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by Feri Afrinaldi

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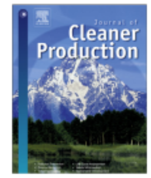

Minimizing economic and environmental impacts through an optimal preventive replacement schedule: Model and application

Feri Afrinaldi [a, *], Taufik [a], Andrea Marta Tasman [a], Hong-Chao Zhang [b], Alizar Hasan [a]

[a] Department of Industrial Engineering, Andalas University, Limau Manis, Padang 25163, Indonesia
[b] Department of Industrial Engineering, Texas Tech University, Lubbock, TX 79409-3061, USA

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A B S T R A C T

This paper presents a mathematical model to determine the optimal schedule of preventive replacement of a component such that the economic and environmental impacts of the component are minimized. For the economic dimension, the model minimizes the operation, failure and replacement costs of the component. From the environmental perspective, the model aims to minimize the environmental impact associated with the use phase and action taken to replace the component. The model is made general and can accommodate any environmental impact category. Due to the complexity of the objective functions of the model, genetic algorithm (GA) is proposed to find the optimal solutions. To reduce GA search space, upper and lower bounds of the solutions are determined based on the numerical analysis of the first derivatives of the objective functions of the model. To show the applicability of the model, a case study aiming to minimize total expected cost and global warming potential (GWP) of a bus tire is presented. The results of the case study show that the optimal preventive replacement schedule minimizing total expected cost per km is when the tire reaches 17,700 km and the schedule minimizing total expected GWP per km is when the tire reaches 19,500 km. The schedules result in US\$23 and 0.2 kg CO_2-eq savings in the total expected cost and GWP per tire. The solutions of the multi-objective optimization problem indicate that a 1000 km increase in the optimal schedule minimizing total cost will result in a 0.4% increase in the total expected cost and a 0.002% reduction in the total expected GWP of the tire. The sensitivity analysis presents that 1% reduction in the operation cost and fuel consumption contributes to a 0.91% reduction in the total expected cost and 0.99% reduction in the total expected GWP, respectively.

1. Introduction

Natural resources depletion, pollution, global warming and other environmental problems have seized global attention (Chang et al., 2014). Furthermore, according to Hallstedt et al. (2015), environmental issues are not the only issues that attract much attention. Sustainability issues involving environmental, economic, and social impacts have also become a global concern and there is an urgent need to ease and reduce the severity of those impacts. This has an influence on how maintenance activity is seen. In the past maintenance was just viewed as an activity to restore the desired functionality of equipment (Jardine and Tsang, 2013). Now the view on maintenance has evolved to an activity that should contribute to the minimization of environmental impact, reduction of life cycle costs, and enhancement of socioeconomic well-being. The capacity of maintenance to support sustainability awareness can be seen from its capability in minimizing energy consumption, reducing total cost of ownership, and promoting safety.

There have been many studies aiming to optimize maintenance activities so that the total cost of ownership is minimized. A collection of maintenance and replacement mathematical models minimizing the total cost can be found in Feldman and Valdez-Flores (2010) and Jardine and Tsang (2013). Feldman and Valdez-Flores (2010) presented age replacement models considering discrete and continuous life times. The decision variable of the models is the replacement age and the objective function is the minimization of the long-run average daily cost. Similarly, one of the models found in Jardine and Tsang (2013) is the optimal preventive replacement age model subject to breakdown. The model balances the benefit obtained from preventive replacement and its cost. The objective function of the model is to minimize the total

* Corresponding author. Department of Industrial Engineering, Andalas University, Limau Manis, Padang 25163, Indonesia. Tel.: +62 812 87291352.
E-mail address: feri_afrinaldi@ft.unand.ac.id (F. Afrinaldi).

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expected cost per unit time and the decision variable is the replacement age.

However, most literature relating maintenance and environmental issues is intended merely to assess the environmental impact of maintenance activities for specific cases. Minne and Crittenden (2015) assessed the environmental impact of residential flooring maintenance. According to the study, ignoring the economic and environmental impacts of the maintenance activity is a major error in comparing flooring choices. In the context of residential flooring, the increase in the intensity of the maintenance activity produces 31%–114% and 30%–49% increases in the environmental impact and cost, respectively. Studies evaluating the environmental impact of pavement systems maintenance activities can be easily found in the literature. Elghali et al. (2006) utilized life cycle assessment (LCA) and multi-criteria decision analysis in choosing the best option for highway maintenance. Giustozzi et al. (2012) also presented a decision support tool that can be used to compare and choose the best strategy for road maintenance. Three criteria were used by the study, environmental impact, cost, and pavement performance. Noland and Hanson (2015) applied LCA method in assessing the amount of greenhouse gas emissions of a road reconstruction. The study found that maintenance activity has a 10% contribution to the total emissions. Study relating product design and the concept of green maintenance can be found in Ajukumar and Gandhi (2013). The study proposed a methodology combining graph theory and multi-criteria decision making to select an optimal design of mechanical systems from the perspective of green maintenance.

Research linking reliability and maintainability with the level of environmental impact of a system can be found in Sikos and Klemeš (2009) and Liu et al. (2016). Sikos and Klemeš (2009) related system reliability and maintainability with the effort to minimize waste. The authors concluded that the reliability and maintainability of a waste management system play a major role in achieving cleaner processing. In order to reduce the impact of the replacement activity to the environment, Liu et al. (2016) presented a remanufacturing timing model minimizing global warming potential of a component based on the reliability and replacement theories. However, this study did not consider the decline in the performance of the component as it ages and the expected length of the use phase in computing the global warming potential of the use phase.

Based on the above literature, it is concluded that maintenance and replacement activities have a significant role in reducing the economic and environmental impacts of a product or system. However, the literature also shows that research aiming to determine the optimal timing of replacement and maintenance actions such that product's environmental and economic impacts are minimized is still limited. This paper aims to fill this gap. Its goal is to develop a mathematical model optimizing the preventive replacement schedule so that the total economic and environmental impacts of an asset are minimized. The developed model is a generic model that can be applied to any technology and product. The model is more geared to long-term planning and decision making.

2. Problem statement and objective

If a component of particular equipment suddenly fails, it needs to be replaced in order to keep the equipment working properly. Since the failure is a random event, then there is a reason to assume that the failure replacement is more expensive than a preventive replacement (Jardine and Tsang, 2013). For example, a company might stop the production because of a sudden failure and this delay might have an economic consequence. The economic consequence can be minimized if the company adopts a preventive replacement policy. In designing the policy, the company needs to balance the benefit obtained from the reduction in the frequency of failure replacements and the cost paid due to preventive replacement actions. The increase in the frequency of preventive replacement (a shorter interval between preventive replacements) causes a higher preventive replacement cost. Since the cost increases then this may not be a desirable situation. However, a shorter interval between preventive replacements will decrease the probability of a failure. This means a lower failure replacement cost and is a desirable situation. Another type of cost involved is the operation cost. The amount of the cost depends on the length of the use phase, working condition, and the efficiency of the component.

If an environmental dimension is added to the aforementioned cost problem, there will be two categories of environmental impact associated with the problem, the environmental impact of using the current component and the environmental impact related to the new component used as a replacement. The decision on when a preventive replacement should be done affects the total environmental impact produced by both components (component currently in service and replacement component). The decrease in the frequency of preventive replacement (a longer interval between preventive replacements) causes a lower environmental impact because fewer replacement components are used. In the opposite, it increases the environmental impact of the use phase of current component because of a longer operation period. The impact becomes more severe if the performance of the component declines as it ages. An automobile is a good example, when it is new, it has a good fuel economy, but as it ages, the fuel consumption per kilometer may increase.

In Fig. 1, it can be seen that there is a conflicting situation for each dimension. The question is at what age a preventive replacement should be done so that the cost and environmental impact produced by the component are minimized. The answer to this question depends on the characteristic of the component, such as its failure rate, and the amount of the economic and environmental consequences caused by the use phase, failure, and preventive replacement actions.

