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A FRAMEWORK FOR SYSTEM DESIGN OPTIMIZATION BASED ON MAINTENANCE SCHEDULING WITH PROGNOSTICS AND HEALTH MANAGEMENT

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ABSTRACT

The optimal maintenance scheduling of systems with degrading components is highly coupled with the design of the system and various uncertainties associated with the system, including the operating conditions, the interaction of different degradation profiles of various system components, and the ability to measure and predict degradation using prognostics and health management (PHM) technologies. Due to this complexity, designers need to understand the correlations and feedback between the design variables and lifecycle parameters to make optimal decisions. A framework is proposed for the high level integration of design, component degradation, and maintenance decisions. The framework includes constructing screening models for rapid design evaluation, defining a multi-objective robust optimization problem, and using sensitivity studies to compare trade-offs between different design and maintenance strategies. A case example of power plant condenser is used to illustrate the proposed framework and advise how designers can make informed comparisons between different design concepts and maintenance strategies under highly uncertain lifecycle conditions.

INTRODUCTION

Increasing global competitiveness and limited engineering resources have pushed engineering firms to design higher efficiency and more reliable engineering systems in a more cost effective manner. Furthermore, the performance of complex engineering systems, such as aerospace systems, power and water plants, must be considered over the system's lifetime, including maintenance and reliability issues. This paper draws on two areas of work, design optimization and maintenance optimization, to address maintenance in complex systems starting from the design stage.

To effectively address competing objectives in a design, one approach is Multidisciplinary Design Optimization (MDO) with consideration of relevant aspects of the system lifecycle from design manufacture, operation to final disposal at the end of life [1, 2]. This integrated design optimization approach is made possible because of advancements in optimization techniques, especially gradient-free algorithms capable of handling a large number of design parameters [3–5]. MDO has been applied extensively in the area of aerospace systems [6], engine design [7], and manufacturing engineering [8].

This work also draws on maintenance strategies. Through-

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out the system lifecycle, components will degrade over time, such as the aging of batteries and wearing out of bearings, that can affect system performance. Therefore complex engineering systems often demand significant resources for maintenance [9, 10]. Traditional maintenance strategies are generally categorized into corrective maintenance and preventive maintenance. In corrective maintenance, maintenance is only performed when system performance drops to an unacceptable level (ie, failure of individual component), which often results in inconvenient and costly downtimes to service the system. In preventive maintenance, maintenance tasks are scheduled at regular intervals to eliminate or minimize system downtime due to unexpected failures, but usually results in unnecessarily high maintenance costs [11]. The importance of more efficient maintenance strategies has recently been emphasized to achieve higher system efficiency and savings in life cycle cost. The emergence of prognostics and health management (PHM), which is the process of diagnosing health conditions based on sensory signals and modeling/prediction of remaining useful life, has led to condition based maintenance (CBM) approaches. The optimal configuration of CBM involves finding a threshold health condition value that both maximize the system availability and minimize lifetime maintenance cost [9]. A body of research literature is available in the fields of electronic components [12], civil infrastructure systems [13, 14], airplane maintenance [15], and battery technologies [16].

Despite substantial research in design optimization and maintenance strategy optimization, there has been very little work that focuses on the integrated optimization of design with maintenance. In many different engineering components there is a strong correlation between the physical properties and degradation, and thus design decisions become coupled to the maintenance decisions, and the traditional approach of designing the system and developing the maintenance strategy separately may not produce a global optimal design. However, integration of maintenance in the design stage can be challenging. The coupling between design decisions and maintenance strategies may not be clearly understood in many systems. And more importantly, the degradation and maintenance processes can include high levels of uncertainty, and thus significantly hamper the effectiveness of traditional design methodologies [17].

