

A. Static Samples Construction

Based on the statistical results of the casing damage dataset in Pubei Oilfield, geological and engineering factors affecting casing damage are observed to design static indicators such as lithology, perforation, sand layer, sedimentation, connectivity, and adjacent wells as shown in Table 2.

Table 2. The static factors for Pubei OilField

Factor name	Symbol	Distribution characteristics
Stratum dip	dcqj	The inclination angle is relatively low, with a slightly steeper inclination angle of 5 degree on the west wing, a gentler inclination angle of 3 degree on the east wing, 2 degree at the northern end, and an inclination of less than 1 degree at the southern end extending further.
Occurrence rate of faults	dcsf	About 22% among all wells encountered faults and 24% of casing damage wells encountered faults.
Casing damage rate of adjacent wells	lj	Different fault blocks are distributed in different districts. Taking a certain fault block as an example, the average casing damage ratio is 50% among adjacent wells within 400 meters.
The types of sedimentary facies	cxj	The sedimentary facies where about 65% casing damage point is located are mainly non-sheet sand, main channel and main sheet sand.
Lithology	yxlx	Most casing damage points are Mudstone.
Sand-mudstone interface distance	yxdis	Most of the casing damages are located within 1 meter from the sand-mudstone interface.
Perforation layer	sksf	About 75% casing damage points are in the perforation layer has and about 25% in the non-perforation layer.
Outer diameter	wj	The outer diameter of 90% casings is 140mm, but about 31% of casings with an outer diameter of 114mm experience casing damages.
Wall thickness	bh	The wall thickness of casings is mainly 7.7mm, but about 36% of casings with a wall thickness of 6.4mm suffer from casing damages.
Casing damage frequency	tscs	80% of casing damage wells experience casing damage once, 16% twice, 3.3% three time, and less than 1% four times.
Service life	sysm	First casing damage is 18 years on average;

Lacking of data values is one of the problems often encountered in data analysis. Without high-quality data, there won't be high-quality findings obtained from data. There are three main types of methods for processing missing values: delete tuples, complete data and leave data aside. If the proportion of missing values is small, it can be discarded directly. If it is relatively large, deletion is not advisable for a lot of information will be lost in this way, causing a systematic difference between the incomplete observation data and the complete observation data. Analysis of such data may lead to wrong conclusions. Data completion is usually based on statistical principles, and fills a missing value according to the distribution of values of other objects in the initial dataset, such as average value filling, special value filling, regression replacement, etc. However, the filling of empty values may not be completely in line with objective facts and incorrect filling of null values might make things worse and cause incorrect results to be produced from data. Therefore, to deal with missing values requires detailed analysis of issues with their own uniqueness taken into consideration. Missing values should be derived and filled by using professional methods combined with their practical application scenarios to reduce the gap between machine learning algorithms and practical

applications. In this study, the main reason for a large number of missing static indicators of casing damage is the incompleteness of well-logging curves, which provide the basic data for calculating the physical parameters of the reservoir, for example, the integrity degree of curve AC is only 68%. For the missing data of well-logging curves, regression methods such as support vector machines and neural networks can be employed to establish data models of the acoustic curves so as to obtain estimations of missing data of the logging curve. After processing the missing values, the static samples of casing damage are constructed as shown in the following table 3.

Table 3. Machine learning samples based on static indicators

sysm	tslx	xch	xc hd	fsy hdb	nzsyhdb	ny hdb	sk ks	VSH	...
20	CD	P101	2.6	0.0	0.3	0.7	15	0.5	...
22	CD	P111	2.4	0.3	0.2	0.3	0	0.0	...
2	CD	P111	2.4	0.3	0.2	0.3	0	0.0	...
13	BX	P110	2.6	0.6	0.1	0.3	26	1.4	...
7	CD	P102	6.7	0.1	0.1	0.8	8	0.4	...
0	CD	P102	6.7	0.1	0.1	0.8	8	0.4	...
20	BX	P104	5.2	0.3	0.2	0.5	21	1.3	...
21	BX	P110	4.6	0.3	0.2	0.5	32	2.0	...
9	PL	P104	5.9	0.6	0.2	0.2	61	3.8	...
20	BX	P110	2.6	0.6	0.0	0.4	53	1.1	...
14	CD	P102	7.6	0.3	0.1	0.6	0	2.5	...
18	BX	P109	4.6	0.1	0.5	0.5	31	1.4	...
17	BX	P107	5.7	0.1	0.4	0.5	42	1.7	...
...

