A Multi-Objective Optimization Model for Vehicle Workshop Service Systems

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***Abstract*—Vehicle workshops frequently suffer from long customer waits, unstable queue lengths, uneven mechanic workloads, and high operating costs. This research builds an NSGA-II-based model that balances several service objectives at the same time. Operational data from 270 customers over a 30-day observation period were analyzed based on service duration, waiting time, queue length, customer satisfaction, mechanic productivity, and service cost. The optimization considers four objective functions: minimizing waiting time, minimizing workload imbalance, minimizing operational cost, and maximizing customer satisfaction. Three decision variables were considered, namely the number of active mechanics, service priority level, and number of workstations. NSGA-II was implemented using 100 iterations, a population size of 80 individuals, a crossover rate of 0.80, and a mutation rate of 0.30. The initial system recorded an average waiting time of 18.72 minutes, customer satisfaction of 4.24, and an average queue length of 3.73 customers. The optimization produced a configuration of 7 active mechanics, priority level 10, and 6 workstations, resulting in a waiting time of 3.10 minutes, customer satisfaction of 4.49, workload imbalance of 0.05, and operational cost of IDR 1.626 million. The results indicate that NSGA-II can generate alternative workshop service configurations by considering trade-offs among service efficiency, customer satisfaction, workload distribution, and operational cost.**

Keywords— NSGA-II; Multi-Objective Optimization; Vehicle Workshop; Waiting Time

I. INTRODUCTION

Long customer wait times and queues are major issues in workshop service systems, potentially compromising service quality [1], [2]. According to Elyasi et al. [3], uneven distribution of mechanic workloads also leads to inefficiencies in the service process. Suboptimal resource utilization often drives up operational expenses, particularly during peak service hours [4]-[6]. The rising number of motor vehicles has led to an ever-increasing public demand for vehicle servicing. Workshops are expected to provide rapid, accurate, and high-quality service [7]-[9]. Service quality depends not only on mechanic proficiency but also on service capacity and the management of the workshop's operational systems [10]-[12]. Customer wait times, the number of active mechanics, and workstation availability are critical factors determining service performance [13], [14]. Increasing the number of mechanics and workstations can boost a workshop's service capacity [15], [16]. According to Zou et al. [17], increasing service capacity helps reduce queues and speed up vehicle servicing; however, this expansion can also lead to higher operational costs. This situation highlights the trade-off between service quality and operational cost efficiency.

The problem of workshop service systems falls under the category of multi-objective optimization, aiming to minimize waiting time, operational costs, and workload imbalance, while maximizing customer satisfaction[18], [19] Several methods can be employed to address service system problems, such as weighted sum [20] , MOPSO [21] , SPEA2 [22] , and MOEA/D [23]. However, each method possesses distinct characteristics and limitations regarding multi-objective problem-solving. The weighted sum approach aggregates multiple objective functions into a single function based on specific weights, meaning the optimization outcome is influenced by the weight assignment [24]. MOPSO utilizes a particle swarm mechanism to search for Pareto solutions, though maintaining solution diversity throughout the search process is essential [25]. SPEA2 employs fitness and solution density mechanisms to identify non-dominated solutions, whereas MOEA/D solves problems by decomposing them into interconnected sub-problems [26], [27]. These characteristics indicate that method selection must consider an algorithm's ability to obtain non-dominated solutions and maintain solution diversity along the Pareto front.

Method selection must consider an algorithm's ability to obtain non-dominated solutions and maintain solution diversity along the Pareto front [28]-[30]. Numerous studies demonstrate that the Non-dominated Sorting Genetic Algorithm II (NSGA-II) is capable of simultaneously optimizing multiple objectives without aggregating all objective functions into a single weighted function [31]-[33] . A non-dominated sorting mechanism is used to identify solutions based on dominance levels, while a crowding distance mechanism maintains solution diversity on the Pareto front [34] . NSGA-II can generate a set of alternative solutions representing the trade-offs between waiting time, operational costs, customer satisfaction, and workload imbalance. These characteristics align well with workshop service problems, which involve trade-offs among objectives. NSGA-II has been applied to various optimization problems [20], [21]. Firouzabad et al. [35], used NSGA-II to minimize waiting times and enhance service efficiency. Zhao et al. [36], applied NSGA-II to optimize service resources. Alikar et al. [37], utilized NSGA-II for queueing system optimization. Peng et al.[38], applied NSGA-II to multi-objective problems

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involving trade-offs. Xie et al. [39], using NSGA-II to improve operational efficiency and service quality.

