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Proceedings of the 22nd International Conference on Industrial Engineering and Engineering Management 2015

Core Theory and Applications of Industrial Engineering (Volume 1)

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Preface

It is my great pleasure to welcome all the delegates come all the way for the 22nd International Conference on Industrial Engineering and Engineering Management 2015 (IEEM 2015). It is their great efforts that bring out the proceedings of IEEM 2015 which records the new research findings and development in the domain of IEEM. What is more excited, they are the experts or scholars with significant achievements in the field. I believe that the proceedings will serve as the guidebook for the potential development in IEEM and play a great role in promoting the IEEM development.

With the ongoing dramatic paradigm shifts of industrial engineering theories and applications, more and more enterprises have realized it is the key to innovate their products by utilizing the advanced technology to enhance their core competitiveness. It is quite imperative to bring professionals form both academia and business together to share their new findings and experience.

IEEM 2015 caters to the purpose by providing a platform to exchange the state-of-the-art research, achievement exhibition, case study, and development in the field of IEEM, as well as promoting its application. The papers selected all center on the main themes of the conference: Industrial Engineering Theory, Industrial Engineering Technology Practice, Information Technology Application and Development, Automation System Theory and Application, Value Engineering, as well as Engineering Management Method and Practice. All the papers included in the proceedings have undergone rigid peer review. We have also invited some prominent experts as our keynote speakers.

The conference is sponsored by Chinese Industrial Engineering Institution, CMES, and organized by Guangdong University of Technology, China. We would like to extend our sincerest thanks to Atlantis Press for their generous support in the compilation of the proceedings. We also would like to extend sincerest thanks to Guangdong University of Technology for holding such an excellent event, and to

all the delegates, keynote speakers, and the staff of the organization committee for their contribution to the success of the conference in various ways.

Thank you very much!

October 2015

Ershi Qi
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Contents

Part I
Industrial Engineering

Modeling and Optimization of Functional Response Based on Kriging Model

Qing-an Cui and Bo He

Abstract In the continuous complex production process, the value of quality characteristics is not only a single observation value, but a continuous response curve existing in a given space, which named functional response. This paper proposed a quality optimization method for functional response. Firstly, it obtained the sample combines with the uniform design method and established a functional response model with the Kriging model. Then, it measured the difference between the objective model and the established model using an integral differential method thus translated the functional response optimization to the single response optimization. And then a relation model of samples and single response was built by Kriging model. Finally, to realize quality optimization, it used the GA method to reach the global optimum. The research on the optimal design of LC filter indicated that, the proposed method overcomes the shortages of the traditional single response optimization and obtained better results.

Keywords Circuit optimization · Functional response · Kriging · Quality optimization

In modern manufacturing, we can get the desired output quality characteristics by controlling and adjusting the appropriate process parameters. Therefore, the process parameter optimization is an important way to realize the improvement of the product quality [1, 2]. In the process of modern industrial production, the value of the response is often a continuous variable, such as contour machining mechanical parts, optimal design of the filter circuit, etc. Traditional single and multiple response studies have been unable to meet the needs of the development of production. Therefore, continuous response theories are proposed. The case of a one-dimensional response variable is known as a 'profile response' [3] or a 'functional response' [4]. The functional response optimization is a method that is

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to select the appropriate level of impact factors, mainly through a series of experiments and to obtain the maximum possible objective function through finding the optimal sequences of factors. Traditional optimization methods are more concentrated in a simple static response, which can only achieve suboptimal results. The optimization results can still be improved. This research on the functional response optimization can compensate for the lack of the above-mentioned optimization and get better optimization results.

Researchers have considered the functional response in the process of quality optimization. An example of the functional response experiment was given by Nair et al. [5] who studied the design of an electric alternator. The response of interest in the experiment was the electric current generated at different rotational speeds at which the alternator operates. This design consisted of 8 controllable factors and 2 noise factors and got the closest target current function by using the Taguchi method. In the modeling, Del and Castillo [6] proposed a full Bayesian two-stage mixed effects regression model to solve the problem of robust parameter design of the functional response. Their method can estimate the probability of a particular function, but it ignores the correlation between functions and may be wrong in setting of the same factor. Alshraideh [7] proposed a spatio-temporal Gaussian random function model which can be more flexible in the modeling of expected function and the correlation between the functions.

