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Research on the Classification Model of Gas Well Water Production Driven by Production Data of Shale Gas Cage Type Throttle Valve

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Abstract. Water production from gas wells is an important factor affecting gas well productivity. The excessive fluctuation of pressure after the wellhead water flows interfere with the pressure control gas production process, making it difficult to accurately control the wellhead pressure as a control target and thus affecting productivity, this paper carried out research on shale gas cage type throttle valve production data-driven gas well water production classification model. Firstly, the pre valve temperature, pre valve pressure, post valve temperature, and post valve pressure data from 6 wells on site were collected and preprocessed. Secondly, 39 kinds of data classification algorithms such as precise tree, linear discrimination, logistic regression, and Gaussian naive Bayes were used to predict the water production of the cage type throttle valve. Finally, the judgment results are directly used in the cage type throttle valve control system to solve the problem of real-time synchronization of data caused by the wellhead metering mechanism. The research results show that due to the complex characteristics of gas-liquid two-phase throttling at the wellhead of shale gas wells, the adaptability of traditional statistical classification models to the judgment of shale gas well water production is different. Through experimental verification, the optimized KNN classification model is more suitable for shale gas cage throttle valve production data processing. Based on data-driven methods, this paper can directly determine the water production situation of the throttle valve, and thus achieve real-time adjustment, laying the foundation for remote control of the throttle valve. The research results have important engineering value for improving the production efficiency and automation level of shale gas wells in Sichuan.

Keywords. Shale gas well, cage type throttle valve, production data, water production classification mod

1. Introduction

Shale gas resources in Sichuan are abundant and the prospect of extraction is bright. As the degree of extraction has deepened over the years, some gas wells are gradually decreasing in gas production in the middle and late stages of extraction. Based on the experience of shale gas production in North America, pressure control production technology using cage type throttle valve as the core equipment can effectively slow

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down the rate of shale gas production reduction and increase the final recoverable reserves of a single well. Currently, most shale wells in Sichuan use the “Stage I fixed nozzle+Stage II cage type throttle valve” ground process [1]. The multi-stage throttling method can reduce the differential pressure of the throttle valve and realize accurate pressure control production [2]. However, water production still exists in gas wells during field development. Water production from gas wells can reduce gas well production and gas well control reserves, make single well production decline faster and lower gas reservoir recovery, which is a key influencing factor limiting stable and increasing gas reservoir production [3-6]. The prediction of the water production of the cage type throttle valve based on production data on site has positive engineering significance for realizing remote real-time regulation of production. How to quickly adjust the throttle valve opening to reduce water production from gas wells is an important research value to ensure efficient shale gas extraction in the Sichuan Basin.

