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A KNOWLEDGE-BASED SYSTEM FOR PURCHASING HARVESTED PISTACHIO NUTS USINC A BAYESIAN STRATEGY

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ABSTRACT

A knowledge based system prototype was developed to simulate the decision making process of plant managers in a pistachio processing plant. Plant managers served as the domain experts. From numerous interview sessions, observations, and practical work in the processing plant, a knowledge rule base was created using the integration of a Bayesian strategy with the daily pistachio marketing situation (observation). The results indicate that the knowledge based system decisions agreed in 88% of the cases with those of the domain experts. The 12% of results where differences occurred presented an intriguing insight into the actual decision making process carried out by the human experts.

Key words: Pistachios, Expert systems, Decision making.

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یک سیستم بر پایه دانش برای خرید پسته برداشت شده با استفاده از استراتژی بیز

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چکیده

یک سیستم خبره جهت شبیه سازی فرآیند تصمیم گیری مدیران کارخانه فرآوری پسته توسعه یافت. از جلسات متعدد مصاحبه، مشاهدات و کار تجربی در کارخانه فرآوری، یک پایگاه دانش (Knowledge base) با استفاده از انضمام استراتژی بیز (Bayes) با وضعیت روزانه بازار پسته (مشاهده) طراحی شد. نتایج نشان می دهد که تصمیمات سیستم خبره در این زمینه، در ۸۸٪ موارد با خبرگان حوزه مطابقت دارد. تفاوت تصمیم ها در ۱۲٪ باقیمانده با توجه به مراحل واقعی تصمیم گیری توسط خبرگان معرفی می گردد.

INTRODUCTION

Kerman province is the most important pistachio producing region in Iran. Nearly 70% of world pistachio and 90% of Iran's pistachio is grown in this region (7). Due to its high production of pistachio, most pistachio processing plants are located in Kerman. A great deal of attention is required for the production of a high quality and marketable product. This is achieved by proper management of the post-harvest pre-processing and processing stages of the product. Attempts have been made to automate various stages of processing pistachio nuts (4, 10) but the research in these areas is still in its infant stages.

In a pistachio processing plant decision making by the plant managers on purchasing a certain amount of harvested pistachio nuts during the harvest season is extremely important. On the other hand, there is considerable uncertainty about the future market demand. What percentage of pistachio loads entering to the plant should be purchased during harvested season to gain maximum profits? Will it be possible to sell the purchased amount of the loads during winter season to minimize the losses? In other words, an important question is how much to stockpile to enjoy maximum sales without running the risk of carry-over into the next selling season (2). In agri-business a lot of decisions are made under uncertain conditions. Achieving the necessary skills to make the correct decisions requires several years of experience.

One way of dealing with uncertainty and anticipating future disruptions is effective planning (6) based on stochastic approach. In this approach one is to learn from the past (background information) and combine it with new information (Bayes'theorem) in order to take the best possible action (Bayes'strategy).

The plant managers are mostly orchard growers. They have to find substitute managers to make proper decisions in the processing plant, and so be able to dedicate themselves to harvesting their orchards during harvest time. Further, since all the trucks have to queue and wait at the same time for the decisions on purchasing before unloading into the lines, there are too many samples and only a few experts in the plant. This creates a bottleneck in the processing. As a result the existing expert managers somehow have to transfer their skills, knowledge, judgment, experience, and the methods they use to apply these to a particular task to others. To cope with these problems and to accelerate the decision making process, a knowledge-based system, often referred to as an expert system, can be used in order to store and transfer their experience. There are 109 pistachio processing plants located in Kerman province (7) and the number is increasing at a rate of approximately 30% per year. Thus more and more human experts are needed. Training a new human expert is time consuming and expensive, so the use of an expert system is convenient because it can be easily distributed as software copies.

This paper is a report on the second stage of the expert system development process that yielded a prototype for purchasing a daily percentage of harvested pistachio nuts delivered to the processing plant in Kerman. The method used was in fact based on a direct expert system scheme called PISTMAN (as in PISTachio MANagement).