This study proposes an NSGA-II-based model to improve service operations in a vehicle repair shop. Four objectives are addressed: shortening waiting time, raising customer satisfaction, reducing operating cost, and balancing workload among mechanics. The decision variables include the number of active mechanics, service priority levels, and the number of workstations. The developed model is used to derive a Pareto front representing various service system configuration alternatives based on trade-offs between the objectives. The study's findings are expected to provide service resource configuration alternatives capable of enhancing service quality, maintaining balanced mechanic workloads, and accounting for operational cost efficiency.

II. Materials and Methods

A. Data Collection and System Description

This study utilizes operational data from a vehicle repair shop, collected over 30 days of operation and comprising records for 270 service customers. Data was gathered directly from shop activities, covering customer arrival times, service types, vehicle types, service durations, waiting times, queue lengths, customer satisfaction levels, mechanic productivity, and service costs. The collected data were used to characterize the baseline condition of the service system and served as the input for the subsequent NSGA-II optimization.. The service system in this study involves multiple active mechanics and workstations handling various types of vehicle services. Key issues within the system include high customer waiting times, unstable queue lengths, uneven distribution of mechanic workloads, and rising operational costs during peak service hours. These conditions indicate that the service system requires optimization to enhance overall operational efficiency and service quality.

B. Decision Variables

This study employs three primary decision variables in the optimization process using the NSGA-II algorithm: the number of active mechanics, the service priority level, and the number of workstations. These three variables are used to determine the optimal configuration of the vehicle workshop service system, taking into account service quality and operational efficiency.

1) The "active mechanics" variable represents the number of mechanics involved in the workshop service process [40].
2) The "priority level" variable is used to determine the priority level of customer service [41].
3) The "workstation" variable indicates the number of vehicle service areas available in the workshop system [42].

C. Objective Functions

This study employs a multi-objective optimization approach to enhance the performance of a vehicle repair shop's service system. The optimization process considers several objective functions simultaneously: minimizing waiting time, maximizing customer satisfaction, minimizing workload imbalance, and minimizing operational costs. A multi-objective approach is utilized because each objective function involves a trade-off regarding the service system's performance.

1) Minimization of Waiting Time

The first objective function aims to minimize customer waiting time within the workshop service system.

$$f_1(x) = WT \tag{1}$$

where:
$f_1(x)$= waiting time minimization function,
WT= customer waiting time.

2) Maximization of Customer Satisfaction

The second objective function aims to maximize the level of customer satisfaction with the workshop service. The mathematical formulation is expressed as:

$$\max f_2(x) = CS(x) \tag{2}$$

where:
$f_2(x)$= customer satisfaction maximization function;
$CS(x)$= customer satisfaction level.

3) Minimization of Workload Imbalance

The third objective function is used to minimize the imbalance in workload distribution among mechanics. The mathematical formulation is expressed as:

$$\min f_3(x) = WI(x) \tag{3}$$

where:
$f_3(x)$= workload imbalance minimization function;
$WI(x)$= workload imbalance level among mechanics.

4) Minimization of Operational Cost

The fourth objective function seeks to reduce the total operating cost incurred by the workshop. It is formulated as:

$$\min f_4(x) = OC(x) \tag{4}$$

where:
$f_4(x)$= operational cost minimization function;
$OC(x)$= operational cost of the workshop service system.

All four objectives are optimized concurrently with NSGA-II, yielding a set of Pareto-optimal service configurations for the workshop.

D. Mathematical Formulation

The mathematical model is developed based on service capacity, system utilization, customer waiting time, customer satisfaction, workload distribution among mechanics, and operational cost of the workshop service system.

1) Service Capacity

The service capacity of the system is determined based on the number of active mechanics and the number of workstations available in the workshop system. The mathematical formulation is expressed as:

$$SC = M \times W \tag{5}$$

where:
SC= service capacity;
M= number of active mechanics;
W= number of available workstations.

