Journal of Engineering Science and Technology Review 17 (6) (2024) 84-91

Research Article

JOURNAL OF
**Engineering Science and Technology Review**

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# Observation Method for the Operation Parameters of Greenhouse Electric Tractor Rotary Tillage Based on GABP-STUKF

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Received 3 September 2024; Accepted 11 December 2024

***Abstract***

Traditional greenhouse electric tractors are not equipped with high-precision sensors, which make it difficult to conduct rotary tillage parameter measurements. Therefore, problems due to imperfect rotary tillage parameter measurements are encountered, such as inconvenient measurement, low data resolution, poor sensing accuracy of operation parameters, and large noise. To improve the accuracy of data collected by electric tractor rotary tillage operations, this study presented a strong tracking untracked Kalman filter (STUKF) parameter observation method based on a genetic algorithm (GA) optimization neural network. First, a back propagation neural network was used to predict the state of the greenhouse tractor, and GA was used to avoid the local minimum in the prediction process. Second, untrace transform and strong tracking filter were applied to solve the strong nonlinearity and imprecision problems of the network model. Third, a method of operation parameter observation based on genetic algorithm back propagation (GABP)-STUKF was proposed. Finally, the actual vehicle test was carried out on the washboard pavement of the Jiangsu Agricultural Machinery Test and Identification Base. Results show that, the mean absolute error (MAE) and root mean square error (RMSE) of longitudinal vehicle speed observation were 0.017 and 0.025 m/s, respectively. The MAE and RMSE of cutter roll speed prediction were 8.941 and 18.413 rpm, respectively. The MAE and RMSE predicted by ploughing depth were 0.029 and 0.038 m, respectively. With the acquisition methods of motor driver and rope sensor taken as the control group, the MAE observed by GABP-STUKF for the above three operating parameters increased by 10%, 46.8%, and 7.54%, respectively. This study provides a new idea for the parameter observation of greenhouse electric tractors..

*Keywords:* Greenhouse, Electric Tractor, Parameter Observation, GABP, STUKF

## 1. Introduction

In recent years, the integral role of agriculture in helping accelerate ecological priority green development in order to achieve the "double carbon" goal has received extensive consideration and attention [1-2]. At present, most small agricultural machinery operating in China's greenhouses use internal combustion engines as their power source. However, these machines face problems such as low levels of automation and intelligence, high labor intensity, and low operational efficiency. Moreover, the emission of polluting gases during their operation seriously affects environmental control within the greenhouse. Greenhouse electric tractors have developed rapidly due to the use of motors as power systems. Currently, some small electric tractors have been applied to agricultural production. As a type of small agricultural machinery, greenhouse electric tractors are characterized by their compact structure, low pollution, and ease of operation [3-5].

However, studies on electric tractors mostly focus on medium and large electric tractors in China and foreign countries [6-7]. Owing to space restrictions and entrance sizes, greenhouses have extremely strict requirements on the size of tractors and can usually accommodate only small tractors. From an operational perspective, greenhouse farming mostly involves shallow and micro-tillage cultivation. The power requirements for greenhouse tillage are lower compared with those for field operations, making electric equipment more suitable. For example, in greenhouse rotary tillage operations, the accurate acquisition of various parameters is essential for controlling tillage depth and ensuring operation quality. However, due to cost, installation challenges, operating environments, and actual working conditions, high-precision sensors are not suitable for small greenhouse agricultural machinery used in greenhouses. Thus, some advanced methods or algorithms for information observation have become important options.

Scholars have used various methods, such as Kalman filter, neural network, and regression analysis, to predict and observe the rotary tillage operation parameters of electric tractors in greenhouses [8-10]. However, they have failed to find an effective method to improve the accuracy of data collection of rotating tillage operation of electric tractors in a greenhouse environment. Therefore, determining how to carry out an accurate collection of the main data (speed, depth, speed) of greenhouse electric tractors under the rotating farming operation mode and find a better data fusion observation method is an urgent problem to be solved.

Therefore, this study established an improved neural network method based on a genetic algorithm (GA) to predict the motion state of a small electric tractor in the laboratory. Traceless transformation and strong tracking (ST) filter were used to solve the strong nonlinearity and inaccuracy problems of the network model. An observation

*E-mail address: ldm123ldm@126.com
ISSN: 1791-2377 
doi:10.25103/jestr.176.11

method of operation parameters based on genetic algorithm back propagation-strong tracking untracked Kalman filter (GABP-STUKF) was proposed and verified in a specific site, which provided a novel idea for conducting parameter observation of greenhouse electric tractors.