At present, it is found that during the field extraction of shale gas wells in Sichuan, the environment of gas well production and development is harsh, the wellhead water metering device is offline, and its collection data cannot be directly transmitted to the cage type throttle valve control system. These factors directly lead to a series of problems such as lagging throttle control and the inability to implement remote control, which in turn affects production capacity [7, 8]. In practice, as the development process progresses and the production pressure difference increases, some gas wells will gradually produce water, and the fluid flow in the formation gradually evolves from single-phase seepage of gas to two-phase seepage of gas and water [9]. On the one hand, the water phase flow rate will occupy the gas percolation channel, increase the gas percolation resistance, and reduce the gas flow rate. On the other hand, the decrease in gas flow rate will lead to an increase in water saturation in the near-well zone of the reservoir and an increase in wellbore liquid area fluid, which in turn will lead to an increase in gas well waste pressure and will seal off a large amount of natural gas in the reservoir [10-12]. It can seriously affect the capacity and drainage radius of gas wells, leading to a rapid decline of pressure and production in the bottom well, shortening the production life cycle of gas wells, and even flooding and shutting down the production [13, 14]. In response to the above problems, some researchers have studied the types of water sources, mechanisms and patterns of water production from gas wells [15]. For example, Zhao et al. argued that at the early stage of water production from gas wells, water production can be identified and evaluated based on the change in chlorine concentration and sudden drop in oil pressure [16], but there was a prediction lag in water production prediction due to the complex sampling process and sampling frequency. Chen Fenjun et al, on the other hand, analyzed the water production sources in a gas field during the middle and late stages of extraction, and concluded that gas wells located in low parts are highly prone to produce side water and side water is the main type of water production. In that work, however, there was no discussion on how to reduce the water outflow and improve the extraction efficiency [17]. In Reference [18], the paper proposed a method for gas well liquid gas identification by establishing a physical-mathematical model, and on this basis, the solutions of foam drainage and suction drainage were investigated to improve the gas production efficiency of gas wells. In Reference [19], the author discussed the problem of gas well liquid production in the Sulige gas field, and concluded that different processes with different water control supporting technologies during the construction of single wells can effectively prevent gas well liquid production. In addition, the author discussed gas well water control techniques from multiple perspectives, such as well location well type optimization, array induction logging to identify gas and water formations, physical sinker water control, and gas lift valve assisting in fracture fluid discharge. The results of the above research have reviewed gas well water identification and water control measures, however, most of the results of the above research are based on passive control methods, while active gas well water control methods are less discussed. According to the author's investigation, there are few research results on the series of techniques and methods for real-time water production prediction and monitoring of gas wells in China. For shale gas well water production and control in Sichuan, there are no research results based on active regulation yet, and there are still many problems that need further discussion on how to quickly recognize water production and regulate it in time.

This paper proposes an innovative method and production model of cage type throttle valve water production prediction for the above-mentioned problem of water production from gas wells in Sichuan shale gas extraction. It aims to use the data of pre valve and post valve throttle temperature and pressure to determine whether a gas well is producing water online by combining artificial intelligence data processing methods. The method solves the problem that the surface water counting device cannot transmit the water counting results in a timely manner compared with the existing methods, and the results can be directly transmitted back to the throttle control system by training and classifying the throttle data, so that the throttle opening can be adjusted in a timely manner to reduce the water output of gas wells. The research method proposed in this paper has important engineering significance for guiding the production of shale gas fields in Sichuan, improving the production of gas wells per well, increasing the reservoir development effect, and reducing the development cost.

2. Application of Shale Gas Cage Type Throttle Valve in Sichuan

2.1. Cage Type Throttle Valve Structure

The structure of cage type throttle valve is shown in Figure 1, which mainly consists of valve stem, slide sleeve, cage sleeve, valve seat and valve spool. It achieves the control of pressure and flow rate by sliding the sliding sleeve on the cage sleeve to produce different over-flow areas. The conical valve regulates the flow rate by changing the distance between the movable sleeve and the fixed cone. The wedge gate valve controls the fluid through the gate, which can only perform the fully open and fully closed functions and is difficult to regulate the flow rate, while the cage type throttle valve has multi-porous characteristics, which can precisely control the flow parameters and improve the flow field distribution of shale gas streams. In shale gas extraction, the high-speed gas flow enters the cage sleeve and collides in the middle, causing some energy to be dissipated. The collided fluid portion is throttled to further dissipate energy and reduce pressure before leaving the outlet. The valve body is relatively separated from the gas stream, reducing valve body wear.

In the extraction of shale gas wells, the well pressure can be effectively controlled by controlling the opening of the cage type throttle valve, which in turn controls the gas and water production. As mentioned earlier, the current wellhead water metering data of shale gas wells in Sichuan cannot communicate with the throttle control system, resulting in more water than gas being produced from the actual outlet. This paper proposes to collect data related to the throttle valve, classify it directly, determine the real-time water production of gas wells, and apply the judgment results directly to the throttle valve control system.

