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Developing an App for make available the knowledge to the farmer: Detection of the most suitable crops for a more sustainable Agriculture

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Abstract. Precision agriculture has different strategies to collect, process and analyze data of different types and nature to be able to make decisions that improve the efficiency, productivity, quality, profitability and sustainability of an agricultural production. Specifically, crop sustainability is directly related to reducing costs for farmers and minimizing environmental impact. In this paper an application to help in the decision making about the most convenient type of crop to plant in a certain zone is developed, taking into account the climate conditions of that zone, in order to make the crop sustainable. This application is integrated within an Internet of Things system, which is adaptable and parameterized for any type of crop and zone. The components of the Internet of Things system are described in detail and a fuzzy clustering model is proposed for the intelligent module of the system. This fuzzy model focuses on making a grouping of zones (zone management), taking into account the climatic conditions of a zone. The model manages fuzzy data, which allows for more extensive information and more natural treatment of the data. Finally, A real study case for the application proposed is presented using data from Region of Murcia (Spain). For this study case it has been described the whole deployed Internet of Things system. Also, the intelligent fuzzy clustering model to create similar areas in terms of meteorology has been validated and evaluated. In addition, the recommendation and decision support module has been implemented, taking into account real production data and resources needed for the crops in the Region of Murcia (Spain).

Keywords: Precision Agriculture, Sustainable Agriculture, Intelligent Data Analysis, Clustering Analysis, App

1. Introduction

In the agricultural sector, numerous decisions are made every day with the aim of obtaining the best possible yield from crops, both in terms of productivity and the resources necessary to obtain a good production. Nowadays, it is important to support this decision making in the large amounts of data that are being stored from the agricultural environment. For this decision making, precision agriculture can be help because provides us with a set of tools and techniques with the aim of improving the quality, productivity, efficiency and sustainability of crops while trying to minimize environmental impact [9].

There are more and more mechanisms to be able to plant any type of crop in any area, however, these mechanisms imply an extra economic cost, as well as a possible over-exploitation of the available natural resources. This causes the lack of sustainability of these crops and a high environmental cost. For example, growing crops in cold areas that are vulnerable to cold weather means that farmers have to use anti-frost

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techniques to prevent the loss of their crops, causing an increase in the cost of producing the crops and an increase in the environmental impact.

Internet of Things (IoT) systems have shown a new direction of innovative research in the agricultural field [16]. These systems, applied in the agricultural field, allow us to obtain a great amount of data, which are analyzed and allow us to monitor and create decision support systems for farmers, in order to improve their benefits, decreasing their costs and increasing the production of their crops, among other functions [4]. The IoT systems are characterized by the fact that they are made up of IoT devices connected by communication technologies that allow the collection of data so they can be analyzed in their intelligent component and then show the possible decisions and/or actions to the end user [14]. These actions or decisions will provide information to the user, always taking into account that this information must be adapted to the type of end user.

In this work, an intelligent component integrated within an IoT system is developed, to advise farmers which type of crop will have more yield and be more sustainable in their area, in order to reduce costs and increase profits. The communication of this component with the farmers will be done through an application (App), proposed and designed in this work, which will have a friendly and configurable interface to be used in different crops and in different areas.

The intelligent component is based on designing and applying a procedure of grouping regions with similar climatic conditions and then performing a yield analysis of each region to advise the farmer in the regions with the worst yield and the type of crop in the regions with the most optimal yield. The procedure takes into account the uncertainty of the climatic conditions transferring it to the SoftComputing framework that will allow us to deal with imperfect data and, therefore, to express in a more correct way the true nature of the data. This procedure is based on Intelligent Data Analysis process (IDA process) using the large amounts of available data from crops and weather stations that allow a non-experimental data analysis to optimize production and make agriculture more resilient to climate change.

Within the data mining phase of the IDA process a fuzzy clustering method is proposed. This method allows regions to be grouped taking into account climatic variables and to make decisions using additional crop sustainability information (zone management). Specifically, we focus on groupings of regions from different areas of the Region of Murcia (south-east of Spain) by means of a this fuzzy clustering technique proposed from the data collected from various weather stations. In addition the proposed intelligent component is validated and implemented in a real case study where the complete IoT system is described, emphasizing the App that provides the recommendations to the farmers can make the best decisions for their crops.

The structure of the work is as follows: In Section 2, works that try to solve problems in agriculture using clustering techniques for zone management are review. In Section 3 the IDA process based on a fuzzy clustering technique implemented to obtain the model that generates knowledge in the IoT system is presented. Section 4 describes and details the development and the different elements that make up the proposed farmer App, indicating its components, its integration and its deployment within the IoT system. Section 5 presents a study case where the whole IoT system is deployed and details specific results of the usefulness and knowledge generated by the App proposed in this work. Finally, Section 6 shows the conclusions of the results obtained and the different future work to be performed.

2. Zone Management in precision agriculture problems

Precision agriculture addresses a wide range of agricultural problems with the aim of making crops more sustainable, enabling farmers to maximise their profits and reduce their losses. One of the tools that precision agriculture uses to predict and help to make decisions is machine learning techniques [9].

The most common problem faced by the farmers is they do not opt crop based on the necessity of soil and weather conditions, as a result they face serious setback in productivity. This problem can be addressed through precision agriculture. This strategy takes into account several parameters, viz: soil characteristics and types, weather conditions and crop yield. Data collection based on these parameters suggesting the farmer suitable crop to be cultivated. Precision agriculture helps in reduction of non suitable crop which indeed increases productivity, apart from the following advantages like efficacy in input as well as output and better decision making for farming.

It should be noted that successful application of precision agriculture on farms requires detailed characterisation of yield limiting factors such as soil water retention capacity and extreme temperatures, identification of agronomically sound and homogeneously managed macro-areas, and selection of the most suitable crops and their management for each zone, this is defined as zone management [13]. In this framework, different contributions have been made in recent years, taking into account that in most of them, clustering and fuzzy clustering techniques are the most successful in results.

