

Article

A Multiobjective Optimization Algorithm for Fluid Catalytic Cracking Process with Constraints and Dynamic Environments

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Abstract: The optimization problems in a fluid catalytic cracking process with dynamic constraints and conflicting objectives are challenging due to the complicated constraints and dynamic environments. The decision variables need to be reoptimized to obtain the best objectives when dynamic environments arise. To solve these problems, we established a mathematical model and proposed a dynamic constrained multiobjective optimization evolution algorithm for the fluid catalytic cracking process. In this algorithm, we design an offspring generation strategy based on minimax solutions, which can explore more feasible regions and converge quickly. Additionally, a dynamic response strategy based on population feasibility is proposed to improve the feasible and infeasible solutions by different perturbations, respectively. To verify the effectiveness of the algorithm, we test the algorithm on ten instances based on the hypervolume metric. Experimental results show that the proposed algorithm is highly competitive with several state-of-the-art competitors.

Keywords: dynamic constrained multiobjective optimization; fluid catalytic cracking; offspring generation; dynamic response strategy

MSC: 90C29



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1. Introduction

The petroleum refining industry is one of the pillars of the world's energy sector, providing energy for many industries, such as transport. The fluid catalytic cracking (FCC) unit for petroleum is an important secondary processing equipment in the refining industry, which cracks long-chain hydrocarbon petroleum molecules into shorter-chain hydrocarbons under the action of a catalyst, obtaining products such as diesel and gasoline. In an FCC unit, the values of the decision variables (e.g., feed temperature, catalyst temperature, flow rate, etc.) determine the economic efficiency of the enterprise and the energy consumption. They are constrained by the demand for production, the production capacity of the unit, etc. In addition, in actual production, the minimax production volume of different fossil fuels is constantly changing over time due to market demand, vessel capacity, unit operating conditions, etc., which in turn affects the economic value of the fossil fuel, the energy consumption of the unit, etc. Therefore, designing an efficient optimization algorithm of the decision variables of the FCC unit in conjunction with dynamic conditions and constraints during the production process is of great significance in reducing the cost of production and improving the economic efficiency of the enterprise.

Changing yield constraints and conflicting objectives of FCC units can pose the following challenges to optimizing the FCC process:

(1) Handling infeasible solutions

In an FCC unit, constraints lead to the fact that a solution may violate the yield constraints, becoming an infeasible solution even if its decision variables are within the range of their maximum and minimum values. Improving some infeasible solutions can easily cause them to become feasible solutions or even nondominated solutions. Additionally, some infeasible solutions are more likely to lead the feasible solution to move toward the Pareto optimal front (POF) when they cross each other. Therefore, determining how to deal with infeasible solutions in the optimization process is a challenging problem.

(2) Designing dynamic response strategies

In an FCC unit, the changing yield constraints and vessel capacity cause irregular changes in the feasible region of the decision variables and objective values. The nondominated solutions in the previous environment may become infeasible ones, while infeasible solutions in the previous environment may become feasible ones in the current environment or even nondominated solutions. Meanwhile, the true POF varies with yield constraints, presenting a discontinuous and unpredictable distribution. Additionally, units usually need to determine the optimal solution in a short period (within two minutes). Therefore, designing a fast and effective dynamic response strategy for the FCC process to cope with the irregular variations of the true POF is difficult.

However, the current algorithms were designed based on the test set of DCMOPs, and no algorithms have been found to solve the DCMOP of the FCC process. Compared with test problems, the constraint regions, POF, etc., of the DCMOP of the FCC process have complex changes in dynamic environments. Therefore, it is necessary to design an effective optimization algorithm in combination with the characteristics of the DCMOP of the FCC process.

To effectively solve the DCMOP of the FCC process, this paper proposes a dynamic constrained multiobjective optimization evolution algorithm for the FCC process (FCC-DCMOEA). The main contributions of this paper are as follows:

(1) This paper uses a neural network to establish the relationship between the decision variables and fossil fuel yields, obtaining a mathematical model which maximizes the production profit and minimizes the energy consumption.

(2) We propose a constraint handling strategy based on the minimax solutions, helping the population explore true POF and preventing the population from falling into local optimal solutions.

(3) We propose a fast dynamic response strategy based on population feasibility, guiding population evolution using the change direction of the centroid of the POF under constraints.

The rest of this paper is organized as follows. Section 2 reviews the relevant research works and points out the existing problems in the current research. Section 3 establishes a mathematical model of dynamic constrained multiobjective problems based on the FCC process. Section 4 designs a dynamic constrained multiobjective algorithm to solve DCMOPs of the FCC process. Section 5 compares the proposed algorithm with the existing dynamic constrained multiobjective optimization algorithms and concludes the superiority of our proposed algorithm. Section 6 summarizes the contributions of this paper, draws conclusions, and proposes a plan for future work.

2. Related Work

In recent years, scholars have carried out preliminary explorations for the FCC optimization problem. John et al. [1] used gPROMS software to determine the optimal operating conditions for maximizing gasoline production. Sildir et al. [2] adopted a linear programming approach to determine the operating variables to improve the economic profitability of the FCC process. Han et al. [3] used the sequential quadratic programming technique to optimize these variables to improve economic profit. However, the optimization problem of the FCC process becomes more complex when this problem contains multiple constraints, and the above methods require a large amount of computational time. Chen et al. [4] designed a fast adaptive differential evolutionary algorithm to solve the constrained single

objective optimization problem of an FCC process. This algorithm showed better results, but it was designed to solve single-objective problems. Kasat et al. [5] used a genetic algorithm to solve operational variable problems with multiple objectives such as maximizing gasoline production and minimizing the air flow rate. However, this algorithm was proposed for solving static optimization problems, and it is difficult to solve dynamic constrained multiobjective optimization problems (DCMOPs). Mulumba et al. [6] proposed a parametric-model-based solution of a nonlinear optimization problem to control the FCC unit.

Currently, there is no method to solve the constrained multiobjective optimization problem of the FCC process. However, many scholars have designed different constrained multiobjective optimization algorithms for solving other problems. Park et al. [7] formulated the energy decomposition problem as a constrained multiobjective problem and solved it using a constrained multiobjective evolutionary algorithm. Zuo et al. [8] combined the constraint-objective separation method with the multioperator method and proposed an autonomous constrained evolutionary optimization algorithm based on the population-feasible state-guided autonomous constrained evolutionary optimization algorithm. Liu et al. [9] presented a state–action–reward–state–action-based constrained multiobjective differential evolutionary algorithm. Wang et al. [10] proposed a constrained multiobjective evolutionary algorithm based on dynamic constraint boundary hairs. Cuate et al. [11] designed a constrained multiobjective evolutionary algorithm based on the continuation method and the NSGA-II algorithm. Sabbaghzade et al. [12] used a combination of population-based metaheuristic ideal gas molecular motion (IGMM) algorithm and endurance time (ET) method to solve a constrained multiobjective optimization problem for seismic design. Xu et al. [13] used a multiobjective antlion optimization algorithm (MOALO) to solve a constrained multiobjective optimization problem in the aluminum electrolysis process. Liu et al. [14] proposed a novel constrained multiobjective optimization framework that includes detection and supervision phases to guide the coevolution of two populations.

