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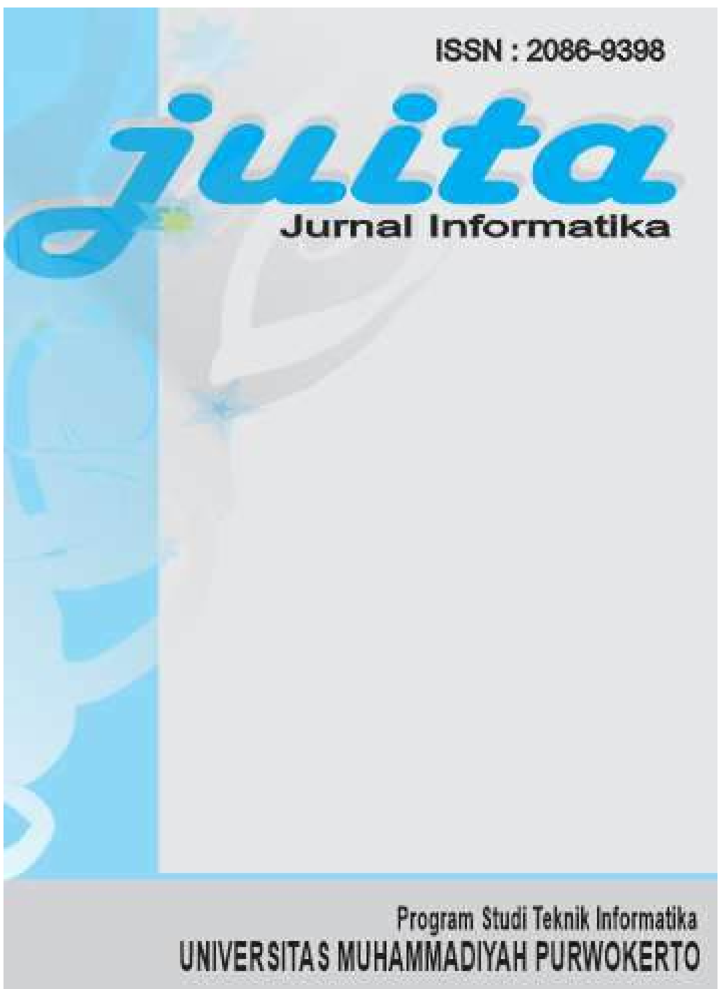

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Improve Coal Blending Optimization in CFPP by Cromosom and Fitness Function Redefinition of the Genetic Algorithm

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Abstract - Blending coal before it enters the power plant boiler unit is necessary to adjust the coal categories according to the boiler unit specifications. The power plant must also comply with the regulations regarding coal-biomass co-firing through blending. Applying a Genetic Algorithm that only considers the composition and fitness based on the blend's quality leads to accumulation issues, decreasing coal quality. This research proposes redefining chromosomes, fitness functions, mutation rules, population determination, and output as the best chromosome used in the Genetic Algorithm. Testing uses various compositions of coal inputs from the barge, coal yard, and biomass to simulate different conditions. The test results demonstrate that the developed algorithm can provide all possible alternative blends between the coal in the barge and at the coal yard. Under specific conditions, operators can choose a blend composition that involves coal stored in the coal yard for an extended period.

Keywords: coal blending, cofiring, genetic algorithm,

I. INTRODUCTION

Indonesia possesses abundant reserves of medium and low-quality coal resources, with medium-quality coal accounting for 63.99% [1]. The optimization of low and medium-rank coals can be achieved through coal blending, coal switching, and coal drying. Coal blending entails mixing coal from different categories to address specific coal stock availability, while coal drying can reduce total moisture content and enhance coal quality [2]. Nationally, 81% of coal consumption is for energy purposes [2]. Utilizing low and medium-calorific coal as an energy raw material can reduce electricity production costs. The government promotes optimizing the utilization of medium and low-quality coal by implementing policies to reduce the cost of providing Component C. Energy providers can accomplish this by replacing Medium Rank coal with Low-Rank coal. Most coal-fired power plants (CFPP) in Java, constructed from 1980 to the mid-2010s, are designed for medium-quality coal [3]. CFPP operators must blend medium-quality and low-quality coal to comply with government regulations, as coal switching without considering the boiler unit design can damage the boiler unit. The use of Low-Rank coal leads to increased coal consumption. Furthermore, CFPP operators should also implement biomass co-firing, although this policy remains controversial regarding reducing greenhouse gas emissions [2]. CFPP Pelabuhan Ratu has developed the NEMESYS application based on Artificial Intelligence to meet the optimization needs of blending [4]. This application utilizes Genetic Algorithms and provides the best blending composition output based on available barge and coal yard coal specifications.

Genetic Algorithms (GA) are population-based metaheuristic algorithms that utilize evolutionary processes such as selection, fitness evaluation, reproduction, crossover, and mutation. The optimal solution in genetic algorithms is represented by a chromosome formulation that can be evaluated for its fitness. Selecting solution representation, objective function, and initial solution generation method is crucial in designing GAs [6]. Crossover and mutation are methods to generate solution variations within the search space. The selection of mutation operators influences solution diversity in the search space and affects model performance [7]. The search for solutions is performed iteratively, where chromosomes with low fitness are removed from the population. GA efficiently provides reasonable solutions quickly and can be applied to real-world problems [8, 6]. Liu stated that GA can produce optimal solutions and has better global search capabilities [8]. This evolutionary approach is suitable for significantly improving the modeling of adaptive and evolutionary systems. However, GA is computationally expensive and requires careful parameter configuration [6]. GA has demonstrated exemplary performance when implemented in real-world problems, including optimizing CNN architecture with a transfer-learning strategy from parent networks [2], shortest path problem [9],optimizing ANN parameters [10], cryptoanalysis [11], community structure in complex networks [12], multi-objective in packing [13], scheduling [9], combinatorial configuration optimization [5], feature selection Ramdhani 2023 [14], intrution detection suhaimi [15]. There are at least five variants of genetic algorithms, namely real and binary-coded, multiobjective, parallel, chaotic, and hybrid GAs [8]. GAs can be categorized as binary-coded and real-coded based on how chromosomes are encoded. Real Coded GA (RGA) is widely applied to real-world problems due to its robustness, efficiency, and accuracy. Premature convergence, a weakness of RGA, has been addressed through modifications in crossover operators [16], mutation techniques, and selection methods. In this study, the RGA approach is more suitable for implementation to represent solutions in the form of compositions of each coal category used.

The previous version of NEMESYS needs to consider the selection of specific coal categories in the coal yard, resulting in prolonged accumulation. This accumulation leads to increased total moisture and reduced coal quality. Additionally, the existing application cannot calculate co-firing with biomass. This study aims to address these issues and provide optimal blending options for each coal category in the coal yard within the updated version of the NEMESYS application. The blending problem falls under combinatorial optimization problems, which seek to find the optimal solution by combining various variables with specific constraints. Traditionally, this problem is considered challenging, but evolutionary algorithms, including genetic algorithms, have proven effective in solving it [5].

