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Improving Fault Prediction Precision of New Energy Vehicle Power System Through Adaptive Deep Gaussian Process Model

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Abstract. In the fault prediction of new energy vehicle power systems, the limitations of traditional methods in capturing complex nonlinear relationships have led to low accuracy of fault prediction. Especially when dealing with changes in data distribution caused by changeable working conditions, it is difficult for traditional fixed parameter models to maintain high accuracy. In this paper, a fault prediction method based on the adaptive (DGP) model is constructed. In the data preprocessing stage, the cell voltage and temperature thresholds are set to eliminate abnormal data effectively. The K-nearest neighbor (KNN) algorithm is used to fill the missing values of missing data in the state of charge (SOC) to ensure the completeness and accuracy of the data. A DGP model is constructed, and its unique multi-layer structure is used to deeply refine different abstract features of the input data layer by layer. By combining random variational inference technology, the model parameters are further optimized, reducing the computational complexity and improving the efficiency of processing large-scale fault data. The adaptive gradient descent (AGD) algorithm is applied and integrated with the DGP model to construct the AGD-DGP vehicle fault prediction model. This model can dynamically adjust the learning rate of each layer of model parameters, accelerate the convergence speed, and avoid unreasonable parameter updates. The experimental results show that in 50 experiments, the error rate of the AGD-DGP model continues to be below 2.15%, and the average error rate is 1.32%. The average accuracy rate of the AGD-DGP model for extracting six kinds of fault predictions such as temperature difference failure, battery high temperature failure, insulation failure, and motor failure is 96.25%. The AGD-DGP vehicle fault prediction model constructed in this paper effectively solves the limitations of traditional methods in complex power system fault prediction and achieves high-precision and high-stability fault prediction.

Key words. Deep gaussian process, Adaptive gradient descent, New energy vehicle, Power system fault, Prediction precision

1. Introduction

As global environmental awareness improves, the new energy vehicle industry has developed rapidly [1,2]. With its environmental protection and high efficiency, it has gradually become a new trend in the vehicle industry. However, the complexity of its system has also brought many challenges, especially in fault prediction and diagnosis. Accurately predicting faults is important for preventing safety accidents and improving vehicle safety. Although traditional fault prediction methods have certain effects, their precision and response speed must be improved. Faced with the complex and ever-changing operating environment and the interactions within the power system, traditional methods have limitations. DGP combines the advantages of deep learning and Gaussian process (GP) has powerful nonlinear modeling and uncertainty quantification capabilities, which has achieved remarkable results in many fields [3-5]. DGP constructs nonlinear mapping through multiple hidden layers, captures complex nonlinear relationships, and automatically adjusts the model complexity. DGP performs well when dealing with high-dimensional inputs and small datasets and modeling complex relationships. Applying it to fault prediction of new energy vehicle power systems can precisely model the complex relationships within the power system. Useful features can also be extracted from massive vehicle data to achieve an accurate prediction of faults through DGP.

Vehicle system fault prediction [6-8] refers to the use of monitoring technology and data analysis methods to monitor and analyze the real-time operating status of the vehicle system before problems occur in the vehicle system so as to estimate the possible types and locations of faults. As global efforts to reduce greenhouse gas emissions intensify, Hossain Md Sazzad studied the application of artificial intelligence in predicting and optimizing fault management of new energy vehicles [9]. The vehicle industry is facing new challenges and increasingly fierce competition. Gan Naifeng proposed a double-layer overcharge fault diagnosis strategy for lithium-ion batteries of electric vehicles based on

machine learning, which detected overcharge by comparing the battery voltage and cut-off voltage [10]. Chen Jinzhou proposed an adaptive energy management strategy to improve the economy and reliability of fuel cell vehicles and constructed a variable horizon speed fault prediction method based on principal component analysis and K-means clustering [11]. As vehicle applications become more autonomous, automated fault diagnosis and health monitoring algorithms become necessary. Biddle Liam proposed a novel multi-sensor system for fault detection of multiple faults, which had an efficient computational burden for real-time implementation [12]. Battery fault diagnosis is crucial to ensure the safe and reliable operation of electric vehicles. Li Da proposed a battery fault diagnosis method based on the combination of long short-term memory (LSTM) and recurrent neural networks. By adopting an improved adaptive enhancement method, the accuracy of the fault diagnosis model was improved, and the computing time was reduced, improving the diagnostic reliability [13].

Fault prediction using an adaptive DGP model is a cutting-edge prediction method. This method combines the essence of deep learning and GP. By creating a DGP model with adaptive characteristics, it can flexibly respond to the complexity of various fault modes [14-16]. Wei Zhiyuan proposed a two-phase battery life early prediction method that combined neural network and GP regression to improve the prediction precision of the remaining service life of lithium-ion batteries [17]. Srivastava Adhishree proposed a method to collect the root mean squared values of three-phase voltage and current data during a fault. The collected data was considered as the input of the fault locator module, providing assistance for fault location prediction using DGP and fault identification using a support vector machine (SVM) [18]. Ma Zhipeng proposed an improved DGP analysis method to detect weak faults of rotating machinery through encoder signals. At the same time, a Gaussian mixture model was used to model the spectral density to improve the robustness of GP regression under weak fault conditions [19]. Deep learning methods have been applied in data-driven bearing fault diagnosis. Liang Mingxuan developed a probabilistic fault diagnosis framework that used GP classifiers as a backbone and combined spatial vibration measurement sensors to further improve the performance of fault diagnosis [20]. Traditional AI-based fault detection methods require large amounts of data for model learning. Chen Jianjun proposed a new DGP-based minority learning method for motor fault detection. This method used a deep residual network to extract the features of the raw data and fed the encoded latent feature vector into a GP with kernel transfer capability so that motor faults can be detected and classified [21]. Mansouri Majdi proposed a new random forest technique based on GP regression for fault detection and diagnosis of wind energy conversion systems. A radio frequency classifier was also developed to classify wind energy conversion faults and improve diagnostic capabilities [22].