Additionally, some dynamic constrained multiobjective algorithms have been proposed for solving DCMOPs. Azzouz et al. [15] designed a dynamic constrained multiobjective optimization algorithm (DC-MOEA) based on constraint deviations and objective values. This algorithm proposes a dynamic response strategy based on a memory scheme to retain some of the solutions obtained from the previous environment. Chen et al. [16] proposed a dynamic constrained multiobjective algorithm (*d*CMOEA) that includes the nondominated selection operator, the memory mechanism, the population selection operator, and a dynamic response strategy. Azzouz et al. [17] improved on the NSGA-II [18] algorithm and designed two dynamic constrained multiobjective algorithms, DNSGA-II-A and DNSGA-II-B, based on adaptive penalty functions to cope with dynamic constraints. Chen et al. [19] proposed the use of a two-phase diversity compensation strategy (TDCEA) based on the CCMO [20] strategy for DCMOPs. In the first stage, some initial individuals are randomly generated to replace the historical individuals to improve the global diversity of the population. The increment between the centroids of the POF in the past environments is calculated and used to perturb the solution in the second stage adaptively. Chen et al. [21] proposed a tribe classification operator dividing the population into different tribes by a feasibility check and the objective values, a population selection strategy to identify promising solutions from tribes, and a scalable generator to simulate diverse movement directions. Guo et al. [22] presented a dynamic constrained multiobjective evolutionary algorithm that uses a decision variable classification strategy to design the offspring generation method and dynamism response strategy. To track the changing POF in DCMOPs, Chen et al. [23] introduced a dynamic constrained multiobjective evolutionary algorithm based on a subspace-knowledge transfer strategy. Zhang et al. [24] proposed a novel prediction-based similar environment identification method and an experience-driven two-state environmental selection strategy to address DCMOPs.

3. Problem Description

The main purpose of optimizing the DCMOP of an FCC process is to reoptimize the best decision variables when the yield constraints and the vessel capacity change, improving production profit and reducing energy consumption.

In this section, we first describe the FCC process, followed by the impact of each decision variable on profit and energy consumption. Finally, we formulate this multiobjective optimization problem as a mathematical model.

3.1. Production Process of the FCC Unit

An FCC unit comprises three main components: a regenerator (on the left), a reactor (in the center), and a fractionator (on the right). The decision variables or yields for each material are included in brackets. For example, $THO(t)$, $FHO(t)$ under the heavy oil (HO) are the temperature and flow rate of HO at t , respectively, and $Y3(t)$ denotes the output of natural gas at t . tp_1 denotes the first tower plate.

In the reactor, the riser is critically important for the FCC process. In this part, the hot regenerated catalyst (HRC) and HO are the primary heat sources in the reactor. The HO reaches the injector (the purple area in Figure 1) of the riser at a particular flow rate ($FHO(t)$) and a specified temperature ($THO(t)$). It vaporizes after contacting the HRC supplied by the regenerator. The lifting steam (LS) at a defined flow rate ($FLS(t)$) is added to the riser's base, providing the upward force essential for moving the HRC and vaporized HO. In the riser, the vaporized HO undergoes cracking to form lighter hydrocarbons (LHs). Meanwhile, coke is deposited on the HRC surface, diminishing its activity. The deactivated HRC then separates from the LHs at the riser's top. This HRC descends into the stripping section (the blue area in Figure 1) of the reactor, while the LHs proceed to the fractionator for further separation.

In the regenerator, the stripping steam (SS) at a given flow rate ($FSS(t)$) is introduced to remove LHs absorbed on the deactivated HRC's surface. Subsequently, the deactivated HRC transitions to the regenerator from the stripping section. In the regenerator, the HRC is reactivated through the combustion of deposited coke, thereby increasing the HRC's temperature. Pollutants after combustion are directed to decontamination equipment, and the HRC is recycled back to the riser's injector at a certain temperature ($TC(t)$) and flow rate ($FC(t)$).

In the fractionator, tray temperatures increase from top to bottom. The LHs are liquified into distillates on respective trays due to the different boiling points of fossil fuel. The distillates collected from trays tp_1 to tp_3 are considered diesel and extracted through an outlet connected to tray tp_3 . The distillates are directed toward the pump around (PA1, PA2, and PA3) for heat exchange. Their calorific values are $HR_1(t)$, $HR_2(t)$, and $HR_3(t)$, respectively, to adjust the corresponding tray temperatures. The unliquified hydrocarbons proceed to the condenser via the fractionator's top. In the condenser, the liquified and unliquified hydrocarbons are classified as gasoline and natural gas, respectively.

The production process of the FCC unit is shown in Figure 1.

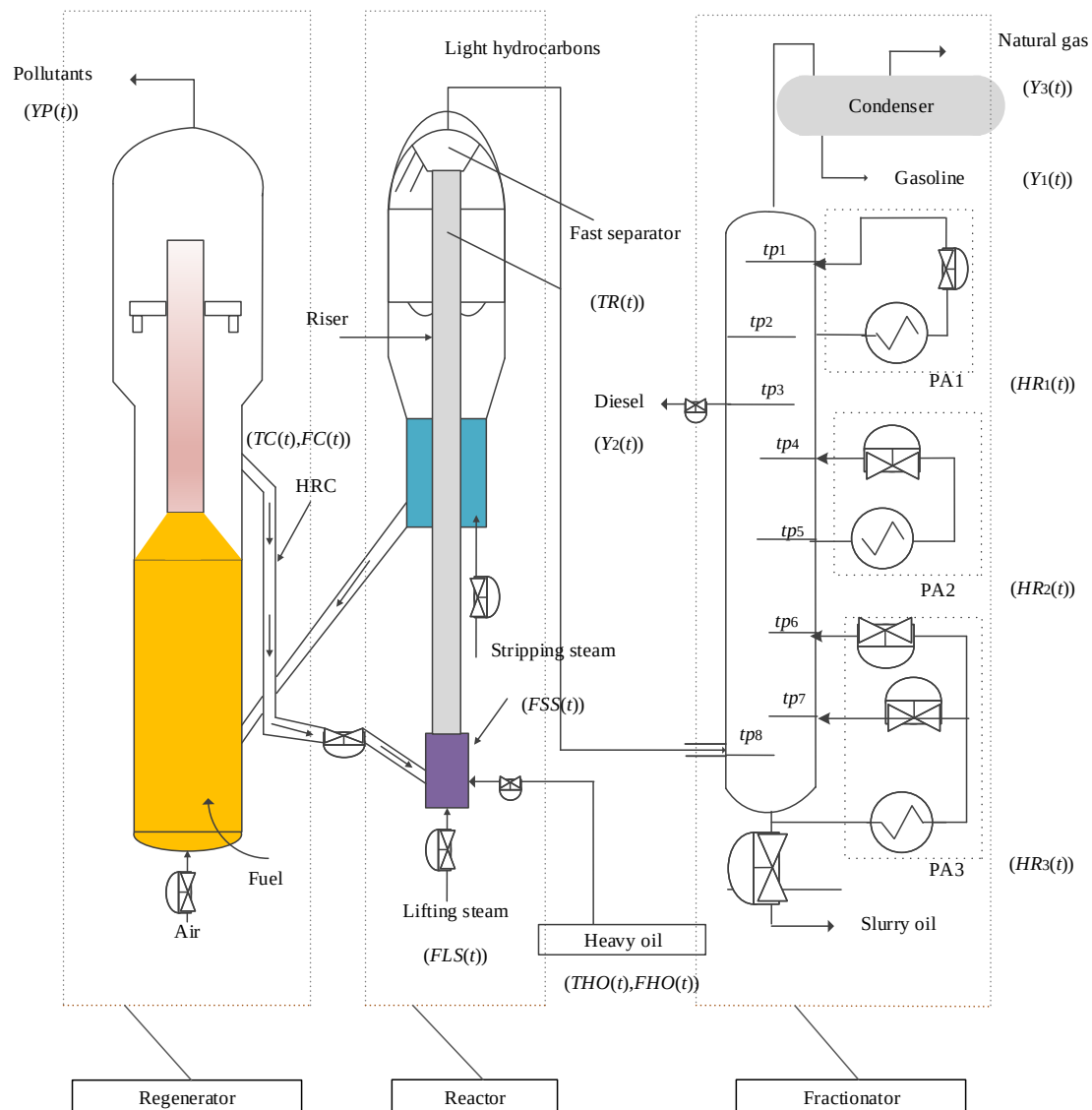


Figure 1. The production process of the FCC unit.

