Adaptive neuro-fuzzy inference systems for epidemiological analysis of soybean rust

Marcelo de Carvalho Alves a,*, Edson Ampélio Pozza b,1, João de Cássia do Bonfim Costa c, Luiz Gonsaga de Carvalho d,2, Luciana Sanches Alves e

a Federal University of Mato Grosso, Faculty of Agronomy and Veterinary Medicine, Department of Soil and Rural Engineering, Av. Fernando Correa da Costa 2367, Boa Esperança, 78060-900 Cuiabá-MT, Brazil
b Federal University of Lavras, Department of Phytopathology, Campus of Federal University of Lavras, Cx 3037, CEP 37200-000 Lavras MG, Brazil
c Federal University of Lavras, Minas Gerais, Brazil, Campus, Cx 3037, CEP 37200-000 (UFLA), Engineering Department (DEG), Brazil
d Federal University of Mato Grosso, Faculty of Architecture, Engineering and Technology, Department of Sanitary and Environmental Engineering, Av. Fernando Correa da Costa 2367, Boa Esperança, 78060-900 Cuiabá-MT, Brazil
e CEPEC/CEPLAC/MAPA, Phytopathology Section, P.O. Box 07, 45650-000 Itabuna, BA, Brazil

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ABSTRACT

The objective of this work was to develop and to evaluate adaptive neuro-fuzzy inference systems as methodology to describe the severity of soybean rust (Phakopsora pachyrhizi) monocyclic process in soybean [Glycine max (L.) Merr.] under effects of leaf wetness, temperature, and days after fungi inoculation. The experiment was conducted in growth chambers with mean air temperatures of 15, 20, 25 and 30 °C and leaf wetness periods of 6, 12, 18 and 24 h. The plants were inoculated by spraying a suspension of P. pachyrhizi inoculum at concentration of 10^4 uredinospore mL⁻¹. A disease assessment key was adopted for estimate amounts of soybean rust at 0, 6, 9, 12 and 15 days after fungi inoculation. A hybrid neural network training with 3 and 3000 epochs was applied to disease severity data for optimization of fuzzy system parameters used to describe the severity of soybean rust based on leaf wetness, temperature and days after fungi inoculation. Higher accuracy and precision of the neuro-fuzzy systems estimates were obtained after training with 3000 epochs. Nevertheless, training with 3 epochs produced smoother estimates. The neuro-fuzzy systems enabled to describe the severity of soybean rust monocyclic process under effects of leaf wetness, mean air temperature and days after fungi inoculation and was better applied for Conquistar cultivar, followed by Savana and Suprema cultivars. Higher soybean rust severity was verified under temperatures among 20 °C and 25 °C, leaf wetness above 6 h, with higher values above 10 h, and 15 days after fungi inoculation. Temperatures near 15 °C increased the latent period of the disease but not inhibited its development after 10 days of fungi inoculation.

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1. Introduction

The soybean rust (Phakopsora pachyrhizi H. Sydow & P. Sydow) which has been reported in areas of tropical and subtropical climates around the world, causes significant soybean [Glycine max (L.) Merr.] yield reduction (Bromfield, 1984; Yang et al., 1991). The disease progress is influenced by biotic factors as interaction pathogen-host and abiotic factors of the environment (Alves et al., 2007; Zambenedetti et al., 2007a; Pivonia and Yang, 2004; Melching et al., 1989; Bromfield, 1984; Casey, 1980).

The success of fungi infection depends on spores germination, apressorium formation, penetration, colonization, uredinial development, sporulation and teliospore formation. Each one of those events is influenced by biotic factors as interaction pathogen-host and abiotic factors as climatic variables (Bromfield, 1984). Among abiotic factors, temperature and leaf wetness exercises fundamental effects in the epidemiology of P. pachyrhizi in soybean cultivars (Alves et al., 2007).

