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Neural Network Pattern Classification and Weather Dependent Fuzzy Logic Model for Irrigation Control in WSN Based Precision Agriculture

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Abstract

Watering system in agricultural lands plays a major activity in water and soil conservations. The future expectation of soil moisture content (MC) utilizing online soil and ecological parameters may give an effective stage to agriculture land watering system prerequisites. This article focuses on two optimization strategies, for example, Scaled Conjugate Gradient and BFGS Quasi-Newton based neural network algorithms utilized to predict hourly requirement of soil MC. The prediction performance of these two optimization techniques are also studied by calculating MSE (Mean Square Error), RMSE (Root Mean Square Error), and R-squared error. The calculations are tried for the forecast of soil MC in every one hour advance by considering eleven distinctive soil and environmental parameters. The best technique is used for the final prediction, and the predicted soil MC is utilized for generating appropriate notifications using fuzzy logic based weather model. The proposed system is hybrid system utilized to solve a single problem that is the generation of best irrigation suggestions for the farmers.

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Keywords: Neural Network Pattern classification; Scaled Conjugate Gradient; BFGS Quasi-Newton; Soil Moisture Content.

1. Introduction

Irrigation is a crucial practice in several agricultural cropping systems in semiarid and arid areas, and also useful water applications and management are key concerns. The efficiency and uniformity of irrigation could be maintained from the complex and diverse information based systems by considering weather, soil, water, and crop data. Sustainable agriculture, in terms of food security, rural employment, and environmentally sustainable technologies such as conservation of soil, sustainable natural resource management, and biodiversity protection as well as the implementation of modern agriculture practices are crucial for holistic rural development. Irrigation water management forms a major aspect of precision agriculture. This involves good assessment of all needs and availability of soil water level for crop cultivation. The statistical data from the United Nations indicate worldwide, agricultural accounts for 70% of all water consumption, compared to 20% for all industry as well as about 10% for domestic uses[1, 16, 17].

There are models developed which uses the remotely sensed data to profile the soil moisture. However, remote sensing can be used to infer directly soil moisture. Microwave emissivities and infrared data were proven to be highly correlated with the soil moisture. A lot of research has been concentrated in this area during the last two decades. Recently many researchers have been

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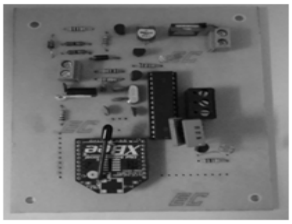
reported for soil moisture level control in an farm land by collecting soil as well as environmental information using various types of wireless sensor network techniques[16].Ruiyu Liang et al. (2008) have proposed a design and implement of a real-time soil moisture prediction system based on GPRS and wireless sensor network. The front-end of the system uses wireless sensor network (WSN) to collect soil moisture content, and again GPRS network to transmit all data; the back-end uses genetic BP neural network to analyze and process data, simulated annealing algorithm to optimize the result, and provides a real-time prediction. Experimental results show that this system has the advantages of low cost, better accuracy and convenient maintenance[2]. The method proposed by Ruiyu Liang et al. (2008) is a direct sensing of soil moisture content using WSN environment[2]. In the similar context, the other land related parameters and environmental parameters may affect the irrigation requirements. Timely prediction of soil moisture content will provide better irrigation management in a land by considering almost all the required parameters which affect the soil water evaporation. This prediction requires efficient algorithms which will produce future irrigation requirements in an agriculture land. In this paper, a comparative analysis of two different types of optimization algorithms for neural network pattern classification technique is performed[17]. The algorithms are tested for the prediction of soil moisture content in one hour advance by considering eleven different soil and environmental parameters. The performance of these two optimization techniques such as Scaled Conjugate Gradient and BFGS Quasi-Newton are compared using MSE (Mean Square Error), RMSE (Root Mean Square Error), and R-squared error.

