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Multi-objective optimization of milk powder spray drying system considering environmental impact, economy and product quality☆

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ABSTRACT

Performance optimization of the milk powder spray drying system is of great significance to the sustainable development of the dairy industry with the growing market demand for milk powder. The present study aims to propose a multi-objective optimization framework for the drying system to improve the environmental performance, economic performance, and product quality of the system. For this purpose, inlet air temperature, feed pump speed, and atomization pressure are taken as the decision variables. A multi-objective optimization model of the system is established to minimize the system's environmental impact and life cycle cost and maximize the quality of milk powder. In order to solve the problem more efficiently, the non-dominated sorting ant colony genetic algorithm is proposed. The artificial neural network is adopted to construct the surrogate model for the life cycle assessment of the system and the Pareto front is obtained. The TOPSIS method is used to make decisions from the Pareto front to obtain the optimal scheme. The deviation index is adopted to evaluate the schemes obtained by different optimization methods. To demonstrate the advantages of the proposed framework, a case study is carried out and the optimal scenario obtained by the framework is compared with two different goal-oriented solutions, including bi-objective optimization that minimizes the environmental impact and life cycle cost of the system, and single-objective optimization that maximizes the quality of milk powder. The results show that the multi-objective optimization scheme can improve the performance of the system more comprehensively compared with dual-objective optimization and single-objective optimization. The optimized system achieves a good trade-off between environmental friendliness, economy, and quality of milk powder at the following conditions: the inlet air temperature of 182.98 °C, the feed pump speed of 80.74 rpm, and the atomization pressure of 180.34 bar. The environmental impact and the life cycle cost of the optimized system are reduced by 9.0% and 10.56%, respectively, compared with the original system, and the quality of milk powder is improved by 4.35%. The performance of the proposed method in the generational distance, spread and inverted generational distance is improved by more than 36.58%, 30.76% and 87.10%, respectively, compared with common algorithms such as NSGA-II, MOEA/D, NSGA-III, SPEA2. The solutions obtained using the proposed approach have the best performance in the three objectives compared with the schemes obtained by the other algorithms. The LCA surrogate model can reduce the solving time of the optimization from 3.5 h to 8.68 s on the premise of meeting the accuracy.

1. Introduction

As one of the essential sources of nutrition, tens of millions of people worldwide consume milk powder every day. The market demand for milk powder continues to grow with population growth and increased income, which not only promotes the improvement of production capacity, but also increases the energy consumption and emissions of milk powder and the related equipment in the whole life cycle. The resulting environmental issues are becoming more and more serious (Mazzetto

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Nomenclature

ACO	ant colony optimization
ANN	artificial neural network
AP	acidification potential
Bd	bulk density
Bi	browning index
Cc	cholesterol content
CFD	computational fluid dynamics
CLCD	Chinese life cycle database
CNN	convolutional neural network
Ds	dispersibility
EI	environmental impact
EP	eutrophication potential
GD	generational distance
GWP	global warming potential
HT	human toxicity
IGD	inverted generational distance
Ii	insolubility index
LCA	life cycle assessment
LM	levenberg-marquardt
MP	milk powder quality
MPSD	milk powder spray drying
NSACGA	non-dominated sorting in ant colony genetic algorithm
NSGA-II	non-dominated sorting genetic algorithm-II
PED	primary energy demand
POCP	photochemical ozone creation potential
RSM	response surface method
SVM	support vector machines
TET	terrestrial ecotoxicity
TGP	treed gaussian process
TOPSIS	technique for order preference by similarity to an ideal solution
WDP	water depletion

et al., 2020). Spray drying is the most energy-consuming step in milk powder production (Finnegan et al., 2017a). Therefore, optimizing the environmental performance of the milk powder spray drying (MPSD) system under the premise of ensuring the excellent quality and reasonable cost of milk powder is of great significance for the sustainable development of the dairy industry.

The increasing number of researchers promote the industry's sustainable development by optimizing the performance of the device. Al-Ahmed et al. (2020) optimized an organic heat storage material used in intelligent and green buildings to improve energy storage and thermal conductivity. Haque et al. (2017) improved the glucose powered biofuel cell anode and explored the possibility of applying the material to the energy devices of electronic equipment. Perveen et al. (2018) optimized an enzyme biofuel cell and determined the maximum current density of the device.

Numerous studies have been carried out to optimize the environmental performance of devices for milk powder production. Walmsley et al. (2018) used a total site heat integration method to optimize the environmental performance of the milk powder factory. The study found that the recovery of waste heat from spray dryers can reduce the use of thermal energy and electricity by 51.5% and 19%, respectively, compared with the modern factory. Atuonwu and Stapley (2017) reduced the energy consumption of the skimmed milk powder spray drying by generating monodisperse droplets. The results show that this method saves 90% of energy consumption than traditional systems. Singh et al. (2021) optimized the triple effect evaporator from the perspective of thermodynamics and environmental impact. The study found that the new program can reduce 17,670 tons of carbon dioxide emissions annually. Atkins et al. (2011) optimized the heat energy consumption of a spray dryer. The study found that the scheme of matching exhaust streams with hot water can reduce heat consumption by 21%. Walmsley et al. (2015) improved the heat recovery system of milk powder spray dryers from the perspective of thermo-economic.

In addition, many researchers have optimized spray drying to improve milk powder quality. Habtegebriel et al. (2021) optimized the whole milk powder quality in terms of surface fat content, yield and insolubility index. The optimization variables are inlet air temperature, feed flow rate and atomization pressure. Amiri-Rigi et al. (2012) improved the solubility of skim milk powder by optimizing inlet air temperature and feed flow rate. Ogolla et al. (2019) optimized the cow and camel milk powder production process from the aspects of dispersibility, wettability, lightness parameter, and compressibility. The study found that the inlet temperature and feed speed have an essential impact on each attribute of milk powder. Hamedi et al. (2021) improved the quality of skimmed milk powder from dispersibility, particle size, and density. Erbay et al. (2015) optimized the inlet air temperature and atomization pressure to obtain the best bulk density, browning index, and solubility of the milk powder. Chitra et al. (2015) improved the production process of whole milk powder and obtained the best values of free fatty content, cholesterol content, brightness, and solubility index.

The characteristics of the current research are shown in Table 1. Previous studies on the optimization mainly focused on a single goal, namely reducing the environmental impact of the equipment or improving the quality of milk powder. However, the optimization of the system should consider the trade-offs between different optimization objectives, including environmental performance, economy, and the quality of the products, which is a multi-objective optimization problem. The Non-dominated Sorting Genetic Algorithm-II (NSGA-II) is one of the most popular and commonly used methods for finding optimal parameter values for such issues (Deb et al., 2002).

Various studies have used the NSGA-II method to optimize the performance of the equipment for milk powder production. Cao et al. (2021) used NSGA-II to optimize the heat exchanger and made a trade-off between the heat transfer area and pressure drop. Deng et al. (2020) used NSGA-II to improve the performance of guide vanes of the axial flow cycle. Jafarzad and Heyhat (2020) used NSGA-II to optimize the heat exchanger. The results showed that the efficiency of the heat exchanger could be improved by 163% by using an appropriate air flow rate. Elsayed and Lacor (2012) used NSGA-II to improve the pressure drop and cut-off diameter of the cyclone separator. Sun and Yoon (2018) used NSGA-II to optimize the performance of gas cyclone separators.

However, since the evolution parameters of the NSGA-II method are set to fixed values, the evolution process cannot be dynamically adjusted in real-time according to the quality of the solution, resulting in the reduction of the optimization efficiency and genetic diversity of the method (Sankararao and Gupta, 2007).

The swarm intelligence algorithm (Abualigah et al., 2021) is a metaheuristic algorithm that simulates animal movement or hunting behaviour. These algorithms can share the biological information of all animals through the optimization process, and the typical algorithms are as follows. Ant Colony Optimization algorithm (Dorigo, 1992) imitates ant foraging behaviour, Reptile Search Algorithm (Abualigah et al., 2022) based on hunting behaviour of crocodile, Dwarf Mongoose Optimization algorithm (Agushaka et al., 2022) imitates predation and compensation behaviour of the dwarf mongoose. Because of the excellent ability of global optimization and exploring nearby solutions, such kinds of methods can be used not only to solve optimization problems but also to improve existing algorithms (Oyelade et al., 2022).

Literature review shows that much work has been done to optimize

Table 1
Summary of the features of articles on milk powder production and the related equipment.

References	Subjects	Variables	Objective functions	Optimization Techniques
Walmsley et al. (2018)	Milk powder production	Exhaust recovery mode, energy structure	Thermal and energy consumption	Total Site Heat Integration approach
Atuonwu and Stapley (2017)	Milk powder production	Droplet diameter	Energy consumption	Monodisperse droplet generation
Patel and Bade (2019)	Spray dryer	Recirculation ratio	Sustainability index	Direct and indirect energy recovery
Singh et al. (2021)	Spray dryer	Electrifying strategy	CO_2 emission	Solar energy assisted
Atkins et al. (2011)	Spray dryer	Heat recovery schemes	Heat consumption	Numerical modeling
Sun and Yoon (2018)	Cyclone separator	Geometrical factors	Pressure drop, Total efficiency	NSGA-II, CFD
Jafarzad and Heyhat (2020)	Heat exchanger	Hot and cold air flow rate, nanofluid concentration	Thermal energy exchange efficiency, exergy efficiency	ANN, NSGA-II
Deng et al. (2020)	Guide vanes for axial flow cyclone	Wrapping angle, outlet angle, and width of guide vane	Separation efficiency, pressure drop	CFD, SVM, NSGA-II
Amiri-Rigi et al. (2012)	Skim milk powder production	Air flow rate, inlet air temperature, feed flow rate	Solubility, mean diameter	RSM
Ogolla et al. (2019)	Cow and Camel milk powder production	Inlet air temperature, feed flow rate	Dispersibility, Wettability, Lightness, Compressibility	RSM
Hamedi et al. (2021)	Skimmed milk powder production	Inlet air temperature, feed flow rate	Wettability, dispersibility, particle size, density	RSM
Erbay et al. (2015)	Milk powder production	Inlet air temperature, atomization pressure	Bulk density, browning index, solubility	RSM
Habtegebriel et al. (2021)	Whole milk powder production	Feed flow rate, inlet air temperature, atomization pressure	Surface fat content, yield, insolubility index	RSM
Chitra et al. (2015)	Whole milk powder production	Inlet air temperature, atomization pressure	Free fatty acid content, cholesterol content, brightness, solubility index	RSM

AbbreviationsCFD: Computational Fluid Dynamics, RSM: Response surface method, SVM: Support vector machine.

the performance of the production equipment of milk powder. However, some problems still need to be solved: (1) The current research on the optimization of milk powder equipment only took a single piece of equipment as the research object. The main pieces of equipment related to the spray drying process were not studied as a whole object, and the interactions between the different devices were not considered. (2) The existing studies only improved the single objective, such as environmental performance or milk powder quality of the equipment, instead of comprehensively considering the performance optimization from the three dimensions of environment, cost and produced products. However, it is necessary to consider the trade-offs between multiple objectives since there may be conflicting relationships between different goals. (3) The NSGA-II method commonly used for multi-objective optimization, has limitations in solving efficiency.