Few researches were done on functional response problems in experimental design, modeling and optimization, besides the existing modeling methods of functional response are often a simple first-order or second-order polynomial. The low-order polynomial representation is poor in global representativeness and only effective in solving some simple relationship problems, but will often lead to the problem of inadequate fitting when the process is more complicated. The existing optimization methods are too simple to handle complex problems and get the optimal value, especially those that do not have a specific form.

This paper proposes a quality optimization method for functional response. Firstly, it obtains the samples combines with the uniform design and establishes a functional response model with the Kriging model. Then, it measures the difference between the objective model and the established model by using an integral differential method, thus transforming the functional response optimization to the single response optimization. And then a relation model between samples and single response is built by Kriging model. Finally, to realize quality optimization, it uses the GA method to reach the global optimum. In this research, the response surface method and functional response theory are briefly analyzed and then a specific method of implementation steps is given. The case study on the optimal design of LC filter indicates the effectiveness of this method.

1 Theory Introduction

1.1 Functional Response Optimization

Functional response means an experiment that can generate a continuous, curvilinear response *Y*(*s*) under the influence of the variable *s*. Before the establishment of the functional response model, we need to find the factors affecting the response curve

$$\mathrm{s} = \{x_1, x_2, \ldots x_k\} \tag{1}$$

Traditional single response needs experimental design and statistical analysis to obtain the statistical factor model to the response of the variable *y*,

$$y = f(x_1, x_2, \ldots x_k) + \varepsilon \tag{2}$$

$f(x_1, x_2, \ldots x_k)$ is a determined function and often takes the form of a first-order or second-order polynomial. ε represents the error, which is generally believed as $\varepsilon \sim N(0, \sigma^2)$ and is independently and identically distributed. As for the functional response we need to establish the statistical factor model on the functional response variable *Y*(*s*)

$$Y(s) = G(x) + \varepsilon \tag{3}$$

The purpose of the functional response optimization experiments is to obtain an ideal curve through the finding of optimal factor sequence. The curve should be as close as possible to the ideal target profile *z*(*x*) as required. After the establishment of the functional response model, we should compare it with the desired target curve. Methods commonly used for comparison are the discrete point method and the integral difference method. We use the integration difference method in this paper,

$$d = \int_{x_1}^{x_2} [G(x) - z(x)]^2 dx \tag{4}$$

After we obtain the gap *d* between the functional response model and the target curve, the functional response optimization can be transformed into a traditional single-response, which is the establishment of the model between impact factors and the single-response *d*. After the global optimization, we can get the optimal factor sequence corresponding to the functional response and achieve the purpose of the functional response optimization.

1.2 Kriging Model

Kriging method is an approximate model based on statistical forecasting method in random process which is widely used in mathematics geology. It also has the statistical characteristics of smooth effect and the statistical characteristics of minimum estimation variance and plays an important role in the linear geostatistics [7]. Kriging has a greater advantage in the simulation experiments, including a given input conditions and determined output values, often used in computer-aided design [8]. Matheron puts Krige's achievement into theories and systems, proposed a 'regionalized variable' [8]. Wu et al. [9] applied the Kriging model to the modeling of complex product in multi-stage manufacturing process, aiming to achieve the minimum mass loss under noise distribution and optimize the design level in manufacturing process control variables offline. Tu et al. [10] proposed modeling approach to the characteristics of compressor based on Kriging algorithm. With marine diesel engine as an example, they discussed the impact of the related initial parameters and relevant models for the prediction error [11].

2 Research on Experimental Design, Modeling and Optimization of Functional Response

2.1 Basic Idea

For functional response, establishing an approximation model of effect factor and functional response is one of the key steps to its implementation. The model should be representative and able to address more complex issues. In order to reduce the cost, the samples which model required should be as few as possible. All points in the scope of feasible region may be a fitting model of optimal solutions, but the experiment is unlikely arrangement at each parameter combination, so the choice of the sample must be reasonable, and can be obtained by a certain experimental design method. After establishing the robust model, we should make a global optimization to the established models, and it is very important to choose the right algorithm for global optimization.

