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The asset replacement problem state of the art.

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The Asset Replacement Problem

State of the Art

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Abstract In this book chapter we summarize how the asset replacement problem has evolved over time. We provide a broad view of different modeling approaches considering the economic life, the repair cost limit, comprehensive cost minimization models and we analyze in detail the parallel replacement models. We suggest a new model for parallel replacement that addresses some of the issues not yet solved in this area. Finally, we discuss the limitations of the current models from a theoretical and applied perspective and identify some of the challenges still faced by academics and practitioners working on this problem.

1. Introduction

As assets age, they generally deteriorate, resulting in rising operating and maintenance (O&M) costs and decreasing salvage values. Moreover, newer assets that have a better performance and better in keeping their value may exist in the marketplace and be available for replacement. Therefore, public and private agencies that maintain fleets of vehicles and/or specialized equipment should decide when to replace vehicles composing their fleet. These equipment replacement decisions are usually based upon a desire to minimize fleet costs and are often motivated by the conditions of deterioration and technological advances, either separately or simultaneously (Hartman, 2005).

The general topic of equipment replacement models was first introduced in the 1950's (Bellman, 1955). By using dynamic programming, Bellman developed a model in order to obtain the optimal age of replacement of the old machine with a new machine. Another important subject was the development of parallel replacement models in which management decisions are made for a group of vehicles instead of one machine or vehicle at the time (Hartman and Lohmann, 1997).

Vehicle replacement is one key role of Fleet provisioning teams. Indeed Field Services operational planning and delivery primarily relies on the assumption that the whole engineering force can be furnished with the vehicle appropriate for the service, at any time. In practice the adequate type, brand, and technology depend on internal factors such as the engineer role, service environment, and (but not systematically) mileage driven, and on external factors such as fuel prices variation, incentives, carbon emission, maintenance cost. This suggests an overall optimisation problem that Vehicle Replacement aims at treating. This implies as well a twofold fleet planning: a planned fleet portfolio and a rental plan for jeopardy situations.

In Addition, Field Services Entreprises face increasing challenges on Carbon and cost reduction. The need for transforming field services impacts the vehicle choices within business and vehicle replacement processes. Optimising the composition of fleet is an important effort toward sustainable services. However several uncertainties come from the intangible reputation of sustainable energy investment, the evolution of market prices, strategic partnerships, and risk sharing; they need to be addressed before being able to use low-carbon vehicles as a feasible alternative for field services operations.

In this chapter we provide a concise history of the development of the asset replacement problem, discuss the limitations of the models developed so far, and introduce a new model which overcomes some of these drawbacks. In section 2 we provide a classification of different asset replacement models, which are broadly classified into serial and parallel models. In section 3 we describe the different approaches to solve the serial problems and in section 4.1 we summarize the methods used to solve the parallel asset replacement problems. Furthermore in section 4.2 we suggest a new formulation to address some of the drawbacks of the work in parallel models. In section 5 we summarize our insights from our literature into the different approaches to the asset replacement problem and in section 6 we analyze the limitations and challenges to the asset replacement models from a practical perspetive. We conclude the article in section 7.

2. The General Classifications of Fleet (Asset) Replacement models

The models generally can be categorized into two main groups based on different fleet (asset) characteristics: homogenous and heterogeneous models. In the homogeneous replacement models, a group of similar vehicles in terms of type and age which form a cluster (each cluster or group cannot be decomposed into smaller clusters) have to be replaced together.

On the other hand, in the heterogeneous model multiple heterogeneous assets, such as fleets with different types of vehicle, have to be optimized simultaneously. For instance, vehicles with the same type and age may be replaced in different periods (years) because of the restricted budget for procurement of new vehicles. The heterogeneous models are closer to the real world commercial fleet replacing problem. These models are solved by Integer Programming and generally the input variables are assumed to be deterministic (e.g., Hartman, 1999, 2000, 2004; Simms et al., 1984; and Karabakal et al., 1994).

The methodology which has been mostly applied for solving homogenous models is dynamic programming. The advantage of the homogenous model is taking into account probabilistic distributions for input variables into the optimization model (e.g., Hartman, 2001; Hartman and Murphy, 2006; Oakford et al., 1984; Bean et al., 1984; Bellman, 1955).

Another important classification of these models regards the nature of the replacement process: parallel vs. sequential, e.g., Hartman and Lohmann (1997). The main difference between parallel replacement analysis and serial replacement analysis is that the former takes into how any policy exercised over one particular asset affects the rest of the assets of the same fleet. An example of parallel replacement would be a fleet of trucks that service a distribution centre. In this case, the total capacity which is available is the sum of the individual capacities of the trucks. However, in series replacement model, the assets operate in series, and consequently, demand is satisfied by the group of assets which operate in sequence. An example of this case is a production line in which multiple machines must work together to meet a demand or service constraint. In general, the capacity of the system is defined by the smallest capacity in the production line (Hartman, 2004).

The following definition of parallel replacement comes from Hartman and Lohmann (1997). Parallel replacement deals with the replacement of a multitude of economically interdependent assets which operate in parallel. The reasons for this economic interdependence are : (1) demand is generally a function of the assets as a group, such as when a fleet of assets are needed to meet a customer's demands; (2) economies of scale may exist due to purchasing assets and promoting large quantity of purchases; (3) diseconomies of scale may exist with maintenance costs because assets which are purchased together tend to fail at the same time; and (4) budgeting constraints may require that assets compete for available funds. These characteristics, either alone or together, can cause the assets to be economically interdependent.

On the other hand, serial replacement analysis assumes a certain utilization level for an asset throughout its life cycle. Hartman (1999) mentioned that as utilization levels affect operating and maintenance costs and salvage values (which in turn influence replacement schedules) a replacement solution is not optimal unless utilization levels are also maximized. For this reason, an asset utilization level depends on the demand requirements, number of assets available, and capacity of each asset.

Next we are going to extensively present the different approaches to the modelling the asset replacement problem: the economic life-cycle, the repair cost limit, the comprehensive cost minimization, and the issue of decreasing utilization with age.

3. Approaches for Replacement Decisions

In this section we consider different approaches for considering the optimal time for replacing the assets. Throughout this section our goal is to identify replacement candidates among fleet or asset members so that total costs are minimized in the long run.