Therefore, this research aims to develop a new framework for multi-objective optimization of the MPSD system to improve the environmental performance, economic performance, and product quality of the system comprehensively. The main contents are as follows: (1) The multi-objective optimization model of the MPSD system is established to minimize the environmental impact and life cycle cost of the system and maximize the quality of milk powder. (2) The non-dominated sorting ant colony genetic algorithm (NSACGA) is proposed and used to solve problem. (3) A case study is conducted in combination with industrial data, the Pareto front is generated by the proposed model and method. The TOPSIS method is used to make decisions on the Pareto front to determine the optimal scheme. (4) The performance of the NSACGA is compared with different methods to verify the advantages of the proposed method. (5) The optimal scheme is compared with the results of the bi-objective optimization, which focus on the environmental performance and economy of the system, and the single-objective optimization, which focuses on maximum milk powder quality, to verify the superiority of the proposed framework.

The research is innovative in three aspects compared with the previous research on the performance optimization of milk powder equipment: (1) A multi-objective optimization model of the MPSD system is raised, and the optimal parameters of the system are determined in terms of the conflict between the environmental performance, economic performance, and product quality of system. (2) The NSACGA method is developed to solve the multi-objective optimization problem. The diversity of the optimal solution is improved on the premise of ensuring the convergence of the solution. Therefore, the capability of multi-objective optimization is improved. (3) The surrogate model of life cycle assessment (LCA) of the system based on an artificial neural network is established to replace the LCA model based on the matrix, which improves the efficiency of the evaluation of the environmental performance of the system on the premise of ensuring the prediction accuracy of the total value of the environmental impact.

2. Methods

The process of multi-objective optimization is determined as shown in Fig. 1. Firstly, the decision variables are selected from the system parameters. Secondly, the LCA model, life cycle cost (LCC) model and score model of milk powder quality are established to determine the environmental impact, LCC of the system and milk powder quality. Thirdly, the multi-objective optimization model of the system is established, and the solution set corresponding to the Pareto front is obtained by NSACGA. Finally, the optimal solution is selected among the solution set by the TOPSIS method.

2.1. System description

2.1.1. Composition of the system

The research object of this article is a set of the MPSD system with an annual production capacity of 3000 tons of whole milk powder, which can dry the cow milk with a moisture content of 50% into the milk powder with a water content of 3%. The main components of the system are shown in Fig. 2. The process of MPSD is as follows. Firstly, the concentrated milk is transported to the top of the drying tower by a feed pump, dispersed into the droplets by an atomizer, and then fully contacted with the hot air introduced by the inlet fan. The droplets become powder and fall into the bottom of the drying tower to complete the primary drying. Secondly, the powder is secondary dried by the vibrating fluidized bed. Finally, the powder is collected by a cyclone separator, and the exhaust gas is discharged by an exhaust fan.

The design model of the system is constructed, and the technical parameters corresponding to the specific production capacity can be obtained (Wu, 2001). Therefore, the consumption of stainless steel,

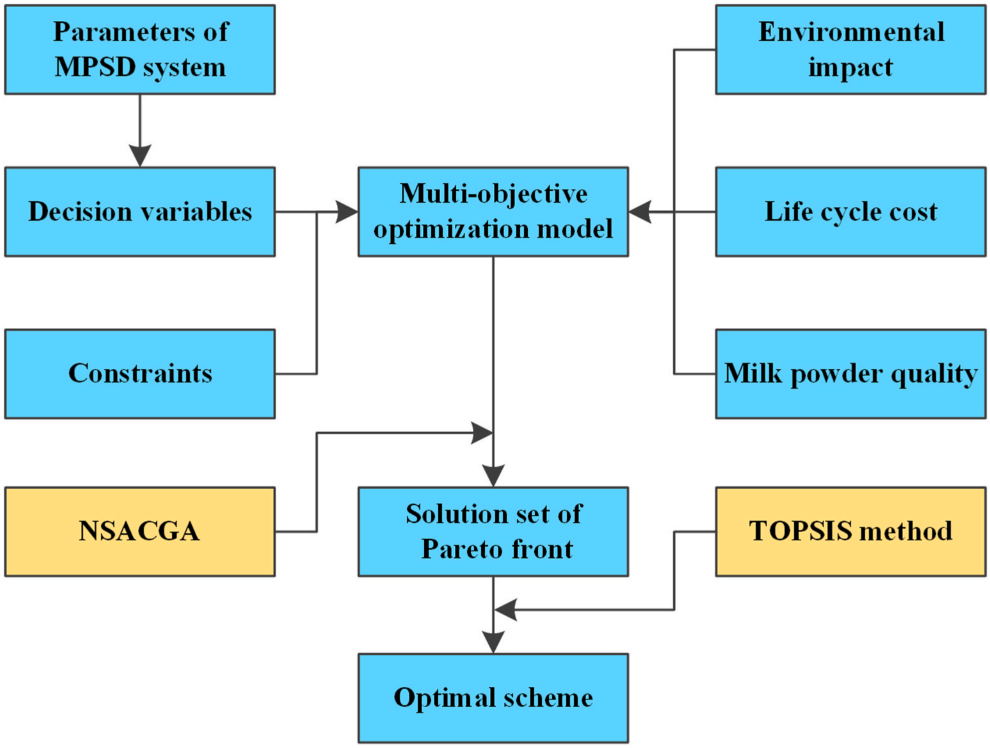

Fig. 1. Process of the multi-objective optimization.

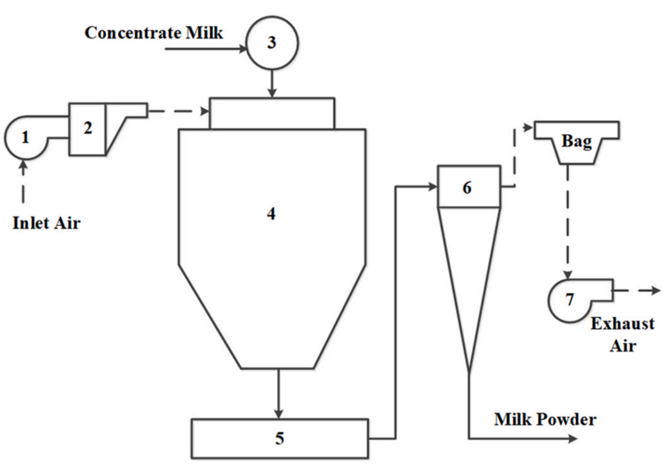

Fig. 2. Composition of the milk powder spray drying system.

steam, and power of the system can be calculated and prepared for the construction of the LCA and LCC models in the next step.

2.1.2. System boundary and inventory analysis

The system boundary is shown in Fig. 3, including the stage of raw materials, transportation, manufacturing and assembly, use, maintenance, and end-of-life of the system. Fig. 4 illustrates the flow of matter and energy in the system's life cycle. The raw material stage is mainly the production process of stainless steel since stainless steel is the primary material of system equipment. The manufacturing and assembly stage is the manufacturing and installation of the system, which mainly consumes electricity and stainless steel. The power consumption for manufacturing 1 kg steel is 0.225 kWh (Rashid and Adolfsson, 2016). The system needs to be transported from the device manufacturing plants to the dairy factory for on-site installation during the manufacturing phase. Moreover, the system requires transport from the dairy plant to the recovery station during the end-of-life phase. Therefore, the two distances need to be considered in the transportation stage. This research takes the data from a field survey of a dairy factory in Heilongjiang Province, China, as an example. The transportation distance of the enterprise in the manufacturing stage is 600 km, and that in the end-of-life stage is 300 km. A medium diesel truck with a load capacity of 8 tons is used for transportation. The consumption in the phase is 7200 t km diesel.

A large amount of steam and electricity is consumed in the use stage. The characteristic of the energy structure in China is considered, the steam comes from thermal power plants, and the consumption of steam and electricity is obtained from the technical parameters of the design model. The maintenance phase mainly refers to the cleaning of equipment, during which acidic cleaning agents (dilute nitric acid), alkaline cleaning agents (sodium hydroxide), and industrial water are consumed, and a large amount of wastewater is produced (Santos et al., 2016). The specific consumption refers to the data of Yan and Holden (2018). Furthermore, dilute nitric acid and NaOH concentrations are 48% and 30%, respectively. The electricity consumption of the cleaning is 3.32×10^{-4} kWh/kg of milk powder (Tsai et al., 2021). The end-of-life stage includes the recycling of stainless steel and the disposal of the remaining parts. The recycling of the system is to melt stainless steel into molten iron for reuse. Each kilogram of steel recovered consumes 0.6 kWh of electricity, and the steel recovery rate is 61.7% (Ziout et al., 2014). Additional details can be found in a separate paper (Zhang et al., 2021).