B. Casing Damage Type Classification Model

Machine learning provides scientists with a set of tools for discovering new patterns, structures, and relationships in scientific datasets that are difficult to reveal through traditional techniques. The important theoretical basis of machine learning algorithms is classical statistics which is centered around the asymptotic theory when the number of samples approaches infinity. In the process of constructing casing damage prediction model for a single well, the samples used for modeling are often limited after filtering some data of blocks, wells, layers, etc. In particular, after all the influencing factors of casing damage are added, the machine learning faces problems such as small samples and high dimensions when it is adopted to analyze casing damage wells. Nonetheless, neural network algorithms often require more learning samples. When there are fewer samples, there are problems such as local extreme values and over-learning. Support vector machine transforms low-dimensional to high-dimensional through non-linear transformation on the principle of structural risk minimization, and then calculates the hyperplane to classify the data. However, when the dimension is too high, feature selection should be performed to meet the needs of SVM. Random forest is a classifier ensemble learning algorithm that does not rely on any model assumptions. It won't lose its action even in high-dimensional space and can achieve high prediction accuracy under any form of classification and regression. Also it is not prone to overfitting, enables MDA and MDI algorithms to evaluate the importance of features and has many other advantages. This paper mainly uses the random forest algorithm to establish classification and regression prediction models which are helpful in automatically finding

rules and characteristics of layers where casing damages are about to occur from data of casing damage wells and wells without casing damages.

In order to analyze the influencing factors of casing damage at different horizons, a static sample set is constructed with the method described above based on static dataset of casing damage at Pubei Oilfield. Select "Small layer, small layer thickness(LT), siltstone thickness ratio(STR), argillaceous sandstone thickness ratio(ASTR), mudstone thickness ratio(MTR), perforation, perforation intervals, distance from the perforation top-bottom interface(MINPID), VSH, lithology, sand-mudstone interface distance(SMID)" and other indicators as input features, " types of casing damage" as a category label, and then a random forest algorithm is used to establish a recognition model of casing damages at different horizon. The identification results are shown in Table 4, which illustrates the differences of influencing factors in different formations. Take the three small layers of P101, P102, and P103 as examples: the sensitive factor of P101 is the "mudstone thickness ratio", the sensitive factor of P102 is the "sand-mud interface distance", and the sensitive factor of P103 is "small layer thickness".

The confusion matrix for the evaluation of model predictions is shown in Table 5. The average accuracy of casing damage identification models in different horizons is 84.2%. Among them, the prediction accuracy of casing deformation is 82.1%, and the recall accuracy is 95.8%; the prediction accuracy of casing fracture is 88.9%, the recall accuracy is 61.5%; the prediction accuracy of casing breakage/rupture is 100%, and the recall accuracy is 100%.

Table 4. Recognition rules in different layers

Layer Number	Identification Rules
P101	XCH = P101
	MTR > 0.408
	MTR > 0.597
	ASTR > 0.108: CD {BX=0, CD=3, PL=0}
	ASTR ≤ 0.108: BX {BX=7, CD=2, PL=0}
P102	MTR ≤ 0.597: BX {BX=6, CD=0, PL=0}
	MTR ≤ 0.408: CD {BX=0, CD=5, PL=0}
	XCH = P102
	SMID > 0.227
	MINPID > 18.190: CD {BX=0, CD=2, PL=0}
P103	MINPID ≤ 18.190
	MINPID > 1.085: BX {BX=10, CD=0, PL=0}
	MINPID ≤ 1.085
	MINPID > 0.770: CD {BX=0, CD=2, PL=0}
	MINPID ≤ 0.770
P103	STR > 0.004
	STR > 0.148: BX {BX=4, CD=0, PL=0}
	STR ≤ 0.148: PL {BX=1, CD=0, PL=3}
	STR ≤ 0.004: BX {BX=3, CD=1, PL=0}
	SMID ≤ 0.227
P103	ASTR > 0.172: BX {BX=2, CD=2, PL=0}
	ASTR ≤ 0.172: CD {BX=0, CD=6, PL=0}
	XCH = P103
	LT > 6.350
	ASTR > 0.179
P103	SMID > 1.305: CD {BX=1, CD=1, PL=0}
	SMID ≤ 1.305: BX {BX=5, CD=0, PL=0}
	ASTR ≤ 0.179
	LT > 6.700: BX {BX=2, CD=1, PL=0}
	LT ≤ 6.700: CD {BX=0, CD=6, PL=0}
P103	LT ≤ 6.350
	VSH > 0.947: BX {BX=14, CD=0, PL=0}
	VSH ≤ 0.947
	ASTR > 0.135: BX {BX=8, CD=1, PL=0}
	ASTR ≤ 0.135: CD {BX=0, CD=2, PL=0}

Table 5. Confusion matrix of casing damage identification model

	True: BX	True: PL	True: CD	Precision
Prediction: BX	23	0	5	82.14%
Prediction: PL	0	1	0	100%
Prediction: CD	1	0	8	88.89%
Recall	95.83%	100%	61.54%	-

IV. BLOCK CASING DAMAGE RISK ASSESSMENT

In order to evaluate the risk of casing damages in different blocks, the risk rank is evaluated according to the annual newly-added casing damages in blocks, as shown in the following table.

