thus, throwboxes work as a "meeting point" for data and distribute it to other interested reachable nodes

(iii) Gateways are the destination elements of the messages generated by the sender nodes. They are connected to the Internet and are in charge of processing and transmitting information to the Cloud. As a result, the collected data can be externally processed, enabling the detection of anomalous patterns in the elderly activity and recognizing a possibly dangerous situation. In the same way, the performance information about livestock can be processed when it is finally delivered

The opportunistic behaviour of the network is mainly based on the routing algorithm we propose to perform distributed communication among the aforementioned elements. In this paper, the idea behind the SACAR OCVN algorithm defined in [2] is applied to the rural scenario in

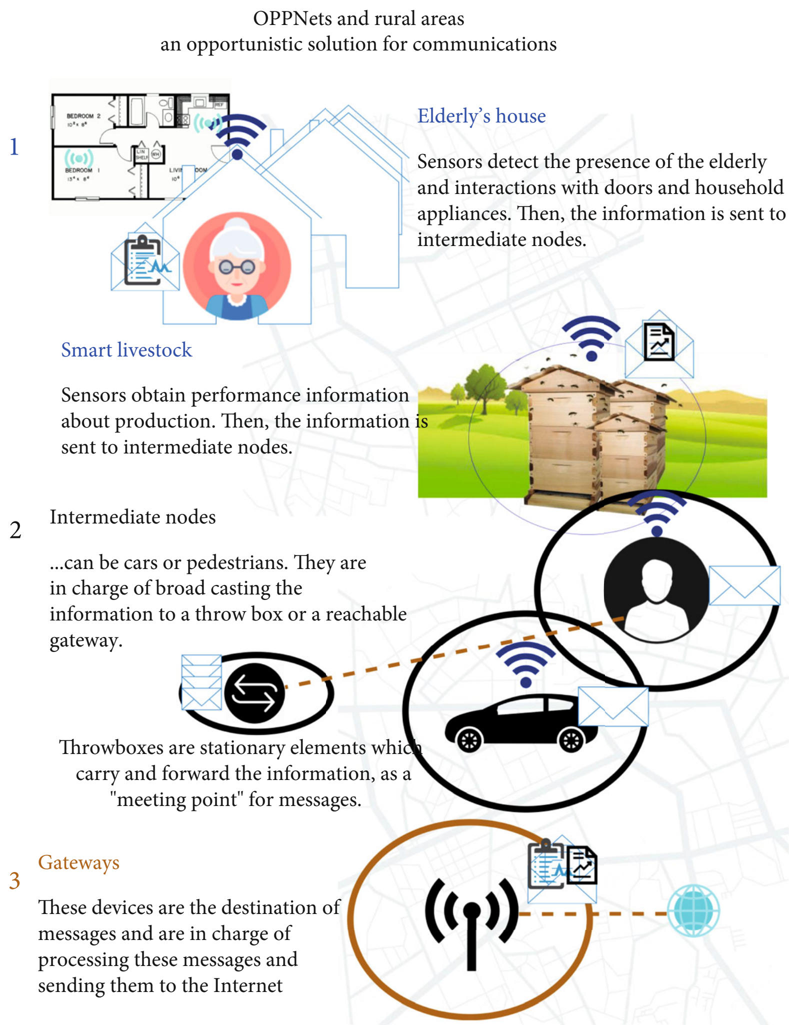

Figure 2: Working scheme of OPPNets in rural areas.

order to relay on cooperating nodes to successfully deliver the information from elders and livestock. The behaviour of the nodes in the scenario is based on the preferences of the nodes, following the Situational-Context model [14]. This paradigm proposes an automatic communication scheme for devices, using a virtual profile which defines the node's capabilities and preferences.

SACAR OCVN [2] applies the Situational-Context scheme as a means to automatise the nodes' encounter process. Thus, the nodes in the scenario have a virtual profile which identifies them as sender nodes, intermediate nodes, or gateways. The different roles available on the virtual profile are Goals and Skills: the first one defines the information preferences, while the Skills indicate the actions the node is able to perform. This model, once it is adapted to the scenario, is used to distinguish between sender elements (represented in Figure 3), carrying nodes (depicted in Figure 4), and end gateways (Figure 5).

The communication takes place when two nodes encounter each other. This way, by using low-energy technologies, the information is exchanged within the corresponding range. Thus, the communication process follows three main steps: (1) devices encounter each other, (2) virtual profiles are gathered, and (3) information is exchanged. All these steps are shown in Figure 6. The proposed scenario raises an opportunistic context where communication provides an improvement in the day-to-day routines of local inhabitants. The idea has been executed as a simulation which has tested the algorithm under different situations, trying to define the most appropriate context for interactions. The next section details the simulation process and the parameters that have been tuned.

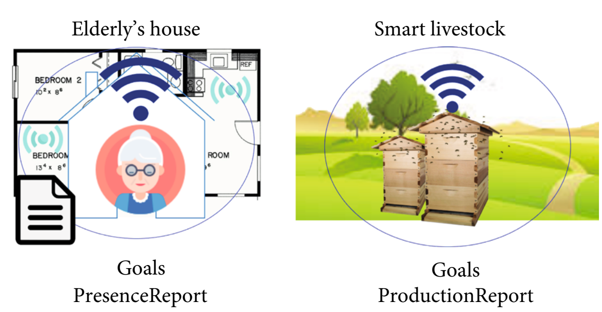

Figure 3: Virtual profile of sender nodes.

FIGURE 4: Virtual profile of intermediate nodes.

FIGURE 5: Virtual profile of gateway nodes.

4. Experimental Results

The result section is organized as follows: firstly, the selected scenario is described. Then, the results are analyzed focusing on two aspects: (i) performance analysis of SACAR OCVN algorithm on the scenario and (ii) comparison with other relevant opportunistic routing solutions.

4.1. Simulated Scenario. Simulations have been carried out using The ONE simulator [15]. This tool provides a development environment for DTNs, allowing the specification of a detailed scenario, movements, and protocols. Thus, the performance of the routing algorithm can be obtained through execution reports. In this work, the simulated scenario recreates a rural area with low connectivity, which reflects a village community and the surrounding roads. Figure 7 represents the simulation map.

The simulation process follows an execution scheme which varies the context inputs and node behaviour. Table 1 summarizes the input configuration. The number of total nodes is $N = 146$, where $N_s = 3$ is the number of destination nodes, $N_i = 66$ is the number of intermediate nodes, and $N_g = 80$ are referred to sender nodes. Destination locations have been established far away from the rural village in order to analyze the effectiveness of the communication. Intermediate nodes are distributed along paths in an area of $A = 81000\,\text{m}^2$ with different movements patterns, P, which specify how the nodes move. The type of interest settings is composed of the Skill set, S, and the Goal set, G. The first group keeps the capabilities of the nodes, in this case, store-and-carry presence information or performance data. Also, the Skill of transmitting messages to the Internet is possible. On the other hand, the Goal set defines, in this case, the kind of information the node generates. The maximum number of Goals in the nodes is $g_n = 2$ and $s_n = 2$ in the case of Skills. Simulation duration is set to $T = 28000\,\text{s}$.

Message generation interval, ω, is in charge of establishing the waiting time before the sender nodes generate new information. It is a key parameter in the simulations since the number of created messages depends actively on it. In this scenario, three times are considered: $\omega = \{900, 1800, 3600\}$s. These intervals adapt the message generation to real values since presence data requires a fluent transmission. In the next section, simulation results are analysed, as well as compared with other well-known opportunistic routing algorithms under different contexts.

4.2. Parameter Setting. Four main outcomes are analyzed after running the simulations: (1) delivery probability (d_{prob}), (2) overhead ratio (θ), (3) average latency (τ), and (4) average number of hops (γ):

(i) d_{prob} is the percentage of messages which reached the destination node. This way, it is a critical value which reflects the success of communication and forwarding. This value is calculated as the relation between the number of messages originally sent, d_{sent}, and the number of messages received at destinations, d_{received}

(ii) θ is the relation between duplicated messages and received messages. It reflects the use of the network

(iii) τ reflects the average time needed to receive a message once it is sent

(iv) γ represents the average number of intermediate nodes needed to reach the destination

These results are obtained when the simulation process is finished. This way, the scenario receives two main inputs which vary the final results. These two variables are interval message generation (ω) and interest distribution at intermediate nodes.