This paper studies the DGP model by integrating deep learning and GP. This model combines the advantages of deep learning in processing large-scale and high-dimensional data and the advantages of GP in predictive uncertainty assessment and nonlinear modeling. With the help of the DGP model, it is helpful to discover the complex nonlinear correlations within the power system of new energy vehicles. This paper applies the AGD algorithm and constructs the AGD-DGP vehicle fault prediction model. It can flexibly adjust learning strategies and parameters according to real-time data feedback and better adapt to the changes of new energy vehicle power systems under various working conditions and fault modes. This can not only help improve the prediction accuracy of the model but also greatly enhance the generalization ability of the fault prediction model.

The first chapter expounds the research background and significance of new energy vehicle power system failure prediction; the second chapter introduces the model construction and implementation details in detail. The data comes from the national monitoring platform for new energy vehicles. After processing, it is used to build a DGP model. The DGP model introduces a multi-hierarchical structure, combines stochastic variational reasoning technology to optimize parameters, and merges with the adaptive gradient descent algorithm (AGD) to form an AGD-DGP fault prediction model. The third chapter shows the experimental design and result analysis.

2. Construction of New Energy Vehicle Fault Prediction Model

A. Data Collection

The data basis for this study comes from the real-time operation data of new energy vehicles provided by the National Monitoring and Management Platform for NEVS. On the basis of covering the 19 common fault types specified by the national standard, the original data messages of 400 electric vehicles are randomly selected from April 2023 as analysis objects. These data are strictly divided into two categories: vehicle static information and dynamic operation data according to national standards. The static information part mainly includes core data such as vehicle identification code and detailed parameters of energy storage devices. The dynamic operation data covers 60 key features. According to national standards, when a fault occurs, the corresponding item is marked as “1”, and in the normal state it is marked as “0”. After an in-depth analysis of the data of 400 electric vehicles throughout their life cycle, it is found that the types of faults that occur during the operation of different vehicles and their frequency of occurrence are significantly different. Table 1 lists some collected data.

Table 1. Statistics on the frequency of faults of new energy vehicles

Number	Fault name	Number of occurrences	Number	Fault name	Number of occurrences
1	Temperature difference fault	12561	8	Transmission system fault	8671
2	Battery high temperature failure	24156	9	Brake system failure	1168
3	Too high SOC leading to fault	10456	10	Inconsistent battery cell failure	16934
4	Insulation failure	33621	11	High voltage interlocking failure	1239
5	Motor failure	23068	12	Too low SOC leading to fault	15682
6	Inverter fault	16742	13	Voltage instability fault	4263
7	Transmission system fault	16781	14	Charging system fault	9634

In Table 1, there are significant differences in the types and frequencies of faults that occur during driving. Battery high temperature failures occur 24,156 times. Insulation failures reach 33,621 times. These data provide support for understanding and analyzing the fault modes of new energy vehicles.

B. Data Preprocessing

In the real world, data often has problems for various reasons. The actual collected data often encounters missing, erroneous, or noisy situations. These problems are difficult to avoid, so it is crucial to properly preprocess the data before data analysis.

1) Outlier Processing

There are various strategies for processing abnormal battery data. A simple method is to set a threshold for data cleaning [23,24]. In the data cleaning process of this paper, the single cell voltage is limited to between 2V and 5V, and the temperature is in the range of 0 degrees Celsius to 60 degrees Celsius. Abnormal values such as 0 and 65 that appear in the single cell voltage data usually come from errors in the data transmission or reception process. Such data can be deleted directly. When the battery is fully charged and the SOC reaches 100%, if the vehicle remains stationary after a period of standing, the lowest voltage of the single cell may drop, while the highest voltage at the corresponding moment remains unchanged. Such voltage data is regarded as a duplicate value. This paper chooses not to deal with this problem because subsequent studies find that whether to retain this part of the data has no significant impact on the accuracy of the model.

2) Missing Value Processing

There are multiple links in the data transmission and reception process. Due to various reasons, some data may not be recorded, resulting in missing data [25,26]. For feature items with only a small number of missing items, these missing rows can be directly deleted to ensure data integrity. However, for feature items with a large number of missing items, they need to be filled with the help of algorithm models. Taking the key feature SOC of the battery system as an example, due to its importance and frequent missing, this paper chooses to use the KNN algorithm to fill it. KNN is a filling method based on the similarity between samples. It first calculates the distance between the missing sample and other samples to find the K neighbors that are most similar to the missing sample [27-29]. The flowchart of the KNN algorithm is shown in Figure 1.

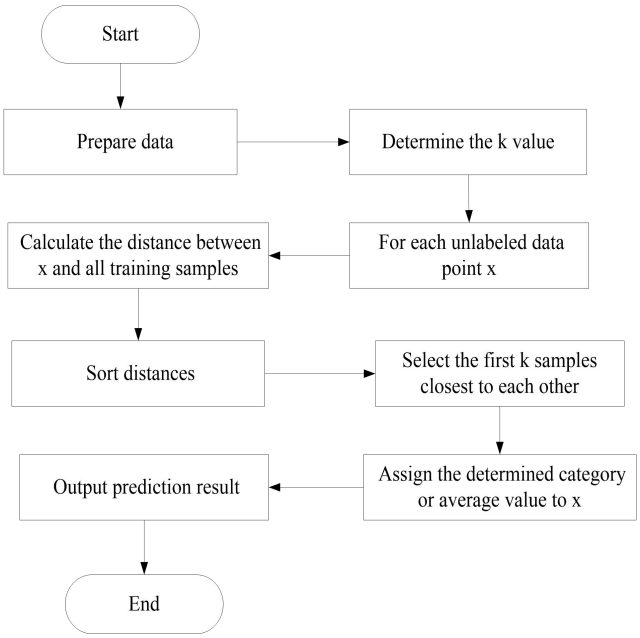

Figure 1. Flow chart of the KNN algorithm.

