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A POMDP Framework to Find Optimal Inspection and Maintenance Policies via Availability and Profit Maximization for Manufacturing Systems

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ABSTRACT

Maintenance can be the factor of either increasing or decreasing system's availability, so it is valuable work to evaluate a maintenance policy from cost and availability point of view, simultaneously and according to decision maker's priorities. This study proposes a Partially Observable Markov Decision Process (POMDP) framework for a partially observable and stochastically deteriorating system in which inspection and maintenance optimal policies of Condition Based Maintenance (CBM) must be determined to maximize the average profit and availability of the system simultaneously. A recent exact method named Accelerated Vector Pruning method (AVP) and some other popular estimating and exact methods are applied and compared in solving such problems.

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1. INTRODUCTION

CBM technique is noticed as the most modern and popular maintenance technique in some references [1]. CBM spends high expenditure for monitoring and data processing, so it needs to precise planning [2, 3]. Beside cost and profit, availability optimization is a key objective in maintenance decision-making, aims to increase proportion of time that a system remains operational [4]. Maintenance actions can be the factor of either increasing or decreasing system's availability; because both failures and maintenance activities can shut down the system [5]. Maintenance cost optimization does not always lead to equipment availability optimization [6], and it is a challenge to optimize equipment availability in a cost-effective way [7]. So it is valuable to evaluate a maintenance policy when both availability and cost are considered [8]. Nevertheless, few structural results are known in CBM optimization considering availability remarks simultaneously with cost/profit goals. Some of such studies are introduced in two categoriesas below:

First category includes multi objective studies with cost and availability related goals. The cost and downtime are objective functions and monitoring intervals are decision variables [9]. Similarly, as literature reported [10] unavailability and cost as objective functions and periodic Test Intervals (TI) and Test Planning (TP) as decision variables are considered. Also discussed in literature [11] determining inspection intervals with considering unavailability and cost was presented. Caballé and Castro [12] determined optimal maintenance strategy considering cost and availability, for systems under internal degradation and shocks. Kumar, et al. [13] presented optimal condition monitoring intervals to maximize availability considering maintenance resources usage. Qiu, et al. [14] proposed optimal inspection intervals determining down time threshold, where the system considered to be operating before that. Qiu, et al. [15] also determined optimal inspection interval with considering availability and total cost.

In the mathematical studies of first category decision variables are mostly related to inspection not to the maintenance policy. Also, partial observability assumption that makes the model more difficult and also closer to real world is not included. A recent survey

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work about CBM optimization models for stochastically deteriorating systems, expresses that popularity of CBM strongly relies on stochastic deterioration models for partially observable systems, which are usually modeled in POMDP framework [16]. POMDP was applied in maintenance concept first in literature [17] and then introduced as an appropriate method for systems under uncertainty, especially for partially observable systems [18].

In the second category, some related studies to partially observable systems will be reviewed. Jin, et al. [19] investigated a POMDP framework for CBM problem to propose an optimal policy which can minimize total cost of a discrete-state deteriorating system. Papakonstantinou and Shinozuka [20] suggested a study in two parts to minimize total cost of a discrete-state deteriorating structure in civil engineering, by determining inspection and maintenance policies using POMDP framework. They found that for solving this kind of problems Perseus method is very efficient.

Present work is based on and takes advantage of the recently mentioned paper and notably extends it by considering availability concept for manufacturing systems (not structures), in a POMDP framework with a more precise form of maintenance actions including keep, regular maintenance (minor repair), overhaul (major repair) and replace. In the remaining of this study, the presented problem is modeled in a POMDP framework in section 2, by a particular attention to availability. Estimating and exact solution methods such as Perseus and AVP are applied in Section 3 while Section 4 reports computational results**.**

2. PROBLEM FORMULATION

The multi-objective CBM problem under study is first explained in 2.1 and then is modeled in 2.2.

2. 1. Problem Statement In the present work a CBM problem was studied to determine optimal maintenance/inspection policy, including best sequence of actions and non periodic inspections, with considering availability features such as Emergency and planned stopping times for each action, in order to simultaneously minimize the cost and maximize the availability of a partially observable stochastically deteriorating system. Assumptions are as following:

- System under study is partially observable.
- When "Keep" is selected manufacturing continues and there is not any planned stopping but there is a probability of unavoidable stopping.
- When "Regular" is selected, some routine repair actions are done without any planned stopping so there is a probability of unavoidable stopping.
- When "Overhaul" is selected, manufacturing stops then inspection and completely repair is done. In this action, true state of the system can be observed.
- "Replacement" stops manufacturing and system state will be as new state (probability vector e_1).
- Customers demands are depended on system state. Companies have many situations for producing environment friendly productions leads to gain higher prices from environment sensitive customers [21].