Objectives

The main objective of this project was to develop a novel expert system, as a managerial decision-making tool, to mimic the role of a pistachio processing plant manager. The developed Expert System (PISTMAN), is to be used by a computer operator to perform the task of the manager while he or she is not present at the plant. The specific objectives of the project are:

1. To develop and evaluate an ES for purchasing the harvested nuts.
2. Implementation in an actual processing plant.

MATERIALS AND METHODS

Modeling for the decision making process

A percentage of the best quality classes are purchased everyday during the harvest season. The percentage is based on the daily purchasing market situation (DPMS) and background selling information obtained through a decade of plant activities. The expert system used in this study is a Bayesian implementation.

The expert system consists of a knowledge-base, an inference engine, and a user interface, as illustrated in Figure 1. The knowledge- base contains facts and rules which the program uses to search for a solution to the problem (9). In this case, to find the most likely action to be taken on the daily percentage of truck loads to be purchased. The inference engine uses the knowledge-base to infer logically valid conclusions, and to logically justify conclusions (3). The inference works forward from the data to the hypothesis and is called a data-driven process where, given some data, a hypothesis is inferred. In this expert system the user supplies inputs to the inference engine. The inputs are matched with the information in the knowledge-base, and then the expert system infers the most likely action to be taken on the daily percentage of loads to be purchased. The inputs come from observation of a specific set of conditions, such as abroad market price (AMP), domestic market price (DMP), foreign demands of the processing plant (FD), stock in market (SIM), export facilities (EF), and yield of the processing plant (Y), which are called daily pistachio market situation (DPMS). The experts' decisions on pistachio market situation are made when the six conditions are observed.

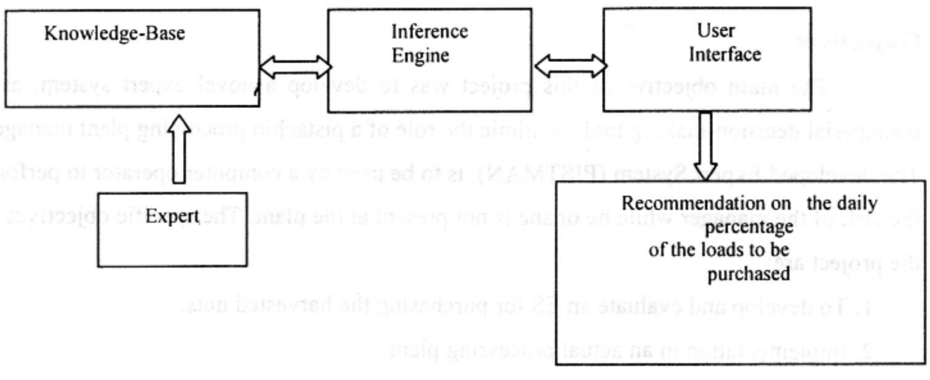

Fig. 1. Components of the expert system.

From interviews with the experts, we could discern the probabilistic nature of the logical link between decisions on purchasing a percentage of total loads everyday during harvest season (fall) and selling them during winter season. The decisions depend on prior distributions for key variables together with new information and these together form the basis for a decision recommendation (5). The various prior probability values were obtained by data collecting and processing. Data collection was done from records of ten years of purchasing and selling the commodity in the pistachio processing plant. Table 1 shows the number of times of occurrence of various combinations of purchasing (Z) during harvest season (fall) and selling (θ) during winter season. The prior probability values of winter selling vs. fall purchasing were calculated for each state of nature in different conditions as: Very poor (V_p), poor (P), normal (N), good (G) and excellent (E), as illustrated in Table 2.

Utility values were obtained by requesting the experts to give their estimates as shown in Table 3. According to Table 3, the values assigned by the experts were between 10, the minimum value $U(\theta_5, a_1)$ and 100, the maximum value $U(\theta_5, a_5)$.

The experts reveal that regret of not purchasing is more unfavorable to them than the stress of not selling the commodity. As shown in Table 3, the minimum value was assigned when winter selling was excellent (θ_5) and the experts purchase only 30% of the loads (a_1). On the other hand, the maximum value was assigned when the winter selling was excellent (θ_5) and the experts

Table 1. Number of times of occurrence of various combinations of purchasing and selling.

