The Comparison of two Adaptive Control Methodologies in System-Level Bridge Management

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ABSTRACT

We present an adaptive optimization approach, known as Open-Loop Feedback Control (OLFC), for Maintenance, Repair and Replacement planning of bridge components. This method improves on the approach used in State-of-the-art Bridge Management Systems such as Pontis. The OLFC approach is guaranteed to provide more accurate models when condition survey data are used to update the bridge component deterioration models, and to yield cost savings over any planning horizon. To illustrate the desirability of this approach, we consider a planning agency managing individual facilities with limited prior knowledge of the deterioration models over a designated planning horizon. We show that OLFC improves model accuracy and reduces system costs. We focus our discussion on bridge decks, as the component of bridge structures that undergoes the fastest deterioration, but the methodology presented in this report is applicable to all bridge components.

INTRODUCTION

In the process of bridge system management, agencies collect and analyze condition data and make maintenance, rehabilitation, and reconstruction (MR&R) decisions of facilities over a planning horizon. Such decisions are often based on optimization, where expected system costs, consisting of agency costs and user costs, are minimized, and where future costs are based on a set of bridge component deterioration models. The deterioration models are therefore essential because they allow agencies to make predictions of facilities' future conditions and system costs. Unfortunately, the true deterioration models are never available to agencies. Typically these models would be developed empirically from field data that agencies regularly collect from in-service bridges. However, the limited availability and insufficiency of data often result in inaccurate models which lead to significant cost increases (Madanat et al, 2006). To address such issues, researchers have come up with Adaptive Control (AC) methods that successively update the deterioration models when new data become available. The underlying belief is that incorporating new data will improve model accuracy and facilitate cost-saving MR&R decisions. State-of-the-art Bridge Management Systems, such as Pontis (Thompson et al 1998), use a class of AC procedures known as Certainty Equivalent Control (CEC). The procedure used in Pontis updates the transition probabilities (i.e., the parameters of the component deterioration models) after each condition survey, and uses the updated probabilities in subsequent planning of MR&R decisions. Unfortunately, CEC does not necessarily lead to more accurate models (Bertsekas, 2005). Moreover, hitherto there has been no research that provided conclusive evidence that CEC can guarantee savings in system costs.

In this paper, we present an improved AC approach, known as Open-Loop Feedback Control (OLFC), which is guaranteed to provide more accurate models when condition survey data are used to update the bridge component deterioration models, and to yield cost savings over any planning horizon (Bertsekas, 2005). To illustrate the desirability of this approach, we herein consider a planning agency managing individual facilities with limited prior knowledge of the deterioration models over a designated planning horizon. We show that Open-Loop Feedback Control improves model accuracy and reduce system costs, though it is not guaranteed to achieve model convergence. We focus our discussion on bridge decks, as the component of bridge structures that undergoes the fastest deterioration, but the methodology presented in this paper is applicable to all bridge components.

LITERATURE REVIEW

The bridge management decision-making is based on two essential components: the deterioration models, which give predictions of future bridge deck conditions, and the optimization routine. We structure the Literature Review section accordingly, starting with a review of the bridge component deterioration models, followed by the evolution of the feedback control algorithms in existing literature.

Bridge component deterioration models

Infrastructure deterioration refers to the process of a gradual loss in a facility's condition, under the influence of traffic loading and environmental factors. Deterioration models are mathematical relationships between a dependent variable, namely deterioration or change in infrastructure condition, and a set of causal variables, including design attributes, traffic loading, age, environmental factors, and maintenance history.

A large fraction of the literature on bridge component deterioration has assumed that bridge element deterioration can be represented by a Markov process, expressed as:

$$P_{ij}(a) = P(S_{t+1} = j \mid S_t = i, A_t = a), \forall i, j, t, a \tag{1}$$

where $P_{ij}(a)$ is the transition probability of the facility condition changing from state i to state j under maintenance activity a; S_t and S_{t+1} are the states of a facility at the start and end of period t, and are drawn from a finite state set; A_t is the MR&R action drawn from a finite action set, applied to the facility at the start of t. The current planning stage t is restricted to take values less than the planning horizon T. The transition probabilities will form a square transition matrix of dimension |S| x |S|.