For example, the spatial-temporal change in agricultural distribution in Thailand is analyzed in [8] during the period 2007-2015 using cluster, outlier and hot spots analysis. The conclusions, and main objectives of the analysis, are to support and contribute to the strengthening of energy and food security through adaptation or survival to climate change for the period 2015-2021.

The authors of [17] address the problem of Indian farmers who do not choose to cultivate according to the need for the soil, and therefore face a serious decline in productivity. They propose a system of recommendation through a majority voting assembly model using techniques such as random tree, k-neighbor and naïve bayes to recommend a suitable crop.

In [19] a study on the effective use of agricultural land by calculating economic indicators is carried out. The authors perform a cluster analysis with which they obtain three clusters in terms of economic efficiency of agricultural land use in the Lviv region.

In [22], the authors attempt to estimate the area under cultivation and the categorization of types of agricultural products in order to achieve sustainable development in agricultural studies. In this study, an unsupervised zoning of the cultivation areas with the same cultivation pattern in the Golestan Province is performed by a multi-stage method with which they obtain the cluster with Spectral Angle Mapper algorithm producing a mapping of the regions with the same cultivation pattern.

The authors of [15] developed a cluster-based method to analyse the spatial relationship between a set of variables and to determine the management zones in a vineyard taking into account areas with homogeneous characteristics that are likely to be affected by multiple interrelated factors. The aim of obtaining these zones is to improve irrigation management and agricultural decision-making. In [10], the expectation maximization algorithm is developed to transform the series of seasonal rainfall in order to identify the homogeneous zones of rainfall in the winter and summer crops in the state of Parana, Brazil. The authors used average monthly rainfall data collected from 157 weather stations over 20 years. The results indicated that in all the crops analyzed, three clusters were presented, indicating low, moderate and high rainfall according to the area of the country. Another work that manages and tries to optimize irrigation by means of precision agriculture is presented in [6]. This study presents a performance evaluation between different statistical and clustering algorithms to analyze an irrigated field with an important spatial variation of the soil. In addition, the main attribute for zoning such as soil apparent electrical conductivity , space-borne satellite images and yield data were required as ancillary data. The results indicate that clustering techniques are more effective with the soil apparent electrical conductivity attribute being the most effective. Another work where clustering methods obtain good results is presented in [12]. In this work, the modified approach of several clustering methods is used to group data based on districts that have temperature, rainfall and soil type on the one hand, and to group data based on districts that are producing maximum crop production, focusing on wheat on the other. Based on the clustering obtained, the optimal parameters to produce the maximum crop production in India are analyzed and obtained.

In [5], a general study and a comparative study on different types of clusters is carried out to group different cultivation areas. Specifically, the evaluation was carried out with data obtained between 2010 and 2015 from three commercial agricultural elders cultivated with soybean and maize in Brazil. In general, the behaviour of all clustering algorithms was satisfactory for the purpose indicated.

The authors of [20] conduct a study on hierarchical and non-hierarchical grouping methods and the Fuzzy C-Means method. As a case study, these methods are applied to the clustering of 15 governorates in Iraq on the basis of some agricultural crops. The authors conduct a comparative study and evaluation of different statistical and fuzzy clustering methods, being the Fuzzy C-Means the best method. Another paper that deals with the management of the area through clustering techniques is presented in [7]. This paper experiments and compares the clustering algorithms K mean, Fuzzy C Means, Possiblistic Fuzzy C Mean and Linde Buzo Gray to delineate management zones in precision agriculture. The objective of the zone delineation determination is for the application of the fertilization process. Sugarcane was selected as a case study for the experimentation of management zone delineation. The study considers 14 important nutrients of the crop for the delimitation. Again a fuzzy clustering technique obtains better results in the experiments.

As the analyzed works represent, the different clustering techniques are used with satisfactory results for the zone management covering different types of problems. Hence, for the problem of creating groups with similar climatic conditions presented in this paper, a fuzzy clustering technique is selected to create the decision support model.

3. IDA process based on a fuzzy clustering technique

Cluster analysis is one of the most outstanding descriptive tasks in the IDA process. The idea is to partition a dataset into groups with similar characteristics. It is an unsupervised task and the groups obtained could be considered as classes.

In this work a fuzzy extension of a classical clustering algorithm [11] is proposed. This technique can work with nominal and numerical attributes described by crisp and fuzzy values. The proposed algorithm will be named CCLUS$_{imp}$. Extending the type of values with which the different measures available in a given problem can be expressed, allows to provide these measures in a more real and natural way. For example, the measurement obtained through a sensor can be expressed by a fuzzy value, incorporating information on the error committed by the sensor, or the different values obtained from the same measurement (for example, the mean value, minimum value and maximum value of the measurement) can be grouped into an interval or fuzzy value that includes this knowledge.

In general, a clustering algorithm groups a dataset E into c partitions trying to keep the data within the same cluster as close as possible and the clusters as far as possible. The objective function plays an important role in a clustering algorithm. Given a dataset $E = \{x^1, x^2, \ldots\}$, where each instance is described by n attributes $x^i = \{x^i_1, x^i_2, \ldots, x^i_n\}$, the objective function to be minimized is defined as $\sum_{j=1}^{|E|} \sum_{i=1}^{c} d(x^j, v^i)$ where c is the number of clusters, $|E|$ is the number of available instances, $v^i = (v^i_1, v^i_2, \ldots, v^i_n)$ is the cluster center i, and $d(x^j, v^i)$ is a function measuring the distance between the instance x^j and the cluster center v^i.

3.1. CCLUS$_{imp}$ Algorithm

Taking as a basis the general clustering algorithm described in [1] an extension of it is carried out This extension allows working with imperfect data, that is, that in the input dataset there can be values expressed by nominal and numerical values, precise and imprecise (intervals and fuzzy sets).