3.1. Approaches that Compute an "Economic Life"

An intuitive method for recognizing replacement candidates is to consider a replacement standard such as the age of the equipment. Assets with the age more than standard threshold should be replaced. Moreover, a ranking profile can be used in order to sort the equipment units by how much they exceed the threshold.

For example, one of the papers which was pioneer in this category, Eilon et al. (1966), considered a model in optimum replacement of fork lift trucks. The parameters in his model were the purchase price, the resale value and the maintenance costs of the equipment. The goal of the model was to derive the minimum average costs per equipment year and the corresponding optimal equipment age policy for a fleet of fork lift trucks.

Now we consider the model proposed by Eilon et al. (1966) in more detail. Let TC (t) be the total average annual (or per time period) cost of an existing truck, assuming it is replaced at age (time) t. Let A stand for the acquisition cost of new truck, S(t) be the resale value of the existing truck at age t, C (t) be the accumulated depreciation costs up to time t, τ be the rate of taxation, and f(t) be the maintenance costs of a truck , t years after acquisition. Then the total average annual cost of an existing truck is represented by (1).

$$TC(t) = \frac{1}{t}(A - S(t) - C(t).\tau) + \frac{1}{t}\int_0^t f(t)dt \qquad (1)$$

The first term in equation (1) represents the average capital costs involved in the acquisition of the existing truck, taking into account the savings from resale value and tax savings from depreciation. The second term in equation (1) expresses the total average maintenance costs for the existing truck over the years up to the present time *t*. The minimum total average annual costs as a function of *t* determines the optimal replacement time.

The economic life of an asset (also known as service life or lifetime of the asset) is defined as the age which minimizes the *Equivalent Annual Cost* (EAC) of owning and operating the asset. The EAC includes purchase and *Operating and Maintenance* (O&M) costs minus salvage values. Generally, O&M costs increase with age while salvage values decrease. As a result, the optimal solution represents a trade-off between the high costs of replacement (purchase minus salvage) versus increasing O&M costs over time.

The concept of economic life is more easily described graphically. In Figure 1 (adapted from Harman and Murphy, 2006), it is assumed that the initial purchase cost is $100000, with the salvage value declining 20% each year. O&M costs are expected to increase 15% per year after $11500 in the first year. Figure 1 illustrates the annualized O&M and capital costs and their sum (EAC) for each possible of age assuming an annual interest rate 8% (Hartman and Murphy, 2006). Once the optimal economic life is determined, the asset should be continuously replaced at this age under the assumption of repeatability and stationary costs (Hartman and Murphy, 2006).

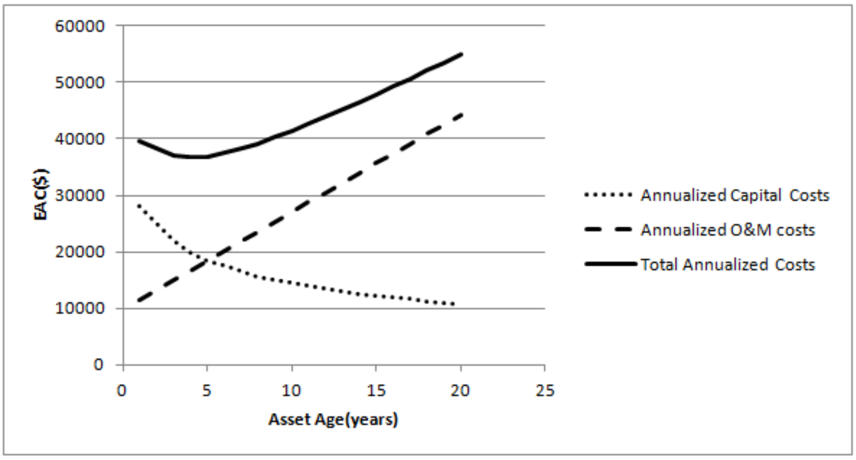

Fig. 1: Annualized purchase cost, O&M cost, and Total (EAC) costs

In order to obtain the EAC, when retaining an asset for n periods, all costs over the n periods must be converted into n equal and economically equivalent cash. Then, the economic life of an asset is typically computed by calculating the EAC of retaining an asset for each of its possible service lives, ages one through n, and the minimum is chosen from this set (e.g., Hartman, 2005; Weissmann et al., 2003; Hartman and Murphy, 2006).

Yatsenko and Hritonenko (2011) have also considered the economic life (EL) method of asset replacement taking into account the effect of improving technology which impacts the maintenance cost, new asset cost, and salvage value. They have shown that, in a general case, the EL method renders an optimal replacement policy when the relative rate of technological change is less than one percent. However, for larger rates, they recommend to minimize the annual cost over two future replacement cycles, which was earlier proposed and implemented by Christer and Scarf, (1994).

3.2. Approaches that Consider a Repair Cost Limit

Another replacement criterion is the repair cost. When a unit requires repair, it is first inspected and the repair cost is estimated. If the estimated cost exceeds a threshold, which is known as "repair limit" then the unit is not repaired but, instead, is replaced. Repair limits have long been used and their values have often been based on the principle that no more should be spent on an item than it is worth.

This criterion is indeed an important one. There is evidence that repair cost limit policies have some advantages in comparison with economic age limit policies. For example, Drinkwater and Hastings (1967) analysed data for army vehicles. They obtained the repair limiting value, in which the expected future cost per vehicle-year when the failed vehicle is repaired, is equal to the cost in which the failed vehicle is scrapped and a new one is substituted. Specifically, they define two options: (a) Repair the vehicle and (b) Scrap the vehicle and substitute a new one. This is called a repair decision. We now present the model used for the repair decision in more detail, following Drinkwater and Hastings (1967).