2.2 Key Issues

Before constructing the approximation model, we need to obtain sample sets of factors which are representative. Orthogonal design, uniform design and spatial grid are common methods to obtain samples. Uniform design is about experimental points uniformly distributed in the feasible region and factors distributed evenly. These factors are only involved in the experiment once, which abandons the repeated participation of factors of orthogonal design experiment approach. Because the factors are arranged uniformly, and all information of factors can be collected, so the information on factors obtained by uniform design is excessive. This method is particularly suitable for experimental processes whose impact factors are numerous.

The key of quality optimization is to establish the approximation model between quality characteristics and influence factors. Kriging model is an unbiased estimate model whose variance is the minimum. Compared with regression analysis, it can provide a better global forecast. Import the sample set of uniform design to MATLAB, after the determination of model parameters include $f(x)$, nuclear function $r(x)$ forms and parameters, we can establish the relational model between output response and input factors. In recent years, we began using Kriging model as approximate models of complex systems to optimize the system in the aerospace, automotive, IC and CAD development, instead of the response surface model.

After the selection of modeling and samples, we need to consider the measure of the gap between fitting model and target model. Because the research problem is the gap between the two curves, so we use the method to make integral difference in a certain interval. To replace the functional response model with integral difference, and regard it as an ultimate objective, namely, when the minimum of integral difference is achieved, the minimum gap between the fitted model and the target model of the input parameters is also achieved, so we can achieve objective and obtain optimal combinations of parameters. There are several methods to optimize a function or model; we can divide them into two major categories: analytical method and the direct method. We can obtain the exact solution by analytical methods, and we can only obtain approximate solutions by direct method.

2.3 Implementation Steps

From the above analysis, the basic steps are presented here about research on optimization of functional response based on Kriging model, the specific implementation steps as follows:

1. Clear research questions and the objective function to determine the expression $z(x)$.
2. Select the impact factors and achieve ranges of each factor based on the prior knowledge.
3. Get the observed samples using a uniform design or a uniform grid based on Joint Table and normalize the data $S = \{x_1, x_2 .. x_i\}, x \in \mathrm{X}$.
4. Obtain the simulation curves for each group of data samples based on field testing.
5. Use Kriging model to build the simulation curve model, use the second-order polynomial to determine $f(x)$, Gaussian kernel function andθwhose initial value is assumed to be isotropic, and size is 10.

$$\hat{f}(x) = f(x)^T \beta^* + r(x)^T \gamma^* \tag{5}$$

$$r(d_k) = \exp\left(-\theta_k d_k^2\right) \tag{6}$$

$$d_k = \left| x_i^k - x_j^k \right|, \quad (j = i, \ldots, m;\ i = 1, \ldots, n) \tag{7}$$

6. Measure the gap d between the objective model $z(x)$ and the simulation curve model $\hat{f}(x)$ using integral differential method

$$d = \int_{x1}^{x2} \left[\hat{f}(x) - z(x)\right]^2 dx \tag{8}$$

7. Transform the functional response optimization to the single response optimization. And then build the relation model of impact factors and gap d by Kriging model.
8. Use GA to optimize the relation model to get the minimum d_{min} and the relative optimal combination of parameters.

3 Case Study

To demonstrate the effectiveness of the proposed method, we take the LC filter circuit optimization as a case study. Filter circuit is a kind of electronic circuit scan which can make the useful signal go through and filter out the useless signal [12]. In the design of the filter circuit, the filtering performance of the system depends mainly on the parameters' values of circuit element. Previous studies are mainly about single response and static response of the filter circuit, such as fluctuation band, stop-band attenuation characteristics and so on. They can only obtain the suboptimal optimization results. Through the experimental design, modeling and optimization of the functional response, we can optimize the dynamic response of filter circuit to achieve the comprehensive optimization effect, improve the optimal results and get better quality characteristics.