This paper measures the similarity between samples by calculating the Euclidean distance and other methods. The K samples with the smallest distance are selected, and the mean of their SOC values is taken to fill the missing values.

$$\hat{SOC}_{\text{miss}} = \frac{1}{K}\sum_{j}^{K} SOC_j \quad (1)$$

The filled SOC value is represented by $\hat{SOC}_{miss}$, and SOC_j is the mean of the SOC values taken from the K nearest neighbor samples. Using KNN to fill in the missing values of SOC can not only ensure the integrity of the data but also minimize the deviation during the filling process, thereby providing an accurate data basis for the fault prediction model's subsequent training. Long-term complete data is selected from the data as samples to conduct the experiment. The dynamic feature column is used as input, and the SOC column is used as output. In the experiment, two methods, KNN and regression imputation (RI), are used, and the true value and the predicted value are compared. Figure 2 presents the results.

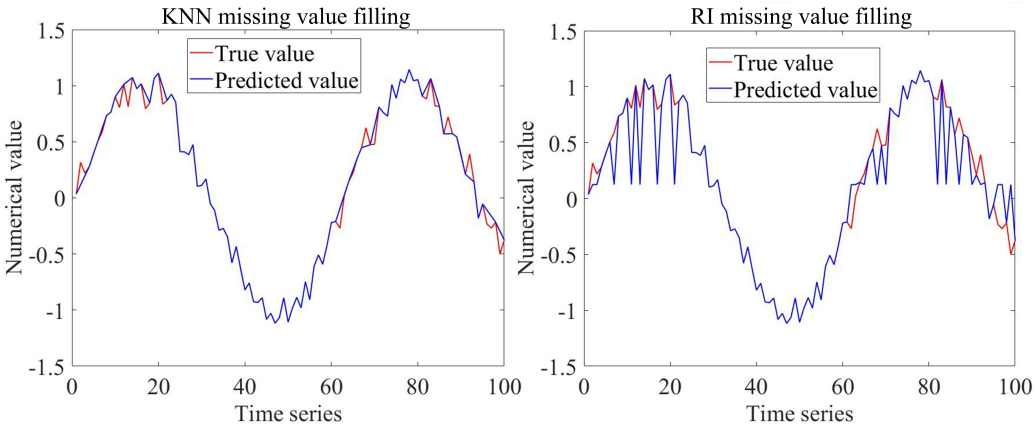

Figure 2. Comparison of missing value filling effects of different methods.

In Figure 2, the red line represents the true value of SOC, and the blue line represents the model's predicted value of SOC. Figures 1A and 1B are the KNN effect diagram and RI effect diagram, respectively. By comparing the results, it can be found that the RI model has a poor prediction effect in local areas, and there is a significant difference between the true value and the predicted value. In contrast, the KNN model has an excellent prediction effect in local areas, and its predicted value is very close to the true value. The specific treated values are shown in Table 2.

Table 2. Comparison of voltage and temperature data before and after KNN algorithm processing

Vehicle_ID	Timestamp	Voltage	Temperature
Initial data			
V001	2023-04-01 00:00	3.75	25
V001	2023-04-01 01:00	3.70	NaN
V001	2023-04-01 02:00	NaN	26
Processed data			
V001	2023-04-01 00:00	3.75	25
V001	2023-04-01 01:00	3.70	25.5
V001	2023-04-01 02:00	3.72	26

3) Data Conversion

In the fault prediction of new energy vehicle power systems, data conversion mainly refers to data standardization, that is, converting raw data into a format suitable for model analysis. In this paper, the focus of data standardization is to adjust the sample data so that it falls in a unified interval, usually from 0 to 1. Standardization is to eliminate the dimension and scale differences between different attributes and prevent certain large-scale features from having too much impact on model training. Minimum-maximum normalization is used for standardization in this study. The data is mapped to the interval of [0,1], reducing data fluctuations and making algorithm optimization smoother. The standardized data can avoid algorithm deviations caused by feature magnitude differences and help the adaptive DGP model converge faster, thus improving fault prediction precision.

4) Data Integration

In the data processing process of vehicle fault prediction, data integration is an important part of preprocessing. The raw data is decoded and cleaned to generate a data matrix containing multiple features. During decoding, the data format of some attributes changes. When a vector [n,1] originally represents a general fault, it may

become a data matrix [n,19] after decoding, with each column corresponding to a different type of fault. According to research and prediction needs, these decoded data attributes are filtered to remove features that are not related to fault prediction. The filtered data is reorganized and combined to form a structured data matrix to provide effective input for subsequent fault prediction models.

The original data matrix is Y_{raw}, so the decoding process can be expressed as:

$$Y_{\text{decoded}} = h\left(Y_{\text{raw}}\right) \quad (2)$$

After decoding, data is screened according to the requirements of fault prediction to select feature items that are closely related to the fault.

$$Y_{\text{filtered}} = M * Y_{\text{decoded}} \quad (3)$$

Among them, M is the selection matrix, and Y_{filtered} is the sorted data matrix. This processed data matrix, as the input of the adaptive DGP model, can significantly improve the model's prediction precision and generalization ability. The setting of the matrix M is based on the results of feature selection, by setting a threshold to determine which features are retained. This screening process ensures that the model can focus more on key features when processing complex data, thus improving prediction performance.