This study aims to build a mathematical model to solve the aforementioned conflicting situations. The decision variable of the model is the preventive replacement schedule of the component and the objective functions are to minimize the economic and environmental impacts of the component. The developed model is a general model designed to be able to accommodate any environmental impact category. If one wants to use the model, he/she can use one of the mid-point impact categories (abiotic depletion, global warming potential, ozone layer depletion, eutrophication, acidification, photochemical oxidation, human toxicity, or ecotoxicity) or one of the end-point impact categories (damage to human health, eco system quality or resources). To quantify selected environmental impact, LCA method can be implemented. The economic impact can be quantified using available costing methodology such as life cycle costing (LCC) method.

Clearly, from a mathematical standpoint, it is a multi-objective optimization problem. A procedure to find the best solution to this multi-objective problem is provided. A case study discussing the application of the model is presented. The effect of changes in the parameters of the model on current optimal solutions will also be discussed through a sensitivity analysis.

3. Material and methods

3.1. Cost minimization

To formulate the problem, let's define the following variables:

x = a random variable denoting time to failure of a component

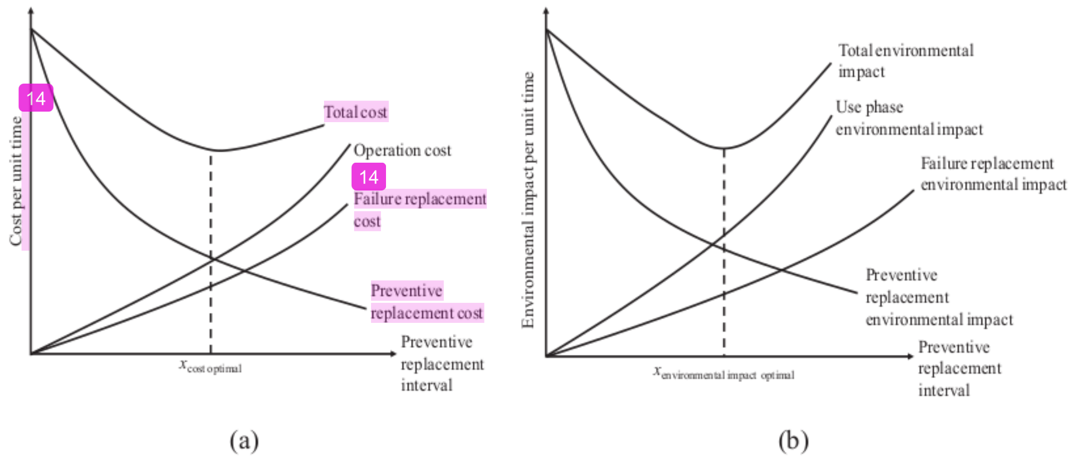


Fig. 1. Optimal preventive replacement interval, (a) cost minimization, (b) environmental impact minimization.

$f(x)$ = failure probability density function of the component
$F(x)$ = cumulative distribution function of the failure, $F(x) = \int_0^x f(x)dx$
x_c = preventive replacement schedule for cost minimization problem which means that, for the cost minimization problem, a preventive replacement action must be done when the age of the component is x_c.

As previously described, two possible events can occur, failure replacement and preventive replacement, see Fig. 2(a) (adjusted from Jardine and Tsang, 2013).

Event 1 – the component is still working when x_c is reached. It means that a preventive replacement needs to be done at x_c. If a preventive replacement action is taken, only replacement cost needs to be paid. There is no failure replacement cost because the preventive replacement is scheduled. The replacement cost, denoted as c_r, is the cost of a new component used to replace the component which is currently in use.

Event 2 – the component fails before reaching x_c. In Fig. 2(a), it is illustrated that the component fails at $x_f < x_c$. In this case, a failure replacement action is taken. Therefore, there are two types of cost that need to be paid, replacement cost c_r and failure cost c_f. The failure cost is the loss of profit due to a failure or unplanned replacement.

Since preventive replacement is done even though the component is still working when x_c is reached, then the probability of a preventive replacement is given by the shaded region of Fig. 2(b), denoted as $R(x_c)$. Knowing the fact that the total probability is one then the probability of a failure replacement is given by the area of the unshaded region of Fig. 2(b), denoted as $F(x_c)$. In reliability theory, $R(x_c) = 1 - F(x_c)$ is known as the survival distribution function. Therefore, total expected replacement cost is given by the following (Jardine and Tsang, 2013; Feldman and Valdez-Flores, 2010):

Total expected replacement cost = expected preventive replacement cost + expected failure replacement cost = $c_r R(x_c) + (c_r + c_f) F(x_c) = c_r + c_f F(x_c)$.

Now let's define $L(x_c)$ as the expected length of the use phase. It is given by the following (Jardine and Tsang, 2013):

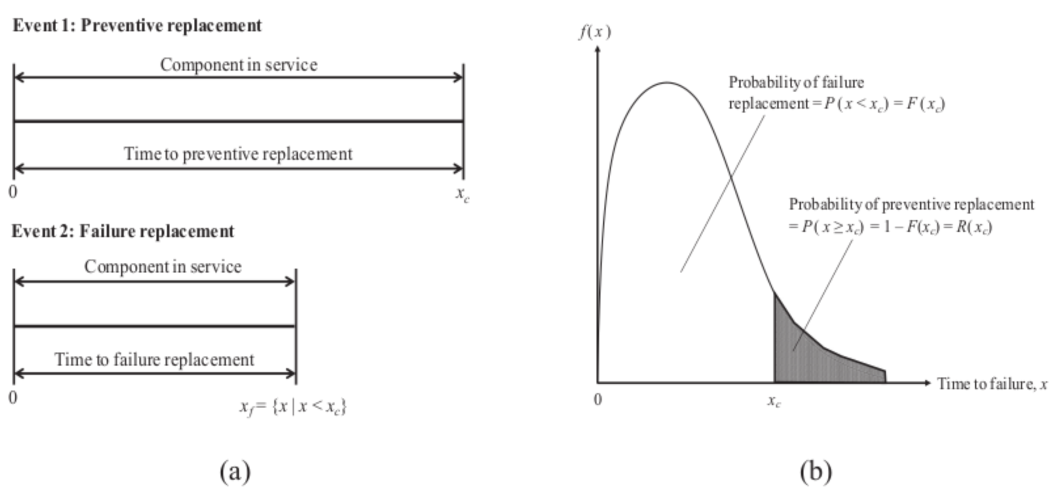


Fig. 2. Preventive and failure replacements and their probability distributions, (a) preventive and failure replacements, (b) probability distributions.

$L(x_c) = x_c R(x_c) + M(x_c) F(x_c)$

$M(x_c)$ is the expected length of time to failure if the preventive replacement is scheduled at x_c and is given by the following (Jardine and Tsang, 2013):

$$M(x_c) = \frac{1}{1 - R(x_c)} \int_0^{x_c} x f(x) dx$$

Therefore, the expected length of the use phase can be rewritten as:

$$L(x_c) = x_c R(x_c) + \int_0^{x_c} x f(x) dx \tag{1}$$

Furthermore, let's define $c_u(x)$ as the operation cost per unit time at time x, such as fuel consumption cost per unit time when the age of the component is x years. It is easy to see that $Z_c(x_c)$, total expected cost per unit time if the preventive replacement is scheduled at x_c, is as follows:

$$Z_c(x_c) = \frac{c_r + c_f F(x_c) + \int_0^{L(x_c)} c_u(x) dx}{L(x_c)} \tag{2}$$

Following Feldman and Valdez-Flores (2010), the first derivative of $Z_c(x_c)$ with respect to x_c is derived. Setting the derivative equals to zero, the following relationship is obtained:

$$\frac{c_r}{c_f} = \frac{1}{c_f}\left[\left[c_f h(x_c) + c_u(L(x_c))\right] L(x_c) - \int_0^{L(x_c)} c_u(x) dx\right] - F(x_c) \tag{3}$$

where:

$$h(x_c) = \frac{f(x_c)}{1 - F(x_c)}$$

If $c_u(x) = a_c x + b_c$, then equation (3) can be simplified as the following:

$$\frac{c_r}{c_f} = \frac{1}{c_f} L(x_c)\left[c_f h(x_c) + \frac{a_c}{2} L(x_c)\right] - F(x_c) \tag{4}$$

a_c is the increase in operation cost with use and b_c is the operation cost during the use phase. In reliability theory, $h(x)$ is known as a failure rate function. x_c satisfying equation (4) is defined as x_c^*, indicating the optimal schedule of preventive replacement such that the total cost per unit time is minimized. If equation (4) is difficult to solve analytically, in Section 3.3, a procedure to find a solution for equation (4) is proposed.

