A Study on the Quantitative Viscosity Detection of Automobile Lubricating Oils Based on Near-infrared Spectroscopy

Xingxing Yang, Zhui Hu, Qiang Xu, Zihao Cai, Xiao Zheng* and Lieqiang Xiong
School of Mechanical Engineering, Wuhan Polytechnic University
*Corresponding Author Email: zhengxiao@whpu.edu.cn

Abstract: A quantitative viscosity prediction of automobile lubricating oils was performed. The near-infrared spectra were preprocessed by using three different techniques, namely, multiple scattering correction (MSC), moving average smoothing (MAS), and Savitzky–Golay smoothing (SG). The characteristic wavelength was extracted by using three different techniques, namely, successive projections algorithm (SPA), synergy interval partial least squares (siPLS), and interval partial least squares (iPLS). The initial data of the viscosity of lubricating oils collected by near-infrared (NIR) spectroscopy were preprocessed by using two different optimization methods, namely, particle swarm optimization (PSO) and genetic algorithm (GA). Finally, the quantitative viscosity detection model of the lubricating oils was built by combining with support vector regression (SVR). The optimal technical route for modeling was explored.

1. Introduction
The viscosity grade of the lubricating oils is determined by the magnitude of viscosity. Lubricating oils are supposed to have a sufficiently high viscosity to reduce the frictional wear of the contact surface between the parts of an operating vehicle's engine[1]. The poor quality of lubricating oils available on the market has been a long-standing problem. The conventional methods to measure viscosity have certain limitations. Therefore, it is an urgent issue to develop a method for fast viscosity detection of the lubricating oils. In the present study, near-infrared spectroscopy (NIR) was combined with different techniques of data processing to establish a quantitative viscosity prediction model. The optimal modeling route was explored to achieve the fast viscosity determination of the lubricating oils.

At present, the common viscosity testing methods for automobile lubricating oils are the falling ball method and capillary tube method. The falling ball method [2] requires only a simple and lightweight testing equipment, which is easy to operate, though the errors may be considerable. The capillary tube method [3] is featured by higher accuracy and lower errors in viscosity determination, but the operation is more difficult and involves complicated washing procedures. Here, the actual magnitude of viscosity in the lubricating oil samples was measured by using the capillary tube method (GB/T 265-88).

2. Experimental

2.1. Experimental Equipment
The experimental equipment used in the present study included the self-developed NIR laser spectrometer[4], electronic balance[5], pipette, and cuvette. The AXSUN-XL410 NIR analyzer was used to acquire the NIR spectra within the wavelength range of 1350–1800nm, the step length being 1 nm. The testing equipment consisted of a thermostatic sample cell, where the temperature was...
controlled within the range of 20~100°C. Cuvettes with three different optical paths, namely, 2 mm, 5 mm and 10 mm, were available for choice for the sample cell during NIR spectroscopy. Here, the cuvette with the optical path of 2 mm was used[6].

### 2.2. Experimental Samples

Seventeen lubricating oil samples of six brands, which had different prices and grades, were purchased from on-line and off-line sources, namely, Castrol, Amsoil, Chevron, Great Wall, Mobil and Shell. Table 1 shows the information and viscosity detection results of the lubricating oil samples.

| Serial No. | Brand                  | Viscosity grade | Kinematic viscosity/(mm²/s, 100°C) |
|------------|------------------------|----------------|-----------------------------------|
| 1          | Castrol Edge           | SAE 5W-30      | 9.876                             |
| 2          | Castrol GTX            | SAE 10W-40     | 14.06                             |
| 3          | Castrol GTX            | SAE 10W-40     | 13.68                             |
| 4          | Castrol Magnatec       | SAE 5W-40      | 13.92                             |
| 5          | Amsoil 112             | SAE 0W-20      | 8.985                             |
| 6          | Amsoil 64              | SAE 0W-20      | 8.471                             |
| 7          | Chevron Havoline       | SAE 5W-40      | 13.87                             |
| 8          | Chevron Havoline       | SAE 5W-30      | 10.28                             |
| 9          | Chevron-Havoline       | SAE 5W-30      | 10.30                             |
| 10         | Great Wall Justar      | SAE 5W-40      | 14.23                             |
| 11         | Great Wall Justar      | SAE 5W-30      | 11.52                             |
| 12         | Great Wall Justar      | SAE 5W-30      | 11.15                             |
| 13         | Mobil 1 Gold           | SAE 0W-40      | 13.12                             |
| 14         | Mobile 1               | SAE 5W-30      | 11.43                             |
| 15         | Mobil Super            | SAE 5W-30      | 10.52                             |
| 16         | Mobil Special          | SAE 15W-40     | 13.74                             |
| 17         | Shell Helix            | SAE 15W-40     | 14.25                             |

