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Original scientific paper

Optimization of Energy Saving and Consumption Reduction of Polysilicon Siemens Method Based on Improved K-means Algorithm

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Abstract: The core technology of polysilicon production by improved Siemens method is still controlled and monopolized by developed countries. Firstly, it is proposed to improve the algorithm instability caused by the random determination of clustering center of K-means algorithm. The initial clustering center is determined by the method of distance to improve the performance of the algorithm, and it is applied to the energy saving and consumption reduction of polysilicon Siemens method. It can be graded from the quality point of view to ensure the quality of supply. Secondly, the convective heat transfer model in Siemens reactor was established, and the total energy consumption of laboratory-scale Siemens reactor predicted by K-means model was compared with the experimental data in the public literature. The relative errors were all within 1%, indicating that the convective heat transfer model established was effective. At the same time, by adding dichlorodihydrosilane to the feed of the traditional process, it is obtained that at 100 kPa, when the molar ratio of dichlorodisilane, trichlorosilane and hydrogen is 1:1:5, the polysilicon yield is increased by 9.6%, the silicon tetrachlorosilane yield is reduced by 8.7%, and the energy consumption is reduced by 35% compared with the traditional process. Finally, combined with the production practice and other factors unchanged, the ratio of mixture flow rate to silicon rod power is taken as the research object, and the furnace times with different feed and power ratio are compared, and the operation results are analyzed and summarized.

Keywords: energy saving and consumption reduction; improved K-means algorithm; polysilicon; Siemens method

1 INTRODUCTION

With the rapid development of China's industrial economy, the metallurgical and chemical industry also needs to accelerate the pace. As far as polysilicon production is concerned, China's polysilicon industry has the dilemma of total excess capacity and insufficient high-quality production capacity. On the one hand, domestic polysilicon production capacity has accounted for about 40% of the global production capacity; on the other hand, China's polysilicon market demand has always been more than 50% dependent on imports [1, 2]. In order to achieve the goal of becoming the world's polysilicon production power, we cannot be satisfied with the current situation of ranking in the polysilicon country only by production. At present, China's polysilicon production technology is mainly based on improved Siemens process, and the key to the transformation from a polysilicon power to a polysilicon power is to improve the existing improved Siemens process, realize the large-scale sizing of Siemens reactors, the refinement of polysilicon products, focus on breaking through the optimization and integration of large-scale improved Siemens method low-cost polysilicon production technology, and further strengthen the research and development of new technologies. Achieve energy saving and consumption reduction targets [3]. This leads to [4] a series of difficult problems such as lifetime design of key equipment of polycrystalline silicon Siemens reactor and visualization of reaction process in furnace. At the same time, it also presents a challenge for how to establish the mathematical model of the reaction process of Siemens polycrystalline silicon reduction furnace, and apply the theories of computational fluid dynamics [5], numerical heat transfer [6] and chemical reaction engineering [7] to complete the research of digital polycrystalline silicon Siemens reactor.

Therefore, aiming at the complex reaction process of the polycrystalline silicon Siemens reactor, the establishment of the multi-field coupling mathematical model and efficient solution method of the system and the scientific calculation and visualization simulation have practical guiding significance for the efficient operation of the reduction furnace in engineering practice, and make due contributions to the discussion of the application of computational fluid mechanics and numerical heat transfer theory and analysis methods in the field of silicon deposition. The Gibbs reactor in Aspen Plus software is used to simulate and optimize the reaction conditions of the reduction process and the addition of dichlorodihydrosilane in the Siemens process, which provides a theoretical reference for production and has great practical significance to promote the sustainable development of metallurgy and chemical industry. The first part is the introduction, the second part is the related work, the third part is the optimization analysis of energy saving and consumption reduction of polysilicon siemens method with improved k-means algorithm, the fourth part is the improved K-means algorithm for energy saving and consumption reduction optimization of polysilicon siemens method, and the fifth part is similation, Section 6 is conclusion.

2 RELATED WORK

Polysilicon is the main material of solar photovoltaic cells, which is mainly produced by the Siemens method [8]. However, the shortcomings of this process such as high energy consumption, low yield and high material consumption [9] result in high production cost of polysilicon, and the energy consumption accounts for about 60% of the total production energy consumption [10], which seriously affects the commercial application of polysilicon solar cells. Therefore, improving polysilicon yield and reducing energy consumption by optimizing the parameters of trichlorosilane reduction reaction has important theoretical and industrial significance. Using chemical simulation software to improve and optimize process parameters is an effective way to achieve high efficiency and energy saving production. In recent years, most of them focus on the rectification of chlorosilane [11], and the research on the process conditions of trichlorosilane reduction [12] in the polysilicon production process is rarely reported in domestic and foreign literature. Using Gibbs free energy minimization principle, the production of electronic grade polysilicon by SiHCl3 method was simulated, the operating parameters were optimized, and a new process of C12 partial oxidation was proposed, which greatly reduced the energy consumption. The SiHCl3 reduction system was also simulated and analyzed [13], and it was obtained that the equilibrium yield of polysilicon could reach 98% under the optimal conditions. These studies provide theoretical guidance for the optimization and energy saving of the reduction process of Polycrystalline silicon, but the actual production situation, cost and utilization of the by-product Polycrystalline silicon are not fully considered.