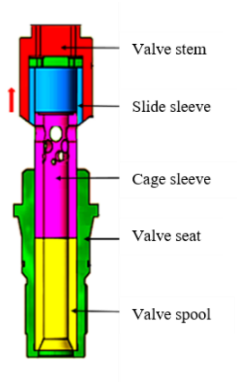
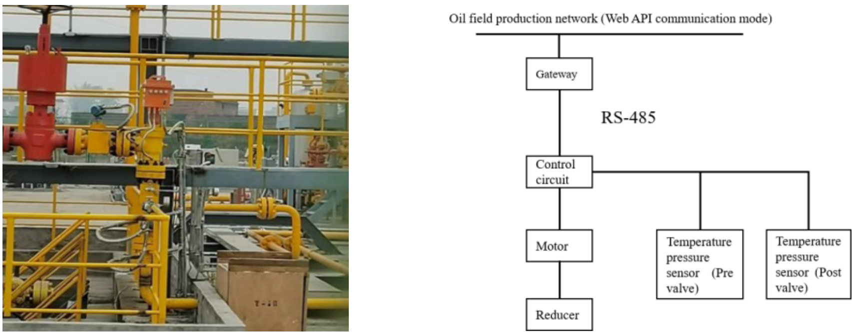


Figure 1. Cage type throttle valve structure sketch.

2.2. Control Logic for Cage Type Throttle Valve

The cage type throttle field work is shown in Figure 2, and the field workflow is shown in Figure 3. The cage type throttle valve is set up with two modes of local control and remote control. The local control will control the target to the cage type throttle controller, and the controller calculates the deviation of the target from the current parameters based on the collected temperature and pressure before and after the valve, further derives the control variable, and then drives the motor to set the valve opening corresponding to the control variable. The remote control method transmits the pre valve and post valve temperature and pressure data collected by the cage type throttle valve to the gateway via RS-485 protocol. Based on the oilfield production network to the oilfield server and the control algorithm on the server, the corresponding control variables and valve opening are calculated, the valve opening is then sent to the cage throttle control circuit through the oilfield production network, and finally the motor is driven to complete the setting of the corresponding opening. As mentioned before, the data before and after the throttle valve is used to directly classify it to determine whether the water is produced or not.



(a) Working diagram of throttle valve on site (b) Electrical schematic of the throttle valve

Figure 2. Working diagram and electrical schematic of cage type throttle valve on site.

The logic of throttle control is shown in Figure 3. When the model training is completed, the field data is tested directly through the model to determine the water production condition. When water is produced, the judgment result is transmitted back to the throttle control system. The well pressure is regulated by adjusting the throttle valve opening, which in turn regulates the water production. If water does not produce, the throttle valve data will continue to be collected for judgment. After adjusting the valve opening, further judgment is needed to determine the water production from the gas well, and if the water production does not improve, then continue to adjust until the water production is within the controllable range. Through the repeated adjustment of the above process, the gas production efficiency of gas wells can be improved.

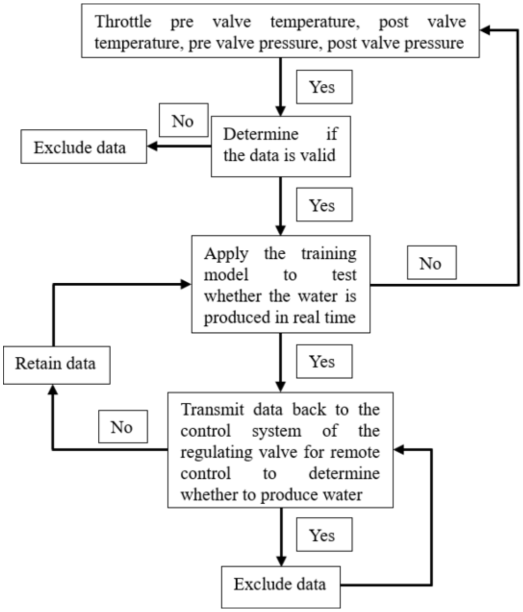


Figure 3. Cage type throttle control logic.

3. Classification Scheme for Cage Type Throttle Water Production Judgment

3.1. Water Production Judgment Logic

The production data-driven throttle water production prediction model investigated in this paper is shown in Figure 4. Firstly, pre valve temperature, post valve temperature, pre valve pressure, and post valve pressure are collected from actual multiple gas wells throttle valves. Next, the collected data are intelligently pre-processed, with the main purpose of eliminating abnormal data in the collection process. Based on this, (n-1) wells data are imported into Matlab for training and the remaining gas well data are used to test the model accuracy. This cycle is repeated, using each well as a test and the remaining well data as training. Finally, the gas production data classification model of each well is obtained and used for the judgment criteria of gas production in actual working conditions.