3.2. DCMOP of the FCC Process

In an FCC unit, the main objectives are to maximize production profit and minimize production energy consumption. The decision variables, some other variables, and constants are as follows:

Decision variables, other variables, and constants with these descriptions are shown in Table 1.

In the reactor of the FCC unit, the energy consumption and the cost increase with the HO temperature $THO(t)$ and the HRC temperature $TC(t)$. Meanwhile, the temperature of the riser increases due to the increase in the temperature of the HO and HRC. Therefore, the degree of HO cracking becomes larger. Conversely, the degree of HO cracking decreases with the temperature. In general, the production of gasoline, natural gas, coke, and pollutants become larger and the production of diesel becomes less when the degree of HO cracking is large. Conversely, the production of diesel becomes larger and other fossil fuels become smaller if the degree of HO cracking is small. When the flow rate $FC(t)$ of the HRC is increased, it usually increases the reaction rate of cracking and the production of gasoline and diesel. Thereby, the profitability of production increases. However, too much HRC can increase the contaminant content in the product, leading to higher costs of decontamination

and lower profits. The flow rate of HO, $FHO(t)$, directly affects the yield of the final product. A suitable flow rate helps to increase the output of desirable light hydrocarbon products (e.g., gasoline) while controlling the ratio of diesel to natural gas. On the other hand, excessive flow rates may cause HRC overloading, reducing reaction efficiency, increasing pollutants, and reducing production margins. The flow rate of lift steam, $FLS(t)$, determines the upward thrust of the steam and affects the contact efficiency between the hot HRC and the HO. The larger the $FLS(t)$, the longer the contact time between the HRC and HO. This measure can improve the yields of light hydrocarbons and medium–light fractions (e.g., gasoline and diesel oil), and increase profitability. However, too large a flow rate may lead to unnecessary energy consumption. In the stripping section of the reactor, increasing the flow rate of SS, $FSS(t)$ can effectively remove adsorbed light hydrocarbons from the HRC surface and improve HRC regeneration. However, excess SS may lead to a sharp increase in energy consumption, which is not favorable to the economy. The cracking reaction is a heat-absorbing process. Thus, the temperature decreases with the height of the riser, which will affect the cracking reaction. The exit temperature of the riser, $TR(t)$, is used to indicate how drastically heat absorption affects the cracking inside the reactor. It is influenced by other decision variables. Higher temperatures help to produce more light hydrocarbons but increase the generation of pollutants.

Table 1. Decision variables, other variables, and constants with these descriptions.

Variables and Constants	Descriptions
$FC(t)$	The flow rate of the HRC at t .
$TC(t)$	Temperature of the regenerated HRC at t .
$FSS(t)$	The flow rate of the SS at t .
$FLS(t)$	The flow rate of lift steam at t .
$FHO(t)$	The flow rate of HO at t .
$TR(t)$	Outlet temperature of the riser at t .
$THO(t)$	Temperature of the HO at t .
$HR_1(t)$	Heat recovered in the first circuit at t .
$HR_2(t)$	Heat recovered in the second circuit at t .
$HR_3(t)$	Heat recovered in the third circuit at t .
$Y_s(t)$	The yield of the s th fossil fuel at t .
$YP(t)$	The yield of pollutants at t .
PHO	Unit price of HO.
PY_s	Unit price of the s th fossil fuel.
PYP	Unit price of removing the pollutant.
ρ	The energy required to raise 1 mol of HRC by 1 °C.
es	The energy required to obtain 1 mol of steam.

In the regenerator of an FCC unit, the HRC needs to be heated by the combustion of fuel. The higher the temperature of the HRC, $TC(t)$, the more energy is consumed.

In the fractionator, the temperature of the tray is controlled by PA1, PA2, and PA3. The temperature of the tray then affects the yields of fossil fuel (gasoline, diesel, and natural gas). $HR_1(t)$, $HR_2(t)$, and $HR_3(t)$ can recover the distillation energy for energy recycling, effectively reducing energy consumption. However, excess energy recovery reduces the yields of fossil fuel.

Based on the above discussion, we obtain the relationship between the two desired objectives and the decision variables, and establish the multiobjective optimization model as follows:

$$\max f_{\text{product}}(X(t)) = \sum_{s=1}^3 Y_s(t) \times PY_s - YP(t) \times PYP - FHO(t) \times PHO \quad (1)$$

$$\min f_{\text{energy}}(X(t)) = (TC(t) - TR(t)) \times FC(t) \times \rho + (FSS(t) + FLS(t)) \times es - \sum_{w=1}^3 HR_w(t) \quad (2)$$

where the decision variables are as follows.

$$X(t) = [FC(t), TC(t), FSS(t), FLS(t), FHO(t), TR(t), THO(t), HR_1(t), HR_2(t), HR_3(t)] \quad (3)$$

The compositions of the objectives and these descriptions are shown in Table 2.

Table 2. The compositions of the objectives and these descriptions.

Compositions of the Objectives	Descriptions
$Y_S(t) \times PY_S$	Revenue from sales of the sth fossil fuel.
$\sum_{s=1}^3 Y_S(t) \times PY_S$	Revenue from sales of all fossil fuels.
$YP(t) \times PYP$	Decontamination cost.
$FHO(t) \times PHO$	HO cost.
$TC(t) - TR(t)$	Temperature of HRC lift.
$(TC(t) - TR(t)) \times FC(t) \times \rho$	The energy required to heat the HRC.
$FSS(t) + FLS(t)$	Required steam flow rate.
$(FSS(t) + FLS(t)) \times es$	The energy consumed by steam.
$\sum_{w=1}^3 HR_w(t)$	Heat recovered from all sideline circuits.

The DCMOPs of the FCC process need to satisfy the following constraints:

(1) The FCC unit production capacity constraints

Each decision variable represents an operating variable controlling the FCC unit. They need to be varied within the range of its reserve production capacity for the k th operational variable at t . In this paper, Equation (4) is used to define the production capacity constraints of the variables.

$$lx_k \leq x_k(t) \leq ux_k \quad (4)$$

(2) Property constraints of fossil fuel

HO needs to undergo complex physicochemical reactions with HRCs in an FCC unit to produce light components with different boiling point ranges. Thus, the properties of light components are related to the degree of cracking of HO and the composition of hydrocarbons with different boiling points in the light components. In other words, the degree of cracking of the HO affects the properties of the fossil fuel. In the case of gasoline, the octane number contained in gasoline is very important for its antidetonation properties, so the octane content of gasoline needs to meet certain constraints. For fossil fuels obtained in the refining process, the properties of fossil fuels can be expressed by their boiling point distillation properties [25]. To ensure that the properties of the sth fossil fuel meet the actual production requirements, this paper expresses the property constraints of the sth fossil fuel in terms of the distillate temperature constraints of the fossil fuel at 10% and 90%.

$$lDT_{s,10\%} \leq DT_{s,10\%}(t) \leq uDT_{s,10\%} \quad (5)$$

$$lDT_{s,90\%} \leq DT_{s,90\%}(t) \leq uDT_{s,90\%} \quad (6)$$

$$DT_{s,10\%}(t) = H_{s,10\%}(X(t)) \quad (7)$$

$$DT_{s,90\%}(t) = H_{s,90\%}(X(t)) \quad (8)$$

where $H_{s,10\%}(\bullet)$ and $H_{s,90\%}(\bullet)$ denote the nonlinear relationship between the decision variable and the temperature of the sth fossil fuel at 10% and 90% distillation, respectively.