2. 2. Problem Modeling a POMDP framework with states, actions and observation sets S, A and O is used for modelling in which $p(j\,|\,i,a)$ shows the transition probability from $i \in S$ to $j \in S$ when maintenance action is $a \in A$. Transition probabilities are members of transition matrixes P, P' and P'' respectively to keep, regular and overhaul actions.

2. 3. Parameters and Decision Variables

Parameters:

- X : Real system state that is a member of set S.
- $S=\{1,...,i,...,j,...,n\}$: Finite set of possible states in which 1 denotes "as new" and n is used for failure.
- $\Pi=\{\pi_1,...,\pi_i,...,\pi_n\}$: Probability vector of prior state, in which π_i shows probability of being in i. All probabilities summation must be equal to one.
- $V(\Pi)$: Expected total objective function value over infinite time horizon if system state is Π.
- D_i : Product demand produced in state i.
- C_i : Operating cost, if system state is i.
- R_i : Replace cost, if system state is i.
- R'_i : Regular cost, if system state is i.
- R''_i : Overhaul cost, if system state is i.
- T_i : Time to apply overhaul, if system state is i.
- T_n : Time duration for emergency replacing a part that usually occurs in "Keep" or "Regular".
- T_F : Time duration for applying "Replacement".
- p_{ij} : Transition probability (i to j) under "Keep".
- p'_{ij} : Transition probability under "Regular".
- p''_{ij} : Transition Probability under "Overhaul".
- $O=(o_1,...,o_k,...,o_L)$: L monitors' output vector. Monitors provide data as $M=(M^{(1)},...,M^{(K)},...,M^{(L)})$ where $M^{(K)}$ is K th monitor's output that is member of $\{1,...,o_k,...,m_k\}$.
- Γ : Conditional probability matrix that explains relationships between O and real system state:

$$\Gamma=\begin{bmatrix}\gamma_1(1,...,1) & ... & \gamma_1(o_1,...,o_L) & ... & \gamma_1(m_1,...,m_L)\\ \vdots & \ddots & \ddots & \ddots & \vdots\\ \gamma_j(1,...,1) & ... & \gamma_j(o_1,...,o_L) & ... & \gamma_j(m_1,...,m_L)\\ \vdots & \ddots & \ddots & \ddots & \vdots\\ \gamma_n(1,...,1) & ... & \gamma_n(o_1,...,o_L) & ... & \gamma_n(m_1,...,m_L)\end{bmatrix} \qquad (1)$$

$$\gamma_j(o_1,...,o_L) = p(O \mid j) = \Pr(M^{(1)} = o_1,...,M^{(K)} = o_K,...,M^{(L)} = o_L \mid X = j) \quad (2)$$

where $X = j$ denotes the real system state.

- $T(\Pi,O)$: Secondary state probabilities vector giving Π and O, under "Keep" action:

$$T(\Pi,O) = (T_1(\Pi,O),T_2(\Pi,O),...,T_n(\Pi,O)) \quad (3)$$

$$T_j(\Pi,O) = \Pr(X = j \mid M = O,\Pi) = \frac{\sum_{i=1}^{n}\pi_i p_{ij}\gamma_{jo}}{\sum_{j=1}^{n}\sum_{i=1}^{n}\pi_i p_{ij}\gamma_{jo}} \quad (4)$$

$$P(O \mid \Pi) = \Pr(M = O \mid \Pi) = \sum_{j=1}^{n}\sum_{i=1}^{n}\pi_i p_{ij}\gamma_{jo} \quad (5)$$

- $T'(\Pi,O)$: Secondary state probabilities vector giving Π and O, under "Regular" action:

$$T'(\Pi,O) = (T_1'(\Pi,O),T_2'(\Pi,O),...,T_n'(\Pi,O)) \quad (6)$$

$$T_j'(\Pi,O) = \frac{\sum_{i=1}^{n}\pi_i p_{ij}'\gamma_{jo}}{\sum_{j=1}^{n}\sum_{i=1}^{n}\pi_i p_{ij}'\gamma_{jo}} \quad (7)$$

2. 3. 1. Objective Function and Decision Variable

$V^{\Omega}(\Pi)$ shows objective function, whole expected objective function value over an infinite horizon, with initial state Π and maintenance policy Ω. Decision variable is optimal maintenance policy, $\Omega^*(\Pi)$, where $\Omega^*(\Pi) = \arg\min_{a \in A} V^{\Omega}(\Pi)$ optimally suggests type and time of actions and inspections give the minimum expected objective function value for Π.

