1. Introduction

The combine harvester is a typical uncertain time varying non-linear complex system. There are many factors (design factors, operating conditions and crop properties) which act on it all together, and no definite relational expression between the factors and results could be found, and it is difficult to establish the accurate model between them.

Regression model is a common method in predicting the mathematical model between the dependent variable and the independent variables and also has used to model the relationship between the grain loss and various components of combine header components using regression analysis and neuro-fuzzy model. Reel index (forward speed of combine harvester divided by peripheral speed of reel), cutting height, the horizontal distance of reel tine bar from cutter bar and vertical distance of reel tine bar from cutter bar were considered as input variables and combine header loss was regarded as output variable. Neuro-fuzzy model showed the coefficient of determination (R²) equal to 0.9817 which is superior to multiple regression method with 0.6354.

Keywords: Combine harvester, Header, Loss, Multiple Regression Model, Neuro-Fuzzy Model.

Junsiri and Chinsuwan [7] (2009) developed a regression equation to predict header losses of a combine harvester when harvesting Thai Hom Mali rice. The results of their study indicated that grain moisture content (M), Reel index (RI), cutter bar speed (V), service life of cutterbar (Y), tine spacing (R), tine clearance over cutter bar (C), stem length (H), product of M and Y (M*Y), product of M and V (M*V), product of RI and R (RI*R), product of V and C (V*C), product of V and H (V*H), V2 and RI2 were the major parameters affecting the losses. The prediction equations had R-squared equal to 0.75.

On the other hand, intelligent solutions, based on artificial intelligence (AI) technologies, to solve complicated practical problems in various sectors are becoming more and more widespread nowadays. AI-based systems are being developed and deployed worldwide in myriad applications; the main reasons behind this issue being: their symbolic reasoning, flexibility and explanation capabilities. (Ghanbari [3] et al., 2010; Metaxiois [9] et al., 2003)
There are several research works which have used from variety of AI methods in the different aspects of combine harvester.

By the neuro-fuzzy method can construct an input-output mapping based on both human knowledge (in the form of fuzzy 'If-Then' rules) and stipulated input-output data pairs. The neural component provided supervised learning capabilities for optimizing the membership functions and extracting fuzzy rules from a set of input-output examples selected to cover the data hyperspace of the sites evaluated. Accordingly, fuzzy logic and artificial neural networks are merged to inherit advantages of both paradigms and to avoid their drawbacks (Huang [5] et al., 2010).

Zhou [16] et al., (2008) introduced the control method of rotation speed of threshing drum based on fuzzy neural network, and designed the fuzzy neural network controller of combine harvester threshing drum. Their simulation result showed that the fuzzy neural network control method was feasible.

De Carvalho Alves [2] et al., (2009) developed and evaluated neuro-fuzzy systems as a methodology to describe coffee harvester machine operational performance when compared to multiple regression models. They demonstrated that neuro-fuzzy models have better performance when compared to multiple regression models.

Craessaerts [1] et al., (2009) developed a fuzzy control system which combines the knowledge of experienced operators with these data-based. Their results showed the benefits of fuzzy control system for the cleaning section of a combine harvester when environmental conditions rapidly change over time.

Mesri Gundoshmian [10] et al., (2010) developed a three-layer perceptron neural network model, which investigated the influence of the wheat yield, crop variety, crop moisture content, crop height, height of cut, threshing drum speed, concave clearance, fan speed, chaffer opening and lower sieve opening on the combine performance.

Omid [12] et al., (2010) developed a fuzzy logic controller (FLC) incorporating human expert knowledge designed for automatic adjustment and control of the harvester to achieve minimal grain losses especially at the position of straw walker and upper sieve. Their experimental tests showed a significant difference between loss mean in the combine equipped with the controller and the one without FLC.

The major percent of the header loss is caused by improper adjustments. In this study, neuro-fuzzy model and regression method were applied to develop forecasting models which can predict the combine header loss for each set of the header parameter adjustments related to site-specific information and therefore can minimize the header loss.

2. Materials and methods

The field experiment was conducted during the harvesting season of 2011 at the research station of Faculty of Agriculture, Shiraz University, Shiraz, Iran. The wheat field (CV. Shiraz) was harvested with a Claas Lexion-510 combine harvester. The main factors which influence the header performance are reel index (RI) (forward speed of combine harvester divided by peripheral speed of reel), in the levels of 1, 1.2, 1.5, cutting height (CH), in the levels of 25, 30, 35 cm, the horizontal distance of reel tine bar from cutter bar (HD), in the levels of 0, 5, 10 cm and vertical distance of reel tine bar from cutter bar (VD), in the levels of 5, 10, 15 cm which are taken as the input variables for neuro-fuzzy model and only combine header loss is output of the model.

Some frames with the dimensions of 50 x 50 cm were used to determine the amount of header loss. In order to determine the header loss, the frame was placed on the ground in the vacant place behind the cutter bar, where output material from the back of the combine was not allowed to pour on the ground. Grains and ears found inside the frame were gathered, weighed and then the amount of pre-harvest loss was subtracted form it (Hassani [4] et al., 2011; Roy [14] et al., 2001). A fractional factorial design based on completely randomized design (CRD) was used to determine the header loss. Each test was repeated three times and for each repetition, the combine harvester was run in the distance of at least 15 meters to ensure the stable workload before data collection at 10 meters (Junsiri and Chinsuwan [7] 2009).