In order to have a unique solution, it is required that the right-hand side of equation (4) to be an increasing function or its first derivative is positive. The requirement is satisfied and presented by the following:

Let $A(x_c)$ be the right-hand side of equation (4), then,

$$A'(x_c) = L(x_c)\left[h'(x_c) + \frac{a_c}{c_f} R(x_c)\right] > 0$$

One important note is that $A'(x_c)$ will always be positive if $h'(x_c)$ is positive, meaning that the failure rate function, $h(x_c)$, needs to be an increasing function too.

3.2. Environmental impact minimization

Let's define x_d as the preventive replacement schedule for the environmental impact minimization problem. Two variables define the environmental impact associated with this problem. The first variable is denoted as $d_u(x)$, defined as the environmental impact per unit time of using a component at time x, such as the global warming potential (GWP) per unit time when the age of the component is x years. The second variable is the environmental impact of the replacement activity, denoted as d_r. It is the environmental impact of producing the component used as a replacement. Therefore, total expected environmental impact is given by the following equation:
Total expected environmental impact = expected environmental impact of preventive replacement + expected environmental impact of failure replacement + expected environmental impact of using the component $= d_r R(x_d) + d_r F(x_d) + \int_0^{L(x_d)} d_u(x) dx = d_r + \int_0^{L(x_d)} d_u(x) dx$

The expected length of the use phase is denoted as $L(x_d)$. The form of this function is given by equation (1). Therefore, $Z_d(x_d)$ denoting the total expected environmental impact per unit time if the preventive replacement is scheduled at x_d is as follows:

$$Z_d(x_d) = \frac{d_r + \int_0^{L(x_d)} d_u(x) dx}{L(x_d)} \tag{5}$$

Similar to the cost minimization problem, the first derivative of $Z_d(x_d)$ with respect to x_d is derived. Setting the derivative equals to zero, equation (6) is obtained.

$$d_u(L(x_d)) L(x_d) = \left[d_r + \int_0^{L(x_d)} d_u(x) dx\right] \tag{6}$$

If $d_u(x) = a_d x + b_d$, then equation (6) can be simplified as the following:

$$\frac{2d_r}{a_d} = L^2(x_d) = \left(x_d R(x_d) + \int_0^{x_d} x f(x) dx\right)^2 \tag{7}$$

a_d is the increase in the amount of environmental impact with use and b_d is the amount of environmental impact during the use phase. x_d satisfying equation (7) is defined as x_d^*, the optimal schedule of preventive replacement such that the total environmental impact per unit time is minimized. If equation (7) cannot be solved analytically, the step-by-step procedure to find a solution for equation (7) is proposed in Section 3.3.

Similar to the cost minimization problem, in order to have a unique optimal solution, the right-hand side of equation (7) needs to be an increasing function or its first derivative is positive. Let's define $B(x_d)$ as the right-hand side of equation (7) and $B'(x_d)$ is presented by the following:

$$B'(x_d) = 2L(x_d) R(x_d) > 0$$

3.3. Methodology to find a solution when x_c^* and x_d^* cannot be solved analytically from equations (4) and (7)

3.3.1. Step 1: Solve the cost minimization problem

Let x_c^{lb} and x_c^{ub} be the lower and upper bounds for the optimal solution of the cost minimization problem, x_c^*. x_c^{lb} and x_c^{ub} are determined numerically. Using x_c^{lb}, x_c^{ub}, and equation (2), a constrained minimization problem given by equation (8) is obtained.

$$\begin{array}{ll} \text{Minimize} & Z_c(x_c) \\ \text{Subject to} & x_c \geq x_c^{lb}, -x_c \geq -x_c^{ub}, \text{ and } x_c \geq 0 \end{array} \quad (8)$$

For the above problem, the Lagrangean and Karush-Kuhn-Tucker (KKT) necessary conditions are the following:

Lagrangean:

$$Y_c = Z_c(x_c) + \lambda_{1c}\left(x_c^{lb} - x_c\right) + \lambda_{2c}\left(-x_c^{ub} + x_c\right) \quad (9)$$

KKT conditions:

$$\begin{array}{lll} \frac{\partial Y_c}{\partial x_c} = \frac{dZ_c(x_c)}{dx_c} - \lambda_{1c} + \lambda_{2c} \geq 0, & x_c \geq 0, & x_c\frac{\partial Y_c}{\partial x_c} = 0 \\ \frac{\partial Y_c}{\partial \lambda_{1c}} = x_c^{lb} - x_c \leq 0, & \lambda_{1c} \geq 0, & \lambda_{1c}\frac{\partial Y_c}{\partial \lambda_{1c}} = 0 \\ \frac{\partial Y_c}{\partial \lambda_{2c}} = -x_c^{ub} + x_c \leq 0, & \lambda_{2c} \geq 0, & \lambda_{2c}\frac{\partial Y_c}{\partial \lambda_{2c}} = 0 \end{array} \quad (10)$$

λ_{1c} and λ_{2c} are the Lagrangean multipliers. It is known that $x_c > 0$ because it does not make sense to replace the component when it is still new. This implies that $\frac{\partial Y_c}{\partial x_c} = 0$. $x_c^{lb} - x_c$ and $-x_c^{ub} + x_c$ are not zeros and therefore $\lambda_{1c}, \lambda_{2c} = 0$. These reduce the above KKT conditions into $\frac{dZ_c(x_c)}{dx_c} = 0$, which is given by equation (4). If equation (4) cannot be solved analytically, this paper applies Genetic Algorithm (GA) to solve the problem presented by equation (8).

However, as indicated by the literature, there are several methods available to solve the problem presented by equation (8) but there is no certainty which method will produce global minimum or maximum. Two well known deterministic gradient based methods, Generalized Reduced Gradient (GRG) and Sequential Programming (SQP) methods can be used to solve the problem. Metaheuristic methods such as Genetic Algorithm (GA), Simulated Annealing (SA), and Tabu Search (TS) can also be used. Among the metaheuristic methods, GA has a more diverse solution population because it uses crossover and mutation operators. The diversity avoids GA to stop in a local optimum and makes it faster in finding a global optimum. A study comparing the performance of GA, GRG and SQP can be found in Yeniay (2005). The study found that GA is highly efficient for all test problems used by the author. GRG and SQP cannot give a better solution. According to the study, GA is also preferred because it is efficient in finding an optimal solution, robust, reliable and easy to implement. Moreover, most solver products are also based on the evolutionary algorithm (Frontline Systems, 2016). GRG and SQP seek the optimum (local or global) solution based on the provided starting points and they are sensitive to them. They may trap in local optimum, depending on the values of the starting points. This makes GA very popular in applications and it is also the reason of using GA in this paper. In order to guarantee that x_c^* found by the GA is an optimal solution, we need substitute it back into the KKT conditions. It is an optimal solution if the KKT conditions are satisfied.