Let's suppose a set of examples $E = \{x^1, x^2, \ldots\}$ to be grouped. Each example is described by n attributes such as $x^j = \{\mu^j_1, \mu^j_2, \ldots, \mu^j_n\}$ where μ^j_k is the membership function of a fuzzy set of a nominal or numerical attribute. For this purpose the objective function is minimized:

$$J = \sum_{j=1}^{|E|} \sum_{i=1}^{c} F(x^j, v^j)$$

where c is the number of clusters, $|E|$ is the number of examples, $v = (v^1, v^2, \ldots, v^c)$ is the vector of centers, $v^i = (v^i_1, v^i_2, \ldots, v^i_n)$ is the center of the cluster i, and $F(x^j, v^i)$ is a function that measures the distance (could also be considered a measure of similarity) between the example x^j and the centroid v^i.

The main steps are shown in the Algorithm 1.

Algorithm 1: CCLUS$_{imp}$ Algorithm

Input Dataset E, Value c; $1 \leqslant c \leqslant |E|$
Initialize randomly the cluster centers vector v
while $v^i(t) - v^i(t-1) > \epsilon$ **do**
  Calculate the index sets $I^i; i = 1, \ldots, c$ composed with the set of instance indexes that are closer to the cluster center v^i than to any of the other cluster centers.
  Recalculate the cluster centers
end while

In Algorithm CCLUS$_{imp}$ since the numerical and nominal values of the input data can be expressed by fuzzy values, the centers of the cluster will also be fuzzy values and the distance function must be a heterogeneous similarity/dissimilarity function between fuzzy values, $F(x^j, v^i) = \frac{\sum_{k=1}^{n} f(x^j_k, v^i_k)}{n}$ where:

- If the k attribute is numerical, the distance of Diamond [2] is used:

$$f(x^j_k, v^i_k) = \frac{\sqrt{\frac{(a-a')^2+(b-b')^2+(c-c')^2+(d-d')^2}{4}}}{max_k - min_k}$$

where x^j_k and v^i_k represent the k-th attribute of example $\mathbf{x}$ and centre $\mathbf{v}$ whose values are defined by the quadruples (a,b,c,d) and (a',b',c',d') respectively. max_k, min_k are the maximum and minimum values of attribute k in the dataset.

– If attribute k is nominal the measure of Dubois and Prade [3] is used:

$$f(x_k^j, v_k^i) = 1 - \frac{Card(x_k^j \bigcap v_k^i)}{Card(x_k^j \bigcup v_k^i)}$$

where x_k^j, v_k^i are crisp/fuzzy nominal values and $Card(x_k^j \bigcap v_k^i)$ and $Card(x_k^j \bigcup v_k^i)$ are defined as the cardinality crisp subsets obtained by the union and intersection of x_k^j and v_k^i, respectively.

The update of the cluster centers from the crisp partition I_i is carried out as follows, where $|I_i|$ is the number of examples belonging to cluster i:

– If attribute k is nominal: $v_k^i = \frac{1}{|I_i|} \bigcup_{x^j \in I_i} x_k^j$
– If it is numeric:

$$\left(\frac{1}{|I_i|} \sum_{x^j \in I_i} a_k^j, \frac{1}{|I_i|} \sum_{x^j \in I_i} b_k^j, \frac{1}{|I_i|} \sum_{x^j \in I_i} c_k^j, \frac{1}{|I_i|} \sum_{x^j \in I_i} d_k^j \right)$$

since v_k^i is a vector (a',b',c',d'). In the same way, the distance between centers that is used as a stop criterion is calculated using the same similarity/dissimilarity measure.

4. Development and description of an App for the farmers

This section describes the different elements that are part of the development of an application, which, making use of the available data from various sources of the agricultural domain and the technique presented in the previous section, provides to the farmer a recommendation about the type of crop that must be produce on his plot with the aim of improving production and sustainability.

In the development of the App, the server is a main element since it will be the one that contains the main control core of the application. Its general operation consists of acquiring data from the cloud from time to time T_u, some of them are sent to the preprocessing module that performs the necessary data transformation to update the mineable view, and other ones, containing information about crop production by area, are incorporated into the recommendation module. The update of the IDA model from the new mineable view will be carried out in offline mode. The updated model will be available on the server together with the rules engine built from this model. This information provides the knowledge extracted from the data that the application provides to the farmers to help them make their decisions through the recommendation module. In addition, previously, information about each type of crop is incorporated into the recommendation module in the form of a database that will be available to other applications, since there is currently no repository that allows obtaining this type of information.

Figure 1 shows the whole architecture of the App. As can be seen in the figure, the architecture is made up of the server and the Data collection, Data preprocessing, Intelligent Data Analysis and Recommendation modules.

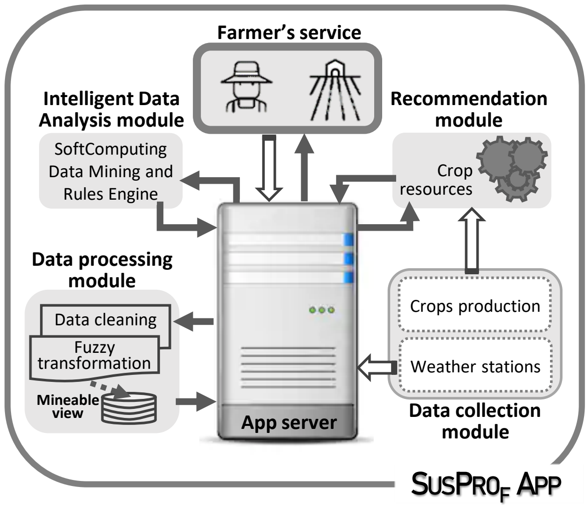


Fig. 1. An App for farmers

The flow chart in Figure 2 shows the working scheme of the main control core of the server to carry out the updating of system data.

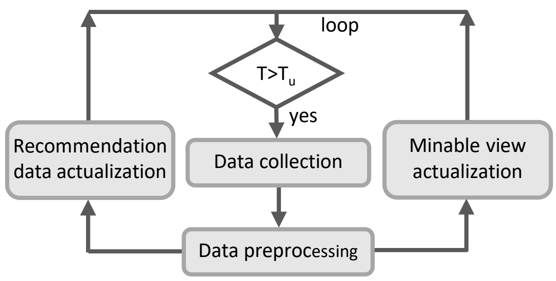


Fig. 2. Functional scheme of the updating of system data

The result provided by the application will be an ordered list of types of crops recommended based on two premises, 1) how important is the production of that crop on grounds with similar climatic conditions and 2) the amount of necessary resources for these crops respecting the sustainability criteria. The farmer can establish the importance of these two requirements in the information provided by the system based on his preferences or the agrarian policies established by the government in said area. In the next sections, the different modules are explained.

