METSK-HD-Angeleno: How to predict fruit quality using Multiobjective Evolutionary learning of TSK systems

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***Abstract*—The United Nations Food and Agriculture Organization (FAO) ranks Spain 13th in the world in plum and sloes production and 4th in the member states of the European Union. Cultivation of this fruit is clearly important in our country, and is even more so in Extremadura, a Mediterranean region in south-western Spain, which focus their economic activity on the primary sector. A plum production must be differentiated by its quality, but the quality of the fruit is traditionally perceived by the experience of farmers and technicians, based solely on their visual perception. This traditional decision-making process sometimes leads to errors in determining the optimum date for harvesting.**

Among the quality parameters used by the food industry are the soluble solids content and/or the firmness. These parameters will measure the fruit quality, allowing to obtain the best quality of the fruit when the optimal values are reached. The parameters must be calculated using destructive techniques and sophisticated laboratory equipment. In this work we present a new method to predict the soluble solids content or the firmness of a fruit, by means of software techniques that do not require a destruction fruit process and expensive laboratory equipment. The results presented in this work allow us to affirm that it is possible to provide farmers and agricultural technicians with software tools that help them make the right decision regarding the ripening of their fruit, in order to obtain the highest quality products and be more competitive in the sector.

I. Introduction

The United Nations Food and Agriculture Organization (FAO) ranks Spain as the world's 13th largest plum and sloes producer and the 4th largest in Europe [1]. The economic importance of growing this fruit in our country is evident. The Spanish Ministry of Agriculture, Fisheries and Food states that Extremadura, where the project presented here is being developed, has 3,599 ha dedicated to plum cultivation, being the first region of Spain in surface of plum [10]. Plum production in Spain in 2016 was 193,598 tonnes and in Extremadura it was 92,700 tonnes [9]. Therefore, our region produces 48% of the production in Spain, also placing us in first place as producers. Obtaining the highest quality fruit means harvesting at the optimum moment of ripeness. In the orchard, the grower is responsible for deciding whether or not the crop has reached the proper minimum maturity for harvest. If, thanks to the tools presented in this work, farmers are able to harvest the fruit at its optimum moment, it can be a great competitive advantage for Extremadura companies compared to their competitors.

The quality of a product is perceived by the consumer as a set of attributes that are evaluated subjectively. If we focus on the fruit, this quality will be measured by: appearance, aroma, taste, etc. But how do we obtain higher quality fruit for successful in consumer quality expectations? We can use techniques to improve a proper harvest maturity stage. In this way, when the fruit reaches the consumer, it will reach the desired quality.

The fruits must be harvested at their optimum state of ripeness, but how is it determined whether the fruit is at its optimum time for harvesting? The decision-making of the fruit harvest date has historically been made by human operators, farmers or technicians, who with the experience gained during years of work, are able to estimate the harvest date. This work is done visually and with basic fruit processing techniques, which has great limitations, since the decisions taken depend largely on their experience. It is therefore a highly subjective method, which can lead to errors in the harvest, either by picking the fruit before time or even with a date after its optimal state. Plums fruit picked at an under-ripe stage do not reach a desirable flavor even if they are stored for long periods. However, fruit harvested too late is prone to fast deterioration and has a short market life. Trying to solve this problem and help operators in the sector, some research has been focused on measuring fruit ripeness non-destructively techniques which are intended to support the correct decision making: impact response [14], spectroscopic techniques and image analysis [20], [15], [16], [21], [19], acoustic properties of the flesh [17], absorbance of chlorophyll [18] and algorithms of machine

[1] http://www.fao.org/faostat

learning [22]. With the above mentioned techniques it is possible to determine varieties and ripening stages, but with the incorporation of tools based on artificial intelligence it will be possible to predict accurately the future quality of the orchard.

The fruit on which this work focuses is plum, without depending on the variety studied, a fruit quality is measured by its physical-chemical properties, such as soluble solids content (SSC), firmness, size, color among others. In order to know these parameters, it is necessary to destroy the fruit by means of expensive processes in a laboratory. Fruit firmness, color and sugar content are the most useful criteria for selecting fruit suitable for picking [11], [12]. Flesh firmness brings its hardness, while the SSC is correlated with the perception of sweetness, plum flavour and plum aroma intensity. Color relates more directly to consumer perception of appearance[13]. To calculate these parameters it is necessary to destroy the fruit and use sophisticated laboratory machine. Farmers cannot incorporate these techniques into their orchards, so the quality of their orchard is measured by their experience and according to the visual aspect (firmness) and its sweetness content (SSC).

The work presented here focuses on the incorporation of tool based on artificial intelligence to aid decision-making for farmers. Currently, the food industries have sophisticated systems for classifying and evaluating fruit, but farmers do not have sufficient means to incorporate these systems into their production. This paper presents the results of a set of algorithms to predict fruit quality, without the use of sophisticated devices. The aim of this work is to develop software tools that, in a simple way, can be used by farmers to know harvest mature.