(3) Constraints on the relationship between variables and fossil fuel yields

The variables in the FCC unit determine the production of each fossil fuel and pollutant. Thus, there is a complex nonlinear relationship between the variables and the production. The stochastic weight neural network model proposed by Alhamdoosh et al. [26] is characterized by fast training and high accuracy. Therefore, this paper establishes the relationship

between the variables and the fossil fuel production and pollutant production based on the model, as shown in Equations (9) and (10).

$$Y_s(t) = G_s(X(t)) \quad (9)$$

$$YP(t) = G_p(X(t)) \quad (10)$$

where $G_s(\bullet)$ denotes the nonlinear relationship between the operational variable and the production of the s th fossil fuel. $G_p(\bullet)$ denotes the nonlinear relationship between the operational variables and the pollutant yield.

(4) Fossil fuel yield constraints

In actual production, the outputs of fossil fuel are limited by the actual production demand and the available capacity of storage tanks in the plant. When the actual production demand or the storage tank capacity changes, the output of the s th fossil fuel needs to satisfy the constraints to ensure that the fossil fuel produced will not lead to phenomena such as bubbling tanks during the production process. The constraints are shown in Equation (11).

$$lY_s(t) \leq Y_s(t) \leq uY_s(t) \quad (11)$$

(5) Constraints on the location of key tower plates and fossil fuel outlets

The light components delivered from the FCC unit enter the fractionator to produce products such as gasoline, light diesel oil, and natural gas. As can be seen in Figure 1, each fossil fuel will exit the fractionator from its specific outlet. For instance, diesel will exit the fractionator from the tp_3 tower plate in the fractionator. Since it is difficult to change the location of the outlets on the fractionator, the key tower plates in the fractionator need to correspond to the outlets of the particular fossil fuel. For this reason, the tower plate index of the fractionating column is used to express its constraints in terms of the fossil fuel index, and the correspondence is shown in Equation (12).

$$r = \begin{cases} tp_1, & \text{if } l = 1 \text{ or } 2 \\ tp_3, & \text{if } l = 3 \end{cases} \quad (12)$$

(6) Material balance constraints

For an FCC unit, during operation, the flow rate of HO should be greater than or equal to the flow rate of gasoline, diesel, natural gas, and residue. In other words, the sum of the flow rates of all fossil fuels needs to be less than or equal to the flow rate of HO. The flow rates of the relevant materials need to satisfy the following relationship, as shown in Equation (13).

$$\sum_{s=1}^3 Y_s(t) + YP(t) < FHO(t) \quad (13)$$

4. Methods

4.1. Framework of FCC-DCMOEA

The basic framework is shown in Algorithm 1.

In FCC-DCMOEA, an initial population P with N solutions is generated (line 3 of Algorithm 1). Then, the algorithm starts renewing the population. FCC-DCMOEA first determines whether the yield constraints and capacity constraints have changed (line 5 of Algorithm 1). Retaining the population in the previous environment can help the algorithm to make an effective dynamic response strategy. Therefore, the algorithm retains the mean of the population's feasible POF under the previous constraint before performing the dynamic response, denoted as PS_{t-1} (line 6 of Algorithm 1). Then, FCC-DCMOEA uses a dynamic response strategy based on population feasibility to update the population P (line 7 of Algorithm 1).

In a DCMOP of an FCC process, the constraints changing irregularly complicate the POF, and even turn into a discontinuous state. FCC-DCMOEA adopts an offspring

generation strategy based on minimax solutions to explore as many feasible regions as possible and avoid the algorithm from falling into local optimality. FCC-DCMOEA uses this strategy to generate N children by the population P (line 9 of Algorithm 1). In an FCC process, the number of feasible solutions is usually small. The feasible solution-first environment selection operator [20] proposed by Tian et al. can preserve more feasible solutions. This strategy utilizes the feasibility-first principle. The feasible solutions are selected first, and then the better-performing solutions are selected from the infeasible solutions for the next generation if the number of feasible solutions is insufficient. Thus, FCC-DCMOEA uses this strategy to select the better-performing solutions to update the population P (line 10 of Algorithm 1). Retaining the solutions that perform well in the population at each generation can make the algorithm more effective. The nondominated solution selection operator [16] proposed by Chen et al. can effectively select the superior solutions of the population during the generation process and retain them. This algorithm selects undominated feasible solutions from the population. Therefore, FCC-DCMOEA uses this strategy to update the elite solution set A by the population P and A of the previous generation (line 11 of Algorithm 1).

The above steps (5–12) are continued until the production session of the FCC process is fully completed.

Algorithm 1: Framework of FCC-DCMOEA

1. **Input:** $P = \emptyset, A = \emptyset$
 2. **Output:** A
 3. *Initialization:* generate initial population P with N random solutions
 4. **while** termination condition is not met **do**
 5. **if** the constraints of production demand or capacity change **then**
 6. Calculate the mean of nondominated solutions of P under the previous constraints, denoted PS_{t-1}
 7. $P = \text{Dynamic Response Strategy based on population feasibility } (P)$
 8. **end if**
 9. $Q = \text{Offspring generation strategy based on minimax solutions } (P)$
 10. $P = \text{Feasible-solutions-first environment selection operator } (P, Q)$
 11. $A = \text{Nondominated selection operator } (P, A)$
 12. **end while**
-

4.2. Offspring Generation Strategy Based on Minimax Solutions

Feasible regions change irregularly with the yield and capacity constraints in the FCC process. This may lead the feasible POF to be discontinuous. Therefore, the algorithm converging quickly to the true POF may lead to the population being trapped in a local optimum.

Handling infeasible solutions and preventing the solution set from falling into a local optimum are difficult. In DCMOPs of the FCC process, the feasible region of a decision variable is often divided into several small discontinuous regions due to complicated constraints. The minimax solutions are usually located at the edges of the feasible region, and they can find small feasible regions in their neighborhood through a minor perturbation. The discontinuous feasible regions can be explored more efficiently by utilizing these solutions. Thus, FCC-DCMOEA introduces a mutation operator based on the minimax solutions to guide the population to escape from the local optimum. The details of the offspring generation strategy based on the minimax solutions are described as follows.

This strategy first calculates the feasibility of the solutions in the population and selects the feasible solutions from the population P , denoted as FP . Meanwhile, the strategy determines the minimax solutions in FP , denoted as min and max .

Then, FCC-DCMOEA uses max and min to generate partial offspring through the mutation operator of the MOEA algorithm [27]. This procedure will continue until the population generates $K*N$ children. These children can increase the exploration range of

the feasible region of the population and help the populations escape the region of locally optimal solutions.

It is difficult to converge the population quickly. Selecting better-performing parents to produce children can help the population converge quickly. The population selection operator [16] proposed by Chen et al. can effectively select promising parents. Thus, the strategy adopts this operator to select the better-performing parents in the population P . The offspring generation operator of MOEA proposed by Tian et al. [20] can efficiently generate well-performing children. Thus, this operator is used to generate the remaining offspring ($N-K*N$ children).