Winter season selling	Purchasing fall season: Very poor Z_1	Poor Z_2	Normal Z_3	Good Z_4	Excellent Z_5	Total
Very poor (θ_1)	12	10	11	8	2	43
Poor (θ_2)	22	3	28	11	7	71
Normal (θ_3)	3	2	38	19	38	100
Good (θ_4)	9	11	40	18	31	109
Excellent (θ_5)	6	10	14	7	20	57
Total	52	36	131	63	98	380

Table 2. Prior probability values of selling calculated for each state of nature.

State of nature description (selling)	Calculation of prior probabilities	
	Number of times observed	Prior probabilities
Very poor (θ_1)	43	0.113
Poor (θ_2)	71	0.187
Normal (θ_3)	100	0.263
Good (θ_4)	109	0.287
Excellent (θ_5)	57	0.150
Total	380	1.000

Table 3. Utility values assigned by the experts.

State of nature description (selling)	Actions a (to purchase)				
	30% of the load (a_1)	50% of the load (a_2)	70% of the load (a_3)	80% of the load (a_4)	100% of the load (a_5)
Very poor (θ_1)	50	40	30	25	15
Poor (θ_2)	35	60	40	35	25
Normal (θ_3)	25	35	80	45	35
Good (θ_4)	20	30	45	85	40
Excellent (θ_5)	10	20	30	35	100

purchase 100% of the loads (a_5). The formal mechanism used to combine the new information (DPMS) with the previously available information (selling records) is known as Bayes' theorem. Prior probabilities can be revised to obtain posterior probabilities using Bayes' formula (1, 8).

$$P(\theta_i / Z) = P_i = \frac{P(Z / \theta_i) P(\theta_i)}{P(Z)} \quad [1]$$

There are four quantities in Bayes' theorem, and, reading from left to right, they have the following meaning. The quantity $P(\theta_i / Z)$, called the *posterior* probability, represents the probability that conclusion θ is true given the weight of evidence Z. The symbol θ represent *conclusion* rather than H for *hypothesis* because Bayes' rule is applied at all stages of the inference process, to intermediate assertions as well as to the hypothesis. The quantity $P(Z / \theta_i)$, called the *likelihood*, represents the probability that evidence Z would be available given that conclusion θ were true. The quantity $P(\theta_i)$, called the *prior* probability, represents our degree of belief to learning of the evidence Z. Finally, the quantity $P(Z)$, called the *marginal* probability, represents the probability that evidence Z would be observed, independent of whether or not conclusion θ is true. Bayes' theorem provides a formula to calculate $P(Z)$:

$$P(Z) = \sum_{i=1}^{n} P(Z / \theta_i) P(\theta_i) \quad [2]$$

For example, the computation to obtain the unconditional probability of purchasing with very poor V_p observation (first column of Table 4) and the prior probabilities in Table 2 is accomplished by the formula (2);

$$P(Z_1) = (0.279)(0.113) + (0.310)(0.187) + \cdots = 0.137 \quad [3]$$

$G[P(\theta_i / Z), A]$ is obtained by multiplying posterior probabilities of each column as $P(\theta_i / Z)$ by the utilities under each action of the utility table $U(\theta_i, A)$ (see Table 3). Maximizing over the $a_j(k = 1,2,...,n)$ under each $Z_k(k = 1,2,...,n)$, give the optimal action, provided that particular Z_k is observed.

The experts determined six basic conditions which had major effect on daily pistachio purchasing market, each with five optional levels determined by the experts and Kerman Agricultural Organization as very high (VH), high (H), medium (M), low (L), and very low (VL). Each option contains a weighting factor an input for each condition assigned by the means of trial and error approved by the experts shown in Table 5. Weighting factors ranges from one to thirty showing the degree of importance of each level of option with respect to the daily pistachio market situation. Weighting factors are used as a pragmatic method of converting the multivariate sets of conditions into univariate observations. In other words, the weighting factors of each observation are added together as a total weighting factor. Bayes' theorem is then used on the univariate observations without approximation. Univariate observations produced by weighting factors are assumed to be sufficient (summary) statistics for the selling parameters. When daily interfacing with the expert system, the users have to choose one of the options as an input for each condition Table 6. This provides the situation of daily pistachio purchasing market (particular Z_k observation) using weighting factors, as very poor (VP), poor (P), normal (N), good (G), or excellent (E).