C. Deep Gaussian Process Model Construction

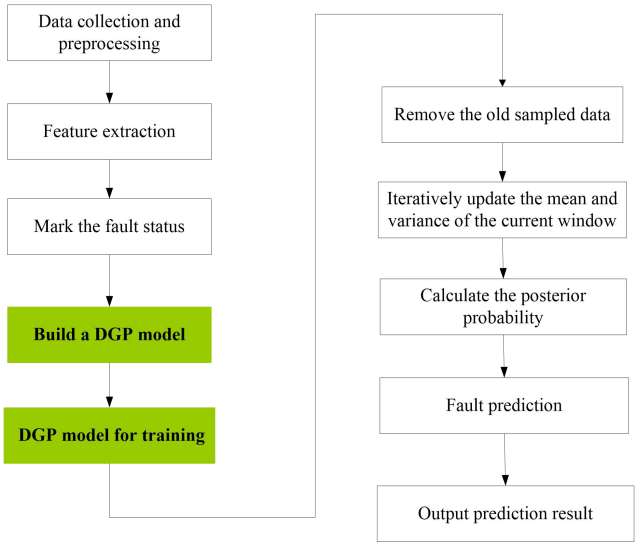

Figure 3. Structure of the fault prediction model for new energy vehicles based on DGP.

In recent years, the problem of fault prediction of new energy vehicle power system has attracted much attention. Traditional prediction methods mostly rely on experience and shallow models. Although they are effective in some simple situations, their prediction precision and stability need to be improved when dealing with complex power systems and changing environments. Deep learning performs well in processing large-scale and high-dimensional data. It has become a key technology for intelligent prediction. GP has significant advantages in small sample learning and regression tasks because it can provide prediction uncertainty assessment and excellent nonlinear modeling capabilities [30-32]. Therefore, integrating the advantages of deep learning and GP to construct an adaptive DGP model can significantly improve the precision and reliability of new energy vehicle fault prediction. Figure 3 shows the structure of the new energy vehicle fault prediction model built based on DGP.

GP is an important type of random process, also known as a normal random process. A random process is a collection of random variables. These variables are not completely independent but have some correlation. Together, they constitute a random system that changes over time. A real-valued random process $\{X_t, t \in T\}$ is a GP if all its finite-dimensional distributions follow a multivariate normal distribution. In other words, for each different value $t_1, \cdots t_k \in T$ chosen, the random vector X is the mean vector $\mu = EX$.

When the covariance matrix is non-singular, the Gaussian probability density function expression of the random vector X can be explicitly given.

$$h_x(x) = (2\pi)^{-n/2} (\det \Sigma)^{-1/2} * \exp\left(-\frac{1}{2}(x-\mu)' \Sigma^{-1} (x-\mu)\right) \quad (4)$$

The mean function and covariance function of the GP are two key factors that determine its characteristics:

$$h(x) \sim N\left(m(x), k(x,x')\right) \quad (5)$$

$h(x)$ is the random variable when inputting x. $m(x)$ is the mean function. $k(x,x')$ represents the covariance function.

GP is a non-parametric Bayesian model. Its feature is that it performs regression analysis by defining the covariance relationship between input variables. Its core advantage is that it can handle complex nonlinear relationships in data and provide good uncertainty estimates. However, when dealing with complex data such as new energy vehicle power systems, the traditional GP model cannot fully capture the multi-layer and multi-dimensional features of the data with its single kernel function. To solve this problem, the DGP model comes into being [33-35]. DGP superimposes multiple GP through a multi-layer structure so that each layer can learn different abstract features of the input data.

Compared with traditional generalized linear models, DGP has a more powerful modeling capability. Especially when dealing with complex high-dimensional data, it can effectively break through the limitations of single-layer models. In fault prediction of new energy vehicle power systems, DGP can capture the complex nonlinear relationship between input features and faults more precisely, improving the accuracy of predictions. In a supervised learning scenario, the standard DGP model training dataset contains observed input $A \in U^{M*Q}$ and observed output $B \in U^{M*P}$, where the number of samples and the dimensions of the input and output vectors are defined. The core objective of the model is to learn a mapping relationship from the input space to the output space. In fault prediction, it means that the possible fault type and severity can be predicted by analyzing the vehicle operation data. The DGP model has a multi-layer structure, and its latent variable set follows a specific recursive relationship. DGP uses a sparse induced input set and an induced variable set. These designs enable the model to maintain efficient computing power when processing large-scale data. In this way, DGP can handle complex nonlinear relationships and maintain efficient operation in a big data environment, providing a powerful tool for fault prediction of new energy vehicle power systems. Figure 4 is a schematic diagram of DGP modeling.