The incorporation of machine-learning techniques by the food industries into selective processes is becoming necessary. We can find application of *random decision forests* [1], Support vector machines [2] or neural networks [3], among other types of machine learning algorithms. These techniques are focused on the evaluation of the quality of the product, applied in the industries where the product arrives once it has been harvested. In this work, we propose a predictive fuzzy rule-based system (FRBS) based on METSK-HD [5], an evolution of TSK-FRBS [4], which improves the accuracy and convergence when high-dimensional and large-scale regression data sets are managed. We compare the results with traditional machine learning approaches such us Linear Regression (LR), Decision Tree (DT), Support Vector Machine (SVM) and Multi-Mayer Perceptron (MLP).

In order to obtain a system capable of correctly predicting the fruit quality of an orchard, we must implement and optimize a TSK-FRBS based on the parameters used by technicians to measure the fruit quality. The fruit parameters used in this study are the following: weight, size, color, firmness and solids soluble content. In this work we focus on predicting the most signicant parameters to measure quality, **SSC and firmness**.

The results show that it is possible to predict these quality parameters with a very low error. The incorporation of these prediction engines in simple software tools aimed at farmers and techniques, will allow them to know the status of their orchard, thus being able to make the right decisions for harvesting at its optimum time.

The rest of the paper is divided into a full description of the type of fruit chosen for this study, Angeleno, is presented in Section II. The methodology used to predict the fruit quality is developed in Section III. The results are presented in Section IV. Finally, the conclusions of the work are presented in Section V.

II. Angeleno as object of study

The study presented in this work has been carried out on a variety of plum at the institute of Agrarian Research Finca La Orden - Valdesequera (CICYTEX, Center for Scientific and Technological Research of Extremadura) [2] from May to September 2018. The plant material consisted of late-maturing Japanese plum (*Prunus salicina* Lindl. cv. Angeleno, on Mariana 2624 rootstock). *P.salicina* cv. Larry Ann and cv. Fortune were planted as pollinizers, and at flowering bee hives were placed in the orchard to ensure pollination. Angeleno is a dark red plum with a pale-yellow flesh and small stone. The flesh is dense and crunchy, without much juice, but sweet with well-balanced flavour due to the long growing time. Fig. 1 shows an Angeleno plum.

Fig. 1. Angeleno plum.

In this study, a series of fruit samples were taken at different ripening dates and a set of analyses was carried out in the agricultural research institutes laboratories. These analyses have allowed us to obtain the values of the parameters used in this work, which have subsequently been used by different techniques with the aim of correctly predicting the fruit SSC or firmness.

A. Test schedule

In this subsection we present the test schedule that carried out in this study (see TABLE I). Angeleno full bloom was in March, but it is not until August when the laboratory tests can obtain significant values of SSC and firmness. In 1 ha orchard (tree spacing 6 m x 4 m), the samples were randomly picked in a randomized complete block design with four replicates. Each plot consisted of four adjacent rows of four trees each. Samples were collected from the first and fourth row in the

[2] http://cicytex.juntaex.es/es/centros/la-orden-valdesequera

second and third tree, having fruits belonging to zones of sun and shade of the trees. (Total 64 fruits: 4 fruit per tree in each plot x 4 plots), these samples acquire different properties during their ripening. Fig. 2 shows one of the fruit testing works done in the laboratory.

TABLE I
TEST SCHEDULE

date of test	samples
8/17/18	64
8/23/18	64
8/28/18	64
9/4/18	64
9/11/18 [3]	64
9/19/18	64

Fig. 2. Testing work in laboratory.

B. Parameters used

The fruit quality analysis, as mentioned above, is measured by its visual aspect (firmness) and its sweetness content (SSC). In order to obtain these values from a fruit, sophisticated devices are currently used. In this work a new approach is presented, by means of which, in relation to other parameters of the fruit, we can predict the SSC or firmness. For this study, we are used the following fruit parameters:

- *weight (g)*: parameter that indicates the fruit weight. ($Min:\ 55g - Max:\ 201g$)
- *size*: was measured with a digital caliper (Mitutoyo, absolute digimatic IP67 15 mm) (mm). ($Min:\ 48mm - Max:\ 74mm$)
- *color*: Skin color was measured at opposite sides of each fruit with a CM-600d Spectrophotometer (Konica Minolta, Tokyo, Japan). The chroma value (C*) was used to characterize changes in skin color during ripening. L*a*b* Color Space. Standart illuminat D65 and 10°observer.
- *firmness*: flesh firmness was measured with a penetrometer (BERTUZZI, FT 327) equipped with a 8 mm diameter plunger tip. A small slice of fruit skin was removed and firmness was recorded from two sides of individual plum fruit. ($Min:\ 2.05 - Max:\ 6.25$) (kg/cm^2)
- *SSC*: the SSC gives us an idea of how sweet the fruit is. The amount of sugar in a fruit increases as it ripens, and as most fruits are done growing in size by the time they start to ripen, this means that the ratio of sugar to liquid in the fruit increases as it ripens. The individual concentration of the different sugars (fructose, sucrose, etc) does not matter as much as the total sugar concentration for the flavor of the fruit, and SSC measure the total amount of sugar in a standard amount of water. SSC was measured with a thermo-balanced PAL-1 refractometer (Atago, Tokyo, Japan) (°Brix). ($Min: 7.25° Brix - 19.60° Brix$)

Fig. 3 shows how the work laboratory was carried out to obtain the parameters described above. It can be observed how the firmness and SSC of the fruits are obtained using a penetrometer and a refractometer.

