A framework for fuzzy modelling in agricultural diagnostics

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ABSTRACT. *Agriculture is the major source of economy in many developing countries. India, containing around 18 percent of the total population of the world, is a typical example where most of its population is directly or indirectly engaged in agricultural activities to earn their livelihood. To the worse, diseases endemic to the crops make lives of poor farmers miserable to the extent that they even take the extreme steps of ending their lives. Technology, as it stands today, can't root out their all worries but definitely it can help those making right decisions at right time. Often the farmers end up bewildered in finding out the correct crop disease and insecticides or pesticides to apply in the right doses to the targeted crop. Such wrong decisions make the poor farmers pay penalties in the form of low yields, insecticide costs, or even absolute crop damage. Thus, an appropriate decision making aid to the uneducated and underprivileged section of the society may help in alleviating their pain to some levels. In this chapter, we propose a framework to build an expert system for managing crop crisis, the focus of the system can be different as per the requirement of the modeller, however; we exemplify the proposed framework by taking an example of crop disease diagnostics. Since, decision making in agriculture is vulnerable to a number of human errors and biases, therefore, we assert to incorporate the use of fuzzy inferences in determining the exact decisions at demanding times. An expert system is a machine representation of a human expert at making decisions. Since, experts may differ on some aspects; therefore, we advocate the use of fuzzy numbers arithmetic in making out a safe decision under the clouds of uncertainty.*

RÉSUMÉ. *L'Agriculture est la principale source d'économie dans de nombreux pays en développement. L'Inde, qui compte environ 18 pour cent de la population mondiale, est un exemple typique où la plupart de sa population est directement ou indirectement engagée dans des activités agricoles pour gagner sa vie. Pire encore, les maladies endémiques aux cultures rendent la vie des agriculteurs pauvres si misérable qu'ils prennent même les mesures extrêmes pour mettre fin à leurs jours. La technologie, telle qu'elle est aujourd'hui, ne peut pas extirper tous leurs soucis, mais elle peut certainement aider ceux qui prennent les bonnes décisions au bon moment. Souvent, les agriculteurs finissent par être déconcertés en découvrant les maladies des cultures et les insecticides ou pesticides à appliquer aux bonnes doses à la culture ciblée. Ces mauvaises décisions font payer aux agriculteurs pauvres des pénalités sous la forme de faibles rendements, de coûts d'insecticide, ou même de dommages absolus aux cultures. Ainsi,*

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une aide appropriée à la prise de décision pour la partie non instruite et défavorisée de la société peut aider à soulager leur douleur à certains niveaux. Dans ce chapitre, nous proposons un cadre pour construire un système expert pour gérer la crise des cultures, l'accent du système peut être différent selon les exigences du modélisateur, cependant; nous illustrons le cadre proposé en prenant un exemple de diagnostic des maladies des cultures. Étant donné que la prise de décisions en agriculture est vulnérable à un certain nombre d'erreurs humaines et de préjugés, nous affirmons qu'il faut tenir compte de l'utilisation d'inférences floues pour déterminer les décisions exactes à des moments difficiles. Un système expert est une représentation mécanique d'un expert humain pour prendre des décisions. Puisque les experts peuvent diverger sur certains aspects, nous préconisons l'utilisation de l'arithmétique des nombres flous pour prendre une décision sûre sous les nuages d'incertitude.

KEYWORDS: *agriculture, crop, diseases, fuzzy logic, fuzzy rules, inference, membership function, defuzzification.*

MOTS-CLÉS: *agriculture, culture, maladies, logique floue, regles floues, inference, fonction de membre, frauzzification.*

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1. Introduction

The unification of food security and agricultural production issues is a big challenge. Since agriculture is readily affected by various drivers like market structures, ecological conditions, political climate etc.; therefore, suitable problem-solving approaches are required which take into account these dynamic and intertwined system variables and drivers (Foley *et al*., 2011; Godfray *et al*., 2010). The inclusion of the differing perspective of multiple stakeholders is equally important (Meynard *et al*., 2017).

In all agricultural planning, uncertainty plays a vital role for the reason that a few factors are not entirely controllable; at the same time as some input parameters for instance, resources, demand, costs, and objective functions are inaccurate (Figure 1).

In order to identify useful and feasible solutions that are plausible, relevant, valid and actionable, unswerving involvement of stakeholders in research on agriculture systems has been widely promoted (Fazey *et al*., 2014; Raymond *et al*., 2010).

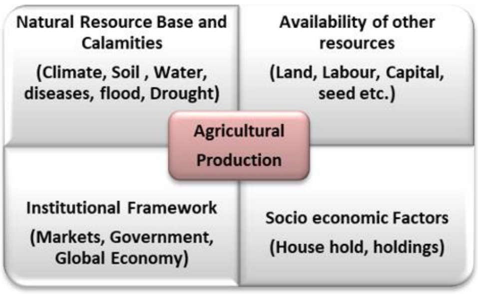

Figure 1. Cnceptual framework of agriculture production

Perspectives on agricultural innovation, rural development and hi-tech changes in cultivating frameworks are liable to a noteworthy change in viewpoint. Agricultural development services increasingly work with a participatory methodology. They put forward the farmers as the chief decision makers, extension workers as process catalyst and scientists as knowledge sources. The previous development strategies deserted the variety of developments that developed from the perception of the farmers (Röling, 2003).