In the similar context, A. Stefanos et al. (2015) have proposed an automated irrigation control technique using WSN environment[8]. The method is proposed by A. Stefanos et al. (2015) utilizes the threshold value of soil moisture content and the algorithm controls the irrigation of the land, but the weather conditions of the location are not included to exactly evaluate the requirement of land irrigation. In our proposed hybrid decision support system, the best optimization technique is used to predict hourly variation of soil moisture, and the predicted values are supplied to a fuzzy logic based weather model to generate adequate irrigation notification depending on weather status of the particular location. This article consists of five sections comprising of the introduction of the complete work, proposed methodology describes the theoretical and practical implementations, results and discussions of the complete weather dependent irrigation strategy, conclusion of the best results and acknowledgement.

2. Proposed Methodologies

Agriculture system models are complex nonlinear systems which can be solved using robust estimation methodologies like neural network algorithms. In this work, neural network pattern classification technique is proposed for the prediction of soil moisture content by considering soil and environmental parameters[16, 17]. A feedforward neural network is trained using different training functions which update weight and bias values. In this work, training algorithms such as Scaled Conjugate Gradient (SCG) and again Broyden Fletcher Goldfarb Shanno (BFGS) Quasi-Newton are studied for the timely prediction of soil moisture content to control the farm irrigation.

The agriculture data collection is performed using our developed WSN platform and gateway node. This proposed work is based on the design of low cost wireless sensor network (WSN) environment for the real-time monitoring and analysis of soil moisture content (MC) of the test site located in the eastern region of India. The test site of (50 m×100 m) is planted with Bermuda grass (Cynodon dactylon) which is used for a stomach ulcer, colitis, and stomach infections as ayurvedic medicine. The test site contains nine WSN nodes with nine individual irrigation valves. The WSN nodes are used to collect data from soil moisture sensors, soil temperature sensor, environmental temperature sensor, environmental humidity sensor, CO_2 sensor, and sunlight intensity sensor for multi-point measurement of land data in agricultural production. The collected data were stored in a gateway node consisting of Raspberry Pi, Zigbee series 2 and wifi connectivity. The real-time data are extracted over wifi network to the server computer for soil MC prediction. The fabricated single node of the WSN is shown in the figure 1. The complete architecture for agriculture data collection is shown in the figure 2. The two optimization techniques used for the neural network training are explained in the subsequent sections of this article.



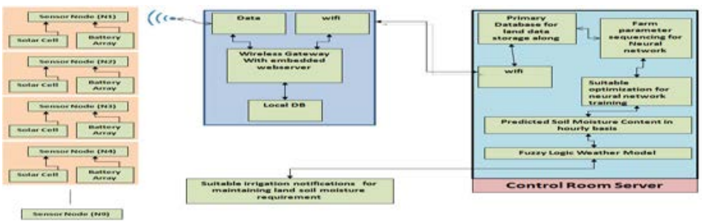


Fig. 1. Proposed Single node fabricated for acquiring farm data. Fig. 2. Proposed architecture of the complete real-time soil moisture content prediction methodology

2.1 Broyden-Fletcher-Goldfarb-Shanno(BFGS) Quasi-Newton

The BFGS method approximates Newton's method, which is a class of hill climbing optimization technique that seeks a stationary point of a function. For such problems, a necessary condition for optimality is that the gradient be zero. BFGS methods are not guaranteed to converge unless the function contains a quadratic taylor-expansion near an optimum point. These methods use both the first and second derivatives of the function. However, BFGS technique has proven to have a good performance even for non-smooth type optimizations.

The search direction P_k at every stage k is given by the solution of the Newton equation as shown below[4].

$$B_k P_k = -\Delta f(x_k)$$

Where B_k is an approximation to Hessian matrix method which is updated iteratively at each stage, and $\Delta f(x_k)$ is the gradient of the function evaluated at x_k. A line searches in the direction P_k is then used to find the next point x_{k+1}. Instead of involving full Hessian matrix at the each point x_{k+1} to be computed as B_{k+1}, the approximate Hessian at each stage k is updated by addition of two matrices[4].

$$B_{k+1} = B_k + U_k + V_k$$

Both the U_k and V_k are symmetric rank but they have different (matrix) bases. The symmetric rank one assumption here means that we may write

$$C = ab^T$$

So equivalently, U_k and V_k construct a rank-two update matrix which is robust against the scale problem often suffered in the gradient descent searching.