The exploration space is increased by using the offspring generation strategy based on minimax solutions. Meanwhile, the population selection operator is utilized to help the population to converge quickly. Combining these two operators allows the algorithm to explore more feasible regions and converge quickly.

The pseudocode of the offspring generation strategy based on minimax solutions is presented in Algorithm 2.

Algorithm 2: The offspring generation strategy based on minimax solutions

```

1. Input:  $P, Q = \emptyset$ 
2. Output:  $P, Q$ 
3.  $FP$  = feasible solutions in  $P$ 
4.  $(max, min)$  = the minimax
   solutions in  $FP$ 
5. while the number of  $Q < N$  do
6.   if the number of  $Q < K*N$  then
7.      $Q$  = Generate offspring based on  $(max, min)$  by mutation strategy of MOEA
8.   else
9.      $P' =$  Mating Selection Operator ( $P$ );
10.     $Q =$  Offspring Generation Operator ( $P'$ );
11.   end if
12. end while

```

4.3. Dynamic Response Strategy Based on Population Feasibility

The dynamic changes in an FCC unit are from production constraints and the capacity of the production vessel. These dynamic changes can be known in advance. Therefore, in DCMOPs of the FCC process, there is no need to perform change detection for specific dynamic changes.

The feasible regions of the decision variables show irregular changes with the production constraints and the capacity of the production vessel. In the present environment, the feasible solution under the previous constraints may become infeasible, and the infeasible solution under the previous constraints may become feasible. It is difficult to use the previous environment's solutions as the next environment's populations directly. Therefore, it is necessary to search the entire feasible region of decision variables when responding to dynamic environments.

The two-stage diversity compensation strategy proposed by Chen et al. [23] can effectively explore the feasible region. Inspired by this strategy, we design a dynamic response strategy based on population feasibility. This strategy introduces some random solutions and adds different incremental terms according to the feasible and infeasible solutions. The specific method is as follows:

If the constraints are changed, the strategy first enhances the diversity of the population. $j*N$ solutions are generated randomly to replace the solutions in the population P . Then, the strategy calculates the constraint deviation values of the solutions in the population and divides them into the feasible solution FS and infeasible solution IS . If there is no solution in the feasible solution set, the strategy regenerates 50% of solutions and divides

them into feasible solution FS and infeasible solution IS . This operation will continue until at least one feasible solution in the population is obtained.

Then, the proposed strategy handles the feasible and infeasible solutions separately. It is important for a dynamic response strategy to explore the feasible regions and quickly track the POF in the new environment. Using promising solutions under the new yield constraints can help the population explore the POF and feasible region. Therefore, the strategy first sorts feasible solutions by the nondominated sort proposed by Deb et al. [18] to find the feasible POF, denoted as DS . The mean of the solutions DS is calculated to help improve the population, denoted as PS_t . PS_t is used to calculate the value of its change between the current and previous constraints, $PS_t - PS_{t-1}$. After that, the proposed strategy uses this value to generate an n -dimensional randomly following a uniform distribution. Subsequently, different perturbation terms are added to the feasible and infeasible solutions, respectively, based on the feasible solution ratios q , and the perturbations and the feasible solution ratio q are calculated in Equations (14) and (15).

$$q = |FS|/N \quad (14)$$

$$X = \begin{cases} X - qU(0, \Delta) & \forall X \in FS \\ X + (1 - q)U(0, \Delta) & \forall X \in IS \end{cases} \quad (15)$$

A schematic diagram of PS feasible domain variation is shown in Figure 2. The feasible solutions E and F can explore the feasible region and approach the promising feasible subregions (the green area of Figure 2) by the feasible perturbation. The infeasible solutions G and H can move into the feasible region (the blue area of Figure 2) quickly by the infeasible perturbation.

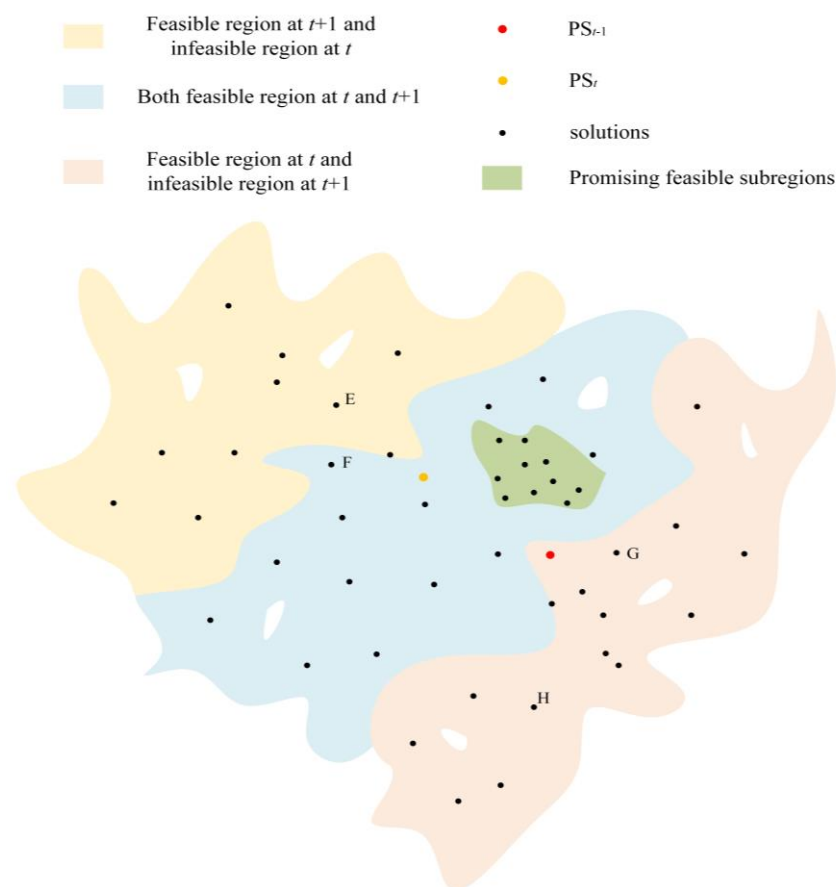


Figure 2. Schematic diagram of PS feasible domain variation.

Finally, the population with perturbation terms and the original population are merged. The feasible solution-first environment selection operator is used to select N solutions.

The pseudocode of the dynamic response strategy based on population feasibility is presented in Algorithm 3.

Algorithm 3: Dynamic response strategy based on population feasibility

1. **Input:** P, PS_{t-1}
 2. **Output:** P
 3. Initialize $j\%$ solutions randomly to replace some solutions in P
 4. Divide P into FS and IS by new constraints (t)
 5. **while** FS is empty **do**
 6. Initialize $N/2$ solutions randomly replace solutions in P
 7. Divide P into FS and IS by new constraints (t)
 8. **end while**
 9. Divide FS into DS and NS by nondominated selection
 10. $PS_t =$ The mean of DS
 11. $Q =$ Improve the diversity of FS and IS by $PS_t - PS_{t-1}$
 12. $P =$ Feasible-solutions-first environment selection operator (P, Q)
-

5. Experimental Results

5.1. Comparison of Algorithms

To compare the performance of different algorithms with FCC-DCMOEA, this paper selects five state-of-the-art dynamic constrained multiobjective algorithms, namely, d CMOEA [16], DC-MOEA [15], DC-NSGA- II-A [17], DC-NSGA- II-B [17], and TDCEA [19]. All algorithms were programmed using MATLAB R2021b and run on a computer with 32 GB RAM and a 2.90 GHz Intel Core i7-10700 CPU using the Windows 10 operating system.