Presently the agricultural diagnostics consider a context-mechanism-outcome trail and also the on-farm research and social surveys are the elements of the change process (Gulotta *et al*., 2018). These types of approaches assume that changes are not just explicated by context but by the management and decision-making process as well.

A most critical apprehension of agricultural development is environmental, societal and economic sustainability for which mixed cultivation frameworks appear to be suitable (Holling, 1995). The switch over to cost-effectively more sustainable production systems is particularly significant for the "license to produce" in agricultural products. This switch to a great extent relies on decisions of the farmers. A significant challenge is to unravelling the interface amid farmers' perceptions of the modernization and their decisions about effective and sustainable assimilation of a variety of farming components. To design more manageable cultivating frameworks researchers often use simulation modelling, wherein the farmers' perceptions and decision-making process for the most part overlooked. The consideration of farmers' perceptions and intentions appears to be critical for the ongoing pattern to utilize models for the study of policy options, as well as for the tools development to support decision-making at the level of the farm.

Diagnostic decision-making through fuzzy modelling is not a simple task in agriculture. The intention and verification of diagnosis must take into account the farming parameters, the components in the farming system and the farmer's experience and knowledge.

2. Background

To make a machine solve an intellectual problem the solution must be known. In other words, knowledge of some specific domain is essential. Knowledge can be defined as a practical or theoretical understanding of a domain or a subject. Knowledge is the sum of currently known facts, and in fact, knowledge is power. Persons who possess knowledge are recognized as experts. Experts are the most influential and key people in their organizations. For any successful company or business, at least a few domain experts are always there.

Anybody can be viewed as a domain expert in the event that he or she has profound information (of the two realities facts and rules) and substantial viable involvement in a specific domain. The domain area may be narrow. For instance, specialists in electrical machines may have expertise in transformers, while expert in medical science might have a limited understanding of orthopaedics specialists throughout everyday life. As a rule, a specialist is a skilful individual who can do things other individuals cannot.

In the computational point of view an expert system is characterized as software or program intended to exhibit the problem-solving capability of a human expert (Durkin, 1994). An alternate definition of the expert system may be "a framework that utilizes human learning captured in a computing machine to handle the issues that conventionally require human skill or expertise." A so-called intelligent computer program that utilizes information and inference procedures to answer the problems that was sufficiently troublesome to acquire significant human expertise for their resolution. For this, it mimics the human thinking process by applying particular information and interfaces (Kalpana and Kumar, 2011; Balocco and Petrone, 2018). Literature, books and other sources consist of enormous information and knowledge yet human needs to peruse and translate the learning for it to be utilized. The thought behind making an expert framework for any domain is that it can empower numerous individuals to get benefitted by the learning of one individual - the expert.

The three essential components of an expert system are knowledge base, inference engine, and user interface module (see Figure 2). The knowledge base consists of the knowledge got from the expert of the domain. Typically, the method for representing knowledge is using rules. The core work of the inference engine is to manipulate the knowledge resided in the knowledge base in order to arrive at a solution. The User Interface is the part that enables the end user to query the framework and get the results of those inquiries. Some expert system provides explanations about how the solution has arrived.

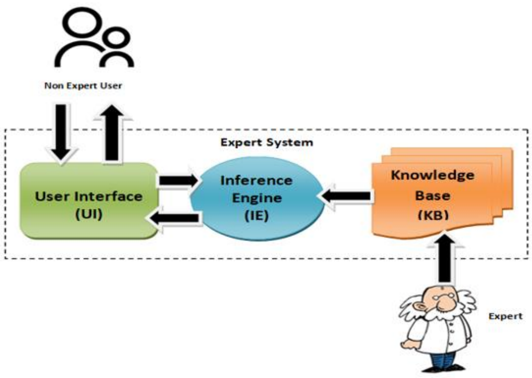

Figure 2. General architecture of an expert system

3. Expert system for agricultural development

Various Expert systems were introduced during the last three decades as a helpful tool in diverse fields of agriculture (Ganesan, 2006; Kalpana and Kumar, 2012). An approach based on Interval Fuzzy Logic is applied for the assessment of the sensing data to inform if the weather conditions are favourable for the emergence of pests, particularly fungi, which depend on factors for instance humidity, temperature and leaf wetness (Rodrigues *et al*., 2013).

Mohammad Rafiuzzaman et al proposed an expert system to assist farmers in taking appropriate decisions for having an improved crop production with less cost, regardless of the adverse nature of the soil on their cultivation area (Mohammad and Ibrahim, 2016).

4. Fuzzy expert system for agricultural development

The domain experts usually depend on the presence of mind when they solve the issues. They additionally make use of dubious and ambiguous terms. For instance, an agriculture expert may state, 'However the Soil condition is good enough, the rainfall will decide the crop production. Other expert has no troubles with comprehension and deciphering this announcement since they have the foundation to hearing issues portrayed this way. Be that as it may, a computer engineer or programmer would experience issues giving a computer with the same level of understanding. The question is, how might we represent the knowledge of agriculture expert that utilizes vague and ambiguous terms in a system.