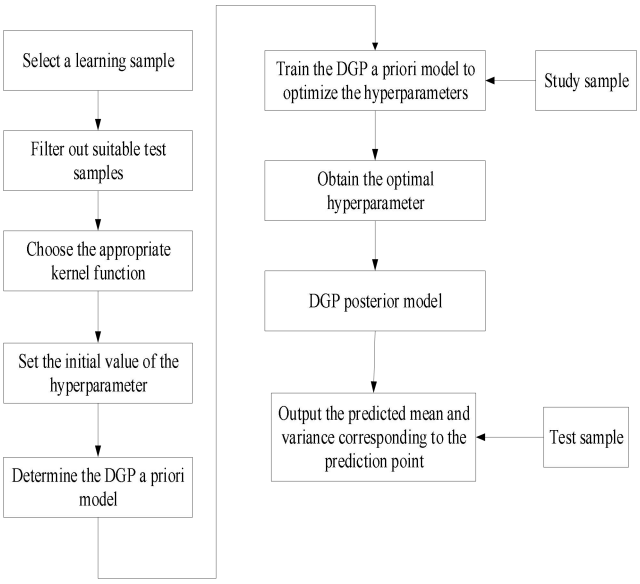

Figure 4. DGP modeling schematic

The recursive relation of the set of latent variables of DGP is:

$$H_k = h_k\left(H_{k-1}, X_k\right) + \theta_k \quad \text{for } k = 1, 2, \cdots, K \quad (6)$$

h_k is the latent variable of the k-th layer. X_k is the induced input. θ_k is the noise term.

In each layer, the covariance function of GP measures the similarity of data. The formula for calculating the covariance matrix is:

$$K\left(A, A'\right) = \sigma^2 \exp\left(-\frac{1}{2}\left(\left(A - A'\right)^T \mathrm{V}^{-1}\left(A - A'\right)\right)\right) \quad (7)$$

A and A' are the input data points, and σ^2 is the variance. The V^{-1} is a matrix, which usually represents the covariance matrix of the input data.

In the setting of regression model, the likelihood distribution of the model is usually assumed to be Gaussian:

$$q\left(A \middle| H_k\right) = N\left(H_k, \sum K + \sum A\right) \quad (8)$$

$\sum A$ is the variance of the observed output sample A.The $q\left(A \middle| H_k\right)$ represents the probability distribution of the output H_k given A. H_k is the predicted value of the model, and $\sum K$ is the covariance matrix of the model.

Due to the deep structure and complex correlation of the DGP model, direct inference of its posterior distribution is insufficient at the computational level. GP uses kernel functions to model the similarity between input data, thereby capturing the nonlinear relationship and uncertainty of the data. However, in the face of multi-layered deep structures, inference not only needs to calculate the posterior distribution of each GP layer but also needs to consider the complex dependencies between layers, further increasing the difficulty of inference. Therefore, approximate inference technology must be used to improve computational efficiency. This paper uses stochastic variational inference (SVI) to solve the problem. SVI uses variational distribution to approximate the true posterior distribution, thereby converting complex inference problems into manageable optimization problems [36,37]. In the DGP model, this method approaches the posterior distribution by raising a lower bound, thereby significantly reducing the computational complexity while maintaining the model performance so that the DGP model can more efficiently cope with large-scale datasets. In vehicle fault prediction, given the high dimensionality and complexity of the data, the model must capture the potential nonlinear relationships and multi-layer dynamic characteristics of the system. The multi-layer structure of DGP can refine features layer by layer and reveal deep patterns in the data. SVI can effectively reduce computational pressure, enabling DGP to process large-scale datasets easily. It plays a key role in the prediction of diversified and complex faults in new energy vehicle power systems.

In the DGP model, the core of SVI is to optimize the model parameters by maximizing a specific lower bound.

This lower bound involves the balance between the model's fit to the data and the complexity of the variational distribution. The expression is:

$$\mathcal{L}(\theta) = E_{p(\theta)}\left[\log q(D,\theta)\right] - E_{p(\theta)}\left[\log p(\theta)\right] \quad (9)$$

θ is the parameter of the model. D is the training data. $p(\theta)$ is the variational distribution.

For a model with a special hierarchical structure such as DGP, it is necessary to approximate the posterior distribution of each layer. If the output of the k-th layer of the model is ak, then the variational inference objective of this layer is to minimize a specific objective function.

$$\mathcal{L}_k = E_{pk(ak)}\left[\log q(ak,\theta k)\right] - E_{pk(ak)}\left[\log pk(ak)\right] \quad (10)$$

θk is the parameter of the k-th layer. $q(ak,\theta k)$ is the likelihood function of the layer. $pk(ak)$ is the variational distribution of the layer.

D. Adaptive Mechanism Application

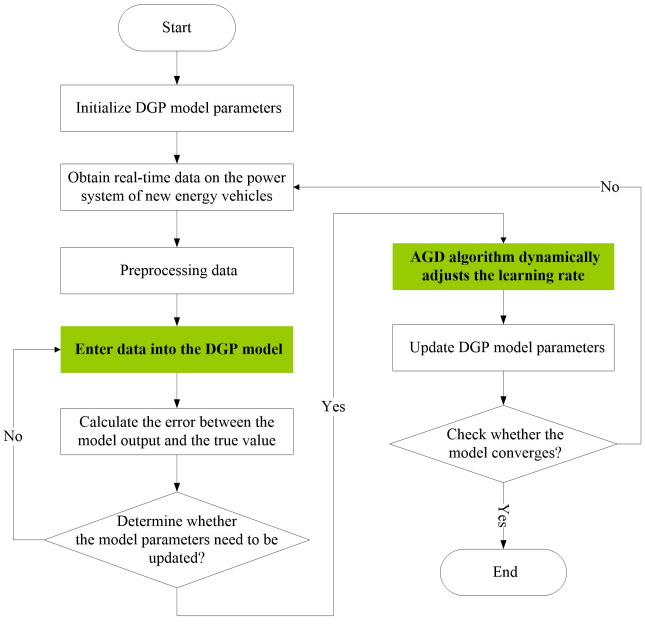

Figure 5. Framework diagram of the vehicle fault prediction model based on AGD-DGP

Faced with massive amounts of data and high-dimensional features, traditional fault prediction methods cannot effectively cope with the complexity and variability of data. As a powerful tool, DGP can establish complex connections between input features and faults on different layers. However, the fixed hyperparameters and lack of adaptability of the DGP model limit its application under variable working conditions. To solve this problem, this paper applies an adaptive mechanism and uses the AGD algorithm to adjust the model parameters in real-time to improve the precision of fault prediction. An AGD-DGP fault prediction model is constructed. The AGD algorithm can intelligently adjust the learning speed of each layer of model parameters, accelerate convergence during training, and avoid unreasonable parameter updates [38-40]. Compared with the traditional gradient descent method, AGD adjusts the learning rate according to the dynamic changes of the gradient, making the parameter update more precise, thereby improving the model's training effect and prediction accuracy. Figure 5 is a framework diagram of the vehicle fault prediction model based on AGD-DGP.