The quasi-Newton condition imposed on this update is

$$B_{k+1}(x_{k+1} - x_k) = \nabla f(x_{k+1}) - \nabla f(x_k)$$

2.2 Scaled Conjugate Gradient (SCG)

SCG is a supervised learning algorithm for feedforward neural networks and also is a member of the catagory of conjugate gradient methods [7]. SCG uses similar concepts of the general optimization strategy but chooses the search direction and step size more carefully by using information from the second order approximation represented by equation 1.

$$E(w + y) \approx E(w) + E'(w)^T + \frac{1}{2} y^T E''(w) y \qquad (1)$$

In SCG, each iteration 'k' computes optimal distance w_i. A line search is then performed to determine the optimal distance to move along the current search direction as equation 2.

$$w_{k+1} = w_k + a_k * p_k \qquad (2)$$

Then the next search direction is determined so that it is conjugate to previous search directions. Actually p_k is a function of a_k, the Hessian matrix of the error function and also the matrix of the second derivatives. SCG uses a scalar a_k which is supposed to regulate the indefiniteness of the Hessian matrix [7].

2.3 Fuzzification and defuzzification

Fuzzification is the mechanism of constructing a crisp fuzzy set. It is performed by recognizing that several of the quantities is thought to be crisp and settled which are actually not deterministic at all [9]. If the shape of uncertainty exists to arise as a result of impreciseness, ambiguity, or unclearness, then the variable may be fuzzy and portrayed by a membership operate. Defuzzification is that the conversion of a fuzzy amount to an explicit quantity, just as fuzzification is the conversion of an explicit amount to a fuzzy quantity. In this work, the fuzzy membership functions are considered as sunlight intensity, wind speed, environmental humidity, environmental temperature and predicted soil moisture content which was obtained using neural network pattern classification. The membership function selected for the fuzzy weather model is a triangular shape function. The fuzzy logic input and output membership functions are listed in the figure 12, figure 13, figure 14, figure 15, figure 16, and figure 17. The fuzzy inference system for weather based irrigation notification generation is shown in the figure 3.

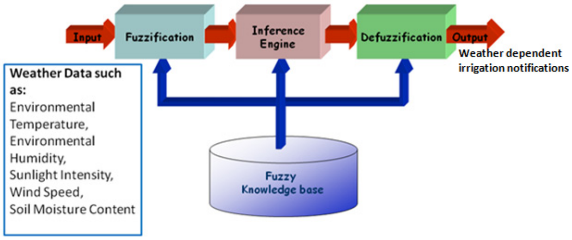


Fig. 3. Fuzzification and Defuzzification of the weather data along with predicted soil moisture content

3. Results and discussions

The overall performance of the optimization techniques for the prediction of soil moisture content is examined by considering eleven soil and environmental parameters. The input and output data are listed in table 1.

Table 1. The input and output data used for neural network prediction

Inputs				Output
Soil Moisture Content	Current Time	UV Index	Air Flow Rate	Soil Moisture Content after one hour duration
Soil Temperature	Environment Temperature	Sunlight Intensity	Air CO2	
Soil Type	Environment Humidity	Sunrise Time		

The predicted soil moisture content for one hour advance is compared with real moisture content at the particular time. MSE (Mean Square Error), RMSE (Root Mean Square Error), and R-squared error for the prediction are calculated and listed. Broyden-Fletcher-Goldfarb-Shanno (BFGS) Quasi-Newton based neural network pattern classification was used to predict soil moisture content from soil and environmental data. The soil moisture content prediction response and error graph is shown in figure 4.