(1) Interval message generation, ω, specifies the waiting time before new messages are created. Thus, it defines a variable which plays an important role in simulation. The considered times are 900, 1800, and 3600 seconds

(2) Since SACAR OCVN is based on node interests, three different distributions of interests are considered: (i) the percentage of nodes only interested in carrying elderly presence information (I_{elderly}), (ii) nodes only interested in carrying industrial production information (e.g., from livestock) (I_{industry}), and (iii) nodes interested in carrying both types of information (I_{hybrid}). Moreover, there are also nodes which are not interested in carrying any type of information (I_{empty}). Table 2 shows the selected values for the three considered scenarios

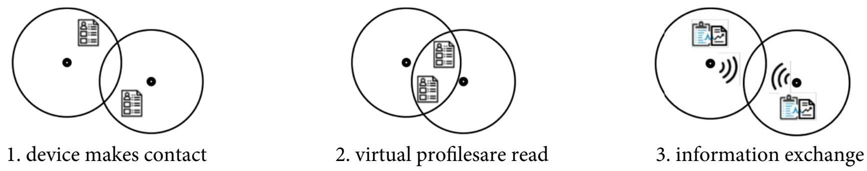

Figure 6: Detailed communication process.

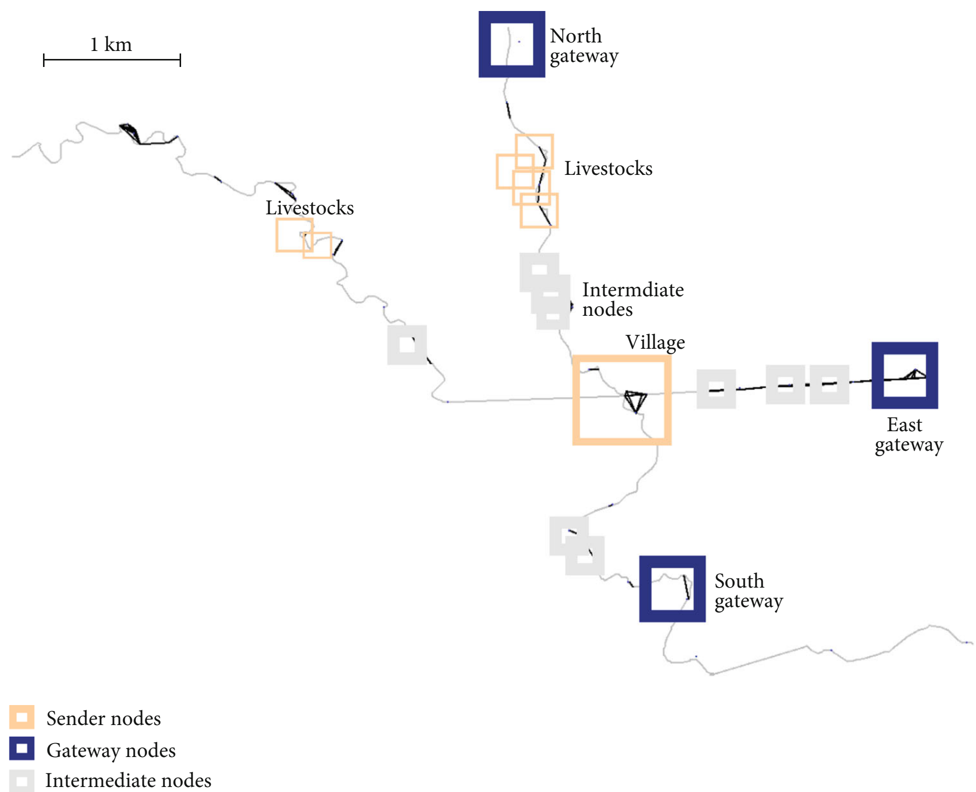

Figure 7: Rural scenario simulated in The ONE.

Table 1: Parameter setting for the rural scenario.

Parameter	Value
A	81000 [m^2]
N	146
N_s	3
N_i	66
N_g	80
S	{SendPresenceInfo, SendproductionInfo, StoragePresenceInfo, StorageProductionInfo}
G	{PresenceReport, ProductionReport}
s_n	2
g_n	2
P	{StationaryMovement for N_s, StationaryMovement for N_g, MapRouteMovement for N_i with stationary time
P	periods in the range of $t = [300,500]$ s.}
T	28000 [s]
ω	{900,1800,3600} [s]

Table 2: Percentage of nodes contemplated for scenario simulations.

Scenario	I_{elderly} (%)	I_{industry} (%)	I_{hybrid} (%)	I_{empty} (%)
Elderly interest scenario	50	20	20	10
Factory interest scenario	20	50	20	10
Hybrid interest scenario	35	35	20	10

5. SACAR OCVN Performance Analysis

The proposed algorithm is executed on each scenario distribution, varying the message generation interval, ω. As Figure 8 reflects, the delivery probability (d_{prob}) obtained by SACAR OCVN is very relevant. Since it is a critical value which captures the success at message transmission, a high percentage is needed. This way, the algorithm experiences the lowest rates when the message generation interval is low. On the other hand, the best results are obtained when

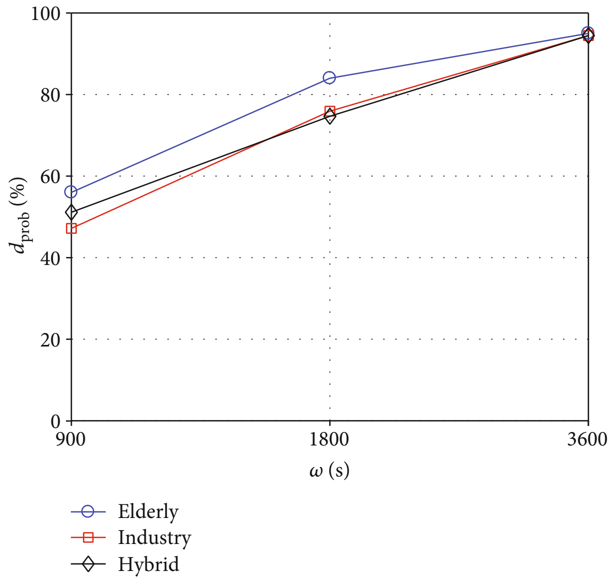

FIGURE 8: Delivery probability in SACAR OCVN.

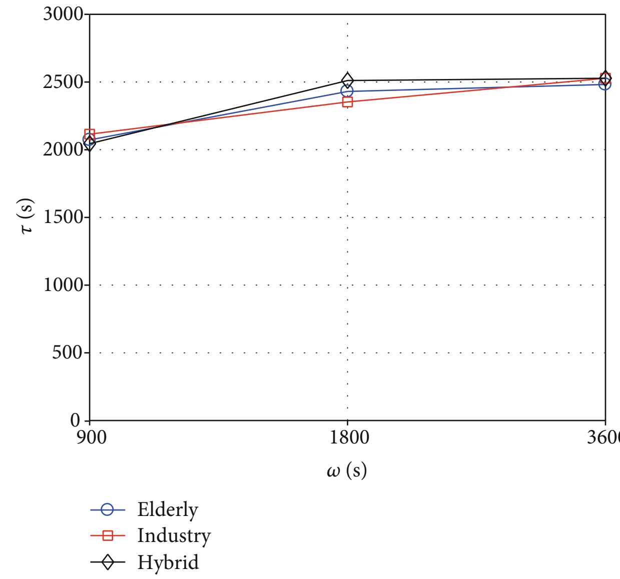

FIGURE 10: Average latency in SACAR OCVN.

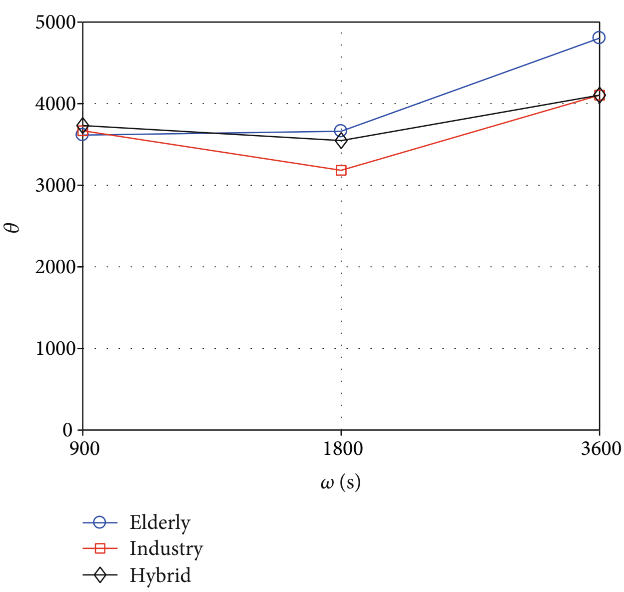

FIGURE 9: Overhead ratio in SACAR OCVN.

