Experimental Study on Creep Properties Prediction of Reed Bales Based on SVR and MLP

Jixia Li  
Shihezi University

Lixin Zhang (lixin_zhang_cn@126.com)  
Shihezi University  
https://orcid.org/0000-0002-9557-2516

Guangdi Huang  
Karamay Vocational and Technical College

Huan Wang  
Shihezi University

Youzhong Jiang  
Karamay Vocational and Technical College

Research Article

Keywords: Reed, Creep, Viscoelasticity, Machine Learning, Prediction.

Posted Date: August 20th, 2021

DOI: https://doi.org/10.21203/rs.3.rs-815296/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License. Read Full License
Experimental study on creep properties prediction of reed bales based on SVR and MLP

Jixia Li\(^1,2\), Lixin Zhang\(^1\)*, Guangdi Huang\(^2\), Huan Wang\(^1\), Youzhong Jiang\(^2\)

\(^1\) Correspondence: Lixin Zhang (lixin_zhang_cn@126.com)
\(^1\) College of Mechanical and Electrical Engineering, Shihezi University, China.
\(^2\) Karamay Vocational and Technical College, Xinjiang, China.

Abstract

**Background:** Reed has high lignin content, wide distribution and low cost. It is an ideal raw material for replacing wood in the paper industry. Reeds are rich in resources, but the density of reeds is low, leading to high transportation and storage costs. This paper aims to study the compression process of reeds and the creep behaviour of compressed reeds, and provide theoretical guidance for the reed compressor management, bundling equipment and the stability of compressed reed bales.

**Results:** We studied the strain-time relationship and strain of the reed bales compressed under constant force and the creep behaviour of the reed bales under different holding forces. Additionally, the creep behaviour of reed bales under various retention forces was investigated. The test curves are fitted by Machine Learning Prediction Algorithms and Support Vector Machine Regression. And use machine learning prediction algorithm model to establish a quaternary model of reed creep. The results show that the creep behaviour of a reed bale was positively correlated with the initial maximum compressive stress. The established Burgers four-element model was capable of simulating the creep process of reed bales. The test curves coincided well with the model-simulated curves. Reed bales were found to exhibit viscoelasticity. During the creep process, the elastic dynamic force and the viscous resistance were mutually constrained. The strain of reeds was composed of elastic, viscoelastic and plastic \(\varepsilon_s\). And elaborated the three stages of the creep process in detail.

**Conclusions:** We studied the relationship between the strain and time of the reed and the strain and creep behaviour of the reed bag under different holding forces under constant force. It is proved that the multi-layer perceptron network is better than the support vector machine regression in predicting the characteristics of reed materials. The three stages of elasticity, viscoelasticity and plasticity in the process of reed creep are analysed in detail. This article opens up a new way for using machine learning methods to predict the mechanical properties of materials. The proposed prediction model provides new ideas for the characterization of material characteristics.

**Key words:** Reed; Creep; Viscoelasticity; Machine Learning; Prediction.

1. **BACKGROUND**

In recent years, over-cultivation of forests and pastures has led to enormous environmental problems\(^{[1, 2]}\). Due to their high lignin content, wide distribution, and low cost, reeds are an excellent candidate for a raw material to replace timber in the papermaking industry\(^{[3, 4]}\). Reed resources are abundant but have extremely low use efficiency, mainly because reed processing sites are relatively distant from reed fields, and reed bales prepared for transportation are low in density\(^{[5, 6]}\). These factors result in high transportation and storage costs. Therefore, it is necessary
to study the reed compression process and the creep behaviour of compressed reeds to provide theoretical guidance on reed compression mechanisms, baling equipment and the stability of compressed reed bales\cite{7,8}.

To date, numerous researchers have conducted extensive studies on the mechanical properties of viscoelastic materials. Reynolds et al\cite{9} examined the effects of compressive load and particle size on the compressibility of various varieties of smashed wheat straw. Krstic et al\cite{10} investigated the compression properties of treated corn stover, grassland rush and switchgrass. These researchers found that when the moisture content is 16-20\%, the yield strength of these materials is relatively low, but the particles of these materials have a higher compaction density. Maraldi et al\cite{11} studied the effects of material, bale density, bale orientation, baling process and loading rate on the mechanical properties of bales. Kashaninejad M et al\cite{12} established a generalized Maxwell model and used this model to analyse the effects of lignocellulose content on the stress relaxation behaviour of 21 varieties of wheat straw. Nona and MD Shaw\cite{13,14} analysed the stress relaxation behaviour of straw under closed compression using a generalized Maxwell model. Maraldi et al\cite{11,15} conducted creep and stress relaxation tests on straw bales moulded under compression. Based on the test results, these researchers established a mathematical model for straw bales. Additionally, these researchers noted that the creep properties of straw bales were directly proportional to the load. Through rheological tests on rice seedling stems, Scharenbroch et al\cite{16} concluded that the occurrence of a creep process and the plastic strain were positively correlated with the creep time and initial stress affecting the rice seedling stems. These studies demonstrate that the compression of straw bales is time-dependent\cite{17,18}. However, analytical studies on the post-compression creep properties of tall, thick and hard stalk crops (e.g., reeds) have yet to be reported.