The 2-order type K band-pass filter circuit [13] is composed of inductance L_1, L_2, capacitance C_1, C_2, resistance R and AC voltage $\tilde{V}$ in this case. The design index of circuit should satisfy these conditions (the center frequency 500 kHz, the

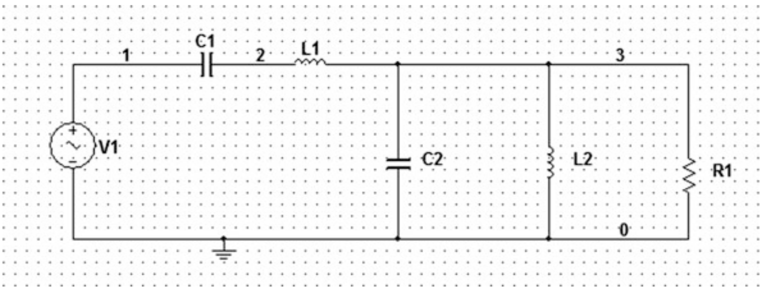
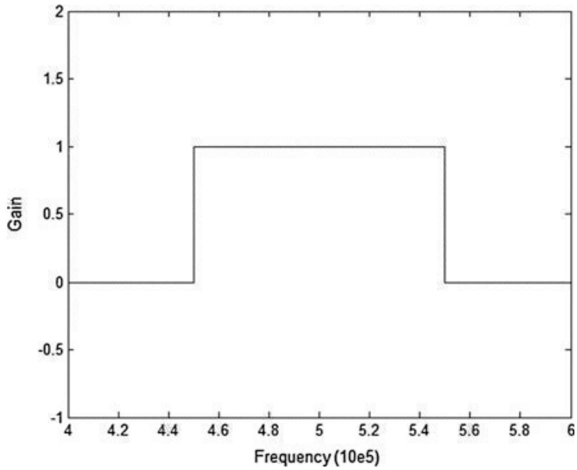


Fig. 1 Two-order type K BPF

Fig. 2 Ideal BPF



bandwidth 100 kHz, band fluctuation, less than 1 dB, the transition bandwidth 80 kHz and the stop-band attenuation greater than 16 dB) (Fig. 1).

The ideal band-pass filter model of the circuit is with the center frequency being 500 kHz, the bandwidth 100 kHz, no fluctuation in the pass band and attenuation tends to infinity (Fig. 2).

In this case, take the resistance R_1 and power supply V_1 as the set value, select C_1, C_2, L_1, L_2 as the influence factor. According to existing knowledge, each value' range of influence factor is shown in Table 1.

3.1 Experimental Design and Modeling

The purpose of parameters optimization of the filter circuit is to make the simulation circuit as close as possible to the ideal target circuit. After normalizing each factor,

Table 1 Range of infleunce factors

	1	2	3	4
Influence factors	C_1/Pf	C_2/pF	L_1/uH	L_2/ uH
Range	96–116	2400–2900	860–1050	34–42

based on Join Table and Uniform Design, we can acquire the observed samples which consist of 64 groups as $S = \{x_1, x_2, x_3, x_4\}$ (Table 2).

For each group sample, Multisim is used to simulate the circuit and obtain the corresponding amplitude-frequency curve. Krining models amplitude-frequency curve and compares it with the target function $z(x)$ when the frequency range is from 400 to 600 kHz. Finally, gap d is received by integral calculus.

Table 2 64 groups of observation samples of influences factors

	x_1	x_2	x_3	x_4
1	115.375	2767.188	931.25	35.5
2	106.625	2696.875	907.5	36.875
3	115.687	2517.188	946.093	41.75
4	107.875	2853.125	1014.375	41
5	101.312	2759.375	916.406	39
6	104.75	2439.063	966.875	38.875
7	111.937	2423.438	925.312	37.25
8	96.625	2540.625	940.156	39.75
9	98.187	2868.75	1041.094	38.625
10	110.062	2564.063	913.437	40.375
11	106.937	2618.75	1050	39.5
12	106	2720.313	895.625	41.25
13	100.687	2837.5	928.281	41.875
14	103.812	2587.5	934.218	34.75
15	105.062	2665.625	922.343	39.875
16	107.562	2493.75	889.687	39.375
17	101.625	2884.375	1011.406	34.875
18	101.937	2571.875	862.968	37.5
19	105.687	2900	943.125	37.375
20	98.812	2704.688	955	40.75
21	111.625	2892.188	960.937	40.5
22	113.812	2735.938	1023.281	40.125
23	99.75	2681.25	963.906	38
24	102.562	2657.813	949.062	35.25
25	112.25	2798.438	1047.031	36.125
26	112.562	2689.063	865.937	38.75