The transition probabilities are assumed constant from year to year, and therefore the deterioration process is time-invariant. The Markovian assumption implies that the transition between any pair of states depends only on the initial condition at the current planning stage given the action to be applied i.e. is independent of history. This Markovian (memory-less) property may not hold in reality, or may hold only for some types of deterioration processes (Mishalani and Madanat, 2002, Frangopol and Das, 1999). Researchers, such as Hawk and Small (1998), Thompson et al (1998), Frangopol and Das (1999), Madanat et al, (1995), have described the limitations of Markovian models as follows: 1) transition rates among condition states of a bridge element are assumed time-invariant; 2) exogenous factors that affect the physical process of deterioration are not explicitly accounted for.

In Mishalani and Madanat (2002) they presented Stochastic Duration Models (SDM) that are more suitable for heterogeneous infrastructure systems. More specifically, SDM model transitions as failure events and represent the probability that a facility continues to stay in its current state as a function of time-in-state and the explanatory variables. Therefore, SDM are capable of accounting for the heterogeneity in the bridge population, which is more realistic than assuming a homogeneous population. Under SDM, the probability that a facility transitions in time interval $[t, t+\Delta]$ is modeled as

$$R(t,\Delta) = P(t < T < t+\Delta \mid T > t) = \frac{F(t+\Delta) - F(t)}{S(t)} \tag{2}$$

where T is the survival duration random variable, $R(t,\Delta)$ is the transition probability in duration $[t, t+\Delta]$, $F(t)$ is the failure cumulative distribution function of t, and $S(t)$ is the survival cumulative distribution function of t. The hazard rate function, subsequently, is defined as $\lambda(t) = \lim_{\Delta \to 0} \frac{R(t,\Delta)}{\Delta} = \frac{f(t)}{S(t)}$, where $f(t)$ is the failure probability density function.

In this paper, we adopt SDM because of the heterogeneity pertaining to our bridge system. It is also worth noting that Markovian Models are just a special class of SDM where the hazard rate is constant regarding time a facility already spends in a state. Therefore, the conclusions are applicable to existing literature that utilizes Markovian Models.

Adaptive Optimization of MR&R Policies

There are two types of uncertainties associated with bridge component deterioration models: aleatoric uncertainty, referring to the stochastic nature of deterioration; and epistemic uncertainty, characterizing the chance variability with respect to model learning. Researchers have realized the epistemic uncertainty concerning the learning process of deterioration models (Thompson 1998, Durango and Madanat 2002). Adaptive control methods were proposed to incorporate new data once they become available in hope of improving model accuracy.

The adaptive control scheme used in in-service bridge management systems is Certainty Equivalent Control (CEC). It is a suboptimal control scheme where optimal decisions are made by fixing the uncertain quantities at their “typical” values. Specific to Pontis, it updates deterioration models by running regression on new data to improve the prior models (Pontis 4.4, User’s Manual). Therefore the typical values in Pontis are the posterior models after each update, and they are point estimates as the optimal outcome of the regression. The posterior models will then give predictions of bridges’ future conditions, and Pontis makes MR&R decisions for that planning cycle accordingly. CEC is light in computation but it could perform strictly worse than an Open-Loop controller where no updating takes place (Bertsekas, 2005).

Bertsekas described two other adaptive control methods: OLFC and Closed-Loop Feedback Control (CLC). Instead of obtaining point estimates as CEC does, OLFC considers the entire space of possible models. The information is then used to predict the bridges' future conditions. OLFC then makes MR&R decisions based solely on all the information available up-to-date, i.e. as if no further measurements will be received, while CLC improves on this basis by explicitly considering future measurements. Therefore CLC is the strict optimal adaptive control scheme.

Durango and Madanat (2002) presented both OLFC and CLC within Markovian Decision Process (MDP). The problem was formulated at individual facility level. Facility deterioration was modeled as a weighted mixture of multiple Markov chains, each characterized by its own transition probability matrix, where the weights represent the belief of each model being the correct model. When new data become available, the probability mass function is updated iteratively by a Bayesian formula. They found that adaptive control methods consistently performed better than Open-Loop control in terms of lifecycle costs. Moreover, with regards to convergence to the true probability mass function and cost-to-go, CLC consistently performed better than OLFC. And this superiority was enhanced as the initial assignment to probability mass function deviated from the true one.

However, even though CLC is a superior approach than OLFC, it is not applicable to system-level bridge management. Because CLC considers the complete topological space, it gives rises to prohibitive computational costs. OLFC, on the other hand, is computationally feasible and can provide satisfactory results (Madanat et al, 2006).

