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Study on Ammonia Concentration Prediction Model of Pigsty Based on LTSM Neural Network

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Abstract **Review Article**

In the large-scale farming, the environment of Pigsty has a direct impact on the health of pig and production capacity. Pigsty major environmental factors such as wind speed, temperature, humidity and ammonia concentration data were collected for one hundred and sixty-seven consecutive days, the acquisition interval was set to 60 seconds. Since the predicted ammonia concentration is 1 hour later, 3975 groups of hourly environmental data were obtained from the original data through calculation. Then, The LTSM neural network model was built to predict the Ammonia concentration. According to the time sequence, the data collected in the first 120 days were taken as training samples, and the rest of the data collected were test samples. It is shown in simulation experiment that network reaches the target error after 40 steps with each batch size of 72, the model has the characteristics of fast network convergence and high efficiency by using adam optimizer, the root mean square error between the actual environmental quality of 2880 groups of test data and the network prediction value is only 1.6%, the accuracy and timeliness of the ammonia concentration prediction of Pigsty is greatly improved. The ammonia concentration prediction model established in the paper can provide support for the Pigsty environment early warning and control.

Keywords: LTSM neural network, prediction model, Ammonia concentration.

INTRODUCTION

Ammonia is a colorless, pungent and harmful gas, which is easy to liquefy into colorless liquid and can burn skin, eyes and respiratory mucosa. When the concentration of ammonia in the pig house is too high, it can cause the lung swelling and death of pigs. In large-scale breeding, the concentration of ammonia has a great impact on the healthy growth of pigs [1, 2]. Therefore, timely prediction and control of ammonia concentration in pig houses plays an important role in pig growth and health.

In recent years, neural network has been widely used in the simulation and prediction of pigsty environment. Ascione built a thermal dynamic state model in the instantaneous state of the barn based on artificial neural network, and quantified the energy benefits brought by dynamic insulation by evaluating the heat transfer of porous media [3]. Lü used neural network to calibrate and calibrate the numerical model, so as to simulate and predict the state and change trend of the temperature field in the cell under different structures [4]. In terms of the prediction of the environment in the pig house, the change trend of NH3 concentration in the pig house is predicted based on BP, Elman, ANFIS and other neural networks [5]. Chen C and Liu X Q constructe the NH3 prediction model of pigsty based on the Internet of things and grey neural network, and proposed a method that combines improved analytic hierarchy process (IAHP) and fuzzy comprehensive evaluation (FCE) was introduced to conduct a quantitative evaluation of the comfortable degree [6]. Yang Liang decomposes the empirical mode of NH3 concentration data under the time series based on the long-term and short-term memory neural network to obtain the inherent mode component, and establishes the prediction model of NH3 concentration in pigsty based on emd-lstm. The prediction accuracy is greatly improved compared with Elman neural network [7]. Neural network is more effective in the simulation and prediction of a single variable in the pigsty environment, but it is less applied in the study of the dynamic change relationship of multiple environmental factors in the pigsty, so it has further research space.

In this paper, the main environmental factors that affect the health of pigs in large-scale pig houses are collected, and the environmental quality prediction model is established based on the collected data and ltsm neural network. Adam optimizer is used in model training, which greatly improves the convergence rate of the network. The model prediction error has little correlation with the actual error, which can well realize the ammonia prediction in the pig house environment and provide model support for the pig house environmental control and early warning.

1 Long Short Term Memory

1.1 Structure of recurrent neural network

Recurrent neural network (RNN) is a fully connected neural network with self cyclic feedback, which is generally used for tasks related to time series. In recent years, RNN has been widely used in natural language processing, stock prediction, machine fault detection [8-10] and other fields. As shown in Figure 1, compared with the traditional neural network, RNN is a cycle module composed of simple neuron structure. It has the characteristic of memory ability, that is, its neurons have memory ability. When processing data, the input of RNN model includes not only sequence data, but also the memory state of the previous time. Such as entering sequence data $e=\{e_1,e_2,\ldots,e_{(n-1)},e_n\}$. Input to RNN model to get output data $d=\{d_1,d_2,\ldots,d_{(n-1)},d_n\}$. The output data d_n is not only the mapping of e_n, but also related to the preorder sequence $e_1,e_2,\ldots,e_{(n-1)}$.