This section attempts to answer this question by exploring the fuzzy logic (Zadeh, 1965). Fuzzy logic can be defined as a set of mathematical principles meant for knowledge representation based on membership degree instead of conventional binary logic. It is found to be a powerful tool to deal with vagueness and ambiguity. It was primarily introduced to improve, robustness, tractability and low-cost solutions for real-world problems.

Fuzzy logic has been applied in numerous real-life situations in which uncertainty plays a crucial role in which agricultural diagnosis is a remarkable case of ambiguity, uncertainty, and vagueness (Pandey *et al*., 2013; Pandey *et al*., 2015; Kalpana and Kumar, 2012; Pandey *et al*., 2017; Harvinder *et al*., 2002; Amelio *et al*., 2017; Pandey *et al*., 2013), (Sumathi and Kumar, 2014). Fuzzy logic can make decisions in the agriculture domain where information is imprecise, uncertain and incomplete. Since fuzzy logic takes human decision making with its capacity to work from surmised reasoning and eventually locate an exact solution, it tends to be connected in the determination and observing of various disease in agriculture production. Early forecasting of diseases is one of the compelling aspects of precision agriculture. The main aim is to predict the possibility of occurrence of different plant diseases in the early stages so that the stakeholders can perform necessary arrangements in this regard.

Fuzzy framework for agricultural diagnostics and plant disease forecasting is proposed in this section. Fuzzy logic is a hopeful practice that can quickly capture the required knowledge of the agriculture domain, and turn up with sound diagnosis decisions. It will calculate and predict the risk of probable diseases in agricultural plants based on the risk factors and the symptoms.

4.1. Fuzzy system architecture

The architecture of the fuzzy logic model for disease diagnosis and forecasting in agriculture is shown in figure 2. The architecture consists of the knowledge engine, user interface and knowledge base which again encompass the database model, the fuzzy logic model.

4.1.1. Knowledge base

The knowledge base design of the plant disease diagnosis and forecasting framework comprises of a fuzzy logic model and database model. Both static and dynamic information about the decision variables is stored by the knowledge base. It contains unstructured knowledge and structured knowledge about the agriculture domain. This knowledge is conjured of facts, rules and environmental manifestation of plant disease built up by the field experts. However, the facts influence diagnostic monitoring decisions, the rules let inferences to be furnished from the information. The structured knowledge is a qualitative knowledge whereas the agriculture scientists/experts obtain unstructured knowledge through experience. The database model comprises of great information regarding farming. The information in the database is both static and dynamic. Database information along with fuzzy logic makes a knowledge base.

4.1.2. Fuzzy Logic model

The fuzzy logic model for plant disease diagnosis and forecasting framework is illustrated in Figure 3. The main processes involved in this sub model are; fuzzification, inference, and defuzzification.

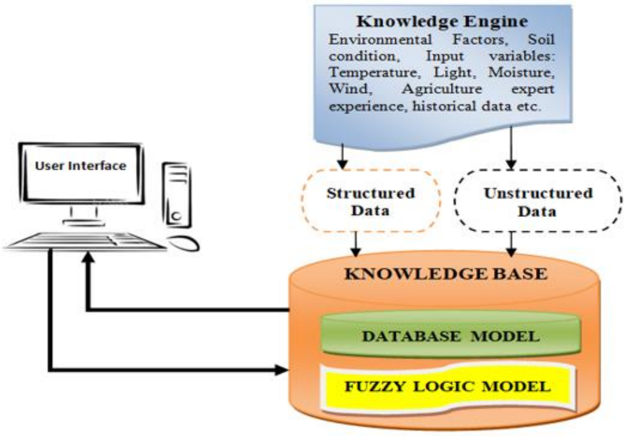

Figure 3. Architecture of a fuzzy expert system for Crop disease diagnosis and forecasting in agriculture

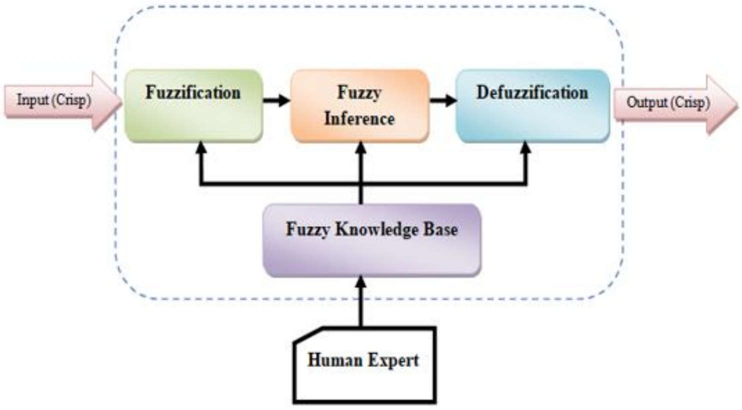

Figure 4. The structure of the fuzzy expert system

(1). Fuzzification

The fuzzification process of data is carried out to determine the degree of membership. It is achieved by adjusting the input parameters into the horizontal axis and projecting vertically to the upper boundary of the membership function. There exist many parameters, which are responsible for the yield in farming. For disease detection and forecasting the parameters used in the fuzzy logic model are temperature (TR) humidity and precipitation (HP), Light (LT), and wind (WD). These parameters contribute to the fuzzy logic input variables on the way to generate the fuzzy logic model, and the output parameter is plant disease (PD).