5.2. Parameter Setting

To investigate the effect of the dynamic change frequency (τ_t), this paper selects ten DCMOPs of the FCC process as test problems. These DCMOPs have different yield constraints. τ_t is set to 10 and 20, respectively. The number of changes n_t is set to 20. To minimize the impact of static optimization, each algorithm runs for 40 generations before the first change occurs, resulting in a total of $n_t \times \tau_t + 40$ generations.

Both the number of parent and offspring populations N are set to 200. The crossover probability and the distribution index are set to 0.9 and 5 in SBX, respectively. The mutation probability and the distribution index are set to 0.05 and 20, respectively, in PM. The other parameters of the five comparison algorithms are the same as those used in referenced papers. The offspring generation strategy based on minimax solutions parameter K is set to 0.1. The dynamic response renews parameter j is set to 0.1.

5.3. Performance Indicators

For the DCMOP of the FCC process, the relationship between the decision variables and the fossil fuel yields is complex and nonlinear. It is impossible to know the true POF of the problem in each environment. Therefore, we adopt only one performance metric, hypervolume (HV) [28], to evaluate the algorithms at the end of each environment, which is formulated in Equation (16):

$$HV(DPOP_t^*) = VOL\left(\bigcup_{x \in A} [f_1(X), z_1] \times \cdots \times [f_m(X), z_m]\right) \quad (16)$$

Furthermore, the objectives of the DCMOP of the FCC process are maximizing the economic benefits generated and minimizing energy consumption from Equations (1) and (2). The order of magnitude of the two objective values is in the hundreds of thousands based on the pre-experiments in this paper. This paper proposes to divide the objective values of f_{product} and f_{energy} by 100,000 and 100,000,000, respectively, to calculate the HV of the

nondominated solutions. Meanwhile, (0,10) is used as the reference point for calculating the HV of the nondominated solutions.

Each DCMOP of the FCC process contains n_t dynamic environments. Therefore, this paper uses the mean HV (MHV) [29] to compare the performance of the algorithms, which is calculated as follows:

$$MHV = \frac{1}{n} \sum_{t=1}^{n_t} HV(DPOP_t^*) \quad (17)$$

A larger MHV value means the algorithm is performing better. For each DCMOP of the FCC process and each combination (τ_t, nt) , each algorithm was run 30 times, and the mean and standard deviation of the MHV values are given in the corresponding tables. This paper exploits the Wilcoxon rank-sum test at the 0.05 significance level to determine whether one algorithm statistically differs from others concerning the performance metrics.

5.4. Algorithm Comparison Results

This section compares FCC-DCMOEA with five other dynamic constrained multiobjective algorithms (*d*CMOEA, DC-MOEA, DC-NSGA-II-A, DC-NSGA-II-B, TDCEA).

Table 3 gives the comparison results of the MHV values of the above six algorithms.

Table 3. Mean and standard deviations of MHV values obtained by six algorithms.

Ins	(τ_t, nt)	<i>d</i> CMOEA	DC-MOEA	DC-NSGA-II-A	DC-NSGA-II-B	TDCEA	FCC-DCMOEA
1	(10, 20)	13.2232 (0.1049) ‡	13.1415 (1.3949) ‡	12.2007 (0.2414) ‡	9.8934 (1.0207) ‡	15.9946 (0.7355) ‡	17.9885 (0.6170)
	(20, 20)	13.8266 (0.1517) ‡	14.0447 (2.8827) ‡	12.6312 (0.3241) ‡	9.6106 (2.3600) ‡	16.5278 (0.8810) ‡	18.0907 (0.9161)
2	(10, 20)	10.5591 (0.1824) ‡	10.4263 (1.0267) ‡	9.6651 (0.3934) ‡	7.4986 (0.6697) ‡	13.2710 (1.1341) ‡	15.5564 (0.8935)
	(20, 20)	11.1794 (0.2181) ‡	10.5535 (2.4645) ‡	9.7803 (0.4065) ‡	7.3904 (0.8189) ‡	13.8392 (1.0801) ‡	15.6215 (0.3388)
3	(10, 20)	13.1162 (0.1275) ‡	12.9078 (1.0552) ‡	12.4359 (0.4031) ‡	10.2493 (2.6239) ‡	16.1017 (0.5475) ‡	17.7006 (0.8600)
	(20, 20)	13.7842 (0.2832) ‡	13.0389 (1.9996) ‡	12.6546 (0.5490) ‡	9.7345 (3.0393) ‡	16.6991 (0.7980) ‡	18.2393 (0.5213)
4	(10, 20)	10.9340 (0.1099) ‡	10.6094 (0.9201) ‡	9.7321 (0.3093) ‡	7.6763 (0.7355) ‡	13.1179 (1.4910) ‡	15.3270 (0.7937)
	(20, 20)	11.4133 (0.2007) ‡	11.0471 (1.2333) ‡	9.8299 (0.7193) ‡	7.3046 (1.4975) ‡	13.2169 (1.6156) ‡	15.8415 (0.4973)
5	(10, 20)	13.2690 (0.2276) ‡	12.8844 (1.3037) ‡	12.1761 (0.2125) ‡	9.8891 (2.1451) ‡	16.0386 (0.6832) ‡	17.9561 (0.8209)
	(20, 20)	13.7151 (0.1537) ‡	13.0050 (1.7478) ‡	12.4595 (0.4664) ‡	9.7635 (1.5637) ‡	16.2892 (1.0776) ‡	18.1681 (0.2921)
6	(10, 20)	10.4259 (0.1675) ‡	10.3070 (1.4135) ‡	9.4730 (0.3525) ‡	7.0418 (0.7157) ‡	13.3522 (1.0626) ‡	15.1668 (0.4120)
	(20, 20)	11.0914 (0.2483) ‡	10.3522 (2.3256) ‡	9.5764 (0.2570) ‡	7.0683 (0.9633) ‡	13.3981 (1.2688) ‡	15.4052 (0.3371)
7	(10, 20)	13.3334 (0.1439) ‡	13.1339 (1.1480) ‡	12.3533 (0.4491) ‡	9.5600 (1.8862) ‡	15.3230 (1.3932) ‡	17.7828 (0.6328)
	(20, 20)	13.8442 (0.2103) ‡	12.9159 (1.3192) ‡	12.5903 (0.4445) ‡	9.6916 (4.1883) ‡	15.4603 (2.4296) ‡	17.9977 (0.6756)
8	(10, 20)	10.5192 (0.1022) ‡	10.2507 (0.9244) ‡	9.4925 (0.3386) ‡	7.7260 (0.7447) ‡	12.7452 (1.7099) ‡	14.8437 (0.7976)
	(20, 20)	11.0346 (0.0680) ‡	10.1178 (2.4775) ‡	9.9005 (1.0311) ‡	7.1227 (0.5774) ‡	13.4554 (0.7523) ‡	15.1881 (0.7300)
9	(10, 20)	13.2816 (0.1505) ‡	13.2986 (1.1947) ‡	12.1494 (0.2784) ‡	10.5160 (2.5765) ‡	15.4635 (1.8418) ‡	17.6300 (0.5549)
	(20, 20)	13.7626 (0.2045) ‡	12.7708 (2.1424) ‡	12.4920 (0.5430) ‡	10.0247 (2.0840) ‡	16.1883 (1.0178) ‡	17.7957 (0.3694)
10	(10, 20)	10.7626 (0.1856) ‡	10.7021 (1.0902) ‡	10.0141 (0.6191) ‡	7.9241 (0.8917) ‡	13.9642 (1.0867) ‡	15.4050 (0.6817)
	(20, 20)	11.4352 (0.2327) ‡	11.0288 (1.4444) ‡	10.1308 (0.7669) ‡	8.0060 (0.7756) ‡	14.1149 (1.5861) ‡	15.6780 (0.5494)

‡ indicate that FCC-DCMOEA performs significantly better than the corresponding algorithm.