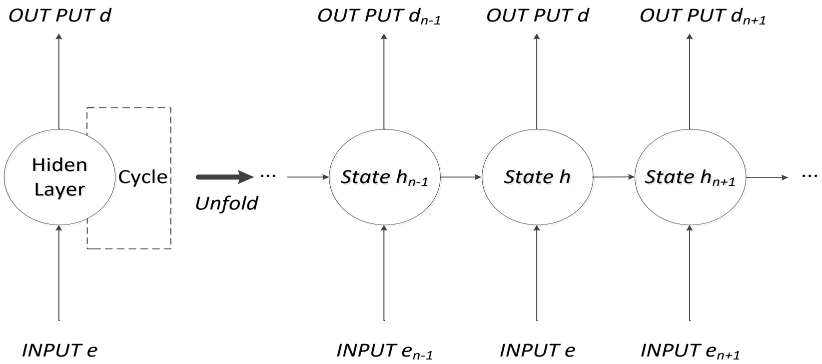

Fig 1: Basic structure diagram of RNN

1.2 Structure of Long Short Term Memory

Long short term memory (LSTM) neural network was proposed by Hochreiter in 1997 [11]. It solves the problem that RNN's learning ability decreases with the increase of time series span, which leads to the failure of model training and the disappearance of gradient. As the development of RNN, LSTM neural network and RNN have the same structure of fully connected neural network with self circulation feedback. However, different from the simple neuron structure of RNN, LSTM neural network adds three-gates structure to the neurons in the hidden layer, including forgetting gate, input gate and output gate. The three-gates structure can make the states in neurons add or lose information, so as to meet the purpose of long-term memory while flowing with the sequence, and realize the update control of information on neurons.

The internal unit structure of LSTM is shown in Figure 2.

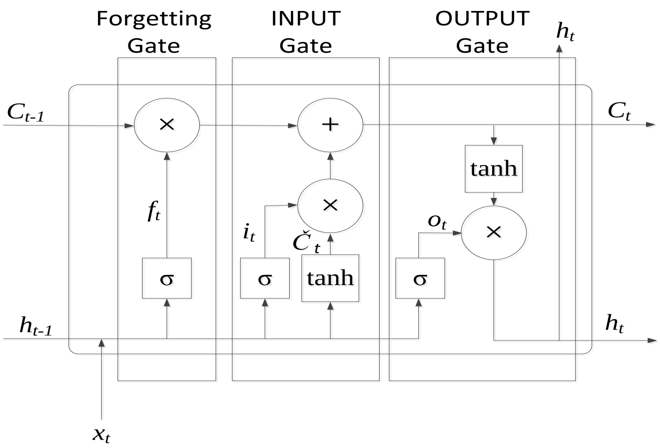

Fig 2: The internal unit structure of the LSTM

In the LSTM neural network, the forgetting gate determines the discarding of historical information according to the activation function σ, as shown in formula (1). Input gate filters information to determine the input of information, as shown in the formula (2) – (4). The output gate determines the final output and retained information, as shown in the formula (5) and (6) [12].

In the formula (1) – (6), f_t, i_t and o_td enote forgetting gate, input gate and output gate respectively. h_t is the output of LSTM unit time t, and it is also the short-term memory state transferred from time t to the next time. σ and tanh are activation functions of sigmoid function and hyperbolic tangent, respectively.

$$f_t = \sigma(W_{xf}x_t + W_{hf}h_{t-1} + b_f \quad (1)$$

$$i_t = \sigma(W_{xi}x_t + W_{hi}h_{t-1} + b_i) \quad (2)$$

$$\tilde{C}_t = \tanh(W_{xc}x_t + W_{fc}h_{t-1} + b_c) \quad (3)$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \quad (4)$$

$$o_t = \sigma(W_{xo}x_t + W_{ho}h_{t-1} + b_o) \quad (5)$$

$$h_t = o_t \cdot \tanh(C_t) \quad (6)$$

2 Prediction model of ammonia in Pigsty environment based on LSTM neural network

2.1 Data Sampling

The environmental monitoring data in this paper are taken from the pigsty of a large-scale pig farm in Harbin, Heilongjiang Province. The environment in the pigsty was monitored continuously from February 22, 2020 to July 13, 2020. The environmental data in the pig house is collected every 10min. Because multiple collection nodes are arranged in the house, the data of these nodes need to be processed. In this paper, the sensor data of the same kind at the same time are processed by using the method of calculating the weighted average value as the environmental data value in the pig house at this time. The environmental data of temperature, humidity, wind speed and ammonia concentration are averaged every 60min to form hourly data, and a total of 3975 groups of environmental data are obtained.

2.2 Establishment of environmental prediction model for pigsty

2.2.1 Design of model structure

The LSTM model is used to train and predict the experimental data. The ammonia concentration in the pig house in the next 1H is predicted by LSTM model. The setting of LSTM neural network model includes input dimension, output dimension, time steps, number of neurons, activation function and batch size. Among them, the number of neurons and activation function affect the convergence speed of the model, and the number of time steps and batch size affect the training efficiency of the model. In order to improve the prediction ability of the model and ensure that more information can be obtained in the hidden layer, the number of neurons, dimensions and parameters of the model are set according to table 1. The number of neurons in the first hidden layer is set to 30, and the dimension of input data is 1-time step and 2 features, which are three dimensions, respectively, 1 hour and temperature, humidity. Tanh activation function is used for input and state transformation, and one neuron in the output layer is used to predict the concentration of ammonia 1. The cost function selects the cross loss function, with 40 training cycles with a batch size of 72.

Table 1: LSTM model structure

Model component	Number of neurons	Dimension	Number of parameters
LSTM	30	3	4320
Dense	1	1	31

2.2.2 Establishment of prediction model

Because the temperature and humidity of the pigsty change greatly in four seasons, in order to reflect the recent environmental change law of the pigsty, the time span of selecting training data and test data should not be too long. In this paper, the temperature, humidity and ammonia concentration data of 167 days were collected from a pig house in a pig farm. The data were collected every 10 minutes, processed every hour and recorded, as shown in Figure 4, a total of 3975 groups of data.