With the information about the effects of environmental variables in soybean rust epidemiology, it is possible to evaluate the disease potential progress and to define risk areas for occurrence of epidemics (Pivonia and Yang, 2004), based on climate change (Scherm and Yang, 1995).
and greenhouse climate control (Castañeda-Miranda et al., 2006), statistics (Wieland and Mirschel, 2008). Fuzzy modeling advantages were also related to the inoculation under effects of leaf wetness, temperature and days after fungi inoculation.

Fig. 1. Neural network architecture used to configure the neuro-fuzzy system in order to describe the severity of soybean rust under effects of leaf wetness, temperature and days after fungi inoculation.

Considering that severity of soybean rust could be influenced by many large scale factors with built-in uncertainties, soft computing, which is an integrated approach based on artificial intelligence techniques, such as neural networks, fuzzy logic and genetic algorithms (Jang et al., 1997), can be used to construct generally satisfactory solutions for characterization of disease pattern, considering effects of biotic and abiotic factors (Kim et al., 2005). Those techniques have been applied to characterize physical, chemical and biological processes (Massad et al., 2003; Ureña et al., 2001; Yang et al., 2003; Amini et al., 2010) as well as in automotive engineering (Von Altrock, 1995), industrial process control (Sugeno, 1985) and greenhouse climate control (Castañeda-Miranda et al., 2006), with higher accuracy and precision when compared to classic statistics (Wieland and Mirschel, 2008). Fuzzy modeling advantages were also related to the flexibility of incorporation of additional variables, knowledge representation of human expertise using fuzzy if-then rules (computing with words), modeling complex nonlinear functions, dealing with perception, pattern recognition and classification problems, control and optimization of processes, learning at unknown or changing environment and easiness integration with sensors (Liu and Abonyi, 2006; Mellit and Kalogirou, 2008), as well as to other soft computing methods, such as neural networks and genetic algorithms (Klir and Yuan, 1995; Tsoukalas and Uhrig, 1997; Zadeh, 1994). Furthermore, there are no exact and precise measurements about the influence of agronomic variables such as climate, soil fertility, cultivars resistance, crop yield and management practices in the progress of soybean rust, being necessary to create a subjective measure to assess the disease potential progress through soft computing methods.

Thus, considering that intelligent hybrid systems enable the combination of knowledge, techniques, methodologies and interaction of environmental variables, to give decision support to solve complex problems, it was aimed at with this work, to develop and to evaluate adaptive neuro-fuzzy inference systems as methodology to describe the severity of soybean rust monocyclic process under effects of leaf wetness, temperature and days after fungi inoculation.

2. Material and methods

The data used in the present study was obtained from experiment accomplished in growth chambers using random blocks design, in factorial scheme 4 x 5 x 5, with 3 repetitions, being four mean air temperatures of 15 °C, 20 °C, 25 °C and 30 °C, five leaf wetness periods of 0, 6, 12, 18 and 24 hours and five days after fungi inoculation at 0, 6, 9, 12 and 15 days, totaling 300 records (n = 300). Soybean seeds of susceptible cultivar Conquista (Zambenedetti et al., 2007a) were sowed in vase containing 5 kg of soil, sand and organic matter (bovine excrement) mixed in the proportion 2:1:0.5. Plants remained at greenhouse until V3 vegetative stadium, according to Ritchie et al. (1982) scale. Fungi inoculums were obtained by collection of P. pachyrhizi urediniospore of Conquista cultivar, in greenhouse, and stored in liquid nitrogen at -180 °C to preserve its viability according to Zambenedetti et al. (2007b) methodology. The inoculum presented 89% of germination before inoculation. The inoculation was accomplished being sprayed all plant leaves with suspension of 10^6 urediniospores of P. pachyrhizi ml^-1. Leaf wetness periods were obtained maintaining inoculated plants closed in humid transparent plastic bags during each treatment period, in separated chambers, with temperature of 15, 20, 25 and 30 °C. For the treatment of 0 h of leaf wetness, the inoculated plants were not submitted to the closed humid transparent plastic bags. Irrigations were accomplished depositing water directly in vases. Evaluations of Severity were accomplished in the central trifoliate leaf of each plant branch. The severity was estimated visually using Keogh (1974) assessment keys, developed to estimate the percentage of leaf area affected by lesions caused by P. pachyrhizi in soybean, where: note 0 = 0%, note 1 = 0.15%, note 2 = 1.0%, note 3 = 2.5%, note 4 = 8.0%, note 5 = 13.0%.