Given the dynamics and complexity of the operating state of the vehicle system, the parameters of the AGD-DGP fault prediction model need to be continuously adjusted to adapt to the changing working conditions. Gradient calculation plays a key role in this, revealing the gap between the model output and the actual results and guiding the parameter adjustment to reduce the error. In DGP research, gradient calculation can help the model move towards the optimal solution. For the AGD-DGP model, gradient calculation not only involves the correlation between input and output but also focuses on the interaction of latent variables in each layer. By evaluating the impact of latent variables in each layer on the error, relevant parameters can be precisely adjusted to achieve efficient optimization. The gradient calculation formula is as follows:

$$\nabla_\theta \mathcal{L}(\theta) = \frac{1}{M}\sum_{i=1}^{M}\frac{\beta}{\beta\theta}\left(\mathcal{L}\left(x_i,\hat{x}_i(\theta)\right)\right) \quad (11)$$

$\mathcal{L}$ is the loss function. θ is the model parameter. $\hat{x}_i(\theta)$ is the predicted value of the model. x_i is the actual observed value. M is the number of samples. AGD responds to different gradient changes by flexibly adjusting the learning rate, making training more efficient and stable. When the gradient changes significantly, AGD increases the learning rate to speed up model convergence. When the gradient changes tend to be flat, AGD reduces the learning rate to allow for more precise parameter fine-tuning. When the gradient is large, the learning rate decreases. This is because the larger gradient indicates that the current parameter position is still far from the optimal solution, and a smaller learning rate is required to avoid oscillation or divergence caused by excessive parameter updates. The gradient is small, and the learning rate is relatively high. A smaller gradient indicates approaching the optimal solution. The larger learning rate can be used for finer parameter adjustments, thereby speeding up the convergence speed. The adaptive learning rate formula is as follows:

$$\mu_t = \frac{\mu_0}{1+\beta\sum_{i=1}^{t}\left\|\nabla\mathcal{L}(\theta_i)\right\|^2} \quad (12)$$

μ_t is the learning rate of the t-th step. μ_0 is the initial

learning rate. β is a constant. $\nabla\mathcal{L}(\theta_i)$ is the gradient of the i-th step.

By adopting AGD, DGP can flexibly adjust learning strategies when facing different input data so as to better adapt to various operating conditions, working conditions, and fault modes. In the power system of new energy vehicles, components such as batteries, motors, and control systems exhibit various fault modes under different working conditions. Traditional static models make it difficult to capture such changes. In contrast, the AGD algorithm can adjust model parameters based on real-time data feedback to ensure high prediction precision under various fault modes.

3. Experimental Analysis of Vehicle Fault Model Effect Evaluation

Key parameters of the AGD-DGP model are shown in Table 3.

Table 3. Key parameters

Serial number	Parameter name	Parameter setting
1	Number of network layers	3
2	Initial learning rate	0.01
3	Learning rate adjustment strategy	Adaptive
4	Number of hidden layer units	[64,32,16]
5	Batch size	32
6	Number of training rounds	100

Changes in the hyperparameters significantly affect the experimental results. In the AGD-DGP model, adjusting the initial learning rate from 0.01 to 0.001 finds that the model convergence is slower, but the final accuracy improves.

In fault prediction tasks, it is important to evaluate the generalization ability of different models. The AGD-DGP model is compared with other latest research models, namely, SVM, deep belief network (DBN), DGP, least squares support vector regression (LSSVR), autoregressive integrated moving average (ARIMA), and LSTM, to prove the performance of the AGD-DGP model in predicting faults in the power system of new energy vehicles. Table 4 lists the specific results.

Table 4. Performance comparison of different vehicle fault prediction models

Algorithm model	Accuracy (%)	Recall (%)	F1 value (%)	Training time (seconds)
SVM	85.64	83.31	84.16	63
DBN	83.73	80.49	82.97	88
DGP	84.26	79.53	81.48	55
LSSVR	89.59	85.69	88.06	120
ARIMA	85.55	81.42	83.38	106
LSTM	88.28	86.69	87.34	154
AGD-DGP	94.13	92.88	93.26	94