The knowledge-base is represented as a probability matrix (11) as shown in Table 4. The knowledge-base used in this implementation of the expert system consists of facts and rules. A fact may be thought of as a type of passive knowledge which is inherent in the knowledge-base, while the rules are active knowledge which are generated by the expert system (12). The expert system rules and facts were obtained by experts' estimation and by data collecting and processing. The fact records the relation between purchasing the loads everyday during harvest season (fall) and selling the commodity during winter season. The facts are formalized as follows:

1. Fact (AMP, [30, 25, 15, 2, 1]), where the list of numbers within square brackets is assigned to the option (Abroad Market Price) as: VH = 30, H = 25, M =15 and so on shown in Table 5.

The knowledge about how to use these facts in the classification process is represented by a set of production rules. Two sample rules are shown as follows:

Rule 3: *If AMP = H and DMP = M and FD = M and SIM = M and EF = H and Y = M, then* Z_k *(observation) = N.*

Table 4. Conditional probabilities.

Selling (θ)	Conditional probabilities $p(Z/\theta)$ Purchasing				
	(Z_1/θ)	$p(Z_2/\theta)$	$p(Z_3/\theta)$	$p(Z_4/\theta)$	$p(Z_5/\theta)$
Very poor (θ_1)	0.279	0.232	0.256	0.186	0.047
Poor (θ_2)	0.310	0.042	0.394	0.155	0.099
Normal (θ_3)	0.030	0.020	0.380	0.190	0.380
Good (θ_4)	0.083	0.101	0.367	0.165	0.284
Excellent (θ_5)	0.105	0.175	0.246	0.123	0.351

Table 5. Weighting factors assigned by the experts to each level of option as an input for each condition.

Conditions	Options				
	VH	H	M	L	VL
AMP	30	25	15	2	1
DMP	1	5	8	10	12
FD	10	8	6	4	2
SIM	5	4	3	2	1
EF	15	12	9	6	3
Y	20	16	12	8	4

2. Fact ($proZ_3$, [0.256, 0.394, 0.380, 0.367, 0.246]), where the list of numbers is assigned to the variable $proZ_3$. For example $p(Z_3/\theta_1)$ = 0.256, $p(Z_3/\theta_2)$ = 0.394, $p(Z_3/\theta_3)$ = 0.380 and so on shown in Table 4.

3. Fact UTa_3 , [30, 40, 80, 45, 30]), where UT stands for utility table and the list of numbers is assigned to the variable UTa_3 . For example $U(\theta_1, a_3)$ = 30, $U(\theta_2, a_3)$ = 40, $U(\theta_3, a_3)$ = 80 and so on shown in Table 3.

It should be noted that the decision making when observing six conditions simultaneously was more preferable by the experts compared to observing each condition at a time. In other words, decision making when having six cards at hand seemed much easier to them than getting cards one at a time (Rule 3).

Rule 4: *If observation of the daily market situation = Normal,*

then use $proZ_3$ to reverse to posterior probability according to equation (1) and UTa_3 to maximize action.

The pistachio market situation has to be observed every day. The result of each observation Z_k is based on answers to the six major questions by the users (inputs). The first rule may be interpreted as follows: If abroad market price AMP is high and domestic market price DMP is medium and foreign demands of the processing plant FD is medium and stock in market SIM is medium and export facilities EF is high and yield Y of the processing plant is medium then particular Z_k is observed as normal N.

The second rule maybe interpreted as follows: If daily pistachio market situation DPMS is observed as normal N, then using $proZ_3$, saves the probability value into an internal array. This array value is used to calculate the value of each cell according to Bayes' equation (1). The UTa_3 to max-action is obtained by multiplying posterior probabilities of each column by the utilities under each action column of the utility table. Max-action 'maximizing action' by the definition of a strategy, that is, a recipe for action given the observation of an event $(a_1, \ldots, a_5)$. The components of the purchasing system are shown in Figure 2.

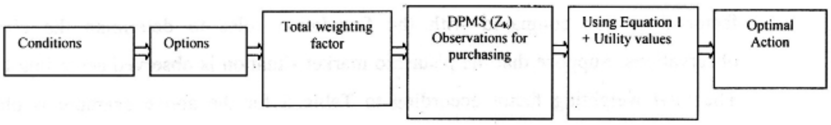

Fig. 2. Components of the purchasing system.