## 2. State of the art

Scholars have conducted extensive research on the parameter observation and fusion correlation of electric tractors. To accurately measure the working area of uneven plots and the tillage depth of rotary tillage, Chen et al. [11] built a rotary tillage quality monitoring system by integrating and processing the data of the Beidou navigation satellite system and various sensors through LabVIEW. Through field tests, they verified that this method can effectively adapt to irregular plots and accurately monitor the tillage depth. However, the system's use of navigation and other sensors made it incompatible with the operational needs of small agricultural machinery in greenhouses. Wei et al. [12] proposed a state parameter estimation method based on volume Kalman filter to solve the complexity and low accuracy problems of state parameter estimation of large tractors for estimating major parameters such as longitudinal speed and lateral speed. However, the method mainly fused and estimated major parameters, such as the development speed of large tractors. As small electric tractors in the greenhouse environment were not considered, the specific experimental results need to be further verified. Pascuzzi et al. [13] installed multiple force sensors on a blade embedded on the suspension system to obtain ploughing depth data while measuring tillage resistance, thus achieving real-time adjustments of ploughing depth. However, since multiple force sensors are in contact with the soil, the soil environment has a certain impact on the blade, resulting in poor data fusion accuracy of the sensors. Askari et al. [14] evaluated the ability of response surface method to predict the traction performance of agricultural tractors in semi-deep tillage operations and comprehensively considered the influence of different operational parameters on tractor traction performance. However, experimental study was lacking on the deeper level of tillage depth and the deep fusion between different parameter data. Aiming at the navigation problem of agricultural tractors, Soitinaho [15] studied the local navigation and obstacle avoidance of agricultural tractors under the rotating tillage operation mode and adopted the method based on nonlinear model predictive control to carry out the work. They derived the control algorithm based on parameter fusion, but it did not consider rotating tillage operation in the greenhouse environment. Zhao et al. [16] proposed a pitch angle prediction model for paddy field graders to identify parameters online, established an ARMA time series model, and estimated and updated the model parameters online base on recursive least square method. The shortcoming of the proposed prediction model is that its effectiveness and the feasibility of pitch angle model parameters require further testing. To improve the performance of the orchard parallel hybrid tractor, Mocera [17] proposed a data fusion algorithm of hardware in the loop technology based on a model. The results showed that the algorithm has good stability in terms of load split and speed control between two power sources. However, the tillage depth adjustment based on this fusion algorithm is not efficient in the rotating tillage scenario. Dou et al. [18] built a radial basis neural network model based on the rotary tillage operation of a large hybrid tractor. They took vehicle speed, acceleration, inequality rate of rotary tillage resistance, and rotary tillage resistance coefficient as inputs and rotary tillage power demand as output to predict the power, but the overall prediction effect was poor. In view of the shortage of tractor field test data and the difficulty of real-time evaluation and accurate prediction of operation quality, Wen et al. [19] combined BP neural network and GA based on agricultural big data to predict and evaluate tractor field rotary farming operations. However, both the relevant data collected and the accuracy of fusion algorithm were insufficient. Hamouda [20] took the sensors applicable to electric tractors as the research object and constructed a network adaptive fusion algorithm based on GA and extended Kalman filter (EKF). The nodes were optimized by this method, but the rotating tillage working conditions of electric tractors were not considered. Vogt [21] improved ploughing efficiency by fusing and estimating battery parameters in various operating configurations of electric tractor energy transmission. However, the plan did not consider the balanced control of electricity and the effect of parameter fusion under rotary ploughing. Ping et al. [22] introduced an ST algorithm into an untracked Kalman filter to estimate the road adhesion coefficient and solve the filtering divergence problem caused by the error of the equation of state and noise statistics. Although this study could provide a theoretical basis for the driving state of vehicles, it did not address the difficulty of obtaining the state equations of some systems. At the same time, the operating conditions of rotary tillage in greenhouses were not considered. Lagnelv [23] applied adaptive methods and models to evaluate the life cycle of tractors, demonstrating the effectiveness of these methods by taking rotary farming as an example. The results showed that the evaluation was successful; however, it did not address rotary farming in a greenhouse environment, and the algorithm's adaptability to greenhouse conditions requires further verification. Zhou et al. [24] proposed an extended synovial observation method based on Hurwitz for electric tractors and carried out data fusion and predictive analysis, achieving good results. However, the shortcomings of the fusion algorithm are that it is not very satisfactory for controlling the stability of rotary tillage. In view of the low prediction accuracy of field traction performance of four-wheel drive tractors, Zhao et al. [25] established a prediction model of rolling and sliding efficiencies of the whole machine and designed a prediction algorithm and process based on the 2-D iterative method. However, the estimation of rotational speed in the algorithm was not accurate enough, and the adaptability of the algorithm in greenhouse tractors was not explained.

The above studies focused on parameter observation and data fusion of medium and large tractors or electric tractors, yet studies on the parameter observation, prediction, and fusion of rotary tillage operations of small electric tractors in greenhouses are few. Different from the traditional crawler electric tractor platform, this study took rotary farming operation as an example and introduced GA to predict the relevant parameters of the neural network. The optimization network model of traceless transformation and ST filter was used to construct the parameter observation method based on GABP-STUKF. Finally, the experimental method was compared with the original data acquisition and measurement method, and the accuracy of the observation method was further verified. The study results provide a basis for parameter observation and optimization of greenhouse electric tractors.

The remainder of this study is structured as follows. In Section 3, GABP neural network parameters are predicted, and ST untracked Kalman operation parameter joint observation is carried out on the basis of GABP. Moreover, the experimental scheme is designed based on GABP-STUKF. In Section 4, experiments and data analysis are carried out to verify the practical effect of the proposed method. Finally, Section 5 summarizes this study and draws relevant conclusions.