4.1. Data collection Module

As we have previously commented, this module must obtain data from two different types of sources. On the one hand, it takes data to update the mineable view in order to obtain the data mining model of the App. On the other hand, it must collect data that allow to build the recommendation to the farmer using the IDA model and the rules built.

To obtain the mineable view, data sources with information about various climatic variables will be used. These data sources are provided by public weather stations located in various terrains of the region where the application is deployed. For the development of the recommendation module, data on the production by zones of the different crops will be obtained. All of them are Open Data Sources available in the cloud. The information about resources needed by crops (fertilizers, water, ...) is previously collected.

4.2. Data preprocessing Module

This module performs the data processing necessary to obtain the mineable view used by the module of Intelligent Data Analysis module. This module will start working every time it is activated the updating of data of the weather conditions from the different considered ground areas of Data collection module.

In this module, among other cleaning and formatting operations, the transformation of certain data into fuzzy values will be carried out. This transformation allows, on the one hand, to decrease the number of attributes in the problem and, on the other hand, to express in a more appropriate way the true nature of certain information. This is the case of attributes that provide the maximum, minimum and average values of the same measure and that can be related and expressed through a fuzzy value. This transformation provides good results when obtained data are used by appropriate intelligent data analysis techniques.

4.3. Intelligent Data Analysis Module

The Intelligent Data Analysis module contains the fuzzy clustering algorithm proposed in this work that can deal with data described by crisp/fuzzy values in both numerical and nominal attributes. Obviously, the modular structure of the application allows the inclusion of other Intelligent Data Analysis techniques that obtain a description of the problem expressed in the form of clusters and can deal with the type of information used. The model obtained in this module is updated offline every time an update of the mineable view is carried out according to the diagram represented in Figure 2. The module also contains specifications of the configurable parameters of the technique and includes the procedure necessary to adjust those that are necessary (for example, the value of c).

Once the model is obtained in the form of clusters using the CCLUS_{imp} algorithm, data from different ground areas with similar weather conditions are grouped. Internally, the percentage of data from each ground area that is grouped in these clusters is known (although the ground area from which each data comes is not used during the model's learning phase). This allows us to relate each cluster to the physical location of the area or areas that cluster represents.

This physical location allows that the Recommendation module generates the output since it can access to other types of information available from those locations, for example, types of crops in those locations, resources used, profitability of crops, etc.

From the knowledge obtained from the IDA model, the set of rules of the rules engine is built. For each attribute of the problem, a partition is defined in the form of 5 fuzzy labels (very low, low, medium, high, very high) to describe the information of each cluster based on them. In general, any value relative to resources needed by a given crop will be expressed in an equivalent way by means of these labels and the similarity of this label with that of the corresponding cluster, will make that crop be considered more or less sustainable.

4.4. Recommendation Module

It is the module in charge of providing the output of the App in the form of recommendations to the farmer. The output consists of an ordered list of types of crops recommended for cultivation on the farmer's plot. The ordering of the elements in this list will be made based on the production amount of each crop and the resources used by them in areas with climatic conditions similar to the farmer's plot and that respect the idea of sustainable cultivation.

A farmer's request for a recommendation will be made using IoT devices. The recommendation module obtains the geographical areas with climatic condition similar to his plot according to the IDA model (information from the cluster to which the instance representing the farmer's data belongs) and generates an ordered list in descending order of crops suitable for his plot .

Therefore, given the instance that represents the user's data, the cluster *i* to which the instance belongs is obtained. In this cluster, there are certain ground areas *a* represented with their weight (p_{a_i}).

In the Recommendation Module there will be information available for each ground area represented in the cluster about the quantity produced of each type of crop in that area. In addition, other information about the resources needed by the crops is also available.

The ordination of crops in the final list provided to the farmer is obtained based on the score obtained for each crop *X* as:

$$V_{crop}(X) = \sum_{a} p_{a_i} \cdot (\alpha_1 \cdot \frac{prod_a(X)}{Tprod_a} + \alpha_2 \cdot Simil(X, i))$$

where α_1 and α_2 indicate the importance assigned to the production amount and the need of resources respectively, $Tprod_a$ is the total production in the ground area a, $pro_a(X)$ is the production of crop X in area a, $Simil(X, i)$ it is a value that measures how similar the characteristics of the crop X are to the information of the cluster i expressed through fuzzy labels. This score is obtained from the rules engine. The weights α_1 and α_2 can be adjusted by the farmer according to his interests and the specific agricultural policies of the area where his plot is located.

The Recommendation module can be scaled to take into account other types of additional or different information for the generation of user recommendations based on other criteria.

4.5. Integrating the App into the IoT system

The developed App is integrated into the IoT system through the App server. For this integration, a FIWARE infrastructure [23] is used for the implementation of the App as it facilitates the process of extracting, transforming and storing the data needed in it. FIWARE is committed to the collaborative development of 'smart-solutions' and technologies such as Internet of Things, Cloud Computing and Open Data.

The App server of the proposed IoT system integrates a FIWARE server. The FIWARE server is in charge of receiving the information from the sensors of the weather stations, storing this information and providing the appropriate web services that will be used by the graphic user interface to visualize this information, as well as to serve as a data source for the Intelligent Data Analysis module. This part of the system can be considered a key element for the proposed software architecture, as it hosts all the proposed software components running in the backend and allows the users to establish the basic virtual infrastructure needed to run the application using the APIs provided by FIWARE.

Figure 3 shows an overview of the elements running on the FIWARE server, including the Intelligent Data Analysis module and the Recommendation module. Although these two modules are not directly part of FIWARE, they have been integrated to complete the functionality and data consumption performed by the databases implemented in the FIWARE server.

