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System Integration and Method for High-efficiency Utilization of Solar Energy and Biomass Energy Thermochemically Based on Neural Network Algorithm

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Abstract: With the rapid development of economy and society, many problems such as environmental pollution and shortage of fossil energy have become increasingly prominent. It is urgent to develop and vigorously utilize renewable and clean energy such as solar energy. The purpose of this work is to study the system integration and biomass thermochemistry based on neural network algorithm. The proposed methanol and electricity cogeneration system is used to complete the step-by-step and orderly conversion of fuel chemical energy, and analyze the thermal characteristics of the cogeneration. Analysis and discussion are made for the academic characteristics and economic performance under different operating modes. The performance evaluation results of the solar-biomass gasification polygeneration system show that the thermal energy loss or exergy loss of the system is 63885kW and 15187.9kW respectively, of which the solar heat collection part has the largest loss, accounting for 43.2% of the total heat loss of the system and 43.2%. The total exergy loss accounts for 48.6%. Based on this, the collaborative optimization of the operating parameters of these devices will greatly promote the effective utilization of system energy.

1. Introduction

Energy is the fundamental driving force for social and economic development. At present, fossil energy (coal, oil, natural gas, etc.) is still the main source of world energy consumption, accounting for about 80% of the world's total energy consumption. The direct consumption of fossil energy will lead to serious environmental pollution, for example, the massive emission of carbon dioxide will cause global warming and affect the normal ecological environment of the earth [1]. Therefore, the increasingly severe energy and environmental problems make the reform of the world's energy structure imminent. The energy production and consumption according to local conditions, and the research and development of multi-energy complementary advanced energy power systems are the key research directions in the current energy revolution process, which can speed up the realization of human beings. Sustainable development of energy, economy and environment in society [2].

In recent years, great progress has been made at home and abroad in the research on neural network algorithm and the integration and method of solar energy and biomass energy thermochemical complementary efficient utilization system. Aoa B proposed a new hybrid network algorithm, Difference Denominator Descriptor (NNA-DE), which combines NNA and DE. Compared with standard NNA and other advanced optimization algorithms, the proposed hybrid NNA-DE optimization performs better. The proposed hybrid NNA-DE algorithm is then used to optimize an intermediate type 2 fuzzy PID controller (OB-IT2FPID) applied to a membrane gas exchange (PEMFC) system. All design parameters of the OB-IT2FPID controller, including scale factor, type interval of 2-element function parameters, and footprint of uncertainty (FOU) are optimized using the proposed hybrid NNA-DE algorithm [3]. Skuratov V describes the modeling process, analysis, and results collected using analytical algorithms and statistical data. The developed algorithm, combined with a previously created neural network pattern detector, can automatically find the exact boundaries of technical analysis charts of various sizes, analyze the context in front of them, and extract patterns. This makes it possible to obtain meaningful statistics that allow one to determine the level of confidence in emerging processes taking into account type, context and other factors. In terms of accuracy and efficiency, the developed algorithms address existing challenges in financial markets, and through the use of graphical and visual data, the efficiency of traders or investors can be improved [4]. M Dubé presents Delphi techniques for developing recommendations and procedures to guide those interested in performing PSSI simulations. The Delphi method is a structured communication process in which information is collected from a specific panel of experts through a series of questionnaires to reach consensus on the judgment of a complex process for which there is no standard information in the literature [5]. It can be seen that the neural network algorithm and the combination of solar energy and biomass energy thermochemical high-efficiency utilization system have certain innovative significance.

This paper will start from the nature of biomass fuel chemical energy, combine the energy attributes and advantages of solar energy, adopt the complementary utilization method of thermochemistry, follow the basic principles of "orderly conversion of energy" and "grade counterpart, cascade utilization", and deeply study solar energy and biomass. Thermochemical complementary energy conversion mechanism and integration law with chemical power system and distributed energy supply system. The research results will provide a new guidance for improving the utilization efficiency of biomass and solar energy.