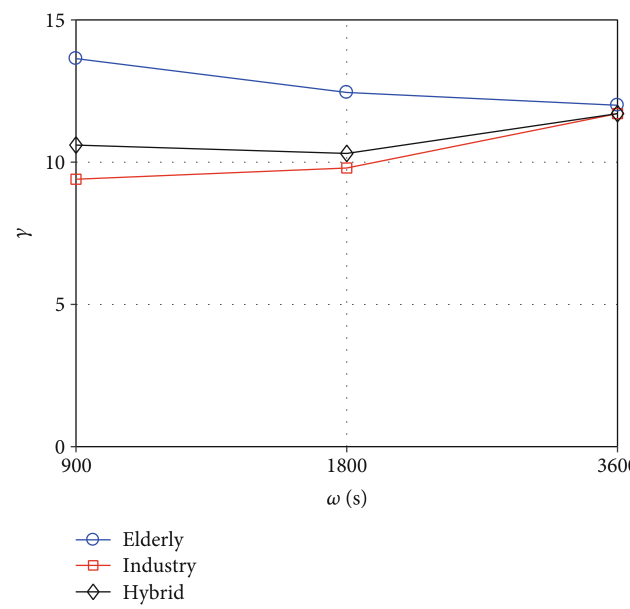

FIGURE 11: Average hops in SACAR OCVN.

the value is increased, reaching $d_{prob} = 0.945$ when $\omega = 3600$ s . This is essentially due to low interval values which involve a larger number of messages to be transmitted.

The overhead ratio results are included in Figure 9. This value is a suitable parameter to know the practical usage of the bandwidth in the network. SACAR OCVN experiences an overhead increase when the predominant interest is the information from elderly people. On the other hand, when industry interest is predominant, the value of θ decreases. As a result, the algorithm experiences an average result when the scenario is mixed.

Since the transmitted information is elderly-care related, the average latency (τ) is critical to minimize the needed time to reach the destination. As Figure 10 shows, SACAR OCVN presents very similar results in each scenario with an average latency of around $\tau = 2500$ s.

Finally, the average number of hops, γ, is the median number of intermediate nodes needed by the messages to reach the destination. The latency value is usually related to the hop rate since the encounters and information transmission at hops improve possibilities of delivery. This way, as Figure 11 shows, SACAR OCVN average hop outcomes follow an inversely proportional trend w.r.t. latency values.

As a conclusion, SACAR OCVN results are positive. The delivery probability in $\omega = 3600$ s is $d_{prob} = 0.945$, guaranteeing a high rate at message broadcasting. Besides, the message generation interval which provides a better performance is $\omega = 3600$ s. This successful result means that the algorithm provides a good communication mechanism for the exposed scenario. As a consequence, the data of presence from the elderly's homes is fluently transmitted through the network. Thus, the system allows the remote detection of possible dangerous situations, derivated from the inactivity of the elderly. Besides, the local industries can transmit performance data from the exploitation.

Once SACAR OCVN best results are obtained, they are compared under the same context conditions with the rest of the DTN algorithms included in The ONE. Furthermore, this second stage of result analysis is addressed.

6. Comparison with Other Opportunistic Routing Solutions

SACAR OCVN experiences better results when the message generation interval is $\omega = 3600$ s. This way, using the same scenario conditions, in this section, we compare these values with the ones obtained when running other well-known opportunistic routing algorithms in The ONE. Note that the analysis uses the same set of parameters described in the previous section. Next, benchmark algorithms are briefly described. DirectDeliveryRouter [16] works based on straight delivery between the sender and the receiver node. Thus, intermediate elements are ignored. EpidemicRouter [17], on the other hand, belongs to the flood algorithm family. Thus, the behaviour is based on duplicating the messages with every encountered node. MaxPropRouter [18] uses the previous node encounters to define the most appropriate path to the destination. ProphetRouter [19] works based on a probabilistic scheme while SprayAndWaitRouter [20] replies to messages by creating copies which can be specified by the user.

The executions take place with $\omega = 3600$ s for the different interest distributions over the same scenario described in Figure 7. Delivery probability is the most significant parameter in performance comparison. As Figure 12 shows, the best delivery probability is $d_{\text{prob}} = 0.95$ and belongs to the SACAR OCVN execution. The other algorithms provide a low delivery rate in the three scenarios.

Overhead ratio results are reflected in Figure 13. DirectDeliveryRouter is based on communicating sender nodes and destination, without using intermediate elements. Thus, message traffic is low. Besides, the lowest values belong to SprayAndWaitRouter, which provides the communication process with better use of the bandwidth than EpidemicRouter and ProphetRouter. SACAR OCVN, in turn, keeps close values to SprayAndWait.

Figure 14 shows the average latency in executions. SACAR OCVN is the algorithm which has the highest latency value, mainly because of the largely supported message traffic, as well as the low hop rates. On the other hand, EpidemicRouter and ProphetRouter keep the results below these numbers. Besides, SprayAndWaitRouter provides the lowest rate.

The average number of hops in each of the algorithms is presented in Figure 15. DirectDeliveryRouter bases its behaviour on senders delivering messages straight to the destination; thus, it is always one hop. On the other hand, SACAR OCVN keeps an average hop number quite low regarding EpidemicRouter and ProphetRouter results, which represent the highest in the hybrid interest scenario. Again, SprayAndWaitRouter provides a good performance and draws on few hops to reach the destination.

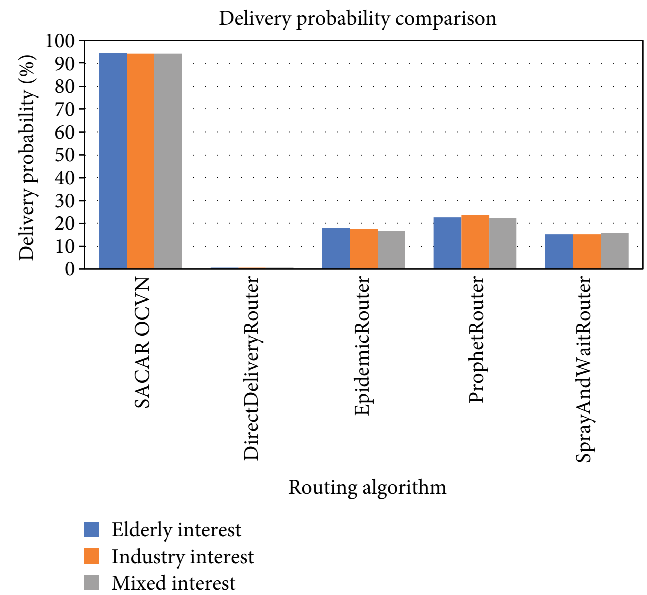

Figure 12: Delivery probability comparison.

The comparison process clearly shows the performance of SACAR OCVN compared with the opportunistic routing algorithms included in The ONE. The high delivery probability value guarantees the applicability of the solution in the described scenario, becoming a powerful tool in the implementation of the project. It is important to remark that SprayAndWaitRouter keeps good results at θ, τ, and γ, but d_{prob} is too low to provide a reliable communication. The possibilities of the router are relevant and follow a promising work line.

7. Discussion

Rural areas represent a big percentage of the population over 65. Only in Spain, around 30% of inhabitants in small villages are older adults. These demographic conditions become a challenge for health, since issues like personal assistance, solitude, and isolation play a big role in the daily routines of seniors. Technology has become a very significant ally for healthcare, providing mechanisms and tools such as eHealth, remote monitoring, and smart systems which ease communication and quick emergency detection. However, many of these rural spaces lack Internet connection, where no infrastructures to deploy eHealth solutions can be exploited.

In this paper, a response to this context is provided. Making use of alternative communication mechanisms like opportunistic networks, a reliable system for remote areas is introduced. Thus, the proposal supplies villages with an architecture for message transmission which allows the detection of possible emergencies of seniors who live alone

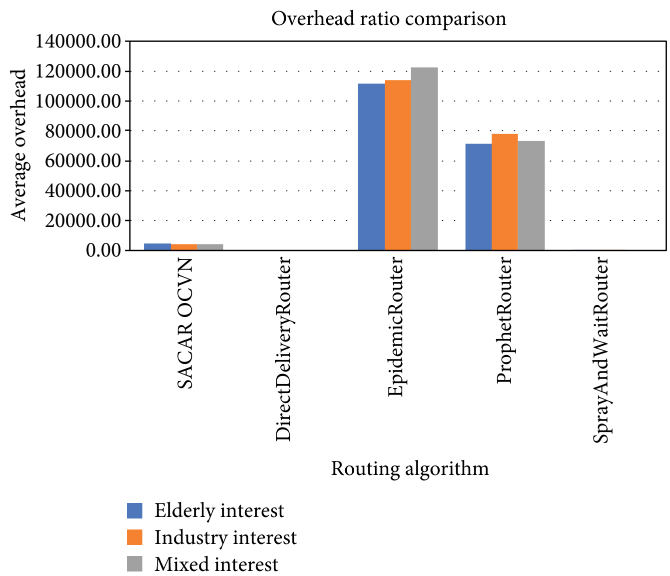

FIGURE 13: Overhead ratio comparison.