OLFC can improve optimization results gradually in terms of system costs and model accuracy. However, due to the locality of OLFC, it does not necessarily converge to the true models (Kumar and Varaiya, 1986). This is because some actions are inadmissible for some states and therefore are never selected. Consequently, the decision-maker will always lack data on certain elements of the transition matrices, and the initial estimates of these elements may never be updated with inspection data. More details are presented in our parallel work.

METHODOLOGY

Stochastic Duration Models as Deterioration Models

In this paper, we adopt the Weibull model specification for SDMs, given its flexibility in incorporating explanatory variables and its superior fit to our data. For simplicity, we consider two explanatory variables that are known to be highly significant: Annual Average Daily Traffic (AADT) and Age of the bridge. Since each bridge deck has its own unique combination of AADT and Age, we should have in total N different transition matrices for Do-Nothing Action, where N is the number of facilities in consideration. The hazard rate formulation for Weibull follows: $\lambda(t) = p\lambda^{p}t^{p-1}$, where $\lambda = e^{-\beta X}$; X is the column vector of exogenous variables (AADT, Age and a Constant); b is the row vector of parameters to be estimated; and p is the shape control parameter to be estimated. The hazard rate function can therefore be expressed as: $\lambda(t) = pe^{-p\beta X}t^{p-1}$.

We can now derive the transition probabilities using the SDM that were calibrated on our data set. For simplicity, we present the procedure using a simplified case with states {2, 1, 0}. Bridge decks in state 2 can transition down by one state to state 1 and by two states to state 0. Likewise, decks in state 1 can transition down by one state to state 0 (Mishalani and Madanat 2002). The probability where no transition in condition state occurs is given by:

$$P_{2,2} = 1 - R_2(t,\Delta) = \frac{\exp[-\lambda_2^{P_2}(t+\Delta)^{P_2}]}{\exp[-\lambda_2^{P_2}(t)^{P_2}]} \tag{3}$$

And the probability that the facility condition transitions by one state is:

$$P_{2,1} = \Pr(S_{t+\Delta} = 1 \mid T_2 = t) = \int_t^{t+\Delta} \Pr(\tau \mid T_2 < \tau + d\tau \mid T_2 > t) \cdot \Pr(T_1 > t + \Delta - \tau) \tag{4}$$

Lastly, the probability that a facility condition transitions by two states is:

$$P_{2,0} = 1 - P_{2,1} - P_{2,2} \tag{5}$$

where $\lambda_i, P_i, i = 1,2$ are scale and shape parameters for *state i*; $T_i, i = 1,2$ is the duration (in years) that the facility stays in state i. Note that the transition probabilities are varying with the times already spent in the state. Therefore, the "States" in our new transition matrices are not the condition states. They are augmented states, containing information on s and time-in-state. The above expressions give us the transition matrices for each bridge in the system given the model parameters. And SDM have been converted to augmented Markovian models.

Optimal Decision-Making

We then perform a system-level unbudgeted Bottom-up optimization, which essentially obtains system costs by performing facility-level Bottom-up MR&R optimizations with respect to each individual facility, with the assumption that the system budget constraint is not binding. The system equations are given as:

$$a^*(i,t) = \arg\min_{a \in A}\{AC(a,i) + U(j) + \alpha \sum_{j \in S} V(j,t+1) P_{(a,t)}(i,j)\} \tag{6}$$

$$V^*(i,t) = \min_{a \in A}\{AC(a,i) + U(j) + \alpha \sum_{j \in S} V(j,t+1) P_{(a,t)}(i,j)\} \tag{7}$$

where $a^*(i,t)$ is the optimal maintenance activity for state i at planning period t, and $V^*(i,t)$ is the minimal cost-to-go; A = {Do-Nothing, Temporary Repair, Maintenance, Reconstruction} is the set of feasible MR&R activities; S is set of feasible states of facilities; and

$P_{(a,t)}(i,j)$ is the transition probability from state i to state j under maintenance activity $a(i,t)$ at the beginning of planning period t.

The authors understand that the presence of a budget constraint may change the results, but for computational simplicity, we did not account for it at the current stage. The effect of ignoring the budget constraint is discussed later in this paper. The cost structure was adopted from Kong and Frangopol (2003).

Cost Baseline Scenarios

To ensure a fair comparison, we set up two cost baselines: Perfect Information and Open-Loop.