2. 3. 2. Modeling

In the following, a new model is presented for partially observable manufacturing systems, using the popular POMDP framework.

$$V(\Pi) = \min\{\text{Keep, Regular, Overhaul, Replacement}\} \quad (8)$$

$$\text{Keep} = \frac{\sum_i \pi_i D_i C_i}{Maxc} + \frac{\sum_i \pi_i p_{in} T_n}{\Delta} + \sum_{\theta_1=1}^{m_1}...\sum_{\theta_L=1}^{m_L}(\sum_j\sum_i \pi_i p_{ij}\gamma_{j\theta})V(T(\pi,\theta)) \quad (9)$$

$$\text{Regular} = \frac{\sum_i \pi_i (D_i C_i + R_i')}{Maxc} + \frac{\sum_i \pi_i p_{in}' T_n}{\Delta} + \sum_{\theta_1=1}^{m_1}...\sum_{\theta_L=1}^{m_L}(\sum_j\sum_i \pi_i p_{ij}'\gamma_{j\theta})V(T'(\pi,\theta)) \quad (10)$$

$$\text{Overhaul} = \frac{\sum_i \pi_i R_i''}{Maxc} + \frac{\sum_i \pi_i T_i}{\Delta} + \sum_j\sum_i \pi_i p_{ij}'' V(e_j) \quad (11)$$

$$\text{Replacement} = \frac{\sum_i \pi_i R_i}{Maxc} + \frac{T_F}{\Delta} + V(e_1) \quad (12)$$

where $Maxc = \max(C_K, C_O, C_{Rm}, C_R)$, $C_K = \sum_i \pi_i C_i$, $C_{Rm} = \sum_i \pi_i (C_i + R_i')$, $C_O = \sum_i \pi_i R_i''$, $C_R = \sum_i \pi_i R_i$ and $\Delta = \max(\sum_i \pi_i p_{in} T_n, \sum_i \pi_i p_{in}' T_n, \sum_i \pi_i T_i, T_n)$.

Objective function includes four actions "Keep", "Regular", "Overhaul" and "Replacement" that will be explained in detail separately:

Equation (9) shows whole expected value of objective function when in current period "Keep" is selected and manufacturing continues without any planned stopping. So there are manufacturing process costs depending on the system state and also emergency downtimes can be occurred. Average system availability will decrease with an increase in the system downtime [4], so in order to simplify the model, downtime minimizing is considered instead of availability maximization. Total standardized cost of manufacturing process is expected cost of manufacturing process divided by maximum possible amount of it ($Maxc$), is shown in the first term of Equation (9). Probability of breakdown in term two of Equation (9) is shown by standardized expected value of system unavailability; (expected value of unavailability divided by maximum possible amount of it Δ). For more studies about such standardization, refer to literature [22]. Equation (10) shows whole expected objective values when "Regular" is selected and manufacturing continues with some routine repairs without any planned stopping. In the first term of Equation (10) expected manufacturing process plus regular repair costs divided by the maximum possible amount of it ($Maxc$) is shown. Downtime probability (probability of transition from current state to failure state) is shown in term two of Equation (10). Term three in Equation (10) shows objective values summation for remaining periods if current maintenance action is "Regular". Equation (11) shows whole expected value of objective function when in current period maintenance action is "Overhaul" and manufacturing stops then major repair according to real system state will be applied. So manufacturing process cost will be omitted and as it is shown in the first term of Equation (11), Expected cost of major repair divided by the maximum possible amount of it ($Maxc$) that shows total standardized cost of overhaul. There is planned stopping in "Overhaul" dependent on the system state, that in term two of Equation (11) is shown by standardized expected value of system unavailability. Term three in Equation (11) shows objective function expected value summation for remaining periods if current action is "Overhaul". Equation (12) shows whole expected objective values when in current period, maintenance action is "Replacement" and manufacturing stops then the intended parts are replaced by new ones. Manufacturing process cost is omitted and total standardized replacement cost that is dependent on the system state is as the first term in Equation (12). In term two of Equation (12) T_F (value of unavailability) divided by maximum possible amount of it (Δ) shows standardized expected value of system unavailability. Term three in Equation (12) shows summation of objective function expected value for remaining periods after current period with "Replacement" action that transits the system from every state to as new state (e_1).

3. SOLUTION APPROACH

Although highly attention to POMDP framework, it's optimal solving for large problems was left for a long time (until 2010) because of the natural complexity and data gathering difficulty. In this section, some efficient methods of solving POMDPs that are presented in two categories, optimal and approximate methods, were studied. First category includes Standard Dynamic Programming (SDP) as a traditional method and Modified Dynamic Programming (MDP) as revised version of it beside the Generalized Incremental Pruning (GIP) as a popular exact method and AVP as a recent efficient version of it. Second category includes Perseus as the most popular approximate method [23]. Optimal solving of the presented problem is done by SDP only for small problems and MDP only for small and medium problems, because of time and memory limitations, in section 3.1. For approximate solving, Perseus is applied for large scale problems in section 3.2. For optimal solving large scale POMDPs, in recent years some methods were proposed in literature [24, 25]. Walraven and Spaan [25] introduces AVP as a pruning method makes fastest kind of them and can improve other existing pruning methods' efficiency. Optimal solving of presented problem for relatively large scales is addressed by AVP in section 3.3.