These different input parameters are used to map the output value specified in the individual rules to an intermediary output evaluating fuzzy sets (mild temperature, moderate temperature, severe temperature, mild precipitation, moderate precipitation, severe humidity and precipitation, mild light, moderated light, severe light, etc. 30 rules are developed for this application.

For this application, the universes of discourse for Temperature (TR), humidity and precipitation (HP), light (LT), and wind (WD) are selected to be [0, 15], [0, 20], [0, 10] and [0, 15] respectively. The sets of linguistic values for the linguistic variables, TR, HP, LT and, DE are [ML, MR, SV] which represent [mild temperature, moderate temperature, severe temperature] [mild humidity and precipitation, moderate humidity and precipitation, severe humidity and precipitation] [mild Light, moderate light, severe light] and [mild wind, moderate wind, severe wind] respectively. The set of linguistic values for Output is [NO, ML, MR, SV] which represent [no disease, mild disease, moderate disease, severe disease] respectively. The linguistic expressions for TR, HP, LT, DE and output (PD) variables and their membership functions are calculated through triangular membership function. These functions are presented in (2) to (17). The generation of triangular curve relies on three parameters A_1, A_2, and A_3 where A_1 and A_3 define the triangular endpoints and A_2 defines the triangular peak location. The triangular curve is described by Equation (1). Throughout the process, linguistic labels (values) are assigned to TR, HP, LT and, DE representing the associated degree of influence of membership for every linguistic term that applies to that input variable. The output membership function delineates the rigorousness level of disease present on the diagnosed crop.

Degrees of membership (Ux) is allocated to every linguistic value as presented in (2) to (17) as mild, moderate and severe. The fuzziness is best characterized by its membership function. A membership function for a fuzzy set A on the universe of discourse X is a pictorial representation of the importance of participation of each input. It is defined as μA:X → [0,1], where every element of X is mapped to a value amid 0 and 1. It is linked with a weight to each of the inputs that are processed, expresses functional overlap between inputs, and finally find out an output response.

$$\mu(x) = \begin{cases} 0, & if\ x < A_1 \\ \frac{x-A_1}{A_2-A_1}, & if\ A_1 \le x < A_2 \\ \frac{A_3-x}{A_3-A_2}, & if\ A_2 \le x < A_3 \\ 0 & if\ x > A_3 \end{cases} \tag{1}$$

The membership functions (MF) and rules defined on the selected input parameters are as follows

$$\text{Temperature}\,(x) = \begin{cases} 0, & if\ x < 5 & "Mild" \\ \frac{x-5}{5}, & if\ 5 \le x < 10 & "Moderate" \\ \frac{15-x}{5}, & if\ 10 \le x < 15 & \text{Severe} \\ 0\ , & if\ x \ge 15 & "Very\ Severe" \end{cases} \tag{2}$$

$$\mu_{mild}(x) = \begin{cases} 0, & if\ x < 1 \\ \frac{x-1}{1.5}, & if\ 1 \le x < 2.5 \\ \frac{6-x}{2.5}, & if\ 2.5 \le x < 5 \\ 0, & if\ x > 5 \end{cases} \tag{3}$$

$$\mu_{moderate}(x) = \begin{cases} 0, & if\ x < 5 \\ \frac{x-5}{3}, & if\ 5 \le x < 8 \\ \frac{10-x}{2}, & if\ 8 \le x < 10 \\ 0, & if\ x > 10 \end{cases} \tag{4}$$

$$\mu_{severe}(x) = \begin{cases} 0, & if\ x < 10 \\ \frac{x-10}{2}, & if\ 10 \le x < 12 \\ \frac{15-x}{3}, & if\ 12 \le x \le 15 \\ 0, & if\ x > 15 \end{cases} \tag{5}$$

$$\text{Humid \& } Preci\ (x) = \begin{cases} 0, & if\ x < 5 & "Mild" \\ \frac{x-5}{10}, & if\ 5 \le x, \le 15 & "Moderate" \\ \frac{20-x}{5}, & if\ 15 \le x < 20 & "Severe" \\ 0\ , & if\ x \ge 20 & "Very\ Severe" \end{cases} \tag{6}$$

$$\mu_{mild}(x) = \begin{cases} 0, & if\ x < 1 \\ \frac{x-1}{1.5}, & if\ 1 \le x < 2.5 \\ \frac{6-x}{2.5}, & if\ 2.5 \le x < 5 \\ 0, & if\ x > 5 \end{cases} \tag{7}$$

$$\mu_{moderate}(x) = \begin{cases} 0, & if\ x < 5 \\ \frac{x-5}{5}, & if\ 5 \le x < 10 \\ \frac{10-x}{5}, & if\ 10 \le x < 15 \\ 0, & if\ x > 15 \end{cases} \tag{8}$$

$$\mu_{severe}(x) = \begin{cases} 0, & if\ x < 15 \\ \frac{x-15}{2}, & if\ 15 \le x < 17 \\ \frac{20-x}{3}, & if\ 17 \le x \le 20 \\ 0, & if\ x > 20 \end{cases} \tag{9}$$

$$\text{Light}\,(x) = \begin{cases} 0, & if\ x < 3 \quad "Mild" \\ \frac{x-5}{10}, & if\ 3 \leq x, \leq 7 \quad "Moderate" \\ \frac{20-x}{5}, & if\ 7 \leq x < 10 \quad "Severe" \\ 0\ , & if\ x \geq 10 \quad "Very\ Severe" \end{cases} \tag{10}$$