Based on these comparison results of MHV metrics, it can be seen that the proposed FCC-DCMOEA algorithm has excellent performance in solving ten DCMOPs of the FCC process with different change frequencies. The TDCEA algorithm has the second-best performance. The *d*CMOEA algorithm and DC-MOEA algorithm have a certain degree of effectiveness. The DC-NSGA-II-A algorithm and the DC-NSGA-II-B algorithms are slightly less effective. *d*CMOEA and DC-MOEA have similar performance on the first, second, sixth, seventh, ninth, and tenth DCMOPs of the FCC process with $\tau_t = 10$ and the first DCMOP of the FCC process with $\tau_t = 20$. Overall, the experiment demonstrates the optimization capability of FCC-DCMOEA in DCMOPs of the FCC process. In fact, FCC-DCMOEA borrows from TDCEA the idea of using perturbation PS to approach the feasible region in the dynamic response strategy, and the relatively poor performance of

TDCEA may be due to the disadvantages of its PS such as calculating without constraints and infeasible solutions handling.

As a supplement to the tabular presentation, Figures 3 and 4 show the evolutionary curves of the HV values on the first and second DCMOPs of the FCC process with $\tau_t = 20$ and $n_t = 20$.

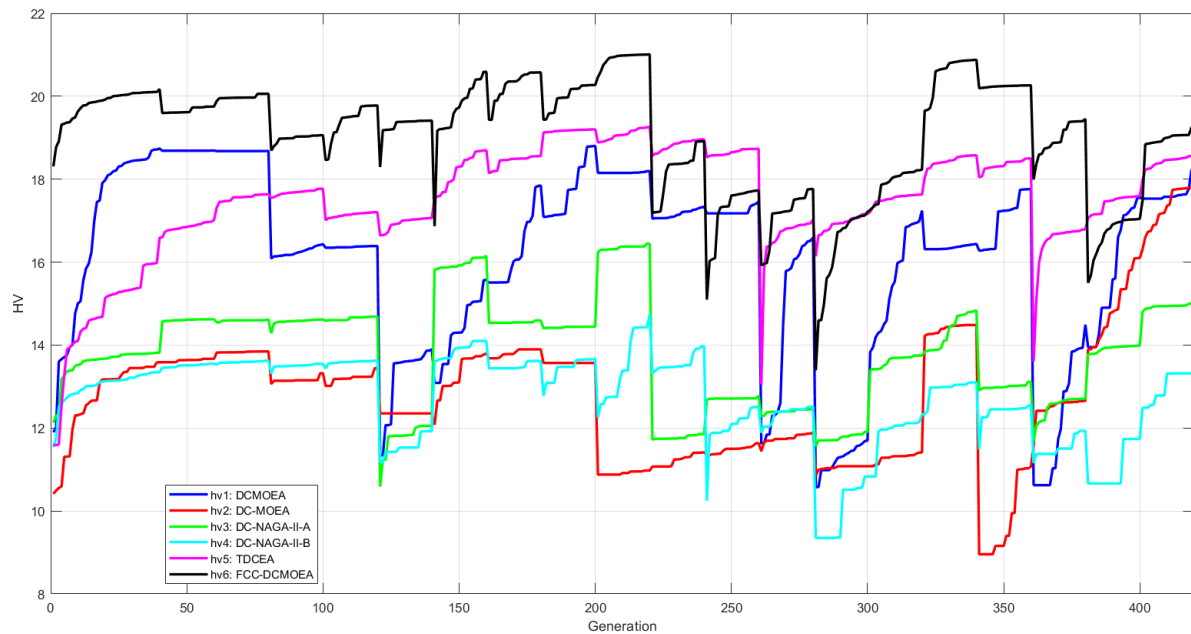


Figure 3. Evolution curves of HV values for the first DCMOP of the FCC process.

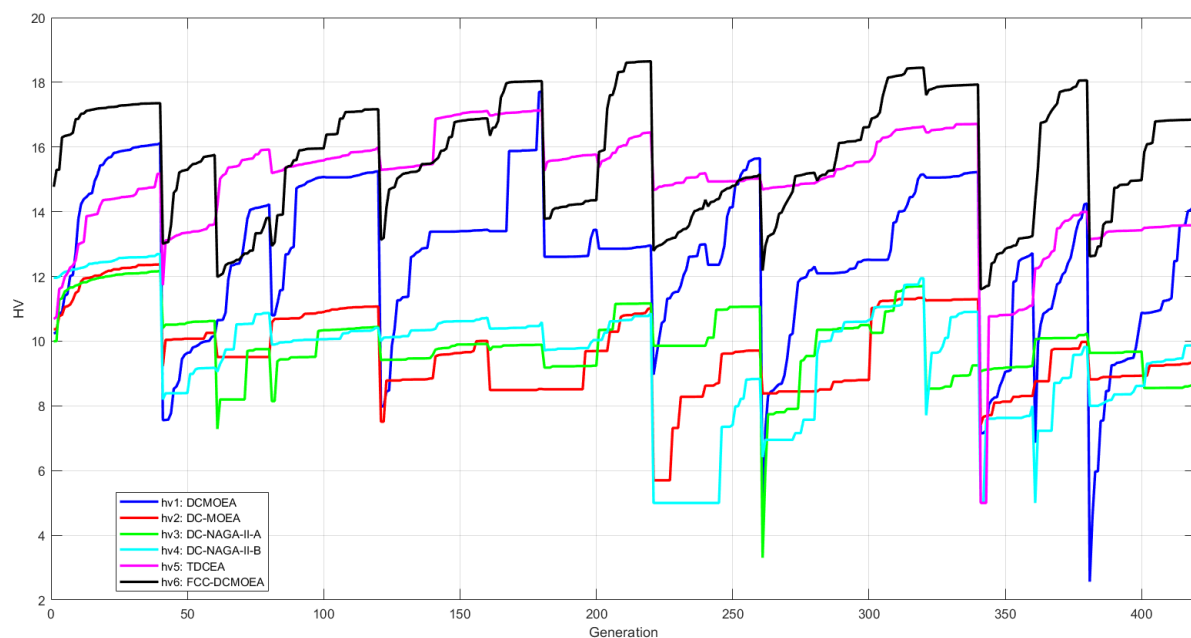


Figure 4. Evolution curves of HV values for the second DCMOP of the FCC process.

Figures 3 and 4 present that in both the first and the second DCMOPs of the FCC process, FCC-DCMOEA shows better dynamic response ability, faster convergence speed, and stronger exploration ability. The dynamic response strategy based on population feasibility can effectively guide the population to converge, and the offspring generation strategy based on minimax solutions can effectively help the population escape from the

local optimal solution. In addition, TDCEA and DCMOEA work better in dealing with both the first and the second DCMOPs of the FCC process. The other three algorithms are less effective.

5.5. Effectiveness of Different Components of FCC-DCMOEA

The proposed FCC-DCMOEA includes two main components, i.e., the offspring generation strategy based on minimax solutions and the dynamic response strategy based on population feasibility. To validate the effectiveness of each component, we exploit different strategies published in the literature to replace the corresponding approaches of FCC-DCMOEA, forming different variants. Specifically, the dynamic response strategy based on population feasibility is used to respond to dynamic environments; thus, we replace it with the dynamic response strategy proposed in [15,16,19], respectively. These variants are called DCMOEA-V1, DCMOEA-V2, and DCMOEA-V3, respectively. DCMOEA-V4 is a variant of FCC-DCMOEA that uses the coevolutionary strategy proposed in [20]. DCMOEA-V5 is a variant of FCC-DCMOEA that uses the constraints handling strategy proposed in [19]. The above variants were compared with FCC-DCMOEA on the DCMOPs of the FCC process with settings of $(\tau_t, nt) = (10, 20)$ and $(20, 20)$. The average values and the deviations of MHV metrics are given in Table 4.

