A DECISION SUPPORT SYSTEM FOR WOOL CLASSIFICATION

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Abstract:

This paper presents the concepts and development of an intelligent system that integrates both a decision support system (DSS) and an expert system (ES) to provide guidance to the decision-maker during the wool grading and classification process. Although uniformity of wool grading can be achieved easily on the basis of quantifiable characteristics such as fibre diameter, staple length and strength, and vegetable matter and content by using an expert system, some other characteristics which are not quantifiable such as the type of vegetable matter, the weathering of the fibre, crimp definition, matting of the fibre and the appearance of the wool have to be judged through the eyes of the human expert. It is for this reason that the intelligent system incorporates the additional component of a decision support system to enable the human component to come into play.

Key words:

Decision support system, expert system, wool classification

1. Introduction

The success of wool grading has given buyers access to wool of the required quality and also fair pricing for the farmers for their wool. At present classification is done manually at auction floors. This is time consuming and tedious tasks for humans to perform. An understanding of complex assessment of the wool grades entails knowledge and expertise and without adequate support, errors in judgement could be made by a less-experienced staff. This paper looks at the concepts and development of decision support system (DSS) for wool classification.

DSSs are a specific class of computerised information systems that supports business and organisational decision-making activities. A properly designed DSS is an interactive software-based system intended to help decision-makers compile useful information from raw data, documents, personal knowledge and / or business models to identify and solve problems and make decisions. A DSS is defined in Finlay [5] as a computer-based system that aids the process of decision-making. It is also defined as an interactive, flexible and adaptable computer-based information system specifically developed for supporting the solution of non-structured problems for improved decision-making [24]. A DSS differs from the traditional information system in that it not only provides the user with information and databases as does an information system, but also provides answers to user queries through its modelling component. Model-driven DSS use data and parameters provided by the user to assists the decision-maker analyse situations. Knowledge-driven DSS provide specialised problem-solving expertise stored as facts, rules, procedures or in similar structures.

Turban [25] suggested two fundamental ES/ DSS integration models and these are ESs integrated into DSS components and an ES as a separate component in the DSS. In the first, the incorporation of ESs aims to enhance the function of particular components in a DSS; for example, integrating an ES into the database management system (DBMS) of a DSS which adds reasoning capability to data manipulation. In the second model the ES complements the DSS in one or more steps of a decision-making process. Such integration can be conceptualised as using the ES to play the role of a human expert who carries out interpretation or alternative evaluation, and the DSS leaves the final decision to the user from a number of alternatives generated. This research adopts the second model in wool classification.

In the grading of wool, automated decisions can easily be made on objective components such as the staple strength, staple length, fibre diameter, yield, the vegetable matter content, colour and staple crimp. But on the subjective components which are not quantifiable such as the type of vegetable matter and style, that is, the weathering of fibre, crimp definition, matting of fibre and appearance of wool, the final decision has to be made by the human being. Therefore the expert systems component of the architecture deals with the automation of wool classification based on standard components, while the DSS architecture deals with the subjective aspects which require the final decision to be made by the human.

The rest of the paper is as follows: Section 2 describes the classing of South African wool. Section 3 reviews related work. Section 4 describes an architecture for the DSS. Section 5 looks at the contributions and conclusion.

2. Classing of wool

In standard processing, raw wool is graded into different classes to ensure uniformity in the characteristics such as the mean fibre diameter, staple length and strength, vegetable matter content and appearance. South African wool is broadly classified into merino-type, white wool, white and coarse coloured wool and crossbred wool [4]. Each of these is, in turn, classed into locks wool, bellies and pieces, broken fleeces, backs, fleece wool and lambs' wool. Fleece wool in the merino type is marked according to a combination of symbols denoting the estimated length (AA-EE) and the average fibre diameter of the wool (FF, F, M, S, SS). The classification is based on the following matrix as shown in Table 1.

Lambs wool is classified according to the following [4]. Various criteria are used in the classification in other grades as shown in Table 2.

3. Related work

There are many decision support systems in place today in various fields. These DSS apply various models in decision making. The models include statistical analysis, sensitivity analysis, case-based reasoning, genetic algorithms, Bayesian casual maps, artificial neural networks, fuzzy logic, linear programming, optimisation model and Markov decision model. Also included in the list of models are rule-based reasoning, data envelope analysis, predictive prolificity analysis, ontology modelling, intelligent agents and GIS technology.

In commerce, Auction Advisor [7] is a DSS that utilises intelligent agents to collect data related to online auctions and use the data to improve decision-making of auction participants. It uses statistical analyses of most current auction data for specific pricing and bidding recommendations.