The plant material compression process is complex, multivariate and unpredictable\cite{19}. Traditional prediction methods are easy to implement\cite{19,20}, but cannot accurately predict nonlinear systems. In addition, adjusting the parameters is troublesome and time-consuming\cite{21,22}. At the same time, the problem of model predictive control for nonlinear and time-varying uncertain systems has not been well resolved\cite{23,24}. As a commonly used prediction method, machine learning has good nonlinear characteristics\cite{25,26}, convergence and a certain generalization ability. Therefore, machine learning technology has been widely used in the agricultural field in recent years\cite{27,28}, such as the study of material characteristics\cite{29,30}, the control of compression mechanisms\cite{31,32} and the inspection of work quality\cite{33,34}.

Therefore, this article aims to establish a model of the reed block creep after compression by understanding the dynamic mechanical properties of the reed bale, analyse the compression process of the reed bale, and provide theoretical guidance for the design of the reed baling mechanism. This paper first analyses the feasibility of using machine learning methods to predict the compression and creep deformation of reeds with highly nonlinear characteristics under the conditions of changing the compression time, strain value, stress and delay time of the material. Based on the experimental results again, a multi-layer perceptron (MLP) network and support vector machine (SVM) regression algorithm are used to establish a predictive model. Finally, the accuracy and stability of the model are studied by comparing the fitting performance of the training set of the model and the prediction performance of the new conditions. This article opens up a new way to predict the long-term mechanical properties of polymers through machine learning methods. In addition to various superposition principles, it can reduce the number of
experimental working conditions, shorten the experimental period, and provide an idea for the accelerated characterization of the long-term mechanical properties of materials.

2. MATERIALS AND METHODS

2.1 MATERIALS

The reed samples used in this study were collected from Bosten Lake in the winter of 2018, as shown in Fig. 1. Table 1 summarizes the physical properties of the reed samples. The compression test results showed that the optimum compression with relatively low energy consumption was achieved with reeds that were 0.10 m in length and had a moisture content of 17%. On this basis, the long reed stalks harvested were cut into 0.10±0.02 m short reed stalks. Before the tests, the reed samples were air-dried in a dry environment for more than a month. When determining the moisture content of the reeds, each reed sample was first dried in an electric blast drying oven. Subsequently, the mass \( m_1 \) of the reed was determined.

\[
\alpha = \frac{m_2}{m_1 + m_2} \times 100\%
\]

where \( \alpha \) is the moisture content, \( m_1 \) is the mass of the reeds after drying, and \( m_2 \) is the mass of water.

![Fig. 1 Experiment material](image)

Table 1 Physical properties of the reed stalks

| Whole-reed height/m | Sample length/m | Wall thickness/×10^{-4} m | Cross-sectional area/×10^{-5} m^2 | \( \alpha \)% |
|---------------------|-----------------|---------------------------|-----------------------------------|-----------|
| 3.50±0.50           | 0.10±0.02       | 9.50±0.50                 | 9.00±0.10                         | 17.00±0.15 |

2.2 TEST EQUIPMENT

The creep properties of the reed samples were studied under closed compression conditions using a compression apparatus developed in-house (as shown in Fig. 2). The compression apparatus, made of 0.014-m-thick #45 steel sheets, consists of a piston rod, a compression cover plate, and a compression box. The compression box has inner cross-sectional dimensions of 0.20×0.20 m^2. The piston rod is 0.15 m in length. Four ribbed plates were added onto the compression cover plate to prevent the plate from deforming under stresses. To facilitate the observations during the test, four rulers were adhered onto the inner walls of the compression box.
A UTM5305 computer-controlled electronic universal material testing machine (Fig. 3) was used in the tests. This machine has a maximum test force of 300 kN, a force measuring the precision of 1 N and a stress precision of 0.001 MPa. Additionally, an electric blast drying oven, an electronic balance, and a Vernier calliper were used in the tests. Moreover, according to the test requirements, an EDC120 digital control system, a GWB-200 high-precision displacement calibration instrument, and an extensometer were used in the tests. Auxiliary tools used in the tests included scissors, a Vernier calliper, a spray bottle, and a straightedge.

2.3 Creep tests

A creep test examines the strain ($\varepsilon$)–time ($t$) relationship under a constant stress ($\sigma$). In essence, creep is a delayed material deformation process. The compression test results showed the following. For 0.05-, 0.10-, 0.15- and 0.20-m reed samples, the 0.10-m reed samples had the highest compaction density after compression under the same conditions (feed quantity, $\alpha$ and $\sigma$). The higher $\alpha$ was, the higher the compaction density was. However, high-$\alpha$ reeds could become mouldy, resulting in a decrease in the nutrient content of the reeds. Pre-test results showed that optimum compression was achieved for reeds with an $\alpha$ of 17%. In this study, the effects of $\sigma$ on the creep properties were analysed. Therefore, reeds with a length of 0.1 m and an $\alpha$ of 17% were selected. These reeds were randomly and evenly placed in test moulds. The reeds in each mould had a mass of approximately 1.150±0.05 kg. The test location was marked. During the tests, the reeds were compressed vertically at a loading rate of $1.67\times10^{-3}$ m/s. Once the set pressure was reached, a constant $\sigma$ was maintained for 800 s. Subsequently, the compression and creep tests were terminated. Table 2 summarizes the test conditions for each group of tests. At least three tests were conducted under each set of conditions. The final test results were averaged after eliminating relatively large errors. All the tests were conducted at a room temperature of 25.2±2.2 °C and a relative humidity of 46±4%.