3.3.2. Step 2: Solve the environmental impact minimization problem

Similarly, determine the value of the lower and upper bounds, x_d^{lb} and x_d^{ub}, of the optimal solution for the environmental impact minimization problem using numerical analysis. Construct the optimization problem given by equation (11) by using the lower and upper bounds as the constraint and equation (5) as the objective function.

$$\begin{array}{ll} \text{Minimize} & Z_d(x_d) \\ \text{Subject to} & x_d \geq x_d^{lb}, -x_d \geq -x_d^{ub}, \text{ and } x_d \geq 0 \end{array} \quad (11)$$

The Lagrangean function and the KKT conditions of the above problem are given by the following.

Lagrangean:

$$Y_d = Z_d(x_d) + \lambda_{1d}\left(x_d^{lb} - x_d\right) + \lambda_{2d}\left(-x_d^{ub} + x_d\right) \quad (12)$$

KKT conditions:

$$\begin{array}{lll} \frac{\partial Y_d}{\partial x_d} = \frac{dZ_d(x_d)}{dx_d} - \lambda_{1d} + \lambda_{2d} \geq 0, & x_d \geq 0, & x_d\frac{\partial Y_d}{\partial x_d} = 0 \\ \frac{\partial Y_d}{\partial \lambda_{1d}} = x_d^{lb} - x_d \leq 0, & \lambda_{1d} \geq 0, & \lambda_{1d}\frac{\partial Y_d}{\partial \lambda_{1d}} = 0 \\ \frac{\partial Y_c}{\partial \lambda_{2d}} = -x_d^{ub} + x_d \leq 0, & \lambda_{2d} \geq 0, & \lambda_{2d}\frac{\partial Y_d}{\partial \lambda_{2d}} = 0 \end{array} \quad (13)$$

λ_{1d} and λ_{2d} are the Lagrangean multipliers. The KKT conditions presented in equation (13) are reduced to $\frac{dZ_d(x_d)}{dx_d} = 0$ which is given by equation (7). If equation (7) cannot be solved analytically, GA will be used to solve equation (11) in order to find the optimum solution, x_d^*. The KKT conditions are then used to check whether x_d^* is an optimal point or not.

3.3.3. Step 3: Solve the multi-objective optimization problem

The multi-objective optimization problem to be solved is given by (14). It has two objective functions which are similar to the objective functions presented in equations (8) and (11). The decision variable is x_{cd}, defined as the schedule of preventive replacements such that cost and environmental impact are minimized.

$$\begin{array}{ll} \text{Minimize} & \begin{cases} Z_c(x_{cd}) \\ Z_d(x_{cd}) \end{cases} \\ \text{Subject to} & \begin{array}{l} x_c^* \leq x_{cd} \leq x_d^* \text{ OR } x_d^* \leq x_{cd} \leq x_c^* \\ x_c^*, x_d^*, x_{cd} \geq 0 \end{array} \end{array} \quad (14)$$

There are three possibilities for the first constraint of the problem presented in equation (14), $x_c^* < x_d^*$ or $x_c^* > x_d^*$ or $x_c^* = x_d^*$. If the first case occurs, then the first constraint of (14) becomes $x_c^* \leq x_{cd} \leq x_d^*$. If the second case occurs, then the first constraint is $x_d^* \leq x_{cd} \leq x_c^*$. If $x_c^* = x_d^*$ then the solution is found, $x_c^* = x_d^* = x_{cd}^*$. x_{cd}^* denotes the optimal schedule of preventive replacements such that cost and environmental impact are minimized. If the first or second case occurs, the solution is searched using multi-objective GA.

4. Results and discussion

In this paper, the economic and environmental impacts of a bus tire are used to show the applicability of the developed model. The bus runs on a diesel engine and is owned by a public transportation company in a city located in Indonesia. The type of the tire used by the bus is a tire with the size of 750-16. For this case study, a retreaded 750-16 tire is analyzed. Tire cost, cost due to a sudden failure of the tire (revenue loss), and fuel consumption cost during tire operation are the aspects considered for the economic dimension. Global warming potential (GWP), caused by retreading the tire and diesel fuel combustion during operation, is the impact category for the environmental dimension.

4.1. Economic and environmental data

Based on the survey conducted in the city where the company runs its business, the average price of a retreaded 750-16 tire is $c_r = $ US$ 31.01. It is also estimated that if a tire suddenly fails while the bus is in operation, a revenue of approximately $c_f = $ US$ 30.77 will be lost. In this study, the result of the LCA study on producing a retreaded tire conducted by Continental (1999) is utilized. According to the study, producing a retreaded tire will result in $d_r = 11{,}450$ g CO_2-eq GWP.

According to the company record, verified by the engineers and drivers of the company, it is known that current fuel consumption rate of the bus using the tire (after running for 150,333 km) is 0.653 L/km. It is also reported that when the bus reaches 109,156 km, its fuel consumption is 0.635 L/km. It means that, assuming a linear relationship, the decrease in the fuel economy with use is 4.461×10^{-7} L/km^2. Therefore, the diesel fuel consumption per kilometer of the bus will increase according to the following linear equation:

$$p(x) = 0.653 + 4.461 \times 10^{-7}x$$

x is the distance, in km, traveled by the bus.

The bus is powered by diesel fuel and according to US EPA (2014) the estimated GWP of diesel fuel combustion is 2694.556 g CO_2-eq/L. Furthermore, according to Continental (1999), the contribution of a tire to the fuel consumption of a car is 5.2%. In this study, it is assumed that the percentage is also applied to the bus. Combining the above values with $p(x)$ results in the GWP per km of the use phase of the tire and is presented by the following:

$$\begin{aligned} d_u(x) &= 0.052 \times 2694.556\left(0.653 + 4.461 \times 10^{-7}x\right) \\ &= 91.496 + 6.250 \times 10^{-5}x \end{aligned} \tag{15}$$

The average price of diesel fuel in Indonesia is US$ 0.577 per liter. Using the same assumption as above, the operating cost of the tire per km is given by equation (16).

$$c_u(x) = 1.960 \times 10^{-2} + 8.743 \times 10^{-9}x \tag{16}$$

In equation (15), the intercept of $d_u(x)$ is the GWP of the tire during use phase, in g CO_2-eq./km, and the slope of $d_u(x)$ is the increase in GWP of the tire with use, in g CO_2-eq./km^2. For equation (16), the intercept of $c_u(x)$ is the operation cost of the tire, in US$/km, and the slope of $c_u(x)$ is the increase in operation cost of the tire with use, in US$/km^2.

It is important to note that the case study does not consider the following:

a. The effect of road roughness and geometry on fuel consumption
b. The effect of the decrease in the depth of the tire tread on fuel consumption
c. The effect of a change in speed on fuel consumption

4.2. Time to failure

A total of 127 observations regarding time to failure of the tire is collected from the company. Note that the data is in terms of the distance traveled, in km, by the tire. The mean time to failure of the tire is 20,602 km and the standard deviation is 1883 km. The minimum value of the time to failure is 16,320 km, and the maximum value is 24,059 km. To fit the observations to a particular theoretical statistical distribution, a goodness of fit test is performed. The method used for the goodness of fit test in this case study is the Anderson – Darling test. The observations (time to failure) collected in this study are fitted to the Weibull distribution using a confidence level of 0.05. The reason to choose the Weibull distribution is that, according to Feldman and Valdez-Flores (2010), the Weibull random variables properly describe the failure time.

The test results, summarized in Table 1, present that the Weibull distribution properly models the data. As it can be seen from the coefficient correlation, 98.5%. Therefore, we conclude that the probability density function, cumulative probability function, survival function, failure rate function, and the expected length of the use phase of the tire are the following:

Probability density function,

$$f(x) = 6.238 \times 10^{-4}\left(\frac{x}{21416.3}\right)^{12.3585} \exp\left[-\left(\frac{x}{21416.3}\right)^{13.3585}\right] \tag{17}$$

Cumulative probability function,

$$F(x) = 1 - \exp\left[-\left(\frac{x}{21416.3}\right)^{13.3585}\right] \tag{18}$$

Survival function,

$$R(x) = \exp\left[-\left(\frac{x}{21416.3}\right)^{13.3585}\right] \tag{19}$$

Failure rate function,

$$h(x) = 6.238 \times 10^{-4}\left(\frac{x}{21416.3}\right)^{12.3585} \tag{20}$$

Expected length of the use phase,

$$L(x) = xR(x) + \int_0^x sf(s)ds \tag{21}$$

4.3. Preventive replacement schedule

4.3.1. Cost minimization

The objective function of the cost minimization problem for the tire is to minimize the expected preventive replacement cost,

Table 1
Goodness of fit test results for Weibull distribution.