### 2.3. Collection of NIR Spectra from the Lubricating Oil Samples

The lubricating oil samples for viscosity detection, totaling 17, were chosen from Table 1. The NIR spectra were acquired for these samples using the NIR laser spectrometer for grease under laboratory settings. A portion of each sample was taken out with a pipette each time for three times in total. For each portion of the sample taken out, the NIR spectra were detected three times, and the average was taken as the model input. Thus a total of 51 groups of NIR spectra were obtained. Fig. 1 shows the original NIR spectra of the lubricating oil samples as output from MATLAB.
2.4. Preprocessing of Spectral Data

When acquiring the NIR spectra of the lubricating oil samples under laboratory settings, environmental noises will lead to interference in the NIR spectra in addition to the useful information. As a result, the problems of spectral overlap, low signal-to-noise ratio, and low information specificity occur, which finally affects the accuracy of the prediction model. Therefore, to increase the prediction accuracy of the model, the spectral data should be preprocessed. The three image preprocessing methods used were multiple scattering correction (MSC)[7], moving average smoothing (MAS)[8], and Savitzky–Golay smoothing (SG)[9]. The characteristic wavelength was extracted by successive projections algorithm (SPA)[10], synergy interval partial least squares (siPLS)[11], and interval partial least squares (iPLS)[12], respectively. The parameter optimizations were done by using particle swarm optimization (PSO) [13] and genetic algorithm (PA)[14], respectively. The original spectral data were input into MATLAB for preprocessing. Fig. 2 shows the spectra preprocessed by MSC, Fig. 3 the spectra preprocessed by MAS, and Fig. 4 the spectra preprocessed by SG.

![Figure 1. Original NIR spectra of the lubricating oil samples as output from MATLAB](image1)

**Figure 1.** Original NIR spectra of the lubricating oil samples as output from MATLAB

![Figure 2. Spectra preprocessed by MSC](image2)

**Figure 2.** Spectra preprocessed by MSC

![Figure 3. Spectra preprocessed by MAS](image3)

**Figure 3.** Spectra preprocessed by MAS

![Figure 4. Spectra preprocessed by SG](image4)

**Figure 4.** Spectra preprocessed by SG
The preprocessed spectra were taken as the inputs for subsequent processing, which consisted of characteristic wavelength extraction and parameter optimization. Finally, SVM was incorporated to build the quantitative viscosity prediction model of lubricating oils.

3. Result and Discussion

3.1. Comparative Analysis of the Models

The combinations of three spectral image preprocessing techniques (MSC, MAS, and SG), three characteristic wavelength extraction techniques (SPA, SiPLS, and iPLS), and two parameter optimization techniques (PSO and GA) led to 18 quantitative viscosity prediction models of the lubricating oils. The model parameters and prediction results are shown in Table 2.