A case-based reasoning DSS system that supports user participation in the customisation of a housing design to a customer's layout, finishing and budget is looked at in Juan [11]. A DSS for evaluating transformer investments in the industrial sector based on the total owning cost by performing sensitivity analysis is described in Georgilakis [6]. Chan [3] describes a DSS for production scheduling, to distribute resources such as manpower and equipment in line with pending orders in a fixed time-frame using genetic algorithms.

Ulengin [26] describes a DSS to support policy makers in their analysis of both socio-economic variables and variables related to transportation on passenger and freight demands in the future using Bayesian casual maps and artificial neural networks. Tan [22] describes an intelligent DSS integrating case-based reasoning and the fuzzy ARTMAP neural network to support managers in making timely and optimal manufacturing technology investment decisions. A DSS that helps the direct mailer to determine mailing frequency for active customers using the Markov decision model is looked at in Jonker [10]. Ioannou [8] describes a DSS that enables management of a retail bank to evaluate and reconfigure its branch network. Its computational engine is based on a linear programming optimisation model.

A DSS framework that employs data envelopment analysis and mixed integer programming models is developed for efficient service location design in government services [16]. Wen [28] describes a hybrid knowledge-based system that integrates case-, rule-, and model-bases for enterprise mergers and acquisitions. A DSS for selecting the proper project delivery method using the analytical hierarchy process is designed in Mahdi [13]. Data envelopment analysis models have been incorporated into a knowledge-based DSS for measuring the performance of government real estate investments in Wang [27].

Pomar [18] developed a knowledge-based DSS to improve sow farm productivity based on predictive prolificity analysis models. Chan [2] designed an expert DSS for monitoring and diagnosis of petroleum production and separation processes incorporating ontology modelling. A DSS tool to support water resource management which integrates environmental (especially hydrological) models with multiple criteria evaluation procedures is looked at in Mysiak [15].

Table 1. Fleece wool classification in merino types.

Length groups	Fineness classes (microns)				
	Superfine (<19)	Fine (19,1 – 20)	Medium (20,1 – 22)	Strong (22,1 – 24)	Overstrong (24, 1 – 27)
> 100 mm	AAFF	AAF	AAM	AAS	AASS
80-100mm	AFF	AF	AM	AS	ASS
70-80mm	BBFF	BBF	BBM	BBS	BBSS
60-70mm	BFF	BF	BM	BS	BSS
50-60mm	CFF	CF	CM	CS	CSS
40-50mm	DDFF	DDF	DDM	DDS	DDSS
30-40mm	DFF	DF	DM	DS	DSS
20-30mm	EEFF	EEF	EEM	EES	EESS
<20mm	EFF	EF	EM	ES	ESS

Table 2. Lamb wool classification in merino types.

Mark	Contents
CL	Lambs' wool longer than 50mm
DDL	Lambs' wool between 40 and 50mm
DL	Lambs' wool between 30 and 40mm
EEL	Lambs' wool between 20 and 30mm
EL	Lambs' wool shorter than 20mm
LBP	Bellies and pieces from lambs
LLOX	Locks from lambs
XXL	Hairy and/or coarse lambs' wool

An OO approach is adopted in modelling a DSS for oncology using rule-based and case-based reasoning in Rosille [19]. A DSS based on neural network and fuzzy type decision-making was developed in Mangalampalli [14] to prescribe medicines for gynaecological diseases based on primary and secondary symptoms of the disease. An online decision support system for irrigation farmers which utilises variables such as temperature sums and hydrological models to calculate soil water balance and also automatically supply weather data from weather databases is looked at in Thysen [23].

The DSS under development in this research will be based on a rule-based reasoning approach, because it is a simpler and yet effective for the limited number of decisions.

4. Architecture of the system

In the grading of wool, standard automated decisions can easily be made on objective components such as the staple strength, staple length, fibre diameter, yield, the vegetable matter content, colour and staple crimp. But on the subjective components which are not quantifiable such as the type of vegetable matter and style, that is, the weathering of fibre, crimp definition, matting of fibre and appearance of wool, the final decision has to be left to the human being.

The architecture proposed for the wool grading DSS is composed of an integration of an ES and DSS as shown in Figure 1. The basic structural components of a DSS are a database, a model base and the user interface [21]. The components of an expert system include the knowledge base, inference engine, knowledge acquisition component, and explanation system [9]. Therefore the architecture of the DSS will integrate all these components as shown in Figure 1.