II. METHOD

This section explains coal blending and Genetic Algorithm (GA) design. In the GA design phase, the method of representing chromosomes, defining the fitness function, and defining and designing solutions referring to the best chromosome are presented to develop NEMESYSWeb. Chromosomes are redefined to support the cofiring policy. The fitness of chromosomes is defined based on parameters that determine the blending quality. The output of GA is adjusted to enable operators to obtain the best composition of coal in the barge with each coal in the coal yard.

A. *Coal Blending and Characteristics of its Blended Product*

Coal blending in power plants aims to achieve the optimal composition of coal for efficient electricity generation. The blending process involves coal from the barge, coal from the coal yard, and biomass as fuel sources. The composition of these three fuel categories is calculated to meet the required heat value based on the specific load demand at a given time. The blending process considers the coal categories in the barge, starting from the oldest stock. The coal in the coal yard is stacked and categorized based on the time it was initially placed there. When selecting coal for blending, a different category of coal is chosen from the coal yard compared to the coal in the barge. For instance, if Medium Rank Coal (MRC) is available in the barge, Low-Rank Coal (LRC) will be selected from the coal yard, and vice versa. The percentage of biomass used in the blending process ranges between 0.01 and 0.05, depending on availability.

The specifications of the coal and biomass used for blending are presented in Table I. There are two categories of coal based on their calorific values: Low Rank Coal (LRC) and Medium Rank Coal (MRC). The calorific value of LRC ranges from 4000 to 4400, while MRC ranges from 4500 to 5100. LRC has a higher Total Moisture (TM) compared to MRC. Conversely, MRC has higher values of Total Sulfur (TS), Ash, Initial Deformation Temperature (IDT), and Carbon (C) compared to LRC.

The characteristics of ash type, slagging index, and slagging type resulting from blending are determined based on calculated characteristics derived from the blending composition. The calculation of the CaO mix, for example, is expressed by (1), where the percentage of each contributing coal determines the characteristics of the resulting CaO in the blend. The ash type is determined based on the values of CaO, MgO, and Fe2O3. If the sum of CaO and MgO in the blend is less than the Fe2O3 in the blend, the ash type is classified as Bituminous. If it is greater than the Fe2O3, the resulting ash type is Lignite. The slagging index is calculated using (2) for the Bituminous ash type. A slagging index below 0.6 is categorized as low, a slagging index between 0.6 and 2 is categorized as medium, and a slagging index above 2 is categorized as high. The slagging index for lignite ash type determined by (3) based on HTmax and IDTReducing. A slagging index below 2100 is classified as severe, between 2100 and 2250 as high, between 2250 and 2450 as medium, and above 2450 as low.

TABLE I
CHARACTERISTICS OF COAL AND BIOMASS

No	Category	Characteristics								
		calorie	**TM**	**TS**	**Ash**	**IDT**	**HTmax**	**SI**	**slagging**	**C**
1	LRC	4070	34.68	0.2	5.24	1205	14000	2271.2	medium	55.4
2	LRC	4111	32.82	0.16	3.83	1230	14000	2307.2	medium	56.15
3	LRC	4200	32.82	0.16	3.83	1230	14000	2307.2	medium	56.15
4	MRC	4500	29.04	0.36	5.82	1256	14000	0.05	medium	61.26
5	MRC	4620	29.64	0.32	5.1	1234	1400	2312.96	medium	59.24
6	MRC	4720	29.04	0.36	5.82	1256	14000	0.05	low	61.26
7	MRC	4830	29.04	0.36	5.82	1256	14000	0.05	low	61.26
8	Biomass	2300	59.35	N/A	N/A	N/A	N/A	N/A	N/A	N/A

$$CaO_{mix} = coal1\_percentage * coal1.CaO + coal2\_percentage * coal2.CaO \quad (1)$$

$$SlaggingIndex_{bitumous} = \frac{(CaO_{mix} + MgO_{mix} + Fe2O3_{mix} + Na2O_{mix} + K2O_{mix})}{SiO2_{mix} + Al2O3_{mix} + TiO2_{mix} + TS_{mix}} \quad (2)$$

$$SlaggingIndex_{lignite} = \frac{\left(\left(HTmax_{mix} * \frac{9}{5}\right) + 32\right) + 4 * \left(\left(IDTReducing_{mix} * \frac{9}{5}\right) + 32\right))}{5} \quad (3)$$

B. *Genetic Algorithm for Coal Blending*

There are many variations of Genetic Algorithms (GAs), but classical GA is used in this research.

1) Redefinition of Chromosome: The GA chromosome in the coal blending optimization case falls under the RGA category. It is used to represent the composition of coal in the barge, coal in the coal yard, biomass, and the fitness value of the solution, as shown in Fig. 1. The blended and co-fired coal's calorific value is randomly determined within a range of 2 percent from the target calorific value. The chromosome consists of 6 genes. Gene 0 represents the calorific value of the blended coal; gene 1 represents the identity of the coal used; gene 2 describes the composition of coal in the barge; gene 3 describes the composition of coal in the coal yard, gene 4 represents the percentage of biomass, and gene 5 represents the fitness value. The portions of coal in the barge and coal in the coal yard are defined as in (4).

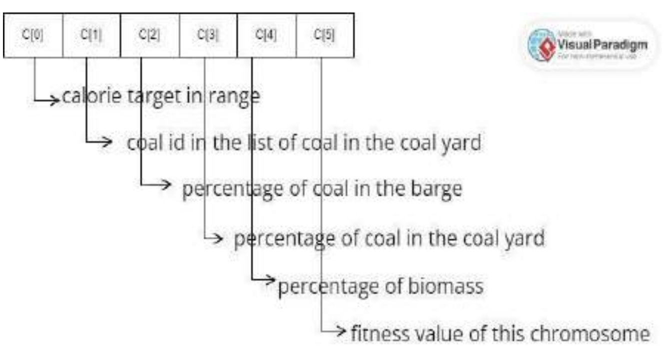


Fig. 1 Chromosome definition

$$K_{target} = a\,.\,k_{tongkang} + b.\,k_{tongkang} + c.\,k_{biomass} \quad (4)$$

$$a + b + c = 1; 0 < a, b < 1; 0 < c < 0.05$$

where a, b, and c are the respective percentages of coal in the barge, coal in the coal yard, and biomass.