2) System Utilization

The system utilization level is used to measure the extent to which the available service capacity is utilized during workshop operations. The mathematical formulation is expressed as:

$$U = \frac{N \times \bar{ST}}{SC \times 480} \tag{6}$$

where:
U= system utilization;
N= total number of customers;

$\bar{ST}$= average service time;
SC= service capacity;
480= total operational time per day (minutes).

3) Waiting Time
The waiting-time equation is used to estimate the customer waiting time based on the service capacity of the system. The mathematical formulation is expressed as:

$$WT = \frac{N}{SC} \tag{7}$$

where:
WT= estimated waiting time;
N= total number of customers;
SC= service capacity.

4) Customer Satisfaction
Customer satisfaction is calculated based on the service priority level and the waiting time experienced by customers. The mathematical formulation is expressed as:

$$CS = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{PL_i}{WT_i}\right) \tag{8}$$

where:
CS= customer satisfaction;
N= total number of customers;
PL_i= priority level of customer i;
WT_i= waiting time of customer i.

5) Workload Imbalance
Workload imbalance is used to measure the degree of workload distribution imbalance among mechanics in the workshop service system. The mathematical formulation is expressed as:

$$WI = \frac{1}{M}\sum_{j=1}^{M}|WL_j - \bar{WL}| \tag{9}$$

where:
WI= workload imbalance;
M= number of active mechanics;
WL_j= workload of mechanic j;
$\bar{WL}$= average workload distribution among mechanics.

6) Operational Cost
Operational cost is calculated based on the utilization of active mechanics and workstations in the workshop service system. The mathematical formulation is expressed as:

$$OC = C_M M + C_W W \tag{10}$$

where:

OC= operational cost (million IDR);
C_M= average operating cost per mechanic;
M= number of active mechanics;
C_W= average operating cost per workstation;
W= number of workstations.

The six mathematical components are subsequently integrated into the multi-objective optimization model. Service capacity and system utilization represent the operational performance of the workshop, while waiting time, customer satisfaction, workload imbalance, and operational cost represent the service quality and resource-efficiency dimensions. These components are simultaneously considered in the NSGA-II optimization process to obtain a set of Pareto-optimal solutions for the vehicle workshop service system.

E. NSGA-II Optimization Algorithm

NSGA-II is employed to solve the multi-criteria decision problem of the workshop. It was chosen because its non-dominated sorting and crowding-distance mechanisms produce Pareto-optimal solutions while preserving diversity. The optimization process represents each individual as a combination of decision variables comprising the number of active mechanics, the service priority level, and the number of workstations. The initial population is generated randomly within the predetermined ranges of the decision variables. The optimization parameters used in this study include:

1) maximum number of iterations: 100,
2) population size: 80 individuals,
3) crossover rate: 0.8,
4) mutation rate: 0.3.

The crossover process is used to generate new solution combinations by exchanging characteristics between individuals. Meanwhile, the mutation process serves to maintain population diversity and avoid local optima during the solution search. Each individual is evaluated using a multi-objective function comprising waiting time, customer satisfaction, workload imbalance, and operational cost. The best solution is selected based on a Pareto-optimal approach to achieve a service system configuration that balances service quality and operational efficiency.

F. Algorithm Performance Evaluation

The performance of the algorithm was evaluated to measure the quality of the Pareto solutions generated by the NSGA-II algorithm during the optimization of the vehicle workshop service system. In this study, algorithm performance was evaluated using two main metrics, namely Hypervolume (HV) and Generational Distance (GD).

1) Hypervolume
Hypervolume (HV) is used to measure the coverage of the Pareto solution set in the multi-objective space relative to a predetermined reference point. The Hypervolume is calculated as follows:

$$HV = \text{Volume}\left(\bigcup_{i=1}^{N}[f_1'(x_i)r_1] \times [f_2'(x_i)r_2] \times \cdots \times [f_{M'}(x_i)r_M]\right) \tag{11}$$

where:
HV= Hypervolume value;
N= number of Pareto solutions;
M= number of objective functions;
r_j= reference point for the j-th objective;
$f_j(x_i)$= value of the j-th objective function for the i-th solution.

The Hypervolume calculation is performed using normalized objective-function values, so that the evaluation values are within the range of 0-1. A larger HV value indicates greater coverage of the objective space by the obtained Pareto solutions.