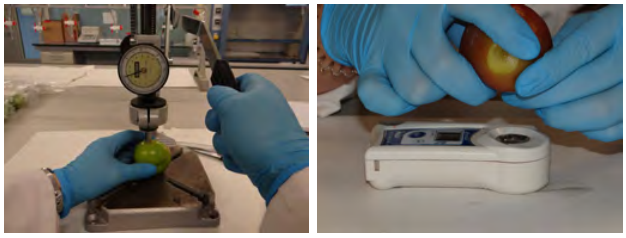

Fig. 3. Obtaining SCC and firmness parameter in laboratory.

Once we know the properties of the plum variety used in this study, this paper focuses on describing the techniques based on machine learning and artificial intelligence that have been used to develop the software tools for predicting fruit quality.

III. METHODOLOGY

As mentioned above, in this paper we propose a new method for predicting the Angeleno plum quality. This quality is measured by its SSC or by its firmness. Both parameters are calculated by fruit destructive processes and using sophisticated devices in a laboratory. With this work, our main objective is to provide farmers and technicians with software tools capable of obtaining the parameters that measure fruit quality without destroying the fruit and without using expensive devices. In order to achieve this goal we have used algorithms based on TSK-FRBS, which is then optimized using a GA.

A. TSK-FRBS module

The prediction model is performed by the TSK-FRBS algorithm. The software predictive model for fruit quality that we propose needs to establish the relationship among the set of parameters previously defined, whose were calculated in the laboratory. These data are included as key information during the learning phase to design the software system based on TSK-FRBS. Once the algorithm is optimized we could evaluate the fruit quality. The variables used by the TSK-FRBS are:

- Input Variables
  - weight

[3] harvest date

- size
- L*
- a*
- b*
- C*

- Output Variable
  - firmness.
  - SSC.

Note: SSC and firmness are predicted separately.

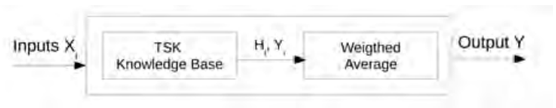

Fig. 4. TSK-FRBS model.

As we mentioned above, in this work we propose a predictive system based on METSK-HD (Multiobjective Evolutionary learning of TSK systems for High Dimensional problems with estimated error) [5], an evolution of TSK-FRBS [4], which improves the accuracy and convergence when high-dimensional and large-scale regression datasets are managed. The structure consists of a Knowledge Base (KB) and Rules Database (RB). The KB stores the knowledge extracted of the problem at hand, and establishes the relationship between the input and output variables by means the well-known Membership Functions(MF). The knowledge is finally stored as fuzzy rules with an *IF-THEN* format. Fuzzy rules have a structure with an antecedent and a consequent. The antecedent is composed of linguistic variables, and the consequent is a polynomial function of the input variables. Thus, the rules format of a TSK-FRBS has the following structure:

IF X_1 is A_1 ... and X_n is A_n
then Y = $p_1 * X_1 + \ldots + p_n * X_n + p_0$

where the system inputs variables are denoted as X_i, Y is the system output variable, p_i represents real-values coefficients and A_i are fuzzy sets.

Fig. 4 shows the flow of the TSK-FRBS model. Considering the KB contains m TSK rules the output of TSK system is computed as the weighted $\bar{x}$ of each individual rule output Y_i as shown (1):

$$\frac{\sum_{m}^{i=1} h_i \cdot Y_i}{\sum_{m}^{i=1} h_i} \tag{1}$$

where $i = 1...m$, $h_i = T(A_1(x_1)...A_n(x_n))$ represents the matching degree between the antecedent part of the ith rule and the current system inputs $x = (x_1...x_n)$, and with T being a t-norm.

TSK-FRBSs have been applied successfully to a large quantity of problems. The main advantage of these kinds of systems is the fact that they present a compact system equation for estimating the parameters p_i using classical methods, and obtaining an accurate system, which can be very useful for accurate fuzzy modeling.

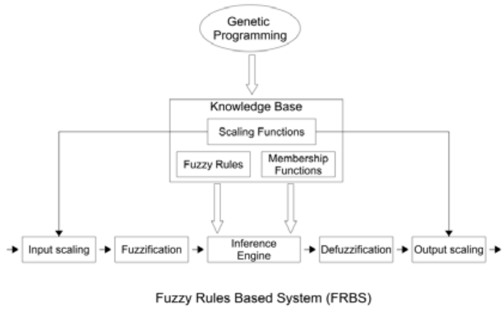

Fig. 5. Processes involved in the FRBS module.