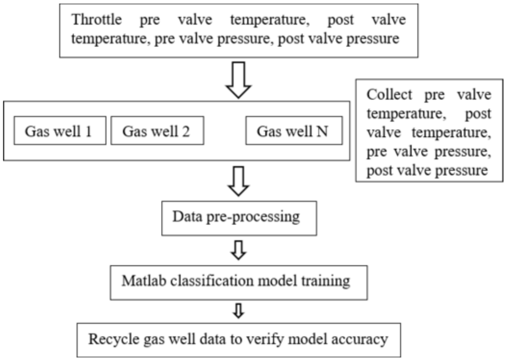


Figure 4. Water production judgment logic diagram.

3.2. Classification Model

The classification model is the classical data mining model. It is a collective name for methods to classify collected data, including algorithms such as decision trees, logistic regression, neural networks, etc. It is mainly divided into two phases, one is the learning phase, which is used to train the classification model, and the other is the prediction phase, which uses the class labels of model prediction type data. Currently classifiers have achieved good applications in business, medical diagnosis, biology, text mining, agriculture, industry, etc., such as accurate determination of target customers and accurate classification of normal and cancerous cells. In this paper, 39 data classification algorithms such as precise tree, linear discrimination, logistic regression, Gaussian naive Bayes, etc. are used for cage type throttle valve water production judgment, and the specific classification algorithms are shown in Table 1.

Table 1. Training method for judging water production from gas wells.

SN	Name	SN	Name	SN	Name	SN	Name
1	Precise tree	11	Optimizable naive bayes	21	Rough KNN	31	Subspace KNN
2	Moderate tree	12	Linear SVM	22	Cosine KNN	32	RUSBoosted tree
3	Rough tree	13	Quadratic SVM	23	Trivial KNN	33	Optimizable set
4	Optimizable tree	14	Trivial SVM	24	Weighted KNN	34	Narrow neural network
5	Linear discrimination	15	Precise gaussian SVM	25	Optimizable KNN	35	Medium neural network
6	Quadratic discrimination	16	Moderate gaussian SVM	26	SVM Kernel	36	Wide neural network
7	Optimizable discrimination	17	Rough gaussian SVM	27	Logistic regression kernel	37	Two-layer Neural Network
8	Logistic regression	18	Optimizable SVM	28	Boosted tree	38	Three-layer Neural Network
9	Gaussian naive bayes	19	Precise KNN	29	Bagged tree	39	Optimizable neural network
10	Kernel naive bayes	20	Moderate KNN	30	Subspace discrimination		

In this paper, the four sets of parameters collected are used as the input of the water production judgment classifier for the large cage type throttle valve. In order to better obtain the accuracy of gas well water production prediction, the above process is cyclically trained and tested through 39 algorithms with the aim of enhancing the credibility and robustness of the training model as much as possible, which in turn provides the regulation basis for the actual throttle remote control.

4. Cage Type Throttle Valve Water Production Forecast Data Analysis

4.1. Cage Type Throttle Valve Water Production Forecast

As mentioned above, due to the limited data that can be collected from the shale gas cage type throttle valve in Sichuan and Chongqing, only the pre and post valve temperature and pressure are available. In this paper, the actual six gas wells field data were collected, the collected data were pre-processed for training and testing, and the throttle valve production data from a single well were used to carry out throttle valve water production judgment model training. Subsequently, the field collected gas production, liquid production, pre valve temperature and pressure, post valve temperature and pressure, and throttle valve opening data were randomly disordered, using 70% as training data and the remaining 30% as validation data through cyclic training and testing. This yields the accuracy for each well under each algorithm, and the training accuracy for Well 2#, for example, is shown in Figure 5.