Table 6. Risk ranks of casing damages in blocks

Levels	Casing damage risk level rules
High	Annual rate of newly-added casing damage ≥ 3%
Medium	1% ≤ Annual rate of newly-added casing damage < 3%
Low	Annual rate of newly-added casing damage < 1%

In order to assess risks of block casing damages, dynamic factors are designed. Oilfield development by water injection is a dynamic process. In different periods, due to different development plans, the casing damage rate changes dynamically with time and it is same case with other factors including formation pressure, differential pressure, water injection pressure, days of overpressure water injection, water injection intensity, completion of injection allocation, injection-production ratio, etc. The main indicators for evaluation of block casing damages are the pressure system and the injection-production relationship, including original formation pressure, average formation pressure, total pressure difference, injection-production pressure difference, water injection pressure difference, pressure difference among blocks, and cumulative injection-production ratio. Generally, the statistics of multiple wells in a block are used to represent the data characteristics of a single indicator, including the degree of concentration of data (mean, median, mode), degree of dispersion (standard deviation, coefficient of variation, quartile range), and distribution shape (skewness coefficient and kurtosis coefficient). In this case, one indicator will be split into eight indexes, which is easy to establish high-dimensional small sample data. Therefore, analysis of related row and similarity is performed on dynamic indicators of blocks.

Table 7. The Samples for evaluation of casing damage risks in blocks

NF	JS	DQYL	ZYC	YJLY	ZCYC	LB	...
1994	95	7.959	-2.841	1.954	14.044	medium	...
1995	96	9.571	-1.229	2.69	15.419	low	...
1996	97	9.088	-1.712	2.145	15.421	medium	...
1997	102	9.726	-1.074	2.242	16.226	low	...
1998	109	8.943	-1.857	1.896	16.054	low	...
1999	113	9.803	-0.997	3.015	15.06	low	...
2000	114	9.619	-1.181	2.63	14.689	low	...
2001	114	9.625	-1.175	3.303	14.029	low	...
2002	115	9.76	-1.04	2.393	16.263	low	...
2003	116	10.172	-0.628	3.005	15.092	medium	...
2004	116	10.343	-0.457	2.527	16.016	medium	...
2005	117	11.322	0.522	3.82	14.907	low	...
...

We select the random forest algorithm to establish a risk identification model in blocks, as shown in the figure below. The average accuracy of the model is 80%. It can be seen that the main influencing factor of No.2 fault block of Pubei oilfield is the "water injection pressure difference".

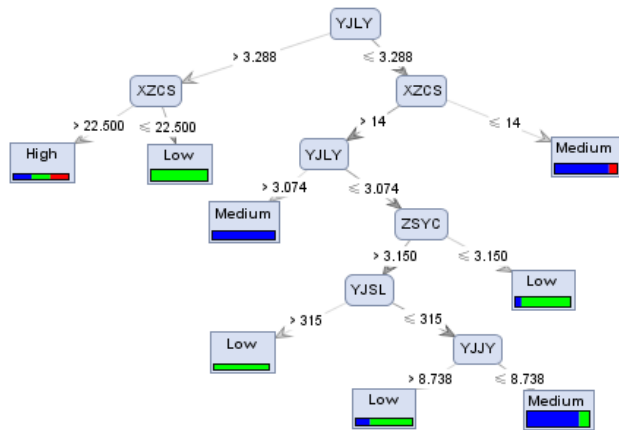


Fig. 3. Decision tree model for risk identification

V. SINGLE WELL CASING DAMAGE PREDICTION

Oil or water wells with casing damages must be correctly judged and repaired in time to ensure the normal production of oilfields. Based on the different characteristics of casing damages shown by different data, this paper adopts machine learning algorithms to mine the key features hidden in them, so as to make single-well casing damage prediction more scientific, accurate and timely.

Sample generation. Extract the production data, measures data, perforation data, hierarchical data, casing damage and other data of the casing damage wells in the 4th fault block in Pubei Oilfield, and select oil pressure, casing pressure, water injection intensity, apparent water injectivity index, maximum allowable pressure difference, mainline pressure, daily water injection amount, monthly water injection amount, annual water injection amount, the number of days in production and other indicators as input features of the algorithm, and whether casing damages occur as the category label. A single well dynamic training sample set is constructed, with a total of 389

records, of which the records of casing damage is 65 and those of normal is 314.