2.2. Multi-objective optimization model

The optimization of the system needs to deal with multiple and conflicting objectives simultaneously. With the improvement of one objective, the performance of other objectives may be reduced. Therefore, there is no single optimal solution that can make multiple objectives reach the minimum or maximum simultaneously, but a set of solutions obtained can make multiple objectives as optimal as possible. The multi-objective optimization problem in the research can be expressed as follows:

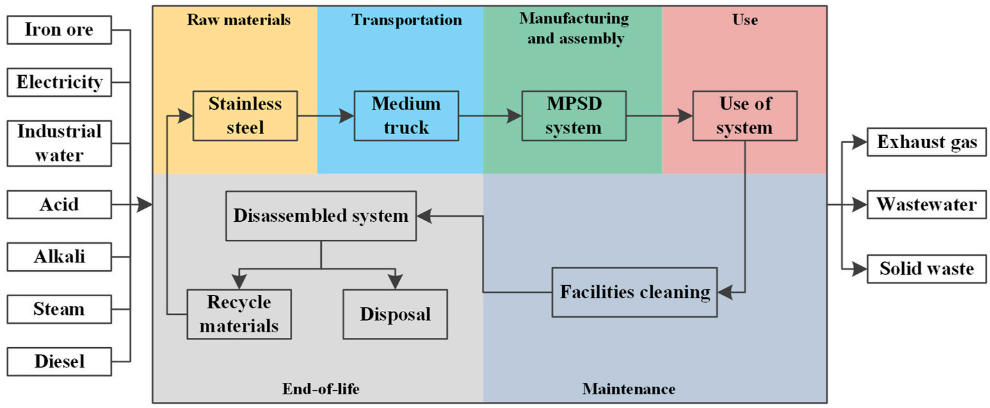

Fig. 3. System boundary.

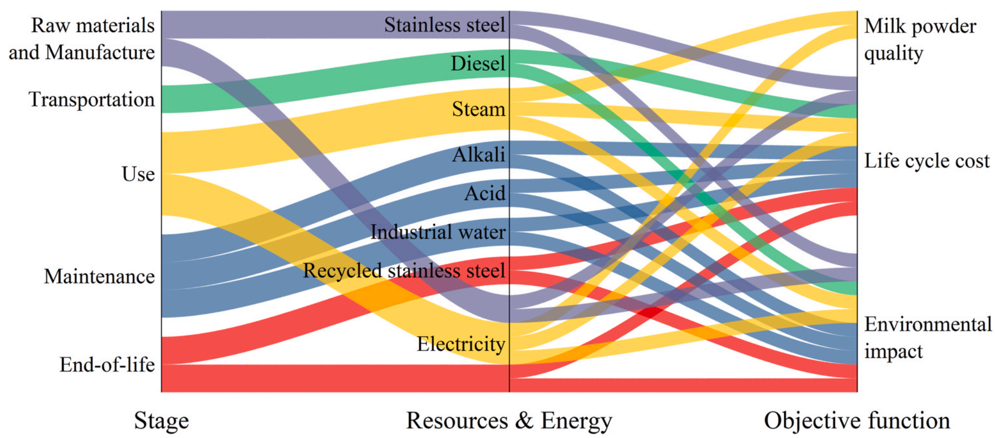

Fig. 4. Material and energy flow of the system.

$$Moof(X) = (f_1(X), f_2(X), ...f_i(X)) = (EI(X), LCC(X), MP(X)) \quad (1)$$

where X is the set of decision variables, f_i (x) is the i-th objective function. Three objectives are considered in the present study. Therefore, $i = 3$. *EI*, *LCC*, and *MP* are the objective functions of the multi-objective problem.

2.2.1. Decision variables and constraints

Eleven system parameters are preliminarily selected through consulting relevant literature, as shown in Table 2. And the constraints of the parameters are determined according to the stability and mathematical feasibility of the system observed by Wu (2001). To improve the efficiency of the optimization, three parameters selected as decision variables are confirmed crucial to the quality of milk powder by the relevant literature (Bansal et al., 2014), including inlet air temperature, feeding pump speed, and atomization pressure.

Table 2
Parameters of the system.

Parameters	Symbol	Unit	Range
Moisture content of the product during primary drying	V1	%	4.5–6
Moisture content of the product during secondary drying	V2	%	2.5–3
Empirical coefficient of inlet air	V3	–	1.1–1.2
Empirical coefficient of exhaust air	V4	–	1.2–1.4
Inlet air temperature of the drying tower	V5	°C	180–200
Temperature of concentrated milk	V6	°C	70–80
Temperature of exhaust gas from drying tower	V7	°C	70–85
Total air pressure of the inlet fan	V8	mmH_2O	80–160
Total air pressure of the exhaust fan	V9	mmH_2O	160–250
Feed pump speed	V10	rpm	73–206
Atomization pressure	V11	bar	100–300

2.2.2. Environmental impact

The functional unit is the MPSD system with an annual production of 3000 tons of whole milk powder. The system works 300 days a year, 12 h a day, and the system life is 20 years. The system boundary is shown in Fig. 3. The changes in resource and energy consumption caused by the changes in inlet air temperature, feed pump speed, and atomization pressure through the design model, which mainly refers to the consumption of stainless steel, electricity, and steam, are obtained on the premise of meeting the demand of production capacity.

The method adopted follows the procedures in the International Standardization Organization (ISO, 2006a, 2006b), and GB/T24040-2008 (Chen et al., 2009) formulated by the National Technical Committee for Environmental Management Standardization. The background inventory data is obtained from the Chinese Life Cycle Database in the eBalance program.The accuracy of the data is verified by the field investigation of a milk powder factory in Heilongjiang Province, China.

The CML 2001 (Aresti et al., 2021) and ReCiPe 2016 Midpoint v1.11 (Huijbregts et al., 2016) methods are used to evaluate the environmental load of the system. The primary environmental emissions of the system (such as CO_2, SO_2, CO, COD, BOD) and the most critical impact categories reported in related literature are considered. Eight categories including primary energy demand (PED, kg ce eq), global warming potential (GWP, kg CO_2 eq), acidification potential (AP, kg SO_2 eq), eutrophication potential (EP, kg NO-3 eq), photochemical ozone creation potential (POCP, kg C_2H_4 eq), human toxicity (HT, kg 1,4-DB eq), terrestrial ecotoxicity (TET, kg 1,4-DB eq), and water depletion (WDP, m^3) are selected in the present research (Üçtuğ, 2019).

The LCA method based on the matrix is used to build the environmental impact assessment model of the system, which is regarded as one of the objective functions of the multi-objective optimization problem. The environmental impact of the system can be calculated by Eq. (2):

$$EI = \omega_{PED}I_{PED} + \omega_{GWP}I_{GWP} + \omega_{AP}I_{AP} + \omega_{EP}I_{EP} + \omega_{POCP}I_{POCP} + \omega_{HT}I_{HT} + \omega_{TET}I_{TET} + \omega_{WDP}I_{WDP} \tag{2}$$

where *EI* is the total value of the system's environmental impact, which is obtained by the weighted sum of the impact of each category. I_{PED}, I_{GWP}, I_{AP}, I_{EP}, I_{POCP}, I_{HT}, I_{TET}, and I_{WDP} are the environmental impact values in the indicators such as PED, GWP, EP, AP, POCP, HT, TET, and WDP, respectively. ω_{PED}, ω_{GWP}, ω_{AP}, ω_{EP}, ω_{POCP}, ω_{HT}, ω_{TET},ω_{WDP} are the weight of the eight impact categories, respectively.

The weight values are calculated by the entropy weighting method to determine the weight of the index according to the amount of information contained in the index. The smaller the information entropy of the index, the greater the amount of the information provided by the index, and the more significant the role in the comprehensive evaluation. Therefore, the weight of the index is higher (Zhao and Wang, 2019). The method is an objective weighting method with higher reliability than the subjective weighting method (Li et al., 2016). The main steps are as follows:

(1) The standardized indicator value is defined from Eq. (3) when there are *m* evaluation objects and *n* indicators:

$$Y_{ij} = \frac{X_{ij} - \min(X_j)}{\max(X_j) - \min(X_j)} \tag{3}$$

where X_{ij} is the value of the *j*-th indicator of the *i*-th evaluation object, and Y_{ij} is the corresponding standardized indicator. min (X_j) is the minimum value of the *j*-th indicator of all the evaluation objects, and max (X_j) is the maximum value of the *j*-th indicator of all the evaluation objects.

(2) Then, the proportion of the index is calculated by Eq. (4).

$$Z_{ij} = \frac{Y_{ij}}{\sum_{i=1}^{m} Y_{ij}} \tag{4}$$

where Z_{ij} denotes the proportion of the *j*-th index of the *i*-th object Z_{ij}.

(3) The information entropy index is given by Eq. (5):

$$E_j = \frac{-\sum_{i=1}^{m} Z_{ij} \ln Z_{ij}}{\ln m} \tag{5}$$

where E_j is the information entropy of the *j*-th index.

(4) Finally, the weight of the index can be obtained through Eq. (6):

$$\omega_j = \frac{1 - E_j}{\sum_{j=1}^{n} (1 - E_j)} \tag{6}$$

where ω_j denotes the weight of the *j*-th index.

2.2.3. Life cycle cost

The life cycle cost of the system includes the cost corresponding to the resource and energy consumption in every stage, which is defined as:

$$LCC = C_{Raw} + C_{Transportation} + C_{Manufacture} + C_{Use} + C_{Main\ tenance} + C_{End-of-life} \tag{7}$$

where *LCC* denotes the total cost of the system in the life cycle. C_{Raw}, $C_{Transportation}$, $C_{Manufacture}$, C_{Use}, $C_{Maintenance}$, $C_{End\text{-}of\text{-}life}$ are the cost of the system in the raw materials, transportation, manufacturing and assembly, use, maintenance, and end-of-life stage, respectively.

The economic parameters are presented in the Chinese Yuan (CHY, monetary units in China, Table 3). The cost involved in the raw material phase is the purchase of stainless steel. Since the transportation company completes the transportation of the system, freight data is directly used, and the starting price has been considered. The electricity charge in the manufacturing, use, and end-of-life stage is calculated concerning the industrial electricity price of Heilongjiang Province, China. A large amount of steam and electricity is consumed in the use of the system. Considering the characteristics of energy structure in China, steam generation needs to consume coal from thermal power plants. Therefore, the corresponding conversion is carried out. Not only the cost of industrial water, acidic cleaner and alkaline cleaner, but also the cost of wastewater treatment is considered in the maintenance stage. The end-of-life phase covers the cost of steel recovery and landfill.