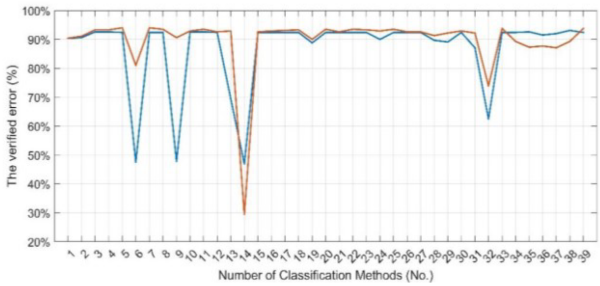


Figure 5. Accuracy when trained by different methods in Well 2#.

The accuracy of each well under different methods can be obtained by the cyclic training method, and the specific results are shown in Table 2. it can be seen that for single-well cage type throttle valve production data, the relative differences in model accuracy between different training methods are small, and the differences in prediction accuracy for different wells by the same method are large. The reason for this is the difference in classification training model algorithms and different sensitivity to data fluctuations, that is, the robustness of each method is different. The difference in throttle spool structure of different wells leads to the different prediction accuracy of classification models. In addition, the accuracy of the field collection data has a large impact on the prediction accuracy, especially the timeliness of the field collection data directly affects the prediction accuracy of the model.

According to the actual training result accuracy, an optimizable KNN classification method is used in this paper. KNN is an instance-based supervised learning algorithm, which can be trained by choosing the appropriate parameter K. And every time when KNN is used for prediction, all the training data are involved in the calculation. In this paper, the cross-validation method is used to get the optimal K value and try to avoid the impact of data value outliers.

Table 2. Prediction accuracy of different training methods for each well.

No.	Method	Well 1#	Well 2#	Well 3#	Well 4#	Well 5#	Well 6#
1	Precise tree	0.877	0.904	0.554	0.706	0.737	0.662
2	Moderate tree	0.884	0.906	0.524	0.733	0.794	0.738
3	Rough tree	0.909	0.926	0.527	0.587	0.842	0.77
4	Optimizable tree	0.913	0.926	0.571	0.589	0.842	0.774
5	Linear discrimination	0.904	0.924	0.562	0.567	0.822	0.765
6	Quadratic discrimination	0.903	0.475	0.456	0.633	0.816	0.762
7	Optimizable discrimination	0.904	0.924	0.565	0.567	0.822	0.765
8	Logistic regression	0.905	0.924	0.539	0.773	0.818	0.764
9	Gaussian naive bayes	0.901	0.478	0.439	0.667	0.818	0.749
10	Kernel naive bayes	0.907	0.926	0.56	0.527	0.806	0.752
11	Optimizable naive bayes	0.913	0.926	0.56	0.527	0.822	0.763
12	Linear SVM	0.905	0.924	0.565	0.771	0.822	0.76
13	Quadratic SVM	0.909	0.694	0.52	0.775	0.816	0.768
14	Trivial SVM	0.892	0.469	0.546	0.43	0.699	0.377
15	Precise Gaussian SVM	0.913	0.924	0.588	0.756	0.82	0.751
16	Moderate gaussian SVM	0.904	0.924	0.565	0.565	0.822	0.767
17	Rough gaussian SVM	0.905	0.924	0.588	0.771	0.822	0.768
18	Optimizable SVM	0.909	0.924	0.578	0.567	0.824	0.77
19	Precise KNN	0.867	0-888	0.535	0.722	0.75	0.657
20	Moderate KNN	0.913	0.924	0.571	0.569	0.826	0.711
21	Rough KNN	0.905	0.924	0.565	0.771	0.822	0.709
22	Cosine KNN	0.907	0.924	0.565	0.585	0.775	0.694
23	Trivial KNN	0.909	0.924	0.59	0.733	0.82	0.711
24	Weighted KNN	0.907	0.9	0.556	0.752	0.814	0.706
25	Optimizable KNN	0.916	0.924	0.609	0.596	0.826	0.763
26	SVM Kernel	0.905	0.924	0.527	0.769	0.814	0.726
27	logistic regression kernel	0.905	0.924	0.569	0.767	0.822	0.736
28	boosted tree	0.888	0.897	0.577	0.746	0.826	0.747
29	bagged tree	0.892	0.891	0.577	0.746	0.794	0.717
30	subspace discrimination	0.909	0.924	0.567	0.567	0.822	0.77
31	Subspace KNN	0.903	0.871	0.533	0.754	0.79	0.768
32	RUSBoosted tree	0.736	0.625	0.546	0.661	0.665	0.651
33	Optimizable set	0.904	0.924	0.594	0.596	0.84	0.774
34	Narrow neural network	0.877	0.924	0.586	0.737	0.816	0.745
35	Medium neural network	0.867	0.926	0.554	0.708	0.725	0.698
36	Wide neural network	0.871	0.915	0.546	0.695	0.725	0.664
37	Two-layer neural network	0.86	0.92	0.573	0.735	0.733	0.732
38	Three-layer neural network	0.844	0．931	0.554	0.558	0.726	0.694
39	Optimizable neural network	0.905	0.924	0.565	0.775	0.814	0.768