Consider a vehicle at age t which requires repair. If we select option a, that is, if we repair the vehicle, the future cost per vehicle-year is represented by (2) in which r is the present cost of repair, $c(t)$ is the expected total cost of future repairs, $l(t)$ is the expected remaining life of the vehicle.

$$\frac{r + c(t)}{l(t)} \tag{2}$$

If we select option b; that is, we scrap the vehicle, the expected future cost per vehicle-year will be δ which is defined by the average cost per vehicle-year up to age t. Obviously, the repairing decision (option a) will be selected if (3) holds. Otherwise, the scrapping decision is chosen. Therefore, the critical value of r is determined by equation (4) in which the future cost per vehicle-year is equals the average cost per vehicle-year up to age t. In (4) we have used $r^*(t)$ to denote. As a result, the optimal repair limit at time t, $r^*(t)$, is determined by (5).

$$\frac{r + c(t)}{l(t)} < \delta \tag{3}$$

$$\frac{r^{*}(t) + c(t)}{l(t)} = \delta \tag{4}$$

$$r^{*}(t) = \delta l(t) - c(t) \tag{5}$$

Drinkwater and Hastings (1967) considered three methods for optimizing the repair policies: simulation, hill-climbing and dynamic programming: they have shown that the repair cost limit policy creates is better than the economic age policy.

The main drawback of the conventional repair cost limit policy is that the repair/replace decision is based only on the cost of one single repair. Under this condition, a system with frequent failures and, consequently, high accumulated repair costs will continue to be repaired rather than replaced. As a result, an improved policy making the repair/replace decision based on the entire repair history has been suggested.

For instance, Chang et al. (2010) developed a generalized model for determining the optimal replacement policy based on multiple factors such as the number of minimal repairs before replacement, and the cumulative repair cost limit. The main characteristic of their model is that the entire repair-cost history is considered. Indeed, if repairable failures occur at random point, then the random repair costs should also be considered to a system. Nakagawa and Osaki (1974) have also suggested an alternative approach which does not focus on repair costs, but on repair time. If the repair process is not completed up to the fixed repair time limit, then the unit under repair is replaced by a new one. The repair time limit is obtained by minimizing expected costs per unit time over an infinite time horizon and taking into account the cases when the repair cost is proportional to time, and when it is exponential.

3.3. Comprehensive Cost Minimization Models

There are other approaches that generalize the problem of optimal replacement by taking into account the optimal decisions for acquisition, operate, and sell policies. For example, Simms et al. (1984) analysed a transit bus fleet in which equipment units in the fleet system was assigned to perform different tasks at different levels subject to changing capacity constraints. Next we analyse in detailed the model proposed by Simms et al. (1984). The aim of the analysis is to minimize the total discounted cost over the finite horizon, as represented in

(15), in which *t* and *a* are the indices for time periods (year) and age of the buses, respectively, and *T* is the length of the planning horizon, in years. The decision variables are: The number of route kilometres travelled by a bus with age *a*, in year *t*, m_{ta}; the number of buses with age *a*, which operate in year *t*, x_{ta}; and the number of new buses which should be purchased, with an acquisition cost L_t, at the beginning of year *t*, denoted by p_t.

Moreover, in each year the price of selling a bus with age a, is represented by S_{ta}. Moreover, $C_{ta}(m_{ta})$ is the cost of operating a bus with age a, in year t for the associated kilometres travelled by m_{ta}. Finally, γ represents the discount factor. So, in equation (6) the first term represents the acquisition costs, the second term represents the revenue received from selling the buses, and the third term denotes the cost of operating the buses. By using dynamic programming, an optimal acquisition, operate and sell policy was obtained by Simms et al. (1984).

$$\underset{m_{ta},x_{ta},p_t}{Min}\ Z=\sum_{t=0}^{T}\gamma^t p_t L_t-\sum_{t=0}^{T}\gamma^{t+1}\sum_{a}(x_{ta}-x_{t+1,a+1})S_{t+1,a+1}+\sum_{t=0}^{T}\sum_{a}\gamma^i x_{ta}C_{ta}(m_{ta}) \tag{6}$$

Now we consider the constraints of the model proposed by Simms et al. (2004). The nonlinear constraint (7) requires that a minimum total route kilometres, per year, M_t, is driven by the fleet. The constraint (8) expresses the boundary conditions for the decision variable m_{ta}. Indeed m_- and m_+ denote the minimum and maximum number of kilometres that a single bus can drive in a given year, respectively. Constraint (9) is due to the fact that at least a minimum number of buses N_t in each year should be in the fleet. In the inequality (10), Q is the minimum age for a bus to be considered for a sell decision. The left hand side of above constraint is equal to the number of buses which are sold at the beginning of the corresponding year. Therefore, we can say that inequality (10) is a consistency constraint in the sense that it does not permit old buses to be bought. Equation (11) means that the buses are not eligible for sale until their reach to the minimum age for sale, i.e. Q. Equation (12) represents the boundary conditions, in which K_a are the initial numbers of buses for the different ages. If budget constraints for capital acquisitions also considered then the constraint (13) is also required, where B_t is the capital budget for period *t*. Furthermore, if there is also an operating budget constraint, then we also need to impose constraint (14) in which O_t is the operating budget, in period *t*.

$$\sum_a x_{ta} m_{ta} \geq M_t \qquad \forall\ t \in \{0,1,2,...,T\} \tag{7}$$

$$m_- \leq m_{ta} \leq m_+ \tag{8}$$

$$\sum_a x_{ta} \geq N_t \qquad \forall\ t \in \{0,1,2,...,T\} \tag{9}$$

$$x_{ta} - x_{t+1,a+1} \geq 0 \quad , a \geq Q-1 \tag{10}$$

$$x_{ta} - x_{t+1,a+1} = 0 \quad , a < Q-1 \tag{11}$$

$$x_{(-1)a} = K_a \quad , x_{(T+1)j} = 0 \tag{12}$$

$$p_t \leq \frac{B_t}{L_t} \tag{13}$$

$$\sum_a x_{ta} C_{ta}(m_{ta}) \leq O_t \tag{14}$$

The model represented by equations (6)-(14) has a non-linear objective function subject to a set of non-linear constraints. By using dynamic programming, Sims et al. (1984) solved it. If we compare the two models proposed by Simms et al. (1984) and Keles and Hartman (2004), we understand that regardless of the methodology for solving two models, the main difference is considering the behaviour of utilization as a function of age of the vehicles and assuming it as a decision variable by Sims et al. (1984). Another difference is that Simms et al. (1984) considered the same types of asset whereas Keles and Harman (2004) considered multiple types of asset. However, for the rest of the components of the two models, i.e., the goal of the objective function and the constraints they are almost the same.