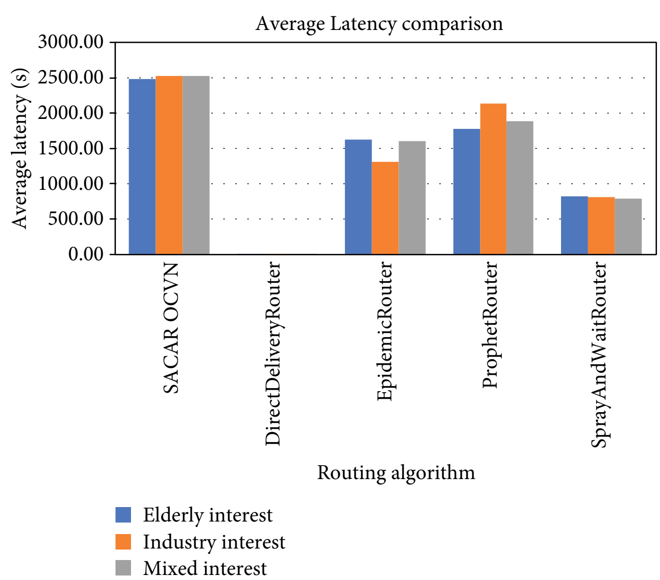

FIGURE 14: Average latency comparison.

while local exploitations are also able to transmit performance reports.

On the one hand, information about the presence habits of seniors who live alone is transmitted. This way, several sensors are installed along the houses, recording the presence of the elderly and sending such information toward the opportunistic network. The possibility of determining the presence patterns of elderly people allows the detection of potentially risky situations that can happen in the solitude of the home. As a result, mortality risks in the elderly who live alone are reduced by exploiting the detection of anomalous behaviour.

On the other hand, the local exploitations in isolated rural areas face the challenge of the lack of Internet infrastructure. The technological gap reduces the competitive advantages compared to the connected industries, and therefore, their maximum performance capabilities cannot be reached. In order to tackle this problem, the proposed solution exploits the use of sensors at the exploitation place like livestocks or hives, playing roles like weight measurement, animal tracking, or food consumption.

The data collected by sensors is broadcasted toward the destination making use of BLE technology and intermediate nodes. These nodes, which serve as mules, can be different types of devices like cars, smartphones, smartwatches, or throwboxes. These lasts are devices installed on the roads, fed by solar panels, which store and forward the information to the devices in their range.

As a result, the proposed solution in this paper is aimed at improving the quality of life in remote areas.

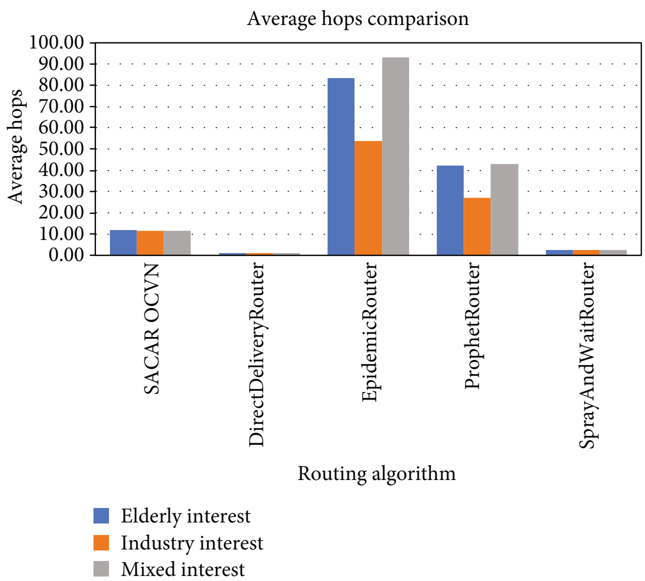

Figure 15: Average hops comparison.

Communication possibilities in these scenarios go further and provide an eHealth architecture for eldercare and local business improvement. In this way, the opportunities of deploying a prototype in a real isolated zone could bring a brand new autonomous model for well-being, alliance, and cooperation.

8. Conclusions and Future Works

Many isolated rural areas do not have an Internet connection. These limitations are often induced by the remote situation and the geographical issues, as well as the lack of interest from telecommunication companies. Thus, inhabitants cannot keep connected in a world where the Internet expansion is exponentially growing. Furthermore, the population in rural areas is usually over 65 years old. Thus, isolated regions face the difficult challenge of providing services and health attention, especially when these elderly people live alone. However, this context can be improved by using technological solutions. Digital elder healthcare is an active work line where many researchers and companies are working on. Nevertheless, the lack of an Internet infrastructure prevents the deployment of many of these solutions. Moreover, the technological gap also affects the local industry and livestock, which are not generally able to implement solutions to monitor and improve performance.

In order to face these challenges, DTN solutions become a suitable technology to provide connectivity in remote places. This paper proposes a DTN routing algorithm based on information interests which transfer elderly presence information and industry performance data to gateway points.

Our proposed algorithm has been simulated on a realistic isolated region of Spain. The obtained results are positive and guarantee a high rate of successful message delivery under different conditions. Furthermore, the outcomes of our proposed algorithm are also compared with other well-known opportunistic routing solutions, outperforming them. Therefore, the proposed scheme brings a solution to the technological gap in isolated rural areas, enabling the monitoring of elders' activity and providing a reliable communication system to improve the performance of livestock industries.

The authors are working on providing the proposed algorithm with a smart behaviour through a machine learning model. Moreover, trajectory prediction in nodes' movement presents other key aspects to be explored.

Data Availability

Data are available on request. Research results are available on request. Thus, in order to be provided with the data report, please, write to Manuel Jesús-Azabal (manuel@unex.es).

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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Research Article

Digital Avatars: Promoting Independent Living for Older Adults

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Population ageing, together with the desire to maintain an autonomous lifestyle, poses today's societies with a challenge that technological advances can help considerably to cope with. The widespread use of smartphones and their increasing computing power and storage capacity make them the ideal tool to achieve this goal. In this paper, we present Digital Avatars, a software framework adapted to the needs of older adults who wish to preserve their lifestyle, but who require assistance through technology. Building on previous work on the *People as a Service* model, *Digital Avatars* takes advantage of a smartphone's capabilities and services to collect information about the people who own them. To do this, it applies Complex Event Processing techniques extended with uncertainty to infer the habits, preferences, and needs of the device owner to build with them an enhanced virtual profile of the user. These virtual profiles are the mechanism for monitoring the quality of life of older adults: analyzing their patterns of activity, reminding them of medication schedules, or detecting risky situations that generate alerts to relatives, caregivers, or the community health system.

1. Introduction

According to the World Health Organization [1], from 2000 to 2016, life expectancy has increased by 5 years (72.5 to 77.5) in Europe and by 5.5 years (66.5 to 72.0) globally. This progressive growth in life expectancy entails an increase in population ageing. The health of this segment of older adults needs continuous supervision and care: regular medical examinations and tests, specific pharmacology, and other therapies. Our ageing societies pose challenges to their public health systems, especially with respect to older adults living in relatively isolated and sparsely populated areas.

Gerontechnology [2] is a multidisciplinary field that brings together gerontology and technology to create technological environments for an inclusive, innovative, and independent life of older adults, improving their social participation. It focuses on the adaptation of technological environments to the health, housing, mobility, communication, leisure, and work of older people [3].

The aim of this work is to promote the well-being and quality of life of older adults by making intensive use of the capabilities offered by smartphones in terms of storage, computation, and sensors. Present day smartphones are able to run demanding applications, such as video games; manage all our social profiles; and work with office applications that required desktop computers not so long ago. This way, smartphones have become the most popular device for accessing computing resources and services.

Our proposal takes advantage of the capabilities currently offered by smartphones [4] to develop a framework based on the *People as a Service* (PeaaS) model [5] extended with Complex Event Processing (CEP) [6] for collecting and processing data.

PeaaS provides a conceptual framework for application development focused on the smartphone as a representative and interface to its owner. By analyzing the data received from the different smartphones' sensors, together with those from personal health devices, we are able to infer the state, preferences, and routines of behavior of their owner and build with them her virtual profile. This information can then be offered to third parties to generate value-added services or to interact with the IoT environment in an automated way.

All the information is stored locally in the smartphone, guaranteeing that its owner keeps full control over which data is being shared and with whom.

In our proposal, we extend the virtual profiles of the PeaaS model with behavioral rules that govern their inference, evolution, and use. This combination of rules and data related to a particular user and her environment is what we call her digital avatar.

For building the digital avatar, we apply CEP techniques [7] in order to process the information obtained from the smartphone and make complex decisions based on the perceived data. The processing of events takes place on the user's own device, without sending personal data to any external server for data processing purposes. This avoids the need of continuous online communication and also reduces the amount of data transmitted over the Internet. It allows us to generate better and more appropriate responses to problems or adverse circumstances that may arise in the daily life of older people, increasing their safety and welfare by taking advantage of the interactivity and computing capabilities of their smartphones.