$$\mu_{mild}(x) = \begin{cases} 0, & if\ x < 1 \\ \frac{x-1}{1}, & if\ 1 \leq x < 2 \\ \frac{3-x}{1}, & if\ 2 \leq x < 3 \\ 0, & if\ x > 3 \end{cases} \tag{11}$$

$$\mu_{moderate}(x) = \begin{cases} 0, & if\ x < 3 \\ \frac{x-3}{2}, & if\ 3 \leq x \leq 5 \\ \frac{7-x}{2}, & if\ 5 \leq x \leq 7 \\ 0, & if\ x > 7 \end{cases} \tag{12}$$

$$\mu_{severe}(x) = \begin{cases} 0, & if\ x < 7 \\ \frac{x-9}{2}, & if\ 7 \leq x < 9 \\ \frac{10-x}{}, & if\ 9 \leq x \leq 10 \\ 0, & if\ x > 10 \end{cases} \tag{13}$$

$$\text{Wind}\,(x) = \begin{cases} 0, & if\ x < 5 \quad "Mild" \\ \frac{x-5}{5}, & if\ 5 \leq x < 10 \quad "Moderate" \\ \frac{15-x}{5}, & if\ 10 \leq x < 15 \quad "Severe" \\ 0\ , & if\ x \geq 15 \quad "Very\ Severe" \end{cases} \tag{14}$$

$$\mu_{mild}(x) = \begin{cases} 0, & if\ x < 1 \\ \frac{x-1}{1.5}, & if\ 1 \leq x < 2.5 \\ \frac{6-x}{2.5}, & if\ 2.5 \leq x < 5 \\ 0, & if\ x > 5 \end{cases} \tag{15}$$

$$\mu_{moderate}(x) = \begin{cases} 0, & if\ x < 5 \\ \frac{x-5}{3}, & if\ 5 \leq x < 8 \\ \frac{10-x}{2}, & if\ 8 \leq x < 10 \\ 0, & if\ x > 10 \end{cases} \tag{16}$$

$$\mu_{severe}(x) = \begin{cases} 0, & if\ x < 10 \\ \frac{x-10}{2}, & if\ 10 \leq x < 12 \\ \frac{15-x}{3}, & if\ 12 \leq x \leq 15 \\ 0, & if\ x > 15 \end{cases} \tag{17}$$

The linguistic expression for output variables is calculate and given in (18) – (21).

$$\mu_{No\ crop\ disease}(x) = \begin{cases} 0, & if\ x < 0 \\ \frac{x}{1.5}, & if\ 0 \leq x < 1.5 \\ 1.5 - x, & if\ 1.5 \leq x < 2.5 \\ 0, & if\ x > 2.5 \end{cases} \tag{18}$$

$$\mu_{Mild\ crop\ disease}(x) = \begin{cases} 0, & if\ x < 2.5 \\ x - 2.5, & if\ 2.5 \leq x < 3.5 \\ \frac{3.5-x}{1.5}, & if\ 3.5 \leq x < 5 \\ 0, & if\ x > 5 \end{cases} \tag{19}$$

$$\mu_{Moderate\ crop\ disease}(x) = \begin{cases} 0, & if\ x < 5 \\ x - 5, & if\ 5 \leq x < 6 \\ \frac{7.5-x}{1.5}, & if\ 6 \leq x < 7.5 \\ 0, & if\ x > 7.5 \end{cases} \tag{20}$$

$$\mu_{Severe\ crop\ disease}(x) = \begin{cases} 0, & if\ x < 7.5 \\ \frac{x-7.5}{0.5}, & if\ 7.5 \leq x < 8 \\ \frac{10-x}{2}, & if\ 8 \leq x < 10 \\ 0, & if\ x > 10 \end{cases} \quad (21)$$

Membership function plots for the temperature (TR) humidity and precipitation (HP), light (LT), and wind (WD) and the outputs (crop disease) are shown in Figures 5-9.