2) Fitness Function Definition: The quality of coal blending is influenced by total moisture (TM), total sulfur (TS), ash, and slagging index. The slagging index, TM, TS, and ash values should not exceed the threshold limits. In addition to blending quality, the chromosome's fitness is also influenced by the difference between the target and estimated calorific values of the blending result. Fitness components, except for the slagging index, are expressed as numerical values. The slagging index is categorized as low, medium, high, and severe. In the previous optimization model, fitness was calculated based on the ratio of the calorific value of the blending result to the combination of TM, TS, and ash. In this study, a normalization process for the fitness components is proposed, and the fitness value is the average of the normalized values of each element. In a power plant unit, the threshold values for TM, TS, and ash are 34.68, 0.36, and 5.82, respectively. The normalization of each component is expressed in (5). The normalization of the slagging index is done by assigning weights to the slagging index categories (low, medium, high, and severe) as 0, 1, 2, and 3, respectively, and normalizing them to a range of 0 to 1.

$$TM_{norm} = \frac{TM_{tongkang} * C[2] + TM_{cyrd} * C[3]}{TM_{max}}$$

$$ASH_{norm} = \frac{TASH_{tongkang} * C[2] + ASH_{cyrd} * C[3]}{ASH_{max}}$$

$$TS_{norm} = \frac{TS_{tongkang} * C[2] + TS_{cyrd} * C[3]}{TS_{max}}$$

$$Calorie_{norm} = \frac{\left(\frac{abs(C[0] - calorie_{target})}{calorie_{target}}\right)}{0.02}$$

$$Slagging_{norm} = \frac{slagging\ index}{3}$$

$$TM_{norm} = \frac{Calorie_{norm} + Slagging_{norm} + TM_{norm} + ASH_{norm} + TS_{norm}}{5}$$

$$fitness = (Calorie_{norm} + Slagging_{norm} + TM_{norm} + ASH_{norm} + TS_{norm})/5 \qquad (5)$$

3) Best Chromosome: The best chromosome represents the solution. The expected solution for the blending is a recommendation of the best composition consisting of coal from the barge, coal from the coal yard, and biomass from each coal category available on the barge. With this solution formulation, the operator can choose the most suitable composition to be used at any given time. If the coal on the barge is of the Medium Rank category, it will be paired with Low-Rank coal from the coal yard, and vice versa. The best chromosome for each category will be updated during the iterations in the execution process of the GA.

4) Crossover and Mutation: Crossover and mutation are consecutive stages in GA that prevent local optima and ensure the availability of new information for evolution. The parent chromosomes represent a solution in the form of a composition of barge coal and coal yard. The crossover process changes the composition pairs and alters the heat target and fitness value. The crossover process is illustrated in Fig. 2. Parents A and B undergo crossover between C2 and C3 positions, generating offspring chromosomes C1 and C2. Subsequently, this process modifies the genetic information in the C0 and C6 segments to match the calorie target from blending and co-firing and the fitness value of the new chromosomes.

Target calories based on the composition of each part are calculated using (6). The fitness of the offspring chromosome is calculated based on the representation of the offspring chromosome and is used to update the fitness represented by the new chromosome.

$$\begin{aligned} Target_{calorie} = {} & percentage\ of\ coal\ in\ barge \\ & * Calorie_{coalinbarge} + \\ & percentage\ of\ coal\ in\ coalyard \\ & * Calorie_{coalincoalyard} + \\ & percentage\ of\ biomasse * \\ & Calorie_{biomass} \end{aligned} \qquad (6)$$

III. RESULT AND DISCUSSION

In this section, the application design, implementation results, and testing of the optimization of blending and co-firing application will be discussed. Part one presents the application interface to facilitate user interaction with the application. In the following part, the testing of the functionality of the genetic algorithm optimization for blending will be discussed.

A. Database Design

To support the data requirements of the optimization of blending application, a database design has been implemented. The logical model of the developed application is presented in Fig. 3.

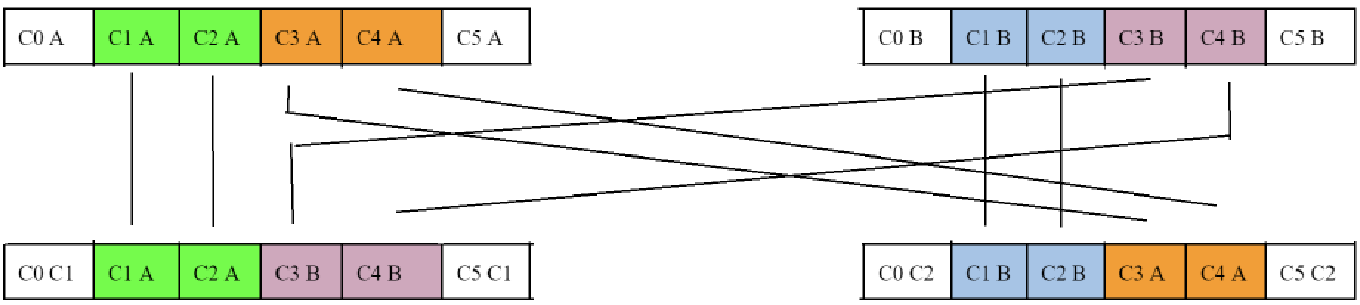


Fig. 2 Crossover

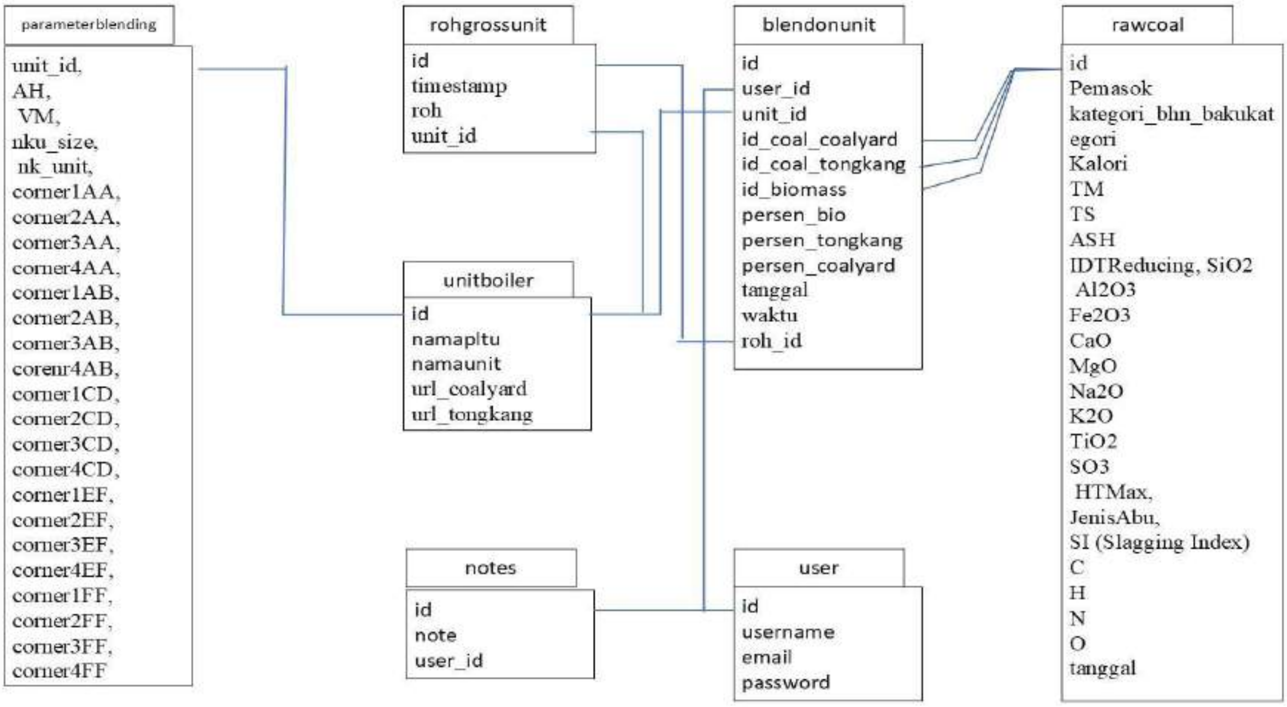


Fig. 3 Logical model of blending application

B. User Interaction

The optimization of blending application is a web-based application developed using the Django Framework with the Python programming language. Some functions supporting the co-firing process still require operator intervention, such as inputting the daily load, determining the categories of coal available on the barge and in the coal yard, and selecting the blending options to be executed at specific times.