The key stage of the improved Siemens process is the chemical vapor deposition (CVD) of purified SCL and hydrogen in a CVD reduction furnace in a bell-jar reactor containing fine, high-purity silicon rods that are electrically heated (direct current or alternating current) to around 1423K. A mixture of high-purity trichlorosilane (TCS) and hydrogen is preheated and fed into a bell-jar reactor, where TCS reacts with hydrogen to produce silicon [14]. The prepared polysilicon is deposited on the silicon rod and the diameter of the silicon rod is gradually increased. When the diameter of the silicon rod has increased to a suitable size, the reactor is stopped and the silicon rod is removed to complete a production cycle [15]. Although the industrial production of polysilicon prepared by Siemens method is very mature, the biggest weakness of the improved Siemens method is high energy consumption and the generation of by-products [16], and high energy consumption and high cost are still the main reasons hindering its development. For this reason, the current technological development trend of Siemens mainly focuses on two aspects: reducing energy consumption and recycling by-products [17-19]. In order to reduce the energy consumption, especially in the reduction process, the following ways are adopted: (1) The use of large multi-pair rod reduction furnace. To increase the output of single furnace, large multi-rod reduction furnaces such as 24 pairs of rods, 36 pairs of rods and even 48 pairs of rods are used. According to the theoretical calculation of the deposition process of different reactors [20], the theoretical radiation energy consumption of different furnace types is given, and the research results show that large-scale reduction furnaces have more advantages in terms of energy saving effect. However, the structure of the reduction furnace is complicated and the operation is difficult. Therefore, it is the key to study the operation technology of large-scale reduction furnace. (2) Increase the reaction pressure and shorten the production time of single furnace. Increase the operating pressure [21], increase the reaction pressure in the reduction furnace to 0.6 MPa, improve the deposition rate of silicon in the reduction process, and shorten the production time of a single furnace. This approach can further reduce the reduction energy consumption, and the development of high-efficiency pressurized reduction furnace system is the development trend of improved Siemens method. (3) Use tail gas heat source to preheat the feed. The exhaust heat source of the reduction furnace is fully used to heat the intake raw material, realize the heating of the feed and the cooling of the exhaust, and thus reduce the energy consumption. With the continuous deepening of research on heat exchange equipment in the reduction process, the mixed air intake raw material has gradually developed from the initial normal temperature mixed feed to the evaporator preheating feed (100 °C), and then to the current tail gas heat source preheating feed (200 °C) [22]. The heat source of the tail gas of the reduction furnace is used to preheat the feed, the heating time of the reaction material in the reduction furnace is shortened, the effective reaction time of the material is increased, and the comprehensive utilization of the waste heat of the tail gas is realized.

At present, there are three main ways of heat transfer in industrial-scale Siemens CVD reactors: convection, conduction and radiation, in which radiant heat loss accounts for 65% - 75% of the total energy consumption of the reduction furnace [23]. Based on the ANSYS CFX numerical simulation platform, the radiation heat transfer in the furnace, the convection heat transfer in the sandwich cooling system [24] and the conduction heat transfer process of each component of the furnace wall were numerically studied. On this basis, the full three-dimensional coupled heat transfer model of the polycrystalline silicon reduction furnace was established. The heat transfer process of 18-rod Siemens polycrystal silicon CVD reduction furnace was analyzed [25], the physical and mathematical model of coupled convection and radiation heat transfer in the reduction furnace was established, the numerical analysis method was used to simulate the heat transfer problem of the coupling under different air intake modes, and the method to reduce heat loss was proposed [26]. Based on the analysis of the heat transfer process of the traditional polycrystalline silicon reduction furnace and the heat transfer model of the existing 12-bar polycrystalline silicon reduction furnace, the arrangement of silicon rods in the traditional polycrystalline silicon reduction furnace is changed, and the traditional ring structure is no longer adopted, but the ring structure is adopted for the outer ring and the vertical structure for the inner ring [27]. The heat transfer analysis model of the coupling of the horizontal push flow and the radiation heat transfer in the furnace is proposed. The results show that the smaller the proportion of the number of the outermost ring silicon rods in the total number of silicon rods, the smaller the radiant heat loss [28]. A laboratory-scale fluid-heat coupling heat transfer model of CVD reduction furnace was established, and the combined heat transfer model was verified through experiments [29]. The results show that heat loss in Siemens CVD reduction furnace is not only radiation heat transfer and convective heat transfer, but also interfluid heat transfer plays a relatively important role in the heat transfer process. In addition, the treatment of Siemens reduction furnace wall and the effect of coating on radiation heat transfer show that reducing the emissivity of the reduction furnace wall from 0.5 to 0.3 through surface treatment or coating can reduce radiation energy consumption by 25% [30]. To sum up, researchers at home and abroad have done a lot of work on the coupled heat transfer of CVD reduction furnace, so as to seek ways to reduce the energy consumption of CVD reduction furnace. There are still some difficulties in the application in enterprises, and how to form knowledge from quality data has attracted more and more attention. Another method of knowledge discovery, data mining, is a method that can automatically find rules from a large number of data. It helps enterprises apply the model of data mining to the quality analysis of polysilicon, enabling enterprise management to discover knowledge and assist its decision-making, to achieve the purpose of improving the quality of polysilicon. According to the data characteristics of polysilicon quality inspection, we select K-means algorithm in cluster mining.