In Table 4, the performance of each model is comprehensively evaluated from four aspects: accuracy, recall, F1-score, and training time. SVM and DBN perform generally in the fault prediction of new energy vehicles, with accuracy rates of less than 86% and low recall and F1-scores, showing their limitations in processing complex fault data. Although the DGP model has a short training time of only 55 seconds, its recall is only 79.53%, and its F1-score is only 81.48%. The accuracy of LSSVR and LSTM reaches 89.59% and 88.28%, respectively, indicating that they perform well in fault identification and prediction, but they are still not as good as the model studied in this paper. LSTM has powerful sequence modeling capabilities, but its training time is long, requiring 154 seconds, which limits its value in real-time fault prediction applications. The accuracy of AGD-DGP is 94.13%, and the recall and F1-score are 92.88% and 93.26%, respectively, which are far higher than those of other models. By dynamically adjusting the learning rate of each layer, the AGD algorithm can more effectively capture complex nonlinear relationships in the data and maintain high computational efficiency when processing large-scale data. Due to the use of a fixed learning rate, the traditional DPG model may not be able to adjust the parameters in time to achieve the best state in the face of complex and changeable data distribution, resulting in its accuracy and convergence speed are not as good as the AGD-DGP model. This shows that AGD-DGP can more effectively capture the nonlinear features of data and improve prediction precision with good generalization ability. Although its training time is 94 seconds, it is still acceptable considering its significant performance improvement. In general, AGD-DGP has significant advantages in fault prediction of new energy vehicles, providing support for enhancing the safety and reliability of vehicles.

The loss trend of different algorithms processing the same dataset is simulated to evaluate their convergence speed and stability so as to verify the convergence effect of the AGD-DGP model and to compare the training efficiency of the model with other methods. Figure 6 shows the details.

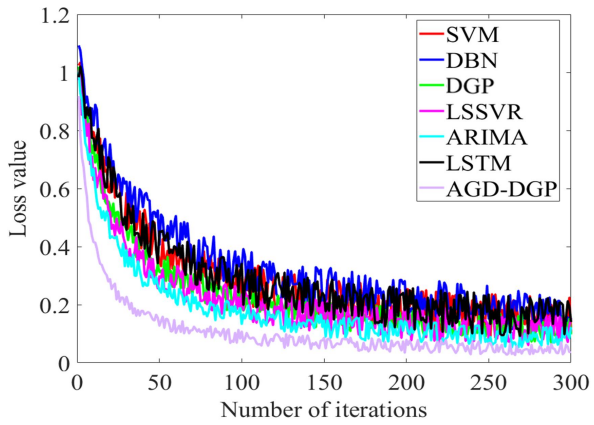

Figure 6. Convergence speed comparison of different algorithms

In Figure 6, the AGD-DGP algorithm has excellent performance in terms of the speed and stability of the loss value during the training process, reflecting the model's excellent convergence performance. At the beginning of the iteration, AGD-DGP shows a clear downward trend. The loss value decreases rapidly and remains stable in subsequent iterations. This fast convergence feature is due to the fact that the AGD-DGP model successfully integrates the advantages of DGP and AGD, enabling it to dynamically adjust the learning speed of model parameters according to actual conditions, effectively avoiding the risk of gradient vanishing or gradient explosion that may occur in traditional optimization techniques. The convergence speed of SVM and DBN is insufficient, and the loss value fluctuates greatly during iterations. The convergence of SVM is greatly affected by its kernel function selection and hyperparameter adjustment. Especially when processing complex high-dimensional nonlinear data, it may be difficult to capture the deep laws in the data, resulting in a slow and unstable reduction of the loss value. In summary, the convergence performance of AGD-DGP during training is significantly better than other algorithms due to its unique model design and optimization strategy.

This paper uses the AGD-DGP model to improve the precision of fault prediction of new energy vehicle power systems, predicts the collected data, and obtains the predicted value. By comparing it with the true value, the error rate can be obtained. The lower the error rate, the better the precision. Multiple experiments are conducted to make the experiment more reasonable, and the experimental results are compared with other methods. Figure 7 presents the specific comparison results.

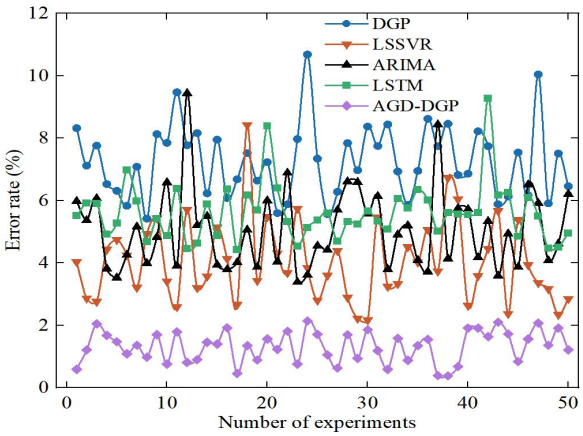

Figure 7. Comparison of vehicle fault prediction error rates using different algorithms

In Figure 7, compared with other methods, the AGD-DGP model performs well in terms of prediction precision. In 50 experiments, the error rate of AGD-DGP is below 2.15%, showing a high level of stability. The error rates of the DGP, LSSVR, ARIMA, and LSTM algorithm models are above 5.41%, above 2.16%, above 3.38%, and above 4.42%, respectively. After 50 experiments, the average error rate of the AGD-DGP model is 1.32%, which is 5.93%, 2.72%, 3.74%, and 4.28% lower than the average error rates of the DGP, LSSVR, ARIMA, and LSTM algorithm models, respectively. This advantage is due to the unique adaptive deep structure of AGD-DGP and the excellent modeling ability of GP, which together achieve high-precision prediction. From the overall trend, the error rate of AGD-DGP does not rise rapidly with the increase in the number of experiments, reflecting that the model has excellent generalization performance and stability. The error rates of DGP and ARIMA fluctuate greatly in some experiments, indicating that they have limitations in processing complex nonlinear data. Through multiple experimental comparisons, the high precision and stability of AGD-DGP in fault prediction of new energy vehicles are fully confirmed. This result is of great significance to the safe operation and fault prediction research of new energy vehicles.