2.2.4. Milk powder quality

The primary task of the drying system is to produce high-quality milk powder. To achieve this goal, an evaluation model for the quality of milk powder is constructed by using the experimental data in the literature. The dispersibility, insolubility index, bulk density, browning index and cholesterol content are used to characterize the milk powder quality because related studies have indicated these indexes as the most crucial attribute of milk powder quality. The relationships between the indexes and decision variables are shown in Eqs. (8)–(12):

$$Ds = +81.23 - 0.5A + 0.12B + 0.64AB - 1.03A^2 \tag{8}$$

$$Ii = +0.05 - 0.02A - 0.03B + 0.15C - 0.07AC - 0.23AB + 0.03BC + 0.10A^2 + 0.10B^2 + 0.05C^2 \tag{9}$$

$$Bd = +235.24 - 4.32A + 2.06C + 3.74A^2 + 5.75C^2 \tag{10}$$

$$Cc = +57.73 - 13.26A - 10.01C - 2.47AC + 6.95A^2 + 6C^2 \tag{11}$$

$$Bi = +0.12 + 0.00554A - 0.00829C - 0.015AC + 0.00542A^2 + 0.017C^2 \tag{12}$$

where *A*, *B*, and *C* represent inlet air temperature, feed pump speed, and atomization pressure, respectively. *Ds*, *Ii*, *Bd*, *Cc*, and *Bi* denote the value of the dispersibility (Ogolla et al., 2019), insolubility index (Habtegebriel et al., 2021), bulk density (Erbay et al., 2015), browning index (Erbay et al., 2015) and cholesterol content (Chitra et al., 2015), respectively.

Dispersibility is the dissolution speed of agglomerates and lumps in milk powder when reconstituted with water, which is one of the most important indexes of reconstituted milk powder (Goula and Adamopoulos, 2005). The insolubility index represents the volume of the insoluble residue obtained when the milk powder is centrifuged after reconstituting (International Dairy Federation, 2005). The bulk density is the weight of a given volume of milk powder which determines the size of the packaging material used to transport the powder (Shafiee

Table 3
The cost for the components.

Indicator	Cost	Unit
Stainless steel	16000	CHY/t
Electricity	0.3161	CHY/kWh
Transportation	4.64	CHY/km
Coal	600	CHY/t
Industrial water	2.7	CHY/t
Acid	48	CHY/L
Alkaline	38	CHY/L
Wastewater treatment	1.2	CHY/t
Recycling	3.7	CHY/kg
Landfill	1	CHY/kg

et al., 2021). The cholesterol content is one of the chemical properties of milk powder, and excessive content can increase the risk of heart disease. Therefore, it is necessary to reduce the content when optimizing the quality of milk powder (Dey Paul et al., 2016). The browning index represents the colour of milk powder. The smaller the value, the better the appearance of milk powder. There is no suitable model for the bulk density, solubility, and browning index of milk powder in the existing research. Meanwhile, numerous studies (Zouari et al., 2020) show that cheese powder and camel milk powder are highly consistent with cow milk powder in terms of physicochemical properties and thermodynamic properties. Therefore, the milk powder quality model established by referring to the above literature is reasonable.

The value range of each attribute of milk powder can be obtained according to the equations. Then the attribute values are standardized by Eq. (13):

$$P_i = \frac{S_i - S_{i\min}}{S_{i\max} - S_{i\min}} \tag{13}$$

where S_i is the value of the i-th attribute, that is, the corresponding value of Ds, Ii, Bd, Bi, and Cc in the given decision variable. S_{imin} is the minimum value of the attribute, and S_{imax} is the maximum value of the attribute. P_i is the normalized value of S_i, such as P_{Ds}, P_{Ii}, P_{Bd}, P_{Bi}, and P_{Cc}, as shown in Table 4.

The larger the P_{Bd} and P_{Ds}, the smaller the P_{Bi}, P_{Ii} and P_{Cc} to indicate the better milk powder quality, according to the research results of relevant literature. In addition, the five attributes are treated as equally important in relevant studies. Therefore, this research assigns the equal weight to the five characteristics, and all the coefficients are set to 1. The scoring function of milk powder quality is constructed as shown in Eq. (14):

$$P = P_{Bd} - P_{Bi} - P_{Ii} - P_{Cc} + P_{Ds} \tag{14}$$

where P is the score of milk powder quality, which ranges from −3 to 2. The higher the score, the better the milk powder quality.

To facilitate the subsequent multi-objective optimization, the formula is improved to limit the value between 0 and 5, as shown in Eq. (15):

$$MP = 2 - (P_{Bd} - P_{Bi} - P_{Ii} - P_{Cc} + P_{Ds}) \tag{15}$$

where MP denotes the score of milk powder quality in the improved equation, the smaller the score MP, the better the milk powder quality.

2.3. Optimization method

2.3.1. The non-dominated sorting ant colony genetic algorithm

NSGA-II is commonly adopted to obtain the solution set on the Pareto front when there are conflicts between multiple targets and the extremum cannot be taken simultaneously. The flowchart of NSGA-II is shown in the left part of Fig. 5. The initial population is created randomly based on the constraints. Each generation of the population is ranked according to fitness and crowding distance. The top-ranked individuals are retained as the parents. A child generation of the population is generated through the crossover and mutation of the parents, and then the generation is merged with the parents and reordered. The top-ranked individuals are retained as the new generation. The above steps are repeated until the termination condition is satisfied.

However, the algorithm has the following shortcomings: (1) The evolution parameters of the individual in NSGA-II are set to a fixed value. As a result, the evolution process cannot be dynamically adjusted in real-time according to the quality of the new solution generated in each iteration. (2) It is difficult to find the appropriate value of the parameters, and the algorithm may fall into the local optimal solution or miss the global optimal solution. (3) It is quite difficult to achieve rapid convergence through the current convergence methods if the randomly generated initial individuals are far from the global optimal solution, which leads to a long time to solve the multi-objective problem.

The Ant Colony Optimization (ACO) method is used to improve the NSGA-II method to solve the above problems. The Non-dominated Sorting Ant Colony Genetic Algorithm (NSACGA) is established, which can adjust the evolution parameters in real-time according to the quality of the solution of each iteration. ACO is an algorithm designed to simulate the foraging behaviour of ants. Pheromones are released by ants along the path searching for food and can be perceived by other ants. The pheromone concentration gradually decreases over time (Dorigo, 1992). The core idea of the ACO is to give a higher pheromone concentration to the path with a shorter distance, such that the path can be more easily selected when the next ant is foraging. The idea is used to improve the NSGA-II algorithm, as shown in the blue area of Fig. 5.

Firstly, the initial values of the weight coefficient of pheromone information and other parameters are determined. Secondly, an evolutionary parameter matrix is generated. Each element in the matrix contains a set of evolutionary parameters, including the values of probability of cross and mutation. A set of parameters is called in each iteration, and then the quality of the solution generated by the iteration is tested, including the number of non-dominated individuals and the average crowding distance of the individuals. The greater weight is given to the group of parameters when the quality of the solution is better than that of the previous iteration, that is, the pheromone concentration is increased to make it more likely to be selected in the next iteration. The concentration of pheromone is updated with each iteration of the algorithm. Therefore, the dynamic adjustment of the evolutionary process of the algorithm is realized. The core idea of the NSACGA method is shown in Eqs. (16)–(20):

$$p_i = \frac{[\tau_i]^\alpha \times [\eta_i]^\beta}{\sum_{i-1}^{i} [\tau_i]^\alpha \times [\eta_i]^\beta} \tag{16}$$

where p_i is the probability of the i-th group of crossover and mutation factors are selected. α and β refer to the weight coefficient of the pheromone information and the heuristic information, respectively. τ_i and η_i denote the pheromone concentration and the heuristic function corresponding to the i-th iteration of the algorithm, respectively.

$$\eta_i = d_i \tag{17}$$

$$d_i = \frac{1}{m}\sum_{j=1}^{m} d_{ij} \tag{18}$$

Eq. (17) and Eq. (18) are used to define η_i, in which d_i is the average crowding distance of solutions on the first Pareto front in the new population generated by the i-th iteration. m denotes the number of

Table 4
The score of milk powder quality.

Milk powder quality	Attribute abbreviation	Unit	Value range	Normalized attribute	Value range after standardization
Bulk density	*Bd*	kg/m^3	[233.99,243.05]	P_{Bd}	[0,1]
Browning index	*Bi*	OD/g dm	[0.12,0.13]	P_{Bi}	[0,1]
Insolubility index	*Ii*	ml/50 ml	[0.03,0.35]	P_{Ii}	[0,1]
Cholesterol content	*Cc*	mg/100g	[44.94,57.73]	P_{Cc}	[0,1]
Dispersibility	*Ds*	%	[81.35,79.70]	P_{Ds}	[0,1]