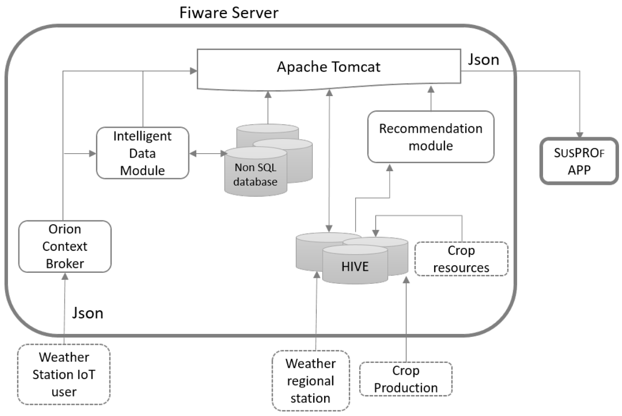


Fig. 3. General scheme of the FIWARE infrastructure used

As shown in the figure, in order to interact with the application, data are collected by means of IoT devices (weather stations) located in the farmers' plots (see Section 5.2.1). The context information is in a non- SQL database (Mongo DB) with the help of the Orion Context Broker. FIWARE data models appropriate to the type of information provided by these devices will be used to integrate these data into the App. In addition, the server is prepared to integrate HIVE tables to collect available data from weather stations at the region level and data to agricultural information of the recommendation module regarding production and resources in order to respect the sustainable criteria maintaining a good production.

5. A study case

As shown in the section 4, the App basically consists of two phases: one in charge of obtaining the intelligent model that captures the knowledge provided by the data, and the other in charge of providing knowledge to the farmer on demand. In this section a specific study case is shown. The case reflects the two phases of the operation of the App, focuses on the Autonomous Community of the Region of Murcia (Spain). Many of the areas focus on agriculture (fruit and vegetables), which represents a strategic sector in the economy of this Region. A crucial aspect in their economy is the agro-food production for export, since it represents a percentage of more than 50% of the regional market. Of their total area, 50% is used for cultivation (67% as dry land and 33% as irrigated land). It should be noted that if the App has already been used previously, the model obtained from the data will have already been calculated and therefore the App will continue directly with phase 2.

5.1. Running the App: Obtaining the models and useful knowledge

During this phase 1, the App activates the modules shown in the Figure 4.

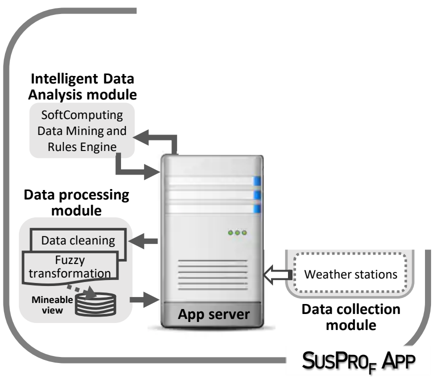


Fig. 4. Architecture activated when the App performs modeling and obtains useful knowledge.

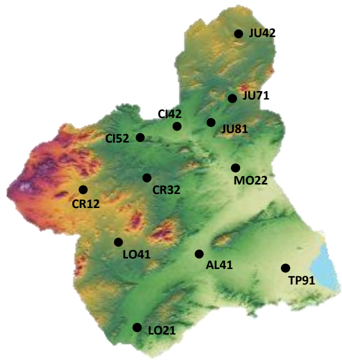
5.1.1. Information collection

The App starts with the "Data collection module" collecting more technical information. The used information of these areas from the point of view of weather information is obtained from the Agricultural Information Service (SIAM, http://siam.imida.es) of this Region. The collected data correspond to 12 weather stations (see Table 1) distributed in the different areas of the Region.

Table 1

Description of the weather stations in study of the Region of Murcia, Spain.

	Altitude
Noroeste area	
Station CR12	869m
Station CR32	433m
Altiplano area	
Station JU71	401m
Station JU81	341m
Station JU42	658m
Vega del Segura area	
Station CI52	275m
Station CI42	244m
Station MO22	146m
Campo de Cartagena area	
Station TP91	56m
Valle del Guadalentín area	
Station AL41	169m
Station LO21	356m
Station LO41	693m



Each station is equipped with the following sensors and ephemeris: weather vane, radiometer, rain gauge, data-logger and thermo-hygrometer. The information collected corresponds to 4 years during the periods from 01/12/2016 to 31/03/2019 (approximately the meteorological winter). The initial data obtained from SIAM sensors correspond to values obtained every 5 minutes and these are grouped 12 by 12 to show only values for each hour. For this reason, some of the measurements show the minimum, mean and maximum values for each hour. The type of information obtained is shown in the Table 2.

5.1.2. Data preparation: dataset

From the information collected, the App continues with the "Data processing module". All measured attributes are used, where attributes with several values for the same measurement (min, med, max) are transformed into fuzzy attributes. The fuzzy attributes are “Relative humidity” (RH_f), “Radiation” (Rad_f),“Wind speed” (WS_f) and “Temperature” (T_f). The other attributes are “Wind direction” (WD), “Cooling units” (Hf_R), “Sunlight” (S), “Rainfall” (R), “Accumulated radiation” (ARad) and “Wind run” (WR).

Table 2
Information collected every hour for each station (noted with its station code)

Wind direction (^{o})	Cooling units
Min relative humidity (%)	Mean relative humidity (%)
Max relative humidity (%)	Sunlight
Rainfall (mm) (R)	Accum. radiation (W/m^2)
Mean radiation (W/m^2)	Max radiation (W/m^2)
Wind run (in to hour)	Min temperature (^{o}C)
Mean temperature (^{o}C)	Max temperature (^{o}C)
Mean wind speed (m/s)	Max wind speed (m/s)

Fuzzy attributes are represented by fuzzy trapezoid values $[v_1, v_2, v_3, v_4]$ where v_1 and v$_4$ have degree of belonging 0, and both v_2 and v_3 have degree of belonging 1. The fuzzy attributes RH$_f$ and T$_f$ are constructed from their three measurement values (min,med,max) as follows: v_2=med-5%med, v_2=med-5%med, v_1=min and v_4=max. The fuzzy attributes R$_f$ and WS$_f$ are constructed from their two measurement values (med,max) as follows: v_2=med-5%med, v_2=med-5%med, v_1=2med-max and v_4=max. In the circumstance that $v_1 \leqslant \text{min}_{\text{global}}$, then $v_1 = \text{min}_{\text{global}}$.