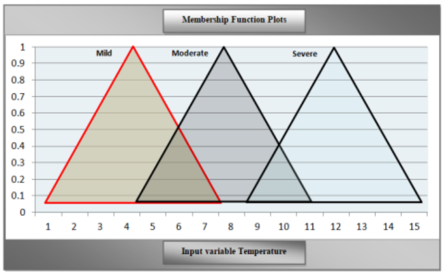

Figure 5. Membership function plots for temperature

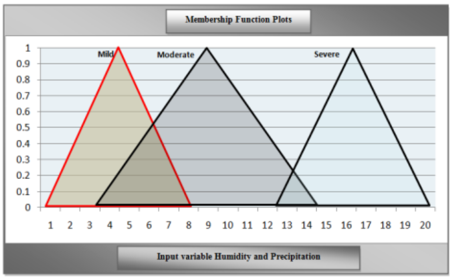

Figure 6. Membership function plots for humidity and precipitation

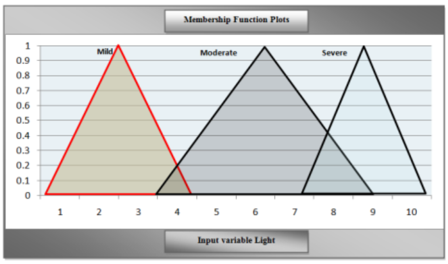

Figure 7. Membership function plots for temperature

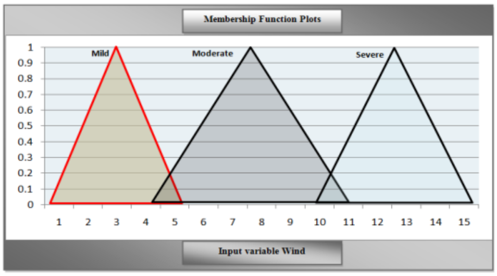

Figure 8. Membership function plots for wind

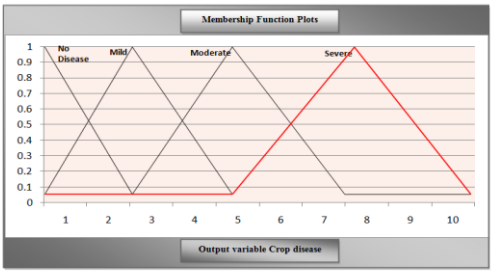

Figure 9. Output membership function plots for crop disease

Table 1. Fuzzy rules for crop disease diagnosis forecasting

#	**Rule**
1	If TR is MILD AND HP is MILD, AND LT is MILD, AND WD is MILD THEN Crop Disease is NO CROP DISEASE
2	If TR is MILD AND HP is MILD, AND LT is MODERATE, AND WD is MILD THEN Crop Disease is MILD
3	If TR is MILD AND HP is MILD, AND LT is SEVERE, AND WD is MILD THEN Crop Disease is MODERATE
4	If TR is MILD AND HP is MODERATE, AND LT is MILD, AND WD is MILD THEN Crop Disease is MILD
5	If TR is MILD AND HP is MODERATE, AND LT is MODERATE, AND WD is MILD THEN Crop Disease is MODERATE
6	If TR is MILD AND HP is MODERATE, AND LT is SEVERE, AND WD is MILD THEN Crop Disease is MODERATE
7	If TR is MILD AND HP is SEVERE, AND LT is MILD, AND WD is MILD THEN Crop Disease is MODERATE
8	If TR is MILD AND HP is SEVERE, AND LT is MODERATE, AND WD is MODERATE THEN Crop Disease is SEVERE
9	If TR is MILD AND HP is SEVERE, AND LT is SEVERE, AND WD is MODERATE THEN Crop Disease is SEVERE

10	If TR is MODERATE AND HP is MILD, AND LT is MILD, AND WD is MODERATE THEN Crop Disease is MILD
11	If TR is MODERATE AND HP is MILD, AND LT is MODERATE, AND WD is MODERATE THEN Crop Disease is MODERATE
12	If TR is MODERATE AND HP is MILD, AND LT is SEVERE, AND WD is MODERATE THEN Crop Disease is SEVERE
13	If TR is MODERATE AND HP is MODERATE, AND LT is MILD, AND WD is MODERATE THEN Crop Disease is MODERATE
14	If TR is MODERATE AND HP is MODERATE, AND LT is MODERATE, AND WD is MODERATE THEN Crop Disease is MODERATE
15	If TR is MODERATE AND HP is MODERATE, AND LT is SEVERE, AND WD is MODERATE THEN Crop Disease is SEVERE
16	If TR is MODERATE AND HP is SEVERE, AND LT is MILD, AND WD is SEVERE THEN Crop Disease is MODERATE
17	If TR is MODERATE AND HP is SEVERE, AND LT is MODERATE, AND WD is SEVERE THEN Crop Disease is SEVERE
18	If TR is MODERATE AND HP is SEVERE, AND LT is SEVERE, AND WD is SEVERE THEN Crop Disease is SEVERE
19	If TR is SEVERE AND HP is MILD, AND LT is MILD, AND WD is SEVERE THEN Crop Disease is MODERATE
20	If TR is SEVERE AND HP is MILD, AND LT is MODERATE, AND WD is SEVERE THEN Crop Disease is MODERATE
21	If TR is SEVERE AND HP is MILD, AND LT is SEVERE, AND WD is SEVERE THEN Crop Disease is SEVERE
22	If TR is SEVERE AND HP is MODERATE, AND LT is MILD, AND WD is SEVERE THEN Crop Disease is MODERATE
23	If TR is SEVERE AND HP is MODERATE, AND LT is MILD, AND WD is MODERATE THEN Crop Disease is MODERATE
24	If TR is SEVERE AND HP is MODERATE, AND LT is MODERATE, AND WD is SEVERE THEN Crop Disease is MODERATE
25	If TR is SEVERE AND HP is MODERATE, AND LT is MILD, AND WD is MODEARATE THEN Crop Disease is MODERATE
26	If TR is SEVERE AND HP is MODERATE, AND LT is MODERATE, AND WD is SEVERE THEN Crop Disease is SEVERE
27	If TR is SEVERE AND HP is MODERATE, AND LT is SEVERE, AND WD is SEVERE THEN Crop Disease is SEVERE
28	If TR is SEVERE AND HP is SEVERE AND LT is MILD AND WD is SEVERE THEN Crop Disease is SEVERE
29	If TR is SEVERE AND HP is SEVERE, AND LT is MODERATE, AND WD is SEVERE THEN Crop Disease is SEVERE
30	If TR is SEVERE AND HP is SEVERE, AND LT is SEVERE, AND WD is SEVERE THEN Crop Disease is SEVERE