3 OPTIMIZATION ANALYSIS OF ENERGY SAVING AND CONSUMPTION REDUCTION OF POLYSILICON SIEMENS METHOD WITH IMPROVED K-MEANS ALGORITHM

3.1 Research Framework of Energy Saving and Consumption Reduction Optimization Algorithm for Polysilicon Siemens Method

The overall modeling process of polysilicon Siemens method for energy saving and consumption reduction includes the construction of geometric model of polysilicon reduction furnace, grid division, flow heat transfer model, heat radiation model, current heating model, transfer dynamics model, model validity verification, model optimization and post-processing, etc. The general numerical modeling process for the overall CVD process of Siemens reactor is shown in Fig. 1.

As shown in Fig. 1, the improved Siemens method adds a complete exhaust gas recovery system and hydrogenation system, and achieves complete closed-loop production, fully utilizing the exhaust gas components. At the same time, the diameter of the reduction furnace has been increased, the deposition rate of polycrystalline silicon has been improved, the production capacity has been expanded, and the heat loss has been reduced. Compared with the traditional Siemens method for producing polysilicon, the improved Siemens method has significant energy-saving and consumption reduction, lower costs, comprehensive material recovery, and basically no environmental pollution. In addition, the mature process operation safety and high product quality of the improved Siemens itself still account for a huge proportion in polysilicon production technology.

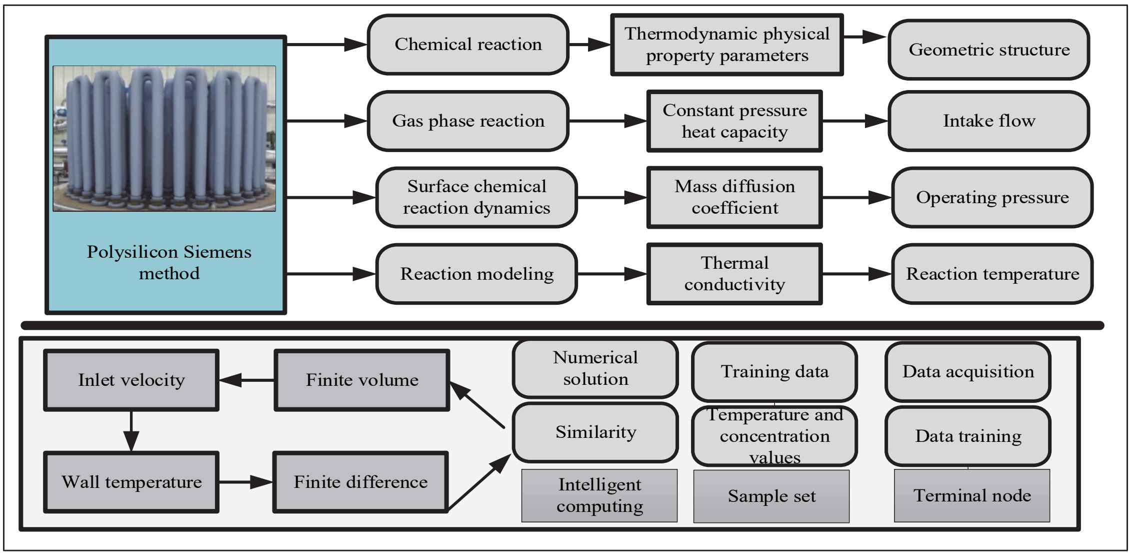

Figure 1 Research framework of energy saving and consumption reduction optimization algorithm for polysilicon Siemens method

Reducing polysilicon production energy consumption, here mainly refers to reducing polysilicon reduction direct power consumption (or reduction power consumption). Taking into account the operating efficiency of the reduction furnace, that is, under the premise of a certain operating cycle, it is necessary to reduce the power consumption per unit of the polysilicon reduction process, and increase the output of the single furnace as far as possible under the condition of a certain growth cycle, or increase the growth weight of polysilicon per unit time, that is, the deposition rate of polysilicon. First of all, through the reasonable design of the heat exchanger, the reduction tail gas and the mixture can fully exchange heat, and then increase the mixture temperature into the furnace, and narrow the step difference between the normal reaction temperature. Secondly, the heat output is reduced to maintain a certain temperature of the furnace wall and chassis. Heat output mainly depends on the reduction furnace and chassis cooling medium (water, thermal oil, etc.); minimize the flow of high temperature water or thermal oil cooling medium, improve the cooling medium outlet temperature, can further reduce electricity consumption, to reduce the effect of polysilicon reduction power consumption. The symbol table in this article is shown in Tab. 1.

Table 1 Symbol definition

Symbol	Definition
CVD	Chemical Vapor Deposition
TCS	Trichlorosilane
SCL	Structured Control Language

3.2 Improved K-means Algorithm

If the results of two consecutive clusters do not change, it is to achieve the convergence of the clustering criterion function of the end condition. The K-means algorithm enters the next iteration. If in the next iteration, all the data objects are classified correctly, all the clustering centers will remain the same without any changes.

(1) Given a sample set x to be divided, and determined by the user to divide the data object into n clusters.

(2) Select k objects randomly from the sample, and c is the initial center of the cluster.

(3) Calculate the distance D from these initial centers for all data objects that are not cluster centers, where the value of i is taken from 1 to n and the value of j is taken from 1 to k.

(4) Calculate the center c of the new cluster as the new clustering center of the cluster according to the divided points, and the calculation formula is as follows:

$$c_j = \frac{1}{n_j} \sum_{x_i} x_i \quad (1)$$

(5) The objective evaluation function is calculated as:

$$D = \sum_{i=1}^{n} \sum_{j=1}^{k} \omega_{ij} d_{ij} \quad (2)$$

(6) Judging that the current center point is the final center point, there is no change in the division, and the algorithm can end. Otherwise, return (3) to continue.