On this same topic, Hartman (1999) has considered the replacement plan and corresponding utilization levels for a multi-asset case in order to minimize the total cost. He generalized equipment replacement analysis as it explicitly considers utilization as decision variable. His model allows assets to be categorized according to age and cumulative utilization, while allowing their periodic utilization to be determined through analysis. As a result, he has considered simultaneously tactical replacement and operational decisions, taking into account the tradeoffs between capital expenses (replacement costs) and operating expenses (utilization costs). The objective was to minimize the total cost of assets that operate in parallel. He solved the problem using linear programming. Furthermore, Hartman (2004) has generalized this same problem by incorporating a stochastic demand. He solved the problem using dynamic programming. Overall, both Simms and Hartman did not introduce any special new replacement criteria and just presented optimization methodologies in order to minimize the cost of corresponding fleets.

Furthermore, an important issue we need to discuss in this topic is the relation between age and utilization. The utilisation intensity (annual mileage) of vehicles exploited by transportation companies decreases with time of exploitation/cumulative mileage probably in all real life cases. The youngest vehicles are usually utilised more intensively than the oldest ones, because their unit exploitation costs are lower (e.g. fuel consumption is lower), and the depreciation costs can be ignored. The occurrence of such pattern can be found in, for example, Kim et al. (2004) and Simms et al. (1984), and it fits well with real world situations, as illustrated in Figure 2 (based on Simms et al., 1984).

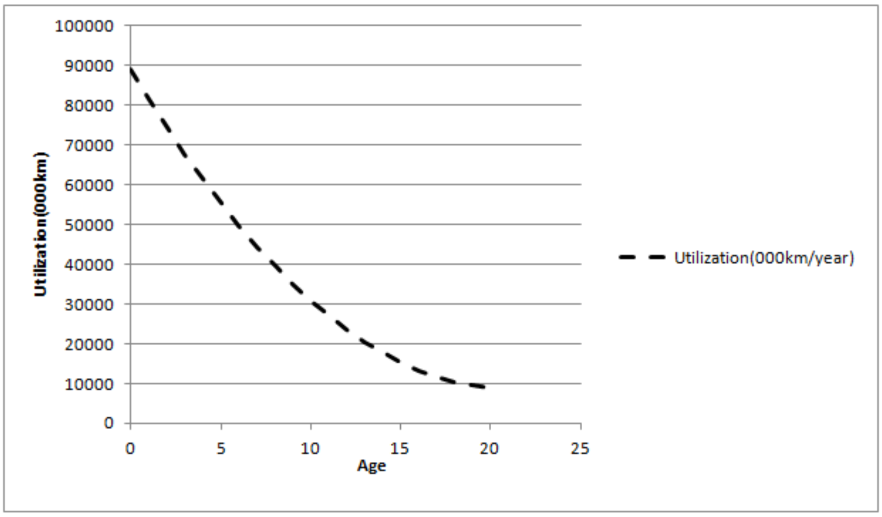

Fig. 2: Annual utilization by age.

Simms et al. (1984) have considered explicitly this issue in a bus fleet data. He mentioned that if the relation between utilization with age is not considered, one would expect that the older buses would be replaced first and younger buses kept. However, in practice this is not the case for two reasons. First, the case in which older buses are kept only to meet the peak daily demand period and these buses accumulate only the minimum number of route kilometres during the year. Second, the resale value of younger buses is much higher than older buses. Therefore, even if the operating cost of older buses is higher, they do not operate enough route kilometres and the extra expense is lower than the gain obtained by selling younger buses. So, they assumed two levels of utilization for an urban transit bus fleet with different ages. They conclude that a high utilization level is considered for buses with less than ten years for satisfying the normal demand and a low utilization level for buses more than ten years in the case of peak demand.

Redmer (2009) has also considered the relationship between utilisation intensity and aging by applying the minimal average costs replacement policy using the following considerations. a) The utilisation intensity (annual mileage) of vehicles for each year of their operational life has to be taken into account. b) The vehicles' exploitation costs have to be divided into fixed costs (independent of utilisation intensity, but varying with time of exploitation/cumulative mileage), running costs (depending on utilisation intensity/mileage and varying with time of exploitation/cumulative mileage) and fuel costs (varying with time of exploitation/cumulative mileage). c) The total costs of exploitation and ownership have to be given per one km or mile. d) The technical durability of vehicles (e.g. maximal mileage) has to be taken into account. e) Different forms of financing the fleet investments (buying for cash, credit, leasing and hiring) have to be considered.

Next, we describe the parallel replacement problem (section 4.1) and we suggest a new model for addressing the issues raised by Redmer (2009) in the context of parallel replacement problem (section 4.2).

4. The General Parallel Replacement Problem

In this section we commonly refer to groups of assets as fleets. However, the model is general in the sense that cost functions are specified without operational details. Thus, this analysis may be applied to a manufacturing setting if the costs can be quantified.

The parallel replacement models are usually difficult to solve due to their combinatorial nature as mentioned by Hartman (2000). Jones et al. (1991) considered a parallel replacement problem on the condition of fixed replacement costs. Rajagopalan (1998) and Chand et al. (2000) have proposed dynamic programming algorithms that simultaneously consider the replacement and capacity expansion problem.

4.1. An Integer Programming Formulation of the Parallel Replacement Problem

Given the complex nature of the problem, the case of multiple alternatives within parallel replacement has been rarely considered in the literature. Keles and Hartman (2004) have proposed an Integer Programming formulation of the bus fleet replacement problem with multiple choices under economies of scale and budgeting constraints. The objective function is cost minimization and it is summarized in equation (1). All costs in the model are assumed to be discounted to time zero using an appropriate discount rate. The fixed cost associated with asset buying is represented by f_t and l_{it} is the new asset unit acquisition cost in each year. The operating and maintenance cost is shown by c_{iat} and the salvage revenue is represented by r_{iat} .