2. Research on Thermochemical Complementary Efficient Utilization System Based on Neural Network Algorithm

2.1. Complementary Utilization of Solar Energy and Biomass Thermochemical

It is a new attempt to apply the solar thermochemical method to the complementary utilization of biomass and solar energy, that is, to use the concentrating equipment to generate high-temperature solar heat to replace the biomass self-combustion process, and to convert the solar energy. and biomass into solar fuel (syngas), which is mainly composed of CO, H2, CH4 components, which can be used for direct combustion in internal combustion engines or gas turbines for power generation and heating, as well as long-distance transportation such as synthetic natural gas (SNG) and methanol It can also be used to produce dimethyl ether, ethylene, hydrogen and other chemical products to meet diversified needs [6-7]. Converting discontinuous and unstable solar energy into clean, long-term storage, and easy-to-transport chemical fuels by thermalization can solve the problem of mismatch between regional resources and consumption to a certain extent. Compared with the traditional biomass gasification technology, the complementary utilization of solar energy and biomass thermochemical technology reduces the air separation unit and biomass combustion furnace, thereby reducing the energy consumption of the gasification process and the construction cost of the gasification reactor [8-9]. At the same time, the use of water vapor as a gasification agent increases the H2 component in the solar fuel product, which is beneficial to further efficient downstream utilization [10-11].

2.2. Neural Network Algorithm

BP algorithm is a supervised learning algorithm. The algorithm usually uses the highest method. There are two types of signals in BP forward multilayer networks. One is the function signal, which is added to the input signal and propagated until the output is a function of the input and the weights; the second is the difference between the actual and expected results of the error signal, the error, which starts at the output and progresses step by step. Layers propagate backwards. It can be seen that the network signal transmission is further propagated and refined in further classification stages [12-13]. The learning samples are sent to the input layer, and after layer-by-layer hidden operations, are sent to the output layer. After the calculation is completed, the error multiplication stage is entered. The error signal is returned from the output layer to the input layer along the original link, and the link weight is adjusted layer by layer to reduce the error. The output layer must be corrected for errors by changing the connection weights between the hidden layer and the output layer. The implementation and hidden layers must be able to change the error passed by the output layer, and must also adjust the connection weights from the previous hidden layer (or input layer) to this layer, etc [14-15].

2.3. Energy Conversion Mechanism of Solar-driven Biomass Gasification Reaction

The solar biomass gasification process utilizes concentrated solar energy to generate high heat, providing the heat obtained by the biomass gasification process and the high temperature heating zone. From the first law of thermodynamics, solar energy is stored in the gasification product in the form of chemical energy (a mixture of CO, H2, CH4, etc., called syngas), and water vapor acts as a gasification agent to increase biomass. Gasification reaction process. The number of H atoms in the product gas, thereby increasing the production of H2 in the product gas [16-17].

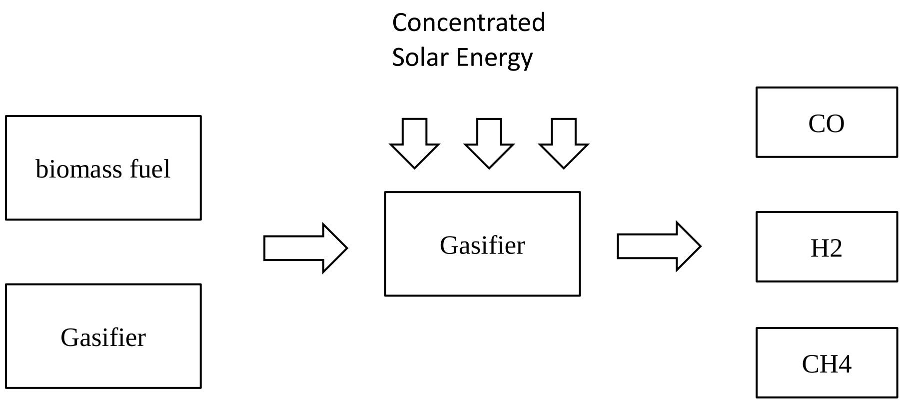

Figure 1. Schematic diagram of solar-driven biomass gasification process

As shown in Figure 1, solar energy and biomass energy not only take into account the cascade utilization of fuel chemical energy, but also store and utilize solar energy stably and efficiently in the form of chemical energy [18].