2) Generational Distance
Generational Distance (GD) is used to measure the distance between the solutions obtained from the optimization process and the Pareto-optimal front. The Generational Distance is formulated as:

$$GD = \frac{1}{N}\sqrt{\sum_{i=1}^{N} d_i^2} \tag{12}$$

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where:
GD= Generational Distance value;
N= number of Pareto solutions;
d_i= Euclidean distance between the i-th obtained solution and the nearest solution on the Pareto-optimal front.

A smaller GD value indicates that the obtained Pareto solutions are closer to the Pareto-optimal front, indicating better convergence of the optimization algorithm. The general structure of the NSGA-II optimization process employed in this study is presented in Fig. 1.

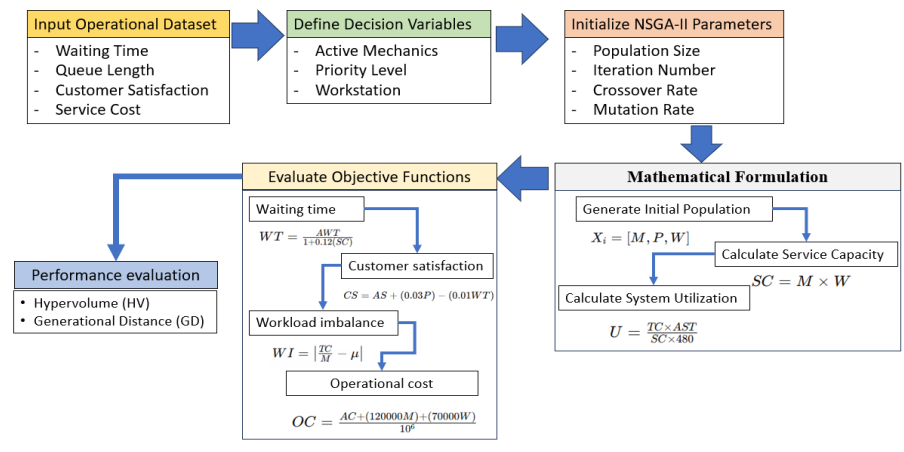

Fig 1. Workflow of the NSGA-II optimization procedure applied to the workshop service system.

III. Results And Discussion

A. Analysis of the Initial State of the Workshop System

An analysis of the workshop system's initial state was conducted to assess operational performance prior to optimization using the NSGA-II algorithm. This stage aimed to identify service system characteristics based on actual data, including customer volume, service time, waiting time, queue length, mechanic productivity, customer satisfaction levels, and operational expenses. Table 1 presents the basic statistics of the workshop system.

TABLE I. Basic Statistics of the Workshop Service System

Parameter	Value
Total Customers	270 customers
Total Mechanics	7 mechanics
Average Service Time	46.94 minutes
Average Waiting Time	18.72 minutes
Average Queue Length	3.73 customers
Average Customer Satisfaction	4.24
Average Productivity	85.16
Average Service Cost	IDR 384,011
Total Operational Cost	IDR 103,683,000

Table 4.1 presents data based on workshop services provided to 270 customers over a 30-day observation period. The average service duration of 46.94 minutes indicates variability in service times across different service types, with major services requiring longer completion times. An average waiting time of 18.72 minutes and a queue length of 3.73 customers indicate that queuing occurs during the service process, particularly under conditions of higher service loads. Although customer satisfaction stands at 4.24 and mechanic productivity at 85.16, the system remains susceptible to workload imbalances resulting from differences in productivity and work distribution among mechanics. Furthermore, an average service cost of IDR 384,011 with a total operational cost of IDR 103,683,000 highlights operational expenses that must be considered in managing the service system. These conditions demonstrate the need for optimization using the NSGA-II algorithm to enhance service efficiency and workshop system performance.

B. Distribution of Workshop Operational Data

An analysis of operational data distribution was conducted to understand the workshop's service patterns regarding customers. Figure 2 shows the distribution of the workshop's operational data.