In (15) the indices are a , t , and i which stand for the age of the assets (buses), time periods, and type of the assets, respectively. I , represents the total number of challengers (i.e., available alternatives for assets) available in each period. The maximum age of any asset associated with its type is shown by A_i and the length of time horizon is assumed to be T (Typically T is assumed to be less than 15 years). The decision variables are the number of the assets that are bought at the beginning of each year, X_{i0t} , the number of assets which are salvaged at the end of each year, S_{iat}, and a binary variable that confirms that an acquisition is made in the corresponding year Z_t .

$$\underset{X,S}{Min}\sum_{i=1}^{I}\left[\sum_{t=0}^{T-1}\left(f_t Z_t+\sum_{a=0}^{A_i-1}l_{it}X_{i0t}\right)+\sum_{t=0}^{T-1}\sum_{a=0}^{A_i-1}c_{iat}X_{iat}-\sum_{t=0}^{T-1}\sum_{a=1}^{A_i}r_{iat}S_{iat}\right] \quad (15)$$

With above definitions we can figure out that the objective function minimizes costs associated with each challenger’s discounted cash flows which are purchasing, operating and maintenance costs subtracting the revenue from salvage values.

We now describe the constraints of the Keles and Hartman (2004)’s model. Constraint (16) requires that enough assets (or capacity) are available to satisfy demand, d_t , which is the number of buses needed in each period. Equation (17) is the capital budging constraint which limits the payment for new asset acquisitions by c_t , which is the predetermined capital budget in each year. In equation (18), h_{ia} represents the initial number of each type of assets with associated age. This constraint imposes that the initial numbers of any types or any ages of assets (not age 0) should be either used or salvaged. The constraint (19) requires that the number of used assets in one year should be either used or salvaged in the next year. The constraint (20) imposes that all assets are sold in the last year of the planning horizon (T). Constraint (21) requires that any asset that has reached its maximal age is not used anymore. The constraint (22) prohibits salvaging any new asset immediately. Indeed, for salvaging of any new purchased asset at least one year should be passed. Finally, constraint (23) requires non-negative, integer solutions.

$$\sum_{i=1}^{I}\sum_{a=0}^{A_i-1} X_{iat} \geq d_t \qquad \forall\ t \in \{0,1,...,T-1\} \tag{16}$$

$$\sum_{i=1}^{I}\sum_{a=0}^{A_k-1} l_{it} X_{i0t} + f_t Z_t \leq c_t \qquad \forall\ t \in \{0,1,...,T-1\} \tag{17}$$

$$X_{ia0} + S_{ia0} = h_{ia} \qquad \forall\ \ a \in \{1,2,...,A_k\}, \forall i \in I \tag{18}$$

$$X_{i(a-1)(t-1)} = X_{iat} + S_{iat} \quad \forall\ i \in I, \forall a \in A_i, \forall t \in \{1,2,...,T\} \tag{19}$$

$$X_{iaT} = 0 \qquad \forall\ a \in \{0,1,2,...,A_i - 1\} \tag{20}$$

$$X_{iA_it} = 0 \quad \forall\ i \in I, \forall t \in \{0,1,2,...,T\} \tag{21}$$

$$S_{i0t} = 0 \qquad \forall i \in I, \forall t \in \{0,1,2,...,T\} \tag{22}$$

$$X_{iat}, S_{iat} \in \{0,1,2,...\},\ \mathrm{Z}_j \in \{0,1\} \tag{23}$$

Keles and Hartman (2004) by solving the model represented in equations (14)-(23), together with an extensive sensitivity analysis, have considered the impact of various parameters on the optimal policies for choosing the appropriate type, and timing, for bus replacement.

The aforementioned papers on the parallel replacement problem have a deterministic framework. Replacement models in the case of existence of uncertainty concentrate mainly on single-replacement problems Ye (1990) presented a single-replacement model in which operating costs and the rate of deterioration of equipment are stochastic. The model find the optimal time for replacing of equipment in a continuous-time setting. Dobbs (2004) developed a serial replacement model in which operating costs are modelled as a geometric

Brownian motion and determines the optimal investment time. Rajagopalan et al. (1998) developed a dynamic programming algorithm for a problem where a sequence of technological breakthroughs is anticipated but their magnitude and timing are uncertain. A firm, operating in such an environment, must decide how much capacity of the current technology to acquire to meet future demand growth.

Keles and Hartman (2004)'s model has been very successful in other types of applications. For example, Feng and Figliozzi (2013) have considered a fleet replacement framework for comparing the competitiveness of electrical with conventional diesel trucks. Their model is adapted from Keles and Hartman (2004). They obtained scenarios with different fleet utilization, fuel efficiency and by using sensitivity analysis of ten additional factors, they show that electrical vehicles are more cost effective when conventional diesel vehicles' fuel efficiency is low and daily utilization is above some threshold. Breakeven values of some key economic and technological factors that separate the competitiveness between electrical vehicles s and conventional diesel vehicles are calculated in all scenarios.

Typically, in the comparison of the performance of electrical and conventional vehicles takes into consideration the high capital costs associated with electrical engine vehicle. The replacement decision depends on the result of a complete economic and logistics evaluation of the competitiveness of the new vehicle type. In addition, as vehicles age, their per-mile operating and maintenance costs increase and their salvage values decrease. When the O&M costs reach a relatively high level, it may become cost effective to replace fossil fuel vehicles since the savings from O&M costs may compensate the high capital cost of purchasing new engine vehicles. Moreover, if fleet managers are enthusiastic in replacing conventional vehicles with new electric vehicles, it is important to understand how the O&M costs and salvage values change over time. Conventional diesel and electric commercial vehicles have significantly different capital and O&M costs.

4.2. A General Parallel Heterogeneous Asset Leasing Replacement Model

In this subsection we introduce a general asset (fleet) replacement model for obtaining optimal replacement decisions regarding K types of assets under leasing framework. This model is adapted from Keles and Hartman (2004). Specifically, a heterogeneous model is developed in which the assets are bounded by common budget constraints, demand constraints, and a fixed cost that is charged in any period in which there exist a replacement. It is assumed that in any period, assets from any of K types can be leased in order to replace retired assets or meet corresponding demand in that period. First, we introduce the general asset replacement model and then we consider the customized model for fleet replacement.

