JOURNAL OF TRANSPORTATION
SYSTEMS ENGINEERING AND INFORMATION TECHNOLOGY
Volume 14, Issue 3, February 2014
Online English edition of the Chinese language journal

Available online at www.sciencedirect.com
ScienceDirect

Cite this article as: J Transpn Sys Eng & IT, 2014, 14(3), 76−84.

RESEARCH PAPER

A Stochastic Dynamic Programming Approach for the Equipment Replacement Optimization under Uncertainty

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Abstract: In this paper, a stochastic dynamic programming (SDP) based optimization model is formulated for the equipment replacement optimization (ERO) problem that can explicitly account for the uncertainty in vehicle utilization. The Bellman approach is developed and implemented to solving the ERO SDP problem. Particular attention is paid to the SDP state-space growth and special scenario reduction techniques are developed to resolve the "curse of dimensionality" issue that is inherent to the dynamic programming method to ensure that the computer memory and solution computational time required will not increase exponentially with the increase in time horizon. SDP software computer implementation techniques, functionalities and the Graphical User Interfaces (GUI) are discussed. The developed SDP-based ERO software is tested and validated using the current Texas Department of Transportation (TxDOT) vehicle fleet data. Comprehensive numerical results, such as statistical analyses, the software computational time and solution quality, are described and substantial cost-savings have been estimated by using this ERO software. Finally, future research directions are also suggested.

Key words: systems engineering, dynamic programming, equipment replacement, transportation

1 Introduction

Public and private agencies that maintain fleets of vehicles and/or specialized equipment must periodically decide when to replace vehicles composing their fleet. The reason is quite simple: as assets age, they generally deteriorate, resulting in rising operating and maintenance (O&M) costs and decreasing salvage values. Furthermore, newer assets that are more efficient and better in retaining their value may exist in the marketplace and be available for replacement. The conditions of deterioration and technological changes, either separately or together, often motivate equipment replacement decisions[1]. Moreover, the decision is usually based upon a desire to minimize fleet costs, which typically include the acquisition, operating and maintenance cost, and salvage value over a definite or infinite horizon.

Much research has been undertaken in equipment replacement optimization (ERO) including Texas Department of Transportation's (TxDOT) ongoing equipment replacement optimization efforts. A detailed literature review of the state-of-the art/practice of the ERO problem and commercial fleet management systems currently available worldwide can be seen and examined in a separate research paper[1]. In summary, previous research efforts have been made to examine the ERO problem, which can be classified into and solved by three categories from the solution approach perspectives:

1) *Minimum Equivalent Annual Cost (EAC) Approach*. It uses the assumption that there is no technological change and that the cost is stationary (i.e., an asset is replaced with the purchase of a new, identical asset at the same cost) over an infinite horizon (i.e., the equipment is needed indefinitely). The EAC approach compares the high cost of replacement (purchase less salvage) against increasing O&M costs over time and decides the age at which the equivalent annual cost of owning and operating the asset is minimized, which is the optimal economic life of an asset. Once determined, the asset should be continuously replaced at this age under the assumption of repeatability and stationary costs[1].

2) *Experience/Rule based Approach*. Many state DOTs use

Received date: Oct 10, 2012; Revised date: Oct 23, 2013; Accepted date: Jun 28, 2014
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DOI: 10.1016/S1570-6672(13)60137-3

this experience/rule based approach to make keep/replacement decisions for their equipment, particularly during early stages of the ERO research[1]. For example, TxDOT uses threshold values for age, use of an equipment unit, and repair cost as inputs for replacement[1,2]. This experience/rule based approach to the ERO problem can work really well for the fleet manager under certain circumstances. However, this approach heavily depends upon the fleet manager's engineering judgment and experience with the ERO.

3) *Dynamic Programming*. There is an enormous amount of research on the ERO with finite time horizon using the deterministic dynamic programming (DDP) [3-9]. DDP can make a decision on whether to replace or retain at each stage (typically annually) by optimizing the ERO decisions over a given horizon, based on the expected purchase cost, annual operating & maintenance cost, and salvage value, and this can be solved with two typical dynamic programming (DP) approaches including Bellman's[4, 5] or Wagner's formulations[6]. Significant cost savings can be produced and such case studies are well documented [3, 7].