3. 1. SDP and MDP presented model can be solved optimally in finite horizon by SDP introduced by Bellman in 1950's [26]. For this reason backward minimization recursive algorithm is coded in C++. Computational results show that for large/medium scale POMDPs this method is not efficient because of its consumedly need to time and memory. In the present paper some C++ methods such as dynamic memory allocation and creating private heap are used to improve SDP efficiency. MDP increases allocated memory and decreases processing time of SDP. Table 1 is related to solving model by SDP and MDP.

3. 2. Perseus For large scale problems usually exact POMDP solving methods are inefficient sosome approximate methods such as Perseus have become popular [27]. In the present paper, Perseus as a randomized Point-Based Value Iteration algorithm will be used thatin its process first selects a relatively large belief points set B from the belief space.

TABLE 1. Solving time of SDP and MDP in finite horizon

No.	# of stg	primary state probability vector	Computing time (s) SDP State gen	SDP Decision making	MDP State gen	MDP Decision making
1	5	(1,0,0)	42	67	0.55	0.98
2	6	(1,0,0)	66	86	0.63	1.7
3	7	(1,0,0)	702	850	2.6	3.1
4	10	(1,0,0)	×	×	17	29
5	20	(1,0,0)	×	×	305	472
6	30	(1,0,0)	×	×	×	×
7	5	(0,1,0)	48	69	0.68	1
8	6	(0,1,0)	73	98	1.7	2.2
9	7	(0,1,0)	857	922	4.5	5
10	10	(0,1,0)	×	×	23	38
11	20	(0,1,0)	×	×	369	530
12	30	(0,1,0)	×	×	×	×
13	5	(0,0,1)	120	179	1.5	1.87
14	6	(0,0,1)	819	883	2.4	3.6
15	7	(0,0,1)	×	×	5.3	6.5
16	10	(0,0,1)	×	×	28	49
17	20	(0,0,1)	×	×	426	610
18	30	(0,0,1)	×	×	×	×
19	5	(0.7,0.2,0.1)	46	65	0.6	0.99
20	6	(0.7,0.2,0.1)	69	88	1.2	2
21	7	(0.7,0.2,0.1)	792	870	3.3	4.5
22	10	(0.7,0.2,0.1)	×	×	20	34
23	20	(0.7,0.2,0.1)	×	×	372	547
24	30	(0.7,0.2,0.1)	×	×	×	×
25	5	(0.15,0.2,0.65)	162	230	1.8	2.2
26	6	(0.15,0.2,0.65)	908	1057	3.7	4
27	7	(0.15,0.2,0.65)	×	×	5.2	7.6
28	10	(0.15,0.2,0.65)	×	×	43	68
29	20	(0.15,0.2,0.65)	×	×	600	725
30	30	(0.15,0.2,0.65)	×	×	×	×

Then an initial value function will be computed as an approximated lower bound usually by $\frac{1}{1-\gamma}\min_{s,a} R(s,a)$. After back up process is started that is explained briefly using a flowchart in Figure 1. In Table 2 some results of solving model by Perseus is reported in wich "# of stg" shows the horizon length and "state gen" shows state generation time.

3. 3. AVP Recent AVP method speeds up existing pruning methods. Value functions in POMDPs are piecewise linear and convex [28] and this is the base of pruning methods to present value function by a finite set of |S|-dimensional vectors and remove dominated (non-necessary) vectors. Mentioned finite set can be written as $\Upsilon=\{v^0,v^1,...,v^k\}$ where value of belief point b is $V(b)=\max_{v^n\in\Upsilon} b.v^n$ and $\cdot$ is "dot product" [29]. In the following, the presented model vector form is shown as a combination of simpler value functions based on literature [30]. Equations (13) to (22) show piecewise linear and convex functions related to proposed model.

$$V(\Pi)=\max_{a\in A} V^a(\Pi) \tag{13}$$

$$V^a(\Pi)=\sum_{O_1=1}^{m_1}...\sum_{O_L=1}^{m_L}\{V^{a,\mathrm{O}}(\Pi)\} \tag{14}$$

$$V^{\mathrm{Keep}}(\Pi)=\sum_{O_1=1}^{m_1}...\sum_{O_L=1}^{m_L}\{V^{\mathrm{Keep,O}}(\Pi)\} \tag{15}$$

$$V^{\mathrm{Regular}}(\Pi)=\sum_{O_1=1}^{m_1}...\sum_{O_L=1}^{m_L}\{V^{\mathrm{Regular,O}}(\Pi)\} \tag{16}$$