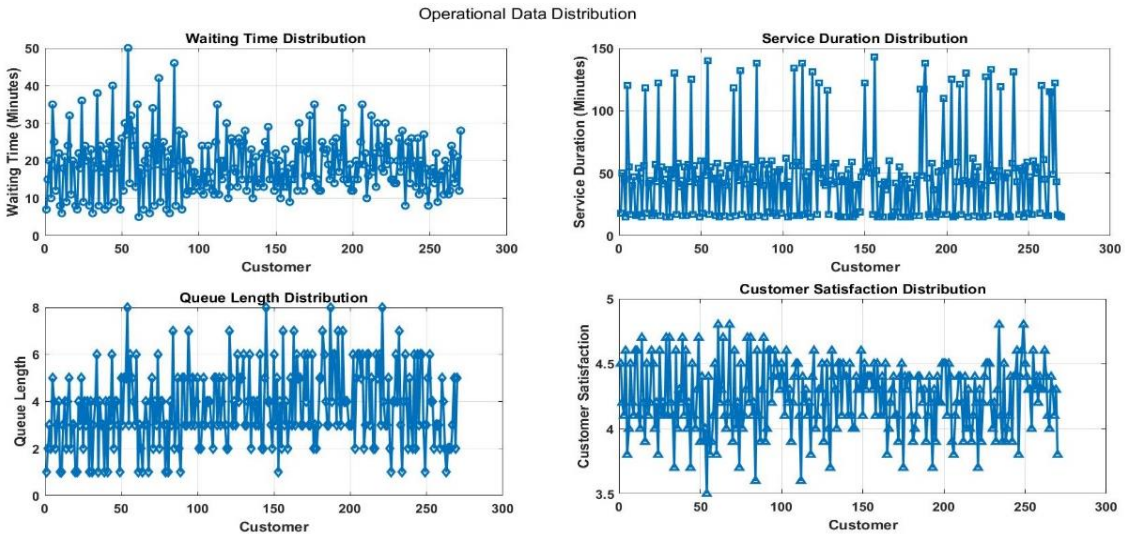

Fig 2. Distribution of Workshop Operational Data

Fig. 2 illustrates that the workshop service system experiences significant performance fluctuations, based on data from 270 customers over a 30-day observation period. The average customer waiting time was 18.72 minutes, peaking at 50 minutes when the queue reached eight customers, while the minimum waiting time was 5 minutes during periods of low queue volume. Service duration averaged 46.94 minutes, ranging from 15 to 143 minutes; major servicing tasks required the longest completion times, leading to increased queue lengths and prolonged workstation utilization. The average queue length was 3.73 customers, with a maximum of eight, indicating fluctuating queue conditions throughout the observation period. Meanwhile, customer satisfaction averaged 4.24 ranging from a high of 4.8 to a low of 3.5 reflecting varying levels of satisfaction under different service conditions. Additionally, productivity levels ranged from 91 to 94 for senior mechanics and stood at 72 for junior mechanics, highlighting a disparity in productivity between the two groups. Overall, the distribution of operational data over the 30-day period reveals that the workshop service system faces challenges regarding waiting times, fluctuating queues, variable service durations, and productivity disparities. Therefore, optimizing these objectives simultaneously with NSGA-II is necessary to improve workshop efficiency.

C. *Variable Correlation Analysis*

Correlation analysis aims to identify the factors that most significantly influence workshop service performance prior to the optimization process using the NSGA-II algorithm, as shown in Fig. 3.