The values of the measures corresponding to the missing values have been maintained. In these cases, the constructed attributes contain trapezoidal fuzzy numbers $[v_1, v_2, v_3, v_4]$ where $v_1 = v_2 = \text{min}_{\text{global}}$ and $v_3 = v_4 = \text{max}_{\text{global}}$.

Therefore, the dataset that the module returns to the server is formed by 104544 instances with 10 attributes joint to the station code. In Figure 3, the descriptive information of this dataset is shown.

Table 3
Descriptive information of the built dataset containing 104544 instances (8712 per station) and 10 attributes and the station code

	Numeric minimum	Numeric maximun	Nominal	Missing value
WD	0	360		184
Hf_R	-1	1		0
RH$_f$	5.57	99.98		250
S			{yes,no}	0
R	0	33		0
ARad	0	4.22		26136
Rad$_f$	0	1173.17		0
WR	0	1.76		0
T$_f$	-9.75	40.45		6
WS$_f$	0	11.72		0

5.1.3. Model construction

At this stage, the App continues with the "Intelligent Data Analysis module". For the operation of this module, the App uses the available dataset. Initially, this module uses the CCLUS$_{imp}$ algorithm described in the Section 3.

CCLUS$_{imp}$ is executed using the parameters $\epsilon = 0.001$ and c taking values from 1 to 15. The App selects the model to be used by the recommender using the Elbow method to find the most suitable number of groups (value for parameter c). The module gets the value of "c"="c$_i$" when the difference between each pair of consecutive values (% ↓) for "c$_i$" and "c$_{i+1}$" is less than 10.

Executing the CCLUS$_{imp}$ algorithm for the different values of c, the following values of the function J are obtained (Table 4). In Table 4 the size of the cluster c= 3 is highlighted, which indicates the "c" where the function J is stabilized.

Table 4
Behavior of the function J according to the parameter c – Relative decline (%↓)

c	J	%↓	c	J	%↓	c	J	%↓
1	4447.70		6	849.73	9.0	11	617.95	1.8
2	1656.15	62.8	7	797.45	6.2	12	614.39	0.6
3	1275.43	23.0	8	712.54	10.6	13	533.08	13.2
4	1059.27	16.9	9	705.70	1.0	14	509.99	4.3
5	934.13	11.8	10	629.25	10.8	15	492.57	3.4

The model obtained is described in Table 5.

Table 5
Model with "c"=3 represented by the centroids of the 3 groups of the cluster

	Group 1	**Group 2**	**Group 3**
WD	[230.4,231.6]	161.6	[201.5,201.6]
Hf_R	0.56	0.67	-0.02
RH$_f$	[66.4,68.8,70,72.4]	[71.9,73.9,76,77.9]	[43.5,46.4,48.2,51.3]
S	{0.01/Y,0.99/N}	{0.04/Y,0.96/N}	{1.0/Y}
R	0.061	0.053	0.005
ARad	0.033	[0,3.56]	[1.14,1.99]
Rad$_f$	[1.7,6.3,12.4,21.8]	[5,12.6,20.7,33]	[300.3,389.3,456,556.2]
WR	0.008	0.011	0.014
T$_f$	[7,7.6,7.9,8.6]	[6.3,6.8,7,7.5]	[13,13.7,14.1,14.8]
WS$_f$	[0,0.8,1.9,3.6]	[0.3,1.3,2.1,3.4]	[0.2,1.5,3,5.3]

This Table 5 shows the characteristics of the groups according to the values of the attributes. As can be seen, the centers of the groups for the attributes RH$_f$, Rad$_f$, T$_f$ and WS$_f$ are fuzzy values (where the attributes RH_f and T_f have been influenced by the missing values they contain). In addition, the centers for attributes WD and ARad are described by intervals/subsets because these attributes contain missing values.

5.1.4. *Obtaining useful knowledge*

"Intelligent Data Analysis module" continues analyzing the "*c*"=3 size cluster obtained. The module analyze each group of the selected cluster using the labels of the stations in order to check similar behaviours with respect to different cultivation areas.

The size in instances of the groups of this cluster is the following (in parenthesis the percentage that represents with regard to the total of the dataset): Group 1 = 53027 (50.72%), Group 2 = 18201 (17.41%), Group 3 = 33316 (31.87%). And, in addition, the information collected from the different groups with respect to the 12 stations is the following:

a. Group 1 (50.72% of the total instances) includes the following stations, where the percentage of the instances included of each station is indicated: CR12 (67.69%), JU71 (67.32%), JU81 (68.22%), MO22 (67.37%), CI42 (69.28%), CI52 (69.79%), CR32 (70.96%), AL41 (65.23%) and TP91 (62.82%).
b. Group 2 (17.41% of instances). This group includes the stations: JU42 (69.82%), LO21 (69.26%) and LO41 (69.83%).
c. Group 3 (31.87% of instances). This group includes the stations: CR12 (32.31%), JU42 (30.18%), JU71 (32.68%), LO21 (30.74%), JU81 (31.78%), MO22 (32.63%), CI42 (30.72%), CI52 (30.21%), CR32 29.04%), AL41 (34.77%), LO41 (30.17%) and TP91 (37.18%).

In order to use the characteristics of each group in a more comprehensible way for the farmer, the domains of the numerical attributes RH_f, R, ARad, Rad_f, WR, T_f and WS_f are partitioned in 5 parts to discretize them in 5 labels (partitioning with fuzzy Ruspini type labels with an overlap between them of 5% with respect to the cut-off values); the domain of the attribute WD is partitioned using the cardinal points; and the attribute Hf_R is partitioned with three labels to collect the information that indicates how the temperature is inducing in the rest of the annual cycle of many plants (in particular, the fruit trees). Table 6 displays the different centroids of the cluster with 3 groups by means of the labels of the different centroids.