Parameters	Estimate	Standard error	95% normal confidence interval Lower	Upper
Shape (α)	13.3585	0.8470	11.797	15.126
Scale (β)	21,416.3	150.944	21,122.5	21,714.2
Anderson-Darling (adjusted)	1.282			
Correlation coefficient	0.985			

expected failure replacement cost and the operation cost per km of the tire. Mathematically, it is given by the following:

$$\text{Minimize } Z_c(x_c) = \frac{\begin{pmatrix}\text{Expected preventive replacement cost of the tire}\\ +\text{ expected failure replacement cost of the tire}\\ +\text{ expected operation cost of the tire}\end{pmatrix}}{\text{Expected length of tire's use phase}}$$

$$= \frac{31.01 + 30.77F(x_c) + \int_0^{L(x_c)} c_u(x)\,dx}{L(x_c)}, \text{ subject to } x_c \geq 0.$$

For the bus tire, $c_u(x)$ is given by equation (16), $F(x_c)$ is given by equation (18), and $L(x_c)$ is given by equation (21). In order to find the best solution $x_c{}^*$, substitute the values of $c_r = \text{US\$ } 31.01$, $c_f = \text{US\$ } 30.77$ and the slope of equation (16) $a_c = 8.743 \times 10^{-9}$ US\$/km^2, into equation (4). It results the following equation:

$$1.008 = 0.0325L(x_c)\left(30.77h(x_c) + 4.3715 \times 10^{-9}L(x_c)\right) - F(x_c) \quad (22)$$

$h(x_c)$ for the bus tire is given by equation (20).

Equation (22) cannot be solved analytically, therefore evaluate it numerically. A computer program written in Matlab® is used to perform the numerical analysis. The results of the numerical analysis are presented in Table 2.

Based on the results of the numerical analysis, it is clear that the optimal value of x_c is between 16,000 km (lower bound) and 18,000 km (upper bound). Therefore, the new cost minimization problem for the tire is given by equation (23).

$$\text{Minimize } Z_c(x_c) = \frac{31.01 + 30.77F(x_c) + 1.960L(x_c) + 4.3715L^2(x_c)}{L(x_c)}$$

$$\text{Subject to } x_c \geq 16{,}000, -x_c \geq -18{,}000 \quad (23)$$

The plot of the objective function of equation (23) is presented in Fig. 3.

The optimization problem, equation (23), is then solved using GA. It is found that $x_c^* = 17{,}700.506$ km and $Z_c^* = \text{US\$}0.0216$ per km. In order to guarantee that $(x_c^*, Z_c^*) = (17{,}700.506, 0.0216)$ is an optimal solution, we substitute the solution back into the KKT conditions. For the cost minimization problem, the KKT conditions are reduced into equation (4). After substituting all economic and failure rate parameters of the tire into equation (4), the KKT conditions for the cost minimization problem of the tire is presented by equation (22). When $x_c^* = 17{,}700.506$, it is found that $L(x_c^*) = 17{,}562.522$, $h(x_c^*) = 5.919 \times 10^{-5}$ and $F(x_c^*) = 0.0754$. When those values are substituted back into equation (22), the right-hand

Table 2
Results of the numerical analysis of equation (22).

$x_c{}^*$ (km)	c_r/c_f	$0.0325L(x_c)(30.77h(x_c) + 4.3715 \times 10^{-9}L(x_c)) - F(x_c)$
100	1.008	9.784×10^{-31}
5000		4.492×10^{-8}
10,000		4.718×10^{-4}
12,000		5.388×10^{-3}
14,000		0.042
16,000		0.251
18,000		1.208
20,000		4.881

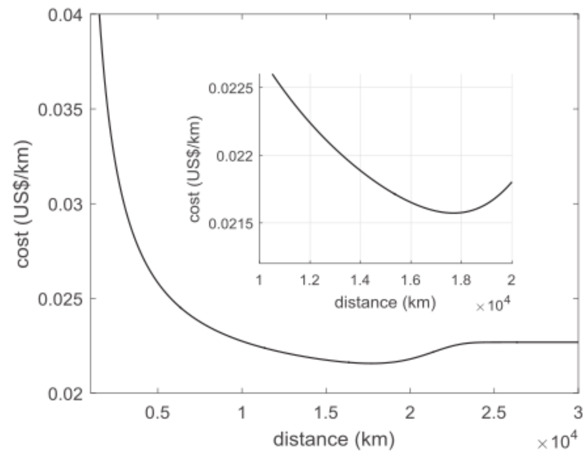


Fig. 3. Plot of cost minimization problem objective function.

side equals to 1.008. This test indicates that $(x_c^*, Z_c^*) = (17{,}700.506, 0.0216)$ is an optimal solution.

This implies that if the company wants to minimize cost per km of the tire, then it is suggested to perform the preventive replacement action when the tire reaches 17,700.51 km, and the total expected cost per km of this schedule is US\$0.0216. Note that GA is a heuristic searching method, which each run of the GA may produce a different solution. The value of $x_c^* = 17{,}700.51$ km is the average value of the optimal solutions produced by GA after 100 runs. The range of the solutions (in km) is [17,696.58, 17,735.80] and the standard deviation equals to 12.40 km.

If a failure replacement policy is implemented, then the total expected cost per km is US\$0.0227/km (note that this amount is calculated based on the actual failure distances of the 127 tires observed in this study). This means that the implementation of a preventive replacement policy results in a total savings of 5% in the total expected cost per km. If calculated over the expected length of the use phase of the tire, the preventive replacement policy results in about US\$23 savings per tire. This value is only US\$8 less than the price of a replacement tire.

4.3.2. GWP minimization

The objective function of the GWP minimization problem is to minimize the expected GWP of the preventive replacement of the tire, expected GWP of the of failure replacement of the tire, and expected GWP of using the tire per kilometer. This problem is given by the following:

$$\text{Minimize } Z_d(x_d) = \frac{\begin{pmatrix}\text{Expected GWP of the preventive replacement of the tire}\\ +\text{expected GWP of the failure replacement of the tire}\\ +\text{Expected GWP of the use phase of the tire}\end{pmatrix}}{\text{Expected length of tire's use phase}}$$

$$= \frac{11{,}450 + \int_0^{L(x_d)} d_u(x)\,dx}{L(x_d)}, \text{ subject to } x_d \geq 0.$$

$L(x_d)$, and $d_u(x)$ are given by equations (1) and (15), respectively. To find the optimal solution $x_d{}^*$, substitute $d_r = 11{,}450$ g CO_2-eq and the slope of equation (15) $a_d = 6.250 \times 10^{-5}$ g CO_2-eq/km^2 into equation (7) and the result is given by equation (24).

Table 3
Results of the numerical analysis of equation (24).

x_d^* (km)	d_r	$\left(x_d R(x_d) + \int_0^{x_d} x f(x) dx\right)^2$
100	3.664×10^8	1.000×10^4
5000		2.500×10^7
15,000		2.247×10^8
16,000		2.553×10^8
17,000		2.872×10^8
18,000		3.197×10^8
19,000		3.514×10^8
20,000		3.800×10^8

$$3.664 \times 10^8 = \left(x_d R(x_d) + \int\limits_0^{x_d} x f(x) dx\right)^2 \tag{24}$$

$R(x)$ and $f(x)$ are given by equations (19) and (17). Similar to equation (22), equation (24) cannot be solved analytically. Therefore, it is evaluated numerically using a computer program written in Matlab®. The results of the numerical analysis are presented in Table 3.