The degree of membership (DOM) is established by placing the chosen input parameter (TR, HP, LT or WD) into the horizontal axis and vertically projecting to the upper boundary of the membership function. The rule base is obtained from derivation based on the historical data, the experience of experts, and observation of the agriculture laboratory features of symptoms of various diseases in the crop. From this knowledge, 30 rules are characterized in the rule base for the decision-making unit and listed in Table 1

(2). Fuzzy inference mechanism

Fuzzy inference mechanism is the main module of a fuzzy logic system which performs decision making. It utilizes the "IF…. THEN" rules together with connectors "AND" or "OR" for framing necessary decision rules. The output of this module is always a fuzzy set regardless of its input which may be fuzzy or crisp.

We make use of Mamdani's MAX-MIN fuzzy inference engine (Mamdani and Assilian, 1975) because previous works proved that it provides precise results. Also, it is intuitive and well suited to human input. In this inference method, the rule utilizes the input membership values as the weighting factors to find out their influence on the fuzzy output sets of the final output conclusion.

In the making of the fuzzy rule, we use the notion of "AND", "OR", and occasionally "NOT." This section explains the most common definitions of these "fuzzy combination" operators which are sometimes referred to as "T-norms."

The fuzzy "AND" is written as:

$$\mu\, A \cap B = T\big(\mu A(x), \mu B(x)\big) \tag{22}$$

Where μ_A is understand writing as "the membership in class A" and μ_B is read as "the membership in class B."

The fuzzy "OR" is written as:

$$\mu\, A \cup B = T\big(\mu A(x), \mu B(x)\big) \tag{23}$$

Where μ_A is understood as "the membership in class A" and μ_B as "the membership in class B."

There are several ways to compute "OR." The most common are max [μ_A (x), μ_B (x)] it simply computes the "OR" by considering the maximum of the two (or more) membership values.

Computing the outcome of a fuzzy rule is a two-step process:

Computing the rule strength by joining the fuzzified inputs using the fuzzy combination process.

Clipping the membership function of output at the rule strength.

Now the outcomes of all of the fuzzy rules are combined to attain one fuzzy output distribution. This is more often than not, but not always, done by using the fuzzy "OR."

(3) Defuzzification

In numerous occasions, it is wanted to come up with a single crisp output from a Fuzzy inference system. For instance, if one were attempting to classify a letter drawn by hand on a tablet, at last, the Fuzzy inference system would need to concoct a crisp number to tell the PC which letter was drawn. This crisp number is gotten in a procedure acknowledged as defuzzification.

The Defuzzification process replaces the fuzzy output of the inference engine into a crisp value making use of membership functions similar to the ones used by the fuzzification process. The defuzzification process takes fuzzy set as input (the combined output fuzzy set), whereas the outcome of the defuzzification process is a number (crisp value). Although there are more than ten methods exists for defuzzification, but few commonly used DE fuzzifying methods are Centroid of area (COA), Bisector of area (BOA), Smallest of maximum (SOM), Mean of maximum (MOM), and Largest of maximum (LOM). For obtaining a crisp value for crop disease diagnosis, we adopt Centroid of area method as shown in 19

$$Crisp\ Output = \mu\,(\boldsymbol{u}) = \left[\sum \mu_A(u).\frac{u}{\sum \mu_A(u)}\right] \tag{24}$$

Where $\mu_A(u)$ = Membership value in the membership function and

u = Center of the membership function

The centroid of area (gravity) is considered to be the most widely used defuzzification technique because, when it is applied, the defuzzified values tend to move smoothly in the output fuzzy region, therefore giving a more precise representation of a fuzzy set of any shape.

5. Experimental analysis and results

Table 2. Rule base evaluation for Input variable at 10, 12, 7 and 6

Rule #	Input Variables				Consequence	Nonzero Minimum
	TR	HP	LT	WD		
10	0.25	0.25	0.40	1	Mild	0.30
12	1	0.50	0.25	0.25	Moderate	0.25
16	0.75	0.75	0.50	0.50	Moderate	0.80
18	1	1	0.70	0.70	Severe	0.45

In this chapter, we explore Fuzzy modelling in agriculture diagnostics. For a better understanding of this system, some possible data is taken to develop a computer simulation showing the fuzzy inference and user interface and to assist the preliminary decision for the best control action. Results of assessment of fuzzy logic-based inference for four ranges of inputs, Temperature (TR), humidity and precipitation (HP), Light (LT), and Wind (WD) are shown in Table 2 and Table 3, respectively.

For instance, if Rules number 10, 12, 16, and 18 fire from the rule base table, when temperature, humidity & precipitation, Light, and Wind values are chosen at 10, 12, 7 and 6 their related degrees of membership are mild = 0.00, moderate = 1.00, severe = 0.00 for temperature, mild = 0.25, moderate = 0.50, severe = 0.1 for humidity & precipitation, mild = 0.40, moderate=0.25, severe = 0.70 for light and mild = 0.00 moderate = 0.50 severe = 0.70 for wind. The relevant output membership function strengths (0-1) from the probable rules are computed using MAX-MIN inference for Crop disease and shown in the respective column of table 2.