## 3. Methodology

### 3.1 Neural network parameter prediction based on GABP

#### 3.1.1 Parameter prediction based on BP neural network

The core idea of the BP neural network is to find the optimal value of the system by calculating the error gradient and following the direction of decline. First, the input of the training set sample is normalized and sent to the input layer. The weight and threshold between the input node and the node of the hidden layer are calculated, and the processed data are passed into the hidden layer. Similarly, the information of the hidden layer is transmitted to the output layer, and the corresponding predicted value is output after processing by the output layer. After each output, the error between the output value and the output of the training sample is calculated and fed back from the output layer to the input layer, layer by layer. Simultaneously, the weight and threshold between the layers are adjusted. Second, several iterations are performed to reduce the error between the network output and the sample output until the set iterations or accuracy requirements are met. Finally, the weights and thresholds after the end of the iteration are used as network parameters, and the corresponding outputs can be obtained for the input information of unknown samples. The structure of the BP neural network model is shown in Fig. 1. The current of the traveling motor, current of the PTO motor, pitch angle, and output of the previous moment are selected as the input of the system, and the outputs are the cutter roll speed and ploughing depth.

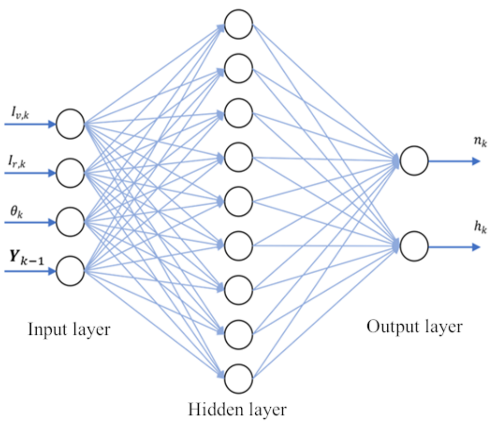


**Fig.1.** BP neural network structure

In Fig. 1, $\boldsymbol{Y}_{k-1}$ is the network model output at k-1; $I_{v,k}$ is the current of the traveling motor, A; $I_{r,k}$ is the PTO motor current, A; $\theta_k$ is the tractor pitch angle, rad; $h_k$ is the working depth at the time k, m; and $n_k$ is the cutter roll speed at k, r/min.

#### 3.1.2 GA-based network parameter optimization

The BP neural network is a type of error gradient descent method. When solving some complex problems, oscillation occurs during the search for the best solution, which slows down the convergence rate of the model. At the same time, when the network finds the optimal solution with gradient 0 in the learning process, the network model stops searching, and the iterative process ends. Therefore, when no constraints are added to the model, the BP neural network may fall into the local optimal solution, resulting in the failure of model training. In the face of complex multidimensional nonlinear problems, the error between the BP neural network output and the sample output is often a complex multidimensional space. Therefore, local minima usually appear in this complex error space. Once the traditional BP neural network model falls into the local minimum point, it can stop autonomous learning and fail to search for the global optimal solution.

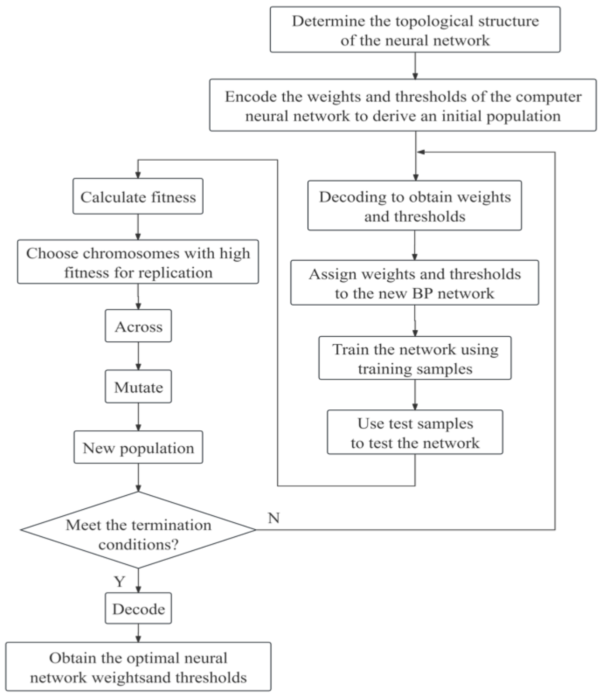


**Fig. 2.** BP neural network structure optimized by genetic algorithm

In view of the above problems of the traditional BP neural network, other algorithms can be introduced to optimize the network weight and threshold and thus solve the problem of local minimum. The GA, with its global random search capability, is an effective tool for solving optimization problems. As an evolutionary algorithm, GA excels in exploring the solution space and finding global optima. The core idea of GA is to learn from the biological evolution theory of "survival of the fittest," find the global optimal solution from the probability perspective, and use the fitness function as the evaluation index of optimization results. It can then learn from the genetic evolution process of natural selection, hybridization, and mutation of biological genes in nature to further improve individual adaptability through multiple iterations. The search direction is automatically obtained and adjusted until the global optimal solution is obtained.