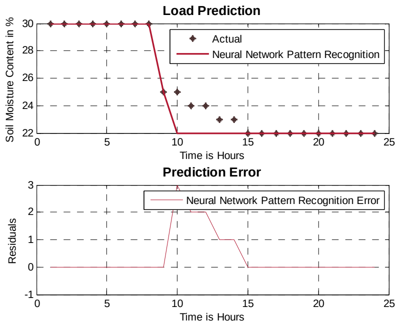


Fig. 4. Actual Soil Moisture Content and Predicted Soil Moisture Content Vs Time in Hours. Error Graph plotted Between Residuals and Time in Hours [BFGS Quasi-Newton based neural network pattern classification]

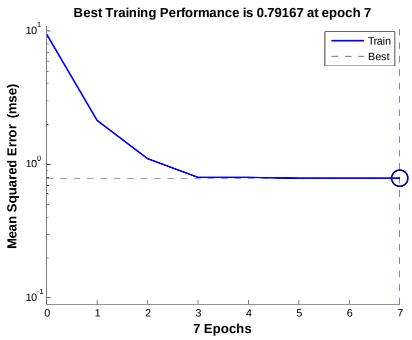


Fig. 5. BFGS Quasi-Newton based neural network pattern classification training performance.

The BFGS Quasi-Newton based neural network pattern classification training performance is shown in figure 5. The best training performance is obtained at 7 epochs. The confusion matrix of BFGS Quasi-Newton based neural network pattern classification is shown in figure 6. It is observed that twenty four datasets are correctly predicted with 100% performance. Also from the neural network training state as shown in figure 7, the best MSE is obtained at epoch 7 with gradient 1.1148e-7. The training error converses very quickly but according to prediction results from figure 4, few predicted soil moisture contents are not matching with the target value.

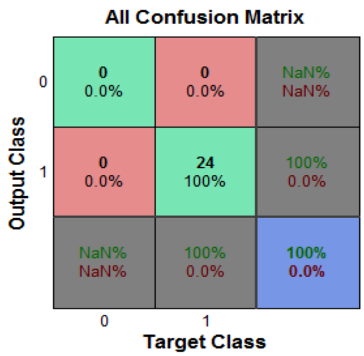


Fig. 6. The confusion matrix of the BFGS Quasi-newton neural network pattern classification training.

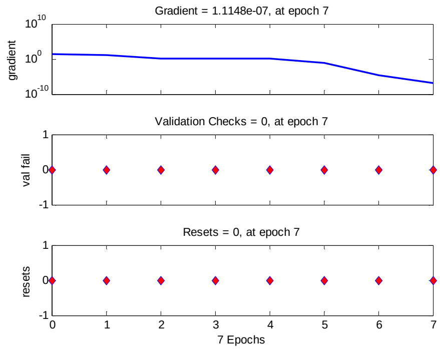


Fig. 7. The training state of the BFGS Quasi-newton neural network pattern classification training.

The soil moisture content prediction response and error graph of Scaled Conjugate Gradient based neural network pattern classification model is shown in figure 8. The Scaled Conjugate Gradient based neural network pattern classification training performance is shown in figure 9. The best training performance is obtained at 574 epochs. The MSE obtained is 6.2944e-08. The confusion matrix of Scaled Conjugate Gradient based neural network pattern classification is shown in figure 10. It is observed that twenty four datasets are correctly predicted with 100% performance. Similarly from the neural network training state as shown in figure 11, best MSE is obtained at 547 epochs with gradient 9.1153e-7. The performance of all the two optimization techniques for neural network pattern classification is also found out using MSE (Mean Square Error), RMSE (Root Mean Square Error), and R-squared error. All the above errors are listed in table 2.