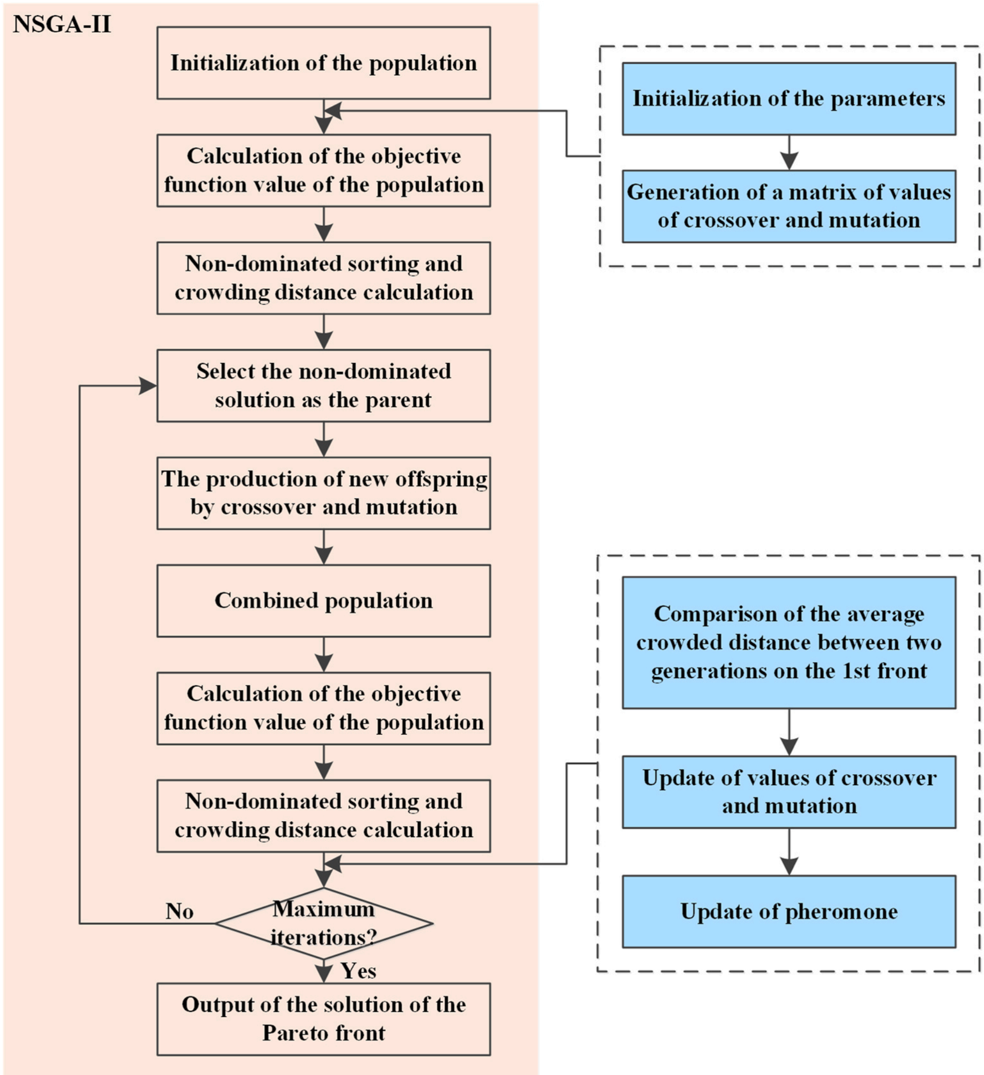

Fig. 5. Flowchart of NSACGA

solutions on the first Pareto front in the population, and d_{ij} is the crowding distance of the j-th solution on the front (Dorigo, 2007). The calculation method of τ_i is shown in Eq. (19) and Eq. (20):

$$\tau_i = (1-\rho) \times \tau_{i-1} + \Delta\tau_{i-1} \tag{19}$$

$$\Delta\tau_i = Q \times d_i \tag{20}$$

where $\tau_{i\text{-}1}$ and $\Delta\tau_{i\text{-}1}$ are the pheromone concentration and the increment of the pheromone concentration corresponding to the i-th iteration, respectively. Q is the strength of pheromone, ρ refers to the pheromone evaporation rate.

As shown in Table 5, the control parameters of NSACGA are selected according to the pre-test based on relevant literature to reach the best trade-off between the computational time and the reliability of the Pareto optimal curve.

Table 5
Parameter setting for NSACGA.

Parameters	Value
Population size	100
Number of generations	100
Lower bound of the cross probability	0.5
Upper bound of the cross probability	0.99
Lower bound of the mutation probability	0.001
Upper bound of the mutation probability	0.1
Weight coefficient of pheromone information α	3
Weight coefficient of heuristic information β	3
Rate of pheromone evaporation ρ	0.5
Strength of pheromone Q	10
Number of iterations	100

2.3.2. *Decision-making in multi-objective optimization*

The solution set on the Pareto front is generated using the NSACGA method, which provides a series of trade-offs between competing objectives. All points of the set are equally well, and additional information is needed to select the optimal point from the set. Therefore, the TOPSIS method is adopted to select the optimal solution by judging the similarity between the solution set and the ideal solution (Wang et al., 2019).

The steps of TOPSIS are as follows. Firstly, the weighted and normalized decision matrix is established by Eq. (21):

$$Fij = \omega_j \frac{f_{ij}}{\sqrt{\sum_{i=1}^{m} f_{ij}^2}}, 1 \le i \le m, 1 \le j \le n \tag{21}$$

where F_{ij} denotes the weighted and normalized decision matrix. f_{ij} is each element in the decision matrix, ω_j is the weight of each objective.

This study regards the three objectives as equally important. Therefore, each objective function is given the same weight.

Secondly, the ideal solution and negative ideal solution are obtained by Eqs. (22) and (23):

$$F^{ideal} = \left(F_1^{ideal}, F_2^{ideal}, \dots, F_n^{ideal}\right) = (\max\{F_{i1}|i = 1, 2, \dots, m\}, \max\{F_{i2}|i = 1, 2, \dots, m\}, \dots, \max\{F_{in}|i = 1, 2, \dots, m\}) \tag{22}$$

$$F^{non-ideal} = \left(F_1^{non-ideal}, F_2^{non-ideal}, \dots, F_n^{non-ideal}\right) = (\min\{F_{i1}|i = 1, 2, \dots, m\}, \min\{F_{i2}|i = 1, 2, \dots, m\}, \dots, \min\{F_{in}|i = 1, 2, \dots, m\}) \tag{23}$$

where $F_1^{ideal}, F_2^{ideal}, \dots, F_n^{ideal}$ are the first to n-th ideal solutions, respectively. $F_1^{non-ideal}, F_2^{non-ideal}, \dots, F_n^{non-ideal}$ are the first to n-th negative ideal solution.

Thirdly, the Euler distances from each solution to the ideal solution and the negative ideal solution are calculated, respectively:

$$D_i^+ = \sqrt{\sum_{j=1}^{n}\left(F_{ij} - F_j^{ideal}\right)^2} \tag{24}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n}\left(F_{ij} - F_j^{non-ideal}\right)^2} \tag{25}$$

where D_i^+ is the Euler distance between each solution and the ideal solution, D_i^- denotes the Euler distance between each solution and the negative ideal solution.

Finally, the value of the maximum relative proximity is given by:

$$P = \max\{P_i\} = \max\left\{\frac{D_i^-}{D_i^- + D_i^+}\right\} \tag{26}$$

where P is the value of the maximum relative proximity. The solution corresponding to P is the optimal solution.

To gain a deeper understanding of the reasonable state of different solutions (including the solution of the single-objective optimization and multi-objective optimization), the deviation index DI is introduced to evaluate the deviation between the optimal solution of each scenario and the hypothetical ideal solution, as shown in Eq. (27).

$$DI = \frac{\sqrt{\sum_{j=1}^{n}\left(F_j - F_j^{ideal}\right)^2}}{\sqrt{\sum_{j=1}^{n}\left(F_j - F_j^{non-ideal}\right)^2} + \sqrt{\sum_{j=1}^{n}\left(F_j - F_j^{ideal}\right)^2}} \tag{27}$$

Where DI is the deviation index, F_j is the j-th objective function value of the scheme, F_j^{ideal} and $F_j^{non-ideal}$ are the positive and negative ideal solutions of the j-th objective function, respectively.

2.4. Surrogate model based on ANN

The total environmental impact of the system is calculated by the matrix-based LCA method, and the calculation process is time-consuming, which dramatically reduces the efficiency of the optimization of system. A feasible technique to solve this problem is to use an artificial neural network to construct a surrogate model instead of the original matrix-based LCA model (Si et al., 2019).

Artificial neural network (ANN) has received increasing attention due to the powerful ability in data prediction, where convolutional neural network (CNN) and back propagation neural network (BP) are widely used, and the two networks have their characteristics (Zhao and Su, 2010). CNN has a multi-layer perceptron structure that can analyze high-dimensional data. Therefore, CNN has not only been used in the prediction of equipment performance (Ma et al., 2020), but also showed excellent performance in the fields of image recognition and signal processing (Louati et al., 2020). BP neural network is not only widely used because of its excellent generalization and robustness (Li et al., 2021), but also has been used to study the spray drying process (Ming et al., 2020). Therefore, this article adopts the BP neural network to construct the surrogate model of the LCA of the system.

BP neural network is an error back propagation algorithm consisting of an input layer, multiple hidden layers, and an output layer. The neural network is determined once all the weights between different layers are identified (Jiang et al., 2017). The structure of the neuron is shown in Fig. 6. $X_1, \dots, X_n$ denote the input variables while Y refers to the output, and F indicates the transfer function. The initial weight of the model is random, but the weight can be adjusted according to the error between the actual output value and the predicted output value through training and returns to the next training until the error is below the given value.

The input of this paper includes inlet air temperature, feed pump speed, and atomization pressure, and the output layer is the total value of the environmental impact of the system in the whole life cycle (Fig. 7). Hsu et al. (1995) found that a three-layer neural network can solve the problem of function fitting. Therefore, a three-layer neural network is used in the research. The number of neurons in the hidden layer is significant to the performance of the neural network. Too few neurons will hinder the reliability of the learning process, and too many neurons will lead to the overfitting of the model (Yu et al., 2021). The number of the neurons is adjusted by the empirical formula (Shen et al., 2008):

$$N_h = \sqrt{n_i + n_o} + a \tag{28}$$

where N_h is the number of neurons in the hidden layer, n_i refers to the number of input layers, n_o denotes the number of output layers, and a is the constant between 1 and 10. Therefore, the value of N_h is between 3 and 13, and the number of neurons is determined to be 11 by trial and error.

Levenberg-Marquardt (LM) algorithm is adopted to train the model. This is because Paul and Dalui (2020) proposed that the LM algorithm is the most effective method among several second-order methods for neural network training. The tangent S-type function is used as a transfer function (Eq. (29)). The performance of the neural network can be evaluated by several standards (Jafarzad and Heyhat, 2020). Mean square error (MSE, Eq. (30)) and coefficient of determination (Eq. (31)) are used to test the performance of the network.

$$f(z) = \frac{2}{1 + e^{-2z}} - 1 \tag{29}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(VT_i - VP_i)^2 \tag{30}$$

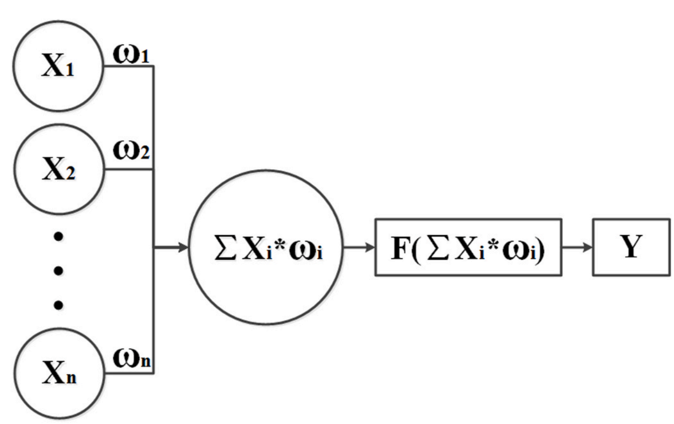

Fig. 6. Structure of artificial neural network.