The notation and formulation to be presented is more easily described by the network in Figure 3. For the sake of simplicity this figure represents the case of two asset types that are available to meet demand (i=2). The age of the asset, a, is defined on the y-axis (maximum A) and the end of the time period, t, is defined on the x-axis (horizon T). Due to the fact that we are considering a commercial setting, the leasing period is assumed to be four years. So, based on this assumption in the figure the model is represented with A = 3 and T = 6. Indeed, at the end of time horizon T=6 all the assets are retired.

Each node is defined according to the pair (a, t) and flow between these nodes represents an asset of age a in use from the end of time period t to the end of period t +1, at which time the asset is of age a+1. Assets are either provided from the initial fleet, represented as flow from supply nodes n_{ia}, or must be leased, represented as X_{i0t} flow in each period t.

An asset when reaches age A must be retired. All assets are retired at the end of the horizon. For meeting the associated demand in each period, the retired assets should be replaced by leasing new assets. In Figure 3, the two types of assets are represented by different arcs (dashed or solid).

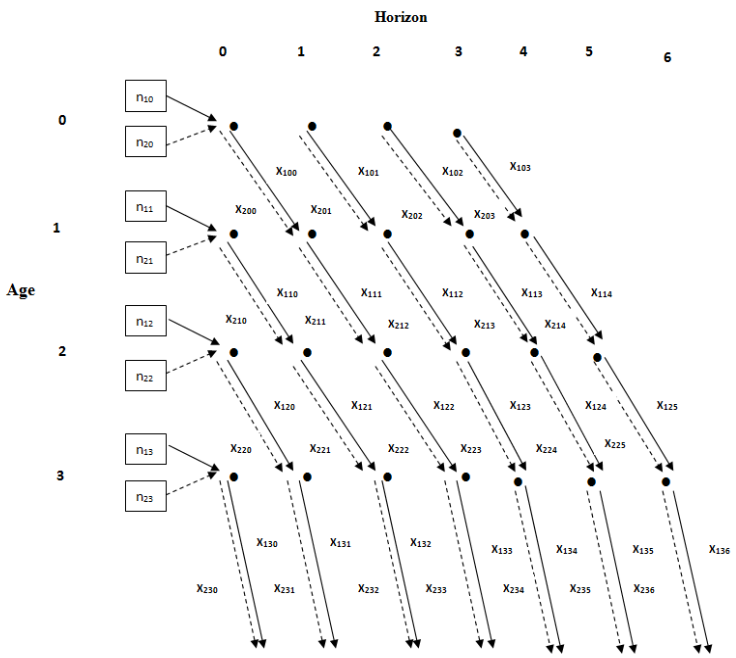

Fig. 3*:* Challengers are denoted by different arcs and different source (initial fleet) nodes. Nodes are labelled *(a,t)* with *a* the age of the asset and *t* the time period. Flow X_{iat} represents asset leased (a=0) and assets in use (a>0).

We consider two types of technologies: the fossil fuel technology (Defender) and the new engine technology (Challenger). Moreover, we take into account the leasing option for financing the commercial fleet investments which is the best option in the commercial setting (Redmer, 2009). This is a deterministic model. Future costs such as lease prices, fuel price, fuel and electricity consumption rate and many other economic and technical factors are assumed to be known functions of time and vehicle type.

The indices in the model are the type of vehicle, $i \in I = \{1,2\}$, the maximum age of vehicles in years, $a \in A = \{1,2,...,A\}$, and the time periods, decisions are taken in each year, $t \in T = \{0,1,2,...,T\}$. The decision variables include the number of type *i*, age *a* vehicles which are currently leased in year *t*, X_{iat}, and the number of type *i* (age *a*) vehicles which are leased at the beginning of year *t*, P_{it}.

The parameters are a) the expected utilization (miles travelled per year) of a type *i* , in age *a* vehicle in year *t* (miles/year), u_{iat}:; b) the expected demand (miles need to be travelled by all vehicles) in year *t* (miles), d_t; c) the available budget (money available for leasing new vehicles) in the beginning of year *t*, b_t; d) the initial number of a type *i* , age *a* , vehicles at the beginning of first year, h_{ia}; e) the lease cost of a type *i* vehicle, l_i; f) the expected per mile operating (running) cost of a type *i* , age *a* vehicle in year *t*, o_{iat}; and g) per mile emissions cost of a type *i* , age *a* , vehicle, e_{ia}. The objective function, equation (24), minimizes the sum of leasing costs for the leasing period (*T-3*) and the operating (running) cost for the entire horizon to the end of year *T*. Moreover, in equation (25) we have the constraint for leasing costs that cannot exceed the yearly budget. Equation (26) shows that the total miles travelled by all used vehicles should meet the yearly demand. Equation (27) represents that in the first year the total number of the vehicles with different ages and types should be equal to the initial condition of the system. In addition, equation (28) shows that planning horizon for decision variable is four years and after that there will be no new leased cars in the system. In equation (29) we determine the number of new leased cars at the beginning of each year in order to be replaced for retired cars at corresponding year. Equation (30) shows that the number of the cars at each year is equal to number of new leased cars plus the number cars which belong to previous year. Finally, expression (31) is the constraint for non-negative numbers of decision variables.

$$\sum_{i=0}^{I}\sum_{t=0}^{T-3}(l_i P_{it}) + \sum_{i=0}^{I}\sum_{a=0}^{A}\sum_{t=0}^{T}[o_{iat} + e_{ia}]u_{ia}X_{iat} \qquad (24)$$

$$\sum_{i=i}^{I} l_i . P_{it} \le b_t \qquad \forall t \in \{0,1,2,...,T-3\} \tag{25}$$

$$\sum_{a=0}^{A}\sum_{i=}^{I} X_{iat} u_{iat} \ge d_t \quad \forall t \in \{0,1,2,..,T-3\} \tag{26}$$

$$X_{ia0} = h_{ia} \qquad \forall i \in I, \forall a \in A \tag{27}$$

$$P_{it} = 0 \qquad \forall i \in I, \forall t \in \{T-3,...,T\} \tag{28}$$

$$P_{it} = X_{i0t} \quad \forall\ i \in I, \forall t \in \{0,1,2,...,T-3\} \tag{29}$$

$$X_{iat} = P_{it} + X_{i(a-1)(t-1)} \quad \forall\ i \in I, \forall a \in A, \forall t \in T \tag{30}$$

$$X_{iat}, P_{it} \in \mathbb{Z}^{+} \tag{31}$$

Having analyzed extensively the different models in the literature and identified some of their limitations, next, in section 5, we summarize the main insights from our review of these different approaches.