In this paper, we introduce our proposal for applying Digital Avatars to promote independent living for older adults, specially those inhabiting rural and low population areas. After this introduction, we present a motivating example for illustrating our proposal (Section 2), and we give an extensive description of the framework (Section 3), presenting its architecture, the digital avatar profiles, how we obtain and treat the necessary data, and how data uncertainty is addressed in our proposal. Some related works are presented in Section 4, while Section 5 discusses both the benefits and the risk of the approach. Finally, Section 6 concludes the paper.

This work is an extension of [8], presented at the Second International Workshop on Gerontechnology (http://4ie.spilab.es/workshop2019/). In this extended version, we present in more depth our proposal, providing many technical details about it. In particular, in Section 3.2, we describe the structure of the digital avatars containing the virtual profiles of the users, while Section 3.3 explains how the avatar in the smartphone interacts with IoT and personal healthcare devices for collecting information from them. Moreover, Section 3.4 presents the integration of CEP into smartphones and shows how to handle uncertainty in the data being processed.

2. Motivation: Older People in Rural Areas

In order to illustrate the application of Digital Avatars to promote independent living, in this section, we present a motivating scenario of an older person living in a relatively isolated rural environment.

María is an older person living in a small village in a rural and almost deserted area. After her husband died, and with her children living away, María started feeling lonely and considered moving to a nursing home. However, she finally decided to stay in her lifelong house while she was able to help herself properly. After all, she is fully autonomous and only needs her blood pressure and sugar levels to be checked regularly, as she now suffers from diabetes.

In order to avoid recurrent and cumbersome trips to the primary healthcare center, which is located in another town, the community health services have provided María with some smart gadgets that can be connected to the smartphone she uses for talking with her children and for texting with her grandson. A glucose meter and a blood pressure monitor send their data by Bluetooth Low Energy (BLE) to her phone. These measurements are recorded there, together with relevant information about her daily activities, such as patterns of movement inside her house and within the village, and usage of the smartphone itself (phone calls, execution of apps, etc.) Bluetooth is also employed to detect proximity to other smartphones, particularly to those of her contacts, which enables detecting patterns of visits and social relations between María and her neighbors.

This way, both the community healthcare center and María's children are aware of her health condition, well-being, and even her mood. For example, abnormal sugar levels in her blood or the fact that she is not visiting her neighbor one afternoon, as she always does on Tuesdays, can be easily detected. In case that something seems to be wrong, the smartphone would request from her some interaction to check whether everything is ok, or it will raise an alert to the appropriate contact person or to emergency services.

In this scenario, the smartphone plays a central role in capturing, processing, and storing information about its owner. For that purpose, it monitors the phone's sensors and also devices in María's environment: movements detected by the phone accelerometer, GPS readings, use of mobile applications, and BLE signals from IOT health devices. The rules for processing all this information and detecting that any significant event has likely occurred are also stored in the phone and are handled by María's digital avatar. Note the importance of dealing with confidence levels (i.e., aleatory uncertainty) when making decisions, given that all detected data is subject to deviations and potential measurement errors (e.g., a sensor may not function properly for a short period of time), as well as María's variations in her regular habits due to environmental conditions (e.g., bad weather) or unexpected situations (e.g. a surprise visit from a relative) that may cause changes in her daily habits but do not represent a challenge to her health.

3. Framework Description

This section describes our proposal to apply Digital Avatars as a means of promoting independent living for older people. In particular, we discuss the functionality of the system, describe the framework architecture, and explain how a CEP engine is used to generate, store, and process virtual profiles of the users on their smartphones.

3.1. Architecture. Digital Avatars builds on previous work on the Internet of People [9] and PeaaS [5] models. In particular, the Digital Avatars framework is a realisation and extension of the PeaaS model, where the role of the inference engine is performed by a CEP engine, as it will be explained below.

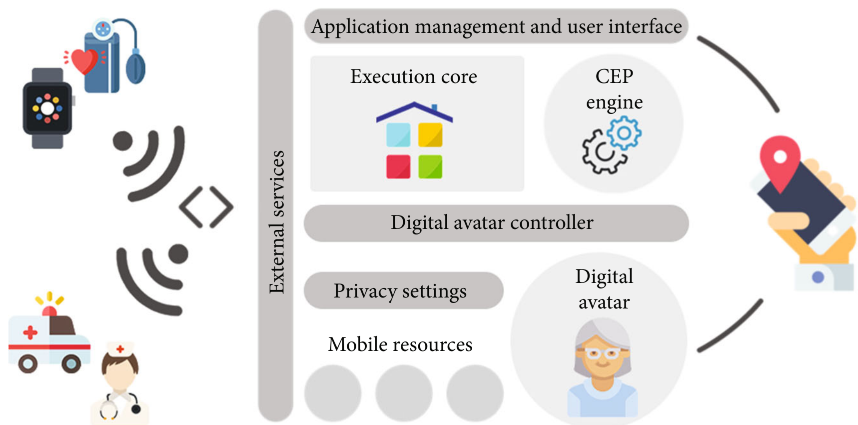

Figure 1: The Digital Avatars architecture.

Not only is the engine responsible for building the profile and for aggregating and summarizing the information in it, but it is also capable of performing more complex and general tasks by means of CEP rules which endow PeaaS virtual profiles with “behavior,” allowing broader applications of the model, including the description of interactions among human users and/or IoT devices.

The Digital Avatars architecture is deployed at the application level due to the restrictions of the Android operating system. Thus, all the modules of the architecture rely on OS calls to access any particular functionality or resource of the smartphone. The architecture is illustrated in Figure 1. It represents the set of software elements required to build, populate, and share in a controlled way the user’s information stored in the smartphone.

The digital avatar is the core element of the architecture. It consists of the user virtual profile and the privacy settings, which define the permissions to access that information. Virtual profiles are represented by JSON documents, stored in the phone with Couchbase Lite, which offers NoSQL database storage for smartphones. The profile keeps both historic records of events of interest, chronologically ordered, and higher-level profile information with meaningful knowledge about the user. In our case, this information is mainly related to health: blood pressure, glucose level, and other health indicators, activity and rest time, and even the places the user has visited or the people with whom she has interacted. The structure of the virtual profile of the digital avatar is presented in Section 3.2.

The digital avatar is built by an inference CEP engine capable of processing the raw data collected by the built-in sensors in the smartphone and through other smart devices connected to it. The CEP engine extracts meaningful information from the raw data coming from all these sources by applying a set of rules and patterns. One of the main advantages of CEP is that it works in real time, reducing latency in the decision-making process. Hence, it is very appropriate for asynchronous and real-time systems which must react quickly to changing or unusual situations. The use of CEP in our framework and how it deals with uncertainly are explained in Section 3.4.

The engine performs two main tasks: detection of alarm conditions and inference of higher-level knowledge. From the first task, we are able to detect particular situations and to derive some actions or changes in the system. For example, if the user suffers from an early stage of cognitive impairment and the smartphone detects that he has gotten lost, it will immediately alert a caregiver [10]. The inference task consists on the analysis of the information stored in the avatar for deriving added-value facts. For instance, based on the user’s daily activities and/or the places frequently visited, it is possible to predict where the user might be at a given time [11]. This high level contextual information of the user is stored back in the digital avatar.

The digital avatar is offered as a service, allowing both applications installed in the phone and external third parties to access it. Privacy concerns are addressed by the Privacy Settings, which define the access privileges to the user’s information. The Privacy Settings are a set of access policies for the digital avatar. The digital avatar is structured in sections or entities, and these policies allow to define the rules for granting read and write permissions for each section and third-party agent. For that, we have defined three privacy levels. The Private level lets no one but the user access that information. The Public level gives access to any certified agent. Finally, the Trusted level allows the user to specify a list of agents who will be able to fetch or update a particular section in the digital avatar.

The Digital Avatar Controller API provides the operations to deal with the information in the profile and making system calls. It prevents unauthorized access to the virtual profile and gives a unique and easy-to-use point of interaction with it. The API takes into account the Privacy Settings to allow or deny access to third-party applications. For instance, health professionals would be able to access only those parts of the profile concerning health issues, but not other private data.

The Mobile Device Resource layer is the element of the architecture that handles access to the sensors available in the smartphone. In addition, wearables and other devices connected to the smartphone are accessed through the External Service module. This module gives support to the interactions of the smartphone with external sources of information, like home-assisting devices or public web services offering contextual information like weather conditions, public transport, air quality, etc. Furthermore, this module manages the communications with third parties when a critical event is detected by the inference engine. For example, if a dangerous high blood pressure episode is detected, it will send an alarm to emergency services. Data collection and interaction with third-party smart devices is presented in Section 3.3.