In the first step, the user must ensure that the daily load has been input into the system. The daily load is uploaded only once a day. If it has been uploaded, the user can view the ROH list on that page. However, if it has yet to be uploaded, the user cannot find it and must upload it first. The operator will use the value of ROH as a reference to determine the required calorific value to be produced.

The user prepares the biomass and coal list for blending in the next stage. There are three steps that the user needs to complete for the fuel preparation stage. First, selecting the biomass; second, choosing the coal on the barge based on the longest time it has been on the barge; and third, selecting the top-layer coal in the coal yard. Based on the barge's coal categories, the system selects coal categories in the coal yard for blending. If the coal on the barge is categorized as MRC, then LRC is chosen, and vice versa.

The user needs to perform the third step to determine the blending time and target calorific value according to the current calorific requirements. The system will prepare a list of the best compositions and display them to the user. The user can choose from the presented recommendations and is free to determine the blending process to be executed, considering the on-site conditions.

C. Functionality Testing of GA Library

The functionality of GA Library is tested and analyzed from the stages of creating chromosomes, creating populations, crossover, mutation, and their effects on population changes as well as the optimization results of blending. In the part of the barge and coal yard, the distribution of data appears to be non-normal. There are barge values below Q1 and coal yard values above Q3, as Fig. 4. The maximum fitness value of a chromosome is 0.5 and never exceeds this value.

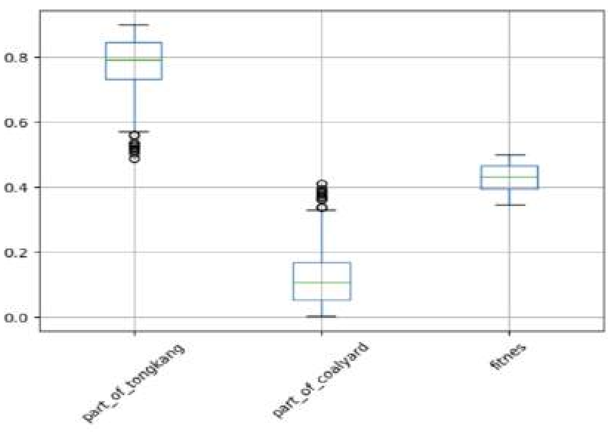


Fig. 4 The Boxplot of chromosomes in GA population

The visualization of the distribution of target calories is grouped based on coal yard IDs and presented in Fig. 5. Although it is not normally distributed, target calorie values vary within the range of 4500 ± 0.02.

Visualization of the distribution of fitness values grouped by coal yard IDs from several generations is shown in Fig. 6. The effects of crossover and mutation are evident in the variation of fitness values grouped by the coal present in the coal yard. In coal yard ID 0, fitness changes occur within approximately 0.45 to 0.5. There are many chromosomes with fitness values within this range in generation 0. Changes occur in generations 5 and 10, and the fitness distribution becomes similar to generation 0.

In generation 5, noticeable changes in fitness are observed for each coal yard ID. Coalyard ID 2 shows an increase in chromosomes with fitness values above 0.45. In the subsequent generations, most of the population is on the right side, representing the individuals with the best fitness. The experiment’s test results on GA parameters can be seen at Table III.

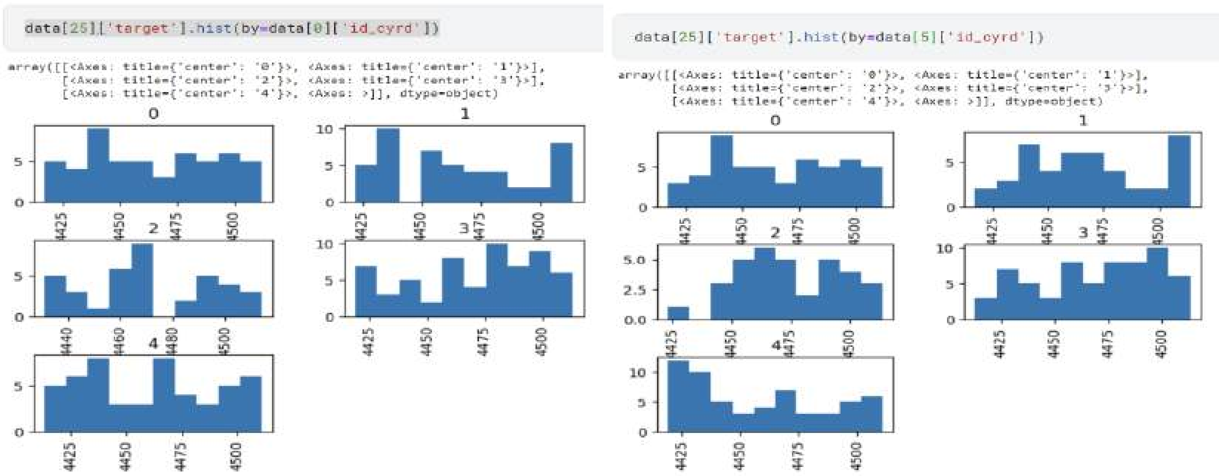
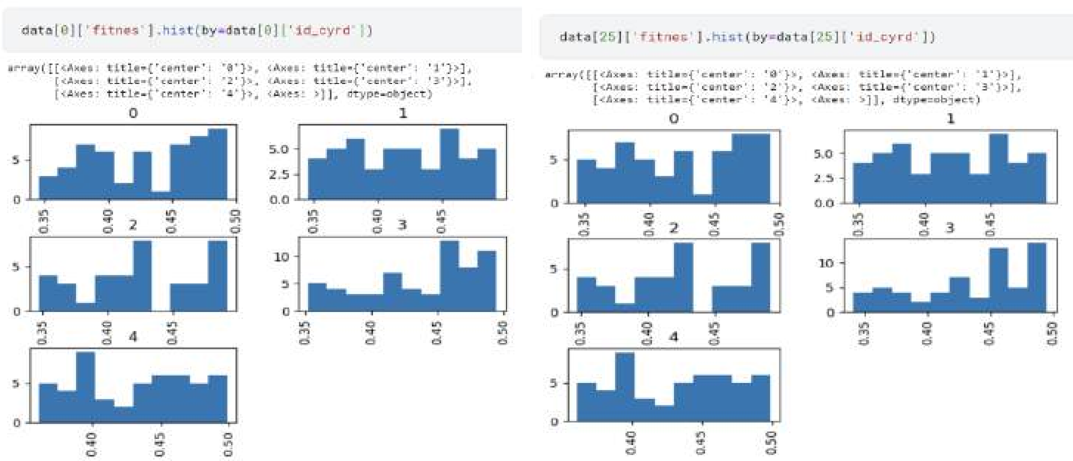


Fig. 5 The distribution of target calories group by coal in coal yard



(i) 0-th generation **(ii) 25-th generation**

Fig. 6 Distribution of fisness value of chromosom in coalyard group by coal yard ID