There is limited work on the integration of design and maintenance optimization. Bodden et al. conducted a study that considers prognostics and health management as a design variable in air vehicle conceptual design. In this work, the redundancy in air vehicles could be reduced with some knowledge of remaining useful life (RUL) [15]. Youn et al. proposed a framework for resilience-driven design of complex systems which integrates PHM into the design process using a reliability-based design optimization strategy [18]. Kurtoglu and Tumer developed a fault identification and propagation framework for evaluating failure in the system in the early design stage [19]. Related research can also be found in disciplines outside mechanical engineering: Camci explored maintenance scheduling with prognostic information which considered the probabilistic nature of prognostics information and its effect on maintenance scheduling [20]. Santander and Sanchez-Silva studied design and maintenance optimization for large infrastructure systems. By applying reliability-based optimization using a deterministic system model, they found that inefficient maintenance policy leads the optimization algorithm to converge to a more robust but expensive design [21]. Monga and Zuo considered both maintenance and warranty in optimal system design in their work. They compared selected system configurations with different failure rate functions, though no predictive maintenance was considered in this study [22]. The above-mentioned work mostly focuses on the integration of design and system reliability, but do not explicitly consider the physical degradation process, and they also do not consider the causal relationship between design decisions and degradation. The work done by Caputo et al. on joint economic optimization of heat exchanger design and maintenance policy considers the interaction between design decisions of a heat exchanger and its degradation (fouling), but this study only considers the traditional maintenance strategy, and does not consider uncertainty associated with degradation [23]. Honda and Antonsson proposed the notion of grayscale reliability to capture system performance degradation and the time dependency of reliability. They also studied design choices and their effects on system degradation, however, their study does not consider the effects of maintenance to system degradation [24].

In this work, we address the current literature gap with our proposed framework for a multidisciplinary design optimization problem by integrating system design models with maintenance scheduling models and capture the associated uncertainties. We will investigate how different maintenance strategies affect the total life cycle cost of a system, and whether different maintenance concepts used in preliminary design optimization will result in different design choices. We apply this framework to a case study design problem of a power plant condenser and evaluate the effect of maintenance decisions on the optimal design choices.

APPROACH

The goal of this proposed framework is to capture design and maintenance interactions in the early design stage and to properly evaluate degradation uncertainties during system operation. This framework will help designers better understand the effects of different maintenance strategies on design decisions and improve system life cycle cost.

The framework is intended for the conceptual/preliminary design phase, when the system functional requirements have been determined and the system architecture has been constructed, but before the detail design stage when component de-

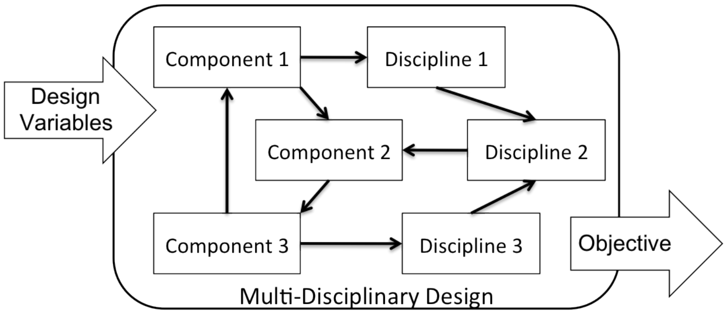

FIGURE 1. MULTI-DISCIPLINARY DESIGN FRAMEWORK

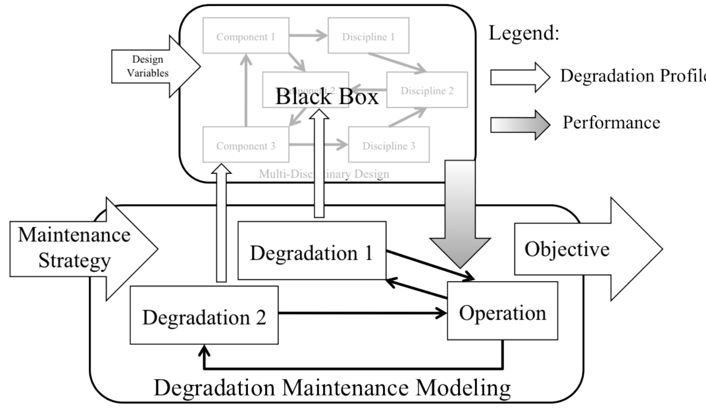

FIGURE 2. PROPOSED FRAMEWORK WITH MAINTENANCE INTEGRATION

tails are determined. Typically, the main task of the preliminary design phase is to perform design optimization to decide on the critical system design criteria and resources. For a multi-disciplinary system, the optimization problem [1] is in the form of:

$$\begin{aligned} &\text{min. } F(\mathbf{x}_{cs},\mathbf{y}) \\ &\quad \text{s.t. } \mathbf{y}_i = Y_i(\mathbf{x}_{cs},\mathbf{x}_i,\mathbf{y}_{cj}),\ i,j=1,2,...,s \\ &\qquad g_k(\mathbf{x},\mathbf{y}) \le 0 \end{aligned} \tag{1}$$

where F is some objective such as cost or performance, $\mathbf{y}$ is a vector output from the corresponding subcomponents and discipline; $\mathbf{y}_i$ is a vector output of subsystem i modeled by Y_i; $\mathbf{y}_{cj}$ is a vector output from other disciplines j; $\mathbf{x}$ is a vector design variables including the system design variables $\mathbf{x}_{cs}$ and subcomponent design variables $\mathbf{x}_i$; s is the number of subcomponents and disciplines, and g_k is a set of constraints.