As discussed, DDP optimizes the ERO decisions over a given horizon based on the expected purchase cost, annual O&M cost and salvage value. However, there is an apparent shortcoming associated with this approach. For example, both the vehicle usage and the annual O&M cost are assumed to be constant or predetermined in DDP. Due to randomness in real operations, these expected equipment utilizations are normally not realized in practice, thus invalidating the replacement optimization decisions in some ways and making the DDP decision sub optimal or even bad under extreme conditions. In such cases, the stochastic dynamic programming (SDP), which can explicitly consider the uncertainty in the vehicle utilization and the annual O&M cost accordingly, will undoubtedly be the preferred approach to solving the ERO problem. Meyer[10] is one among the very few to study the ERO problem under uncertainty perhaps due to computational constraints. With the advances in computing technology, a lot of research effort has examined the ERO problem under uncertainties during the past decade as can be seen by much of Hartman's research work[11]. However, none of these previous research efforts made uses the real world fleet cost/usage data and all previous case studies are limited and based on small examples. One will have reasonable doubts about whether the results presented were convincing or can be implied/extended to the real world applications. As a result, many underlying characteristics of the ERO SDP problem are yet to be explored and identified. To our best knowledge, this is the first ERO SDP software that is targeted at the real world application (using TxDOT's current fleet data) and can explicitly consider the uncertainty in the vehicle utilization and the annual O&M cost[12]. It is believed that the pilot SDP-based work is very general to make some very broad statements regarding the ERO and can potentially be an example to demonstrate the promising feasibility. When enough cost/mileage data is collected, the SDP-based optimization solution can also be of immediate use and will yield substantial cost savings for years to come in the fleet management industry worldwide.

The remainder of this paper is organized as follows: Section 2 presents the model formulation of the ERO SDP problem. Section 3 describes the SDP-based solution approach. The Bellman formulation is developed for solving the ERO SDP problem. Particular attention is paid to the SDP state-space growth and special scenario reduction techniques are presented in detail. Section 4 presents case studies in which comprehensive numerical results based on the real world TxDOT vehicle fleet data system using two typical classcodes as an example are also given. Finally, a summary and discussion of future research directions concludes this paper in section 5.

2 Model Formulation

The solution procedures are divided into three concrete steps: 1) Definitions of appropriate stages and states; 2) Definition of the optimal-value function; and 3) Construction of a recursive computation relation[13-16].

2.1 Stages and States

Since the TxDOT fleet manager makes decisions as to whether to keep or replace a piece of equipment at the beginning of each year, it is very natural to consider each year a stage. As a result, we refer to the year count (or index) as the *stage variable* and the age of the equipment in service and the level of cumulative utilization (i.e., mileage) at the beginning of each year as the *state variable*. For the convenience of presentation, the following mathematic notations are introduced:

Set/Indices/Input Variables

i_0 —— the age of the unit of equipment at the starting stage.

j_0 —— the usage of the unit equipment (represented in mileage) at the starting stage.

Y —— the current year in which the unit of equipment is waiting for the keep/replacement decision at the starting stage.

N —— the user-specified maximum planning horizon for considering the keep/replacement decision.

n_k —— the number of possible utilization levels during year k, $k = Y, Y+1, \ldots, Y+N-1$.

m_{t_k} —— the average vehicle utilization (represented in mileage) for annual discretized level index t_k during year k, $t_k = 1, 2, \ldots, n_k, k = Y, Y+1, \ldots, Y+N-1$.

l_k —— the realized mileage level used to represent the actual average vehicle utilization m_{t_k} during year k, $k = Y, Y+1, \ldots, Y+N-1$.

U_{i,j,l_k} —— the usage (represented in mileage) of a unit of equipment (with cumulative utilization j already at the