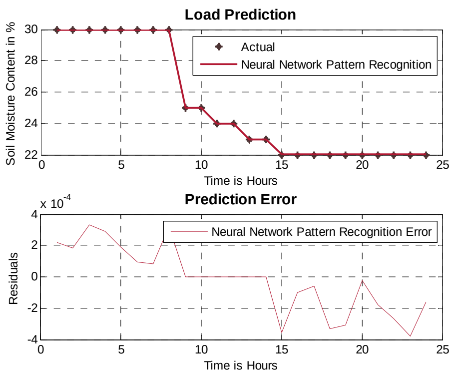


Fig. 8. Actual Soil Moisture Content and Predicted Soil Moisture Content Vs Time in Hours. Error Graph plotted Between Residuals and Time in Hours [Scaled Conjugate Gradient based neural network pattern classification]

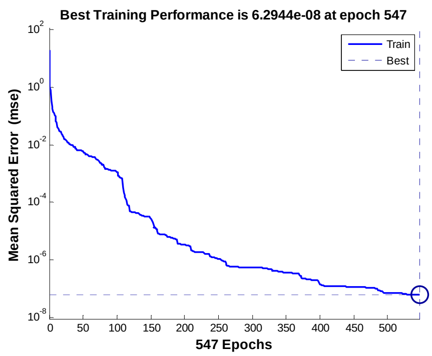


Fig. 9. Scaled Conjugate Gradient based neural network pattern classification training performance.

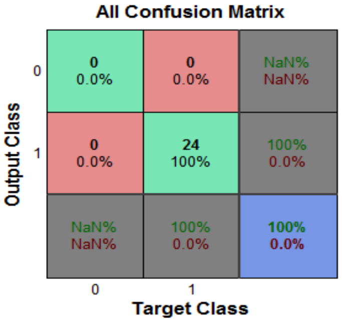


Fig. 10. The confusion matrix of the Scaled Conjugate Gradient neural network pattern classification training.

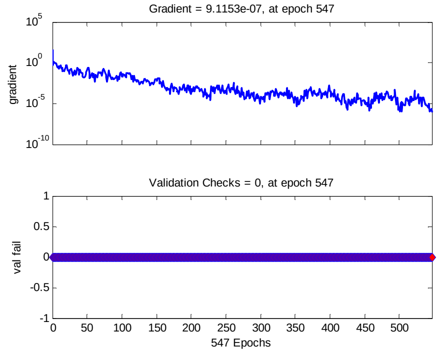


Fig. 11. The training state of the Scaled Conjugate Gradient neural network pattern classification training.

Table 2. The errors obtained during soil moisture content prediction

Sl. No.	Algorithm type	MSE	RMSE	R-squared
1	BFGS Quasi-Newton	0.79167	1.207614729	0.997741935
2	Scaled Conjugate Gradient	6.2944e-08	0.000194606	1

It is observed from the errors listed in table 2 that Scaled Conjugate Gradient based neural network pattern classification produces better result during soil moisture content prediction by considering the inputs as mentioned in table 1.

It is observed from the errors listed in table 2 that Scaled Conjugate Gradient based neural network pattern classification produces better result during soil moisture content prediction by considering the inputs as mentioned in table 1. After successful prediction of soil moisture content, the predicted soil MC is supplied to fuzzy logic weather model for generating appropriate irrigation suggestions. The fuzzy input and output membership functions are shown in the figures 12, 13, 14, 15, 16, 17. The proposed hybrid irrigation model is tested with different test inputs and it is observed that the neural network and fuzzy logic algorithms are performing very nice. Some of the test conditions are listed in the table 3.