| Test No. | Test reed sample length/m | $\alpha$/% | Loading rate/m/s | Maximum compressive $\sigma$/Pa | Retention time/s | Feed quantity/kg | Bale orientation |
|---------|---------------------------|-----------|-----------------|-----------------|-----------------|-----------------|-----------------|
| 1       | 0.10                      | 17        | $1.67\times10^{-3}$ | $3\times10^6$   | 800             | 1.150           | Flat            |
| 2       | 0.10                      | 17        | $1.67\times10^{-3}$ | $4\times10^6$   | 800             | 1.150           | Flat            |
| 3       | 0.10                      | 17        | $1.67\times10^{-3}$ | $5\times10^6$   | 800             | 1.150           | Flat            |
| 4       | 0.10                      | 17        | $1.67\times10^{-3}$ | $6\times10^6$   | 800             | 1.150           | Flat            |
2.4 DATA ANALYSIS

2.4.1 INPUT AND OUTPUT VARIABLES OF THE MODEL

\( \varepsilon \) is used to represent the strain of the reeds in the vertical direction and can be calculated using Equation (2).

\[
\varepsilon = \frac{u}{l_0}
\]

(2)

where \( u \) is the change in the displacement of the reeds lying flat in the vertical direction (unit: mm) and \( l_0 \) is the initial height of the reeds lying flat (unit: mm).

The creep properties of a linear viscoelastic material are generally described using the Burgers four-element model, which consists of a Maxwell model and a Kelvin model connected in series, as shown in Fig. 6. Equation (3) shows the constitutive equation for the Burgers four-element model.

\[
\varepsilon(t) = \frac{\sigma_0}{E_m} + \frac{\sigma_0}{E_k} \times \left( 1 - e^{-\frac{E_k}{\eta_k} t} \right) + \frac{\sigma_0}{\eta_m} \times t
\]

(3)

where \( \varepsilon(t) \) is the strain at the time \( t \) (%), \( \sigma_0 \) is the initially applied stress (Pa), \( E_m \) is the instantaneous elastic modulus (Pa), \( E_k \) is the delayed elastic modulus (Pa), \( \eta_k \) is the coefficient of delayed viscosity (Pa × s), and \( \eta_m \) is the coefficient of viscosity (Pa × s). Equation (4) shows the delay time \( T_k \).

\[
T_k = \frac{E_k}{\eta_k}
\]

(4)

The creep rate \( v_c \), a measure of the creep speed, represents the change in \( \varepsilon \) within unit \( t \). Equation (3) shows the expression for \( v_c \).

\[
v_c = \left| \frac{d\varepsilon(t)}{dt} \right|
\]

(5)

where \( \varepsilon(t) \) is the strain that changes with \( t \). The unit for \( v_c \) is %/s.

The creep compliance \( J(t) \), representing the \( \varepsilon \) that changes with \( t \) under unit \( \sigma \), is a function that monotonically increases with \( t \). Equation (6) shows the expression for \( J(t) \).

\[
J(t) = \frac{\varepsilon(t)}{\sigma_0}
\]

(6)

where \( \varepsilon(t) \) is the strain that changes with \( t \), \( \sigma_0 \) is the applied stress, and \( J(t) \) is the creep compliance (%/MPa).

\( J(t) \) is composed primarily of elastic \( J(t) \), viscous \( J(t) \) and plastic \( J(t) \), as shown in equation (7).

\[
J(t) = J_e(t) + J_{ve}(t) + J_p(t)
\]

(7)

where \( J_e(t) \) is the elastic \( J(t) \) (%/MPa), \( J_{ve}(t) \) is the viscous creep \( J(t) \) (%/MPa), and \( J_p \) is the plastic \( J(t) \) (%/MPa).

Equation (8) can be used to analyse the proportion of each type of \( \varepsilon \) in the \( v_c \) of reeds.

\[
P_i(t) = \frac{\varepsilon_e(t)}{\varepsilon(t)} \times 100\% = \frac{J_e(t)}{J_e(t)+J_{ve}(t)+J_p(t)} \times 100\%
\]

(8)

where \( i \) can be \( e \) (elastic), \( ve \) (viscous) or \( v \) (plastic). The proportion is related to the magnitude of each type of \( J(t) \) and unrelated to the initial \( \varepsilon \).

\[
\varepsilon_e(t) = \sigma_0 J_e(t)
\]

(9)
\[ \varepsilon_{ve}(t) = \sigma_0 J_{ve}(t) \]  \hfill (10) 
\[ \varepsilon_v(t) = \sigma_0 J_v(t) \]  \hfill (11)

where \( \varepsilon_e(t) \), \( \varepsilon_{ve}(t) \) and \( \varepsilon_v(t) \) are the elastic, viscoelastic and viscous \( \varepsilon \)s, respectively. If a material undergoes an \( \varepsilon_e(t) \), the material can immediately recover to its initial state when unloaded. If a material experiences an \( \varepsilon_{ve}(t) \), the material can gradually recover to its initial state when unloaded. An \( \varepsilon_v(t) \) is irreversible.

The factors affecting the compression performance of reed include compression time, stress, strain and delay time. In order to reflect the elastic strain, viscoelastic strain and viscous strain of reed compression from formula 9-10, the compression time \( t \), strain value \( \varepsilon(t) \), stress \( \sigma_0 \) and delay time \( T_K \) are taken as the input \( x = [t, \varepsilon(t), \sigma_0, T_K]^T \), and the elastic creep compliance \( J_e \), viscous creep compliance \( J_v \) and plastic creep compliance \( J_p \) are taken as the output.