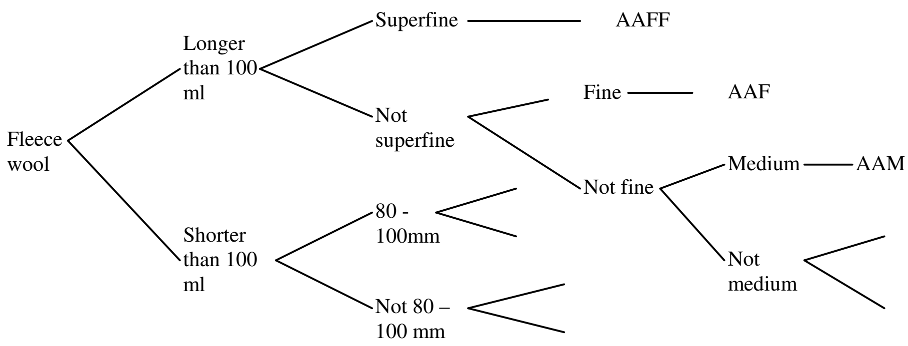

Figure 2. Structure of the fact base.

4.1. Knowledge base

The permanent knowledge of an expert system is stored in a knowledge base. It contains the information that the expert system uses to make decisions. This information presents expertise gained from top experts in the field. This knowledge comes in the form of facts and rules. Facts are minimal elements of the knowledge which must be identified before anything else. Rules consist of if....then statements, where a given set of conditions will lead to a specified set of results. If a condition is true then an action takes place. The knowledge base in wool classification contains expertise about the domain of wool classification.

Facts base. The attributes of the knowledge in the facts base would be the staple length, staple strength, fibre diameter, yield, vegetable matter content, colour and staple crimp. Figure 2 is the structure of an example of a fact base that is drawn from the contents of Table 1.

Rule base. Each rule in the knowledge base is in the form of IF <condition> THEN <action>. If the condition is true then the actions are true. Some rules for the merino wool are presented below:

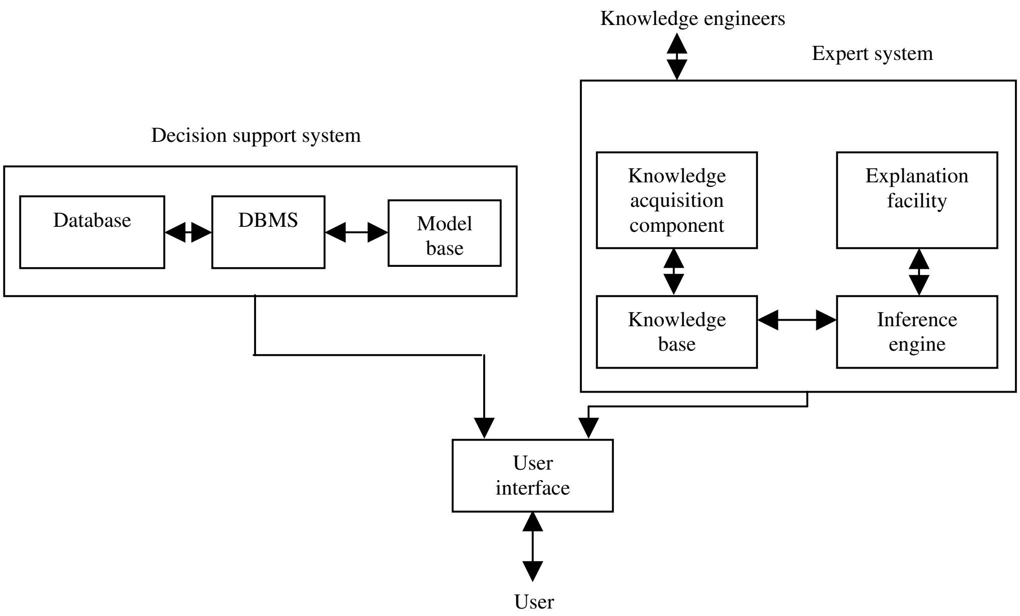

Figure 1. Architecture of DSS for wool classification and grading.

RULE 1:
If length groups > 100mm and fineness class < 19 then the wool grade is AAFF.

RULE 2:
If length groups < 20mm and fineness class is between 24.1 and 27 microns THEN the wool grade is ESS.

4.2. Inference engine

The purpose of the inference engine is to seek information and form relationships from the knowledge base and provide answers. It determines which rules will be applied to a given question, and in what order, by using information in the knowledge base. The inference engine drives the system by drawing an inference from relating user-supplied facts to a knowledge-base rule and then proceeding to the next fact and rule combination [1]. The inference engine compares each rule stored in the knowledge base with the facts captured at the user interface. The structure of the inference engine drawn from the contents of Table 1 is as follows:

```
Method FLEECE WOOL
{
  if (length > 100)
    call method LONGER THAN 100
  else
     if (length < 100)
       call method SHORTER THAN 100
}

Method LONGER THAN 100
{
   if (super fine wool)
     THEN class is AAFF
  else
    call method NOT SUPER FINE
}

Method NOT SUPER FINE
{
   if (fine wool)
     THEN class is AFF
  else
    call method NOT  FINE
}

Method NOT FINE
{
  If (medium wool)
     THEN class is AAM
 Else call method NOT MEDIUM
}
```