- Perfect Information baseline. Evaluate system costs by assuming that perfectly accurate deterioration models are available to the agency. Therefore, the average cost over a planning horizon, taken over a large sample, would be a good representation of the true cost minimum. This baseline is not observable in real world; and

- Open-Loop baseline. Evaluate system costs by assuming that the agency believes the incorrect models they initially have are correct and make policy decisions accordingly without any updating.

Intuitively, the Perfect Information (PI) and Open-Loop (OL) baselines should form the lower and upper bounds on the costs of an adaptive control approach if the said approach can achieve cost savings. We then apply CEC and OLFC to our bridge system and compare their performances with respect to system costs and model convergence.

COMPUTATIONAL STUDY AND RESULTS

The data of this study consist of two parts: field data and simulation data. We first extracted data from National Bridge Inventory (NBI), for bridges in California, and estimated bridge deck deterioration models (using the Weibull Stochastic Duration Modeling approach). The estimated parameters of the model are shown in Table 1. Then we randomly sampled 200 bridges from the California NBI to form our bridge system.

However, it is worth noting that even though the values of the parameters are only specific to California NBI, the findings are generic. We indeed tried different starting parameters and obtained similar results as well as the same conclusion.

A Computational Illustration of CEC

As described in the Methodology section, we constructed the PI and OL baselines from the estimated parameters of the model. States 3, 2, 1 and 0 are specified as forbidden states in the optimization due to formidable user costs.

To illuminate on the drawbacks of CEC, we now present a computational example with the following two scenarios of CEC:

- CEC starting with PI. The models that our agency starts with are the true models; and
- CEC starting with OL. The models that our agency starts with are the wrong models, the same set of models we adopted for OL baseline scenario (and OLFC scenario).

Table 1 Perfect Information Deterioration Models

State	P-Parameter	Betas		
		Beta-AADT	Beta-Age	Beta-Constant
9	2.5	-5.00E-07	-0.0001	0.8
8	2.25	-6.00E-07	-0.00015	0.75
7	2	-9.00E-07	-0.0005	0.7
6	1.8	-1.50E-06	-0.001	0.9
5	1.6	-2.00E-06	-0.002	0.8
4	3	-2.50E-07	-5.00E-05	0.6

In both cases, we only update one parameter: the p shape parameter. The performance of the estimating algorithm was tested beforehand and the average estimation error/mean is quite small. The updating protocol for the p parameter is given as:

$$\begin{cases} \mu^{t+1} = \dfrac{\mu^t / \sigma^t + \mu^{New} / \sigma^{New}}{1/\sigma^t + 1/\sigma^{New}} \\ \sigma^{t+1} = \dfrac{1}{1/\sigma^t + 1/\sigma^{New}} \end{cases} \tag{8}$$

where μ^t and μ^{t+1} are the mean values of the p parameter at the start and end of the planning period t; σ^t and σ^{t+1} are the variances of the p parameter at the start and end of the planning period t; μ^{New} and σ^{New} are the mean and variance of the p parameter estimated from data generated in time period t.

The set of wrong models we adopt for OL scenario are presented in Table 2.

Table 2 Wrong Models adopted for OL Baseline Scenario

State	OL				CEC starting with OL
	Candidate 1	Candidate 2	Candidate 3	Candidate 4	
9	1	2	2.25	4	1.2
8	1	1.85	2	3.75	1.16
7	1	1.75	1.8	3.6	1.125

6	1	1.6	1.6	3.2	1.05
5	1.4	1.6	1.6	1.6	1.5
4	3	3	3	3	3
Prior Mass	0.8	0.1	0.05	0.05	---

In the OL set, we included candidate models that are slower (Candidate 1 through 3), as well as faster (Candidate 4), than the true models. Then the transition probability matrices generated by the candidate models are weighted by the categorical prior listed in the last row of Table 2, and summed to generate the matrices for OL baseline scenario. The last column listed the Weibull models that are equivalent to the OL baseline scenario, and they also serve as the starting point for CEC. We applied the unbudgeted Bottom-up optimization and the system costs statistics over a 20-year planning horizon are shown in Table 3. Each scenario is verified with a 100-repetition simulation.