In the first step of the analysis, multiple regression analysis was implemented to develop a model which can establish the relationship between independent variables and a dependent variable based on obtained data in this study.
Multiple regression analysis is a powerful technique used for predicting the unknown value of a variable from the known value of two or more variables - also called the predictors. In general, the multiple regression equation of $Y$ on $X_1, X_2, ..., X_n$ is given by:

$$Y = b_0 + b_1 X_1 + b_2 X_2 + \ldots + b_n X_n \tag{1}$$

Where, $b_0$ is the intercept, representing the amount the dependent $y$ will be when all the independent variables are 0. $b_1, b_2, b_3, ..., bn$ are regression coefficients, representing the amount the dependent variable $y$ changes when the corresponding independent variable ($X_i$) changes one unit. They can be interpreted the same way as slope.

On the other hand, in neuro-fuzzy systems, membership functions and if-then rules were defined through neural networks. Sugeno-type fuzzy inference model was applied to generate fuzzy rules from a given input-output data set due to its less time-consuming and mathematically tractable defuzzification operation for sample data-based fuzzy modeling (Jang et al., 1997; Pan and Yang 2007; De Carvalho Alves et al., 2009). The fuzzy rules using Sugeno-type fuzzy model are expressed in following form:

**Rule 1:** IF $x_1$ is $A_{11}$ and $x_2$ is $A_{21}$ and ... and $x_n$ is $A_{n1}$, THEN $f_1 = a_0^1 + a_1^2 x_1 + a_2^2 x_2 + \ldots + a_n^2 x_n$ \tag{2}

**Rule 2:** IF $x_1$ is $A_{12}$ and $x_2$ is $A_{22}$ THEN $f_2 = a_0^2 + a_1^2 x_1 + a_2^2 x_2 + \ldots + a_n^2 x_n$

**Rule p:** IF $x_1$ is $A_{1p}$ and $x_2$ is $A_{2p}$ and ... and $x_n$ is $A_{np}$, THEN $f_p = a_0^p + a_1^p x_1 + a_2^p x_2 + \ldots + a_n^p x_n$ \tag{3}

Where $x_i, i = 1, 2, ..., n$, is the $i^{th}$ input variable, $A_{ij}$ is the $j^{th}$ linguistic value (for example, low, medium, high) related to $x_i$. Function $f_p$ is the consequent output of the rule, and $a_p^j$ is the Sugeno parameter. A general structure neuro-fuzzy system was shown in Figure 2. The structure for this study has four inputs and each input variable as mentioned and three membership functions (mf), result in 81 rules.

As indicated in Figure 1, the system has a total of five layers. The functioning of each layer is described as follows.
In the third layer (normalization layer), each node calculates the ratio of the \( i \)th rule’s firing strength to the sum of all rule’s firing strengths as normalized firing strengths.

\[
O_p^N = \frac{w_p}{\sum_{p=1}^{m} w_p}, \quad p = 1, 2, ..., m^n
\]  

(5)

The fourth layer (consequent layer) multiplies the normalized firing strength with the linear consequence.

\[
O_p^E = w_p f_p
\]  

(6)

The fifth layer (output layer) computes the overall output as the summation of all obtained values from layer 4.

\[
O^N = \sum_p w_p f_p = \frac{\sum_p w_p f_p}{\sum_p w_p}
\]  

(7)

3. Results and Discussion

In this study, for four input variables under consideration, a multiple regression method was used for modeling and the coefficients of regression model were estimated from the experimental results. The multiple regression equation obtained for combine header loss is as follows:

\[
\text{Header loss} = 0.655 + 1.327(\text{RI}) + 0.241(\text{CH}) - 0.1(\text{HD}) + 0.236(\text{VD})
\]  

(8)

A neuro-fuzzy system was developed for predicting the combine header loss with reel index, cutting height, the horizontal distance of reel tine bar from cutter bar and vertical distance of reel tine bar from cutter bar as input variables. Model has three membership functions for each input. Gaussian membership functions and rules were defined for knowledge representation of header loss.

It was verified good performance of neuro-fuzzy model based on \( R^2 \) obtained from observed and predicted combine header loss. Neuro-fuzzy model explained 98.7% combine header loss (Figure 3).

Figure 3. Observed and predicted values for combine header loss by Neuro- Fuzzy model

Neuro-fuzzy model performed better when compared to multiple regression model. According to Liu and Abonyi (2006) and de Carvalho Alves et al., (2009) neuro-fuzzy is an extension to existing modelling methods and not their replacement. Predicting header loss is an important issue in minimizing amount of harvest grain loss. Neuro-fuzzy model presented satisfactory application to describe header loss of a combine harvester. It showed \( R^2 \) equal to 0.987 which is superior to multiple regression method with 0.635. In fact, the amount of R-squared is a good indicator to check the prediction performance of the model. Based on developed neuro-fuzzy system model, levels of reel index, cutting height, the horizontal distance of reel tine bar from cutter bar and vertical distance of reel tine bar from cutter bar could be recommended according to minimize header loss.
Conclusion

A multiple regression model and neuro-fuzzy model were developed to predict combine header loss. Models were validated and compared by means of the coefficient of determination ($R^2$) values. The obtained $R^2$ amounts for these two models indicated that neuro-fuzzy model forecasted combine header loss better than multiple regression model. So, neuro-fuzzy model can be considered as a good tool for minimizing the uncertainties in prediction of combine header loss.

References


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