Table 6

Centroids with labels: VL-very low, L-Low, M-medium, H-High, VH-very high; for WD, N∈[337.5^o,22.5^o], NE∈[22.5^o,67.5^o], E∈[67.5^o,112.5^o], SE∈[112.5^o,157.5^o], S∈[157.5^o,202.5^o], SO ∈[202.5^o,247.5^o], O∈[247.5^o,292.5^o], NO∈[292.5^o,337.5^o]; for Hf_R, P∈[0.4,1], C∈[-0.2,0.4], N∈[-1,-0.2]

	1	**2**	**3**
WD	SO	SE-S	S-SO
Hf_R	P	P	C
RH$_f$	H	H	M
S	N	N	Y
R	VL	VL	VL
ARad	VL	all	L-M
Rad$_f$	VL	VL	L-M
WR	VL	VL	VL
T$_f$	L-M	L	M
WS$_f$	VL-L	VL-L	VL-L-M

Thus, with this more comprehensive characterization of the cluster, the analysis of the Table 6 and the information related to the stations in each group, the following knowledge is obtained:

- All groups obtain a very low average rainfall value for the period analysed.
- Groups 1 and 2 have the common characteristics of very low solar radiation, predominantly non-sunny days, high relative humidity, wind speed is very low/low and positive units of cold.
- Group 1 include 9 stations located in the Central and South Altiplano, Vega del Segura, West Valle del Guadalentín and Cartagena areas. And Group 2 includes the rest of the areas, that is, the 3 stations located in the East Valle del Guadalentín, and the Northern Altiplano. Group 2 differs from Group 1 by showing south-west/south winds, a lot of variation in accumulated radiation and low temperature while in Group 1 there is a south-west wind direction, very low accumulated radiation, and a low/medium temperature.
- Group 3 has the characteristic of predominantly sunny days, units of cold media, very low radiation, low/medium accumulated radiation, relative humidity media, medium temperature and very low to medium wind speed from the south/south-west.

As described in the "Intelligent Data Analysis module", the rules whose resources have been activated by the selected crops in the farmer's similar areas will be used. These rules will be those that include the component of resource used by the crops most in line with the climatic conditions of the specific area. Later, when the recommender is activated, some of the rules that will be activated in this study case are shown.

5.2. Running the App: Obtaining the recommendations

During this phase, the App activates the modules shown in Figure 5.

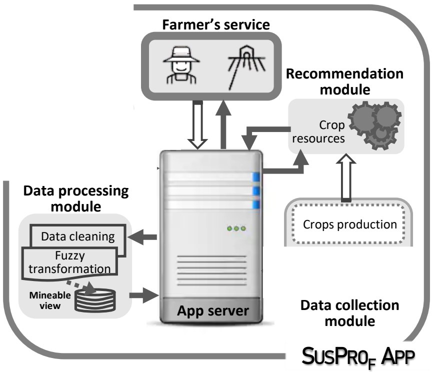


Fig. 5. Architecture activated when the App performs the recommendation process on a request.

The server already has a model described with 3 clusters and knowledge that characterizes different zones by means of their climatic conditions. In this phase 2, the App makes use of the information related to the production of the different areas of study and develops recommendations for the farmer when requested.

5.2.1. Information collection

Again, the App uses the "Data collection module" to collect production information (it uses official pages[1]).

5.2.2. Interaction with the Farmer

The interaction with the farmer is performed by means of personalized information of his area. This can be done using an IoT system (e.g. a local weather station). The IoT system used in this study case is currently deployed on a plot of land in the municipality of Cieza (altitude 324 m) of the Region of Murcia, Spain. The deployment of the system is shown in Figure 6.

This Figure 6 shows some of the components that make up the IoT system, such as the different sensors for collecting information and the aerials for communication[2]. The sensors and communication of the proposed IoT system use the Waspnote Plug and Sense Smart Agriculture Xtreme device from the company Libelium[3]. The communication technology used to connect the sensors to the module that sends the information is XBee ZigBee 3 radio. The data collected by this module are sent via GPRS to the server where the recommendation to the farmers is made based on the data provided. The system is totally autonomous since it has a solar panel that supplies energy to all the sensors and given the XBee protocol used the energy consumption is optimized.

Fig. 6. System of local collection of meteorological data.

Finally, it is important to note that this device, shown in Figure 6, has more sensors than are needed for the intelligent component proposed, however, this allows us to collect accurate information and in the future add this information to the clustering technique, for example soil characteristics, leaf wetness or vaporization.

5.2.3. Building recommendations

This local IoT system collects the information for several days and the server activates the “Data processing module” to obtain the average of the input instances and transforming it into the attributes collected in the model. From this instance of information from the farmer’s plot, the server uses the available model

[1]https://econet.carm.es/inicio/-/crem/sicrem/PU_##Cifras/P8004/sec4.html where ## is the name of the town that composes the different areas of the Region of Murcia.

[2]These sensors collect information on air humidity and temperature, pressure level, rainfall, wind direction, wind speed, soil temperature, soil conductivity, soil permitivity, leaf wetness, vaporization, solar radiation and luminosity.

[3]http://www.libelium.com/

to obtain the areas of the Region with similar weather conditions. From this information, the knowledge obtained in “phase 1”, the resources needed by crops, and the data collected regarding production, the “recommendation module" generates a list in decreasing order of crops suitable for the plot. This order is influenced by the weights indicated by the farmer with respect to the production information and resources of the plot and crops of the areas similar to it.

In the specific case that is going to be developed, once the local IoT system readings have been taken for 15 days, the mean vector (I_P) corresponding to the farmer's plot is shown in the Table 7.