Table 3 System Costs for Different PI, OL, CEC starting with Pi and CEC starting with OL

Cost Statistics (**$Millions**)	CEC starting with PI	PI	OL	CEC starting with OL
Mean	215.54	201.97	207.78	209.32
[Min, Max]	[211.77, 219.06]	[194.51, 207.08]	[202.58, 213.33]	[203.59, 214.19]
Stand Error	1.55	2.38	2.22	1.99
Two-sided T-test P-Value	2e-46	9e-33	4e-07	

It follows that CEC starting with OL performed worse than Open-Loop, and even strayed further away from Perfect Information. The bi-scenario comparison t-statistics are listed in the bottom row, all of high significance level. This means that the system costs differences arise from the control strategy we applied.

Note that our stock consists of only 200 bridges, as opposed to over 20,000 bridges alone in California. In other words, a $2 million increase in our paper could be potentially inflated to $200 millions, i.e. the increase is expensive.

We now look at the average models obtained from CEC starting with OL after 20 years of updating and the results are presented in Figure 1. The means strayed away from the true values, yielding models that are faster than the true models. More important, the variances did not show convergence to 0. In other words, CEC failed to achieve parameter convergence. Recall that we only allowed one parameter to be updated. Multi-parameter control optimizations showed that the results are even more pronounced than Table 3, with even greater system costs increases pertaining to CEC, partially due to: 1) the introduction of non-convexity of the parameter space; and 2) the increase in the degrees of freedom of the parameter space.

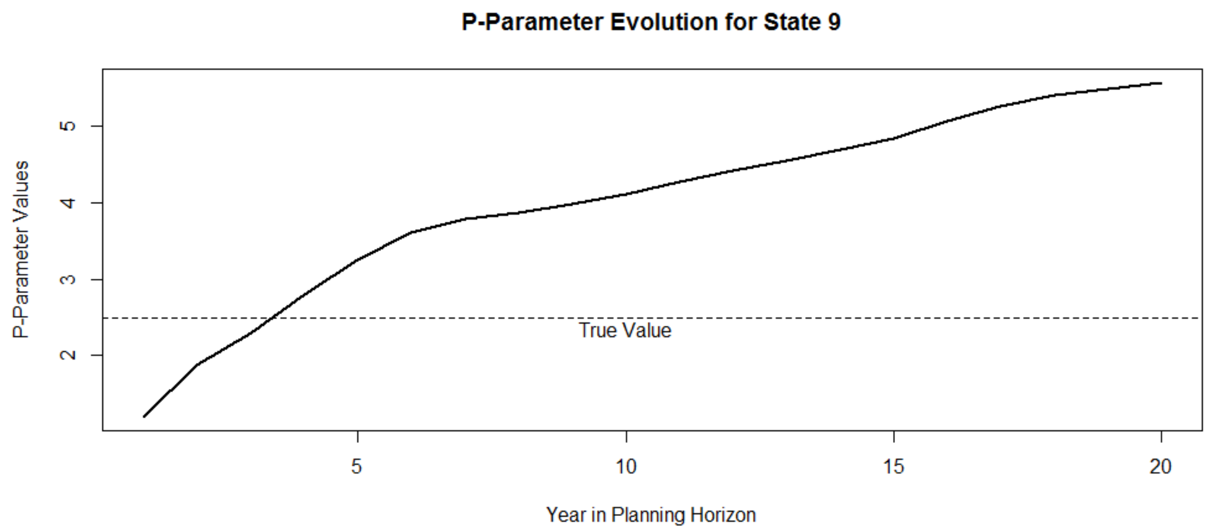

Figure 1 Illustration of the Evolution of P-Parameter's means under CEC starting with OL

All in all, CEC generally suffers from the following drawbacks:

- There is no guarantee that CEC will lead to convergence, and even if it does converge, consistency of convergence is not guaranteed. It is subject to strong locality. Subsequent data tend to reinforce the erroneous estimates from the last update (Bertsekas 2005). Under a linear setting of prediction models and quadratic cost functions it might work, but unfortunately most infrastructure systems do not satisfy such requirements;

- The updating power heavily depends on the size N_{new} of newly generated data. If N_{new} is small, the updating will be overridden by inherent randomness and consequently unable to reveal much information about the models. One might argue that by increasing the time between two updates would the controller be able to accumulate enough data for more efficacious updates. However, since the updating is not guaranteed to be consistent, such strategy is hardly effective; and

- Specific to the context of bridge management, the data generated are not random samples from the natural deterioration process. By the nature of Bottom-up, the mapping of actions to states is deterministic. Therefore we would never observe some actions-to-states pairs. (A potential solution is probing which randomizes MR&R actions. But the approach is criticized for its impracticality due to high costs.) In other words, CEC is attempting to infer the entire distribution while only partial data are observed. Hence, CEC would not be able to reveal the true models due to this serious lack of information.