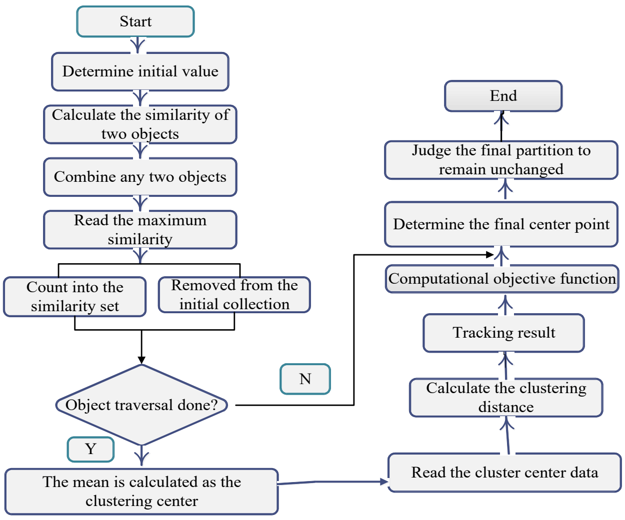

Figure 2 Flowchart of the improved algorithm to determine the clustering center

Table 2 Improved algorithm for determining cluster center

(1) Determine the initial value K, and the field value of how many objects a cluster has; (2) Any pair of groups, calculate the distance between the two pairs and select the two objects with the smallest distance and merge them into Ai, and delete these two objects in X; (3) Calculate the similarity between the two objects with the smallest distance and other objects, select the object with the highest similarity to the two objects and combine it with Ai, and delete the object in X; (4) Determine whether the number of objects in Ai is greater than the domain value; if it is less than the domain value, go to (3); (5) Calculate the mean of the objects in Ai as the center of the initial clustering; (6) Determine whether i is less than K, if so, go to (2) otherwise the end.

The similarity in the same cluster is very high, while the similarity between clusters becomes low. If the similarity is expressed by distance, the similarity of the same cluster is much higher than that of a non-cluster, the distance between objects in the same cluster is much smaller than the distance between different clusters. We can use distance to determine the initial cluster center. The flow chart of the improved K-means algorithm is shown in Fig. 2. The algorithm is described in Tab. 2.

1) From the whole sample X, let I = 1, and randomly select K data objects in X as the initial clustering center m_j, where j = 1, 2, ..., K.

2) Let $d(i, j)$ be the distance between K clustering centers m_j, and each object X in the power load big data sample x, that is:

$$d(i,j) = (x_{i1} - m_{j1})^2 + (x_{i2} - m_{j2})^2 + \ldots + (x_{ik} - m_{jk})^2 \quad (3)$$

3) $m_j(i + 1)$ is set as the center point of the new cluster:

$$m_j(i+1) = \frac{1}{M_j} \sum_{j} x_i \quad (4)$$

where m_j is the number of data objects in the JTH class.

4) Set the criteria to determine whether the criteria are met. If yes, proceed to the next step. If no, go to Step 2.

5) The clustering dispersion function is:

$$F(i) = \sum_{x_i \in s_j} (x_i - m_j(i))^2 \quad (5)$$

3.3 Analysis of Energy Saving and Consumption Reduction Ratio of Polysilicon Siemens Method and Establishment of Radiation Model

Through the correlation between the furnace feed and the silicon rod power, the reduction power consumption at different ratios of the two is obtained, as shown in Fig. 3. It can be seen from the above trend line that when the ratio of feed to power of the reduction furnace increases from 0.2 to 0.8, the reduction power consumption changes in a parabolic trend, that is, it decreases rapidly at first and then rises gradually after reaching the lowest point, indicating that different feed ratios have a greater impact on the reduction power consumption. When the ratio is small, the feed amount of the reduction furnace is small, and the growth rate of silicon rods is slow, resulting in high power consumption.

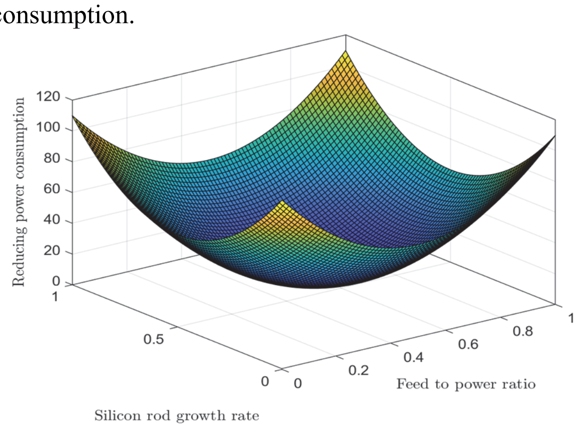

Figure 3 Reduction power consumption trend chart at different feed to power ratio

When the ratio is large, the feed amount of the reduction furnace increases, and the growth rate of silicon rods is accelerated. Therefore, only by selecting the appropriate ratio of feed and power can the power consumption of the reduction furnace be ensured at the best level.