Problems with large or high-dimensional data sets make non-feasible an ad-hoc implementation and need an automatic learning process for the KB and RB. The process is divided into different stages due to the high complexity of the search space involved, although KB and RB should be learned and optimized together. Different techniques have been applied for this task, but the Genetic Fuzzy Systems (GFS) [6] has the best results. EAs are able to learn the antecedents and consequents of the rules system together, and to optimize the MF of the KB. Fig. 5 shows the summary of the optimization process of TSK-FRBS.

This process is divided into two stages, called *Learning* and *Tuning*. In the first stage, *Learning*, the initial Data Base (DB) based on a fuzzy grid in order to obtain zero-order TSK candidate rules, is learned using an effective Multi-Objective Evolutionary Algorithm (MOEA)[7], [8]. The second stage, *Tuning*, applies an advanced post-processing for fine scatter-based evolutionary tuning of MFs combined with a rule selection. Fig. 6 shows the process described previously.

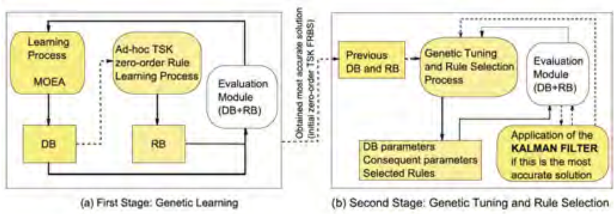

Fig. 6. TSK-FRBS optimization process.

Once the TSK-FRBS has been optimized, a new algorithm of the METSK-HD type is obtained, which we will call **METSK-HD-Angeleno**.

B. A comparison with classic machine learning techniques

In order to compare the new proposed algorithm METSK-HD-Angeleno with classic techniques of machine learning used in other works, we have used the following well-known algorithms:

- Linear Regression.
- Decision Tree.

- Support Vector Machine.
- Multi-Layer Perceptron.

C. Experiments

A set of 8 experiments have been designed, where in 4 of them the value to predict is SSC and in the other ones is firmness. A different number of input parameters have been used for each experiment. The objective of this set of experiments is to minimize the number of values necessary to obtain the prediction of the SSC or firmness values. As the number of parameters decreases, it becomes easier for the user to use the system, since it depends on fewer input parameters, but this parameter reduction makes the prediction more complex, since the system works with less fruit information. The results show that if we decrease the input parameters number, the problem is more complex, but the predictions obtained by the system are within acceptable parameters. TABLE II shows a summary of the experiments that have been performed.

TABLE II
EXPERIMENTS DETAIL

N°of Experiment	Input Parameters	Value to predict	N°of Experiment	Input Parameters	Value to predict
1	weight size L* a* b* C* firmness	SSC	2	weight size L* a* b* C* SSC	firmness
3	weight size	SSC	4	weight size	firmness
5	L* a* b* C* firmness	SSC	6	L* a* b* C* SSC	firmness
7	L* a* b* C*	SSC	8	L* a* b* C*	firmness

We can observe that experiments 1 and 2 use all the parameters extracted in the laboratory and predict SSC and firmness respectively. Experiments 3 and 4 are more restrictive, only use the weight and size of the fruit to predict its quality. On the other hand, there is another set of experiments related to the fruit color, expressed by the parameters L*, a*, b* and C*, in order to predict the final quality. These experiments are focused on, in a future work, using fruit images, instead of numerical parameters, to predict their quality. If color parameters are used correctly to predict quality, they can be obtained from an image without the use of a spectrophotometer.

IV. RESULTS

In the subsection II-A we present the number of samples collected on the dates that the different samplings are carried out. We can observe that a total of 64 samples were taken per day, obtaining 384 samples throughout the fruit ripening period. The samples collected were in different stages of ripening, which gives a complete view of the ripening cycle of the fruit.

In order to validate the results obtained, the data set was divided using the well-known 5-fold cross validation method. Applying this method, 5 subsets of data are obtained which are combined to obtain a training set with the 80% of the samples and a test set with the 20%. Once the training and test sets have been obtained, the set of 8 experiments detailed in TABLE II have been done. For each experiment, the parameters indicated as input have been selected and an attempt has been made to predict either the SSC or firmness.

TABLE III shows the results of experiment 1 using the classical machine learning algorithms. We can observe the Decision Tree algorithm has overfitting, obtaining a RMSE of 2.14. On the other hand, the Multi-Layer Perceptron has the best results.

TABLE IV shows the results of the experiment 1 using the new METSK-HD-Angeleno algorithm presented in this paper. As we explain above, this algorithm has 2 phases (Learning and Tunning) and is an evolution of a TSK-FRBS using a Multiobjective Evolutionary learning process. Due to the stochastic nature of these algorithms, it is necessary to perform a significant set of executions, in our case we have performed 30 executions. A further feature of METSK-HD-Angeleno is that, in the algorithm tuning process, it is able to eliminate input variables that are not significant for prediction purposes. In the case of the experiment presented in TABLE IV, METSK-HD-Angeleno uses only the input parameters corresponding to size, b* and firmness, unlike the classical machine learning algorithms that use all the input parameters. The results obtained by METSK-HD-Angeleno are the best if we compare them with the classical machine learning algorithms.