Finally, the Execution Core module is where the front-end application is running. It is here where third-party applications run and make use of the CEP engine and the digital avatar through the Digital Avatar Controller. These applications offer specialized services to the user, for instance, adding new domain-specific information to the avatar.

All the components of the architecture reside in the smartphone. Third parties are able to access the digital avatar from the outside, provided they have the corresponding permissions, following the GDPR recommendations. The traditional client/server approach breaks down into a decentralized architecture in which each smartphone node acts as a server of its own produced data.

3.2. The Digital Avatar. The digital avatar is continuously evolving and growing from each interaction with the user, the sensors in the smartphone, and external IoT devices. Hence, it must be stored in an open and scalable format which permits to extend the syntax and includes mechanisms for considering privacy settings. We have designed a common ontology and notation based in YAML to create a standard and controlled environment. This notation is parsed from the JSON documents that compose the virtual profile database, providing a more readable and clearer representation of the data.

In order to enable developers to create applications compliant with the Digital Avatars framework, we provide a standard and easy-to-use structure for the digital avatar. This structure is based on an entity-driven metamodel. Entities are the basic information container, and they can be nested. The metamodel is designed to give a great level of freedom that allows the model to scale through the nesting of entities. We have defined five attributes present in every avatar entity. These attributes constitute keywords which represent the *Name* of the entity, its *Type*, its reading and writing *Privacy levels*, its *Value*, and a *Timestamp* indicating the last time the entity was updated. The *Value* of an entity may store either a simple value or a nested entity. According to this, the *Type* of the entity may be either the *Entity* or a basic data type. Additionally, the type *Sensor* allows storing information on the sensors in the smartphone.

Our YAML-based notation implements an indentation-structured language but with three parameters per line. As the *Timestamp* and the *Type* of the entity are already implicit in the implementation, we omit them. The *Privacy levels* are expressed by the third parameter of the representation using reserved words and symbols. We use *Public* and *Private* meaning that anybody or no one has a particular permission, respectively, and the symbols "?" and "!" express read and write permissions, respectively. If the privacy level is omitted, we assume that it is inherited from the parent entity.

```
– Personal: ?!private
    – Me:
        – Name: "Maria Zambrano": ?public
        – Phone: 555–2368: ?Family, ?Friends
        – Location: ?Family, ?Friends
            – Latitude: 36.718967
            – Longitude: –4.4337306
        – Birth: 20/07/1939
        – Certificate: "F0:89:B1:..": ?public

    – Health: ?!Doctors
        – Sleep: "0 7:32:16": ?Doctors, ?Family
        – Steps: 2315: ?Doctors, ?Family, ?Friends
        – Glucose: 183:
        – BloodPressure:
            – High: 132
            – Low: 74
        – HeartRate: 81
```

Code 1: Excerpt of a digital avatar showing some personal data.

Aside from the YAML notation, we have defined an ontology of entities for Digital Avatars. The ontology is a common standard structure based on root entities or sections inside which we organize the information of the digital avatar. These sections provide default spaces for information storage and offer a mechanism for secure and correct functioning of the framework. Each section implements a certain privacy level which is extended to all the information stored in it, guaranteeing that every piece of information in the digital avatar is protected.

We have defined a number of default and commonly used sections: *Personal*, *Relations*, *Places*, and *External*. The *Personal* section contains personal, health, and contact information about the user and about the smartphone itself, e.g., the sensors available in it, manufacturer, and precision. *Relations* is a collection or agenda containing information of each trusted interactor for the user. It may contain family member data, doctors, or even privacy groups with a valid certificate for an external application. The user can specify privacy groups like family or doctors for grant-specific permissions for sharing certain data. The *Place* section stores frequently visited places for the user along their daily routines. Last, the *External* section is used by the interactors or installed applications to store their data. A common structure is given to more quickly identify the sensors to which the interactor has permission to pool and for specific data storage rights. For example, an application can have access to the pulsometer and the step counter to monitor María's physical activity and exercising patterns.

Code 1 shows an excerpt of María's virtual profile, in particular, the *Me* and *Health* entities within her *Personal* section. As we can see, though the default privacy level for all *Personal* data is *Private*, some entities like *Location* or *Steps* declare *Trusted* privacy for reading purposes. This is done by enumerating the agents or privacy groups that have this permission and putting the reserved symbol "?" in front of

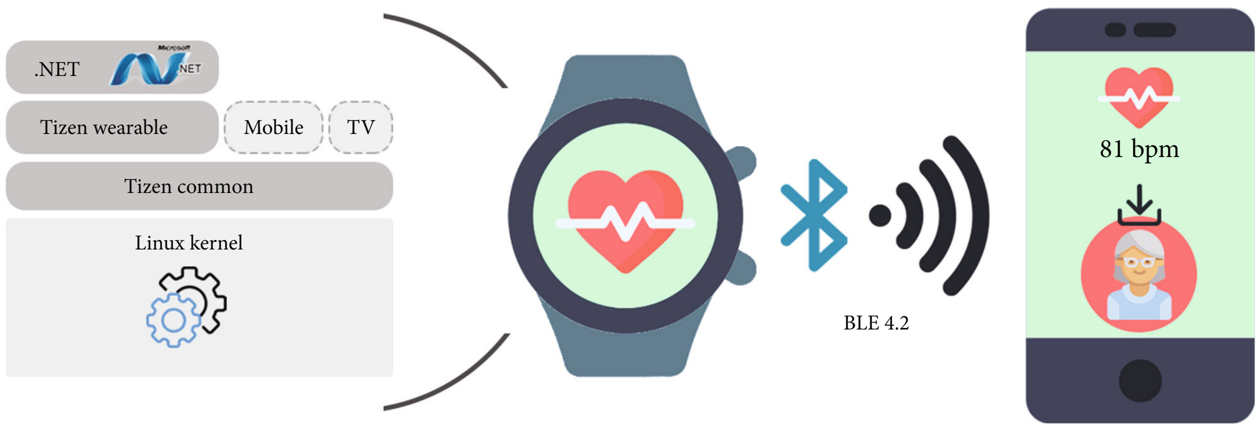

Figure 2: Tizen communication.

them. In the *Step* entity, the privacy level is composed of three predefined privacy groups, *Doctors*, *Family*, and *Friends*, where the authenticated healthcare providers, family members, and friends of the user are stored with the hash fingerprints of their certificates. The writing permissions ("!") are left as default.

3.3. Data Collection. The raw data to feed the digital avatar comes from several sources. The most important of them is the smartphone itself, which provides basic data on the use of the device, such as the battery level, or whether it is connected for charging. Other sources of information can be wearables such as smartwatches or sport bands. By accessing the accelerometers and other sensors provided by these devices, it is possible to monitor the activity of the user (obviously, only if she carries them with her) and recognize different activities, such as typing, walking, and driving. It is also possible to detect how much time has passed since the last time the user handled the device.

The movements of the user can be monitored with the phone's GPS sensor, in conjunction with network detection via Wi-Fi, inferring if the user leaves home and the distance travelled during walks or visits to other places or people. In this sense, it is possible to infer when the user interacts with other people (who use Digital Avatars on their phones) since her smartphone will read Bluetooth signals coming from other smartphones and detect the close presence of their owners. This way, we learn whether the user is accompanied or if she is related to other people in her everyday environment [12].

One step further is being able to detect the mood of the user, as discussed in [13, 14]. To do that, we observe the activity with the smartphone, analyzing the record of calls and their frequency, the use of various applications, programmed alarms, etc. This data is available on most smartphones.

Finally, other sources of information are health devices that communicate with the smartphone to send their data. Today, most home medical devices communicate via Bluetooth Low Energy (BLE) with their smartphone applications. Examples of such data can be provided by glucose meters or blood pressure monitors that are commonly and easily used in a domestic environment. In many cases, the communication protocol of the health devices is proprietary, so it falls onto the user to add the gathered information to their digital avatar manually. When the users take a measure, we can display a message asking them to introduce the value to add it to their profile. However, some devices offer the possibility of writing applications to gather and manage these data, which allows us to automatically record this information into the user's digital avatar. The following subsection addresses this issue in more depth.

Accessing Third-Party Wearable Devices. As we have remarked, it is not easy to find wearable devices that measure health indicators and provide an open communication protocol or an API that can be used by third-party applications. In the search we have carried out, we have found a family of Samsung devices equipped with the Tizen operating system, which we have chosen for a first proof of concept of our proposal. Tizen is based on Linux and offers some SDKs for external developers to code their own applications and to have access to the data collected by the sensors embedded in these devices. In particular, for our tests, we have used the smartwatch Samsung Galaxy Watch equipped with a 3-axis accelerometer, a heart rate sensor, and a pedometer, among other sensors. We have not used the smartwatch's GPS as we are using the GPS embedded in the smartphone, but it could be employed to improve the accuracy and reduce the uncertainty of the measurements.