### 2.4.2. DATA NORMALIZATION

The range of input variables and strain results of the creep experiment showed that the input and output variables were not in the same order of magnitude. However, multiple machine learning methods, such as ANN, require that the weights and other parameters in the model are parallel in order of magnitude. If the difference of input variables is large, the input variables with a smaller order of magnitude will be covered by those with a larger order of magnitude during the error propagation. Furthermore, the effect of each input variable on the output cannot be rendered properly. Consequently, normalizing the input and output variables is crucial before modeling.

In this research, the z-score method, which is commonly used alongside machine learning, was considered to normalize the input and output variables, so that the mean value of each variable equals 0 while the variance equals 1. The method can be expressed as

\[ \tilde{x}^{(x)} = \frac{x^{(x)}-\bar{x}}{S} \]  \hfill (12)

where \( x^{(x)} \) are the original samples, \( n = 1, 2, \ldots, N \), and \( N \) is the number of samples, \( \bar{x} \) is the mean value of samples, \( S \) is the variance of samples, \( \tilde{x}^{(x)} \) are the normalized samples. After normalization, the input variables can be expressed as \( \tilde{x} = [\tilde{t}, \tilde{\varepsilon}(t), \tilde{\sigma}_0, \tilde{T}_K]^T \), while the output variables change to \( \tilde{J} = [\tilde{J}_e, \tilde{J}_{ve}, \tilde{J}_p]^T \).

### 2.4.3 Multilayer Perceptron Network

Multilayer Perceptron Network (MLP) network is a typical ANN, which is a nonlinear complex network system composed of a large number of “biological neurons”. As shown in Fig. 4, a mathematical model is used to describe the biological neural network structure, so that the intelligent behavior to some extent can be simulated under the guidance of the algorithm. In this research, MLP based on the backpropagation algorithm is considered to train the prediction model. It is composed of an input layer, an output layer and at least one hidden layer. The training consists of two processes: signal forward propagation and error backpropagation. During the forward propagation, the input samples are transmitted from the input layer to each hidden layer and output layer. Then, the backpropagation stage begins if the output value is not equal to the real value. The error is allocated among all neural of the hidden layer by transmitting the output error back, and the error of neurons in each layer is obtained as the basis for optimizing the weights of neurons. The above processes are repeated until the output error is acceptable or reaches the training iterations’ limitation.
The nonlinear properties of the reed creep strain–time curve were considered to have initially identified the main structural parameters range of the MLP network. The range of MLP network structure hyper-parameters is shown in Table 3. In order to avoid unnecessarily increasing the complexity of the model, the number of the hidden layer is set to 1 or 2. The number of neurons is setting from 1 to 100. Subsequently, the MLP network prediction model of creep properties is constructed by optimizing the hyper-parameters of the model.

| Hyper-Parameters         | Range                  |
|--------------------------|------------------------|
| Activation function      | Logistic, Tanh, Relu   |
| Number of hidden layers  | 1–2                    |
| Number of hidden layer neurons | 1–10                |
| Training method          | L-BFGS, SGD, Adam      |

**2.4.4. SUPPORT VECTOR MACHINE REGRESSION**

As one of the most common methods in the machine learning field, support vector machine regression (SVR) has shown its unique advantages in solving the problems of small sample, nonlinear and high-dimensional pattern recognition. SVR is developed from the optimal classification surface of a linearly separable problem, using nonlinear transformation defined by the inner product function to transform the sample input space into another higher dimensional space, and then solving the generalized optimal classification hyperplane. SVR mainly solves the finite sample problem and finds the best compromise between the complexity and the learning ability of the model in order to obtain the best generalization ability, as shown in Fig. 5. The SVR method successfully avoids the traditional process from induction to deduction, and effectively realizes the "conversion inference" from training data to prediction data.
The basic idea of nonlinear SVR is to use nonlinear mapping $\phi$ to map data $x$ to Hilbert feature space, then linear regression is carried out in this space. The kernel function $k(x_i, x_j) = \phi(x_i) \cdot \phi(x_j)$ is used to realize the correspondence between linear regression in high-dimensional space and nonlinear regression in low-dimensional space. A three-order RBF kernel was considered in this study. The main hyper-parameter range of SVR was initially identified to include C and gamma, as shown in Table 4.

| Hyper-Parameters | Range          |
|------------------|----------------|
| C                | 1–5000         |
| gamma            | $[1 \times 10^{-5}, 0.1]$ |

### 3 RESULTS

#### 3.1 OPTIMIZATION RESULTS OF HYPER-PARAMETERS

The cross-validation method and genetic algorithm mentioned in Section 2.3.4 were used to optimize the hyper-parameters of the MLP and SVR machine learning prediction models. The results are shown as:

- **MLP**: activation function = logistic, number of hidden layers = 2, number of hidden layer neurons = 8, training method = Adam;
- **SVR**: $C = 4298$, gamma = $7.2 \times 10^{-4}$.

Fig. 6 shows the $\varepsilon$–$t$ curves during the creep test process under various $\sigma_0$ s. As demonstrated in Fig. 4, the trends of $\varepsilon$ were consistent during all the tests. $\varepsilon$ changed at a high rate within the initial minute and subsequently at a decreasing rate. Overall, $\varepsilon$ increased nonlinearly at a high rate initially and subsequently at a low rate. During this process, as a result of the internal viscosity of the reeds, $\varepsilon$ continued to increase under constant $\sigma$. This process is the creep process of the reeds. The $\varepsilon$ values were calculated based on the test data using Equation (2).