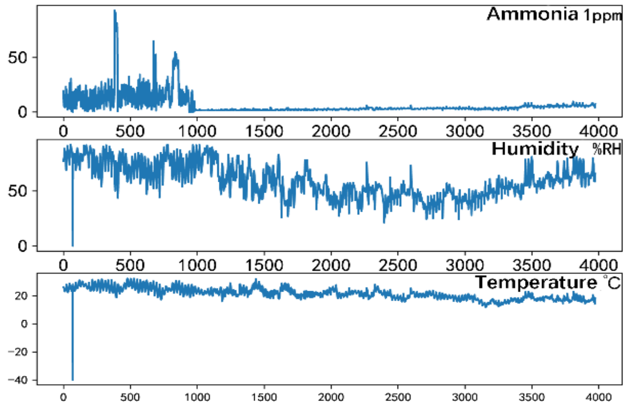

Fig 4: Environmental data in a pigsty

The data set obtained after collection and processing is a data set about time series. First, convert the time into labels and standardize the input variables. In the time series data set, the ammonia concentration in the pigsty at time t is closely related to the temperature and humidity in the pigsty at time T-1. Therefore, according to the time sequence, the data collected in the first 120 days are used as training samples, and the rest of the data collected are test samples.

2.3 Simulation results and analysis

The loss function curve of the LSTM neural network based on MAE is shown in Figure 5. The LSTM model converges quickly, indicating that the generalization ability of the LSTM model is strong and the design performance is fully achieved. After 40 training cycles, the root mean square error between the actual environmental quality of 2880 groups of test data and the network prediction value is 1.6% through Adam optimizer.

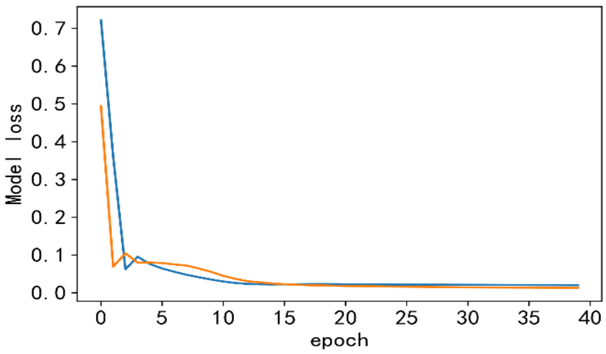

Fig 5: Model loss function of LSTM

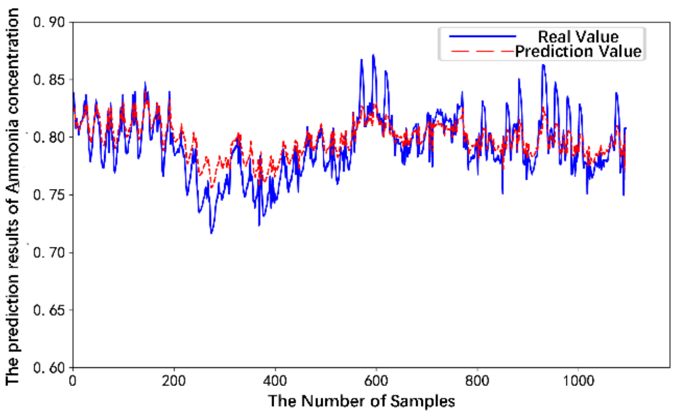

Fig 6: Comparison of LSTM model prediction results

In order to effectively evaluate the prediction results, all feature sets and labels have been standardized before the training model, that is, the data values have been scaled to between 0-1, so our prediction results are also between 0-1. The standardized processing of prediction results can more intuitively analyze data and realize the monitoring of pig house concentration. It can be seen from Figure 5 and Figure 6 that the prediction performance of LSTM neural network is good, and the relative error between the predicted value and the actual value is very small, which can meet the needs of pig house environment prediction.

3. CONCLUSION

By setting up sensor nodes in the pigsty, this paper collected the data of wind speed, temperature, humidity and ammonia concentration, the main factors affecting the pigsty environment, for 167 consecutive days, and then obtained the hourly data values of wind speed, temperature, humidity and ammonia concentration in the pigsty through calculation, and obtained 3975 groups of data. Taking the data of the first 120 days as the training samples of the prediction model, and the rest as the test samples, the LSTM neural network model of the pigsty environment is established. The model takes time as a sequence, and the number of neurons in the input layer is 30. In order to better predict the ammonia concentration in the pig house and realize the detection of the ammonia concentration in the pig house, the time step is set to 1H, and the tanh function is used for the input gate and output gate activation functions of the model. The model established in this paper uses a large number of actual environmental data as input samples and test samples. The simulation results show that the established network has fast convergence speed and small error, which greatly improves the accuracy and timeliness of pig house environmental prediction, and can provide a data model for pig house environmental early warning and control.

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