Table 2. Parameters and prediction results of different viscosity prediction models of lubricating oils

| Model               | Parameter (C, g) | Calibration set | Test set | Relative error between the true value and predictive value (%) |
|---------------------|------------------|-----------------|----------|---------------------------------------------------------------|
|                     | C, g             | R(%)            | MSE (10^-4) | R(%)            | MSE (10^-4) |
| MSC-SPA-PSO-SVR     | 1000, 126.14     | 99.659          | 139.040   | 99.9669         | 32.8021     | 0.4361       |
| MSC-SPA-GA-SVR      | 999.10, 93.98    | 98.934          | 416.140   | 98.1366         | 885.6070    | 1.5428       |
| MSC-SiPLS-PSO-SR    | 1000, 17.21      | 99.967          | 13.0164   | 99.9862         | 6.8333      | 0.1812       |
| MSC-SiPLS-GA-SVR    | 5.07, 251.99     | 99.982          | 7.5978    | 99.9868         | 6.2345      | 0.1535       |
| MSC-iPLS-SVR        | 602.33, 34.51    | 58.784          | 15962.3   | 38.8782         | 25085.2     | 10.7717      |
| MSC-iPLS-GA-SVR     | 607.97, 210.69   | 90.468          | 3914.28   | 48.6018         | 25381.1     | 6.4962       |
| MAS-SPA-PSO-SVR     | 28.00, 1000      | 99.990          | 2.5943    | 99.9895         | 7.9405      | 0.1699       |
| MAS-SPA-GA-SVR      | 86.37, 984.34    | 99.998          | 0.9683    | 99.9817         | 9.0467      | 0.1724       |
| MAS-SiPLS-PSO-SR    | 868.23, 196.61   | 99.991          | 0.9914    | 99.9906         | 6.4802      | 0.1900       |
| MAS-SiPLS-GA-SVR    | 180.82, 69.29    | 99.999          | 0.9424    | 99.9926         | 3.2235      | 0.1365       |
| MAS-iPLS-SVR        | 77.32, 1000      | 99.990          | 1.1513    | 99.9836         | 19.3238     | 0.3063       |
| MAS-iPLS-GA-SVR     | 437.51, 976.01   | 99.995          | 1.0048    | 99.9835         | 19.0329     | 0.3023       |
| SG-SPA-PSO-SVR      | 1000, 1000       | 26.788          | 37229.9   | 18.0213         | 51545.0     | 16.7816      |
| SG-SPA-GA-SVR       | 998.51, 995.35   | 26.788          | 37229.2   | 18.0213         | 51509.5     | 16.7777      |
| SG-SiPLS-PSO-SVR    | 1000, 1000       | 53.508          | 23341.6   | 39.8150         | 59376.5     | 15.0311      |
| SG-SiPLS-GA-SVR     | 620.09, 652.10   | 35.256          | 32992.8   | 29.5099         | 68689.5     | 15.8296      |
| SG-iPLS-SVR         | 1000, 1000       | 31.749          | 37165.9   | 34.7809         | 51639.3     | 17.1514      |
| SG-iPLS-GA-SVR      | 999.47, 999.72   | 31.749          | 37170.6   | 34.7809         | 51643.3     | 17.1517      |

It can be seen from the table above that the six prediction models resulting from the use of SG had a slightly lower accuracy. In contrast, among the models resulting from the use of MSC and MAS preprocessing techniques, the coefficients of correlation between the correlation set and test set in all models were above 98% except for MSC-iPLS-PSO-SVR and MSC-iPLS-GA-SVR, which had a lower accuracy. As seen above, SC achieved a less satisfactory result when used to eliminate the interference from the NIR spectra.

3.2. Prediction Performance of the Models

Since all of the ten models in Table 2 had an accuracy above 98%, MSC-SPA-PSO-SVR was
randomly chosen from these models and used as an example to analyze the model prediction effect. Fig. 5 shows the viscosity prediction result on the calibration set using MSC-SPA-PSO-SVR; Fig. 6 shows the viscosity prediction result on the test set using MSC-SPA-PSO-SVR.

It can be seen from Fig. 5-6 that the coefficients of correlation between the calibration set and test set using SC-SPA-PSO-SVR were 0.996529 and 0.999669, respectively.