After data collection, neuro-fuzzy approach was used as decision support modeling to describe the monocyclic processes of soybean rust, using Matlab® and Fuzzy Logic Toolbox®. The basic structure of a fuzzy inference system consists of three conceptual components: a rule base, with a selection of fuzzy rules, a database, to define the membership functions used in fuzzy rules, and a reasoning mechanism, to perform an inference procedure upon the rules and given facts, to derive a reasonable output or conclusion (Klir and Yuan, 1995; Jang et al., 1997).

Fig. 2. Error results of the neural network trained with 3 (upper) and 3000 epochs (down) used to develop the fuzzy systems to represent leaf wetness, temperature and days after fungi inoculation in relation to severity of soybean rust epidemiology.
Neuro-fuzzy system rules defined through a neural network to estimate the severity of soybean rust under effects of leaf wetness (LW), temperature (T) and days after fungi inoculation (D), after 3 and 3000 training epochs.

<table>
<thead>
<tr>
<th>Rule</th>
<th>If input 1 is</th>
<th>And input 2 is</th>
<th>And input 3 is</th>
<th>Then output parameter after 3 epochs is</th>
<th>Then parameter after 3000 epochs is</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>LW 1</td>
<td>T 2</td>
<td>D 1</td>
<td>0.0009432</td>
<td>0.000006834</td>
</tr>
<tr>
<td>2</td>
<td>LW 1</td>
<td>T 3</td>
<td>D 2</td>
<td>-0.005411</td>
<td>-0.005188</td>
</tr>
<tr>
<td>3</td>
<td>LW 2</td>
<td>T 1</td>
<td>D 3</td>
<td>0.006073</td>
<td>0.03576</td>
</tr>
<tr>
<td>4</td>
<td>LW 1</td>
<td>T 2</td>
<td>D 3</td>
<td>0.0007918</td>
<td>0.001195</td>
</tr>
<tr>
<td>5</td>
<td>LW 2</td>
<td>T 1</td>
<td>D 3</td>
<td>-0.003641</td>
<td>-0.001819</td>
</tr>
<tr>
<td>6</td>
<td>LW 1</td>
<td>T 3</td>
<td>D 3</td>
<td>-0.003457</td>
<td>0.01988</td>
</tr>
<tr>
<td>7</td>
<td>LW 1</td>
<td>T 3</td>
<td>D 1</td>
<td>0.00003924</td>
<td>-0.00008491</td>
</tr>
<tr>
<td>8</td>
<td>LW 2</td>
<td>T 3</td>
<td>D 2</td>
<td>-0.0001244</td>
<td>-0.0003019</td>
</tr>
<tr>
<td>9</td>
<td>LW 1</td>
<td>T 3</td>
<td>D 2</td>
<td>0.006056</td>
<td>-0.00235</td>
</tr>
<tr>
<td>10</td>
<td>LW 2</td>
<td>T 1</td>
<td>D 1</td>
<td>0.003344</td>
<td>0.001156</td>
</tr>
<tr>
<td>11</td>
<td>LW 2</td>
<td>T 1</td>
<td>D 2</td>
<td>-0.019224</td>
<td>0.04168</td>
</tr>
<tr>
<td>12</td>
<td>LW 2</td>
<td>T 1</td>
<td>D 2</td>
<td>0.3329</td>
<td>0.5413</td>
</tr>
<tr>
<td>13</td>
<td>LW 2</td>
<td>T 2</td>
<td>D 1</td>
<td>-0.01778</td>
<td>0.001565</td>
</tr>
<tr>
<td>14</td>
<td>LW 2</td>
<td>T 2</td>
<td>D 2</td>
<td>0.1206</td>
<td>0.1949</td>
</tr>
<tr>
<td>15</td>
<td>LW 2</td>
<td>T 2</td>
<td>D 3</td>
<td>0.2822</td>
<td>0.2393</td>
</tr>
<tr>
<td>16</td>
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<td>T 3</td>
<td>D 1</td>
<td>-0.00066491</td>
<td>-0.0002569</td>
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<tr>
<td>17</td>
<td>LW 2</td>
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<td>D 2</td>
<td>-0.0006309</td>
<td>-0.01713</td>
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<tr>
<td>18</td>
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<td>D 2</td>
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<td>19</td>
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<td>D 2</td>
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<td>0.004146</td>
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<tr>
<td>20</td>
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<td>T 1</td>
<td>D 2</td>
<td>-0.003272</td>
<td>0.003089</td>
</tr>
<tr>
<td>21</td>
<td>LW 1</td>
<td>T 2</td>
<td>D 1</td>
<td>-0.003463</td>
<td>0.6958</td>
</tr>
<tr>
<td>22</td>
<td>LW 1</td>
<td>T 2</td>
<td>D 2</td>
<td>0.003176</td>
<td>-0.0005172</td>
</tr>
<tr>
<td>23</td>
<td>LW 1</td>
<td>T 2</td>
<td>D 2</td>
<td>0.1894</td>
<td>0.305</td>
</tr>
<tr>
<td>24</td>
<td>LW 1</td>
<td>T 2</td>
<td>D 3</td>
<td>0.3663</td>
<td>0.2506</td>
</tr>
<tr>
<td>25</td>
<td>LW 1</td>
<td>T 3</td>
<td>D 1</td>
<td>0.0009284</td>
<td>0.0004425</td>
</tr>
<tr>
<td>26</td>
<td>LW 1</td>
<td>T 3</td>
<td>D 2</td>
<td>0.0059911</td>
<td>-0.002856</td>
</tr>
<tr>
<td>27</td>
<td>LW 1</td>
<td>T 3</td>
<td>D 3</td>
<td>0.20213</td>
<td>0.04406</td>
</tr>
</tbody>
</table>