After optimization by GA, the optimized weights and thresholds are taken as the initial weights and thresholds of the BP neural network. The optimization process is shown in Fig. 2.

**3.2 Joint observation of operation parameters based on strong tracking untracked Kalman**

**3.2.1 Untraced Kalman filter**

Untraced Kalman filter (UKF) does not need to linearize nonlinear functions, so EKF does not need to calculate the Jacobian matrix of the state and measurement equations. UKF approximates the probability density function of the nonlinear function and uses a series of sampling points to approximate the posterior probability density of the state and measurement equations.

The state equation of longitudinal velocity is as follows:

$$v_{x,k} = v_{x,k-1} + \dot{v}_{x,k} \cdot T + q_{v,k} \tag{1}$$

Where T is the sampling duration, s; $q_{v,k}$ is the longitudinal vehicle state noise at time k, m/s; $v_{x,k}$ is the longitudinal speed at time k, m/s; and $\dot{v}_{x,k}$ is the longitudinal acceleration at time k, $m/\mathrm{s}^2$.

With acceleration, PTO motor current, traveling motor current, and pitch angle as the control vector untraced Kalman of the system, and longitudinal vehicle speed, cutter roll speed, and tillage depth as the observation targets, the equation of the state of the observation system can be obtained combined with the aforementioned GA-BP neural network model.

$$\mathbf{X}_k = f(\mathbf{X}_{k-1}, \boldsymbol{u}_k) + \boldsymbol{q}_k \tag{2}$$

Where

$$\mathbf{X}_k = \begin{bmatrix} v_{x,k} \\ n_k \\ h_k \end{bmatrix} \quad \boldsymbol{u}_k = \begin{bmatrix} \dot{v}_{x,k} \\ I_{v,k} \\ I_{r,k} \\ \theta_k \end{bmatrix} \quad \boldsymbol{q}_k = \begin{bmatrix} q_{v,k} \\ q_{n,k} \\ q_{h,k} \end{bmatrix} \tag{3}$$

Where $v_{x,k}$ is the longitudinal speed at time k, m/s; $n_k$ is the cutter roll speed at time k, r/min; $h_k$ is the operation depth at time k, m; $\dot{v}_{x,k}$ is the longitudinal acceleration at time k, $\mathrm{m/s}^2$; $I_{v,k}$ is the traveling motor current at time k, A; $I_{r,k}$ is the PTO motor current at time k, A; $\theta_k$ is the tractor pitch angle at time k, rad; $q_{v,k}$ is the longitudinal vehicle state noise at time k, m/s; $q_{n,k}$ is the cutter roll speed state noise at time k, r/min; and $q_{h,k}$ is the depth state noise at time k, m.

According to the previous laboratory results [26], the measurement equation of the observation system can be obtained by using the original measurement method on the platform and the abovementioned conversion formula of ploughing depth.

$$\boldsymbol{z}_k = h(\mathbf{X}_k) + \boldsymbol{r}_k \tag{4}$$

Where

$$\boldsymbol{z}_k = \begin{bmatrix} n_{v,k} \\ n_{m,k} \\ l_{h,k} \end{bmatrix} \qquad \boldsymbol{r}_k = \begin{bmatrix} r_{v,k} \\ r_{m,k} \\ r_{h,k} \end{bmatrix} \tag{5}$$

Where $n_{v,k}$ is the traveling motor speed measurement value at time k, r/min; $n_{m,k}$ is the PTO motor speed measurement at time k, r/min; $l_{h,k}$ is the total length of hydraulic cylinder measurement at time k, m; $r_{v,k}$ is the travel motor speed measurement noise at time k, r/min; $r_{m,k}$ is the PTO motor speed measurement noise at time k, r/min; and $r_{h,k}$ is the total length of hydraulic cylinder measurement noise at time k, m.

According to the obtained state equation (2) and measurement equation (4), the implementation steps of UKF are as follows:

(1) Initialize the system status.

$$\hat{\mathbf{X}}_0 = E(\mathbf{X}_0) \tag{6}$$

$$\boldsymbol{P}_0 = E\left[(\mathbf{X}_0 - \hat{\boldsymbol{\chi}})(\mathbf{X}_0 - \hat{\boldsymbol{\chi}})^T\right] \tag{7}$$

$$\begin{cases} \xi_1 = \lambda / (\eta + \lambda) \\ \xi_i = 1/2(\eta + \lambda) \end{cases}, i = 2, \ldots, 2\eta + 1 \tag{8}$$

Where η is the number of parameters to be estimated, 3; λ is the regulator, 2; $\boldsymbol{P}_0$ is the initial covariance matrix; and $\xi_1, \xi_i$ are Sigma point weights.

(2) Solve the prediction step.