Finally, Tables V and VI show the set of 8 experiments results that we have done in this work. We can observe that in all experiments the METSK-HD-Angeleno algorithm obtains the best results. In the next subsection we present a complete statistical study to demonstrate the goodness of our algorithm, in contrast to classical techniques of machine learning.

A. Statistical study

This subsection presents a complete statistical study to compare the results obtained by the different algorithms presented in this work. The study presented here demonstrates that the algorithm proposed in this work METSK-HD-Angeleno, in addition to obtaining the best results, these results are significantly different from those obtained by classical machine learning algorithms. The following tables show the results of all the tests performed.

TABLE VII shows the average ranks obtained by each method using the Friedman test on experiments 1, 3, 5 and 7 (P-value computed by Friedman Test: 0.010339)

TABLE VIII shows the adjusted P-values obtained through

TABLE III
RESULTS OF EXPERIMENT 1 USING CLASSICAL MACHINE LEARNING ALGORITHMS

Linear Regression

Kfold	Correlation coefficient		Mean absolute error		Root mean squared error		Relative absolute error (%)		Root relative squared error (%)	
	Training	Test	Training	Test	Training	Test	Training	Test	Training	Test
1	0.6911	0.6526	1.0805	1.1487	1.3876	1.4313	70.2112	72.3406	72.2793	76.0276
2	0.7034	0.5639	1.0778	1.1567	1.357	1.577	68.8792	77.4469	71.0761	81.6075
3	0.6828	0.6903	1.095	1.0847	1.4018	1.3862	70.7197	70.1539	73.0567	73.6291
4	0.6754	0.6975	1.0781	1.1561	1.3937	1.4071	70.9181	69.744	73.7434	69.9871
5	0.6735	0.7132	1.1155	1.0407	1.4157	1.3319	71.3999	70.0637	73.9232	70.1252
$\bar{x}$	0.6852	0.6635	1.0894	1.1174	**1.3912**	**1.4267**	70.4256	71.9498	72.8157	74.2753
σ	0.0123	0.0600	0.0162	0.0524	**0.0218**	**0.0917**	0.9638	3.2411	1.1682	4.8182

Decision tree

Kfold	Correlation coefficient		Mean absolute error		Root mean squared error		Relative absolute error (%)		Root relative squared error (%)	
	Training	Test	Training	Test	Training	Test	Training	Test	Training	Test
1	1	0.4233	0.0076	1.6014	0.0177	1.9825	0.4916	100.8563	0.9208	105.3061
2	1	0.3242	0.0084	1.7126	0.0188	2.2685	0.5343	114.6701	0.9832	117.3941
3	1	0.4343	0.0059	1.6531	0.0147	2.218	0.3809	106.9114	0.7644	117.8113
4	1	0.4856	0.0076	1.5789	0.0186	2.0247	0.5019	95.2499	0.9828	100.7042
5	1	0.3092	0.0056	1.6688	0.0155	2.2398	0.3602	112.3495	0.8103	117.9251
$\bar{x}$	1.0000	0.3953	0.0070	1.6430	**0.0171**	**2.1467**	0.4538	106.0074	0.8923	111.8282
σ	0.0000	0.0757	0.0012	0.0535	**0.0019**	**0.1327**	0.0779	8.0365	0.1004	8.2193

Support Vector Machine

Kfold	Correlation coefficient		Mean absolute error		Root mean squared error		Relative absolute error (%)		Root relative squared error (%)	
	Training	Test	Training	Test	Training	Test	Training	Test	Training	Test
1	0.6879	0.6551	1.0789	1.1328	1.3986	1.4175	70.1072	71.3402	72.8489	75.2971
2	0.6988	0.5649	1.0763	1.1619	1.3683	1.5811	68.7844	77.7984	71.6672	81.8191
3	0.6775	0.662	1.0938	1.1156	1.418	1.4499	70.6462	72.1525	73.8992	77.011
4	0.6662	0.683	1.0775	1.1817	1.4168	1.4377	70.8757	71.2915	74.9651	71.5108
5	0.6638	0.7078	1.1135	1.0483	1.4353	1.341	71.2686	70.5777	74.9468	70.6025
$\bar{x}$	0.6788	0.6546	1.0880	1.1281	**1.4074**	**1.4454**	70.3364	72.6321	73.6654	75.2481
σ	0.0147	0.0542	0.0159	0.0514	**0.0254**	**0.0869**	0.9640	2.9414	1.4182	4.5232