In order to make use of the data provided by the Samsung Galaxy Watch, we have developed two paired applications, one running on the smartwatch and the other one running on an Android smartphone storing a digital avatar. Both ends interact with each other in a full duplex communication. The application running on the smartwatch collects data from the aforementioned sensors and sends that information to the application running on the smartphone. The latter processes the incoming information and updates the digital avatar according to its own rules.

Figure 2 shows the communication scheme of the two applications developed: the one that operates on the smartwatch and the one that runs on the smartphone where the digital avatar is installed. The smartwatch application has been developed using the .NET framework. This application runs on the Tizen Wearable layer of the smartwatch operating system, which uses a Linux kernel as the base layer. Both applications communicate in a bidirectional way. The smartwatch application collects data from its sensors and sends this information to the smartphone application, which processes this information and adds it to the digital avatar.

Tizen allows three ways of programming applications. The first one is to code a native application on the C programming language. This option includes some interfaces to directly control the device hardware and offers better performance. However, it lacks a managed run time. The second option is to build a Web application, on top of HTML5, CSS, and JavaScript. This option has limited capacities and worse performance. The third option is to build the application on top of the .NET framework and the C# programming language. We have chosen this last option because it allows accessing all the device's resources, the application is easier to develop, and it presents good performance. For the application that runs on the smartphone, we have used the Tizen library for Android.

To get both applications in touch, the first step is to create an agent in both ends. The agent acts as the connection and communication manager. After creating the agent, it looks for peers to connect to, and it pairs to the peers with the desired identifier. Once the connection is established, the devices stay connected in a way similar to Bluetooth connections. The app in the smartphone takes the active role. It polls periodically the smartwatch's sensors to collect data from them and asks to send those data to the smartphone, where an Android service running in the background is waiting for them. Once the data have been received by the application, they are available for updating the digital avatar of the user.

As a proof of concept, we have successfully received data from the smartwatch's accelerometer, heart rate sensor, and the number of steps the user has taken since the beginning of the day.

This simple data is the low-level events that feed the CEP engine. Based on them, CEP rules are executed to detect user-relevant states or to react to specific circumstances in real time.

3.4. Complex Event Processing with Uncertainty. The definition and detection of situations of interest from the analysis of low-level event notifications [15] is a form of information processing known as Complex Event Processing (CEP) [6, 7]. Allowing the analysis of large amounts of data from different sources, CEP detects significant information and reacts to a new situation in real time. The discovery of domain-specific critical situations via CEP engines is generally carried out on servers or desktop computers.

However, with the aim of building in the smartphone a digital avatar or complex virtual profile with high level information on the health and habits of the user, our proposal introduces CEP in the Digital Avatars architecture in the smartphone. Known as mobile CEP [16], this approach has useful inherent characteristics without the need to implement communication between the engine and the sensors, making the system information private and correlated and relying totally on the smartphone.

Typically, events received from physical systems, sensors, and networks, as described in our motivating scenario, are not free from uncertainty. Predictions of future events, estimations, physical measurements, or unknown properties of a system are a quality or state known as uncertainty, and they involve imperfect and/or unknown information.

In particular, *measurement uncertainty* is a type of uncertainty referring to the inability to know the value of a quantity, an intrinsic aspect of any physical setting with complete precision, such as unreliable data sources and communication networks, tolerance in the measurement of the physical elements values, estimates due to the lack of accurate knowledge about certain parameters, or the inability to determine whether a particular event has actually happened or not are the main causes of measurement uncertainty.

The uncertainty of sensor measurements is given by the accuracy and precision of these devices. The accuracy is usually provided by the sensor or smart device manufacturer in their product specifications, although this is not always the case. For example, for blood glucose meters, they must meet the ISO 15197:2013 [17] standard that establishes the accuracy for blood glucose measurements.

Regarding the verification of this uncertainty, each of these sensors or measuring devices is usually calibrated before they go on sale and should be recalibrated after a certain period indicated by the manufacturer. The main reason for carrying out this recalibration is that after that period, the measurements of the device become uncertain. Therefore, to learn, for example, the accuracy of devices that measure blood pressure, validation protocols are applied to sphygmomanometers [18].

A critical issue in any realistic model of a physical system is the explicit representation and management of measurement uncertainty. To do that, we have used a probabilistic approach, instead of employing fuzzy logic or possibility theory. We have worked on the representation of measurement uncertainty in software models [19, 20] and in CEP systems [21]. Our solution, presented in the form of a library that can be added to existing CEP engines, focuses on measurement information (also known as *epistemic uncertainty*), the confidence we have in the data we handle, and the rules determining the behavior of the digital avatars (*aleatory uncertainty*).

Incorporating the uncertainty that exists in the real world ensures models and applications that are more realistic. For this reason, we have detected and incorporated measurement uncertainty in both the events received by the different sensors and the information stored in the digital avatars, as well as in the system of rules managing the generation of new complex events and alarms.

As mentioned before, the Digital Avatars framework avoids using a centralized server and keeps data and computations on the smartphone of the user for which a virtual profile is being built. Therefore, a fast, lightweight CEP engine that processes events directly on mobile devices was needed. Esper-Android is the name of a mobile CEP prototype of the Esper CEP engine for Android on which Sebastian et al. [22]

```
from every (bp = BloodPressure )[bp.high >= 140 or bp.low >= 90]
select eventTimestamp() as ts,
      bp.high as high,
      bp.low as low
insert into HighBloodPressure
```

Code 2: Rule for detecting high blood pressure situations.

```
from every (bp = BloodPressure)[
      UBooleans.toBoolean(UReals.ge(bp.high, 140.0))
            or
      UBooleans.toBoolean(UReals.ge(bp.low, 90.0))]
select eventTimestamp() as ts,
            bp.high as high,
            bp.low as low,
            bp.prob∗
            UBooleans.uor(UReals.ge(bp.high, 140.0), UReals.ge(
      ↪bp.low, 90.0)). getC()∗
            P( HighBloodPressure) as prob
insert into HighBloodPressure
```

Code 3: Rule for detecting high blood pressure adding uncertainty.

```
from every(e1 = WakeUp)-> e2 = GlucoseLevel[e1.id = e2.id &&
      ↪e2.level > 200]
select eventTimestamp() as ts,
            gl.id as id,
            gl.level as level
insert into HighGlucoseLevel
```

Code 4: Rule for detecting high glucose levels.

started working some years ago, but unfortunately, there is no updated version of Esper-Android compatible with current smartphones, given the dependence on third-party libraries no longer compatible with updated versions of Android.

As an alternative, we have decided to use Siddhi [23], a feature-rich stream-processing platform from WSO2, which has been successfully ported to both Android and Raspberry Pi devices. The SiddhiQL query language and Esper's EPL (SQL-based) are very similar. SiddhiQL includes the main operators required to define the rules: select, filter, window, aggregations, group by, having, join, and pattern. As previously mentioned in Section 3.2, rules implementing the functional requirements that infer a person's behavior and habits, or rules that trigger alarms when a person's biometric values are outside the healthy range, can be built by combining these operators.

Consider for instance the selection rule shown in Code 2. By means of this rule, the Siddhi CEP engine monitors *BloodPressure* events received by Bluetooth in the smartphone from an associated blood pressure gadget, and it raises a *HighBloodPressure* event every time that at least one of the two constraints, systolic *BloodPressure* ≥ 140 or diastolic *BloodPressure* ≥ 90, is observed.

Code 2 shows a standard Siddhi CEP rule, which is only executed when its Boolean condition holds. However, we are able to incorporate data uncertainty to the rule by using the uncertain data types (*UBooleans*, *UReals*, *UIntegers*, etc.) defined in the libraries we have implemented and presented in previous works [19, 21]. Thus, Code 3 presents the same high pressure detection rule but adding uncertainty to the data received from the blood pressure monitor. The operators (*ge*, *gt*, *equal*, *add*, *mult*, etc.) are also extended to handle and propagate this uncertainty in a transparent way. The resulting *HighBloodPressure* event also has an associated uncertainty, which is recorded as a probability (*prob*) and calculated in the rule itself. In this way, uncertainty is present in all calculations and process steps, and it spreads in a simple way without the need to incorporate complex probabilistic calculations.

Similarly, a more complex rule with a combination of *GlucoseLevel* and *WakeUp* events detects a high glucose level according to the glucose value measured when the user has just woken up and starts their daily activities. The rule is shown in Code 4.