Table 3 suggests that x_d^* is between 18,000 and 20,000 km. Based on this, the new GWP minimization problem is formulated and given by equation (25).

$$\begin{aligned} &\text{Minimize} \quad Z_d(x_d) = \frac{11{,}420 + 91.549 L(x_d) + 3.125 \times 10^{-6} L^2(x_d)}{L(x_d)} \\ &\text{Subject to} \quad x_d \geq 9{,}000, -x_d \geq -20{,}000 \end{aligned} \tag{25}$$

The plot of the objective function of equation (25) is presented in Fig. 4.

The GWP minimization problem, equation (25), is solved using GA and it is found that $x_d^* = 19{,}503.762$ km and $Z_d^* = 92.745$ g CO_2-eq per km. For the GWP minimization problem of the tire, the KKT condition is given by equation (7). After substituting all GWP and failure rate parameters of the tire into equation (7), equation (24) is obtained. When $x_d^* = 19{,}503.762$ it is found that $R(x_d^*) = 0.751$ and $\int_0^{19503.762} x f(x) dx = 4498.119$. When those values are substituted back into equation (24), the right-hand side equals to 3.664×10^8. This guarantees that $(x_d^*, Z_d^*) = (19{,}503.762, 92.745)$ is an optimal solution.

This means that if the company wants to minimize the GWP of the tire, then it is suggested to perform the preventive replacement when the tire reaches 19,503.762 km. This schedule produces 92.745 g CO_2-eq per km. Similar to the solution to the cost minimization problem, the value of $x_d^* = 19{,}503.76$ km is the average value of the optimal solutions produced by GA after 100 runs. It is also found that the range of the solutions (in km) is [19,052.80, 19,054.76] and the standard deviation equals to 0.472 km. If a failure replacement policy is implemented, it will produce a total GWP of 92.748 g CO_2-eq per km. This means that the implementation of the preventive replacement results in about 0.2 kg CO_2-eq savings on the GWP over the expected length of the use phase of the tire.

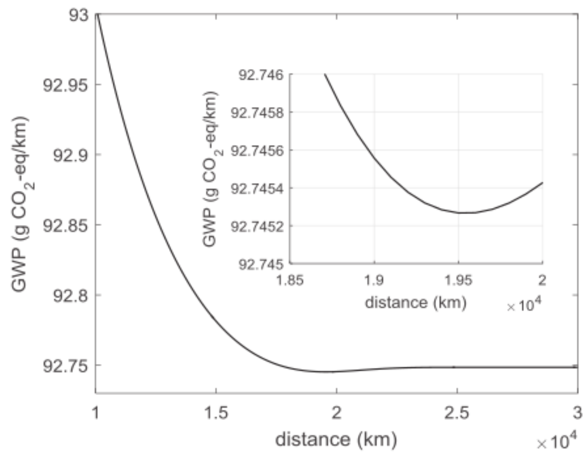


Fig. 4. Plot of GWP minimization problem objective function.

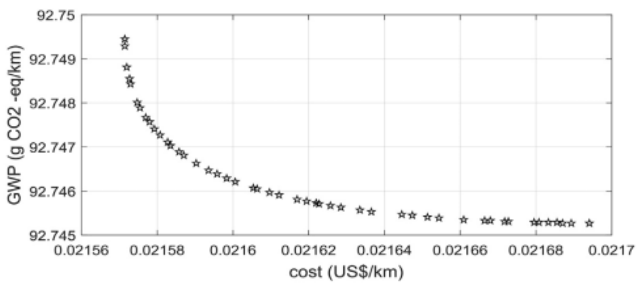
4.3.3. *Multi-objective (cost and GWP) minimization*

Based on the above results, it is concluded that the best distance to replace the tire, such that the economic consequence and GWP are minimized, is between 17,700.506 km and 19,503.762 km. Therefore, the multi-objective minimization problem is given by the following:

$$\begin{aligned} &\text{Minimize} \quad \begin{cases} Z_c(x_{cd}) = \dfrac{31.01 + 30.77F(x_{cd}) + 1.960L(x_{cd}) + 4.3715L^2(x_{cd})}{L(x_c)} \\ Z_d(x_{cd}) = \dfrac{11{,}420 + 91.549L(x_{cd}) + 3.125 \times 10^{-6}L^2(x_{cd})}{L(x_{cd})} \end{cases} \\ &\text{Subject to} \quad 17{,}700.506 \leq x_{cd} \leq 19503.762 \end{aligned} \tag{26}$$

The multi-objective GA is applied to solve the above problem. Since this is a multi-objective optimization problem, there is no a unique solution that simultaneously optimizes the two objective functions. The solutions of the problem are given in the form of a Pareto optimal front, Fig. 5(a). The Pareto optimal front gives a set of optimal solutions. In this case, the solutions provided by the Pareto optimal front are equally good. Fig. 5(b) presents all the solutions with their objective function values. From Fig. 5(b) it can be seen that there is a conflicting situation between the objective functions. The directions to minimize the two objective functions are contradictory.

From Fig. 5(b), it can also be seen that the optimal solutions are between 17,700 km and 19,500 km. This range is within the range of the time to failure of the tire that is between 16,300 km and 24,000 km. In order to have a unique solution, decision maker's preference plays an important role. As a consideration for policy



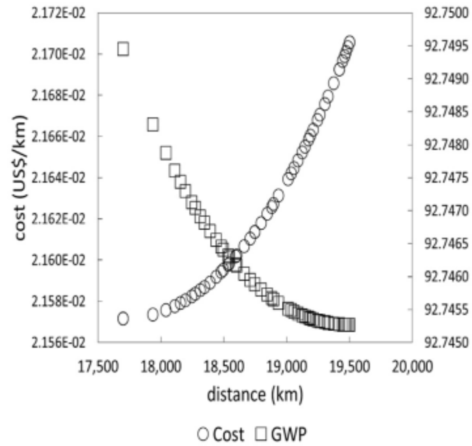


Fig. 5. Optimal solutions, (a) Pareto optimal front, (b) optimal distances and their objective function values.

makers, if they want to have a single schedule, a 1000 km increase in the optimal schedule minimizing expected total cost results in a 0.4% increase in the expected total cost and a 0.002% decrease in the expected total GWP. This indicates that cost is relatively more important than GWP. Furthermore, it is important to note that if a different environmental impact category is chosen, such as eco-toxicity or ozone layer depletion, the model may produce a different set of optimal solutions. Moreover, as it is mentioned in Afrinaldi et al. (2016), using a single environmental impact category may not be enough for the decision makers to make a decision or to formulate a policy.

4.4. Sensitivity analysis

4.4.1. Shape parameter of the failure rate function is less than 1

There is a very critical point that must be noted. According to Jardine and Tsang (2013), a preventive replacement policy must only be applied to a component which has an increasing failure rate. The same argument applies to the model presented in this case study. The reason is that, if the tire has a constant failure rate, a preventive replacement action will not have an effect on the probability of tire to fail in the future. If the tire has a decreasing failure rate, taking a preventive replacement action will reset the tire failure rate to its original value, which is higher than the current failure rate. From the economic and environmental considerations, applying the model to a tire (or any other component) having a constant or decreasing failure rate means wasting the money and increasing the environmental impact. The easiest way to spot the above phenomena is from the value of α, the shape parameter of the failure probability density function. If $\alpha \leq 1$ then the failure rate is constant or decreasing.