In fact it would lead to faster models as opposed to true models due to the existence of MR&R actions. Bridges that deteriorate faster are assigned with correcting MR&R actions (i.e. Temporary Repair, Maintenance, and Reconstruction) earlier in terms of time spent in a state, compared to bridges with the same condition state but deteriorate more slowly. The dependent interference will yield faster models when the data generated are used for estimation.

Bertsekas (2005, Chapter 6) gave an elegant summary of the issues abovementioned: "… It is possible, however, that a CEC performs strictly worse than the optimal open-loop controller…." On the other hand, "… a nice property of OLFC is that it performs at least as well as an optimal open-loop policy…." In other words, the incorporation of new data will preserve or improve the level of optimality in comparison to OL. This is illustrated in the following section.

Computational Study of OLFC

The Bayesian way to frame OLFC is to specify prior distributions for the model parameters to be updated and sequentially update the distributions as new data become available. In this paper, the updating protocol for OLFC follows:

$$P(Model_m^{t+1} \mid Data^{t+1}) = \frac{L(Data^{t+1} \mid Model_m^t)P(Model_m^t)}{\sum_k L(Data^{t+1} \mid Model_k^t)P(Model_k^t)} \tag{9}$$

where $L(Data^{t+1} \mid Model_m^t), m = 1,\ldots,4$ is the likelihood evaluated with new data under Model m at the end of period t; and $P(Model_m^t)$ is the updated prior distribution at the end of period t. We applied OLFC to our bridge system, and the system costs statistics for a 20-year planning horizon are presented in Table 4. Once again, all results are obtained from simulations with 100 repetitions.

Table 4 System Costs Comparison among PI, OLFC, OL and CEC starting with OL

<table>
<tr><td>Cost Statistics ($millions)</td><td colspan="2">PI</td><td colspan="2">OLFC</td><td colspan="2">OL</td><td colspan="2">CEC starting with OL</td></tr>
<tr><td>Mean</td><td colspan="2">201.97</td><td colspan="2">204.76</td><td colspan="2">207.78</td><td colspan="2">209.32</td></tr>
<tr><td>[Min, Max]</td><td colspan="2">[194.51, 207.08]</td><td colspan="2">[199.86, 210.04]</td><td colspan="2">[202.58, 213.33]</td><td colspan="2">[203.59, 214.19]</td></tr>
<tr><td>Stand Error</td><td colspan="2">2.38</td><td colspan="2">2.14</td><td colspan="2">2.22</td><td colspan="2">1.99</td></tr>
<tr><td>Two-sided T-test P-Value</td><td colspan="3">9e-14</td><td colspan="2">2.5e-15</td><td colspan="3">4e-07</td></tr>
</table>

It follows that OLFC has achieved significant savings than OL. We indeed obtained the same conclusion when different OL sets were used. Recall that the true models were not included in the OL set, but OLFC still managed to save on system costs over OL.