The estimate of the state equation at time k-1 is split into several sampling points, so that the mean and variance near a certain point (called Sigma point) generally meet the Gaussian distribution. The split estimate at k-1 is as follows:

$$\begin{cases} \varsigma_{1,k-1} = \mathbf{X}_{k\text{-}1} \\ \varsigma_{i,k-1} = \mathbf{X}_{k\text{-}1} + \sqrt{\eta + \lambda}(\sqrt{\boldsymbol{P}_{k\text{-}1}})_{\eta \times i} (i = 2, \ldots, \eta + 1) \\ \varsigma_{i,k-1} = \mathbf{X}_{k\text{-}1} - \sqrt{\eta + \lambda}(\sqrt{\boldsymbol{P}_{k\text{-}1}})_{\eta \times i} (i = \eta + 2, \ldots, 2\eta + 1) \end{cases} \tag{9}$$

Where $\boldsymbol{P}_{k\text{-}1}$ is the covariance matrix at time k-1; and $\varsigma_{1,k-1}$ and $\varsigma_{i,k-1}$ are estimates corresponding to the Sigma points of the prediction step at time k-1. By substituting the predicted value of each sampling point after resolution into the equation of state, the prior estimate of each sampling point can be obtained as follows:

$$\overline{\sum}_{i,k} = \varsigma_{i,k-1} \tag{10}$$

Where $\overline{\sum}_{i,k}$ is the prior estimate corresponding to the Sigma point of the prediction step at time k.

According to the Sigma point weight defined by Equation (9), the prior estimate and covariance of the final prediction step is as follows:

$$\hat{\mathbf{X}}_k^- = \sum_{i=1}^{2\eta+1} \xi_i \sum_{i,k}^{-} \tag{11}$$

$$\boldsymbol{P}_k^- = \sum_{i=1}^{2\eta+1} \xi_i (\hat{\mathbf{X}}_k^- - \sum_{i,k}^{-})(\hat{\mathbf{X}}_k^- - \sum_{i,k}^{-})^T + \boldsymbol{Q}_{k-1} \tag{12}$$

(3) Update step.

Similarly, the prior estimate of the measurement equation at time k is split into several sampling points, and the split prior estimate is as follows:

$$\begin{cases} \boldsymbol{\sigma}_{1,k} = \hat{\mathbf{X}}_k^- \\ \boldsymbol{\sigma}_{i,k} = \hat{\mathbf{X}}_k^- + \sqrt{\eta+\lambda}(\sqrt{\boldsymbol{P}_k^-})_{\eta\times i}(i = 2,\dots,\eta+1) \\ \varsigma_{i,k-1} = \hat{\mathbf{X}}_k^- - \sqrt{\eta+\lambda}(\sqrt{\boldsymbol{P}_k^-})_{\eta\times i}(i = \eta+2,\dots,2\eta+1) \end{cases} \tag{13}$$

Wher $\boldsymbol{\sigma}_{1,k}$ and $\boldsymbol{\sigma}_{i,k}$ are the prior estimates corresponding to each sampling point in the update step.

(4) Filter output.

The prior estimate and covariance of the final update step are as follows:

$$\vartheta_{i,k}^- = h(\boldsymbol{\sigma}_{i,k}, \boldsymbol{u}_k) \tag{14}$$

$$\hat{\boldsymbol{z}}_k = \sum_{i=1}^{2\eta+1} \xi_i \vartheta_{i,k}^- \tag{15}$$

$$\boldsymbol{P}_{z,k} = \sum_{i=1}^{2\eta+1} \xi_i (\vartheta_{i,k}^- - \hat{\boldsymbol{z}}_k^-)(\vartheta_{i,k}^- - \hat{\boldsymbol{z}}_k^-)^T + \boldsymbol{R} \tag{16}$$

$$\boldsymbol{P}_{\chi z,k} = \sum_{i=1}^{2\eta+1} \xi_i (\hat{\mathbf{X}}_k^- - \sum_{i,k}^{-})(\vartheta_{i,k}^- - \hat{\boldsymbol{z}}_k^-)^T \tag{17}$$

System output

$$\boldsymbol{K}_k = \boldsymbol{P}_{\chi z,k} \boldsymbol{P}_{z,k}^{-1} \tag{18}$$

$$\hat{\mathbf{X}}_k = \hat{\mathbf{X}}_k^- + \boldsymbol{K}_k (\boldsymbol{z}_k - \hat{\boldsymbol{z}}_k^-) \tag{19}$$

$$\boldsymbol{P}_k = \boldsymbol{P}_k^- - \boldsymbol{K}_k \boldsymbol{P}_{z,k} \boldsymbol{K}_k^T \tag{20}$$

### 3.2.2 Reconstruction of the prediction step based on strong tracking filter

In Section 3.2.1, the equation of state obtained according to the GABP neural network model does not conform to the real time domain characteristics of ploughing depth and rotation speed of the tractor during operation. Therefore, to overcome the problem of the equation of state set in Equation (2) being incapable of accurately tracking the time-varying system, this study used ST filtering theory to optimize the covariance matrix in the Kalman filtering process. Specifically, the fading factor was introduced to increase the weight of new data on the predicted value of new state updates and thus improve the robustness of the system. Therefore, the updated prediction step prior covariance matrix is

$$\boldsymbol{P}_{k,new}^- = \boldsymbol{\Delta}_k (\boldsymbol{A}_k \boldsymbol{P}_{k-1} \boldsymbol{A}_k^{\mathrm{T}} + \boldsymbol{W}_k \boldsymbol{Q}_{k-1} \boldsymbol{W}_k^{\mathrm{T}}) \boldsymbol{\Delta}_k^T + \boldsymbol{Q}_{k-1} \tag{21}$$