3. System Integration Diagnostic Model

3.1. Description of the Diagnostic System Model

According to the integrated form of neural network and expert system adopted in this paper, the diagnostic system model can be designed as shown in Figure 2.

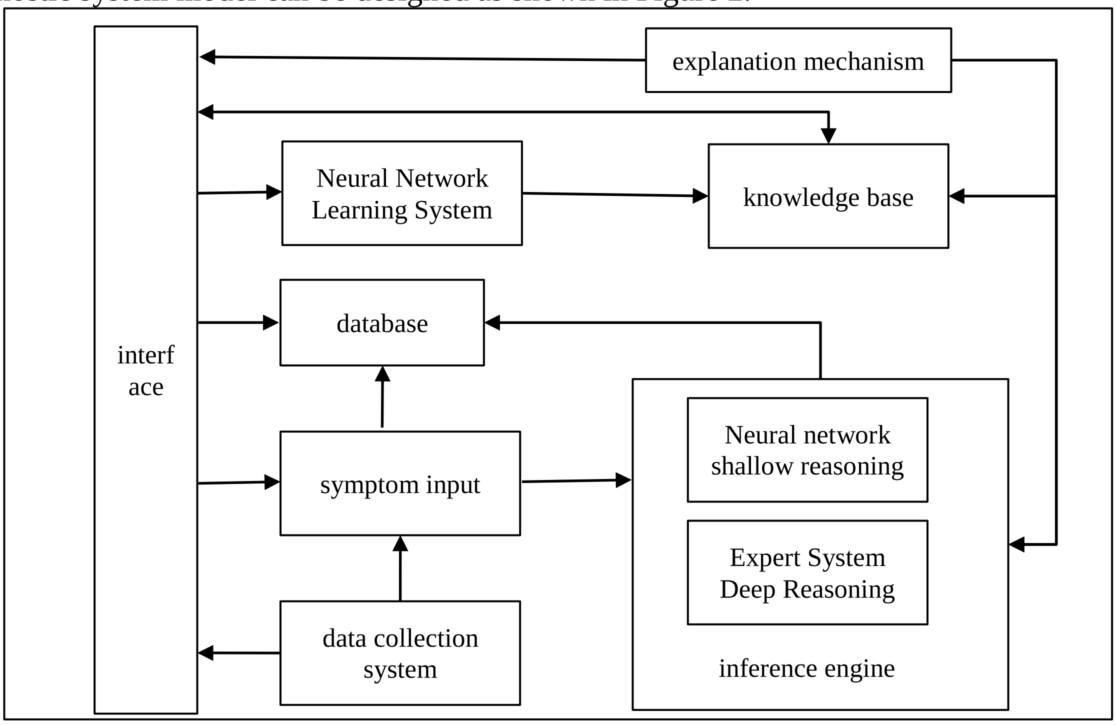

Figure 2. The structure and flow chart of the neural network diagnosis system model

We can be seen from Figure 2 that the system model consists of six parts: the main database, the neural network learning system, the inference engine, the knowledge base, the interpretation mechanism and the human-computer interaction interface.

Knowledge base: In this system model, the knowledge in the knowledge base includes fault training sample knowledge and fault diagnosis knowledge. Failure mode knowledge Obtain failure mode knowledge by querying and analyzing system failure cases and consulting domain experts.

Database: In this system model, the database is divided into two parts: dynamic database and static database. The dynamic database is used to store the real-time detected job data required for online monitoring and diagnosis, as well as various diagnostic information required and generated in the reasoning process.

Neural network learning system: The learning form of this system model is to use the established fault samples to train the neural network, and then store the fault diagnosis network knowledge in each neuron of the neural network in the form of neural network weights and closed values. Therefore, the establishment of the learning system is the establishment of the neural network model.

Inference engine: In a fault diagnosis system, inference is the process of obtaining fault types by inputting fault symptoms. In this system model, according to the classification of shallow knowledge and deep knowledge, the reasoning engine is divided into two parts: neural network reasoning and expert system reasoning.