4. Conclusion
Viscosity prediction of automobile lubricating oils was performed based on NIR spectra, and the SVM model was built for quantitative viscosity detection. The influence of different data processing methods on the prediction performance of the SVR model was studied. The experiments showed that all of the ten models built by using the MSC or MAS spectral preprocessing technique achieved excellent prediction effect, the prediction accuracy being above 98%. Among them, the model built via the route of MAS-SiPLS-PSO-SVR had the best prediction performance. It could be concluded that NIS spectroscopy was a feasible method to predict the viscosity of automobile lubricating oils quantitatively. This method was featured by fastness, convenience, and low cost. Our study provided a new pathway for the fast viscosity detection of lubricating oils.

5. References
[1] Li Jinbang. The development direction of modern lubricating oils from the perspective of economic technology [J]. Lubricating Oil,1989(05):31-34.
[2] Yang Weiwei. A study on the measuring system for kinematic viscosity of the petroleum products [D]. Journal of Northeast Petroleum University, 2015. Li Qin. A study on the fully automated measuring equipment for kinematic viscosity of the petroleum products [J]. Metrology and Measurement Technique, 2017,44(04):24-26.
[3] Li Qin. A study on the fully automated measuring equipment for kinematic viscosity of the petroleum products [J]. Metrology and Measurement Technique, 2017,44(04):24-26.
[4] Zeng Lulu, Tu Bin, Yin Cheng et al. Qualitative and quantitative analysis of peanut oil adulteration by laser Near infrared spectroscopy with SVM [J]. Journal of the Chinese Cereals and Oils Association, 2016, 31(08):126-130+137.
[5] Luo Qingsong. Spectral quantitative detection of acid value and aflatoxin in edible oil and identification of oil species characteristic value [D]. Wuhan Polytechnic University, 2019.
[6] Yu Yaru. Study on detection of adulterated sesame oil and tea seed oil by near infrared spectroscopy [D]. Wuhan Polytechnic University, 2018.
[7] Divo Dharma Silalahi,Habshah Midi,Jayanthi Arasan,Mohd Shafie Mustafa, Jean-Pierre Caliman. Robust generalized multiplicative scatter correction algorithm on pretreatment of near infrared spectral data[J]. Vibrational Spectroscopy,2018,97.
[8] Zhengjun Qiu. Identification of monosodium glutamate by visible and near infrared reflectance spectroscopy[C]. The Chinese Institute of Electronics(CIE).Proceedings of 2006 8th International Conference on Signal Processing(Volume I of IV).The Chinese Institute of Electronics(CIE):IEEE BEIJING SECTION,2006:264-267.

[9] Patchava Krishna Chaitanya,Alrezj Osamah,Benaissa Mohammed,Behairy Hatim. Savitzky-Golay coupled with digital bandpass filtering as a preprocessing technique in the quantitative analysis of glucose from near infrared spectra.[J]. Conference proceedings: Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual Conference,2016,2016.

[10] Chen Bin, Meng Xianglong, Wang Hao. Application of successive projections algorithm in optimizing near infrared spectroscopic calibration model [J]. Journal of Instrumental Analysis, 2007(01):66-69.

[11] Zhenfa Yang,Hang Xiao,Lei Zhang,Dejun Feng,Faye Zhang,Mingshun Jiang,Qingmei Sui,Lei Jia. Fast determination of oxides content in cement raw meal using NIR spectroscopy combined with synergy interval partial least square and different preprocessing methods[J]. Measurement,2020,149.

[12] Zou Xiaobo, Zhu Zeng, Zhao Jiewen. Selection of the efficient wavelength regions in agricultural product NIR spectroscopy based on interval partial least-squares (iPLS) [J]. Modern Scientific Instruments, 2007(01):86-88.

[13] XU Bao-ding,QIN Yu-hua,YANG Ning,GAO Rui,YUAN Cheng-cheng. Study on Feature Selection of Near Infrared Spectra Based on Feature Hierarchical Combining Improved Particle Swarm Optimization[J]. Spectroscopy and Spectral Analysis, 2018,39(03).

[14] Wang Xiang. An overview of the genetic algorithms [C]. Proceeding of Joint Annual Conference of Hebei Software Information Service Industry Association. Hebei Electronics Society, Hebei Radio Association: Hebei Electronics Society, 2007:154-155+163.