Additionally, as shown in Fig. 6, $\sigma_0$ affected the creep properties of the reeds. The higher $\sigma_0$ was, the higher the ultimate stable $\varepsilon$ ($\varepsilon_\infty$) was.

![Fig.6 Reed bales vertical strain over time](image)

In order to verify the fitting and prediction performance of the above model hyper-parameters, the creep curves under three loading forces are set as the training set, and the creep curve under another loading force is set as the prediction set. In addition, 10 training groups were also carried out. The result is shown in Fig. 7.
3.2 COMPARISON OF PREDICTION PERFORMANCE UNDER DIFFERENT APPLIED FORCES

The medium pressure value fluctuates. Therefore, different applied forces will affect the compression efficiency of reeds, so it is necessary to further verify the prediction performance of MLP and SVR under different applied forces. During the reed compression process and the retention stage of the creep process, because the universal testing machine was unable to retain a completely constant $\sigma$, $\sigma$ fluctuated during the retention stage. Fig. 8(a)–(e) shows the changes in the applied $\sigma$ with $t$ during the five groups of tests. As demonstrated in Fig. 5, during the compression process, $\sigma$ changed exponentially with $t$. The compressive $\sigma$ fluctuated once reaching the preset maximum value. Within the initial minute, $\sigma$ fluctuated relatively significantly. As $t$ increased, the fluctuations in $\sigma$ gradually weakened. The average $\sigma$ basically remained at $\sigma_0 \pm 0.10$ kN. In the first 60 s of the $\varepsilon-t$ curves, the applied $\sigma$ fluctuated relatively significantly. During this process, a constant $\sigma$ was relatively difficult to maintain because of the relatively large reaction force from the compressed reeds as a result of the structural damage to and viscosity of the reeds. As $t$ increased, the reaction force from the compressed reeds became relatively small, rendering it easier to maintain a constant $\sigma$. As a result, the applied $\sigma$ changed smoothly. Table 5 summarizes the changes in impulse during the five groups of tests. As the maximum compressive $\sigma$ increased, the corresponding impulse gradually increased.

The fitting curve of the MLP model is better than the fitting curve of the support vector regression model under five different applied forces. Under the applied force of 160kN and 280kN, the measurement coefficient $R^2$ of the fitting curve of the MLP model is 0.9115 and 0.9047, respectively, which means that the fitted curve has a large deviation. The fitting measurement coefficient $R^2$ of the remaining three working conditions is greater than 0.997. Therefore, the parameter fitting and correlation of the MLP model will be analysed.
Table 5 Impulse values under various $\sigma_0$s

| $\sigma_0$ (MPa) | 3   | 4   | 5   | 6   | 7   |
|-----------------|-----|-----|-----|-----|-----|
| Impulse (N×s)   | $9.72\times10^7$ | $1.14\times10^8$ | $1.62\times10^8$ | $1.94\times10^8$ | $2.27\times10^8$ |

3.3 Reed Material Characteristics Based on MLP Model

The creep model parameters fitted to the creep test data obtained under various $\sigma_0$s differ. $E_m$ reflects the elastic deformability of the reeds. The higher $E_m$ is, the lower the elastic deformability is, and the lower the compliance of the tissues inside the reed stalks is. In Table 5,
\( E_m \) ranges from 3.480 to 7.928 Pa, with an average of 5.715 Pa, an SD of 1.573 Pa and a CV of 27.52%. \( E_k \) ranges from 500 to 1,166.667 Pa, with an average of 838.095 Pa, an SD of 235.895 Pa and a CV of 28.15%. \( E_m \) is lower than \( E_k \) in each case. This result suggests that of the internal structural models for the reeds, the elastic deformability of the elastic component (\( E_m \)) is higher than that of the elastic component (\( E_k \)) in the Kelvin model. The compliance of the elastic component in the Kelvin model is lower than that of the elastic model in the Maxwell model. The fitting coefficients of the MLP model are shown in Table 6.

| Test No. | \( \sigma_0 \) (MPa) | Model coefficients |
|---------|-------------------|-------------------|
|         | \( E_m \) | \( E_k \) | \( \eta_m \) | \( \eta_k \) | \( T_k \) |
| 1       | 3     | 3.480 | 500.000 | 0.685\times 10^6 | 41666.667 | 83.333 |
| 2       | 4     | 4.630 | 666.667 | 0.931\times 10^6 | 47619.048 | 71.429 |
| 3       | 5     | 5.682 | 1000.000 | 1.395\times 10^6 | 66666.667 | 66.667 |
| 4       | 6     | 6.857 | 857.143 | 1.546\times 10^6 | 45112.782 | 52.632 |
| 5       | 7     | 7.928 | 1166.667 | 2.034\times 10^6 | 61403.509 | 52.632 |
| Average |       | 5.715 | 838.095 | 1.318\times 10^6 | 52493.734 | 65.338 |
| SD      |       | 1.573 | 235.895 | 0.474\times 10^6 | 9754.204  | 11.710 |
| CV      |       | 27.52%| 28.15%  | 35.94%            | 18.58%    | 17.92% |

\( \eta_m \) reflects the deformation-resistant viscous resistance of the reeds. The higher \( \eta_m \) is, the higher the deformation-resistant viscous resistance is, and the poorer the fluidity of the internal structure is. In Table 5, \( \eta_m \) ranges from 0.685 to 2.034 P\( \text{a}\)\( \text{s}\), with an average of 1.318 P\( \text{a}\)\( \text{s}\), an SD of 0.474 P\( \text{a}\)\( \text{s}\) and a CV of 35.94%. \( \eta_k \) ranges from 41,666.667 to 61,403.509 P\( \text{a}\)\( \text{s}\), with an average of 52,493.734 P\( \text{a}\)\( \text{s}\), an SD of 9,754.204 P\( \text{a}\)\( \text{s}\) and a CV of 18.58%.