Again, Code 5 shows the rule for detecting high glucose levels, extended with data types and operations for incorporating uncertainty.

```
from every(e1 = WakeUp)-> e2 = GlucoseLevel[e1.id = e2.id
            &&
        UBooleans.toBoolean(UReals.gt(e2.level, 200.0))]
select eventTimestamp() as ts,
        gl.id as id,
        gl.level as level,
        e1.prob * e2.prob *
        UReals.gt(e2.level, 200.0).getC() *
        P(HighGlucoseLevel) as prob
insert into HighGlucoseLevel
```

Code 5: Rule for detecting high glucose levels with uncertainty.

Additional rules would use these *HighBloodPressure* and *HighGlucoseLevel* events for purposes such as automatically sending a message alerting the user or even administering the appropriate dose of insulin based on their personal health records. The basics of these records with personal health data are stored in the user's digital avatar too, which allows customizing the alert message and determining the appropriate dose.

4. Related Works

The large number of sensors integrated into smartphones, wearables, and other devices present in people's lives generates a huge amount of information about the users themselves and their environment. Ambient Intelligence appears as a discipline whose goal is to make a person's daily environment sensitive and responsive to their needs [24].

The main reason to gather information about the users of a system is to learn from them. With this knowledge, we can proactively meet their needs, minimizing manual intervention. Contextual data is used to infer virtual profiles with more specific information about the users [25, 26]. These profiles may be used to learn important aspects of the user's habits and health condition such as diets, movements, exercise habits, and specific health information: heart rate, blood pressure, or glucose levels, among others. Currently, there are different approaches to create these virtual profiles [27–29].

Many existing solutions related to the monitoring of older people focus on geopositioning the user. Keruve and Neki (http://www.keruve.es/ and https://neki.es/) are two of the best-known enterprise solutions that allow the caregiver to locate the user in real time. However, the GPS devices that these and other companies sell are expensive, limiting their universal accessibility. In contrast, there are economic solutions based on mobile applications like CerQana and Tweri (https://cerqana.com/ and http://www.tweri.com/). However, none of them offer any further information other than GPS positioning.

A greater amount of information and consequently higher-quality knowledge can be apprehended by tapping into all the data that sensors in smart devices have to offer. This allows inferring user routines, movements, and health information. Several studies [13, 30] relate the performance of outdoor activities, smartphone usage, and sleep routines with the probability of suffering depression. All these indicators can be extracted from the data recollected by the sensors available in present day smartphones. Moreover, there is also a good number of studies about detecting the emotions of the users [31, 32]. In many of them, smartphones have a great influence, since the users interact quite frequently with them, and some capabilities of phones, such as the possibility to take pictures of the users, facilitate this task.

The idea of transferring CEP processing from a centralized server to the smartphone is proposed in [22], using the sensors embedded in the device as a source of simple events. A similar idea is proposed in [33], where smartphone resources are used as part of the processing of the events generated by their sensors. However, none of the proposals analyzed incorporate the treatment of uncertainty in the data collected or being processed.

5. Discussion

In this paper, we have presented some of our research work exploring alternative models for Social Computing, and we have shown how it is applied to the promotion of independent living for older adults. In this particular field, Digital Avatars offers benefits at three levels: for the older adults, for their caregivers, and for the community health systems. The most important of these benefits are discussed below.

First, we adopt a collaborative model with a peer-to-peer architecture built on smartphones, as opposed to the more common client-server architecture. This way, Digital Avatars becomes a tool where the users are able to decide with which other avatars or third parties to share their data and which external data they want to incorporate into their own avatar. This puts the exploitation of personal data in the hands of their owners, who are then able to control their information, alternatively to their data being processed and commercialized by third parties—without either transparency or clear benefits to the producers of the data.

Indeed, the framework is based on having one single virtual profile of the user, which can be shared to any third party with interests in offering some kind of personalized service to them. This discourages building multiple user profiles, one for each service provider, with redundant and inconsistent information about the user.

Moreover, our proposal takes into account the uncertainty that occurs in the real world, incorporating this uncertainty in the data obtained from sensors and external devices, in the rules of the CEP engine, and in the complex events that are generated from them.

In this work, we have applied the Digital Avatars framework to monitor user health, particularly for older adults living alone and independently. We have shown how we are able to monitor their health indicators, their habits, their social activities, and even their mood. The system reminds users of their health patterns through warnings, while it can also alert their caregivers or health professionals if the situation requires it.

This way, Digital Avatars facilitates continuous contact and monitoring of older people's well-being by their family and caregivers. If authorized to do so, the caregiver can request health data from the user for monitoring it and, in any case, receives alerts as soon as they occur.

Finally, for the community health systems, our proposal allows health professionals to be informed of older people's health conditions in sparsely populated environments, avoiding complicated, expensive, and time-consuming visits and consultations that can be scheduled less frequently. Digital Avatars immediately communicates any health alarm and regularly transmits the biometric parameters that the family doctor deems necessary.

On the other hand, the proposal also poses some challenges and potential risks. The most significant of them are the following. First of all, data collected in real time from different sources can generate a very large volume of information and its storage may exceed the capacity of a standard smartphone. The solution is to store raw data only for a limited time (which would depend on each data stream), aggregating the information at various levels, and storing only these aggregated data in the long term.

Furthermore, CEP engines require high processing power and are primarily oriented to run on servers or in the cloud. However, there are few alternatives for its execution on smartphones, as discussed in Section 3.4. Moreover, if the number of CEP rules and patterns to be processed is large, and the data collection is also performed at a high sampling rate, the smartphone may not be able to process all this information properly. Nevertheless, we can envision strategies for addressing this problem: data can be collected at a nonconstant rate and a first level of data filtering can be carried out where events of little significance or spurious or disabled events are discarded.

Moreover, one may fear that the CEP engine can cause a big penalty in energy consumption terms. However, in the proof of concept we have implemented, we have observed that the CEP engine worked well without incurring battery efficiency loss. The developed application, continuously running during a whole day, supposed an average of 7% of battery expense for a fully charged smartphone. This is a promising number, and more precise efficiency tests will be carried in the future.

As discussed in Section 3.3, most personal healthcare devices employ proprietary and secured protocols for communicating via Bluetooth with their associated smartphone applications. These applications are usually closed, not providing any kind of public API for accessing their data. However, some open solutions exist, from which proofs of concept can be built, and as in many other fields, open standards may appear in the future for making easier the interconnection of gadgets from different vendors.

An additional technology risk comes with the evolution of Android and other mobile operating systems. Indeed, the general trend in recent Android versions poses a challenge to our proposal, as it tends to close access to their internal data, sensors, and background applications. The framework presented in this work is based on these data sources that must be accessible in the smartphone. Increasing restrictions in their access would greatly hinder the implementation of Digital Avatars and the development of applications based on it.

Finally, a nontechnology risk is that the user may not be paying enough attention to the smartphone. For a number of reasons, the users may not always carry the smartphone with them, preventing the digital avatar to get important data about their activities and health indicators. Among these reasons, we can mention forgetful users, being uncomfortable with the use of a smartphone, a certain reluctance to technology, running out of battery, or many other possibilities.

6. Conclusions

In this work, we have shown the feasibility of using smartphones to promote independent living and quality of life of older adults. In particular, we aim to empower older people living alone in small villages and nearly uninhabited areas by reducing their dependence on caregivers and increasing their chances of remaining at their home places despite growing older.

The architecture of the Digital Avatars framework is related to what is known as Fog Computing. Indeed, the smartphone acts as a fog device, processing the raw data obtained from its built-in sensors and other personal healthcare devices connected to it, and generating more complex and added-value information, which in turn can be hosted locally in the smartphone, communicated to the user through notifications, or even shared with remote nodes hosted in the cloud.

In the healthcare monitoring scenario presented in this paper, these remote nodes—managed by healthcare professionals—can access the older person's health indicators collected on personal care smart gadgets.

Going further into the case study used to illustrate our proposal, there are situations in which it would be interesting to directly connect two or more smartphones from different users to cooperate and reach common objectives or just to elaborate new and more complex information. In future iterations of the architecture, we aim to extend the communication capabilities of our framework, creating a distributed CEP ecosystem in which digital avatars are able to send out events to be processed by other smartphone nodes, which would be endowed with their own digital avatars, CEP patterns, and mobile apps.

Additionally, this research work discusses the technological limits of current smartphones and whether CEP engines can be run directly on these devices. In particular, our focus is put on issues such as data storage capacity, processing performance, accuracy of data collected by sensors and connected medical devices, and reliability of complex data generated by CEP tools. For addressing the two last issues, we integrate in our proposal the concept of uncertainty in the data collected and in CEP patterns and rules.

Our work represents a step forward towards making the smartphone become a personalized interface to its owner. Related research work by the authors of this paper considers further scenarios based on the Digital Avatars framework, in which fully programmable smartphone devices interact by executing scripts on-the-fly. This way, we are able to seamlessly configure smart things in the user environment based on the information contained in the digital avatar.

Data Availability

Data can be available upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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