5. Insights from the Literature on Fleet (asset) Replacement Models

The aforementioned replacement policies and methods represent only a small part of all efforts that have been done to solve the equipment replacement problem in general (Nakagawa, 1984; Ritchken and Wilson, 1990), and the vehicle replacement problem in particular (Eilon et al., 1966).

Despite the fact that the vehicle replacement policy has an important role on different effectiveness parameters of transportation companies and belongs to an important class of the fleet strategic management problems that have been extensively considered in the literature during last 50 years (Dejax and Crainic, 1987), there are many obstacles for applying the existing methods. Such obstacles exist from the following features of the existing replacement methods (Redmer, 2009):

- Most of the methods are assumed to be applied in a stable environment which is not the case for most of the vehicles in under operational conditions. For example, they way those vehicles are utilised and the loads carried, the climate, and other factors from road conditions which can have impact on fuel economy of the vehicles,
- Focused on a given group (type) of vehicles instead of a single vehicle,
- Taking into account a constant utilisation rate of the equipment during its operational life.

In Practice, the existing models have at least one of the above drawbacks. For instance, Eilon et al. (1966), consider particular vehicles, but assume a fixed utilisation pattern, whereas Simms et al. (1984), relax the assumption of the constant utilisation, but constrain an age to the replacement problem by placing a lower bound which equals 15 years . Suzuki and Pautsch (2005) also constrain an age to the replacement model by giving the upper bound of 5 years and they conclude that vehicles of age 6 or beyond may not be suitable for business operations, that contradicts the assumption of Simms et al.(1984).

Moreover, the significant part of the vehicle replacement models assumes budget constraints (Simms et al., 1984), which is important when replacement policy is defined for fleet of vehicles but not particular vehicles. However, such constraints generally result in the replacement of the limited group of the oldest vehicles only (Redmer, 2009). Because of the listed above drawbacks of the existing replacement methods, a direct application of them to the vehicles deployed by freight transportation companies is difficult, if not impossible.

6. Practical Challenges for the Fleet Replacement Problem

Typically providing fleet for field services requires finding the right vehicle of right capacity for the right business and fitting the required features into the serviced work type. In practice, these decisions are twofold:

- Firstly, identifying the vehicles portfolio needs in terms of volume capacity, driving features (speed, driving wheels for instance).
- Secondly, calculating a replacement plan over one to generally five years that ensures the provision of the right brand, model, and vehicle asset supplier for each identified fleet item.

The second step can be modeled as a multi-objective combinatorial optimization problem. However there is not a single solution, as a matter of fact, the solution is in the form of a ranking of the technology and brands available based on the most economical and ecological choice. The accuracy of such a ranking is generally limited to a number of years; due to high variation in energy prices market, fleet managers generally are advised to look at one year in advance.

Nevertheless, is it possible to maintain accuracy beyond this limit when transforming fleet portfolio?

The combinatorial aspect of the operation is complicated by the fact that the matching of vehicle types and running technology can depend either on the driver's behaviour, or on the variation of usage over days, months or years. For instance a simple analysis suggests that Petrol engine tends to be cost effective when dealing with short annual mileage usage, and a mixed Diesel and Hybrid technology are suitable for normal distances while affording a risk exposure reduction. Moreover, Electric technology is the optimal choice both for risk and cost minimization when the annual mileage usage is high.

Among challenges faced by fleet provisioning decision, the above can be mentioned:

- Fleet provisioning decision can hardly be made independently from the mileage driven. Thus in the process of constructing a replacement tactical plan, it is required to implement a method for forecasting annual mileage at the vehicle type or service operations type granularity.
- The length of equipment life is not fixed; despite a rental duration can be taken as hypothesis. The decision of replacement may happen before the planned end of life, depending on the maintenance cost, fuel prices variation forecast, electric energy recharge constraints, geography and volume of the field service demand.
- Overall both risk exposure and O&M cost criteria need to be balanced with the understanding of the utilization of vehicles, the frequency of long, medium or short distance driven by each vehicle. A fine granularity analysis of mileage, fuel consumption and geographical information monitoring data will help in adjusting the approach for realizing sustainable field operations.
- There is a need for taking into account the uncertainty of fuel prices, the variation of real fuel consumption in each technology, leasing costs and the accessibility of vehicles based on the data for accidents.

The decisional process of fleet management can be as well impacted by vehicle utilization governance within Business. This is possible when processing fleet portfolio life cycle at a global level over the whole organization. If so, a vehicle is seen as an item that can be swapped across business units and transferring unused vehicles from a line of business to another demanding line of business seems to be a sustainable alternative to replacing a vehicle by a new one. Several questions arise: Which option leads to the best cost and risk trade-off? How can the cost of vehicle reuse option be recorded?

This decision needs to be supported at a tactical level, by 1) planning the number of vehicles per technology (source of energy), capacity and various mileages, in short, medium and long term, and, 2) according to a forecasted demand and supply life cycle, analysing the risk exposure reduction when transforming the fleet portfolio and the impact on environment.

7. Conclusion

If we consider the conventional vehicle replacement decisions that exist among fleet managers of the companies and the impact of emerging new technologies on adoption of optimal replacement policies, the main questions that should be addressed for the fleet manager are: First, what kind of vehicle technologies has a better performance in terms of cost efficiency? Second, what is the impact of market uncertainties on vehicle replacement decisions? Third, given a default vehicle fleet system as and defender, what are the best practices for replacing vehicles in the future with combination of different vehicle technologies?

The suggested model improves some of the aforementioned questions and drawbacks of the existing replacement methods that were mentioned by Redmer (2009). First, it takes into account variability of vehicles' operational (running) costs. Indeed, the majority of the parameters of the model depend on time and the cost parameters are divided into fixed and variable. Hence, the expected utilization (annual mileage driven) per year is assumed variable in each year. In addition, CO2 emissions costs are also taken into account.