For a first-order sugeno fuzzy model, a common rule set with two fuzzy if-then rules is

\[ \text{Rule 1: } \text{If } x \leq L_1 \text{ and } y \leq T_1 \text{ and } z \leq D_1 \text{ then } f_1 = p_x + q_y + g_z + r_1 \]

\[ \text{Rule 2: } \text{If } x > L_2 \text{ and } y > T_2 \text{ and } z > D_1 \text{ then } f_2 = p_x + q_y + g_z + r_2 \]

Table 1

<table>
<thead>
<tr>
<th>Inputs</th>
<th>Number of the membership function</th>
<th>Parameters after 3 epochs</th>
<th>Parameters after 3000 epochs</th>
</tr>
</thead>
<tbody>
<tr>
<td>L</td>
<td>1</td>
<td>[5.904, -0.001446]</td>
<td>[3.335, 0.05388]</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>[5.097, 12]</td>
<td>[4.356, 13.54]</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>[5.095, 24]</td>
<td>[2.118, 25.67]</td>
</tr>
<tr>
<td>T</td>
<td>1</td>
<td>[3.149, 15]</td>
<td>[3.67, 15.4]</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>[3.165, 30.13]</td>
<td>[3.117, 22.92]</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>[3.192, 0.004591]</td>
<td>[1.031, 3.914]</td>
</tr>
<tr>
<td>D</td>
<td>1</td>
<td>[2.191, 7.504]</td>
<td>[2.298, 12.48]</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>[3.193, 15]</td>
<td>[1.265, 13.79]</td>
</tr>
</tbody>
</table>