(continued)

Table 2 (continued)

	x_1	x_2	x_3	x_4
27	108.187	2603.125	937.187	38.5
28	115.062	2579.688	1038.125	37.625
29	103.5	2728.125	999.531	37.75
30	109.75	2845.313	910.468	34.25
31	116	2829.688	978.75	38.375
32	114.125	2478.125	892.656	36.5
33	114.75	2634.375	877.812	40.875
34	105.375	2532.813	1026.25	36.75
35	97.562	2821.875	990.625	36.625
36	96.312	2642.188	1020.313	37.125
37	111.312	2610.938	969.843	35.875
38	100.062	2626.563	898.593	36.25
39	112.875	2548.438	1002.5	39.125
40	113.5	2876.563	901.562	39.625
41	109.125	2407.813	1017.344	38.125
42	96.937	2743.75	886.718	34.625
43	108.812	2814.063	952.031	37
44	106.312	2485.938	993.593	35.625
45	104.437	2860.938	874.843	35.75
46	97.875	2454.688	904.531	38.25
47	108.5	2525	871.875	35
48	110.687	2782.813	883.75	37.875
49	99.125	2806.25	868.906	40.25
50	111	2462.5	987.656	41.125
51	114.437	2673.438	1005.469	35.125
52	101	2556.25	981.718	34.125
53	97.25	2595.313	975.781	41.375
54	103.187	2415.625	880.781	41.5
55	100.375	2470.313	1008.438	40
56	104.125	2775	1032.188	41.625
57	113.187	2446.875	957.968	34.5
58	99.437	2431.25	1035.156	35.375
59	107.25	2751.563	972.812	36.375
60	102.25	2509.375	1044.063	40.625
61	102.875	2790.625	984.687	39.25
62	98.5	2501.563	919.375	36
63	109.437	2650	996.562	42
64	110.375	2712.5	1029.219	34.375

$$d = \int_{400k}^{600k} \left[\hat{f}(x) - z(x)\right]^2 dx \tag{9}$$

Transform the functional response into a single response and use software builds a Kriging model between factors C_1, C_2, L_1, L_2 and gap d. Here, the second-order polynomial, Gaussian kernel function and θ whose initial value is assumed to be isotropic, whose size is 10 are combined to determine the $f(x)$.

$$\hat{f}(x) = f(x)^T \beta^* + r(x)^T \gamma^* \tag{10}$$

3.2 Optimization of Functional Response

For optimization, it adopts genetic algorithm. The range of factors is in Table 1. After 63 iterations, the minimum objective gap d is obtained at 48062 and the combinations of optimal parameters are shown in Table 3.

Genetic optimization results of the optimal design (Fig. 3).

3.3 Discussion

The original design is based on the traditional EDA optimization algorithm whose shortcomings are that too many iterations, no convergence or local convergence. These problems, make the result not the best optimal solution within the design space. Hence, this paper proposes functional design optimization based on Kriging model that can solve these problems and achieve better performance. The result of comparing between the original design and optimum design is shown in Fig. 4.

From the above chart, the frequency in the stop-band in the original design is attenuating too slowly. While the proposed not only keeps the original design's advantage of small ripple (less than 1 dB) but also makes transitional zone more stepper (attenuation rate is 2 dB greater than the original design). Over the entire spectral range, the proposed can meet the requirement of the performance indicators. Moreover, the filtering performance is significantly better than that of the original design.