In forward chaining the inference engine compares each rule stored in the knowledge base with the information supplied by the user. When the IF condition part of the rule matches a fact, the rule is fired and its THEN part executed. In backward chaining the inference engine first has a goal and attempts to find the evidence to prove it. The inference engine starts by searching for rules. The inference engine searches for rules that produce the desired solution and achieves the goal in the THEN part. This system uses forward chaining, because the values of the parameters such as the fibre diameter, staple length and strength and vegetable matter are known beforehand. The values of these attributes are captured at the user interface and supplied to the rules in the knowledge base to come up with the wool grade.

4.3. The database and DBMS

This part of the DSS comprises all the necessary information and data required to perform analysis of the problem at hand. Data management is performed through the database management system (DBMS). The database in this case is a collection of data on the subjective aspects of wool and how they influence the class of the wool. The database is queried for access to information by the DBMS. The DBMS defines the structure of the database and houses a query language to actively interrogate the database. In this case the DBMS queries the database for the level of matting of the wool, the appearance of the wool, the crimp definition and the type of vegetable matter whose values would have been entered at the user interface into the database. These values are passed on to the model base for assessment for the class of wool.

4.4. The model base

The model base of a DSS is a collection of decision analysis tools that are used to support decision-making. Mathematical and analytic models are the major components of a model base. The model base utilises data and parameters provided by the decision maker to aid in analysing a situation. The model base and database are directly related so that the models are fed with the necessary information and data. A model-base management system is responsible for handling the model base including the storage and retrieval of models that are developed, their update and adjustment

The model base in this architecture provides methods for evaluation of data passed on from the database. For example the human being may say that if the fibre is matted, weathered and of a poor appearance the grade of the wool is reduced by a single grade. The model base used in this architecture utilises rule-based reasoning. This is a particular type of reasoning which uses “if-then-else” rule statements. Rules are patterns which can be searched for on the basis of data supplied by the user. The “if” means ‘when the condition is true”, the “then” means “take action A’ and the “else” means “take action B”. One of the reasons why a rule-based approach was used is that rules are simpler to state and transmit.

If vegetable matter type is burr
And the weathering fibre is poor
And crimp definition is low
And appearance of wool is extremely yellow
Then the wool market class is C

4.5. Knowledge acquisition

Most expert systems continue to evolve over time. New facts and rules can be added to the knowledge base by using the knowledge acquisition subsystem.

4.6. Explanation subsystem

Another unique feature of an expert system is its ability to explain its advice or recommendations and even to justify why a certain action was recommended. The explanation subsystem enables the expert system to examine its own reasoning and explain its operations. The ability to trace responsibility for conclusions to their sources is crucial, both in the transfer of expertise and in problem solving. In this case, for example, the system will come up with an explanation on how it reached the conclusion of a particular wool grade.

4.7. The user interface

The user interface is responsible for the communication of the user with the system. Values of both the subjective and objective variables are captured at the user interface.

4.8. System functionality

The expert systems functionality processes the grade of the wool. The information on the fineness and length of the wool is captured at the user interface. The inference engine, in conjunction with the knowledge base then processes the information to come up with the grade of the wool. On the other hand to come up with the market class of the wool, the DSS does the processing. The type of vegetable matter (chive, burr, leaves), the crimp definition (high, low), the matting of the fibre (high, low), the weathering of the fibre (high, low), and the appearance of the wool (white, yellow, black) are captured into the database at the user interface. The DBMS then extracts this information and passes it to the model base for processing. The wool market class, whether it be A, B or C grade is derived from this interaction. At this point in time the user is given the option to change the class derived if they are not agreed, since the final decision is left to the human being.

When it comes to objective component assessment the system currently does match the expert. On the other hand on the subjective component, the expertise of the human being surpasses the functionality of the system. The system functionality is limited to a few options while the human being who is on the ground assessing the wool objectively can make an informed decision.

5. Analysis and conclusion

In this paper the concept and structure of a DSS to support wool classification and grading is outlined. The architecture is a merger of a DSS and an ES. This has several advantages. The ES and DSS complement the efforts of each other in decision making. This is to cater for standard decisions based on objective components and unstructured decisions based on subjective components. Decisions tend to be more uniform and of better quality when a DSS is available. A DSS is good at handling unstructured problems. Although a DSS supports all aspects and phases of decision-making, it does not replace the decision-maker. The human still has the final decision. With a shortage of experts in the field of textiles, there is an increased risk of knowledge becoming scarce; hence the automation of the decision-making process is vital.

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