According to the above method, the primary conversion of the reduction furnace under different feed to power ratio is obtained, as shown in Fig. 4

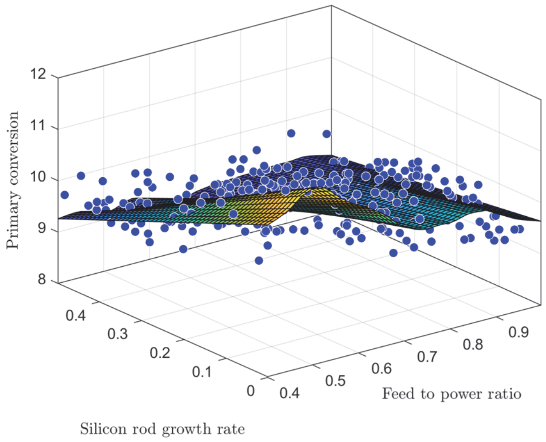

Figure 4 Primary reduction rate of reduction furnace at different feed to power ratio

As can be seen from the above curve, when the ratio of feed to power in the reduction furnace is increased from 0.4 to 0.9, the primary conversion rate has been declining. This is because the ratio is small, the feed in the reduction furnace is less, and the materials available for reaction are relatively small, and the materials entering the reduction furnace can effectively participate in the reaction, so the primary conversion rate is high. When the ratio is large, there is more feed in the reduction furnace, and a considerable part of the material passed into the reduction furnace has been taken out without participating in the reaction, so the primary conversion rate is low.

It can be seen from the above data analysis that there are certain contradictions between the two indicators of polysilicon reduction power consumption and primary conversion rate in actual production, so different enterprises need to choose the appropriate ratio of feed and power according to their own characteristics to ensure that the production can reach the best balance point.

The angular coefficient is defined as the percentage of radiant energy emitted by one surface i that falls on another surface j. For two finite size areas, the Angle coefficient of the microplane d_{a1} to d_{a2} is:

$$F_{d1,d2} = \frac{\cos d_{\alpha_1} \cdot \cos d_{\alpha_2}}{d^2{}_{\alpha_1} \cdot d^2{}_{\alpha_2}} \tag{6}$$

In a Siemens reactor, the radiation leaving a surface k consists of its own radiation and the reflection of the incident radiation. Among them, the reflection part depends on the incident radiation of the surrounding object, and this part of the incident radiation can be expressed as the radiative heat flow p emitted by the rest of the surface. For a surface k, the total radiant heat flow is:

$$J_k = \varepsilon_k d_k + \rho_k m_k \tag{7}$$

For N surfaces, the reciprocal (relativity) relation of the Angle coefficient is:

$$F_{jk} = \alpha_1 F_{kj} \tag{8}$$

The relevant parameters used in the simulation calculation are shown in Tab. 3.

Table 3 Parameter used in the simulation

Parameter	Val ue
Rod radius R	8 cm
Reactor wal 1 radius Rw	82 cm
Rod length L	1.5 m
Rod surface temperature	1376 k
Wall surface temperature TW	375 k
Rod emissivity	0.8
Wall emissivity	0.2 - 0.9

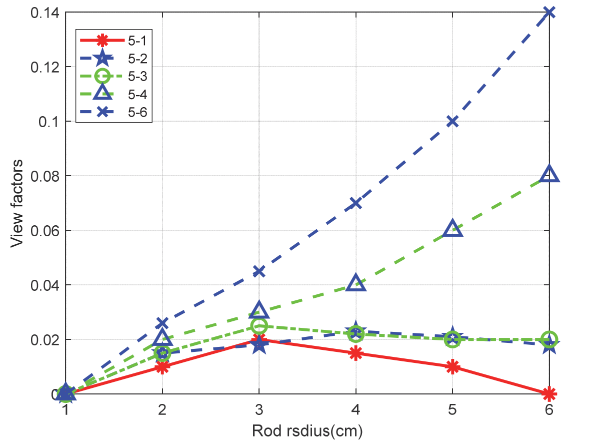

Figure 5 Angle coefficient between outer ring silicon rod 5 and other silicon rods

Fig. 5 shows the Angle coefficient between the outer ring silicon rod 5 and other silicon rods. Due to the position symmetry, only the variation of Angle coefficients between silicon rods 1, 2, 3, 4 and 6 is analyzed. As can be seen from Fig. 5, the Angle coefficient between silicon rod 5 and other silicon rods is less than 0.1, and even when the radius of silicon rod is increased to 10 cm, the Angle coefficient between silicon rod 5 and 1 is only 0.167, which indicates that the radiation between the outer ring silicon rod and other silicon rods is relatively small.

4 IMPROVED K-MEANS ALGORITHM FOR ENERGY SAVING AND CONSUMPTION REDUCTION OPTIMIZATION OF POLYSILICON SIEMENS METHOD

4.1 K-means Algorithm was Improved to Optimize the Process Conditions

The modified Siemens process uses hydrogen as carrier gas, and polysilicon is generated by gas phase deposition of trichlorosilane gas on the surface of silicon rods at high temperature in the reduction furnace. The deposition rate of polysilicon depends on the gas flow rate, fluid dynamics characteristics, silicon rod surface temperature, furnace pressure, and gas ratio (the amount ratio of hydrogen to silane gas substances). There are mainly the following reactions in the reduction furnace:

$$SiHCI_3(g) + H_2(g) = Si(s) + 3HCI(g) \tag{9}$$

$$4SiHCI_3(g) = 2H_2(g) + Si(s) + 3SiCI_4(g) \tag{10}$$

Eq. (9) and Eq. (10) are the main reactions to generate silicon, so conditions should be created as much as possible to promote the occurrence of these two reactions, so as to improve the deposition rate of polysilicon. The details are as follows:

Improve mixed gas flow. The increase of flow rate is beneficial to increase the flow rate of gas into the furnace and improve the distribution of gas and heat field in the furnace. At the same time, some theoretical studies believe that the increase of flow rate can drive HC1 gas formed on the surface of silicon rods, so that the probability of trichlorosilane molecules to contact and react with the surface of silicon rods increases. Under the same ratio conditions, increasing the mixed gas flow rate appropriately can achieve a more significant single furnace yield increase effect, but it will not significantly affect the conversion efficiency of trichlorosilane into the furnace. If the conversion rate of trichlorosilane is 10%, the corresponding increased gas volume is basically formed into polysilicon according to the conversion rate. However, the gas volume cannot be increased indefinitely, because the reaction speed is very fast, the deposition rate is relatively slow, excessive increase in gas volume will lead to the reduction of trichlorosilane conversion rate or silicon effective growth rate, thus affecting the effective yield of single furnace polysilicon. At the same time, due to the high purity raw materials not participating in the reaction and directly in the dry recovery system, increasing the load of the dry recovery system, which is not conducive to the reduction of energy consumption in the subsequent process.

In addition, changing the gas mixture ratio is the most direct and effective way to reduce power consumption and increase output at the same time. Especially when the H2 ratio decreases, the effect of reducing the power consumption is very obvious. According to reaction (2), when H2 concentration is reduced, more TCS will participate in the thermal decomposition reaction to generate silicon, and the concentration of trichlorosilane per unit volume increases, further improving the probability of contact between trichlorosilane molecules and silicon rods, thus improving the silicon deposition efficiency, as shown in Fig. 6.

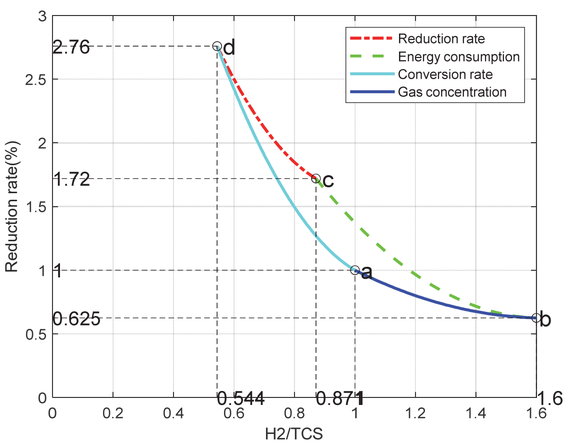

Figure 6 Influence law of mixture ratio change (pressure: 0.5 MPa)

Table 4 Simulation results of the flow stock using the split feed process

Stream	Molar fraction				
	H2	HCI	SiH2CI2	SiH2CI3	H2CI4
1	0.978	0.028	304 PPM	0.004	458 PPM
2	0.997	92 PPM	232 PPM	0.003	187 PPM
4	5 PPM	1.05	68 PPM	108 PPM	3 PPM
6		0.975	0.003	0.014	682 PPM
7		177 PPM	4.427	0.708	0.265
10		175 PPM	0.026	0.71	0.264
11	4 PPM	0.019	0.028	0.698	0.257
14	5 PPM	0.019	0.028	0.698	0.257

From Tab. 4, according to the simulation results, the separation effect of each column is basically unchanged after adopting the process plan of split feed, and the separation requirements can be reached, and the molar fraction of hydrogen and hydrogen chloride can reach more than 0.98%.

4.2 Energy Saving And Consumption Reduction Optimization To Improve Equipment Level

Application of multi-pair rod large reduction furnace is the main way to upgrade polysilicon equipment at present. From the early 12 pairs of rods, to the 24 pairs of rods currently widely used, to the new 36 pairs, 40 pairs, 48 pairs of rods, 51 pairs of rods now in operation, and even large reduction furnaces, are based on the increase in the number of silicon rods, to improve the output of a single furnace, and to make more full use of the space in the furnace and radiant heat between silicon rods.

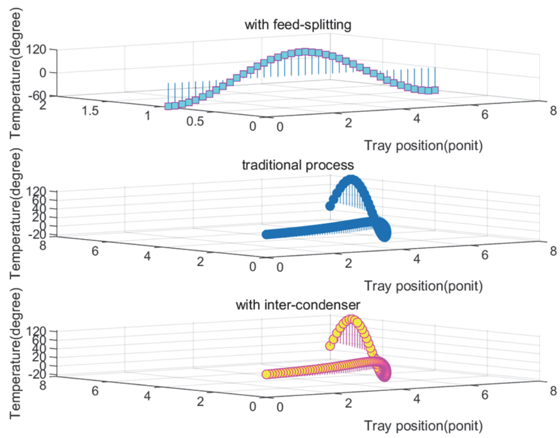

Figure 7 Temperature distribution in desorption tower

Table 5 Comparison of energy consumption between original process and improved process

Process flow	Energy consumption //kW		
	Low temperature cooling capacity	Steam plant	Circulating water
Original technology	4728.347	4382.091	
Split feed process	3457.573	3113.565	
Intermediate condenser man	4509.551	4243.438	
Energy saving rate of split feed process /%	27.85	28.85	83.145
Intermediate heat exchanger process energy saving rate /%	4.79	4.16	

As shown in Fig. 7, compared with the original process flow, the split feed process and the process using the intermediate condenser both appropriately reduce the temperature at the top of the suction tower, condensing more ground gas phase, thereby increasing the liquid flow in the tower, strengthening the mass transfer process, and improving the analysis effect. Therefore, the split feed process enables the top of the desorption tower to obtain higher purity hydrogen chloride and reduce the energy consumption of the device.