4.4.2. Operation cost is a constant

The operation cost of the tire is denoted as $c_u(x)$. Now, let's assume that the new form of $c_u(x)$ is $c_u(x) = 1.960 \times 10^{-2}$ US$/km, a constant. This change modifies equation (22) into the following:

$$1.008 = L(x_c)h(x_c) - F(x_c) \quad (27)$$

A comparison of the effects of the new and original forms of $c_u(x)$ on x_c^* is presented in Fig. 6. The original form of $c_u(x)$ is given by equation (16), an increasing function. In Fig. 6, $x^*_{c,New}$ and $x^*_{c,Original}$ are given by the x-coordinate of the intersection points. The figure shows that $x^*_{c,New} > x^*_{c,Original}$. The reason is that, during the use phase, the new scenario incurs less cost than the original scenario. Therefore, it is reasonable to use the tire for a longer distance.

4.4.3. Environmental impact of the use phase is a constant

The environmental impact of the use phase of the tire is denoted as $d_u(x)$. If $d_u(x)$ is a constant, from the environmental impact standpoint only, it is not wise to adopt a preventive replacement policy. Let's assume that $d_u(x) = q$. Then the expected environmental impact of using the tire per km is $\int_0^{L(x_d)} q dx / L(x_d) = q$. The consequence of this is that $Z_d(x_d)$ will always decrease as x_d increases, which means that it is better to wait for the tire to fail and then take a replacement action (a failure replacement policy). Furthermore, since the source of the environmental impact is the

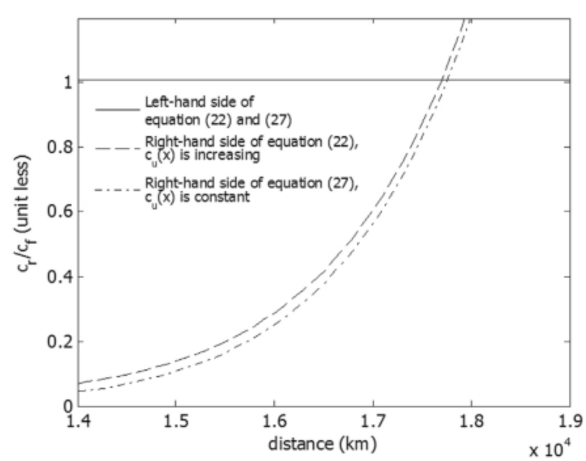


Fig. 6. The effect of $c_u(x)$ on x_c^*.

consumption of the diesel fuel, this implies that, when $d_u(x)$ is a constant, $c_u(x)$ will also be a constant. As a consequence, fuel cost will not be an important factor anymore. The expected fuel cost per km will always decrease as x_c increases.

4.4.4. Change in the values of cost parameters

The model has four cost parameters, c_r (preventive replacement cost, in US$), c_f (failure replacement cost, in US$), b_c (operation cost, in US$/km), and a_c (increase in operation cost with use, in US$/km^2). From Fig. 7(a) it can be seen that the increase in the value of c_r/c_f increases the optimal preventive replacement distance for the cost minimization problem, x_c^*. c_r/c_f increases when c_r increases or c_f decreases. A higher value of c_r means a more expensive preventive replacement cost. Therefore, it is reasonable to increase x_c^* in order to have a lower total cost per km. A lower value of c_f implies a cheaper failure replacement cost then it is better to have a higher value of x_c^*. If the tire fails before x_c^*, it will not be a problem because c_f is small.

Fig. 7(b), (c), (d), and (e) present the effect of a change in the values of c_r, c_f, a_c, and b_c on the optimal value of the objective function of cost minimization problem, Z_c^*. The figures prove that if the values of the parameters increase then Z_c^*also increases. The change in the values of c_r, a_c, and b_c have a linear relationship with the change in the value of Z_c^* but the relationship between the change in the value of c_f and the change in the value of Z_c^* is non-linear. According to the figures, 1% reduction in the values of c_r, c_f, a_c, and b_c contributes to 0.09%, 0.01%, 0.004% (on average), and 0.91% reduction in the value of Z_c^*, respectively. This finding gives an important insight. The analysis suggests that, in order to further reduce the total cost, more focus must be put on the reduction in the value of b_c, operation cost of the tire, because it gives the greatest advantage. It is influenced by the fuel economy of the bus and tire rolling resistance. Therefore, an improvement in the fuel economy of the bus and tire performance in terms of rolling resistance must be put as the top priorities.

4.4.5. Change in the values of environmental impact parameters

There are three environmental impact parameters of the model, d_r (replacement action GWP, in g CO_2-eq), b_d (use phase GWP, in g CO_2-eq/km), and a_d (increase in GWP with use, in g CO_2-eq/km^2). Fig. 8(a) shows that an increase in the value of d_r/a_d produces a longer optimal preventive replacement distance for the environmental impact minimization problem, x_d^*. The increase in the value of d_r/a_d happens if d_r increases or a_d decreases. The increase in the value of d_r implies that a higher GWP effect is produced during the retreading process of the tire. Therefore, in order to minimize GWP per km, it is reasonable to increase the optimal preventive replacement distance. A lower value of a_d means a lower increase in the amount of GWP during the use phase. As a consequence, a longer value of x_d^* is resulted.

Moreover, if the value of $2d_r/a_d$ is equal to or higher than the asymptotic line of Fig. 8(a), then the problem has an unbounded optimal solution. This means that it is better to wait until the tire fails and then perform a replacement action. In other words, a preventive replacement policy is not profitable in this situation. A failure replacement policy is a better option. This situation may occur when d_r is too high, or a_d is too low.

From Fig. 8(b), (c), and (d), it can also be seen that the increase in the values of d_r, a_d, and b_d increases the optimal value of the objective function of the environmental impact minimization problem, Z_d^*. The change in the values of a_d and b_d exhibits a linear relationship with the change in the value of Z_d^* but the change in

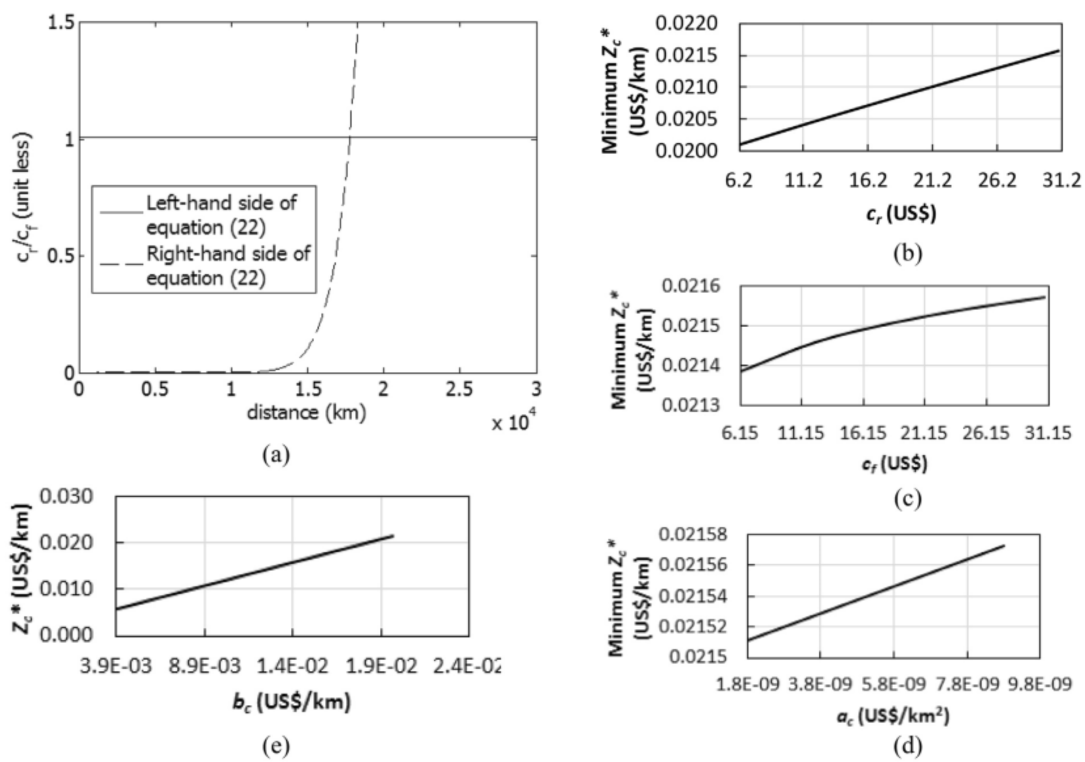


Fig. 7. Effect of change in the value of cost parameters, (a) plot of equation (22), (b) change in c_r, (c) change in c_f, (d) change in a_c, (e) change in b_c.