At last, a defuzzification strategy is applied to get a deterministic control action. For inputs [TR, HP, LT, WD] = [10, 12, 7, 6] in Table 2, the crisp output can be computed as;

Crisp Output = ((0.30 x 5) + (0.25 x 5) + (0.80 x 7.5) + (0.45 x 7.5)) / (0.30 + 0.25 + 0.80+0.45) = 6.7 (67%) Moderate Crop disease

It implies that if these particular input conditions occur in agriculture farm the crop has 6.7 (67% Moderate) degree of crop disease.

Table 3. Rule base evaluation for Input variable at 6, 10, 3 and 9

Rule #	Input Variables				Consequence	Nonzero Minimum
	TR	HP	LT	WD		
8	0.50	0.80	0.40	0.40	Mild	0.40
11	0.50	0.80	0.40	0.60	Moderate	0.50
12	0.50	0.70	0.40	0.60	Moderate	0.20
13	0.50	0.60	0.70	0.40	Moderate	0.30
14	0.50	0.50	0.70	0.40	Moderate	0.40
16	0.50	0.50	0.30	0.50	Moderate	0.60
17	0.50	0.50	0.30	0.50	Moderate	0.50
19	0.50	0.40	0.30	0.50	Moderate	0.20
21	0.50	0.40	0.50	0.60	Severe	0.20
23	0.25	0.50	0.8.	0.60	Severe	0.30
24	0.25	0.20	0.60	0.40	Severe	0.35

For inputs [TR, HP, LT, WD] = [6, 10, 3, 9] in Table 3, the crisp output can be computed as;

Crisp Output = ((0.40 x 2.5) + (0.50 x 5) + (0.20 x 3) + (0.40 x 5) + (0.60 x 7.5) + (0.50 x 2.5) + (0.20 x 2.5) + (0.30 x 5.5) + (0.35 x 7)) / (0.40+0.50+0.20+0.40+0.60+0.50+0.20+0.30+0.35

= 4.65 (47 %) Moderate Crop disease

This indicates that the crop has 47% (Moderate) degree level of disease; therefore, moderate disease is expected with 47% possibility being required system response.

6. Discussions

The agriculture precision is a lighted area of research. The disease diagnosis and forecasting system for the agriculture domain is based on the fuzzy logic model. Fuzzy logic is applied to this problem to eliminate ambiguity, uncertainty, and vagueness inherent in this field. It is explained in the context of diagnosing the extent of diseases in crops. The framework consists of three input variables: Temperature, humidity & precipitation, Light, and Wind. The rule base is composed of twenty-seven rules to determine the four different values of output parameter viz No crop disease, Mild crop disease, Moderate crop disease, Severe crop disease, by four input values. For the evaluation of membership function triangular fuzzifier is employed. The basis of rule base design is the historical facts and domain expert's knowledge. The fuzzy modelling utilizes Mamdani's inference engine technique for a better explanation of the application. Centroid of area method is employed for the defuzzification process. Despite assigning linguistics variables, for instance mild, moderate, and severe to the diagnosis and forecasting, the degree of mildness, moderateness and severity are evaluated as well.

Rule evaluation is carried out for different values of input parameters. Three input variables give linguistic values. These values are further used by the inference engine to apply 30 inference rules. There exist many tools to simulate the fuzzy inference model like Fuzzy Logic Toolbox™ UI, FuzzyTECH™ Toolbox, FIDE™, FISTA [25]. The most recent existing fuzzy tools are the MATLAB™ Fuzzy-Toolbox™ and Fuzzy CLIPS. For model building and simulation, this provides a full set of built-in functions for controlling fuzzy systems. In the framework for fuzzy Modelling in agricultural diagnostics, this chapter demonstrates the diagnosis and forecasting of crop diseases in a hypothetical scenario, and the obtained results give an idea about a better understanding and excellent performance, being in the array of the pre-defined limits by the agriculture experts. The spirit of designing this framework is to determine the degree to which the fuzzy modelling technique represent the precise diagnosis and monitoring of diseases in agricultural plants as compared with those of agriculture scientists.

7. Conclusion and future directions

The modelling and management of agricultural processes are relatively a complicated business. A large number of variables and factors are taken into consideration for decision making and system analysis. The majority of the agricultural processes are uncertain, ambiguous, and incomplete and also involve human intuition characteristics. These processes are highly constrained by their atmosphere like climate, market, seasons, production, demand, etc. at the same time; they are highly subjective to human factors like stakeholders' perceptions. The application of fuzzy sets in the agriculture sector is significant and desirable. Fuzzy modelling of agricultural processes is capable of managing and representing uncertainty. It can make sure that incomplete information is valued and present solutions to crucial agricultural issues like crop production, crop disease, fertilization, soil erosion, land degradation, and climate variability. Fuzzy models have achieved steadily growing research interest in the last two decades and have established great applicability in the agricultural domain, serving stakeholders to take more accurate decisions for cultivation.

The authors acknowledge the fact that a total of four input variable are insufficient for making a reliable and precise forecasting support system. However, the demonstration results obtained are hopeful and more variables will be included in future for making a robust, workable agriculture disease diagnosis and forecasting support system.

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