Table 7
Vector that represents the weather conditions of the farmer's plot

	$\mathbf{I}_P$
WD	257.6
Hf_R	0.40
RH$_f$	[55.1,59.3,61.6,66]
S	{0.33/Y,0.67/N}
R	0
ARad	0.49
Rad$_f$	[112.9,129.0,143.2,164.6]
WR	2.28
T$_f$	[5.8,6.7,7.2,8.1]
WS$_f$	[0,0.2,1.1,2.6]

From the available cluster model, the distances of the vector associated with the plot to the different cluster centers are $d(I_P, G1)$=0.232, $d(I_P, G2)$=0.30 and $d(I_P, G3)$=0.341. Therefore, the farmer's plot has more similar weather conditions to those of group 1. The most similar areas (and the average weight obtained from the weight of the stations it groups) are Northwest (69.33%), Central and South Altiplano (67.77%), Vega del Segura (68.81%) and Cartagena (62.82%).

Therefore, the weights of the areas p_{a_i} used to prioritize crops are as follows:

$p_{North-west_1}$=0.258
$p_{Central-South-Altiplano_1}$=0.252
$p_{Vega-Segura_1}$=0.256
$p_{Cartagena_1}$=0.234

The information collected about the main crops in these areas is shown in the Table 8. Specifically, the main fruit trees of each area are shown with the weight of their production and measures related to the attributes modeled in the system that characterize them (water they need, cooling units, humidity, sun and temperature). The more similar the characteristics of a crop X to those of the areas considered in the selected cluster i ($Simil(X, i)$), the more sustainable its production will be because the crop adapts to its climatic conditions.

In Table 8 value “¿?” indicates a missing measure. In this table, the values of many attributes are expressed with imprecise values because they have been found this way in the data sources consulted. This fact shows the importance of incorporating in the systems and IDA models the treatment of imprecise data.

With all the information available, the value $V_{crop}(X)$ according to the expression indicated in Section 4.4 can be calculated for the 4 crops considered in the case: peach, apricot, almond and pear. Values p_{a_i} are those previously indicated, values α_1 and α_2 are set by the user to indicate his preference on production or necessary resources respectively, values $\frac{prod_a(X)}{Tprod_a}$ are those defined for each crop (X) and each area a in Table 8 ($W_{production}$) and $Simil(X, i)$ are scores provided by means of rules that are defined for each feature of the crops that affects its sustainability.

For example, if we focus on the water resource, according to the partition of this attribute and the information about this resource in the cluster i (R=VL from Table 6), the defined rules are as follows:

If water(X) is VL then $Simil(X, i)$=4
If water(X) is L then $Simil(X, i)$=3
If water(X) is M then $Simil(X, i)$=2
If water(X) is H then $Simil(X, i)$=1
If water(X) is VH then $Simil(X, i)$=0

where X is the crop considered. In general, the rules defined for each resource considered indicate that the more similar the requirements of a crop are to the features of the cluster to which it belongs, the more sustainable it is and therefore a higher score is assigned. This way, the output generated by the system takes into account, in addition to production, which crops can be grown in a more natural way and with fewer artificially provided resources.

When values $V_{crop}(X)$ are calculated for the particular case considered, the lists shown in Table 9 are obtained.

Table 9 shows the effect of considering or not the sustainability of crops. When values $\alpha_1 = 1$ and $\alpha_2 = 0$ are considered, the order of the crops changes indicating that the almond is grown in these areas but is less sustainable than the apricot.

Table 8
Main fruit trees by area and their characteristics

Area	Crop	$W_{production}$	Water(mm)	Cooling Units	Humidity	Sun	Temperature
Altiplano	Peach	0.53	[1.53,1.64]	[0.046,0.091]	{VL,L,M}	Y	[21,27]
	Pear	0.26	[1.53,1.64]	[0.103,0.205]	{VL,L,M}	Y	[20,25]
	Apricot	0.22	[1.53,1.64]	[0.043,0.086]	¿?	Y	¿?
Campo Cartagena	Almond	0.90	0.96	[0.029,0.057]	{VL,L}	Y	[20,25]
	Peach	0.10	[1.53,1.64]	[0.046,0.091]	{VL,L,M}	Y	[21,27]
Noroeste	Apricot	0.55	[1.53,1.64]	[0.043,0.086]	{VL,L,M}	Y	¿?
	Peach	0.29	[1.53,1.64]	[0.046,0.091]	{VL,L,M}	Y	[21,27]
	Almond	0.16	0.96	[0.029,0.057]	{VL,L}	Y	[20,25]
Vega del segura	Peach	0.72	[1.53,1.64]	[0.046,0.091]	{VL,L,M}	Y	[21,27]
	Apricot	0.23	[1.53,1.64]	[0.043,0.086]	{VL,L,M}	Y	¿?
	Almond	0.05	0.96	[0.029,0.057]	{VL,L}	Y	[20,25]

Table 9
$V_{crop}(X)$ values to fruit trees in the case

(α_1=0.4, α_2=0.6)	(α_1=1, α_2=0)
peach with 0.5	peach with 0.36
apricot with 0.38	almond with 0.21
almond with 0.34	apricot with 0.20
pear with 0.11	pear with 0.05

6. Conclusions

In this work, an intelligent component integrated within an IoT system is developed, to advise farmers which type of crop will have more yield and be more sustainable in their area, in order to reduce costs and increase profits. As part of the intelligent component, a fuzzy clustering technique, CCLUS_{imp}, is proposed. The technique can deal with imprecise values that express knowledge in a more natural way. A study case is presented working over geographical areas of the Region of Murcia. The CCLUS_{imp} technique has been applied to data from these areas and the groups obtained have been characterized by their weather conditions. Knowledge extracted from the model and the rules engine built from it has been used to provided recommendations for a specific input instance. The results obtained illustrate how the recommendations obtained may be different according to the preferences established by the farmer regarding production or sustainability.

As future work, we propose the inclusion in the proposed fuzzy clustering model of soil information parameters, which can help to identify the similarities of areas not only from the climatic point of view, taking advantage of the natural resources of the area. This has not been included in this study due to lack of information on soil types in the area where the study has been carried out.

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