Tab. 5 shows the simulation data of the process before and after the improvement. Compared with the load of the original process, both the intermediate condenser process and the split feed process show signs of energy saving. Relatively speaking, the energy saving of the intermediate heat exchanger process is not particularly obvious, but the energy saving of the absorption and desorption system is very obvious when the split feed process is adopted. It can save 27.85% of the low temperature cooling capacity and 29.85% of the steam consumption. It can be seen that the split feed technology can obviously achieve the effect of energy saving in the reduction tail gas recovery in polysilicon production.

5 SIMULATION VERIFICATION

The flow field distribution in 12 pairs of rod reduction furnace under the air intake mode of distributed air intake and centralized air intake is simulated. Taking the silicon rod diameter of 12cm as an example, the velocity vector diagram of the central vertical section is shown in Fig. 8, and the velocity vector diagram of the cross-section of the hypersilicon rod is shown in Fig. 9.

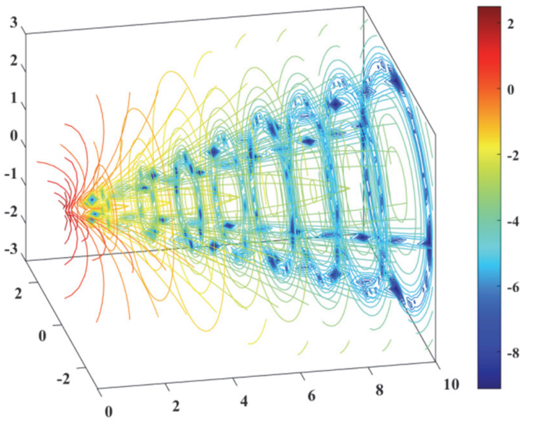

Figure 8 Center section (y = 0) Velocity vector diagram (12 pair rod reduction furnace)

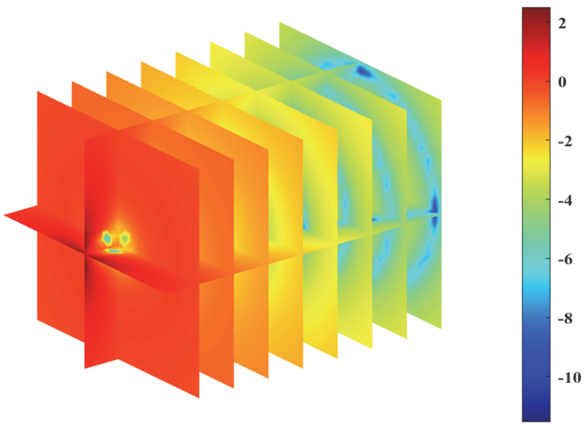

Figure 9 Cross section of persilicon rod (y = 0.15) Velocity vector diagram (12 pair rod reduction furnace)

In the above 12 pairs of rod data sets, energy saving and consumption reduction tests and comparisons were carried out on the classical K-means algorithm, WK-means algorithm, ZK-means (ZooKeeper means) algorithm, DCK-means algorithm and the algorithm in this paper. Each algorithm was run 50 times respectively, and the results were averaged. Fig. 10 shows the average clustering accuracy of the five algorithms on the experimental data set.

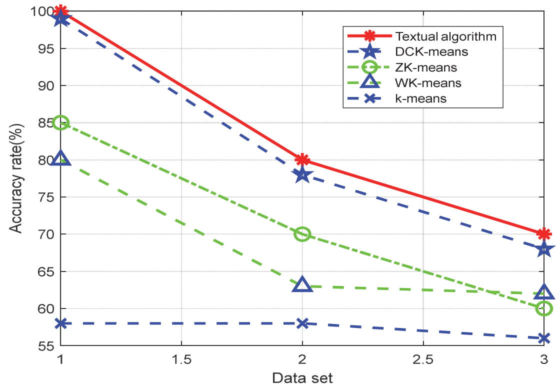

Figure 10 Comparison of clustering accuracy results of the five algorithms

Tab. 6 shows the test results of five different algorithms on the data set.

Table 6 Clustering result indicators of the algorithm on the Glass dataset

Algorithm	Accuracy / %	PC(t)	PE(t)	XB(t)
K-means	48.2	0.456	1.189	3.178
WK-means	54.3	0.618	0.673	0.678
ZK-means	58.6	0.657	0.578	0.654
DCK-means	61.9	0.716	0.463	0.478
Textual algorithm	64.7	0.736	0.437	0.452

In order to further illustrate that the improved K-means algorithm is more suitable than DBI algorithm in terms of accuracy for selecting the optimal cluster number for K-means, K-means clustering is performed on a certain data set, and k = 3 is selected. The clustering results are shown in Fig. 11, which can clearly distinguish three types of data. However, for this data set, the improved K-means algorithm can solve K = 2. Other clustering algorithms solve for k = 3.