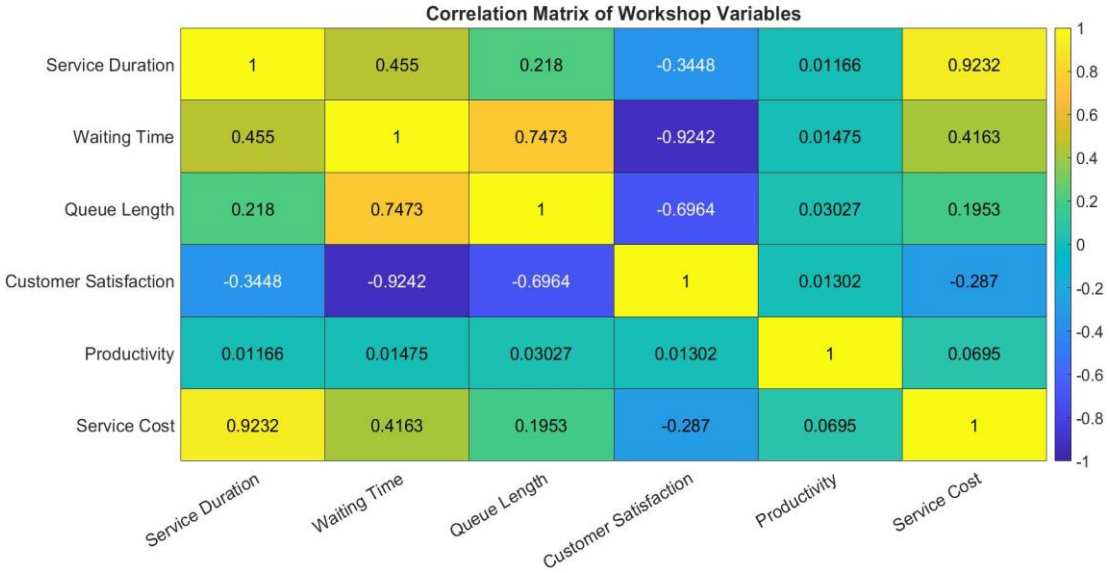

Fig 3. Correlation Heatmap of Operational Variables for the Workshop Service System

Fig. 3 illustrates that the relationships between operational variables exhibit varying levels of correlation. Service duration shows a moderate positive correlation with waiting time (0.455) and a strong positive correlation with service cost (0.9232). These values indicate that an increase in service duration tends to be accompanied by increases in both waiting time and service cost, with a particularly strong relationship between service duration and service cost. Waiting time demonstrates a strong positive correlation with queue length (0.7473) and a forceful negative correlation with customer satisfaction (−0.9242). These relationships indicate that longer waiting times tend to coincide with increased queue lengths and decreased customer satisfaction. Queue length also shows a strong negative correlation with customer satisfaction (−0.6964), indicating that longer queues are associated with lower levels of customer satisfaction. The productivity variable exhibits fragile correlations with service duration (0.01166), waiting time (0.01475), queue length (0.03027), customer satisfaction (0.01302), and service cost (0.0695). This suggests that mechanic productivity has a relatively weak linear relationship with the other service variables in the analyzed dataset. Overall, the strong correlations observed among waiting time, queue length, and customer satisfaction highlight that waiting time and queue conditions are critical variables in the workshop service system. Consequently, applying multi-objective optimization using NSGA-II is essential to simultaneously consider waiting time, customer satisfaction, workload imbalance, and operational costs.

D. *Optimization of workshop service systems based on NSGA-II*

The optimization of the workshop service system was carried out using the Non-dominated Sorting Genetic Algorithm II (NSGA-II). The study employed several optimization parameters, including the number of iterations, population size, crossover rate, mutation rate, and the range of decision variables used in the optimization process.

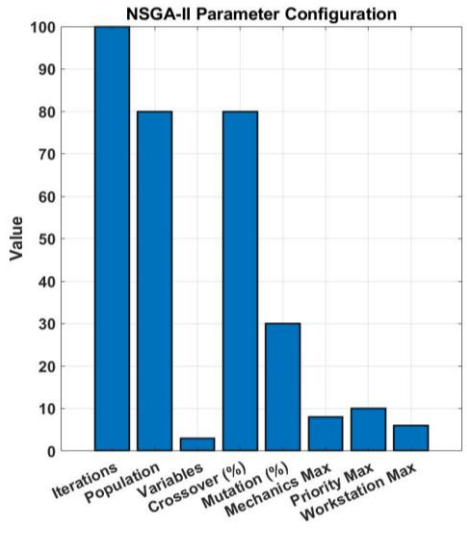

Fig 4. NSGA-II Optimization Parameters for the Workshop Service System

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Fig. 4 illustrates the NSGA-II algorithm executed over 100 iterations with a population size of 80 individuals. The number of iterations ensures a sufficient solution search process during optimization, while the population size of 80 fosters solution diversity within the search space. A crossover rate of 0.80 indicates that the crossover process is applied with an 80% probability to generate new solution combinations, and a mutation rate of 0.30 is employed to maintain population diversity throughout the evolutionary process. This study utilizes three primary decision variables within the NSGA-II model: active mechanics, priority level, and workstations. The constraints are set at a maximum of 8 active mechanics, a maximum priority level of 10, and a maximum of 6 workstations. These parameters serve as search boundaries during optimization to identify a workshop service system configuration that balances waiting time, customer satisfaction, workload imbalance, and operational costs.