Model Evaluation

By means of trial and error and by requesting the experts to determine the level of the six basic conditions so as to fulfill the minimum requirement for each class of observation as VP, P, N, G, E, the following rules were established;

Rule 1: If total weighting factor (t.w.f.) satisfies $82 \leq$ t.w.f.≤ 92

Then the Z_k observation = Excellent (E).

Rule 2: If total weighting factor (t.w.f.) satisfies $72\leq$ t.w.f.≤ 81

Then the Z_k observation = Good (G).

Rule 3: If total weighting factor (t.w.f.) satisfies $59\leq$ t.w.f.≤ 71

Then the Z_k observation = Normal (N).

Rule 4: If total weighting factor (t.w.f.) satisfies $32\leq$ t.w.f.≤ 58

Then the Z_k observation = Poor (P).

Rule 5: If total weighting factor (t.w.f.) satisfies $12\leq$ t.w.f.≤ 31

Then the Z_k observation = Very Poor (VP).

These five rules are the foundations for the expert system decision making on observing the pistachio market situation by the use of trial and error method.

An experiment was conducted to measure the accuracy of the expert system (PISTMAN) when observing the pistachio market situation. Fifty observations were simulated randomly by assigning a level (VH, H, M, L, VL) as an input to each condition (AMP, DMP, FD, SIM, EF, Y). These observations were classified as excellent (E), Good (G), Normal (N), Poor (P), and Very Poor (VP). Classification of the simulated observations by a team of three experts was based on their experience whereas the expert system classification was done using the total weighting factor of each observation by adding up the weighting factor given to each level for each condition. The total weighting factor then was compared with the foundation rules to determine the class of the observations. Suppose that the pistachio market situation is observed according to Table 6. The total weighting factor according to Table 5 for the above example is obtained by adding up the weighting factors as follows;

$$(25+8+6+3+12+12)=66. \qquad [4]$$

Since the total weighting factor (t.w.f.=66) lies between the two thresholds 59 and 71 then according to the foundation rule 3 the observation class is normal (N).

Table 6. An example for the observation of the pistachio market.

Conditions	Options
AMP	H
DMP	M
FD	M
SIM	M
EF	H
Y	M

RESULTS AND DISCUSSION

The comparison between the decisions made by the experts and PISTMAN when observing the pistachio market situations are shown in Tables 7-11. Table 7 shows that the same decisions between experts and the expert system have been made when the market situation is excellent. The experts' classifications of the simulated observations were based on their experience whereas the expert system classification was done using a total weighting factor for each observation.

Tables 8, 9, 10, 11 show the decisions made by the experts and the expert system on different classes of observations. The underlined levels of options and total weighting factor highlight differences between the decisions on the classes of observations. For example the 1st and 7th columns in Table 8a are underlined because the experts do not match the expert system decisions. These columns can be viewed in the 3rd and 14th columns of the Table 9b, classified as Normal N instead of Good G. The reason behind the first difference (3rd column) was explained by the experts such that "both SIM, and Y conditions are medium and so for EF" and for the second one (14th column)" imagine that everything is in good conditions but when you look at the medium abroad market price you change your mind." Another difference occurred in the second column of Table 10a. This column can be viewed in the first column of the Table 11b, classified as very poor VP instead of poor P. This difference is justified by the experts as follows "even though there are enough loads at hand, foreign demand is very low and there are no facilities to export them abroad." Considering Tables 11a and 10b, again we see that the three observations in columns 8, 11, and 12 (Table 11a) are transferred to columns 2, 4 and 8 (Table 10b). This means that these three observations were classified by the experts as poor instead of very poor. The experts justified the differences such that "even though the market is unsatisfactory, since there are medium and high export facilities (EF) for the three observations we can still tolerate it."

Table 7. The same decisions made when observing the daily pistachio market situation (DPMS) as excellent (expert system vs. experts).

Observation	Decisions					
AMP	VH	H	VH	H	VH	VH
DMP	L	L	VL	VL	L	L
FD	VH	VH	VH	VH	VH	H
SIM	H	VH	VH	H	VH	H
EF	VH	H	VH	VH	H	VH
Y	H	VH	VH	H	VH	VH
Total W.F.	85	82	92	82	87	87

Table 8a. Expert system decisions on observations (Good).