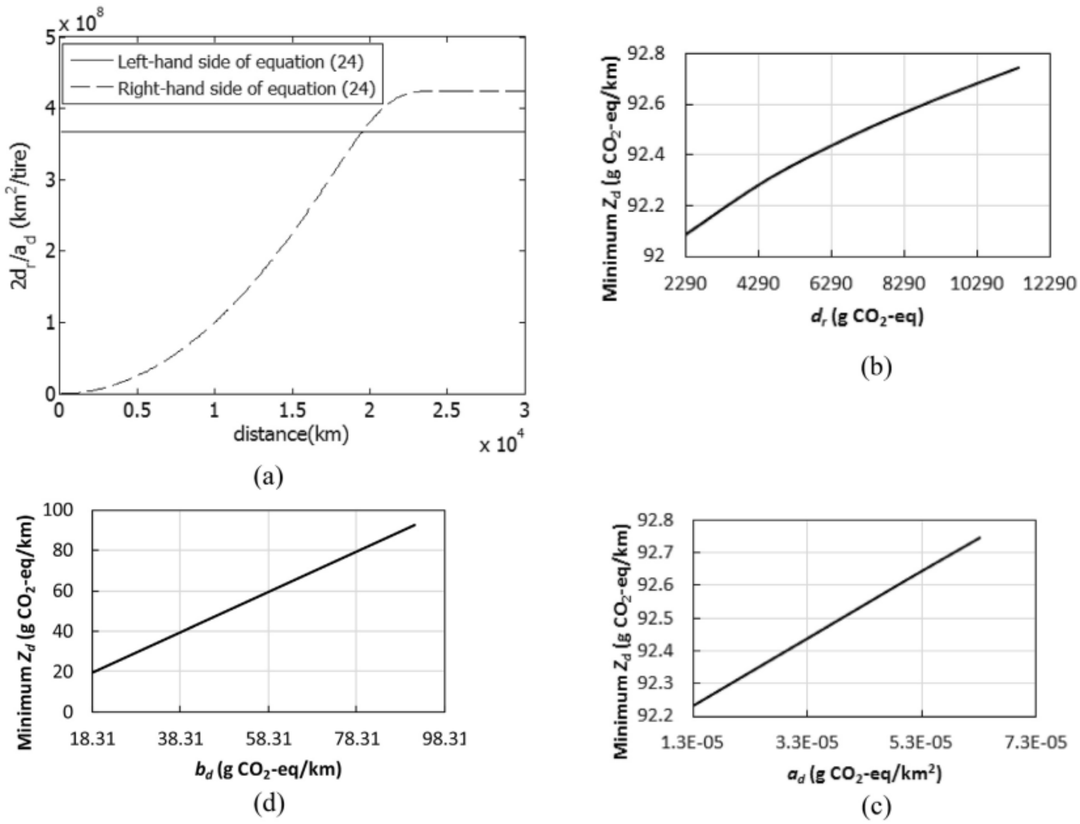


Fig. 8. Effect of change in the value of environmental impact parameters, (a) plot of equation (24), (b) change in d_r, (c) change in a_d, (d) change in b_d.

the value of d_r has a non-linear relationship with Z_d^*. It is found that 1% reduction in the values of d_r, a_d, and b_d contributes to 0.01% (on average), 0.01%, and 0.99% reduction in the value of Z_d^*, respectively. Therefore, reduction in the value of b_d must be put as the highest priority. The parameter b_d, expressed in g CO_2-eq/km, is the use phase GWP of the tire. Similar to b_c, the value of b_d is influenced by the fuel economy of the bus and tire's rolling resistance. Those two factors must be put as the top priorities since they give the highest advantage in reducing total environmental impact.

5. Conclusions

This research answers a question of when a component should be replaced such that the economic and environmental impacts per unit time of the component are minimized. A mathematical model is developed in order to answer the question. The developed model is an extension of currently available replacement models in the literature in which most of them only consider cost in their objective functions.

The determination of the optimum replacement timing of a component is a complex problem because it depends on the distribution of the time to failure of the component and usually involves a nonlinear optimization problem. In the literature, different nonlinear programming algorithms are developed to solve particular types of nonlinear programming problem. In this paper, GA is utilized and in order to guarantee that the solution found by GA is optimum, the solution is checked using KKT conditions for optimality. GA is preferred because it is easy to implement, efficient, and robust. If compared to other metaheuristic methods, GA has a more diverse solution population. It makes GA faster in finding the optimum point and avoids GA to stop in local optimum. If compared to GRG and SQP algorithms, GA is preferred because GRG and SQP are sensitive to the initial solution provided and they may trap in local optimum depending to the value of the initial solution used.

This study shows that the proposed preventive replacement model is only applicable to a component which has an increasing failure rate function. If the failure rate of the component is constant or decreasing, a failure replacement policy is a better option. Furthermore, the sensitivity analysis shows that the model is very sensitive to the value of the economic and environmental parameters of the model. A higher replacement cost and severe environmental impact caused by the replacement action lead the model to produce a longer interval between preventive replacement actions. Similarly, a lower value of operation cost and a decrease in the value of environmental impact during the use phase also make the model to produce a longer interval between preventive replacements. The sensitivity analysis also suggests that, in order to get a greater reduction in the value of total cost per km and environmental impact per km, focus must be put on improving the fuel efficiency, operation cost, and environmental impact during the component use phase. Furthermore, the severe environmental impact produced by the replacement action and a considerably low environmental impact emitted during the use phase may cause the model to have an unbounded optimal solution. This means it is better to wait for the component to fail and then take a replacement action (a failure replacement policy).

Since the proposed model is a multi-objective optimization model, then it produces a set of optimal solutions. In order to have a single solution, policy makers' preferences need to be taken into consideration. To incorporate their preferences, a simple weighting method and an eco-efficiency analysis can be implemented to produce a single solution. The case study conducted in this research selects GWP as the environmental indicator. Choosing another environmental impact category may result in a different set of optimal solutions. This indicates the main drawback of the model.

Notation list

a_c	increase in operation cost with use
a_d	increase in the amount of environmental impact with use
b_c	operation cost
b_d	environmental impact of the use phase
c_f	failure cost
c_r	replacement cost
d_r	environmental impact of the replacement activity
x	a random variable denoting time to failure
x_c	a random variable denoting preventive replacement schedule for cost minimization problem
x_c^{lb}	lower bound of x_c
x_c^{ub}	upper bound of x_c
x_d	a random variable denoting preventive replacement schedule for environmental impact minimization problem
x_{cd}	schedule of preventive replacement such that cost and environmental impact are minimized
x_d^{lb}	lower bound of x_d
x_d^{ub}	upper bound of x_d
$c_u(x)$	operation cost per unit time at time x
$d_u(x)$	environmental impact per unit time at time x
$f(x)$	failure probability density function
$F(x)$	cumulative distribution function of failure
$h(x)$	failure rate function
$R(x_c)$	survival distribution function
$L(x_c)$	expected length of the use phase
λ_{1c}, λ_{2c}	Lagrangean multipliers for the cost minimization problem
λ_{1d}, λ_{2d}	Lagrangean multipliers for the environmental impact minimization problem
$M(x_c)$	expected length of time for failure
Y_c	Lagrangean function for the cost minimization problem
Y_c	Lagrangean function for the cost minimization problem
$Z_c(x_c)$	total expected cost per unit time
$Z_d\ (x_d)$	total expected environmental impact per unit time

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