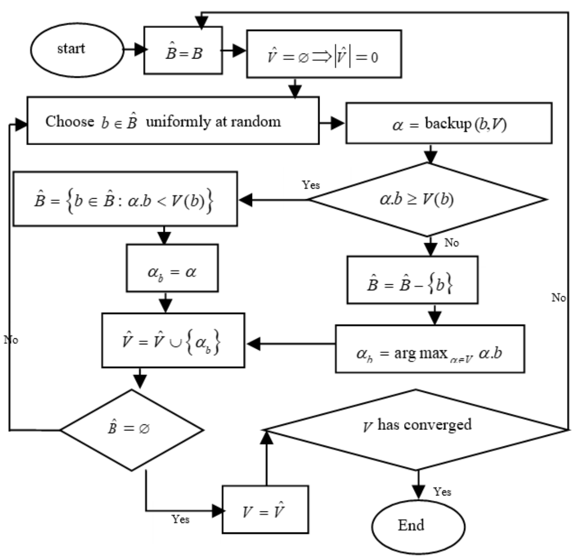

Figure 1. flowchart of the Perseus algorithm

TABLE 2. Solving time of Perseus, GIP and AVP for infinite horizon

No.	$\lvert S\rvert$	primary state probability vector	Computing time (s) Perseus % error	Perseus Time	GIP	AVP
1	2	(0.7,0.3)	0	0.23	38	29
2	2	(0.35,0.65)	0	0.5	118	82
3	2	(0.7,0.3)	0	24	161	55
4	2	(0.35,0.65)	0	72	462	125
5	2	(0.7,0.3)	6.5E-8	41	270	208
6	2	(0.35,0.65)	9.8E-7	99	781	595
7	2	(0.7,0.3)	9.0E-7	69	762	418
8	2	(0.35,0.65)	9.7E-7	207	1816	956
9	4	(0.7,0.1,0.1,0.1)	6.7E-8	9.2	64	57
10	4	(0.11, 0.11,0.13,0.65)	9.7E-5	36	172	149
11	4	(0.7,0.1,0.1,0.1)	9.5E-7	25	239	140
12	4	(0.11, 0.11,0.13,0.65)	9.6E-5	59	709	364
13	4	(0.7,0.1,0.1,0.1)	0	60	587	351
14	4	(0.11, 0.11,0.13,0.65)	9.5E-5	142	1539	1004
15	4	(0.7,0.1,0.1,0.1)	9.2E-7	97	948	495
16	4	(0.11, 0.11,0.13,0.65)	9.7E-5	227	2484	1369
17	4	(0.7,0.1,0.1,0.1)	9.5E-6	133	1431	625
18	4	(0.11, 0.11,0.13,0.65)	9.6E-4	328	4329	1780
19	8	(0.7,…)	9.6E-5	117	1504	632
20	8	(…,0.65)	9.5E-4	350	4196	1653
21	8	(0.7,…)	9.2E-5	165	2191	1085
22	8	(…,0.65)	9.7E-4	315	7032	2855
23	12	(0.7,…)	9.2E-6	21	119	72
24	12	(…,0.65)	9.5E-4	54	438	180
25	12	(0.7,…)	9.5E-6	73	795	429
26	12	(…,0.65)	9.8E-4	215	2562	1336
27	20	(0.7,…)	9.5E-5	116	1275	869
28	20	(…,0.65)	9.7E-4	297	3281	2090
29	28	(0.7,…)	9.6E-4	44	312	105
30	28	(…,0.65)	9.8E-4	108	865	283
31	40	(0.7,…)	9.5E-4	225	1871	1103
32	40	(…,0.65)	9.8E-4	602	5427	2964

$$V^{\text{Overhaul}}(\Pi)=\sum_{O_1=1}^{m_1}\dots\sum_{O_L=1}^{m_L}\{V^{\text{Overhaul,O}}(\Pi)\} \tag{17}$$

$$V^{\text{Replace}}(\Pi)=\sum_{O_1=1}^{m_1}\dots\sum_{O_L=1}^{m_L}\{V^{\text{Replace,O}}(\Pi)\} \tag{18}$$

$$V^{\text{Keep,O}}(\Pi)=\frac{1}{|O|}\left\{\frac{\sum_i \pi_i C_i}{Maxc}+\frac{\sum_i \pi_i p_{in}T_n}{\Delta}\right\}+ (\sum_j\sum_i \pi_i p_{ij}\gamma_{j\theta})V(T(\pi,\theta)) \tag{19}$$

$$V^{\text{Regular,O}}(\Pi)=\frac{1}{|O|}\left\{\frac{\sum_i \pi_i (C_i+R'_i)}{Maxc}+\frac{\sum_i \pi_i p'_{in}T_n}{\Delta}\right\}+ (\sum_j\sum_i \pi_i p'_{ij}\gamma_{j\theta})V(T'(\pi,\theta)) \tag{20}$$

$$V^{\text{Overhaul,O}}(\Pi)= \frac{1}{|O|}\left\{\frac{\sum_i \pi_i R''_i}{Maxc}+\frac{\sum_i \pi_i T_i}{\Delta}+(\sum_j\sum_i \pi_i p''_{ij}V(e_j))\right\} \tag{21}$$

$$V^{\text{Replace,O}}(\Pi)=\frac{1}{|O|}\left\{\frac{\sum_i \pi_i R_i}{Maxc}+\frac{T_F}{\Delta}+V(e_1)\right\} \tag{22}$$