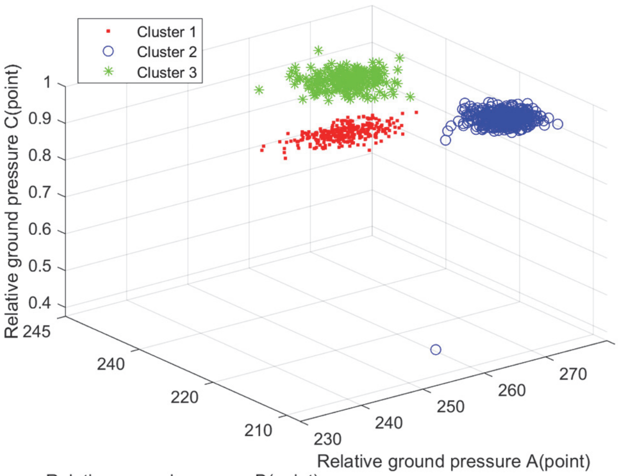

Figure 11 Clustering results of the improved K-means algorithm when k = 2

Further analysis shows that overfitting occurs when the cluster number is greater than 5. When the number of clusters is 5,16 respectively, the improved K-means clustering results are shown in Fig. 12 and Fig. 13. Fig. 12 is the optimal cluster, while Fig. 13 overfits the normal data into 4 clusters (cluster 1, cluster 6, cluster 11, cluster 16), which is not conducive to data analysis.

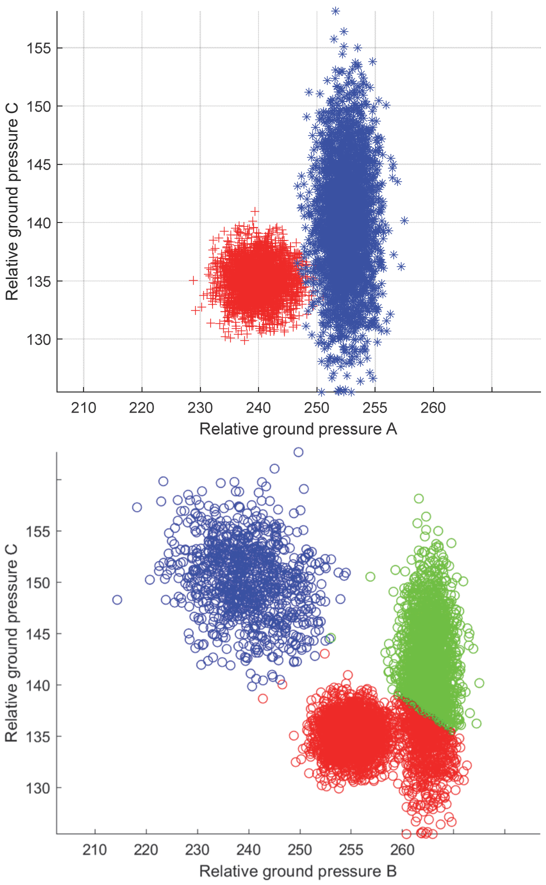

Figure 12 Improved K-means clustering results when the number of clusters is 5

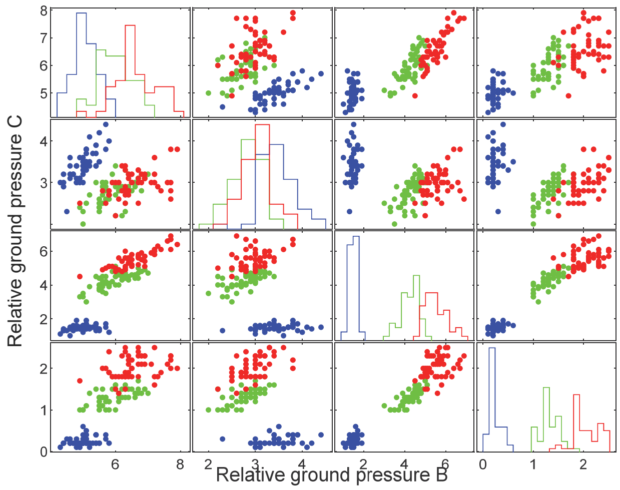

Figure 13 Improved K-means clustering results when the number of clusters is 16

It can be seen that an improvement is proposed to solve the problem that K-means algorithm is easy to cause algorithm instability and reduce cluster quality when it randomly determines the initial cluster center. The performance of K-means algorithm can be improved by using distance calculation method to optimize it.

6 CONCLUSION

This paper analyzes and optimizes the energy saving of polysilicon production process by Siemens method, and puts forward improvement measures to realize system energy saving, which is of great significance to the research of energy saving of polysilicon production at home and abroad. On the premise of not affecting the conversion rate of trichlorosilane, using a high-pressure reduction furnace, appropriately increasing the flow rate of the mixture, reducing the concentration of hydrogen in the mixture, and selecting a low hydrogen ratio can greatly reduce the power consumption of polycrystalline silicon. The application of multi-pair rod large reduction furnace and the optimization of electrical system can maximize the scale effect of large reduction furnace and achieve the effect of energy saving and consumption reduction. To improve the level of polysilicon production organization and decision-making, to market-oriented, with the least resources to create the greatest benefits, while through innovation and management improvement, reduce the consumption of polysilicon production auxiliary materials and process assistance systems, so as to further reduce the polysilicon equivalent energy consumption. In the future research process, several other chemical energy saving methods can also be combined to study energy saving and consumption reduction in the actual production process, such as heat pump rectification energy saving, multi-effect rectification energy saving, etc., which can play a key role in energy saving and consumption reduction in chemical production separation. In the process of establishing a mathematical model for heat transfer in polycrystalline silicon VD process, although corresponding simulation calculations were conducted on the convective heat transfer heat loss on the surface of the silicon rod, the influence of Siemens reactor structure on the convective heat transfer on the surface of the silicon rod was not thoroughly studied.

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