4.2. Analysis of Pressure Fluctuations Excluding Produced Water Data

As mentioned before, there are intense fluctuations in the pre and post valve acquisition data in the process of collecting data from shale gas wells in Sichuan. In the actual field data acquisition, the uncertainty interference cannot be avoided, resulting in some abnormal data in the acquisition data, and the data fluctuation has a large impact on the model accuracy, which needs to be pre-processed before the data can be used to train the classification model. In this paper, the impact of fluctuations in the throttle field pressure acquisition data on the prediction accuracy is discussed, the fluctuation data are excluded for six wells respectively, and the standard deviation of the data before and after the exclusion is given.

Figures 6-11 show the results of the throttle pre valve pressure data for the six wells before and after exclusion. There are some serious deviations in the collected data, and the possible reasons for this phenomenon are as follows: (1) The data are collected online, and in the process, there may be random fluctuations due to unknown downhole conditions, such as random fluctuations in the pressure itself; (2) The throttle valve works in a harsh environment, and after a long period of work, random drift occurs due to its own controller or actuator parameters, causing the pressure and temperature to deviate from the group value; (3) The sensor of data collection also has a random fluctuation of data collection after working for a long time, causing some data outlier; (4) The data transmission turns to be abnormal. Due to the unavoidable field interference and uncertainty, there are data anomalies in the acquisition data transmission.

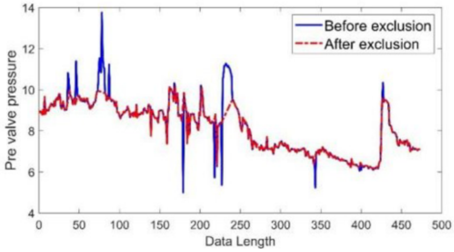


Figure 6. Throttle pre valve pressure fluctuation at Well 1# before and after exclusion.

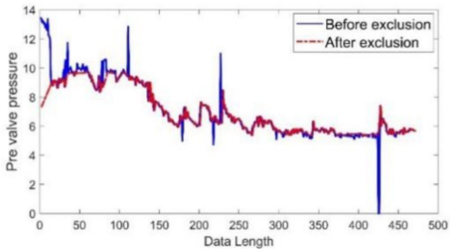


Figure 7. Throttle pre valve pressure fluctuation at Well 2# before and after exclusion.

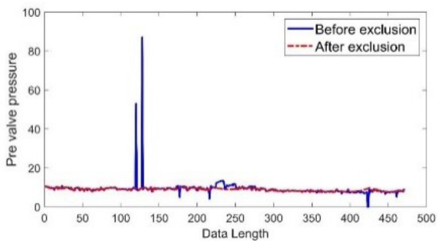


Figure 8. Throttle pre valve pressure fluctuation at Well 3# before and after exclusion.