TABEL III
EXPERIMENT ON GA PARAMETERS: POPULATION, ITERATION, AND MUTATION RATE

III.a Best Chromosome based on population

Population	Target	ID Coalyard	Tongkang	Coalyard	Biomass	Fitnes
200	4500	3	0,86	0,04	0,1	0.49
200	4500	0	0,87	0,03	0.1	0.49
200	4500	2	0,87	0,03	0.1	0,49
200	4500	1	0,87	0,03	0,1	0.49
200	4500	4	0,84	0,06	0,1	0.5

III.b Best Chromosome based on Iteration

Iteration	Target	ID Coalyard	Barn	Coalyard	Biomass	Fitness
15	4500	4	0,84	0,06	0,1	0,5
15	4500	3	0,86	0,04	0,1	0,49
15	4500	1	0,87	0,03	0,1	0,49
15	4500	2	0,87	0,03	0,1	0,49
15	4500	0	0,87	0,03	0,1	0,49

III.c Best Chromosome based on mutation rate

Mutation Rate	Target	ID coalyard	Barn	Coalyard	Biomass	Fitnes
0,7	4500	3	0,86	0,04	0,10	0,49
0,7	4500	0	0,87	0,03	0,10	0,49
0,7	4500	1	0,87	0,03	0,10	0,49
0,7	4499	4	0,84	0,06	0,10	0,50
0,7	4500	2	0,87	0,03	0,10	0,49

The fitness value of each best chromosome representing the solution is compared across several GA parameters: population size, iterations, and mutation rate. The test results presented in Table III.a show that a chromosome population of 200 has achieved the optimal heat target. Based on the test results, the optimal population size is then tested for the optimal number of iterations. GA can achieve the optimal heat target as early as iteration 15. The mutation rate that results in the optimal heat target is performed at a mutation rate of 0.7.

IV. CONCLUSION

The Optimization Application for coal blending in a Coal-Fired Power Plant using Genetic Algorithm has been successfully implemented, and its functionality has been tested. The application is web-based, built using the Django Framework, and utilizes PostgreSQL as the DBMS. The main stages of the genetic algorithm include population formation, crossover, and mutation. Each chromosome has been appropriately defined, where the target calorific value falls within the minimum and maximum threshold of 2% of the desired calorific value. The population members for each coal category in the coal yard are generated equally, and the best chromosome is maintained for each type. The visual effects of crossover and mutation on the fitness values of the population members have been demonstrated, showing improvements toward better fitness values. The Genetic Algorithm testing results have achieved optimal output based on the calorific target, with the parameters set as follows: a population size of 200, 15 iterations, and a mutation rate of 0.7.

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coal

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Improve Coal Blending Optimization in CFPP by Cromosom and Fitness Function Redefinition of the Genetic Algorithm

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Abstract - Blending coal before it enters the power plant boiler unit is necessary to adjust the coal categories according to the boiler unit specifications. The power plant must also comply with the regulations regarding coal-biomass co-firing through blending. Applying a Genetic Algorithm that only considers the composition and fitness based on the blend's quality leads to accumulation issues, decreasing coal quality. This research proposes redefining chromosomes, fitness functions, mutation rules, population determination, and output as the best chromosome used in the Genetic Algorithm. Testing uses various compositions of coal inputs from the barge, coal yard, and biomass to simulate different conditions. The test results demonstrate that the developed algorithm can provide all possible alternative blends between the coal in the barge and at the coal yard. Under specific conditions, operators can choose a blend composition that involves coal stored in the coal yard for an extended period.

Keywords: coal blending, cofiring, genetic algorithm,

I. INTRODUCTION

Indonesia possesses abundant reserves of medium and low-quality coal resources, with medium-quality coal accounting for 63.99% [1]. The optimization of low and medium-rank coals can be achieved through coal blending, coal switching, and coal drying. Coal blending entails mixing coal from different categories to address specific coal stock availability, while coal drying can reduce total moisture content and enhance coal quality [2]. Nationally, 81% of coal consumption is for energy purposes [2]. Utilizing low and medium-calorific coal as an energy raw material can reduce electricity production costs. The government promotes optimizing the utilization of medium and low-quality coal by implementing policies to reduce the cost of providing Component C. Energy providers can accomplish this by replacing Medium Rank coal with Low-Rank coal. Most coal-fired power plants (CFPP) in Java, constructed from 1980 to the mid-2010s, are designed for medium-quality coal [3]. CFPP operators must blend medium-quality and low-quality coal to comply with government regulations, as coal switching without considering the boiler unit design can damage the boiler unit. The use of Low-Rank coal leads to increased coal consumption. Furthermore, CFPP operators should also implement biomass co-firing, although this policy remains controversial regarding reducing greenhouse gas emissions [2]. CFPP Pelabuhan Ratu has developed the NEMESYS application based on Artificial Intelligence to meet the optimization needs of blending [4]. This application utilizes Genetic Algorithms and provides the best blending composition output based on available barge and coal yard coal specifications.

Genetic Algorithms (GA) are population-based metaheuristic algorithms that utilize evolutionary processes such as selection, fitness evaluation, reproduction, crossover, and mutation. The optimal solution in genetic algorithms is represented by a chromosome formulation that can be evaluated for its fitness. Selecting solution representation, objective function, and initial solution generation method is crucial in designing GAs [6]. Crossover and mutation are methods to generate solution variations within the search space. The selection of mutation operators influences solution diversity in the search space and affects model performance [7]. The search for solutions is performed iteratively, where chromosomes with low fitness are removed from the population. GA efficiently provides reasonable solutions quickly and can be applied to real-world problems [8, 6]. Liu stated that GA can produce optimal solutions and has better global search capabilities [8]. This evolutionary approach is suitable for significantly improving the modeling of adaptive and evolutionary systems. However, GA is computationally expensive and requires careful parameter configuration [6]. GA has demonstrated exemplary performance when implemented in real-world problems, including optimizing CNN architecture with a transfer-learning strategy from parent networks [2], shortest path problem [9],optimizing ANN parameters [10], cryptoanalysis [11], community structure in complex networks [12], multi-objective in packing [13], scheduling [9], combinatorial configuration optimization [5], feature selection Ramdhani 2023 [14], intrution detection suhaimi [15]. There are at least five variants of genetic algorithms, namely real and binary-coded, multiobjective, parallel, chaotic, and hybrid GAs [8]. GAs can be categorized as binary-coded and real-coded based on how chromosomes are encoded. Real Coded GA (RGA) is widely applied to real-world problems due to its robustness, efficiency, and accuracy. Premature convergence, a weakness of RGA, has been addressed through modifications in crossover operators [16], mutation techniques, and selection methods. In this study, the RGA approach is more suitable for implementation to represent solutions in the form of compositions of each coal category used.

The previous version of NEMESYS needs to consider the selection of specific coal categories in the coal yard, resulting in prolonged accumulation. This accumulation leads to increased total moisture and reduced coal quality. Additionally, the existing application cannot calculate co-firing with biomass. This study aims to address these issues and provide optimal blending options for each coal category in the coal yard within the updated version of the NEMESYS application. The blending problem falls under combinatorial optimization problems, which seek to find the optimal solution by combining various variables with specific constraints. Traditionally, this problem is considered challenging, but evolutionary algorithms, including genetic algorithms, have proven effective in solving it [5].