Where $\boldsymbol{\Delta}_k$ is defined as the fading factor, and $\boldsymbol{P}_{k,new}^-$ is the updated prediction step prior covariance matrix.

$$\boldsymbol{\Delta}_k = \mathrm{diag}(\Delta_k, \Delta_k) \tag{22}$$

$$\Delta_k = \max(1, \mathrm{tr}(\boldsymbol{N}_k)/\mathrm{tr}(\boldsymbol{M}_k)) \tag{23}$$

Where,

$$\boldsymbol{M}_k = \boldsymbol{H}_k \boldsymbol{F}_k \boldsymbol{P}_{k-1} \boldsymbol{F}_k^T \boldsymbol{H}_k^T \tag{24}$$

$$\boldsymbol{N}_k = V_k - \boldsymbol{H}_k \boldsymbol{Q}_k \boldsymbol{H}_k^T - r_{k-1} \tag{25}$$

$$V_k = \frac{\sum_{i=1}^{k-1} (z_i - \hat{z}_i^-)^2}{k-1} \tag{26}$$

In summary, the implementation process of GABP-STUKF is shown in Fig. 3.

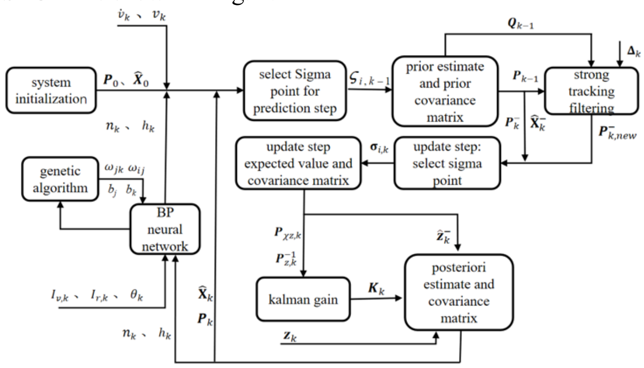


**Fig. 3**. GABP-STUKF identification method framework

## 4. Result Analysis and Discussion

### 4.1 Overview of observation test platform

To verify the practicability and accuracy of the GABP-STUKF algorithm in rotary farming operations, this study carried out a parameter acquisition test on the washboard pavement of the Jiangsu Agricultural Machinery Test and Identification Base (Pukou District, Nanjing, longitude 118.70509°, latitude 32.13504°), with a test pavement length of 20 m, as shown in Fig. 4.

**Fig. 4.** Test site

As shown in Fig. 5, the test platform was equipped with additional high-precision sensors as the control group to collect the main parameter information of rotary tillage:

(1) Collection of longitudinal vehicle speed information: GNSS equipment (Shanghai Huatan Navigation Technology Co., LTD., RTK accuracy ±(8+1×10-6ε) mm, static accuracy ±(2.5+0.5×10-6ε) mm; ε is the distance from the mobile station to the reference station, km) was used to measure the longitudinal speed of the platform.

(2) Tool roll speed information acquisition: A speed sensor (Model CZ480, Shanghai Vibration Transmission Electronic Technology Co., LTD.) with a measuring range of 0–1000 rpm) was installed at the output shaft of the tool roll on the experimental platform to measure the rotary tiller speed.

(3) Tillage depth information collection: An ultrasonic distance sensor (Model: UB500-18GM75, Wenzhou Yesi Electric Co., LTD.) with a measuring range of 0–0.5 m) was installed at the suspension mechanism of the experimental platform to measure the distance between the rotary center of the cutter roll and the road surface.

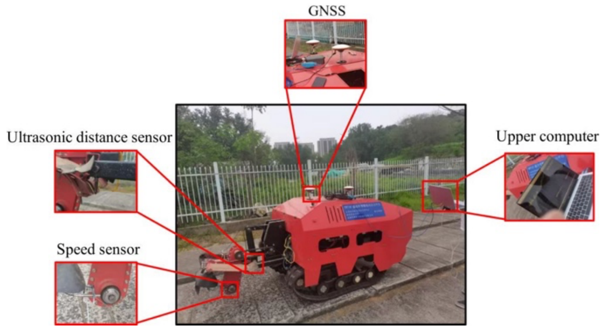


**Fig. 5.** Test Platform

## 4.2 Test results and analysis

For the collection of original data of the electric tractor in the test, the longitudinal speed information is directly collected by the upper computer through RS485 protocol, and the cutter roll speed and ploughing depth information are collected by the PLC analog module and transmitted to the upper machine through the RS485 protocol. The data collected in the test are shown in Fig. 6.

The data in Fig. 6 were input, GABP-STUKF was used to estimate rotary farming operation parameters, and GABP-UKF and the estimated results of the original values were used as the control group ( $P_0 = 1, Q_0 = 0.1, R_0 = 0.5$ ). The estimated results are shown in Fig. 7.

Mean absolute error (MAE) and root mean square error (RMSE) are calculated based on the data in Fig. 7, and the results are shown in Table 1.