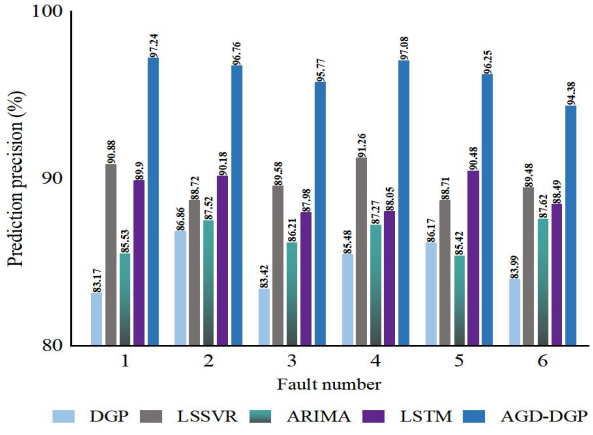

Figure 8. Comparison of vehicle fault prediction precision of different algorithms

Table 1 records the data of different faults, and these faults are numbered in Table 1. This paper selects faults numbered 1-6 for research. By using these data to predict these faults, the prediction precision can be obtained. The experimental results obtained are compared with other methods. Figure 8 presents the specific results.

In Figure 8, for the fault prediction numbered 1, AGD-DGP shows an extremely high prediction precision of 97.24%, which significantly surpasses algorithms such as DGP, LSSVR, ARIMA, and LSTM, indicating the excellent ability of AGD-DGP in processing complex and nonlinear fault data. This paper extracts 6 types of vehicle faults for prediction precision research. The average prediction precision of the AGD-DGP model is 96.25%, which is 11.4%, 6.48%, 9.65%, and 7.07% higher than the average prediction precision of the DGP, LSSVR, ARIMA, and LSTM algorithm models, respectively. The high prediction precision of AGD-DGP is due to its ability to flexibly adjust parameters through an adaptive mechanism to adapt to different fault modes. DGP and ARIMA have limitations in processing complex faults due to their linear assumptions or fixed parameters. Although LSSVR and LSTM have certain nonlinear modeling capabilities, they face problems such as high computational complexity or overfitting, and it is difficult to maintain high precision and stability in all types of faults. Therefore, AGD-DGP not only performs well in single fault prediction but also demonstrates excellent generalization ability in multi-class fault prediction.

The time required for different models to detect and analyze different amounts of fault data is different. Table 5 lists the specific research results.

Table 5. Comparison of vehicle fault prediction analysis time of different algorithms (unit: seconds)

Data volume	DGP	LSSVR	ARIMA	LSTM	AGD-DGP
100	2.5	2	1.8	1.6	1.2
200	4.8	3.5	3.3	2.8	1.8
300	7.2	5.6	4.5	4	2.4
500	12.2	8.5	7.5	6.5	3.5
1000	24.5	17	15.5	12.6	5.5
1500	36	25.5	22.5	18.1	7.5
2000	48.8	34.4	30	24.4	9.2
3000	72.3	51.8	45.6	36.5	12

In Table 5, as the amount of fault data increases, the detection time of all models shows an increasing trend, but when different models process the same amount of data, the detection time is significantly different. When processing 100 data, AGD-DGP only takes 1.2 seconds, which is better than DGP's 2.5 seconds, LSSVR's 2 seconds, ARIMA's 1.8 seconds, and LSTM's 1.6 seconds. When the amount of data increases to 2,000, the detection time of DGP, LSSVR, and ARIMA increases to 48.8 seconds, 34.4 seconds, and 30 seconds. AGD-DGP only takes 9.2 seconds, showing its apparent advantage in big data processing. Due to the complexity of the algorithms of DGP and LSSVR, the detection time increases dramatically when the amount of data increases, which is not conducive to scenarios with high real-time performance requirements. Although LSTM has strong modeling capabilities in theory, its actual detection time is still not as good as AGD-DGP. Especially when the amount of data is large, the time consumption is higher. In the fault prediction of new energy vehicles, AGD-DGP demonstrates excellent computing efficiency. When processing data of different scales, its detection time is significantly shorter than other models, indicating that AGD-DGP can efficiently process big data while maintaining prediction precision.

4. Conclusion

The purpose of this paper is to improve the accuracy of fault prediction of new energy vehicle power system through the AGD-DGP model.By using the DGP model to accurately simulate the complex associations within the power system, combined with the ability of the AGD algorithm to dynamically adjust the learning strategy and parameters, it effectively overcomes the limitations of traditional methods in processing complex data and can flexibly adjust the learning strategy and parameters based on actual data feedback to better adapt to the changes of new energy vehicle power systems under various conditions and failure modes. The AGD-DGP model breaks the limitations of traditional methods, provides a new perspective and technical support for related research, and helps to identify potential problems in a timely manner and take preventive measures to improve the safety and reliability of new energy vehicles. Although the AGD-DGP model performs well in the experiment, its actual application effect still needs to be verified. Secondly, the failure prediction of new energy vehicle power system involves many factors. This research is mainly discussed from the perspective of data modeling. In the future, it is necessary to combine more field knowledge for in-depth research. In general, the AGD-DGP model provides a new and effective tool for fault prediction of new energy vehicle power systems, which helps to detect potential problems in a timely manner and take preventive measures to improve vehicle safety and reliability.

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Consent to Publish

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Data Availability Statement

The data that support the findings of this study are available from the corresponding author, upon reasonable request.

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Author Contribution

Zhaoming Huang: Edited and refined the manuscript with a focus on critical intellectual contributions.

Xuhui Yang: Participated in collecting, assessing, and interpreting the date. Made significant contributions to date interpretation and manuscript preparation.

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Conflicts of Interest

The authors declare that they have no financial conflicts of interest.

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