II. METHOD

This section explains coal blending and Genetic Algorithm (GA) design. In the GA design phase, the method of representing chromosomes, defining the fitness function, and defining and designing solutions referring to the best chromosome are presented to develop NEMESYSWeb. Chromosomes are redefined to support the cofiring policy. The fitness of chromosomes is defined based on parameters that determine the blending quality. The output of GA is adjusted to enable operators to obtain the best composition of coal in the barge with each coal in the coal yard.

A. *Coal Blending and Characteristics of its Blended Product*

Coal blending in power plants aims to achieve the optimal composition of coal for efficient electricity generation. The blending process involves coal from the barge, coal from the coal yard, and biomass as fuel sources. The composition of these three fuel categories is calculated to meet the required heat value based on the specific load demand at a given time. The blending process considers the coal categories in the barge, starting from the oldest stock. The coal in the coal yard is stacked and categorized based on the time it was initially placed there. When selecting coal for blending, a different category of coal is chosen from the coal yard compared to the coal in the barge. For instance, if Medium Rank Coal (MRC) is available in the barge, Low-Rank Coal (LRC) will be selected from the coal yard, and vice versa. The percentage of biomass used in the blending process ranges between 0.01 and 0.05, depending on availability.

The specifications of the coal and biomass used for blending are presented in Table I. There are two categories of coal based on their calorific values: Low Rank Coal (LRC) and Medium Rank Coal (MRC). The calorific value of LRC ranges from 4000 to 4400, while MRC ranges from 4500 to 5100. LRC has a higher Total Moisture (TM) compared to MRC. Conversely, MRC has higher values of Total Sulfur (TS), Ash, Initial Deformation Temperature (IDT), and Carbon (C) compared to LRC.

The characteristics of ash type, slagging index, and slagging type resulting from blending are determined based on calculated characteristics derived from the blending composition. The calculation of the CaO mix, for example, is expressed by (1), where the percentage of each contributing coal determines the characteristics of the resulting CaO in the blend. The ash type is determined based on the values of CaO, MgO, and Fe2O3. If the sum of CaO and MgO in the blend is less than the Fe2O3 in the blend, the ash type is classified as Bituminous. If it is greater than the Fe2O3, the resulting ash type is Lignite. The slagging index is calculated using (2) for the Bituminous ash type. A slagging index below 0.6 is categorized as low, a slagging index between 0.6 and 2 is categorized as medium, and a slagging index above 2 is categorized as high. The slagging index for lignite ash type determined by (3) based on HTmax and IDTReducing. A slagging index below 2100 is classified as severe, between 2100 and 2250 as high, between 2250 and 2450 as medium, and above 2450 as low.

TABLE I
CHARACTERISTICS OF COAL AND BIOMASS

No	Category	Characteristics								
		calorie	TM	TS	Ash	IDT	HTmax	SI	slagging	C
1	LRC	4070	34.68	0.2	5.24	1205	14000	2271.2	medium	55.4
2	LRC	4111	32.82	0.16	3.83	1230	14000	2307.2	medium	56.15
3	LRC	4200	32.82	0.16	3.83	1230	14000	2307.2	medium	56.15
4	MRC	4500	29.04	0.36	5.82	1256	14000	0.05	medium	61.26
5	MRC	4620	29.64	0.32	5.1	1234	1400	2312.96	medium	59.24
6	MRC	4720	29.04	0.36	5.82	1256	14000	0.05	low	61.26
7	MRC	4830	29.04	0.36	5.82	1256	14000	0.05	low	61.26
8	Biomass	2300	59.35	N/A	N/A	N/A	N/A	N/A	N/A	N/A

$$CaO_{mix} = coal1\_percentage * coal1.CaO + coal2\_percentage * coal2.CaO \quad (1)$$

$$SlaggingIndex_{bitumous} = \frac{(CaO_{mix} + MgO_{mix} + Fe2O3_{mix} + Na2O_{mix} + K2O_{mix})}{SiO2_{mix} + Al2O3_{mix} + TiO2_{mix} + TS_{mix}} \quad (2)$$

$$SlaggingIndex_{lignite} = \frac{\left(\left(HTmax_{mix} * \frac{9}{5}\right) + 32\right) + 4 * \left(\left(IDTReducing_{mix} * \frac{9}{5}\right) + 32\right))}{5} \quad (3)$$

B. Genetic Algorithm for Coal Blending

There are many variations of Genetic Algorithms (GAs), but classical GA is used in this research.

1) Redefinition of Chromosome: The GA chromosome in the coal blending optimization case falls under the RGA category. It is used to represent the composition of coal in the barge, coal in the coal yard, biomass, and the fitness value of the solution, as shown in Fig. 1. The blended and co-fired coal's calorific value is randomly determined within a range of 2 percent from the target calorific value. The chromosome consists of 6 genes. Gene 0 represents the calorific value of the blended coal; gene 1 represents the identity of the coal used; gene 2 describes the composition of coal in the barge; gene 3 describes the composition of coal in the coal yard, gene 4 represents the percentage of biomass, and gene 5 represents the fitness value. The portions of coal in the barge and coal in the coal yard are defined as in (4).

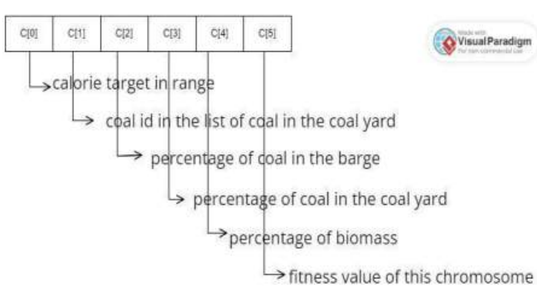


Fig. 1 Chromosome definition

$$K_{target} = a . k_{tongkang} + b . k_{tongkang} + c . k_{biomass} \quad (4)$$

$$a + b + c = 1; 0 < a, b < 1; 0 < c < 0.05$$

where a, b, and c are the respective percentages of coal in the barge, coal in the coal yard, and biomass.