A graphical representation of the MDO problem is shown in Figure 1. The components in the problem are all the physical entities: for example the wings of an aircraft, or turbines in a power plant. The disciplines describe the physical performance, and can include structural, thermodynamic, or economic. Designers can make decisions on the design variables, and the different physical modules output the objective functions in terms of cost and performance. This figure shows the complexity of a typical MDO problem with many feedback couplings between different system components shown by the small arrows indicating the interdependencies between subsystems.

To achieve our goal of integrating maintenance and design, we propose a framework that decomposes a system into two major divisions as shown in Figure 2. The first division is the system design division. This division contains the forms and functions of the system and its subcomponents and disciplines. The second division contains everything related to system maintenance, including the degradation profile for the different components, and the operation of the system over its lifecycle. We assume that the form and function of the system can be modeled deterministically, while in the maintenance division, the component degradations are probabilistic events over the system lifetime. Monte-Carlo simulation is needed to evaluate the life cycle performance by generating random degradation profiles. The degradation profiles are used in the multi-disciplinary model to compute the system performances at each degradation level. The calculated performance values are feedback to the maintenance models for the evaluation of operational performances. Since we assume the system multi-disciplinary model is deterministic, it can be treated as a black box in the Monte-Carlo simulation. The multi-disciplinary model only needs to evaluated a few times to create a look-up table, and the Monte-Carlo lifecycle simulation can use the look-up table instead of calling the system model to reduce computing complexity.

Despite the reduction of computing complexities, the computing requirement is still significant, and thus balancing between model fidelity and complexity is a major challenge. For a multi-disciplinary system, domain specific models are usually high fidelity models that have very low discrepancies with reality but require significant computational time (on the order of hours or days). Furthermore, high fidelity discipline-based models are usually represented using different software tools, making the data transfer between models complicated. Thus, high-fidelity models will not be suitable for this study. A common approach for model complexity reduction is to generate low-fidelity models from high fidelity models using metamodeling methods such as Kriging or response surface method [1]. Low fidelity models can be evaluated very quickly, and is used widely in Monte-Carlo simulations and optimization, but they can have very high discrepancy and require the availability of high fidelity models.

A mid-fidelity model is a simplified representation of a system, which captures the essence of the different domains by using first order approximation of physics based models [25]. Because they are physics-based, no special software is needed, and allows simple integration of different domains and subsystems. A mid-fidelity model has the advantages of short simulation time on the order of several seconds. Mid-fidelity models are commonly used in the early design phases to identify promising design strategies. For the purpose of this study, mid-fidelity models are suitable for both the multi-disciplinary models and maintenance models.

The steps below are followed for setting up the integrated design and maintenance optimization problem:

1. Identify key components and their degradation modes that contribute to system performance loss and require regular maintenance services. Engineering systems usually have a large number of components that degrade at varying rates over time. Not all degrading components have equal effect on the system state or demand the same level of maintenance resource. When constructing the mid-fidelity system model, it is important to focus on the critical degrading components that have the most affect on performance and/or demand highest maintenance cost/time to keep model complexity low.
2. Determine the relationship between physical parameters and degradation. For each of the degrading components identified, find all the available information on how the designer-controlled parameters can affect the development of degradation. For certain components, a large amount of research literature dedicated to their degradation process can be found. Alternatively, on-site data from similar projects in the past, or the designers' intuition can also be used to create an approximate relation if public literature is limited.
3. Propose feasible maintenance concepts. Common maintenance strategies include corrective maintenance, preventive maintenance and condition based maintenance using prognostics of future degradation. Determine the conditions for triggering maintenance in CBM, constraints on the frequency of maintenance, and also the accuracy of prognostics.
4. Construct system model. Setup the domain models for the system design with design inputs of the degrading components defined earlier, incorporate the degradation relationship, simulate for the life time operation of the system and compute different objective functions such as life time efficiency, mean time between maintenance, capital investment, operation cost, and etc.