Neuro-fuzzy systems were used as supervisory controllers of fuzzy models of dynamical processes, while Mamdani fuzzy systems are usually used as direct closed-loop controllers (Liu and Abonyi, 2006).
From the proposed ANFIS architecture, given the values of premise parameters, the overall output can be expressed as a linear combination of the consequent parameters and the output $f$ can be rewritten as (Jang, 1993):

$$f = \frac{w_1}{w_1 + w_2 + w_3} f_1 + \frac{w_2}{w_1 + w_2 + w_3} f_2 + \frac{w_3}{w_1 + w_2 + w_3} f_3 = \mu f_1 + \mu f_2 + \mu f_3$$

which is linear in the consequent parameters $p_1, q_1, r_1, p_2, q_2, r_2, p_3, q_3, r_3$. Assuming that the adaptive network has only one output, output $o = F(\bar{T}, S)$, where $\bar{T}$ is the set of input variables and $S$ is the set of parameters, and that there exists a function $H$ such that the composite function $H \circ F$ is linear in some of the elements of $S$. These elements can be identified by the least square method. Considering that $H$ and $F$ are the identity function and the function of the fuzzy inference system, respectively, the hybrid learning algorithm can be applied directly. In the forward pass of the hybrid learning algorithm, functional signals go forward till layer 4 and the consequent parameters are identified by the least square estimate. In the backward pass, the error rates propagate backward and the premise parameters are updated by the gradient descent (Jang and Sun, 1995).

The fuzzy systems precision and accuracy were evaluated for each soybean cultivar, considering 100 data of Conquista cultivar, 100 data of Savana cultivar and 100 data of Suprema cultivar, separately. The fuzzy models were tested based on the values of root mean squared error (RMSE), $R^2$ and adjusted $R^2$ statistics, a value closer to 1 indicates a better fit. After the neural network training completed, the root mean squared error was 0.0659369 and 0.0578711 for the 3 and 3000 epochs, respectively (Fig. 2).

Two adaptive neuro-fuzzy inference systems were developed each one with 27 rules (Table 1) and 9 Gaussian membership functions (Table 2, Fig. 3). This enabled the knowledge representation of leaf wetness, temperature and days after fungi inoculation as input variables. Rule view interactive interfaces were developed to access individual output values of severity of soybean rust according to input values of leaf wetness, temperature, leaf wetness and days after inoculation.

3. Results and discussion

The neuro-fuzzy systems enabled to describe the severity of soybean rust monocyclic process considering leaf wetness, temperature and days after fungi inoculation as input variables. After the neural network training completed, the root mean squared error was 0.0659369 and 0.0578711 for the 3 and 3000 epochs, respectively (Fig. 2).

Two adaptive neuro-fuzzy inference systems were developed each one with 27 rules (Table 1) and 9 Gaussian membership functions (Table 2, Fig. 3). This enabled the knowledge representation of leaf wetness (LW), temperature (T) and days after fungi inoculation (D), in way to compose inference diagrams of the severity of soybean rust monocyclic process. The difference between the two neuro-fuzzy systems could be observed in parameters of the rules and membership functions (Tables 1 and 2). Some parameters of rules and membership functions determined lower output results of the

![Fig. 3. Membership grades of Gaussian fuzzy sets (L1, L2, L3, T1, T2, T3, D1, D2, D3) defined with a neural network training, in order to represent leaf wetness, temperature and days after fungi inoculation in relation to severity of soybean rust epidemiology, trained with 3 (left) and 3000 epochs (right).](image-url)
models, but are important to characterize the disease monocyclic process under unfavorable conditions.