The Non-dominated Sorting Genetic Algorithm II (NSGA-II) is employed to obtain Pareto-optimal solutions for the multi-objective problem of a workshop service system. The optimization process simultaneously considers four objective functions: minimizing waiting time, minimizing workload imbalance, minimizing operational cost, and maximizing customer satisfaction. The optimization is conducted over 100 iterations with a population size of 80 individuals, a crossover rate of 0.80, and a mutation rate of 0.30. The decision variables include the number of active mechanics, the service priority level, and the number of workstations, with maximum limits of 8 mechanics, 10 priority levels, and 6 workstations, respectively. The optimization results are visualized as a Pareto front in Fig. 5.

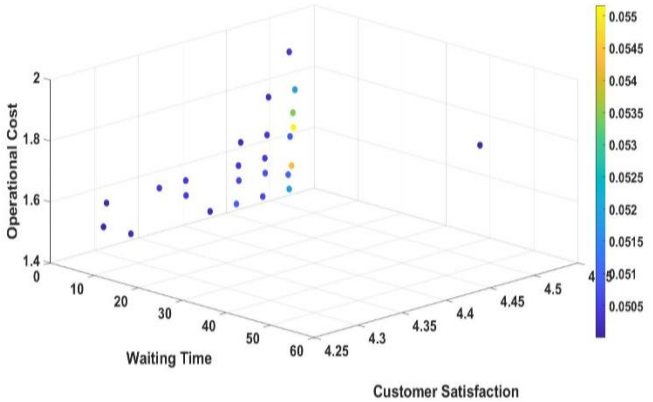

Fig 5. NSGA-II Pareto Front NSGA-II workshop service system

Fig. 5 shows the 3D Pareto Front results of NSGA-II optimization, which illustrates the trade-off relationship between waiting time, customer satisfaction, and operational costs. Each point on the Pareto front represents alternative solutions that do not dominate each other based on the objective function used. The waiting time value in the Pareto solution shows a variation of around 5-55 minutes, while customer satisfaction is in the range of around 4.25-4.50. Operational costs show variations of around 1.4-2.0 according to the value scale on the graph. The distribution of points shows that improving quality in one objective can be accompanied by changes in other objectives, resulting in a trade-off relationship between objectives. The color of the dots represents the workload imbalance value with a range of around 0.050-0.055. The Pareto solution distribution shows that NSGA-II is able to produce several alternative service configurations that can be considered based on the balance between waiting time, customer satisfaction, operational costs, and equal distribution of mechanical workload. The final solution selection can be adjusted to the workshop service system management priorities for each objective.

E. Convergence Analysis

The convergence analysis aims to evaluate the ability of the NSGA-II algorithm to obtain stable solutions during the optimization process. The optimization process was conducted over 100 iterations, monitoring changes in the best waiting time value as a performance indicator for the workshop service system. Figure 6 illustrates the convergence of the objective function value using NSGA-II.

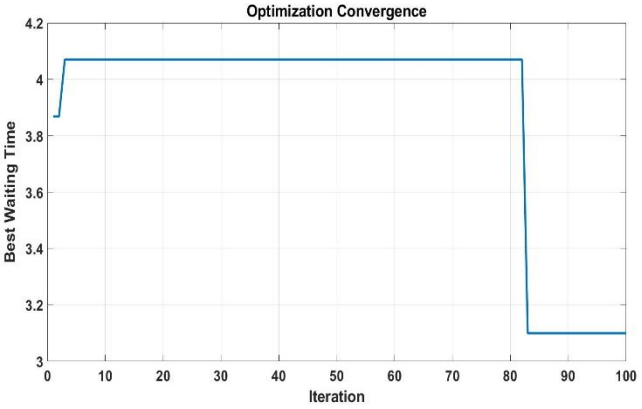

Fig 6. Objective Function Value Convergence Using NSGA-II workshop service system

Fig. 6 illustrates the variation in the best waiting time value throughout the NSGA-II algorithm's iteration process. In the initial iterations, the best waiting time was approximately 3.87 minutes, rising to about 4.07 minutes by the third iteration. This value remained relatively stable until around the 82nd iteration, indicating minimal changes to the best solution during the majority of the optimization process. An improvement occurred around the 83rd iteration, with the best waiting time dropping to approximately 3.10 minutes. This value was maintained through the 100th iteration, demonstrating solution stability in the final stage of optimization. The results indicate that the Pareto solution obtained via NSGA-II achieves a waiting time of approximately 3.10 minutes while simultaneously accounting for customer satisfaction, workload imbalance, and operational costs as additional objective functions. The relationships between these objective functions reveal trade-offs; consequently, the resulting solution balances waiting time minimization with service quality, workload distribution, and operational costs. These findings demonstrate that NSGA-II is capable of generating stable multi-objective solution alternatives during the final stages of the workshop service system optimization process.