Table 4. Mean and standard deviations of MHV metric obtained by five algorithms.

Ins	(τ_t, nt)	DCMOEA-V1	DCMOEA-V2	DCMOEA-V3	DCMOEA-V4	DCMOEA-V5	FCC-DCMOEA
1	(10, 20)	15.2859 (0.1071) ‡	17.4329 (0.7379) ‡	17.1962 (1.2492) ‡	16.4348 (0.4252) ‡	17.0474 (0.5227) ‡	17.9885 (0.6170)
	(20, 20)	15.9700 (0.0712) ‡	17.7224 (0.4091) ‡	17.7283 (0.5416) ‡	16.8898 (0.4467) ‡	17.6288 (0.5154) ‡	18.0907 (0.9161)
2	(10, 20)	12.6227 (0.0752) ‡	14.4839 (0.8918) ‡	14.8434 (1.1032) ‡	13.8234 (0.5551) ‡	14.1636 (0.6949) ‡	15.5564 (0.8935)
	(20, 20)	13.2364 (0.0520) ‡	15.0848 (0.3856) ‡	15.0820 (1.3526) ‡	14.3277 (0.6704) ‡	14.5788 (0.4847) ‡	15.6215 (0.3388)
3	(10, 20)	15.2064 (0.0934) ‡	17.0467 (0.8147) ‡	17.3316 (0.8364) ‡	16.4590 (0.6022) ‡	16.6256 (0.4913) ‡	17.7006 (0.8600)
	(20, 20)	15.7874 (0.0681) ‡	17.4778 (0.4498) ‡	17.8187 (0.7282) ‡	16.7216 (0.5043) ‡	17.2159 (0.6367) ‡	18.2393 (0.5213)
4	(10, 20)	12.6787 (0.1503) ‡	14.2534 (1.1296) ‡	14.6843 (0.6042) ‡	13.7308 (0.8675) ‡	14.1267 (1.0037) ‡	15.3270 (0.7937)
	(20, 20)	13.4070 (0.0697) ‡	14.6563 (0.9450) ‡	14.9332 (2.0754) ‡	14.2069 (0.5024) ‡	15.0563 (0.6048) ‡	15.8415 (0.4973)
5	(10, 20)	15.1846 (0.0805) ‡	17.0256 (1.0235) ‡	17.3227 (1.0507) ‡	16.1835 (0.5870) ‡	16.7539 (0.6221) ‡	17.9561 (0.8209)
	(20, 20)	15.8428 (0.0649) ‡	17.1596 (0.9265) ‡	17.5879 (0.7971) ‡	16.9896 (0.5899) ‡	17.3613 (0.2540) ‡	18.1681 (0.2921)
6	(10, 20)	12.4319 (0.0563) ‡	14.3923 (0.5400) ‡	14.5651 (1.7316) ‡	13.4974 (0.5049) ‡	14.3169 (0.3585) ‡	15.1668 (0.4120)
	(20, 20)	13.0374 (0.0368) ‡	15.1214 (0.5648) ‡	15.3464 (0.4518) ‡	13.8809 (0.8100) ‡	14.7854 (0.3061) ‡	15.4052 (0.3371)
7	(10, 20)	15.1058 (0.0742) ‡	16.9756 (1.0937) ‡	16.7525 (1.2345) ‡	15.8288 (0.6837) ‡	16.7672 (0.8430) ‡	17.7828 (0.6328)
	(20, 20)	15.8097 (0.0675) ‡	17.0349 (1.0684) ‡	17.7480 (1.2347) ‡	16.6323 (0.4533) ‡	17.2161 (0.6343) ‡	17.9977 (0.6756)
8	(10, 20)	12.6063 (0.0632) ‡	14.0249 (0.8389) ‡	14.4196 (1.1307) ‡	13.6409 (0.4840) ‡	13.8957 (0.4884) ‡	14.8437 (0.7976)
	(20, 20)	13.1731 (0.0589) ‡	14.5276 (0.8651) ‡	14.8591 (1.1844) ‡	13.9267 (0.3853) ‡	14.6318 (0.4402) ‡	15.1881 (0.7300)
9	(10, 20)	15.1135 (0.0934) ‡	16.9301 (0.6887) ‡	17.3979 (0.6242) ‡	16.4301 (0.5529) ‡	16.4239 (1.0109) ‡	17.6300 (0.5549)
	(20, 20)	15.8817 (0.0937) ‡	17.5789 (0.9071) ‡	18.0091 (0.7209) ‡	16.8906 (0.4961) ‡	16.9530 (0.4494) ‡	17.7957 (0.3694)
10	(10, 20)	12.8211 (0.0844) ‡	15.0399 (0.7329) ‡	14.7108 (2.0734) ‡	14.2442 (0.6257) ‡	14.4767 (0.8323) ‡	15.4050 (0.6817)
	(20, 20)	13.4611 (0.0712) ‡	15.4522 (0.4608) ‡	15.6594 (0.8628) ‡	14.7032 (0.4253) ‡	14.9607 (0.8163) ‡	15.6780 (0.5494)

‡ and † indicate that FCC-DCMOEA performs significantly better than and equivalently to the corresponding algorithm, respectively.

The results show that FCC-DCMOEA outperforms its variants except for DCMOEA-V3 on all DCMOPs of the FCC process. DCMOEA-V3 achieves the best MHV values on the ninth DCMOP of the FCC process with $\tau_t = 20$. It is worth noting that there is no statistical difference in performance between FCC-DCMOEA and DCMOEA-V3 when DCMOEA-V3 performs better than FCC-DCMOEA. DCMOEA-V3 adopts the advantages of the dynamic response strategy and shows good performance in some DCMOPs of the FCC process. The dynamic response strategy of FCC-DCMOEA considers the dynamic constraint regions and the direction of evolution. Thus, it is better than DCMOEA-V3. The offspring generation strategy based on minimax solutions is more effective in handling dynamic constraints and exploring discontinuous feasible regions than DCMOEA-V4 and DCMOEA-V5.

6. Conclusions

This study proposed an FCC-DCMOEA algorithm for optimizing the DCMOP of the FCC process with diverse changes in fossil fuel yield constraints and vessel capacity. The offspring generation strategy based on minimax solutions is designed to generate partial children, and the offspring generation operator of MOEA is used to generate the other children, helping the population explore more feasible regions and converge quickly. The dynamic response strategy based on population feasibility uses different perturbation terms to reobtain feasible and infeasible solutions respectively. The feasible solutions can approach the promising feasible subregions, and the infeasible solutions can move into the feasible region quickly. FCC-DCMOEA was investigated in ten DCMOPs of the FCC process with different yield constraints and vessel capacity. It was compared with its four variants and five other dynamic constrained multiobjective algorithms. The FCC-DCMOEA was demonstrated to outperform other algorithms and variants according to the MHV values and Wilcoxon's rank-sum test.

In future work, we intend to consider the DCMOPs with three or more objectives of the FCC process, such as maximum service life and minimum pollutants production. Additionally, a strategy that can handle the DCMOPs of the FCC process with more objectives should be exploited.

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