\( T_k \) reflects the time required for the components in the Kelvin model to reach strain equilibrium. In Table 5, \( T_k \) ranges from 83.333 to 52.632 s, with an average of 65.338 s, an SD of 11.710 s and a CV of 17.92%. This result suggests that the average time for reaching creep equilibrium was 65.338 s.

As \( \sigma_0 \) increased, \( E_m \), \( E_k \), \( \eta_m \) and \( \eta_k \) all increased, whereas \( T_k \) gradually decreased. This result suggests that the higher \( \sigma_0 \) was, the lower the elastic deformability was, the lower the compliance of the tissues inside the reeds was, the higher the deformation-resistant viscosity resistance was, the poorer the fluidity of the internal structure was, the higher the stability of the moulded reed bale was, and the shorter the time needed to reach creep equilibrium was.

The CV ranges from 17.92% to 35.94%, suggesting high dispersion. This result demonstrates relatively significant individual variation under various \( \sigma_0 \)s.

### 3.4 Analysis of \( v_c \) and \( J(t) \)

#### 3.4.1 Analysis of \( v_c \)

The \( v_c \) during the creep process of the reeds consists of a viscoelastic \( v_c \) and a viscous \( v_c \). Fig. 9 shows the \( v_c–t \) curves during the creep process of the moulded reed bales.
As demonstrated in Fig. 9, the $v_c$ of the reeds exhibited similar trends under various $\sigma_0$s. As $t$ increased, $v_c$ was initially high, then deceased, and gradually tended to zero. Based on the changes in $v_c$, the creep process can be divided into three stages. During the first stage, $v_c$ was high. During this stage, the deformation is mainly composed of elastic deformation and viscous deformation, which was mainly a result of $\sigma_0$. From a microscopic perspective, the macromolecular chains of the elastic tissue structures (e.g., cellulose and lignin) in the reed stalks continued to extend, and the number of macromolecular bonds continued to increase. During this stage, the viscous creep resistance of the viscous tissue structures inside the reed stalks was relatively low. During the second stage, as $t$ increased, $v_c$ changed at a low rate. During this stage, deformation consisted mainly of viscous deformation. This effect mainly occurred because the viscous resistance of the viscous tissue structures inside the reed stalks to continuous deformation gradually increased. As a result, continuous extension of macromolecular chains and increases in macromolecular bond angles inside the reed stalks were prevented. During the third and final stage, $v_c$ gradually decreased to a constant value. This stage was primarily characterized by irreversible plastic deformation. During this stage, the elastic dynamic force and the viscous resistance inside the reeds gradually reached equilibrium, and the tissues inside the moulded reed bale formed a new tissue structure. In the Kelvin creep model for the reeds, the elastic and viscous elements are mutually constrained. Additionally, when the elastic dynamic force increases, the viscous resistance decreases, and vice versa. Finally, the elastic dynamic force and the viscous resistance reached an equilibrium.

### 3.4.2 Analysis of $J(t)$

Calculated by formula (7) and MLP model, the creep compliance composition of the five sets of creep tests is shown in Table 7.

| $\sigma_0$ | $J_e(t)$ | $J_{ve}(t)$ | $J_0(t)$  |
|----------|-----------|-------------|-----------|
| 3        | 0.287     | 0.002 × (1 − $e^{-0.012t}$) | 1.46 × 10^{-6} |
| 4        | 0.216     | 0.0015 × (1 − $e^{-0.014t}$) | 1.0745 × 10^{-6} |
| 5        | 0.175     | 0.0014 × (1 − $e^{-0.019t}$) | 7.762 × 10^{-7} |
| 6        | 0.147     | 0.00083 × (1 − $e^{-0.015t}$) | 5.973 × 10^{-7} |
| 7        | 0.126     | 0.00086 × (1 − $e^{-0.019t}$) | 4.916 × 10^{-7} |

$$\epsilon_e(t) = \sigma_0 J_e(t)$$  \hspace{5cm} (13)
\[
\epsilon_{ve}(t) = \sigma_0 J_{ve}(t) \quad (14) \\
\epsilon_v(t) = \sigma_0 J_v(t) \quad (15)
\]

Table 8 summarizes the various types of creep during the five sets of creep tests of the MLP model calculated according to equations (9)-(11).

| \(\sigma_0\) | \(\epsilon_\varepsilon(t)\) | \(\epsilon_{ve}(t)\) | \(\epsilon_v(t)\) |
|-------------|-----------------|-----------------|-----------------|
| 3           | 0.861           | 0.006 \times (1 - e^{-0.012t}) | 4.381 \times 10^{-6}t |
| 4           | 0.864           | 0.006 \times (1 - e^{-0.014t}) | 4.298 \times 10^{-6}t |
| 5           | 0.875           | 0.007 \times (1 - e^{-0.019t}) | 3.881 \times 10^{-6}t |
| 6           | 0.882           | 0.005 \times (1 - e^{-0.015t}) | 3.584 \times 10^{-6}t |
| 7           | 0.882           | 0.006 \times (1 - e^{-0.019t}) | 3.441 \times 10^{-6}t |