Purged setsare presented by $purg()$ that for $V(\Pi)$, $V^a(\Pi)$ and $V^{a,\text{O}}(\Pi)$ are $\Upsilon(\Pi)$, $\Upsilon^a(\Pi)$ and $\Upsilon^{a,\text{O}}(\Pi)$:

$$\Upsilon(\Pi)=purg(\bigcup_{a\in A}\Upsilon^a(\Pi)) \tag{23}$$

$$\Upsilon^a(\Pi)=purg(\oplus_{o\in O}\Upsilon^{a,\text{O}}(\Pi)) \tag{24}$$

$$\Upsilon^{a,\text{O}}(\Pi)=purg(\{v^{a,\text{O},i}\,|\,v^i\in\Upsilon\}) \tag{25}$$

$$v^{a,\text{O},n}(S)=\frac{R(i,a)}{|O|}+\sum_{j\in S}P(o\,|\,a,j)P(j\,|\,a,i)v^n(j) \tag{26}$$

$\oplus$ defined as $A\oplus B=\{a+b\,|\,a\in A, b\in B\}$ for sets A and B.

Detecting dominated vectors is time consuming in mathematical methods done by solving some Linear Programming problems. In present paper pruning is done using two different LP related methods; a well known pruning algorithm, GIP [31] and a new AVP algorithm. Related steps are shown in Figures 2 and 3.

GIP flowchart is shown in Figure 2 where LP parts are bold. $<_{lex}$ shows lexicographic ordering that is completely described in literature [32]. In Figure 3 AVP method is illustrated where decomposing the mentioned linear programs is done by Benders decomposition.

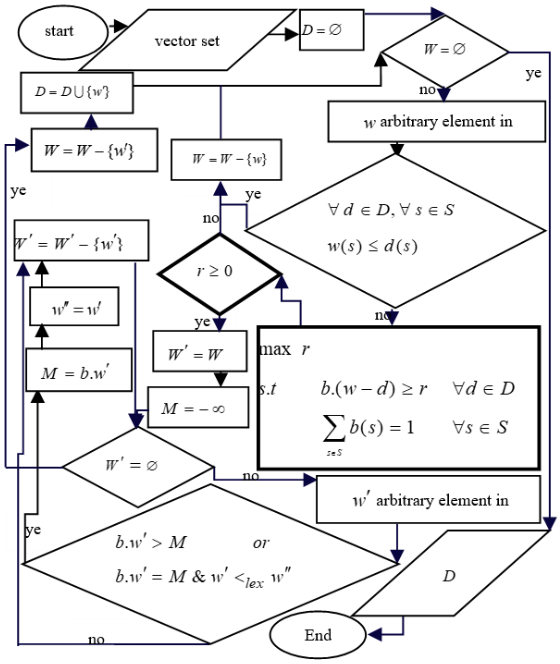

Figure 2. Classical pruning (GIP) flowchart

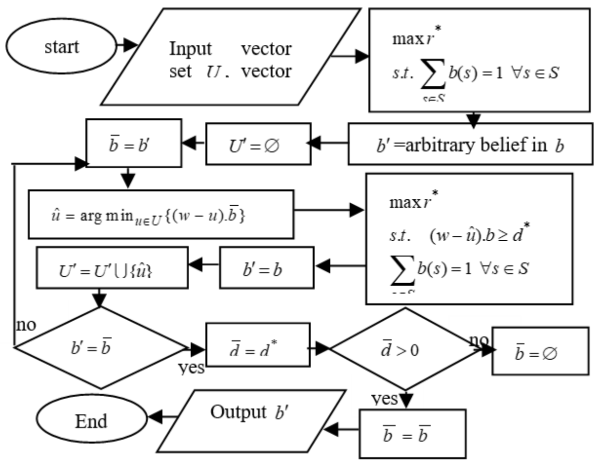

Figure 3. AVP's LP part flowchart

Except to LP part, other AVP steps are similar to GIP but AVP is faster because just a small part of classical LP's constraints is considered in decomposed LP.
In the next section illustrated methods will be compared in solving the presented model.

4. COMPUTATIONAL RESULTS

In this section computational results of coding and running SDP, MDP, Perseus, IP and AVP in C++ and Java using a PC with 2.4 GHz Pentium are presented.

In Table 1, solving time of SDP and MDP is compared in small instances with maximum 20 stages, 2 monitors and 3 states (as new, middle and damaged) and some intuitive primary states probabilities as (1,0,0) for as new, (0,1,0) for middle, (0,0,1) for damaged primary states and (0.15, 0.2, 0.65) and (0.7, 0.2, 0.1) for fairly damaged and fairly new primary states. Solving the model includes two parts: state generation and decision making. "Memory limitation" occurs in some cases shown by "×". Results show that although MDP needs less time and memory than SDP but is unable to solve problems larger than 20 stages.