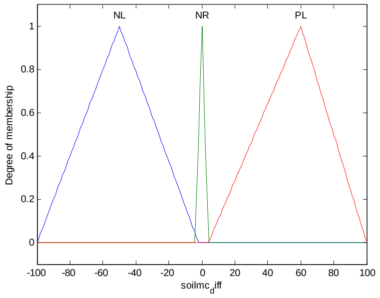


Fig. 12. Fuzzy logic membership function for soil moisture content difference [Fuzzy Logic Input]

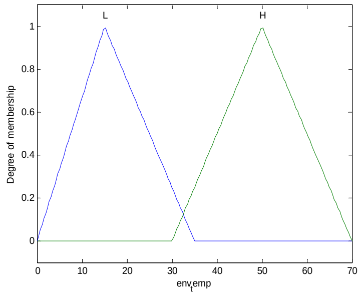


Fig. 13. Fuzzy logic membership function for environmental temperature [Fuzzy Logic Input]

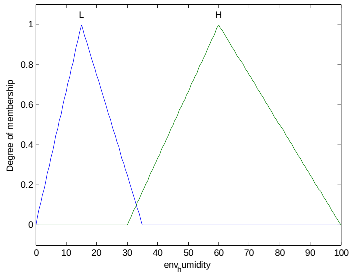


Fig. 14. Fuzzy logic membership function for environmental humidity [Fuzzy Logic Input]

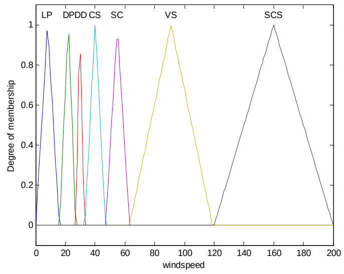


Fig. 15. Fuzzy logic membership function for wind speed [Fuzzy Logic Input]

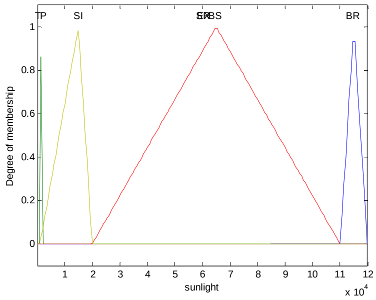


Fig. 16. Fuzzy logic membership function for sunlight intensity [Fuzzy Logic Input]

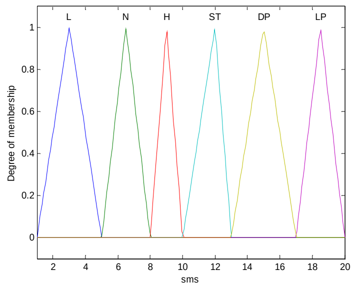


Fig. 17. Fuzzy logic membership function for weather dependent irrigation suggestions [Fuzzy Logic Output]

Table 3. Test input and output of the proposed irrigation model

Sl. No.	Input parameters [Soil MC difference (%), Environment temperature (centigrade), Environment humidity (RH), Wind speed (Knots), Sunlight intensity (Lux)]	Irrigation suggestions
1	[7.5872, 27, 40, 40, 1500]	Cyclonic Storm. Irrigation Valve Closed.
2	[5, 40, 30, 10, 110400]	Required water level is less, and irrigation is required.
3	[-2, 29, 38, 20, 1800]	The required water level is maintained, and irrigation is not required.
4	[-5, 29, 38, 20, 2300]	The required water level is high, and water extraction pump should be activated.

4. Conclusion

The soil moisture content in one hour advance is efficiently predicted by taking various soil and environmental parameters. The performance analysis of all the two proposed optimization techniques for neural network pattern classification is done by calculating MSE, RMSE, and R-squared error. From the errors obtained during prediction shows that the performance of Scaled Conjugate Gradient based neural network pattern classification gives better result in soil moisture content prediction. The MSE and RMSE obtained by Scaled Conjugate Gradient based neural network pattern classification are 6.2944e-08 and 0.000194606 where as BFGS Quasi-Newton produces much higher MSE and RMSE. Hence, it is found that Scaled Conjugate Gradient based neural network pattern classification technique for the prediction of soil MC will produce better prediction result. The predicted soil moisture content is successfully used in the fuzzy logic weather model for generating adequate irrigation suggestions. Hence, it concluded that the proposed weather condition dependent hybrid irrigation model will help to predict soil MC and to generate necessary irrigation recommendations using real-time sensor data from the agriculture locations. This will contribute to predicting soil MC using real-time sensor data from the agriculture locations.

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