CASE STUDY

We will use a case example of power plant condenser design to evaluate the effects of maintenance strategies on design choices. The condenser is needed in a steam power plant at the exit of the low-pressure turbine to condense the exiting steam into liquid. Condensers are shell-and-tube heat exchangers. The steam flows through the shell side, which is usually kept at a very low pressure to achieve higher cycle efficiency. The heat ejected from the steam condensation is carried away by cooling water in the tube side of the condenser.

Fouling (and scaling) is the major degradation mode of a condenser. Fouling is the build-up of foreign materials inside the tubes due to bio-particles and inorganic salt in the cooling water. Fouling causes high thermal resistance in the condenser (commonly measured in fouling resistances with units of [m^2K/kW]), which increases the shell side pressure and ultimately reduced plant efficiency. It is recognized as one of the biggest problems associated with efficiency loss in power plants [26].

The build-up of fouling resistance in a condenser usually follows an asymptotic curve [27]. The asymptotic values of fouling and the rate of build-up are highly stochastic. Over the past fifty years much research has focused on finding the underlying physics that govern fouling. The results have suggested that the amount of fouling and the rate of fouling are proportional to temperature, and inversely proportional to the cooling water flow rate, assuming unchanging water quality and tube material [28, 29].

Maintenance of condenser is performed offline during a scheduled power plant outage. Specialized scrapers are shot through the tubes with pressurized water to physically remove built-up foulant. Cleaning can usually be completed within 48 hours before returning the condenser to its original condition.

Model Configuration

Power Plant Models Power plant design is a multidisciplinary process. The Rankine cycle is first designed by following thermodynamic principles, which involves the selection of appropriate steam temperatures, pressures, number of turbine stages and reheat cycles to satisfy the required power rating and achieve optimal efficiency. Boiler, turbine, condenser, and the pumping system are designed by separate teams to satisfy the thermal requirements. For the case study, we simplified the plant design to only include the power cycle module and the condenser design module, and assume the other components are perfect. Figure 3 shows the integration of system components and degradation following the framework proposed in the early section.

The condenser model computes the condenser heat duty based on inlet conditions, geometry, and fouling resistance using the log-mean-temperature-difference method [30]. The condenser inlet conditions are provided from the power cycle models, the geometry parameters: the number of tubes (N_t) and the tube length (L) are designer-specified, and the fouling resistance is obtained from the fouling model. The output heat duty is used in the power cycle model as an input.

The power cycle model is a simple Rankine cycle with a single stage turbine. The model is based on a steam property lookup table [31] to obtain the entropy and enthalpy values of each cycle components, and calculates the cycle efficiency. A

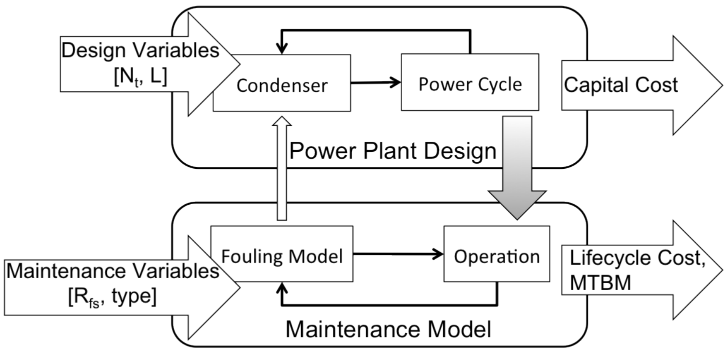

FIGURE 3. MODEL INTEGRATION FOR POWER PLANT CONDENSER CASE STUDY

detailed description of the power plant models and the constant parameters used can be found in the Appendix.

Fouling Trend Model The fouling resistance over time is assumed to follow an asymptotic curve described in Equation 2:

$$R_f(t) = R_f^*(1 - e^{-bt}) \tag{2}$$

The asymptotic value R_f^* is shown in past studies to be a normally distributed random value that has a coefficient of variation of roughly 20%. The mean value of R_f^* and the time constant b are related to the cooling water velocity v_c inside the condenser tube by the following approximations [23].

$$R_f^* = 5 \times 10^4 \cdot v_c{}^{-1.33} \tag{3}$$

$$b = 0.0016 \cdot v_c{}^{-0.35} \tag{4}$$

The fouling trend model computes the fouling trend parameters R_f^* and b based on condenser design variables, and also simulates the fouling growth curve for the system lifecycle modeling. The temperature effects are not considered in this study for simplicity.