Table 3 Parameters contrast of original design and optimization design

	C_1/pF	C_2/pF	L_1/uH	L_2/uH	Y_{min}
Original design	106.103	2652.582	954.929	38.194	52,073.78
Optimizaton design	100.15	2899.816	1029.446	34.827	48,062.24

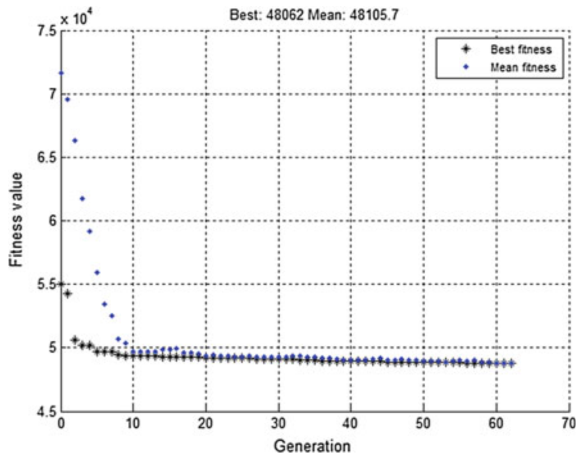


Fig. 3 Genetic optimization diagram

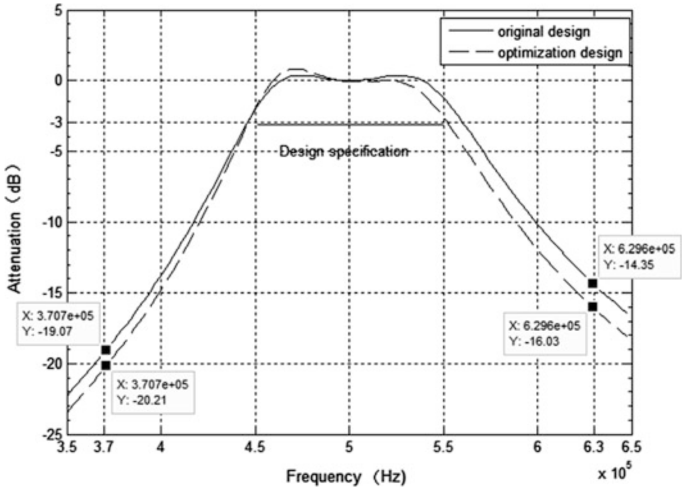


Fig. 4 Comparison between original design and optimum design

4 Conclusion

For parameter design optimization, this paper presents functional response optimization ideas based on Kriging model. It establishes the model between the impact factors and the output factors in Kriging model. Then it obtains the samples by using the uniform design and adopts the GA method to reach the global optimization and realize quality optimization. Compared with the traditional static response optimization, this method can get better optimization results and make up for the shortage of other research in this area. This paper also gives the specific implementation steps of the method. The design and optimization are reasonable and the results of the case study can also demonstrate the practicality and effectiveness of the method in circuit optimization. This paper discusses the basic theory of Kriging Model and conducts system optimization by using GA combined with Kriging model and proves it capable of running in the MATLAB environment.

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Evaluation of Auto Parts Industry Cluster in Jiangxi Province

Hui Chen and You-yuan Wang

Abstract The formation of industrial clusters to strengthen the contact each enterprise in the cluster and reduce transaction cost. Auto parts industry cluster is new power of the development of the auto industry. Industrial cluster competition will effectively promote the development of auto industry. In this paper, combining with the basic theory of industrial cluster, evaluation on the auto parts industry cluster in Jiangxi province by using the geographic concentration index of industrial cluster, then gives some countermeasures.

Keywords Auto parts · Geographic concentration · Industrial cluster

1 Introduction

The formation of industrial cluster will strengthen the relationship all related enterprise, reduce the cooperation between the various costs. Industrial cluster is drive regional growth engine [1]. Industrial cluster is beneficial to form regional innovation system, improve the regional competitive advantage and promote regional economic development [2]. Industrial cluster development pull function on the regional economic growth can be achieved by improving the enterprise's productivity and optimize the allocation of resources.

Chinese auto parts industry cluster in got great development in recent years, however, compared with foreign counterparts, there are big gap. As the demand for cars and car production is growing, also in the rapidly growing demand for auto parts, but the core components depends heavily on foreign imports. According to

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customs statistics, foreign brand market share accounted for about 70 %. Foreign brands are dominant position in the high-end market [3].