2) Fitness Function Definition: The quality of coal blending is influenced by total moisture (TM), total sulfur (TS), ash, and slagging index. The slagging index, TM, TS, and ash values should not exceed the threshold limits. In addition to blending quality, the chromosome's fitness is also influenced by the difference between the target and estimated calorific values of the blending result. Fitness components, except for the slagging index, are expressed as numerical values. The slagging index is categorized as low, medium, high, and severe. In the previous optimization model, fitness was calculated based on the ratio of the calorific value of the blending result to the combination of TM, TS, and ash. In this study, a normalization process for the fitness components is proposed, and the fitness value is the average of the normalized values of each element. In a power plant unit, the threshold values for TM, TS, and ash are 34.68, 0.36, and 5.82, respectively. The normalization of each component is expressed in (5). The normalization of the slagging index is done by assigning weights to the slagging index categories (low, medium, high, and severe) as 0, 1, 2, and 3, respectively, and normalizing them to a range of 0 to 1.

$$TM_{norm} = \frac{TM_{tongkang} * C[2] + TM_{cyrd} * C[3]}{TM_{max}}$$

$$ASH_{norm} = \frac{TASH_{tongkang} * C[2] + ASH_{cyrd} * C[3]}{ASH_{max}}$$

$$TS_{norm} = \frac{TS_{tongkang} * C[2] + TS_{cyrd} * C[3]}{TS_{max}}$$

$$Calorie_{norm} = \frac{\left(\frac{abs(C[0] - calorie_{target})}{calorie_{target}}\right)}{0.02}$$

$$Slagging_{norm} = \frac{slagging\ index}{3}$$

$$TM_{norm} = \frac{Calorie_{norm} + Slagging_{norm} + TM_{norm} + ASH_{norm} + TS_{norm}}{5}$$

$$fitness = (Calorie_{norm} + Slagging_{norm} + TM_{norm} + ASH_{norm} + TS_{norm})/5 \quad (5)$$

3) Best Chromosome: The best chromosome represents the solution. The expected solution for the blending is a recommendation of the best composition consisting of coal from the barge, coal from the coal yard, and biomass from each coal category available on the barge. With this solution formulation, the operator can choose the most suitable composition to be used at any given time. If the coal on the barge is of the Medium Rank category, it will be paired with Low-Rank coal from the coal yard, and vice versa. The best chromosome for each category will be updated during the iterations in the execution process of the GA.

4) Crossover and Mutation: Crossover and mutation are consecutive stages in GA that prevent local optima and ensure the availability of new information for evolution. The parent chromosomes represent a solution in the form of a composition of barge coal and coal yard. The crossover process changes the composition pairs and alters the heat target and fitness value. The crossover process is illustrated in Fig. 2. Parents A and B undergo crossover between C2 and C3 positions, generating offspring chromosomes C1 and C2. Subsequently, this process modifies the genetic information in the C0 and C6 segments to match the calorie target from blending and co-firing and the fitness value of the new chromosomes.

Target calories based on the composition of each part are calculated using (6). The fitness of the offspring chromosome is calculated based on the representation of the offspring chromosome and is used to update the fitness represented by the new chromosome.

$$Target_{calorie} = percentage\ of\ coal\ in\ barge * Calorie_{coalinbarge} + percentage\ of\ coal\ in\ coalyard * Calorie_{coalincoalyard} + percentage\ of\ biomasse * Calorie_{biomass} \quad (6)$$

III. RESULT AND DISCUSSION

In this section, the application design, implementation results, and testing of the optimization of blending and co-firing application will be discussed. Part one presents the application interface to facilitate user interaction with the application. In the following part, the testing of the functionality of the genetic algorithm optimization for blending will be discussed.

A. Database Design

To support the data requirements of the optimization of blending application, a database design has been implemented. The logical model of the developed application is presented in Fig. 3.

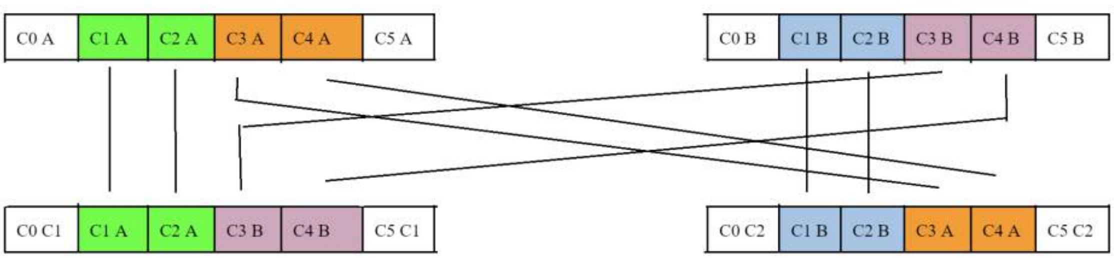


Fig. 2 Crossover

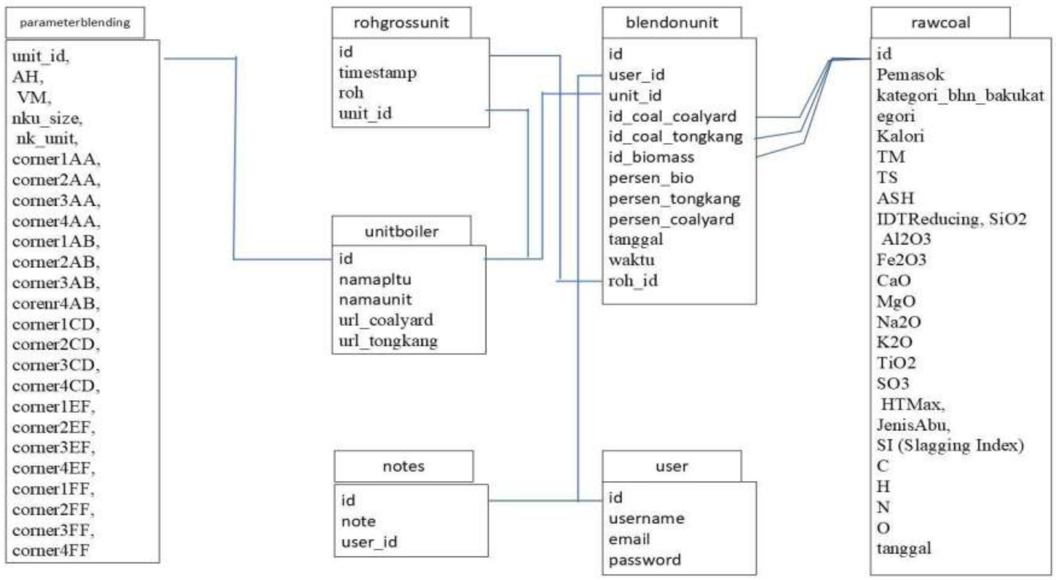


Fig. 3 Logical model of blending application

B. User Interaction

The optimization of blending application is a web-based application developed using the Django Framework with the Python programming language. Some functions supporting the co-firing process still require operator intervention, such as inputting the daily load, determining the categories of coal available on the barge and in the coal yard, and selecting the blending options to be executed at specific times.

In the first step, the user must ensure that the daily load has been input into the system. The daily load is uploaded only once a day. If it has been uploaded, the user can view the ROH list on that page. However, if it has yet to be uploaded, the user cannot find it and must upload it first. The operator will use the value of ROH as a reference to determine the required calorific value to be produced.

The user prepares the biomass and coal list for blending in the next stage. There are three steps that the user needs to complete for the fuel preparation stage. First, selecting the biomass; second, choosing the coal on the barge based on the longest time it has been on the barge; and third, selecting the top-layer coal in the coal yard. Based on the barge's coal categories, the system selects coal categories in the coal yard for blending. If the coal on the barge is categorized as MRC, then LRC is chosen, and vice versa.

The user needs to perform the third step to determine the blending time and target calorific value according to the current calorific requirements. The system will prepare a list of the best compositions and display them to the user. The user can choose from the presented recommendations and is free to determine the blending process to be executed, considering the on-site conditions.