The proportions of \(\epsilon_\varepsilon(t)\), \(\epsilon_{ve}(t)\) and \(\epsilon_v(t)\) in the total \(\epsilon\) can be calculated using Equation (8). Here, test 1 is used as an example. Fig. 10 shows the changes in the proportion of each type of \(\epsilon\) in the total \(\epsilon\) with \(t\) under a \(\sigma_0\) of 3 MPa. The left axis shows the changes in the \(\epsilon_\varepsilon(t)\) data. The right axis shows the changes in the \(\epsilon_{ve}(t)\) and \(\epsilon_v(t)\) data. The proportion of \(\epsilon_\varepsilon(t)\) was the highest during the initial stage and gradually decreased to 99.19% with \(t\). As \(t\) increased, the proportion of \(\epsilon_{ve}(t)\) increased rapidly initially and slowly subsequently. The proportion of \(\epsilon_{ve}(t)\) ultimately stabilized at 0.69%. The proportion of \(\epsilon_v(t)\) in the total \(\epsilon\) linearly increased with creep \(t\) and ultimately reached 0.39%. This result suggests that the degree of damage to the inherent structure of the reeds gradually increased with \(t\).

![Fig. 10 Proportion of each type of \(\epsilon\) in the total \(\epsilon\) during stress relaxation under a \(\sigma_0\) of 3 MPa](image)

4 DISCUSSIONS

4.1 LIMITATIONS

The creep characteristics of reeds are closely related to compression time, strain value, stress and delay time, showing strong nonlinear characteristics. The MLP model is better than the SVR model in the prediction of creep curve and creep characteristics under different applied forces. The method described in this research is an application case of machine learning technology in the study of material properties, which can provide new research ideas for the accelerated characterization of material mechanical properties.

Although a new idea for predicting the compression creep performance of reeds is proposed,
the author believes that the current research still has the following limitations:

- Few experimental working conditions are considered, and the total data set is relatively small. With larger data sets, the accuracy and reliability of machine learning models such as MLP and SVR will be improved;
- Only four more important creep-related variables are considered, including compression time, strain value, stress and delay time. However, the creep characteristics of reeds are more complicated. Therefore, follow-up research should involve more variables to further optimize the MLP prediction model.

4.2 Future Work

In order to further improve the fitting accuracy of the training set, the hyper parameter optimization method of the machine learning model combining genetic algorithm and k-fold cross-validation will be studied:

- Introduce more variables, such as pattern size and material thermal properties, to optimize the prediction model more comprehensively;
- Enhance the inherent laws of patterns under different working conditions, further strengthen nonlinear characteristics, and improve prediction accuracy.

5 Conclusions

This study uses a series of machine learning methods (based on MLP and SVR) to predict the compressive creep deformation of reeds. Considering variables such as compression time, strain value, stress and delay time, a compression creep test was carried out on the reed samples. Using the established MLP model to analyze the parameters of creep rate and creep compliance, it verified the model's fitting accuracy in the training set and its predictive ability under new conditions. According to the results, the following conclusions can be drawn: There is an irreversible plastic strain in the creep process of the reed block, and the creep process is a process in which elastic dynamics and viscous resistance are restrained by each other. In the experiments of different loading forces, the creep process trend of reed is the same. The strain change rate is fast in the first minute, and then it becomes slow, showing a non-linear growth trend of fast first and then slow overall. Different loading stresses have an impact on the creep of reeds. The greater the loading force, the greater the final stable strain value. According to the creep characteristic parameters, the Burgers four-element model established by the virtual prototype software can simulate the creep process of the reed block. The simulation curve has the same trend as the test curve, and the overlap effect is good. The stress of reed creep is mainly composed of elastic strain, viscoelastic strain and plastic strain. Among them, the elastic strain accounts for the largest proportion, and it decreases with the increase of time. The viscoelastic strain first increases and then becomes stable with the increase of time. The strain increases linearly with time, and the damage to the structure of the reed gradually increases. The method described in this study is an application case of machine learning technology in the study of material characteristics, which can provide new research ideas for the accelerated characterization of material mechanical properties.

Acknowledgements

Not applicable.

Authors’ contributions

LJX carried out the experiments, data analysis, paper writing. LJX and ZLX participated in
the design of the study, all authors prepared and checked the materials. LJX, ZLX and HGD revised the manuscript. All authors read and approved the final manuscript.

Funding
This research was funded by the National Natural Science Foundation of China (51565049).

Availability of data and materials
The datasets used and analyzed during the current study are available from the corresponding author on reasonable request.

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
The authors declare that they have no competing interests.