F. Algorithm Performance Evaluation

The algorithm was assessed by examining the quality of the Pareto solutions produced by NSGA-II, using two metrics: Hypervolume (HV), which quantifies how much of the objective space the solution set covers, and Generational Distance (GD), which measures how close the solutions lie to the optimal front. Hypervolume was used to measure the extent of the Pareto solutions' coverage within the objective space, while Generational Distance was used to measure the proximity of the optimized solutions to the optimal Pareto solutions. Figure 7 illustrates the variations in customer waiting time characteristics based on the day of service and time of arrival.

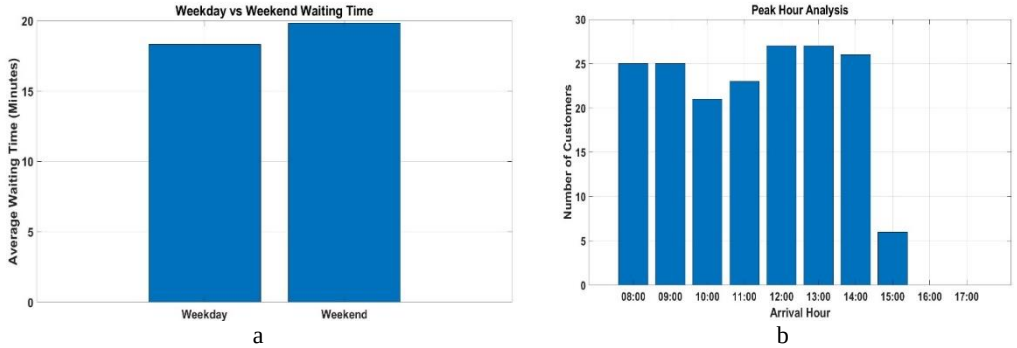

Fig 7. Waiting time analysis based on customer arrival day and time: (a) comparison of waiting times between weekdays and weekends; (b) distribution of customer arrivals by time of day (peak hour analysis).

Fig. 7 illustrates the variation in waiting time based on the day and customer arrival patterns. The average waiting time on weekdays, shown in Figure 7(a), is approximately 18.3 minutes, whereas on weekends it rises to about 19.8 minutes. Figure 7(b) indicates that the highest number of customers occurs at 12:00 and 13:00 with 27 customers at each time while the number drops to 6 customers by 15:00. The waiting time variation pattern reveals that the 12:00-14:00 period experiences relatively high arrival intensity, potentially leading to increased queues and waiting times. These conditions were taken into account when determining the number of active mechanics, workstations, and priority levels for the NSGA-II optimization. The optimization process, conducted over 100 iterations, yielded a configuration comprising 7 active mechanics, a priority level of 10, and 6 workstations; this resulted in a waiting time of 3.10 minutes, a customer satisfaction score of 4.49, a workload imbalance of 0.05, and an operational cost of Rp1.626 million. These results demonstrate the capability of NSGA-II to generate solution alternatives by balancing trade-offs between objective functions within the workshop service system.

IV. Conclusion

This study presented an NSGA-II-based model for optimizing service operations in a vehicle workshop. Data from 270 customers over 30 days showed an average waiting time of 18.72 minutes, an average queue of 3.73 customers, satisfaction of 4.24, and productivity of 85.16. Running 100 iterations with a population of 80, crossover rate 0.80, and mutation rate 0.30, the algorithm arrived at a configuration of 7 mechanics, priority level 10, and 6 workstations. This configuration cut waiting time to 3.10 minutes, raised satisfaction to 4.49, held workload imbalance at 0.05, and kept operating cost at IDR 1.626 million. These findings show that NSGA-II can offer alternative service configurations by weighing waiting time, satisfaction, workload distribution, and cost together.

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