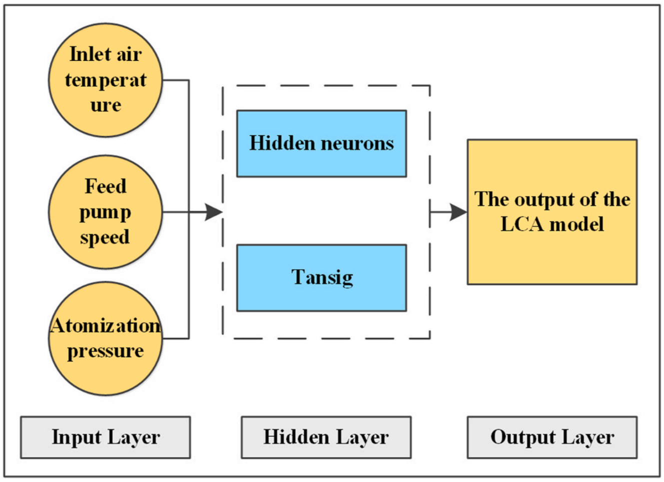

Fig. 7. The structure of the BP neural network.

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n} (VT_i - VP_i)^2}{\sum_{i=1}^{n} VT_i^2} \right) \tag{31}$$

Where n is the number of sample data, VT_i is the actual value of the i-th sample output, and VP_i is the predicted value of the i-th sample output. And 100000 data samples are obtained through the matrix-based LCA model. According to the recommendations by Si et al. (2019), the proportions of the training set, test set, and verification set are taken as 70%, 15%, and 15%, and the maximum number of iterations is 1000.

2.5. Sensitivity analysis

The decision variables are selected according to the importance of the quality of milk powder. Therefore, the global sensitivity analysis of the environmental load of the system is carried out to understand the dependence of the environmental performance on the decision variables. This paper adopts the treed Gaussian process (TGP) method to study the relative importance of parameters in Table 2 to the total value of environmental load in the system.

TGP is a global sensitivity method that combines static Gaussian process and decision tree (Song et al., 2019). The steps of the TGP method are as follows. Firstly, the Gaussian process is obtained according to the matrix of input and output variables. Secondly, the importance of variables is obtained by using the sensitivity analysis method based on variance. This method includes two indicators: main effect and total effect (Eq. (32) and (33)).

$$M_i = \frac{Var(E(Y|X_i))}{Var(Y)} \tag{32}$$

$$T_i = 1 - \frac{Var(E(Y|X_{-i}))}{Var(Y)} \tag{33}$$

Where M_i and T_i are the main effect and total effect of the i-th input variable, respectively, E is the expected value, Var is the variance value, X_{-i} is the set of all variables except X_i, Var $(E$ $(Y \mid X_i))$ represents the variance of expected values of outputs Y when X_i is specified, and Var (Y) represents the variance of output variable Y. The main effect represents the effect of change in input variables on the output. On this basis, the total effect also includes the output change caused by the interaction between the input variable and others. The higher the main effect or the total effect, the more influential the variable is.

2.6. Validation of the design model and LCA model

The results calculated by the model are compared with the data in the relevant studies to validate the accuracy of the design model and LCA model of the system, as shown in Table 6. The production data of five milk powder factories in Ireland were analyzed (about 2013) by Finnegan et al. (2017a). The production process and LCA data of skimmed milk powder and fat-filled powder in four companies (2014, 2015) were counted by Yan and Holden (2018). The production process data of milk powder in 18 dairy factories in Ireland were counted, and primary energy use and GWP were analyzed by Finnegan et al. (2017b). The primary energy use of the Netherlands milk powder was calculated by Xu and Flapper (2011). These studies are represented by P1, P2, P3, and P4, respectively.

All the energy sources in the literature come from combined heat and power plants. The volume of raw milk, electricity, energy, and steam consumptions calculated by the design and LCA models in the paper are within the range of data in the relevant literature. And the environmental impacts such as GWP and AP are also close to the relevant literature data. The primary energy use is relatively small compared with the reference literature. The main reason is that the primary energy data in the pieces of literature consider the entire production process of milk powder, including not only the drying stage, but also the pretreatment and evaporation stages. In general, the design model and LCA model established in the present research are verified to be reasonable and accurate for multi-objective optimization.

3. Results and discussion

3.1. Sensitivity analysis results

Fig. 8 shows the results of sensitivity analysis of the environmental impact of the system based on the TGP method. Fig. 8(a), (b), (c) correspond to the main effect, the first-order effect, and the total effect of the system parameters, respectively. The main effect shows the environmental impact of the system changing with the parameters. As can be seen from Fig. 8(a), the impact is significantly positively correlated with the inlet air temperature (V5), feed pump speed (V10), and atomization pressure (V11), indicating that the increase in these parameters will significantly improve the environmental impact. Fig. 8(b) shows that the influence of V6 on the environment accounts for about 48%, and the V10 and V11 account for about 19% and 20%, respectively. Other parameters have little influence on the environment. Fig. 8 (c) shows that the interaction between the parameters is not apparent. In summary, three variables (inlet air temperature, feed pump speed, and atomization pressure) not only are crucial to the quality of milk powder, but also have a significant impact on the environmental performance of the system, which proves that the choice of the parameters as decision variables is reasonable.

3.2. Performance analysis of the surrogate model

The MSE of the surrogate model based on the BP neural network is 1.05E-4, and the value of R^2 is 9.99E-1. Fig. 9 shows that the prediction results of the neural network and the actual results are highly consistent, which illustrates that the model trained by the BP neural network can satisfy the requirements. In conclusion, the surrogate model has high accuracy in predicting the environmental impact of the system for multi-objective optimization.

Table 7 shows the comparison between the calculation time of the multi-objective optimization using the matrix-based LCA model and using the surrogate model. As can be seen, the use of the surrogate model can significantly reduce the optimization time under the premise of ensuring accuracy.

Table 6
Comparison of results obtained from the LCA model with data in other literature (Manufacture of 1 kg of milk powder).

Inputs	Unit	Model	P1	P2	P3	P4
Raw milk	L	6.84–9.45	5.12–9.22	–	–	–
Energy & resources						
Electricity	kWh	0.12–0.18	0.27–0.56	0.14–0.17	–	–
Steam	kg	4.20–4.62	3.59–9.95	–	–	–
Environmental impact						
GWP	$kgCO_2eq$	1.69–1.92	1.09–1.48	0.91–1.96	1.83	–
AP	gSO_2eq	5.71–6.60	3.50–8.84	–	–	–
Primary energy use	MJ	19.1–21.8	–	14.06–42.26	23.44	8.7–18.00

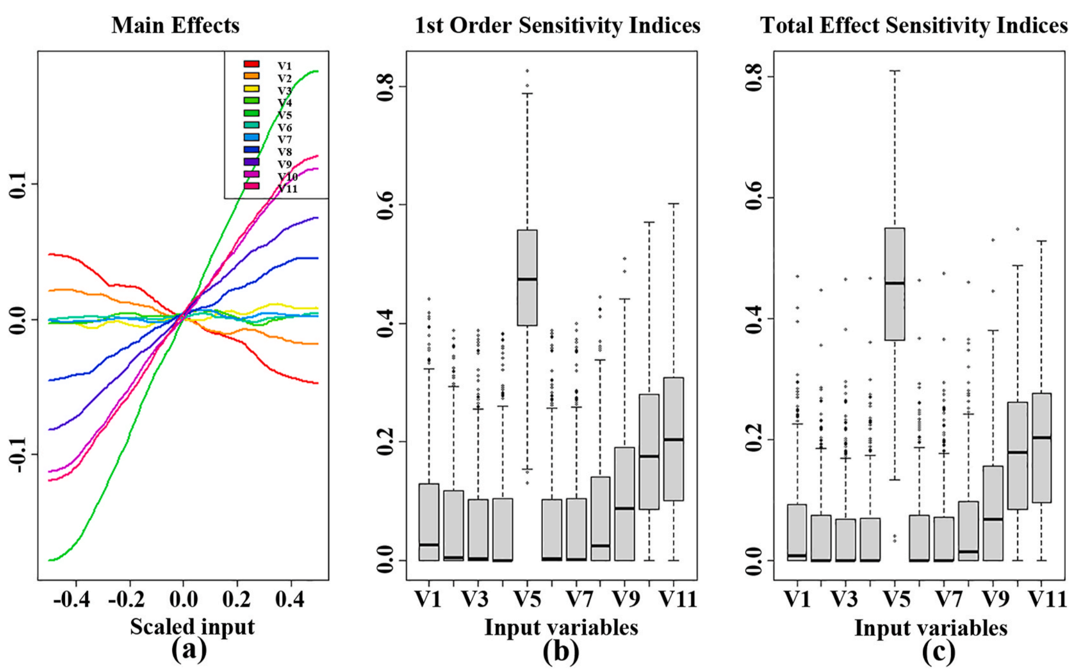

Fig. 8. Results of sensitivity analysis of the environmental impact of the system.

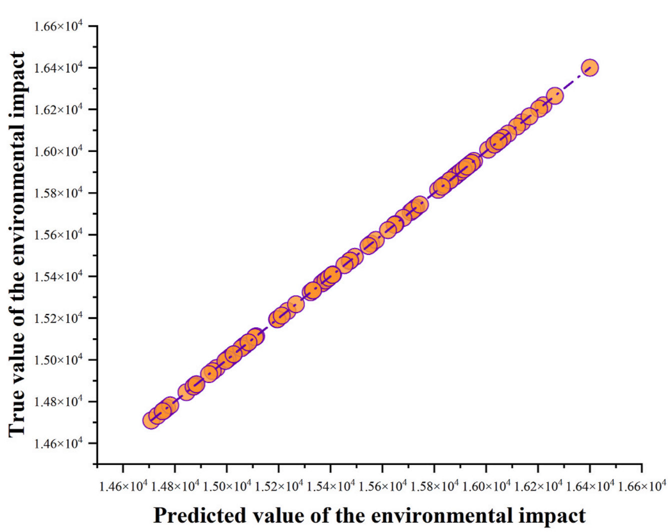

Fig. 9. The linear fitting between the prediction result of the BP neural network model and the actual result.