Observation	Decisions								
AMP	<u>VH</u>	H	H	H	H	VH	<u>M</u>	VH	H
DMP	<u>M</u>	M	L	VL	M	M	<u>L</u>	L	M
FD	<u>VH</u>	H	M	H	H	H	<u>H</u>	H	H
SIM	<u>M</u>	H	H	M	M	H	<u>H</u>	VH	H
EF	<u>M</u>	H	VH	H	H	H	<u>VH</u>	H	VH
Y	<u>M</u>	H	VH	H	H	H	<u>VH</u>	M	M
Total W.F.	<u>72</u>	73	80	76	72	78	<u>72</u>	77	72

Table 8b. Experts' decisions on observations (Good).

Observation	Decisions						
AMP	H	H	H	H	VH	VH	H
DMP	M	L	VL	M	M	L	M
FD	H	M	H	H	H	H	H
SIM	H	H	M	M	H	VH	H
EF	H	VH	H	H	H	H	VH
Y	H	VH	H	H	H	M	M
Total W.F.	73	80	76	72	78	77	72

Table 9a. Expert system decisions on observations (Normal).

Observation	Decisions													
AMP	H	VH	M	H	VH	M	VH	M	H	VH	H	H	VH	M
DMP	H	VH	M	M	M	M	VH	M	M	H	L	H	L	VL
FD	M	M	H	M	L	VH	H	M	L	M	L	H	L	L
SIM	H	VH	H	M	M	VH	M	H	M	VH	M	M	M	M
F	VH	VH	H	H	M	VH	H	H	M	M	M	H	M	H
Y	M	L	VH	M	M	M	M	VH	H	M	VH	M	M	VH
Total W.F.	67	65	67	66	66	65	66	65	65	67	71	65	68	66

Table 9b. Experts' decisions on observations (Normal).

Observation	Decisions															
AMP	H	VH	<u>VH</u>	M	H	VH	M	VH	M	H	VH	H	H	<u>M</u>	VH	M
DMP	H	VH	<u>M</u>	M	M	M	M	VH	M	M	H	L	H	<u>L</u>	L	VL
FD	M	M	<u>VH</u>	H	M	L	VH	H	M	L	M	L	H	<u>H</u>	L	L
SIM	H	VH	<u>M</u>	H	M	M	VH	M	H	M	VH	M	M	<u>H</u>	M	M
EF	VH	VH	<u>M</u>	H	H	M	VH	H	H	M	M	M	H	<u>VH</u>	M	H
Y	M	L	<u>M</u>	VH	M	M	M	M	VH	H	M	VH	M	<u>VH</u>	M	VH
Total W.F.	67	65	<u>72</u>	67	66	66	65	66	65	65	67	71	65	<u>72</u>	68	66

Table 10a. Expert system decisions on observations (Poor).

Observation	Decisions								
AMP	L	L	M	VH	M	VH	L	L	L
DMP	L	L	H	VH	L	VH	L	L	L
FD	L	VL	L	VH	M	L	L	L	M
SIM	M	VH	VH	L	L	L	L	L	L
EF	VL	VL	H	H	M	M	M	VL	M
Y	M	VH	L	L	M	M	M	M	L
Total W.F.	34	42	49	63	54	58	39	33	37

Table 10b. Experts' decisions on observations (Poor).

Observation	Decisions										
AMP	L	L	M	L	VH	M	VH	L	L	L	L
DMP	L	VH	H	H	VH	L	VH	H	L	L	L
FD	L	L	L	L	VH	M	L	L	L	L	M
SIM	M	H	VH	M	L	L	L	L	L	L	L
EF	VL	H	H	H	H	M	M	M	M	VL	M
Y	M	L	L	VL	L	M	M	L	M	M	L
Total W.F.	34	31	49	30	63	54	58	30	39	33	37

Table 11a. Expert system decisions on observations (Very poor).

Observation	Decisions											
AMP	L	L	L	VL	L	L	VL	L	VL	M	L	L
DMP	L	VH	M	VH	VH	M	H	VH	VH	H	H	H
FD	L	L	M	L	L	L	M	L	VL	VL	L	L
SIM	L	L	L	L	VH	M	M	H	M	L	M	L
EF	VL	VL	VL	VL	VL	VL	VL	H	L	VL	H	M
Y	L	L	L	VL	L	L	VL	L	M	VL	VL	L
Total W.F.	29	20	29	15	23	28	22	31	25	31	30	30

Table 11b. Experts' decisions on observations (Very poor).