3.2. The Working Process of the Diagnostic System Model

(1) Use a neural network learning system to learn sample knowledge

Specifically, the training samples in the sample knowledge base stored in the system are called to train the neural network, and the training results are obtained, which are stored in the diagnosis knowledge base for use in diagnosis.

(2) Input of symptoms

Users can indirectly input fault data or symptom information into the diagnosis system through the human-computer interaction interface or connect the diagnosis system with the data acquisition system, and directly send the real-time data monitored online into the diagnosis system for diagnosis.

(3) Diagnose and explain the input fault information

The diagnosis system sends the received fault information to the inference engine, invokes the knowledge in the knowledge base, first performs shallow neural network inference on the fault information to obtain the final diagnosis result, and then sends the diagnosis result to the dynamic database for query. At the same time, the explanation mechanism is used to explain the diagnosis results, and output to the human-computer interface to guide the user.

(4) Querying the diagnosis results

After the diagnosis is completed, the results of each fault diagnosis can be queried at any time according to the needs of the user.

3.3. Complementary Thermodynamic Processes of Thermochemistry

Based on the previous research on the thermochemical energy conversion mechanism, the thermodynamic process of the complementary process of solar energy and biomass thermochemistry was further explored, which laid a theoretical foundation for the subsequent gasifier design and chemical power system integration. The thermochemical complementary process of solar energy and biomass mainly includes three parts: high temperature concentrated solar energy collection process; biomass-steam gasification process.

Advanced solar focusing systems rely on traditional focusing devices such as heliostats and parabolic mirrors. The received effective solar energy can be calculated as follows:

$$Q_{sol,re} = As_{sol} \cdot DNI \cdot (1 - \eta_{opt,loss}) \tag{1}$$

In the formula, Qsol,re represents the collected solar energy, which is also equal to the solar energy intercepted by the receiving surface of the reactor, kW; Assol is the area of the solar concentrator, generally refers to the cross-sectional area of the reflecting mirror, m2, which is determined by the Determined by biomass scale; DNI is solar radiation intensity.

The effective solar energy Qsol absorbed by biomass gas can be calculated from the following equation:

$$Q_{sol,absorb} = Q_{sol,re} - (Q_{con} + Q_{cov} + Q_{rad})_{loss} \tag{2}$$

In the formula, Qcon represent the heat conduction caused by the temperature difference between the gasifier reactor.

4. Performance Analysis of Solar and Biomass Thermochemical Complementary High-efficiency Utilization System Based on Neural Network Algorithm

4.1. Biomass Gasification Reaction Kinetic Mechanism Experiment

In the process of solar thermochemical reaction, in order to further study the characteristics of biomass gasification reaction, on the basis of the analysis of biomass equilibrium reaction characteristics, thermogravimetric analysis method will also be used to analyze the pyrolysis gasification of cotton paddy rice in water vapor atmosphere. Mechanistic experimental study on the reaction kinetics is carried out. The characteristic parameters of the pyrolysis gasification reaction process of the material samples at different humidification rates are shown in Table 1.

Table 1. Characteristic parameters of cotton straw pyrolysis gasification reaction

Heating rate	Ts/K	Tmax/K	Tg/K	Tg,max/K	M
0K/min	439.2	572.4	954.5	982.4	89.2
5 K/min	482.4	582.5	925.5	1002.4	84.2
10 K/min	462.3	592.2	924.2	1032.4	87.3
15 K/min	472.4	589.2	923.5	1042.2	86.4

As shown in Table 1, with the increase of the reaction heating rate, the maximum weight loss rate in both the low-temperature pyrolysis stage and the high-temperature gasification stage increases significantly. It can be seen that increasing the heating rate can improve the heat and mass transfer characteristics in the reaction field. It plays a good role in improving the gasification reaction rate.

4.2. System Performance Evaluation

The heat balance and the heat balance are calculated to analyze the energy conversion process caused by the heat loss or irreversible loss of the system, and then the subsequent analysis and optimization are carried out, as shown in Table 2.