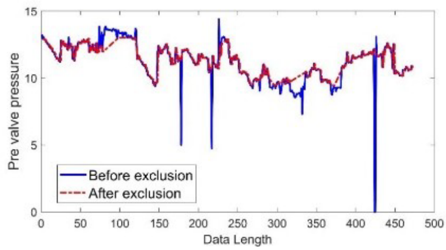


Figure 9. Throttle pre valve pressure fluctuation at Well 4# before and after exclusion.

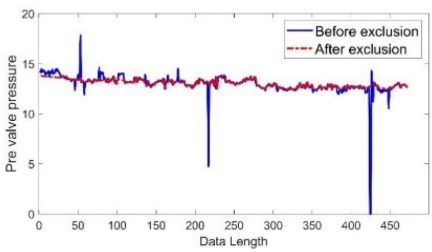


Figure 10. Throttle pre valve pressure fluctuation at Well 5# before and after exclusion.

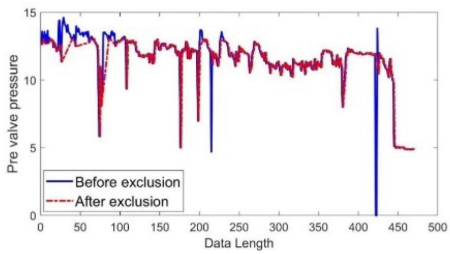


Figure 11. Throttle pre valve pressure fluctuation at Well 6# before and after exclusion.

As mentioned earlier, outlier data is not part of the normal operating data range of the throttle, and its direct use will affect the result of determining whether water is produced, so it needs to be excluded. In this paper, the percentile abnormality detection method is used to determine whether the value is abnormal by calculating the percentile of the data in the data set. By setting the upper and lower thresholds to determine whether the data exceeds the threshold, the data is considered abnormal if it exceeds, and the abnormal data is excluded, while linear interpolation is used to interpolate the data in order to ensure the consistency of the data. By excluding the abnormal data, the training model accuracy can be effectively increased.

On the other hand, it can be seen from Figures 6-11 that some data fluctuations still exist after data exclusion, mainly due to the unavoidable uncertainty of the throttle operating environment itself, and there are non-strong random data fluctuations in the data collected by the sensor, which, according to field experience, are most likely characteristics of the gas well operation itself and cannot be excluded by human factors. Therefore, in this paper, after data exclusion, there are still some data fluctuations. In addition, in order to facilitate the observation of data fluctuations, Table 3 lists the standard deviation of the pre valve pressure before and after data exclusion. From Table 3, it can be seen that the concentration of data can be effectively enhanced by excluding abnormal data, which is also consistent with the actual field acquisition. By processing the data, the accuracy of gas well water production judgment is effectively improved.

Table 3. Standard deviation of throttle pre valve pressure before and after exclusion.

	Well 1#	**Well 2#**	**Well 3#**	**Well 4#**	**Well 5#**	**Well 6#**
Before exclusion	1.3428	1.9695	4.4328	1.5471	1.0968	2.1104
After exclusion	1.0605	1.5324	0.7213	1.0594	0.3836	1.8431

5. Conclusion

This paper proposes a data-based water production prediction model for shale gas wells in Sichuan to address the problem that water production metering and regulating valves cannot communicate in real-time. The model directly collects throttle valve-related data for classification learning and determines the water production of gas wells. The findings of this paper are as follows:

(1) Through the training of the field data collection and collation, the difference in accuracy between different methods for the same well is small, the training results of different wells vary greatly, and the data sample size has an impact on the prediction accuracy.

(2) Single wells are trained through multiple learning algorithm cycles, which can enhance the robustness of the model and eventually enhance the generalization ability of each well's water production prediction.

(3) Fluctuations in the collected data have an impact on the prediction accuracy due to unavoidable disturbance factors in the field conditions. By increasing the sampling frequency of the data, the prediction accuracy of the classification model can be effectively enhanced.

The production data-driven water production classification judgment model for shale gas wells proposed in this paper provides a technical reference for fine pressure control of shale gas cage type throttle valve, a basis for remote control of regulating valve, and a certain reference value for water production judgment and regulating valve control of similar gas wells.

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