Observation	Decisions									
AMP	L	L	L	L	VL	L	L	VL	VL	M
DMP	L	L	VH	M	VH	VH	M	H	VH	H
FD	VL	L	L	M	L	L	L	M	VL	VL
SIM	VH	L	L	L	L	VH	M	M	M	L
EF	VL	VL	VL	VL	VL	VL	VL	VL	M	VL
Y	VH	L	L	L	VL	L	L	VL	M	VL
Total W.F	42	29	20	29	15	26	28	22	28	31

Table 12. Different decisions made by the experts in comparison with PISTMAN.

Experts' Differences	ES Ex Class
2	G→N
1	P→VP
3	VP→P

After observing different purchasing conditions, the actions can be determined using the Bayesian strategy. Table 13 shows the recommended actions for each observation.

The results indicated that the expert system represented the decisions made by the plant managers and as shown in Table 12; only six decisions out of fifty (12%) were in disagreement with the experts. A detailed further study of the cases where differences were obtained between the human experts and the expert system was very revealing. In each case, the human had applied extra parameters which could be regarded as personal heuristics or even human bias whereas the expert system produced a result based on hard evidence.

Table 13. The comparison between the decisions on observations and recommendations.

Purchasing	Observations The experts	Observations PISTMAN	Action	Recommendations
VP	10	12	a_2	50% of the load
P	11	9	a_5	100% of the load
N	16	14	a_4	80% of the load
G	7	9	a_3	70% of the load
E	6	6	a_3	70% of the load

Another important reason was due to the fact that the method of trial and error in our case was not able to differentiate and cover all the decisions made by the experts. Only six decisions out of fifty (12%) were in disagreement with the experts on final recommendations (actions). These differences between the decisions made by the expert system and those of the experts were due to the different decisions on DPMS (Z_k) observations that resulted in different recommendations. The plant managers ' knowledge and the expert system knowledge base was based on the records of previous years of purchasing and selling the commodity in the plant, so the prior and conditional probabilities stored in the expert system reflect the knowledge and experience of the plant managers. That is why they so often resulted the same decisions. Table 13 shows the comparison between the decisions made by the experts and PISTMAN. The observed data were also compared with the expected results using chi-square goodness of fit test. The test indicated that with 5% level of significance there was no difference between the two sets of results.

CONCLUSIONS

The aim of this work was to simulate the decision making process of pistachio processing plant managers for purchasing the daily percentage of harvested pistachio nuts delivered to the plant with the use of an expert system based on the Bayesian strategy. The development of the expert system for purchasing addressed three problems; problem 1 defines the state of purchasing market according to various observations. This is done by establishing rules by the method of trial and error with the use of weighting factors instead of probabilities. Problem 2 estimates the winter selling market when observing the fall season purchasing market. A probabilistic approach, based on past observations is used. These observations are used to calculate the posterior probabilities. And finally problem 3 estimates the utility of different purchasing actions according to the selling state and optimizes the purchasing level. This function is estimated from the experts and gives the utility of an action, knowing the selling market. If we take into account the probabilities of selling market in different states and evaluate these probabilities by observing the purchasing market, then the chosen level of purchase is the maximum value.

The comparison between the decision made by the experts and those made by the PISTMAN indicated an accuracy of 88%. Six decisions out of fifty (12%) were in disagreement with the experts on final recommendations (actions). A detailed further study of the cases revealed that the human had applied extra parameters which could be regarded as personal heuristics or even personal bias whereas the expert system produced a result based on hard evidence. The discrepancies between the expert system and the experts were due to the different Z_k observations that resulted different recommendations. The differences occurred between the adjacent classes, the differences between the recommendations on observations as very poor to poor were two times the recommendation by expert system. Although it was attempted to minimize the differences by the means of trial and error using total weighting factors for each observation, the existence of motivational bias, which is highly situation-dependent, was difficult to detect and interpret in our case and could cause even more differences. Further evaluation of the model in terms of redundancy, ambivalence, circularity and deficiency did not indicate any problems.

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