Multi-Layer Perceptron

Kfold	Correlation coefficient		Mean absolute error		Root mean squared error		Relative absolute error (%)		Root relative squared error (%)	
	Training	Test	Training	Test	Training	Test	Training	Test	Training	Test
1	0.7324	0.677	1.0228	1.0958	1.3072	1.3841	66.4656	69.009	68.0919	73.523
2	0.7338	0.6342	1.0295	1.0949	1.3137	1.4519	65.7879	73.312	68.8066	75.1347
3	0.7215	0.6914	1.0542	1.0722	1.3323	1.3866	68.0881	69.3462	69.4347	73.6511
4	0.7272	0.6713	1.0403	1.2092	1.3251	1.4541	68.431	72.9473	70.1174	72.3261
5	0.7219	0.75	1.0851	1.0181	1.3819	1.2721	69.4552	68.5434	72.1596	66.976
$\bar{x}$	0.7274	0.6848	1.0464	1.0980	**1.3320**	**1.3898**	67.6456	70.6316	69.7220	72.3222
σ	0.0057	0.0421	0.0247	0.0697	**0.0295**	**0.0740**	1.4942	2.3018	1.5553	3.1504

the application of the post hoc methods (Friedman) on experiments 1, 3, 5 and 7.

TABLE IX shows the average ranks obtained by each method using the Friedman test on experiments 2, 4, 6 and 8 (P-value computed by Friedman Test: 0.009686)

TABLE X shows the adjusted P-values obtained through the application of the post hoc methods (Friedman) on experiments 2, 4, 6 and 8.

We can observe that in the total of the 8 experiments carried out we can reject the null hypothesis H_o and to affirm that the results obtained by METSK-HD-Angeleno are significantly different from those obtained by the algorithms with which the technique presented in this work has been compared.

V. CONCLUSIONS

This work presents a software tool based on fuzzy systems, optimized with a genetic algorithm by means of which it is possible to predict the quality of a type of plum, Angeleno. As the introduction to the work indicates, the production of this type of plum in the region where this project is being developed, Extremadura, is very significant, as well as being a very strong economic engine. Obtaining quality fruit

TABLE IV
RESULTS EXPERIMENT 1 FROM METSK-HD-ANGELENO ALGORITHM

N°Exec.	Learning Rules	Learning RMSE tra	Learning RMSE tst	Tunning Rules	Tunning RMSE tra	Tunning RMSE tst
1	70	0.9297	1.0466	44	0.7302	1.0843
2	80	0.8980	1.1229	50	0.7272	1.0401
3	80	0.9001	1.1384	47	0.7205	1.0696
4	95	0.9318	0.9748	57	0.7418	1.0183
5	100	0.9276	0.9714	53	0.7399	1.1258
6	80	0.8973	1.0664	52	0.6972	1.1118
7	92	0.9011	1.1323	52	0.7370	1.0643
8	100	0.9086	1.1483	58	0.6877	1.1497
9	91	0.8960	1.1282	50	0.7160	1.1366
10	89	0.9002	1.1071	56	0.7092	1.0672
11	100	0.9166	1.2170	54	0.7343	1.1559
12	100	0.9151	1.1503	60	0.7234	1.1872
13	92	0.9140	1.1278	46	0.7077	1.1204
14	100	0.8998	1.1216	60	0.6945	1.1233
15	100	0.8847	1.1174	62	0.6848	1.2724
16	78	0.9047	1.2184	52	0.7248	1.1842
17	100	0.9180	1.1763	61	0.6896	1.2306
18	100	0.8982	1.0858	60	0.7083	1.2147
19	100	0.9140	1.1616	53	0.6756	1.2054
20	89	0.8983	1.0715	57	0.7025	1.0892
21	92	0.8993	1.3900	47	0.7268	1.5005
22	98	0.9026	1.3073	63	0.6934	1.2760
23	94	0.8956	1.3091	58	0.6808	1.1555
24	100	0.8938	1.1464	61	0.6868	1.4039
25	92	0.9182	0.9356	55	0.7385	0.9796
26	92	0.9384	0.9971	54	0.7273	1.0845
27	100	0.9399	0.9326	57	0.6902	0.9864
28	100	0.9360	0.9432	58	0.7401	0.9605
29	97	0.9422	0.9941	65	0.7349	1.0336
30	100	0.9170	0.9907	65	0.7254	1.0387
$\bar{x}$	93.3667	0.9112	1.1077	55.5667	0.7132	**1.1357**
σ	8.2649	0.0159	0.1129	5.5936	0.0208	**0.1192**

makes growers more competitive with other markets and also provides a quality certificate.

The quality of a fruit is determined by certain parameters such as SSC and firmness. Quantifying these values by the farmers is a tedious task as it is completely subjective as they cannot incorporate the sophisticated equipment that can carry out this task into their productions. Providing farmers with software tools that can help them make this decision means that the fruit harvested is of the highest possible quality by harvesting it at its optimum ripening date.

As we can see in the results, the prediction algorithm presented, called METSK-HD-Angeleno obtains very good results compared to other classical techniques. This allows us to affirm that it is possible to design and implement software tools that allow farmers to improve their plum production.