3.3. Multi-objective optimization results

The multi-objective optimization results are shown in Fig. 10 in the form of Pareto fronts. EI represents the total value of the environmental impact of the system, LCC refers to the life cycle cost of the system, and MP denotes the score of the milk powder quality. The improvement of milk powder quality leads to the increase in environmental impact and cost of the system throughout the life cycle, and the impact on EI and LCC is similar. The projection of the solution set on two surfaces is also shown. With the decrease of EI and LCC, the effect of the change of EI and LCC on MP increases gradually. Specifically, the reduction of EI leads to the rapid decline of MP when the value of EI is between 1.44×10^4 and 1.63×10^4. Further reduction of EI will lead to a sudden decline in MP when EI decreases to 1.46×10^4. Similarly, the decrease of LCC will lead to the rapid decline of MP when the value of LCC is 1.56×10^7 to 1.82×10^7. Further reduction of LCC will lead to a sudden decrease in MP when the LCC is reduced to 1.58×10^7.

Table 7
Comparison of calculation time for multi-objective optimization.

Objective function	Length of 10000 operations
Matrix-based LCA model	3.5 h
Surrogate model based on BP neural network	8.68 s

3.4. Performance test of the algorithm

Generational distance (GD), Spread and Inverted generational distance (IGD) are used as indicators to test the performance of the proposed method, which characterize the diversity and convergence of the

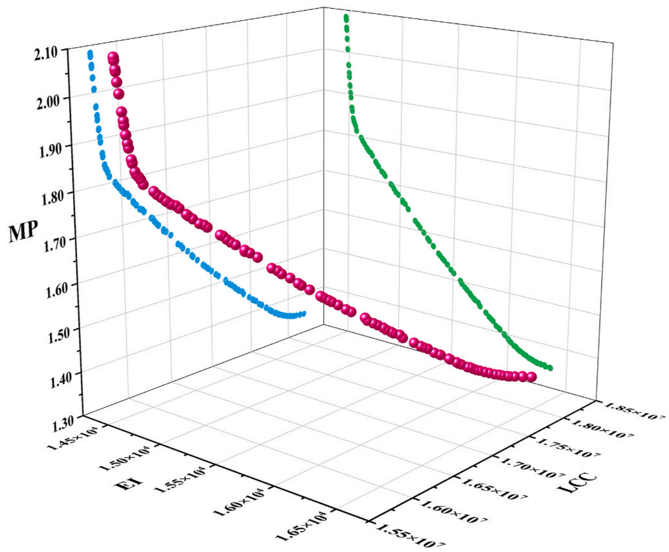

Fig. 10. The set of Pareto solutions for multi-objective optimization.

algorithm. The smaller the score of the indexes, the better the performance of the algorithm (Wang et al., 2009). The results are compared with NSGA-II, MOEA/D, NSGA-III, and SPEA2, which are commonly adopted in multi-objective optimization, as shown in Table 8. The advantages of the NSACGA can be clearly seen. The GD score is 36.58%–39.31% lower than other algorithms, the Spread score is 30.76%–35.40% lower than other algorithms, and the IGD score is 87.10%–87.22% lower than the others. Therefore, NSACGA has better convergence and diversity in solving the multi-objective optimization problem.

The results obtained using TOPSIS combined with four methods to solve the problem, such as NSGA-II, MOEA/D, NSGA-III, and SPEA2 are listed in Table 9. Scenario A is the optimal result obtained using NSACGA and the TOPSIS method. Different schemes are evaluated by deviation index. The results show that the scheme obtained by the NSACGA method has the best performance compared with the others because the deviation index of the scheme is the smallest. Specifically, compared with scenario A, the scheme obtained by the NSGA-II reduces EI and LCC by 0.68% and 0.62%, respectively, but the quality of milk powder decreases by 1.13%. The environmental and economic performance of the system obtained by the MOEA/D method is worse than that of scenario A. The EI and LCC of the scheme obtained by the NSGA-III method increased by 0.07% and 1.24%, respectively, compared with scenario A, and the quality of milk powder decreased by 4.5%. Although the EI and LCC of the scheme obtained by the SPEA2 are reduced by 1.35% and 1.24%, respectively, compared with scheme A, the quality of milk powder decreased by 3.98%. Therefore, the multi-objective optimization scheme obtained by the NSACGA method has better comprehensive performance than other algorithms.

3.5. Scenario analysis

The optimization results of different scenarios are listed in Table 9. The current state is the scenario based on the design model and the case presented in the literature (Atkins et al., 2011). Scenario A is the optimal scheme obtained by using the proposed method. Scenario B is driven by two objectives for minimizing both environmental impacts and life cycle costs. Scenario C is driven by the single objective that maximum milk powder quality. The deviation index of the schemes is 2.23E-1, 4.16E-1, and 5.84E-1, respectively. The deviation index of scenario A is the smallest, which indicates that the optimal solution obtained by multi-objective optimization is more ideal than the single-objective optimization and bi-objective optimization schemes. Therefore, the solution of scenario A is the most preferable.

Table 8
Comparison of algorithm performance.

Algorithm	NSGA-II	MOEA/D	NSGA-III	SPEA2	NSACGA
GD	9.76E-2	1.02E-1	1.03E-1	9.79E-2	6.19E-2
Spread	9.87E-1	1.00	1.00	9.33E-1	6.46E-1
IGD	1.07	1.08	1.07	1.07	1.38E-1

Specifically, the environmental performance, economy, and product quality of the system in scenario A are significantly improved compared with the current state. The EI is reduced by 9.20%, the LCC of the system is saved by 10.56%, and the MP is improved by 4.35%. Compared with scenario A, the EI of scenario B is reduced by 2.02% and the LCC is saved by 2.48%. However, the MP of scenario B is not only 18.18% worse than that of scenario A, but also 13.04% lower than the current state. The above conclusions are consistent with the law revealed in Fig. 10. The reduction of the environmental impact and life cycle cost can significantly reduce the quality of milk powder. Ensuring excellent milk powder quality is one of the most essential tasks of the system. Therefore, the environmental impact and life cycle cost of the system cannot be reduced by sacrificing milk powder quality. The quality of milk powder in scenario C is 23.22% better than in scenario A, but the environmental impact and the life cycle cost of the former are increased by 10.81% and 13.04%, respectively, compared with the latter. In conclusion, scenario A achieves a good trade-off between the three objectives.

Fig. 11 illustrates the contribution of the MPSD system in different scenarios to the eight impact categories. The x-axis shows each impact category, and the y-axis shows the contribution of the system in the impact categories. The contribution of the system to PED accounts for the largest proportion of the total environmental load regardless of the scenario used, and the contribution of different schemes ranges from 44.23% to 44.93%. Followed by the contribution of the system in TET and GWP, accounting for 17.62%–18.17% and 10.28%–10.43%. The contribution of the system in EP ranges from 9.51% to 10.22%. The contribution in AP and HT is about 8.3% and 5.3%, respectively. The others account for a small proportion of the total environmental impact. This is mainly because a large amount of electricity and steam is consumed by the system in the life cycle. Meanwhile, the energy structure of China is primarily based on thermal power, and the electricity and steam are generated by burning large amounts of the coal, which leads to the emission of a large amount of CO_2, SO, and heavy metal elements such as mercury (Inamuddin et al., 2017).

As can be seen from Fig. 12, the contribution of the system to PED is dominated by the consumption of steam and electricity. The contribution of steam consumption of systems with different schemes accounts for 49.99%–90.55% in the PED, while the electricity consumption accounts for 9.43%–49.99%. Therefore, the optimization of the environmental performance of the system is achieved by adjusting the inlet air temperature, feed pump speed, and atomization pressure to reduce the consumption of steam and power.

Table 10 and Fig. 13 show the performance of different scenarios in the score of milk powder quality and the specific properties, respectively. The higher the dispersibility and bulk density, the lower the insolubility, browning index, and cholesterol content, which indicates the better quality of the milk powder. Compared with the current state, the bulk density and dispersion of scenario A are increased by about 2%, and the insolubility is reduced by 11%. Scenario C reduced the cholesterol content by 13.32% and increased the insolubility index by 18.60% compared with scenario A. The cholesterol content in scenario B increased by nearly 10% compared with scenario A, but the insolubility is lower than that of scenario A. This is because the insolubility can be significantly decreased after reducing the inlet air temperature, feed pump speed, and atomization pressure. In conclusion, scenario A obtained by multi-objective optimization finds a balance point among the three objectives. Thereby the optimization method proposed in the

Table 9
Comparison of different scenarios.

Parameter/Function	Unit	Current state	Scenario A	Scenario B	Scenario C	NSGA-II
Inlet air temperature	°C	200	182.98	180	195.94	181.74
Feed pump speed	rpm	140	80.74	73	206	84.19
Atomization pressure	bar	250	180.34	100	275.03	170.21
EI	–	1.63E+04	1.48E+04	1.45E+04	1.64E+04	1.47E+04
LCC	CHY	1.80E+07	1.61E+07	1.57E+07	1.82E+07	1.60E+07
MP	–	1.84	1.76	2.08	1.35	1.78
Deviation index			2.23E-1	4.16E-1	5.84E-1	2.78E-1
Parameter/Function	Unit	MOEA/D	NSGA-III	SPEA2	Positive ideal point	Negative ideal point
Inlet air temperature	°C	182.14	180.41	180.08	–	–
Feed pump speed	rpm	125.63	139.41	75.05	–	–
Atomization pressure	bar	162	217.23	211.06	–	–
EI	–	1.48E+04	1.49E+04	1.46E+04	1.45E+04	1.64E+04
LCC	CHY	1.62E+07	1.63E+07	1.59E+07	1.57E+07	1.82E+07
MP	–	1.76	1.84	1.83	1.35	2.08
Deviation index		2.94E-1	3.32E-1	2.81E-1	0	1

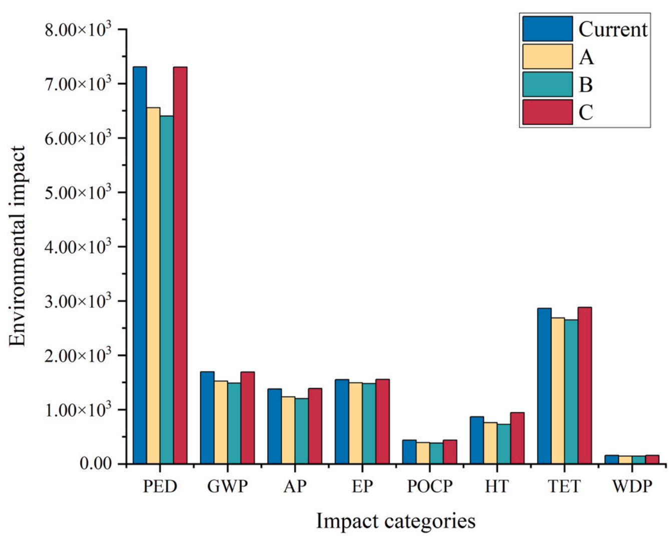

Fig. 11. Environmental impacts corresponding to different scenarios.

present research is proved to be able to obtain a convincing solution, and these results have important implications.