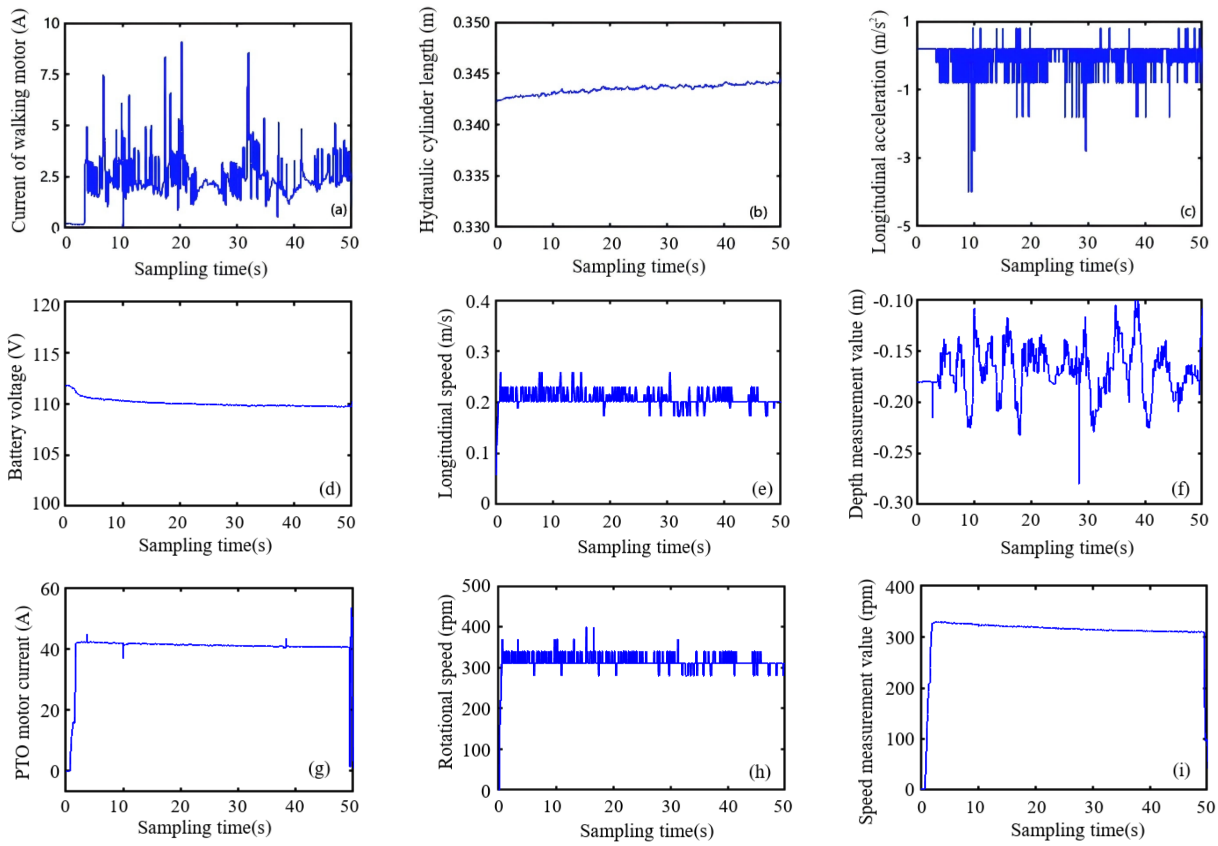


**Fig. 6.** Actual vehicle data

**Table 1.** Observation result statistics

| Parameter | MAE | | | RMSE | | |
|---|---|---|---|---|---|---|
| | GABP-STUKF | GABP-UKF | Original value | GABP-STUKF | GABP-UKF | Original value |
| Longitudinal speed (m/s) | 0.017 | 0.019 | 0.019 | 0.025 | 0.027 | 0.029 |
| Rotational speed (rpm) | 8.941 | 10.328 | 16.814 | 18.413 | 18.668 | 27.020 |
| Tilling depth (m) | 0.029 | 0.029 | 0.031 | 0.038 | 0.038 | 0.040 |