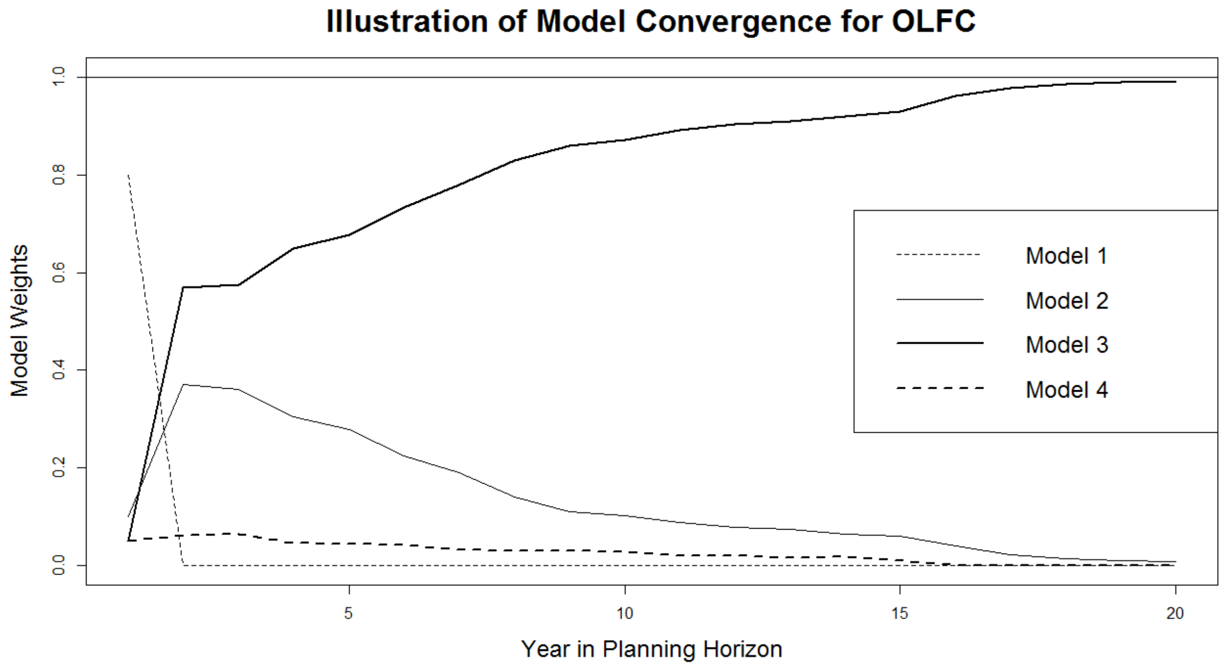

Figure 2 Model Weights Evolution for a 20-year updating for OLFC

We then graph the evolution of the updated beliefs in each year of the 20-year planning horizon in Figure 2. The y-axis delineates the model weights after each update (identified by the year in the planning horizon along the x-axis) for each candidate model. We can see that the weights for candidate 3, the set that's the closest to the true models, climbed up steadily. Candidate 2, which was fairly close to candidate 3, was correctly dropped out as updating goes. Candidate 1 was ruled out after the first update, and the weights for candidate 4 have dropped below 1e-04 after 15 years. Recall that CEC favored faster models, but OLFC does not suffer from this problem, because it only evaluates the likelihoods instead of inference on the entire distribution. The weights statistics at the end of the 20-year planning horizon are presented in Table 5.

Table 5 Model Weights after 20-year updating under OLFC

State		Candidate 1	Candidate 2	Candidate 3	Candidate 4
9	Mean	0	0.0082	0.9918	0
	Stand. Error	1e-14	0.0354	0.0354	1e-9
8	Mean	0	0.0558	0.9442	0
	Stand. Error	1e-14	0.0776	0.0776	1e-10
7	Mean	0	0.4518	0.5482	0
	Stand. Error	1e-14	0.0762	0.0762	1e-10
6	Mean	0	1		0
	Stand. Error	1e-14	1e-10		1e-10

We also present the breakdown of the system costs in Table 6, along with the statistics from the two-sided t-tests. Because CEC led to faster models (which as a result selected more proactive MR&R actions), it has shifted the costs from users to agencies. OLFC has balanced the cost increases proportionally.

Table 6 System Cost breakdown for PI, OLFC, OL and CEC

<table>
<tr><td colspan="2">Cost Type ($Millions)</td><td colspan="2">PI</td><td colspan="2">OLFC</td><td colspan="2">CEC s.w. OL</td><td colspan="2">OL</td></tr>
<tr><td rowspan="2">Agency Cost</td><td>Mean</td><td colspan="2">145.33</td><td colspan="2">147.66</td><td colspan="2">160.84</td><td colspan="2">165.68</td></tr>
<tr><td>Two-sided T-statistic P-value</td><td colspan="3">2.9e-12</td><td colspan="2">5.5e-69</td><td colspan="3">5.6e-31</td></tr>
<tr><td rowspan="2">User Cost</td><td>Mean</td><td colspan="2">56.65</td><td colspan="2">57.10</td><td colspan="2">48.49</td><td colspan="2">42.11</td></tr>
<tr><td>Two-sided T-statistic P-value</td><td colspan="3">8.6e-6</td><td colspan="2">6.8e-102</td><td colspan="3">4.8-e96</td></tr>
</table>

OLFC under Markov Setup

A nice property of OLFC under the setup of Markovian models is that the parameter combinations can be well numerated given reasonable discretization. When applied to a comprehensive candidate set that contains the true models or models that are close to the true models, OLFC would eventually yield deterioration models that can perform almost as well as the true models, given enough updating.