Perseus, GIP and AVP are applied to solve infinite horizon problems in Table 2, for primary states probabilities with first member 0.7 for a most likely healthy system (70%) and with last member 0.65 for a most likely damaged system (65%).

Table 2 shows that AVP is very successful in optimal solving infinite horizon problems and improves GIP performance in all cases. Also Perseus generates estimated solutions with low errors.

5. CONCLUSIONS

In the present paper CBM model is notably extended by considering availability concept for manufacturing systems by a more precise form of maintenance actions in a POMDP framework. Emergency and planned stopping times as the most important factors of unavailability are considered in formulation of each action. For both finite and infinite horizon the model is solved approximately by Perseus and exactly by the new method AVP. Computational results show that AVP is effective to solve proposed model and this kind of problems can be solved exactly by that. Considering multiple objectives (sometimes conflicting) and weighting them according to Decision Maker's point of view is valuable work and brings the model closer to the real-world. Availability and cost related terms in the presented POMDP model can be weighted to analysis sensitivity of the total objective function. In systems with heavy downtime aftereffects such as power plants, availability related term may be weightier. Also in some systems availability related term can be omitted by weight zero. Optimal related weight for each term can be computed depending on especial condition of the problem under study and relevant managers' point of view.

6. REFERENCES

1. Ahmad, R., and Kamaruddin, S., "An overview of time-based and condition-based maintenance in industrial application", ***Computers & Industrial Engineering***, Vol.63, No. 1, (2012), 135-149.
2. Rasay, H., FallahNezhad, M. S., and ZareMehrjardi, Y., "Application of the multivariate control charts for condition based maintenance", ***International Journal of Engineering***, Vol. 31, No. 4, (2018), 204-211.
3. Rahimi Komijani, H., Shahin, M., and Jabbarzadeh, A., "Optimal policy of condition-based maintenance considering probabilistic logistic times and the environmental contamination issues", ***International Journal of Engineering***, Vol. 31, No. 2, (2018), 357-364.
4. Jiang, R., Kim, M.J., and Makis, V., "Availability maximization under partial observations", ***OR Spectrum***, Vol. 35, No. 3, (2013), 691-710.
5. Keizer, M. C. O., Flapper, S. D. P., and Teunter, R. H., "Condition-based maintenance policies for systems with multiple dependent components: A review", ***European Journal of Operational Research***, Vol. 261, No. 2, (2017), 405-420.
6. Ruschel, E., Santos, E. A. P., and Loures, E. D. F. R., "Industrial maintenance decision-making: A systematic literature review", ***Journal of Manufacturing Systems***, Vol. 45, (2017), 180-194.
7. Bousdekis, A., Magoutas, B., Apostolou, D., and Mentzas, G., "Review, analysis and synthesis of prognostic-based decision support methods for condition based maintenance", ***Journal of Intelligent Manufacturing***, (2015), 1-14.
8. Ghorbani, S., "Reliability analysis for systems subject to degradation and shocks", ***PhD diss., Rutgers University-Graduate School-New Brunswick***, (2014).
9. Ferreira, R.J., de Almeida, A.T., and Cavalcante C.A., "A multi-criteria decision model to determine inspection intervals of condition monitoring based on delay time analysis", ***Reliability Engineering & System Safety***, Vol. 94, No. 5,(2009), 905-912.
10. Martorell, S., Carlos, S., Villanueva, J. F., Sanchez, A. I., Galván, B., Salazar, D., and Cepin, M., "Use of multiple objective evolutionary algorithms in optimizing surveillance requirements", ***Reliability Engineering & System Safety***, Vol. 91, No.9, (2006), 1027-1038.
11. Zio, E., and Viadana, G., "Optimization of the inspection intervals of a safety system in a nuclear power plant by Multi-Objective Differential Evolution (MODE)", ***Reliability Engineering & System Safety***, Vol. 96, (2011) 1552-1563.
12. Caballé, N. C., and Castro, I. T., "Assessment of the maintenance cost and analysis of availability measures in a finite life cycle for a system subject to competing failures", ***OR Spectrum***, (2018), 1-36.
13. Kumar, G., Jain, V., and Gandhi, O. P., "Availability analysis of mechanical systems with condition-based maintenance using semi-Markov and evaluation of optimal condition monitoring interval", ***Journal of Industrial Engineering International***, Vol. 14, No. 1, (2018), 119-131.
14. Qiu, Q., Cui, L., and Shen, J., "Availability analysis and maintenance modelling for inspected Markov systems with down time threshold", ***Quality Technology & Quantitative Management***, (2018), 1-18.
15. Qiu, Q., Cui, L., and Gao, H., "Availability and maintenance modelling for systems subject to multiple failure modes", ***Computers & Industrial Engineering***, Vol. 108, (2017) 192-198.
16. Alaswad, S., and Xiang, Y., "A review on condition-based maintenance optimization models for stochastically deteriorating system", ***Reliability Engineering & System Safety***, Vol. 157, (2017), 54-63.
17. Pak, P. K., Kim, D. W., and Jeong, B. H.,"Machine Maintenance Policy Using Partially Observable Markov Decision Process", ***Journal of the KSQC***, Vol. 16, (1988).