3.6. Theoretical contribution

The optimization of the MPSD system should consider the trade-off between different objectives, including environmental performance, economy, and the quality of the products of the system. However, there is no comprehensive consideration of these aspects in the existing literature. This research proposed the multi-objective optimization method of the MPSD system, which fills the critical gap in the literature. Related enterprises can benefit from the combination and realize environmentally conscious production by combining the concept of cleaner production with the control of product quality and the cost of energy consumption.

The multi-objective optimization framework proposed in the present research can be extended to the optimization of other equipment. The NSACGA method can be applied to other multi-objective optimization problems and can significantly improve the convergence and diversity of the solution. In addition, the study adopts the artificial neural network to establish the surrogate model of the environmental impact assessment of the system. The improvement of the efficiency of optimization by introducing the surrogate model becomes more evident with the increase of the model complexity.

3.7. Managerial implications

Increasing attention has been paid to sustainable development, whether in the field of dairy product processing or equipment manufacturing. Manufacturers of milk powder and the equipment need to emphasize environmental protection to prolong the life cycle of the products and pursue the sustainable operation of enterprises, which is an essential part of social responsibility. The results of this research not only provide valuable insights for the relevant practitioners, but also offer the decision support in the design and management of the devices for milk powder production. The specific implication is as follows:

(1) A optimization method from the perspective of environmental friendliness, economy and product performance of the system is proposed, which assists the managers in adjusting the parameters of the system in real-time to take cost-effective solutions to reduce the environmental burden of the system on the premise of ensuring the quality of the product.
(2) The results of scenario analysis of the environmental impact of the MPSD system provide managers insights into the environmental hotspots of the system, which helps the manufacturers to develop equipment with environmental friendliness.
(3) Although the article gives equal weight to all the objectives in the optimization, managers can assign different weights to the objectives according to the requirements and obtain corresponding optimization results.
(4) Sensitivity analysis helps the research and development sector identify the critical parameters of the system to improve the system more efficiently.
(5) The method of multi-objective optimization proposed in the paper can be extended to the performance optimization of high energy consumption equipment in other industries, to promote the sustainable development of the related industries.

4. Conclusions

The optimization of the milk powder spray drying system is crucial for the sustainable development of the dairy industry. This paper proposes a multi-objective optimization method for the MPSD system, which comprehensively aims to improve the system performance from three aspects: environmental performance, economic performance, and product quality. Therefore, a multi-objective optimization model of the system is established to minimize the environmental impact and life cycle cost of the system and maximize the quality of milk powder. The non-dominated sorting ant colony genetic algorithm is proposed to improve the optimization ability of the multi-objective problem. The LCA surrogate model based on the BP neural network is established to improve the efficiency of the optimization. The TOPSIS method is used

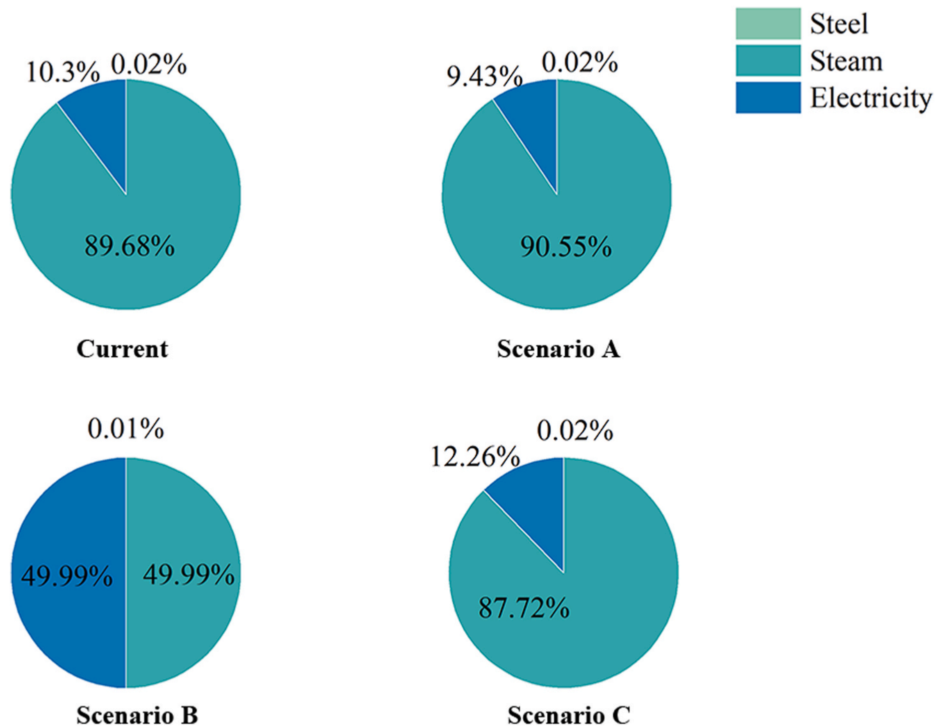

Fig. 12. Contributions of energy and resource consumption in PED.

Table 10
Properties of milk powder of different schemes.

Properties	Unit	Current	A	B	C
Bulk density	kg/m^3	239.44	236.43	235.24	240.38
Browning index	OD/g dm	0.13	0.11	0.12	0.13
Insolubility index	ml/50 ml	0.12	0.11	0.05	0.13
Cholesterol content	mg/100g	45.44	52.71	57.73	45.69
Dispersibility	%	80.08	81.15	81.23	80.81

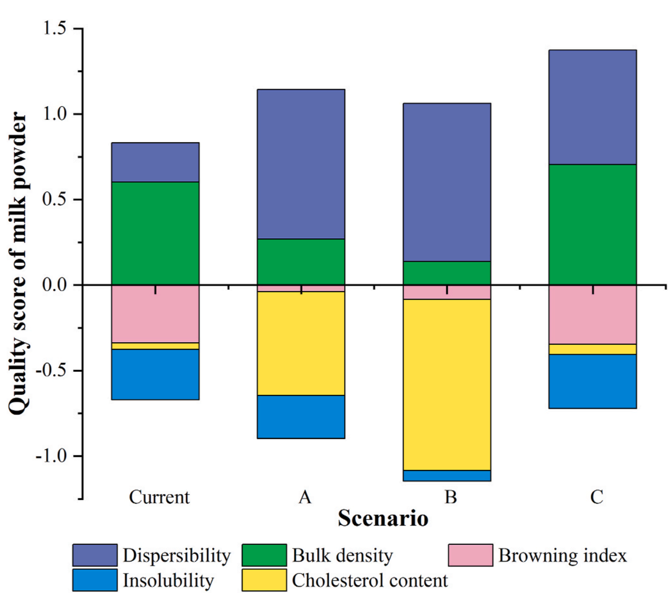

Fig. 13. The quality score of milk powder of different scenarios.

to make the decision on the Pareto front, and the optimal scheme is determined. The main conclusions are as follows:

- The quality of milk powder decreases rapidly with the reduction of environmental impact and life cycle cost of the system.
- The comprehensive performance of the MPSD system is the best when the inlet temperature is 182.98 °C, the feed pump speed is 80.74 rpm and the atomization pressure is 180.34 bar. The environmental impact of the system adopting the optimal scheme is reduced by 9.20%, the life cycle cost of the system is saved by 10.56%, and the quality of milk powder is improved by 4.35% compared with the original system.
- The performance of the NSACGA approach in GD, SP, and IGD is improved by more than 36.58%, 30.76%, and 87.10%, respectively, compared with NSGA-II, MOEA/D, NSGA-III, and SPEA2. Furthermore, the solution obtained by the proposed method is the best in the three objectives compared with the solutions obtained by the four optimization methods.
- The scheme obtained using the multi-objective optimization framework proposed in the article is proved to be the best in the three aspects through the comparative analysis of the optimal scheme with the results of dual-objective optimization and single-objective optimization.
- The solving time of the multi-objective optimization of the system can be shortened from 3.5 h to 8.68 s on the premise of accuracy by using the surrogate model.

This research has two limitations. On the one hand, the energy of the system mainly comes from thermal power plants according to the characteristics of energy structure in China. The influence of different energy structures on the environmental and economic performance of the system can be considered to improve the generalization of the research. On the other hand, the impact of wastewater treatment has not been considered. Future research can start from the following aspects. The impact of changes in energy structure on system performance can be considered, such as solar energy, wind energy and cogeneration. The impact of wastewater treatment on the environmental and economic performance of the system can also be considered. This paper adopts the ant colony algorithm to improve the NSGA-II method. The effect of adopting other swarm intelligence algorithms such as reptile search algorithm and dwarf mongoose optimization to improve NSGA-II can be explored in the future.

CRediT authorship contribution statement

Zunhao Zhang: Conceptualization, Methodology, Software, Formal analysis, Investigation, Visualization, Resources, Writing – original draft. **Junxia Zhang:** Conceptualization, Investigation, Writing – review & editing, Supervision, Funding acquisition, Project administration. **Wei Tian:** Validation, Formal analysis, Writing – review & editing. **Yang Li:** Formal analysis, Supervision. **Yahui Song:** Investigation, Supervision. **Peng Zhang:** Formal analysis, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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