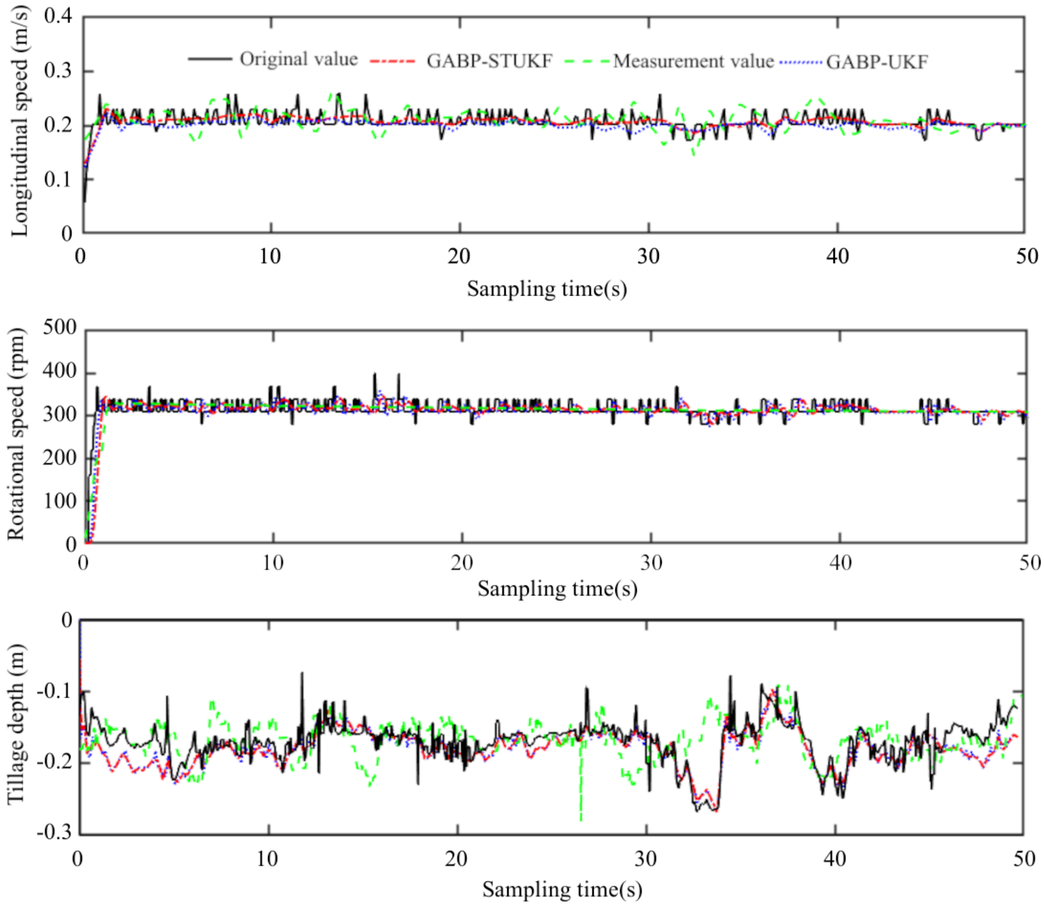


**Fig. 7.** Observation results of operating parameters of greenhouse electric tractors

As can be seen from Fig. 7 and Table 1:

(1) The longitudinal speed value obtained based on GABP-STUKF is between the original and measured values, close to the test and GABP-UKF values, indicating that GABP-STUKF can approximate the measured value relatively.

(2) The speed value obtained based on GABP-STUKF is also between the original and measured values, and the curve is almost identical with the test value. The value obtained by GABP-UKF is also almost identical, indicating that GABP-STUKF is highly accurate in predicting speed.

(3) Under different measurement methods, the change of ploughing depth data showed a relatively obvious “zigzag” change, which is mainly related to the test road condition. However, the ploughing depth value based on GABP-STUKF is also basically between the original and measured values. The change of ploughing depth data based on this method is also consistent with the test value in terms of the overall trend.

(4) The original platform uses the Hall sensor of the motor driver to measure motor speed. Owing to its low resolution, the longitudinal speed collected is “serrated” with the knife roll speed, which affects the accurate collection of status information.

(5) For the results of tillage depth observation, outliers are eliminated in the observation process to “smoothen” the signal curve. GABP-STUKF can reduce signal noise while approaching the measured value.

(6) The MAE and RMSE of longitudinal vehicle speed observation are 0.017 and 0.025 m/s, respectively, which are 10% higher than the original values.

(7) The MAE and RMSE observed for cutter roll speed are 8.941 and 18.413 rpm, respectively. MAE is increased by 46.8% compared with the original value, showing the most obvious effect.

(8) The MAE and RMSE of tillage depth observation are 0.029 and 0.038 m, respectively. MAE is increased by 7.54% compared with the original value, and the effect is the least improved compared with the speed.

## 5. Conclusions

This study proposed a GABP neural network model to solve the problems of unstable measurement of rotary farming operation parameters and low sensor accuracy of greenhouse electric tractors. STUKF was used to observe the main parameters of rotary farming. Finally, the following conclusions could be drawn:

(1) The operation parameter prediction method is developed based on the BP neural network, and the weight and threshold values of the network are optimized by GA to solve the problem of falling into the local optimal in the prediction process of the BP neural network.

(2) Based on the established prediction model, GABP-STUKF algorithm is designed to solve the problem of strong nonlinear equation of state.

(3) The observation results show that the GABP-STUKF algorithm has a certain improvement in longitudinal speed,

rotational speed, and tillage depth than the original rotating tillage operation parameter acquisition method of electric tractors.

This study combined theory and experiment to optimize the BP neural network by GA and proposed an observation method based on GABP-STUKF, which has certain reference value for the estimation of rotating tillage state and parameter optimization of greenhouse electric tractors. Since this study did not consider the observation of rotating tillage parameters of electric tractors under different working and soil environments, the proposed method is only applicable to the greenhouse environment. Therefore, the change of state parameters of electric tractors under different environments can be fully considered in future study, and the observation method obtained by integrating various factors can be more realistic.

**Acknowledgements**
This work was supported by the Key Science and Technology Projects in Jinhua (Grant No. 2022-1-075).



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