Table 2. System heat balance and exergy balance analysis of the polygeneration system

	Heat loss/kW	Heat loss ratio /%	Exergy loss /kW	Exergy loss ratio/%
Solar heat collection process	51372	43.2	5893.3	48.6
Biomass Gasification	11923	20.3	3945.2	30.2
Syngas compressor	590	36.5	5349.4	21.2
Total	63885	100	15187.9	100

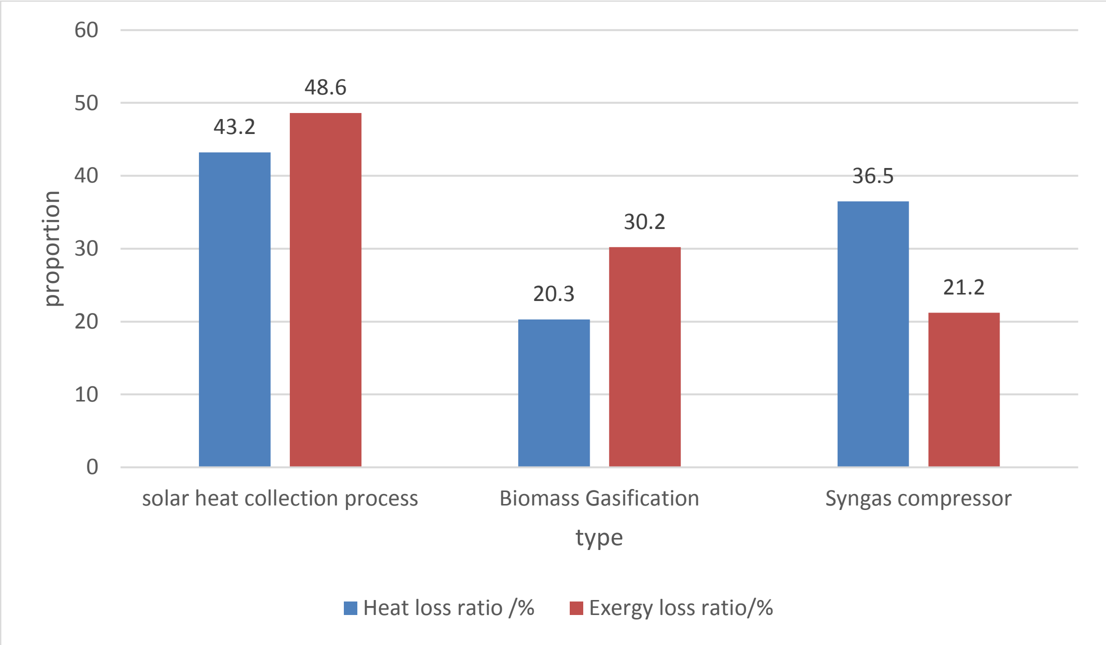

Figure 3. System heat balance and exergy balance analysis diagram

As shown in Figure 3, the heat loss or exergy loss of the system is 63885kW and 15187.9kW respectively, of which the solar heat collection part has the largest loss, accounting for 43.2% of the total system heat loss and 48.6% of the total system exergy loss. The main reason is When the concentrating and collecting temperature of solar energy is too high, a large amount of irreversible losses will inevitably occur. In addition, the heat loss of the condenser in the system ranks second in the heat loss term, reaching 20.3% of the total heat loss of the system. There is a large temperature difference between the two parts, which makes the irreversible loss of these two parts larger, and the resulting calcium loss accounts for 30.2%. Based on this, the collaborative optimization of the operating parameters of these devices will greatly promote the effective utilization of system energy.

5. Conclusion

This work investigates a system integration and method for the thermochemical compatibility of biomass using solar energy and energy based on neural network algorithms. Exploring the complementary synthesis of solar energy and biomass thermochemistry. To this end, a new method for the thermochemically compatible utilization of solar energy and biomass was developed, and an integrated solution for ammonia production, storage and transportation based on solar energy and biomass gas was proposed to achieve high efficiency and differentiation. In-depth study of the energy conversion mechanism of solar energy and biomass thermochemistry and the complementarity and integration law of chemical energy system and energy distribution system. The research results will provide new guidance for improving the efficiency of biomass and solar energy utilization.

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