DISCUSSIONS AND PROPOSED WORK

One limitation of the work presented in this paper is that we did not include system budget constraints. Had a budget constraint been imposed, some facilities that were assigned Temporary Repair, Maintenance or Reconstruction might instead be assigned Do-Nothing due to the shortage of funding. This would actually yield an increase in the number of observations of deterioration, which would therefore improve the convergence of the deterioration model parameters. Therefore, in the presence of a budget constraint, we can expect faster improvement in the accuracy of the deterioration models. Our proposed work will include the system budget constraints and further illustrate the desirability of OLFC under such circumstances.

OLFC has also shown its superiority with the application of the Markovian deterioration models. Our calculation has shown that it actually achieved faster convergence than with the Weibull specification.

Note that in developed countries, the overall deteriorated infrastructure systems and the shortage of funding have imposed on planning agencies the burden of effective allocation of the resources available to agencies. CEC leads to models that are faster than the true models, which in return increases the expense than what is necessary. This can be troublesome for planning agencies.

CONCLUSIONS

In this paper, we presented two adaptive control schemes: CEC and OLFC. CEC updates the deterioration models that are used for optimal MR&R decision-making by weighing the models obtained up to last cycle against the re-estimated models. On the other hand, OLFC specifies a model prior distribution for the parameter(s) and then updates the prior distribution by incorporating new data.

Our computational results showed that:

- CEC generally does not guarantee convergence. And in his book in 2005, Bertsekas stated that CEC, even when converged, does not guarantee consistent convergence. OLFC, on the other hand, guarantee improvements in model accuracy. And whenever convergence is achieved, OLFC is capable of achieving consistent convergence. Our results showed that OLFC quickly ruled out models that are quite erroneous and was able to distinguish correctly between models that are relatively close.

- CEC does not guarantee system cost-savings. It can increase the system costs as opposed to where it starts. OLFC, on the contrary, can achieve cost-savings, each given an adverse starting point; and

- OLFC does not incur higher computational costs than CEC.

OLFC also appears to be attractive under the Markovian setup because of the numerable parameter space. Given reasonable discretization, OLFC is capable of picking out the models that are the most accurate. In a developed country where funding falls short and the infrastructure systems are deteriorated after decades of service, OLFC is desirable to planning agencies because it does not favor faster models as CEC does.

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REFERENCE:

Bertsekas, D., 2005. Dynamic Programming and Optimal Control, Volume I, 2005, Third Edition

Durango, P.L. and Madanat, S., 2002. "Optimal maintenance and repair policies in infrastructure management under uncertain facility deterioration rates: an adaptive control approach." *Transportation Research Part A: Policy and Practice*, 36(9), p.763-778

Frangopol, D. M., and Das, P.C., 1999. "Management of Bridge Stocks based on future reliability and maintenance costs." *Current and future trends on Bridge design, construction and* *maintenance*. P.C. Das, D. M. Frangopol, and A. S. Newak, eds., Thomas Telford, London, p.45-58

Hawk, H., and Small, E.P., 1998. “The BRIDGIT bridge management system.” *Structural Engineering International*, 8(4), p.309-314

Kong, Jung S., and Frangopol, D. M., 2003. “Life-Cycle Reliability-Based Maintenance Cost Optimization of Deteriorating Structures with Emphasis on Bridges.” *Journal of Structural Engineering*, 129(6), p. 818-828

Kumar P. and Varaiya P., 1986, Stochastic systems: Estimation, identification, and adaptive control, Prentice-Hall, Englewood Cliffs, N.J.

Madanat, S., and Wan Ibrahim, W.H., 1995. “Poisson and negative binomial regression models for the computation of infrastructure transition probabilities.” *Journal of Transportation Engineering*, *ASCE*, 121(3), p.267-272

Madanat, S., Park, S. and Kuhn, K., 2006. “Adaptive optimization and systematic probing of infrastructure system maintenance policies under model uncertainty.” *Journal of infrastructure systems*, 12, p.192-198.

Mishalani, R., and Madanat, S., 2002. “Computation of infrastructure transition probabilities using stochastic duration models.” *Journal of infrastructure systems*, 8(4), p.139–148

Thompson, P.D., Small, E.P., Johnson, M., and Marshall, A.R., 1998. “The Pontis bridge management system.” *Structural Engineering International*, 8(4), p.303–308