Independent components of enterprise manufacturing capacity 90 % were focused on the parts of the low-end products, only 10 % of the enterprises producing high technology content of components in the domestic auto parts market, But the most part this 10 % of high-end, is also the foreign joint venture production [4]. Low technology content and low profit of low-end products for the domestic auto parts industry is hard to get fast development. Most building or have built auto parts industry cluster are in low stage of development, product added value is not high in China [5]. Domestic scholars believe that the evolution of the industrial cluster and the cluster there are inverted u-shaped relationship between [6]. Cluster development is divided into four stages: the early stage, the rapid growth stage, the steady development stage and decline stage.

Automobile industry cluster has developed to a certain period, but, as with other domestic industry, it is difficult to achieve breakthrough in Jiangxi province. Now, analyze the present situation of auto parts industry cluster in Jiangxi province to determine the stage of development, found the problem, and prompt improvement. Making full use of the unique advantages in Jiangxi province, developing the auto parts industry, makes it the power to promote the development of economy in Jiangxi province. It is significant to the revitalization and realize the rise of central of Jiangxi province.

2 Auto Parts Industry Cluster in Jiangxi Province

2.1 The Present Situation of the Auto Parts Industry Cluster in Jiangxi Province

Jiangxi province automobile industry started earlier, it began in the 1950s. Now Jiangxi has grown into the industry cluster area. The Nanchang, Ganzhou, Fuzhou three automobile industry cluster has formed. According to the statistical yearbook analysis in Jiangxi province And after calculation, from 2010 to 2013 the industrial contribution rate are 7.8, 11.4, 12.12 and 17.70 in Jiangxi province automobile industry. Mainly auto parts industry in the rapid development of automobile industry in Jiangxi province, Production of automobile type is more widely, from light, medium to large passenger cars, cars. Automotive market segments have sprung up Quanshun, Lufeng, Changhe and a series of popular models.

In order to take the initiative to adapt to the new normal economic development, in-depth implementation of the five functional areas in Jiangxi province development strategy, based on the new urban development function, firmly seize development does not relax, vigorously promote the new industrialization and urbanization, adhere to the incremental tuning structure, promoting the upgrade with innovation, to speed up cultivating new economic growth point, and strive to create distinctive modern industrial clusters. After long time of development, the center of Nanchang city XiaoLan accessories parts radiation industry cluster has been initially formed in Jiangxi province another local auto parts industry is a pillar industry.

2.2 Jiangxi Province Auto Parts Industry Cluster Identification

In many of the literature in foreign countries, industrial cluster identification is usually based on location quotient. Wang [7] think regional commercial method can pass the location quotient coefficient to judge whether the regional industrial agglomeration. Location quotient is also called specialization rate, its economic meaning is refers to the industry occupies a share of a given area occupies the share ratio of the industry and the economy as a whole.

Location quotient in between 0.85 and 1.15, the industry location quotient of the coefficient is not significant in statistical sense, can be regarded as equal to 1.

$$LQ = (X_{jm} \div X_m) \div (X_{jk} \div X_k) \tag{1}$$

It is the calculation formula of location quotient, this paper USES the production output value to calculate the coefficient of location quotient. On this equation, LQ means Location quotient, X means output value, m said a region, k said a national region, j said the industry, X_{jm} represents the output value of a certain area industry, X_m means one regional output value, X_{jk} means the production value of k national j industry, X_k means k country's total output value.

Identify the auto parts industry cluster in Jiangxi province by location of commercial. To this end, we choose nine auto industry development mature provinces, location quotient coefficient calculated using the formula (1), then compared with Jiangxi province. Refer to obtain 'China statistical yearbook 2014' and the provincial statistical yearbooks data and calculation. The following Table 1

Table 1 Part domestic province automobile industry cluster corfficient of location quotient in 2014 [8]

Number	Region	LQ
1	Beijing	2.431238704
2	Liaoning	1.53467411
3	Shanghai	3.278786355
4	Jiangsu	1.413301243
5	Zhejiang	0.89686092
6	Shandong	1.470377792
7	Hubei	2.944260467
8	Guangdong	1.098215417
9	Chongqing	3.450335155
10	Jiangxi	0.849994927