Feature importance analysis. The random forest algorithm supports two methods, MDA and MDI, to effectively evaluate the importance of each feature in the modeling process, so as to determine the combination of features used in the modeling and exclude the effect of too many invalid features on the accuracy of the model. Table 9 shows the results of feature importance analysis of the casing damage prediction model for the injection wells in the fourth fault block in Pubei oilfield, indicating "oil pressure, maximum allowable differential pressure, mainline pressure, and water injection intensity" are the main influencing factors for casing damage of the injection wells in this fault block.

Table 9. The MDA and MDI for the injection well factors

Factors	MeanDecreaseAccuracy	MeanDecreaseGini
oil pressure	33.07	32.17
mainline pressure	32.85	14.68
pressure difference	24.93	28.98
injectivity index	19.38	9.62
casing pressure	14.72	12.24
daily water injection	14.67	5.45
water injection intensity	13.78	5.23
water injection	12.79	5.17
production days	8.23	4.03
yearly water injection	8.09	3.48

Forecasting model. Random forest model is a classifier that uses multiple trees to conduct trainings and make predictions based on samples. Random forests consist of multiple classification and regression trees (CART) with each tree representing a decision tree. Each decision tree model quantitatively represents the rules of different parameters for casing damage identification and early warning.

Model evaluation. The confusion matrix of the early-warning model of single-well casing damages for the fourth fault block in Pubei oilfield is shown in Table 11, with an accuracy rate of approximately 95.6%.

Model application. The random forest model established in the above section is employed to make predictions for the other 18 wells without casing damages in the 4th fault block in Pubei oilfield. The prediction results are shown in Table 10. In order to verify the validity of the model, the operation records of 12 water wells in the first half of 2019 are extracted of which the prediction results of 11 wells are consistent with the operation results, with the coincidence rate about 91%.

The same forecasting method is used to extract the relevant data of the second fault block in Pubei oilfield to establish a prediction model of single-well casing damage for the block and make predictions for and carry out the verification of wells with casing damages in the block, with a coincidence rate about 75%. It can be seen that due to different number of wells and casing damage samples in different blocks, the accuracy and coincidence rates of the model are also different. The follow-up research will focus on the study on casing damage prediction methods based on small samples of blocks.

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Table. 10. The prediction results of the fourth fault block

Well Number	Casing damage prediction probability	Casing damage prediction probability in the last 2 years	Final forecast results	Downhole operation verification
JH715	0.87	0.667	Casing damage	consistent
JH726	0.674	0.905	Casing damage	consistent
JH765	0.091	0.762	Normal	consistent
JH76F5	0.255	0.333	Normal	consistent
JH775	0.6	0.857	Normal	
JH7848	0.617	0.857	Normal	
JH7851	0.186	0.048	Normal	consistent
JH7950	0.723	0.952	Casing damage	inconsistent
JH8053	0.404	0.571	Normal	consistent
JH8052	1	0.952	Casing damage	consistent
JH8153	0.433	0.905	Normal	
JH8250	0.957	0.952	Casing damage	
JH8349	0.467	0.476	Normal	consistent
JH8351	0.352	0.905	Normal	
JH8353	0.623	0.667	Normal	consistent
JH8450	0.596	0.381	Normal	consistent
JH8751	0.023	0	Normal	
JH124	0.537	0.429	Normal	consistent

VI. CONCLUSION

On the basis of the data-driven concept, this paper establishes a set of methods for casing damage identification and prediction, including the construction of a big database of casing damage, dynamic and static sample generation, model construction, and model application. The established prediction model for single-well casing damage has a coincidence rate of 91% and 75% in the fourth and second fault block in Pubei oilfield, respectively, proving that the model has a good application value and provides a scientific basis and a clear direction for following prevention and management of casing damages. Compared with the traditional concept characterized by "reason-based measures, multiple remediation plans", the data-driven concept characterized by "data-driven decision-making, data-based governance" has truly made the automatic data service possible, and pushed the oilfield work model to transform from "digital mode" to "automatic mode" and "intelligent mode". However, petroleum data is a complex geophysical information system that spans a wide range of time and space. Even a simple business analysis involves many aspects of multiple discipline such as geology, exploration, logging, and development. The data quality, data integrity, random noise in data, and imbalance of the data set all pose a great challenge for the construction of machine learning data sets. Data is compared to petroleum in the new era. With the development of data science, a group of professional scientists in petroleum data will be born. Together with other professionals in petroleum, they will draw a grand blueprint for the past and present of petroleum data.

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