The diagram was used to perform logical operators of aggregation, activation, defuzzification and accumulation inference engine steps. After that, output surfaces were develop in order to characterize the effects of interaction between leaf wetness, temperature and days after fungi inoculation in the severity of soybean rust, for the systems trained with 3 and 3000 epochs (Fig. 4). According to neuro-fuzzy system control, higher soybean rust severity was verified under temperatures among 20 °C and 25 °C, leaf wetness above 6 h, with higher values above 10 h, and 15 days after fungi inoculation. Temperatures near 15 °C increased the latent period of the disease but not inhibited its development after 10 days of fungi inoculation. In agreement with Alves et al. (2007), intensity of soybean rust progress in Conquista cultivar was favored under 22 °C and leaf wetness above 12 h. Casey (1980), in Australia, studying soybean rust progress starting from artificially inoculated focus in Lee cultivar, in the field, also observed temperatures from 18 to 26 °C and leaf wetness periods close to 10 h a day, as necessary for the occurrence of epidemics with higher intensity. In the same way, Melching et al. (1989), studying temperature and leaf wetness effects in soybean rust, cultivar Wayne, in Taiwan, didn’t find rust lesions at temperatures closed to 9 °C and 28.5 °C. The main difference of the present work when compared to other studies is that the effects of days after fungi inoculation in the disease severity progress were quantified. Another difference was the use of neuro-fuzzy technique to describe the rust epidemiology under effects of temperature and leaf wetness variables.

The rule view interactive interfaces enabled to access individual output values of severity of soybean rust according to input values of leaf wetness, temperature, leaf wetness and days after inoculation, trained with 3 and 3000 epochs in order to evaluate the performance of the fuzzy systems (Fig. 5).

In general, it was verified best performance of neuro-fuzzy system trained with 3000 epochs when compared to the neuro-fuzzy system trained with 3 epochs, based on adjusted $R$-square and root mean square error.
square error coefficients. The neuro-fuzzy system trained with 3 epochs explained 89.9%, 71.7% and 55.8% of the severity of soybean rust monocyclic process for Conquista, Savana and Suprema cultivars, respectively. The neuro-fuzzy system trained with 3000 epochs explained 89.3%, 83.2% and 72.2% of the severity of soybean rust monocyclic process for Conquista, Savana and Suprema cultivars, respectively (Fig. 6). Kim et al. (2005) also used a fuzzy logic system to describe the apparent infection rate of soybean rust, in TK5 and G8587 cultivars, based on day minimum and maximum temperature and night mean temperature. According to the authors, the technique presented promising results, and could explain 85% of disease severity. Batchelor et al. (1997) developed a neural network to forecast the severity of soybean rust, TK5 cultivar, using information about planting date, days to soybean reach maturity stage, the first day when disease was observed, age of crop in the evaluation period, accumulated days with relative humidity above 90%, accumulated degree days for rust occurrence and accumulated degrees days for soybean development. Based on 73 observations of epidemics and 577 scenarios, during 2 years of evaluation, the model also enabled to explain 85% of disease severity. Considering the results of the present work, besides the best quality of the r-square value of the neuro-fuzzy system trained with 3000 epochs, the neuro-fuzzy system trained with 3 epochs seemed to be more intuitive to explain soybean rust pathogenesis, according to the output surfaces. Nevertheless,
both models could be useful in the development of strategies and tactics of integrated rust management and control. Pan and Yang (2007) evaluating trial and error sensitivity of the epochs training period during the development of neuro-fuzzy systems for livestock farm odour modeling, observed that when the learning rate was higher, the network converged faster, however, if the learning rate was too large, the network oscillated, causing redundancy in the non-linear relationship of data.

Despite the satisfactory performance of the neuro-fuzzy system control, the proposed model is an extension of existing methods and not their replacement. It provides an extra set of tools which the control engineer has to learn its useful application where it makes sense. According to Liu and Abonyi (2006), fuzzy techniques provide a man-machine interface, facilitating the acceptance, validation and transparency of the modeling process. However, based on the present results, the developed neuro-fuzzy system could be useful for the implementation of a soybean rust alert system at field conditions, similarly to Castañeda-Miranda et al. (2006) system. These authors developed a fuzzy logic system to control the environment inside greenhouse environment, based on temperature, relative humidity, global radiation and wind speed. The system was implemented through a field programmable gate array (FPGA) using hardware description language (VHDL), and could be applied as alternative tool to control processes and to reduce cost of energy inside a greenhouse, when compared to conventional controllers.