18. Kaelbling, L. P., Littman, M. L., and Cassandra, A. R., “Planning and acting in partially observable stochastic domains“, ***Artificial Intelligence***, Vol. 101, (1998), 99-134.
19. Jin, L., Mashita, T., and Suzuki, K., “An optimal policy for partially observable Markov decision processes with non-independent monitors“, ***Journal of Quality in Maintenance Engineering***, Vol. 11, No. 3, (2005), 228-238.
20. Papakonstantinou, K. G., and Shinozuka, M., “Planning structural inspection and maintenance policies via dynamic programming and Markov processes. Part I: Theory“, ***Reliability Engineering & System Safety***, Vol. 130, (2014), 202-213.
21. Kumar A., and Meenakshi, N., “Marketing management“, ***Vikas Publishing House***, (2011).
22. Ahmadi-Javid, A., and Ghandali, R., “An efficient optimization procedure for designing a capacitated distribution network with price-sensitive demand“, ***Optimization and Engineering***, Vol. 15, No. 3, (2014), 801-817.
23. Spaan, M. T., and Vlassis, N., “Perseus: Randomized point-based value iteration for POMDPs“, ***Journal of Artificial Intelligence Research***, Vol. 24, (2005), 195-220.
24. Qian, W., Liu, Q., Zhang, Z., Pan, Z., and Zhong, S., “Policy graph pruning and optimization in Monte Carlo Value Iteration for continuous-state POMDPs“, ***In Computational Intelligence (SSCI), 2016 IEEE Symposium Series on IEEE***, (2016), 1-8.
25. Walraven, E., and Spaan, M. T. “Accelerated Vector Pruning for Optimal POMDP Solvers“, ***In AAAI***, (2017), 3672-3678.
26. Ahuja. D., www.codeproject.com/Articles/9898/Heap-Walker, (2005).
27. Agrawal, R., Realff, M. J., and Lee, J. H., “MILP based value backups in partially observed Markov decision processes (POMDPs) with very large or continuous action and observation spaces“, ***Computers & Chemical Engineering***, Vol. 56, (2013), 101-113.
28. Smallwood, R. D., and Sondik, E. J.,“The optimal control of partially observable Markov processes over a finite horizon“, ***Operations Research***, Vol.21, No. 5, (1973), 1071-1088.
29. Özgen, S., and Demirekler, M., “A Fast Elimination Method for Pruning in POMDPs“, ***In Joint German/Austrian Conference on Artificial Intelligence***, (2016), 56-68, Springer International Publishing.
30. Cassandra, A., Littman, M. L., and Zhang, N. L., “Incremental pruning: A simple, fast, exact method for partially observable Markov decision processes“, ***In Proceedings of the Thirteenth conference on Uncertainty in artificial intelligence***(1997), 54-61,Morgan Kaufmann Publishers Inc.
31. White, C. C., “A survey of solution techniques for the partially observed Markov decision process“, ***Annals of Operations Research***, Vol. 32, No. 1, (1991), 215-230.
32. Littman, M. L., “The witness algorithm: Solving partially observable Markov decision processes“, ***Brown University, Providence, RI***, (1994).

A POMDP Framework to Find Optimal Inspection and Maintenance Policies via Availability and Profit Maximization for Manufacturing Systems

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چکیده

نگهداری و تعمیرات (نت) به‌عنوان فعالیتی هزینه‌بر و در عین حال سودآور می‌تواند هم عامل افزایش دسترس‌پذیری سیستم باشد و هم عامل کاهش آن، بنابراین ارزیابی یک سیاست نت از لحاظ هزینه و دسترس‌پذیری به‌طور همزمان و با توجه به اولویت‌های فرد تصمیم گیرنده جهت ارائه‌ی یک برنامه‌ریزی جامع برای ایجاد توازن بهینه بین اهداف مذکور می‌تواند بسیار ارزشمند باشد. مطالعه‌حاضر چارچوبی نوین برای برنامه‌ریزی ریاضی مسئله‌ی نت وضعیت محور در قالب فرآیند تصمیم‌گیری مارکف قابل مشاهده جزئی، در مورد تجهیزات قابل مشاهده‌ی جزئی رو به زوال تصادفی در سیستم‌های تولیدی، با در نظر گرفتن فاکتورهای هزینه و دسترس‌پذیری و نیز روابط ما بین آنها، در جهت ارائه‌ی سیاست بهینه‌ی بازرسی و نت، پیشنهاد می‌نماید.

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