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TABLE V
RESULT OF EXPERIMENTS BASED ON SSC PREDICTION

Experiment 1

	Training $\bar{x}$	Training σ	Test $\bar{x}$	Test σ
Linear Regression	1.3912	0.0218	1.3912	0.0218
Decision Tree	0.0171	0.0019	2.1467	0.1327
Support Vector Machine	1.4074	0.0254	1.4454	0.0869
Multi-Layer Perceptron	1.3320	0.0295	1.3898	0.0740
METSK-HD-Angeleno	0.7132	0.0208	**1.1357**	**0.1192**

Experiment 3

	Training $\bar{x}$	Training σ	Test $\bar{x}$	Test σ
Linear Regression	1.7838	0.0487	1.7851	0.1877
Decision Tree	0.0112	0.0011	2.5669	0.3306
Support Vector Machine	1.7898	0.0486	1.7924	0.1856
Multi-Layer Perceptron	1.9551	0.1681	1.9373	0.1102
METSK-HD-Angeleno	1.2165	0.0387	**1.2909**	**0.1307**

Experiment 5

	Training $\bar{x}$	Training σ	Test $\bar{x}$	Test σ
Linear Regression	1.4554	0.0387	1.4678	0.1543
Decision Tree	0.0182	0.0013	2.0914	0.3019
Support Vector Machine	1.4679	0.0404	1.4695	0.1675
Multi-Layer Perceptron	1.4837	0.1037	1.5632	0.1939
METSK-HD-Angeleno	0.7734	0.0265	**1.1560**	**0.0961**

Experiment 7

	Training $\bar{x}$	Training σ	Test $\bar{x}$	Test σ
Linear Regression	1.6752	0.0387	1.6778	0.1446
Decision Tree	0.0168	0.0009	2.3082	0.2683
Support Vector Machine	1.6911	0.0341	1.6893	0.1325
Multi-Layer Perceptron	2.3339	0.4790	2.3496	0.3475
METSK-HD-Angeleno	1.0600	0.0357	**1.2629**	**0.0761**

REFERENCES

[1] Pal, M. *Random forest classifier for remote sensing classification,* International Journal of Remote Sensing, 26(1), 217-222. 2005.

[2] Danfeng Wang, Xichang Wang, Taiang Liu and Yuan Liu, *"Prediction of total viable counts on chilled pork using an electronic nose combined with support vector machine,"* Meat Science, Volume:90, pag:373 - 377, 2012.

[3] Krizhevsky, A., Sutskever, I., Hinton *Imagenet classification with deep convolutional neural networks. In: Bartlett, P., Pereira, F., Burges, C., Bottou, L., Weinberger, K. (eds.),* Advances in Neural Information Processing Systems 25, pp. 11061114, 2012

[4] Takagi, T., Sugeno, M.: Fuzzy identification of systems and its applications to modeling and control. IEEE transactions on systems, man, and cybernetics (1), 116–132 (1985)

[5] Gacto, M. J., Galende, M., Alcalá, R., Herrera, F.: METSK-HDe: A multiobjective evolutionary algorithm to learn accurate TSK-fuzzy systems in high-dimensional and large-scale regression problems. Information Sciences, 276, 63-79. (2014)

[6] Herrera, F.: Genetic fuzzy systems: taxonomy, current research trends and prospects. Evolutionary Intelligence 1(1), 27–46 (2008)

[7] Coello, C. A. C., Lamont, G. B., Van Veldhuizen, D. A.: Evolutionary

TABLE VI
RESULT OF EXPERIMENTS BASED ON FIRMNESS PREDICTION

Experiment 2

	Training		Test	
	Average	Std. Dev.	Average	Std. Dev.
Linear Regression	0.5745	0.0054	0.5821	0.0189
Decision Tree	0.0017	0.0016	0.7799	0.0802
Support Vector Machine	0.5787	0.0062	0.5898	0.0196
Multi-Layer Perceptron	0.6514	0.0437	0.6801	0.0590
METSK-HD-Angeleno	0.2924	0.0139	**0.4500**	**0.0247**

Experiment 4

	Training		Test	
	Average	Std. Dev.	Average	Std. Dev.
Linear Regression	0.0000	0.0000	0.9351	0.0216
Decision Tree	0.0000	0.0000	0.9351	0.0216
Support Vector Machine	0.6993	0.0098	0.7022	0.0418
Multi-Layer Perceptron	0.8446	0.0543	0.8442	0.0918
METSK-HD-Angeleno	0.4793	0.0068	**0.5015**	**0.0205**

Experiment 6

	Training		Test	
	Average	Std. Dev.	Average	Std. Dev.
Linear Regression	0.5749	0.0048	0.5891	0.0192
Decision Tree	0.0010	0.0014	0.8571	0.0443
Support Vector Machine	0.5793	0.0058	0.5894	0.0279
Multi-Layer Perceptron	0.6041	0.0359	0.6415	0.0577
METSK-HD-Angeleno	0.3031	0.0102	**0.4693**	**0.0384**

Experiment 8

	Training		Test	
	Average	Std. Dev.	Average	Std. Dev.
Linear Regression	0.6605	0.0159	0.6679	0.0647
Decision Tree	0.0010	0.0014	0.9383	0.0755
Support Vector Machine	0.6604	0.0162	0.6648	0.0648
Multi-Layer Perceptron	0.7902	0.0913	0.7797	0.0818
METSK-HD-Angeleno	0.3992	0.0202	**0.5100**	**0.0529**

TABLE VII
AVERAGE RANKINGS OF THE ALGORITHMS PREDICTING SSC.