Considering the possibility to characterize the monocyclic process of soybean rust using neuro-fuzzy systems, the present work could be useful to encourage the implementation of field programmable gate array using hardware description language to alert producers when is the best moment to control or prevent soybean rust progress in the field, according to climate conditions.

Thus, it was possible to describe and to analyze the interaction between the severity of soybean rust monocyclic process, leaf wetness, temperature and days after fungi inoculation. Considering
that control engineering is a step closer to achieve higher level of automation in places where it has not been possible before (Liu and Abonyi, 2006), it is intended to encourage future sensor development for soybean rust epidemics alert under field conditions, based on dynamical data acquisition of temperature and leaf wetness in climatic stations. Based on the neuro-fuzzy system control, climatic geographical models could be developed to characterize the vulnerability of soybean agroecosystems to soybean rust occurrence, in Conquista cultivar, similarly to Pivonia and Yang (2004) methodology.

It is worth emphasizing that the results of the neuro-fuzzy model may have differences when compared to other studies, probably due to the difference between genotypes, vegetative stage, nutritional and genetic variability of soybean rust (Alves et al., 2007; Zambenedetti et al., 2007a,b). However, the satisfactory performance of the neuro-fuzzy model, illustrate the possibility to adopt this methodology as an alternative approach to traditional statistic models, generally used for plant disease forecast and disease risk analysis.

According to Tsoukalas and Uhrig (1997), neural networks and fuzzy systems represent two distinct methodologies that deal with uncertainty. Neural networks approach the modeling representation by using precise inputs and outputs which are used to train a generic model which has sufficient degrees of freedom to formulate a good approximation of the complex relationship between the inputs and the outputs. Otherwise, in fuzzy systems, the input and output variables are encoded in fuzzy representations, with interrelationships defined by if then rules. According to the authors, Zadeh observed that the uncritical pursuit of precision may be not only unnecessary but actually a source of error. Nevertheless, neural networks and fuzzy logic systems have own advantages and disadvantages. Neural networks can represent complex nonlinear relationships and are very good at classification of phenomena into preselected categories used in the training process. Contrary to this, the precision of the outputs is sometimes limited because the variables are effectively treated as analog variables, and minimization of least squares errors does not mean zero error. In relation to fuzzy logic systems, the imprecision of the input and output variables are directly addressed by fuzzy numbers and fuzzy sets expressed in linguistic terms. Furthermore, this method presented greater flexibility in formulating system descriptions at the appropriate level of detail. Fuzzy descriptions are more parsimonious and hence easier to formulate and modify, more tractable, and perhaps more tolerant of change and even failure (Tsoukalas and Uhrig, 1997).

According to Jang et al. (1997), Zadeh also observed that the essence of soft computing is aimed at an accommodation with the pervasive imprecision of the real world. Thus, the guiding principle of soft computing is to exploit the tolerance for imprecision, uncertainty and partial truth to achieve tractability, robustness, low solution cost and better rapport with reality. In the main, fuzzy logic and neurocomputing are complementary rather than competitive. For this reason, it is frequently advantageous to use these techniques in combination rather than exclusively, leading to so-called hybrid intelligent systems. At this juncture, the most visible systems of this type are neuro-fuzzy systems.

4. Conclusions

The neuro-fuzzy system enabled to describe the severity of soybean rust monocular process under effects of leaf wetness, mean air temperature and days after fungi inoculation. Higher soybean rust severity was verified under temperatures among 20 °C and 25 °C, leaf wetness above 6 h, with higher values above 10 h, and 15 days after fungi inoculation. Temperatures near 15 °C increased the latent period of the disease but not inhibited its development after 10 days of fungi inoculation. Higher accuracy and precision of the neuro-fuzzy systems estimates were obtained after training with 3000 epochs. Nevertheless, training with 3 epochs produced smoother estimates.

References