Moreover, unlike most of the papers in the literature the leasing option is considered as a way for financing the vehicles in the fleet system which is commonplace in the most of the commercial logistics systems of the firms. By taking into account leasing of the new vehicles at the beginning of each year for a finite time horizon (4 to 5 years), many issues regarding the optimal age (economic life) of vehicles and relation with age and utilization will be resolved, due to young structure of the fleet system.

However, the model requires a certain number historical input and forecasted data like fuel prices, fuel consumption and CO2 prices, utilization of the vehicles in different years. This data should be collected, updated and processed with the application of a modern database. This database combined with the suggested model provides a Decision Support System (DSS) for a strategic fleet management in any transportation company.

References

Bean, J. C., Lohmann, J. R., & Smith, R. L. (1984). A dynamic infinite horizon replacement economy decision model. *The Engineering Economist*, *30*(2), 99–120.

Bellman, R. (1955). Equipment replacement policy. *Journal of the Society for Industrial & Applied Mathematics*, *3*(3), 133–136.

Chand, S., McClurg, T., & Ward, J. (2000). A model for parallel machine replacement with capacity expansion. *European Journal of Operational Research*, *121*(3), 519–531.
Chang, C.-C., Sheu, S.-H., & Chen, Y.-L. (2010). Optimal number of minimal repairs before replacement based on a cumulative repair-cost limit policy. *Computers & Industrial Engineering*, *59*(4), 603–610.
Christer, A. H., & Scarf, P. A. (1994). A robust replacement model with applications to medical equipment. *Journal of the Operational Research Society*, 261–275.
Dejax, P. J., & Crainic, T. G. (1987). Survey Paper—A Review of Empty Flows and Fleet Management Models in Freight Transportation. *Transportation Science*, *21*(4), 227–248.
Dobbs, I. M. (2004). Replacement investment: Optimal economic life under uncertainty. *Journal of Business Finance & Accounting*, *31*(5-6), 729–757.
Drinkwater, R. W., & Hastings, N. A. J. (1967). An economic replacement model. *Operational Research Society*, 18(2), 121–138
Eilon, S., King, J. R., & Hutchinson, D. E. (1966). A study in equipment replacement. *Operational Research Society*, 17(1), 59–71.
Feng, W., & Figliozzi, M. (2013). An economic and technological analysis of the key factors affecting the competitiveness of electric commercial vehicles: A case study from the USA market. *Transportation Research Part C: Emerging Technologies*, *26*, 135–145.
Hartman, Joseph C., & Lohmann, J. R. (1997). Multiple options in parallel replacement analysis: Buy, lease or rebuild. *The Engineering Economist*, *42*(3), 223–247.
Hartman, J. C. (1999). A general procedure for incorporating asset utilization decisions
into replacement analysis. *The Engineering Economist*, *44*(3), 217–238.
Hartman, J. C. (2000). The parallel replacement problem with demand and capital budgeting constraints. *Naval Research Logistics (NRL)*, *47*(1), 40–56.
Hartman, Joseph C. (2001). An economic replacement model with probabilistic asset utilization. *IIE Transactions*, *33*(9), 717–727.
Hartman, J. C. (2004). Multiple asset replacement analysis under variable utilization and stochastic demand. *European Journal of Operational Research*, *159*(1), 145–165.
Hartman, J.C. (2005). A note on "a strategy for optimal equipment replacement". *Production Planning & Control*, *16*(7), 733–739.
Hartman, J. C., & Murphy, A. (2006). Finite-horizon equipment replacement analysis. *IIE Transactions*, *38*(5), 409–419.
Jones, P. C., Zydiak, J. L., & Hopp, W. J. (1991). Parallel machine replacement. *Naval Research Logistics (NRL)*, *38*(3), 351–365.Karabakal, N., Lohmann, J. R., & Bean, J. C. (1994). Parallel replacement under capital rationing constraints. *Management Science*, *40*(3), 305–319.

Keles, P., & Hartman, J. C. (2004). Case study: Bus fleet replacement. *The Engineering Economist*, *49*(3), 253–278.

Kim, H. C., Ross, M. H., & Keoleian, G. A. (2004). Optimal fleet conversion policy from a life cycle perspective. *Transportation Research Part D: Transport and Environment*, *9*(3), 229–249.

Nakagawa, T., & Osaki, S. (1974). The optimum repair limit replacement policies. *Operational Research Quarterly*, 311–317.

Oakford, R. V., Lohmann, J. r, & Salazar, A. (1984). A dynamic replacement economy decision model. *IIE transactions*, *16*(1), 65–72.

Rajagopalan, S. (1998). Capacity expansion and equipment replacement: a unified approach. *Operations Research*, *46*(6), 846–857.

Rajagopalan, S., Singh, M. R., & Morton, T. E. (1998). Capacity expansion and replacement in growing markets with uncertain technological breakthroughs. *Management Science*, *44*(1), 12–30.

Redmer, A. (2009). Optimisation of the exploitation period of individual vehicles in freight transportation companies. *Transportation Research Part E: Logistics and Transportation Review*, *45*(6), 978–987.

Ritchken, P., & Wilson, J. G. (1990). (m, T) group maintenance policies. *Management science*, *36*(5), 632–639.

Simms, B. W., Lamarre, B. G., Jardine, A. K. S., & Boudreau, A. (1984). Optimal buy, operate and sell policies for fleets of vehicles. *European Journal of Operational Research*, *15*(2), 183–195.

Suzuki, Y., & Pautsch, G. R. (2005). A vehicle replacement policy for motor carriers in an unsteady economy. *Transportation Research Part A: Policy and Practice*, *39*(5), 463–480.

Weissmann, J., Jannini Weissmann, A., & Gona, S. (2003). Computerized equipment replacement Methodology. *Transportation Research Record: Journal of the Transportation Research Board*, *1824*(-1), 77–83.

Yatsenko, Y., & Hritonenko, N. (2011). Economic life replacement under improving technology. *International Journal of Production Economics*, *133*(2), 596–602.

Ye, M. H. (1990). Optimal replacement policy with stochastic maintenance and operation costs. *European Journal of Operational Research*, *44*(1), 84–94.