References
[1] Al-Aufi K, Al-Wardy M, Choudri B S, et al. Analysis of crops cultivation trend: a shifting scenario in a coastal Wilayat, Oman[J]. Environment, Development and Sustainability, 2019.
[2] Liu X, Watts R J, Howitt J A, et al. Carbon and nutrient release from experimental inundation of agricultural and forested floodplain soil and vegetation: influence of floodplain land use on the development of hypoxic blackwater during floods[J]. Marine and Freshwater Research, 2020, 71.
[3] Schroedter L, Schneider R, Remus L, et al. L-(+)-Lactic Acid from Reed: Comparing Various Resources for the Nutrient Provision of B. coagulans[J]. Resources, 2020, 9(7):89.
[4] Li Y, Nie J, Chao X. Do we really need deep CNN for plant diseases identification?[J]. Computers and Electronics in Agriculture, 2020, 178: 105803.
[5] Myhan R, Markowski M. The compression specificity of plant tissue[J]. Journal of Texture Studies, 2020, 51(4).
[6] Li Y, Yang J. Few-shot cotton pest recognition and terminal realization[J]. Computers and Electronics in Agriculture, 2020, 169:105240-.
[7] Li Y, Yang J. Meta-learning baselines and database for few-shot classification in agriculture[J]. Computers and Electronics in Agriculture, 2021, 182(5):106055.
[8] Hofmann A, Hauptmann M. Ultrasonic Induced Material Compression During the Gap-controlled Reshaping of Dry Paper Webs by Embossing or Deep Drawing[J]. Bioresources, 2020, 15(2):2326-2338.
[9] Wr A, Mc A, Sma B, et al. Pressure drop, mechanic deformation, stabilization and scale-up of wheat straw fixed-beds during hydrothermal pretreatment: Experiments and modeling - ScienceDirect[J]. Chemical Engineering Journal, 2019, 360:1587-1600.
[10] Yu I, Chen H, Abeln F, et al. Chemicals from lignocellulosic biomass: A critical comparison between biochemical, microwave and thermochemical conversion methods[J]. Critical Reviews in Environmental Science and Technology, 2020(2):1-54.
[11] Maraldi M, Molari L, Regazzi N, et al. Analysis of the parameters affecting the mechanical behaviour of straw bales under compression[J]. Biosystems Engineering, 2017, 160:179-193.
[12] Kashaninejad M, Tabil L G, Knox R. Effect of compressive load and particle size on compression characteristics of selected varieties of wheat straw grinds[J]. Biomass & Bioenergy, 2014, 60(jan.):1-7.
[13] Nona K D, Lenaerts B, Kayacan E, et al. Bulk compression characteristics of straw and hay[J]. Biosystems Engineering, 2014, 118(1):194–202.
[14] MD Shaw, Tabil L G. Compression and Relaxation Characteristics of Selected Biomass Grinds[C]// Minneapolis, Minnesota, June. 2007.
[15] Maraldi M, Molari L, Regazzi N, et al. Method for the characterisation of the mechanical behaviour of straw bales[J]. Biosystems Engineering, 2016.
[16] Scharenbroch, BC, Flores-Manguel, et al. Tree Encroachment Impacts Carbon Dynamics in a Sand Prairie in Wisconsin[J]. SOIL SCI SOC AMER J, 2010,74(3) (-):956-968.
[17] Ramesh M, Deepa C, Selvan M T, et al. Mechanical and water absorption properties of
Calotropis gigantea plant fibers reinforced polymer composites[J]. Materials Today: Proceedings, 2020.

[18] Njike M, Oyawa W O, Abuodha S O. Structural Performance of Straw Block Assemblies under Compression Load[J]. The Open Construction and Building Technology Journal, 2020, 14(1):350-357.

[19] Ang K H, Chong G, Yun L. PID Control System Analysis, Design, and Technology[J]. IEEE Transactions on Control Systems Technology, 2005, 13(4):p.559-576.

[20] Wang Y G, Shi Z G, Cai W J. PID autotuner and its application in HVAC systems[C]/American Control Conference. IEEE, 2001.

[21] Chen H, Liu Z Y, Xie X H. Nonlinear model predictive control: The state and open problems[J]. Kongzhi zu he Juece/Control and Decision, 2001, 16(4):385-391.

[22] Xie Z W, Hai-Ying H U. Self-adaptive Neuron Control Using in Robotic Hand Joint Control[J]. Small & Special Machines.

[23] Hashimoto Y, Murase H, Morimoto T, et al. Intelligent systems for agriculture in Japan[J]. Control Systems IEEE, 2001, 21(5):71-85.

[24] Wang L, Zhu Z Q, Hong B, et al. Current Harmonics Suppression Strategy for PMSM with Non-Sinusoidal Back-EMF Based on Adaptive Linear Neuron Method[J]. IEEE Transactions on Industrial Electronics, 2019, PP(99):1-1.

[25] Li Y, Chao X. Semi-supervised few-shot learning approach for plant diseases recognition[J]. Plant Methods, 2021, 17(1).

[26] Yang Y, Zhang Z, Mao W, et al. Radar target recognition based on few-shot learning[J]. Multimedia Systems, 2021(3).

[27] Li Y, Chao X. ANN-Based Continual Classification in Agriculture[J]. Agriculture, 2020, 10(5):178.

[28] Guyot D, Giraud F, Simon F, et al. Overview of the use of artificial neural networks for energy-related applications in the building sector[J]. International Journal of Energy Research, 2019(4).

[29] Stoll A, Benner P. Machine Learning for Material Characterization with an Application for Predicting Mechanical Properties[J]. 2020.

[30] Luo X, Dessie W, Wang M, et al. Comprehensive utilization of residues of Magnolia officinalis based on fiber characteristics[J]. Journal of Material Cycles and Waste Management, 2021.

[31] Ugwuoke I C, Abolarin M S. Design and Development of Class 2B-lpl Compliant Constant-Force Compression Slider Mechanism[J]. International Journal of Engineering and Manufacturing, 2019, 9(3):19-28.

[32] Yan L I, Xuan J J. Feeding Speed Control of Packing Material for Pillow Type Packing Machine[J]. Packaging Engineering, 2019.

[33] Ouytsel C, Given-Wilson T, J Minet, et al. Analysis of Machine Learning Approaches to Packing Detection[J]. 2021.

[34] Chao X, Zhang L. Few-shot imbalanced classification based on data augmentation[J]. Multimedia Systems:1-9.