Algorithm	Ranking
Linear Regression	2.25
Decision Tree	4.75
Support Vector Machine	3.25
Multi-Layer Perceptron	3.75
METSK-HD-Angeleno	1

TABLE VIII
ADJUSTED p-VALUES (FRIEDMAN) (I)

i	algorithm	unadjusted p	p_{Bonf}
1	Decision Tree	0.000796	0.003185
2	Multi-Layer Perceptron	0.013906	0.055625
3	Support Vector Machine	0.044171	0.176685
4	Linear Regression	0.263552	1.05421

TABLE IX
AVERAGE RANKINGS OF THE ALGORITHMS PREDICTING FIRMNESS

Algorithm	Ranking
Linear Regression	2.875
Decision Tree	4.875
Support Vector Machine	2.5
Multi-Layer Perceptron	3.75
METSK-HD-Angeleno	1

TABLE X
ADJUSTED p-VALUES (FRIEDMAN) (I)

i	algorithm	unadjusted p	p_{Bonf}
1	Decision Tree	0.000528	0.002114
2	Multi-Layer Perceptron	0.013906	0.055625
3	Linear Regression	0.093533	0.37413
4	Support Vector Machine	0.179712	0.71885

algorithms for solving multi-objective problems (Vol. 5). New York: Springer. (2007)

[8] Deb, K.: Multi-Objective Optimization Using Evolutionary Algorithms. John Wiley and Sons. Inc., New York, NY. (2001)

[9] Anuario de estadística agrária 2017. Ministerio de Agricultura, Pesca y Alimentación. Spain.

[10] Encuesta sobre Superficies y Rendimientos de Cultivo. Ministerio de Agricultura, Pesca y Alimentación. Spain. (2017)

[11] Crisosto, C. H., Crisosto, G. M., Echeverria, G., Puy, J.: Segregation of plum and pluot cultivars according to their organoleptic characteristics. Postharvest Biology and Technology, 44(3), 271-276. (2007)

[12] Robertson, J. A., Meredith, F. I., Lyon, B. G., Norton, J. D.: Effect of cold storage on the quality characteristics of 'AU-RUBRUM' plums. Journal of food quality, 14(2), 107-117. (1991)

[13] Abbott, Judith A.: Quality measurement of fruits and vegetables. Postharvest biology and technology 15.3 pp 207-225. (1999)

[14] Garca-Ramos, F. J., Ortiz-Canavate, J., Ruiz-Altisent, M., Dez, J., Flores, L., Homer, I., Chávez, J. M.: Development and implementation of an on-line impact sensor for firmness sensing of fruits. Journal of Food Engineering, 58(1), 53-57. (2003)

[15] Lleó, L., Barreiro, P., Ruiz-Altisent, M., Herrero, A.: Multispectral images of peach related to firmness and maturity at harvest. Journal of Food Engineering, 93(2), 229-235. (2009)

[16] Valente, M., Leardi, R., Self, G., Luciano, G., Pain, J. P.: Multivariate calibration of mango firmness using vis/NIR spectroscopy and acoustic impulse method. Journal of Food Engineering, 94(1), 7-13. (2009)

[17] Zdunek, A., Cybulska, J., Konopacka, D., Rutkowski, K.: New contact acoustic emission detector for texture evaluation of apples. Journal of Food Engineering, 99(1), 83-91. (2010)

[18] Infante, R., Contador, L., Rubio, P., Mesa, K., Meneses, C.: Non-destructive monitoring of flesh softening in the black-skinned Japanese plums Angelenoand Autumn beauton-tree and postharvest. Postharvest Biology and Technology, 61(1), 35-40. (2011)

[19] Wang, H., Peng, J., Xie, C., Bao, Y., He, Y.: Fruit quality evaluation using spectroscopy technology: a review. Sensors, 15(5), 11889-11927. (2015)

[20] Riquelme, M. T., Barreiro, P., Ruiz-Altisent, M., Valero, C.: Olive classification according to external damage using image analysis. Journal of Food Engineering, 87(3), 371-379. (2008)

[21] Pathare, P. B., Opara, U. L., Al-Said, F. A. J.: color measurement and analysis in fresh and processed foods: a review. Food and bioprocess technology, 6(1), 36-60. (2013)

[22] Cubero, S., Aleixos, N., Moltó, E., Gómez-Sanchis, J., Blasco, J.: Advances in machine vision applications for automatic inspection and quality evaluation of fruits and vegetables. Food and Bioprocess Technology, 4(4), 487-504. (2011)