C. Functionality Testing of GA Library

The functionality of GA Library is tested and analyzed from the stages of creating chromosomes, creating populations, crossover, mutation, and their effects on population changes as well as the optimization results of blending. In the part of the barge and coal yard, the distribution of data appears to be non-normal. There are barge values below Q1 and coal yard values above Q3, as Fig. 4. The maximum fitness value of a chromosome is 0.5 and never exceeds this value.

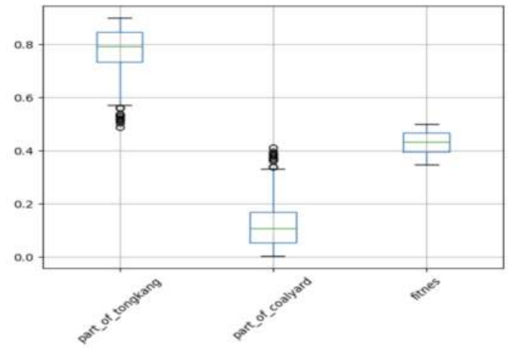


Fig. 4 The Boxplot of chromosomes in GA population

The visualization of the distribution of target calories is grouped based on coal yard IDs and presented in Fig. 5. Although it is not normally distributed, target calorie values vary within the range of 4500 ± 0.02.

Visualization of the distribution of fitness values grouped by coal yard IDs from several generations is shown in Fig. 6. The effects of crossover and mutation are evident in the variation of fitness values grouped by the coal present in the coal yard. In coal yard ID 0, fitness changes occur within approximately 0.45 to 0.5. There are many chromosomes with fitness values within this range in generation 0. Changes occur in generations 5 and 10, and the fitness distribution becomes similar to generation 0.

In generation 5, noticeable changes in fitness are observed for each coal yard ID. Coalyard ID 2 shows an increase in chromosomes with fitness values above 0.45. In the subsequent generations, most of the population is on the right side, representing the individuals with the best fitness. The experiment's test results on GA parameters can be seen at Table III.

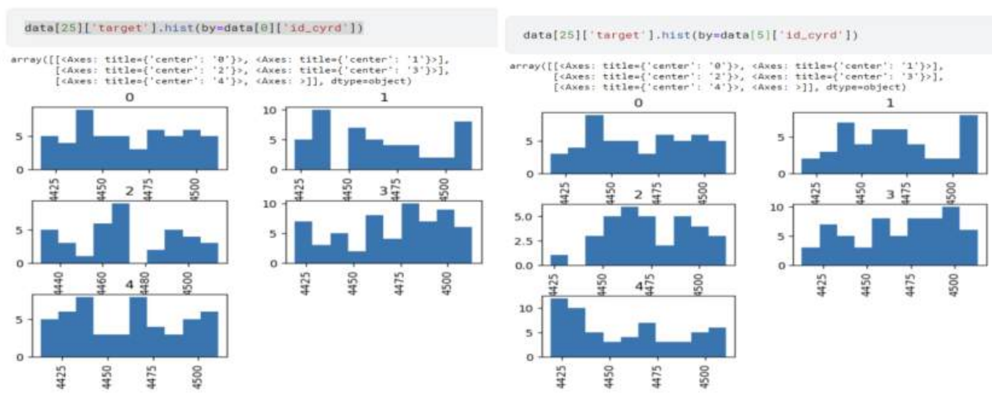
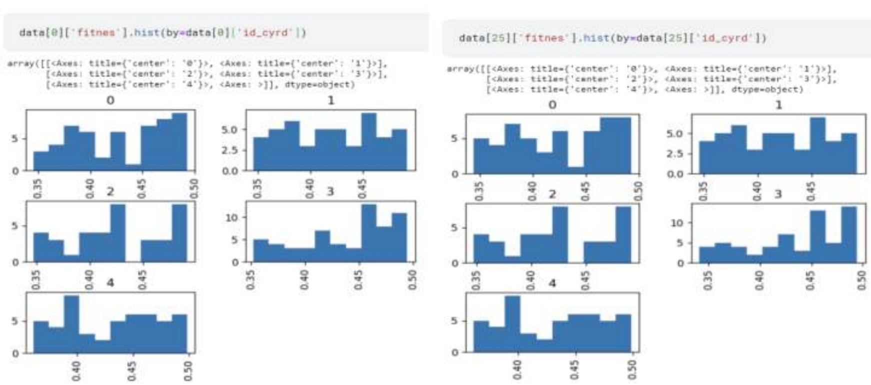


Fig. 5 The distribution of target calories group by coal in coal yard



(i) 0-th generation **(ii) 25-th generation**

Fig. 6 Distribution of fisness value of chromosom in coalyard group by coal yard ID

TABEL III
EXPERIMENT ON GA PARAMETERS: POPULATION, ITERATION, AND MUTATION RATE

III.a Best Chromosome based on population

Population	Target	ID Coalyard	Tongkang	Coalyard	Biomass	Fitnes
200	4500	3	0,86	0,04	0,1	0.49
200	4500	0	0,87	0,03	0.1	0.49
200	4500	2	0,87	0,03	0.1	0,49
200	4500	1	0,87	0,03	0,1	0.49
200	4500	4	0,84	0,06	0,1	0.5

III.b Best Chromosome based on Iteration

Iteration	Target	ID Coalyard	Barn	Coalyard	Biomass	Fitness
15	4500	4	0,84	0,06	0,1	0,5
15	4500	3	0,86	0,04	0,1	0,49
15	4500	1	0,87	0,03	0,1	0,49
15	4500	2	0,87	0,03	0,1	0,49
15	4500	0	0,87	0,03	0,1	0,49

III.c Best Chromosome based on mutation rate

Mutation Rate	Target	ID coalyard	Barn	Coalyard	Biomass	Fitnes
0,7	4500	3	0,86	0,04	0,10	0,49
0,7	4500	0	0,87	0,03	0,10	0,49
0,7	4500	1	0,87	0,03	0,10	0,49
0,7	4499	4	0,84	0,06	0,10	0,50
0,7	4500	2	0,87	0,03	0,10	0,49

The fitness value of each best chromosome representing the solution is compared across several GA parameters: population size, iterations, and mutation rate. The test results presented in Table III.a show that a chromosome population of 200 has achieved the optimal heat target. Based on the test results, the optimal population size is then tested for the optimal number of iterations. GA can achieve the optimal heat target as early as iteration 15. The mutation rate that results in the optimal heat target is performed at a mutation rate of 0.7.

IV. CONCLUSION

The Optimization Application for coal blending in a Coal-Fired Power Plant using Genetic Algorithm has been successfully implemented, and its functionality has been tested. The application is web-based, built using the Django Framework, and utilizes PostgreSQL as the DBMS. The main stages of the genetic algorithm include population formation, crossover, and mutation. Each chromosome has been appropriately defined, where the target calorific value falls within the minimum and maximum threshold of 2% of the desired calorific value. The population members for each coal category in the coal yard are generated equally, and the best chromosome is maintained for each type. The visual effects of crossover and mutation on the fitness values of the population members have been demonstrated, showing improvements toward better fitness values. The Genetic Algorithm testing results have achieved optimal output based on the calorific target, with the parameters set as follows: a population size of 200, 15 iterations, and a mutation rate of 0.7.

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