Operation Model The operation model takes inputs of one of three types of maintenance: 1) fixed interval, 2) fixed threshold, 3) fixed threshold with prediction, and a second input of either time between cleaning or threshold resistance (R_{fs}) depending on the type of maintenance selected. It should be noted that power plants are usually shut down once a year during the spring when energy demand is the lowest for general maintenance and inspection. For any maintenance strategy, it only makes sense for the cleaning to occur during the regular scheduled shut down, therefore, a minimum continuous operation time of 1 year must be satisfied. Method 1, the fixed interval method, is straightforward: a fixed cleaning interval is specified such as once every three years, and the condenser is cleaned following this schedule. Method 2 is to clean the condenser when some threshold has been reached. This is the typical strategy in industry: the condenser will only be cleaned when the power plant efficiency/maximum power output is severely below the designed efficiency/power output. In this study we will use the fouling resistance as the threshold. Method 3 is similar to method 2 except the health of the condenser (fouling resistance) is monitored and future fouling value is predicted using PHM. The cleaning decision is made if in the next year of operation, the fouling resistance is predicted to rise above the threshold. In this paper we assumed the predictive algorithm can perfectly predict the exact future fouling resistance. The effects of prediction uncertainty is not considered in this work.

The net outputs from fouling model and power plant models also feed into the operation module. The outputs of the operation module include the efficiency over entire lifetime, and the mean time between maintenance.

Economics The objective of optimization is the lifecycle cost of the condenser, which consists of the condenser capital investment, the maintenance cost, and fuel cost due to lost efficiency. The capital investment is assumed to be the cost of the condenser tubes. The maintenance costs occur when the plant is shut down to perform mechanical cleaning. We assume the cost is dominated by the cost of scrapers, and one scraper is needed to clean one tube. The fuel cost due to lost efficiency can be found by calculating the average efficiency over the lifetime, and then calculating the extra fuel required and the fuel cost. Since the operating cost that occurs in the future is compared to the capital investment, a discount rate can be included to calculate the present value of operating cost. It is not included in this study for simplicity.

Model Integration For simplicity, many of the plant and condenser design variables are kept constant, and only the condenser tube length, number of tube, the type of maintenance and the fouling threshold/clean time are considered as designer-selected variables. Other constant parameters include: lifetime of plant is 50 years, the minimum and maximum continuous operating time is 1 and 10 years respectively for the fixed threshold and fixed interval with prediction maintenance method.

For each design, quasi-Monte-Carlo simulations are used to simulate 500 independent runs of the lifetime of the designed plant, the average of the lifecycle costs (LCC), mean time between maintenance (MTBM), and efficiency are computed. We decided to use a quasi-Monte-Carlo simulation to ensure we can obtain valid gradient information using finite difference methods. The lifecycle cost of the system and the efficiency should

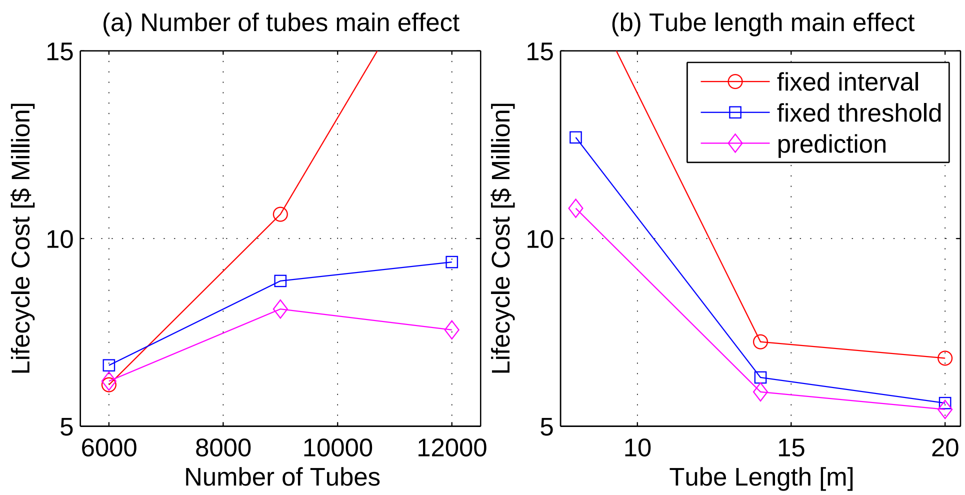

FIGURE 4. DESIGN OF EXPERIMENT RESULTS

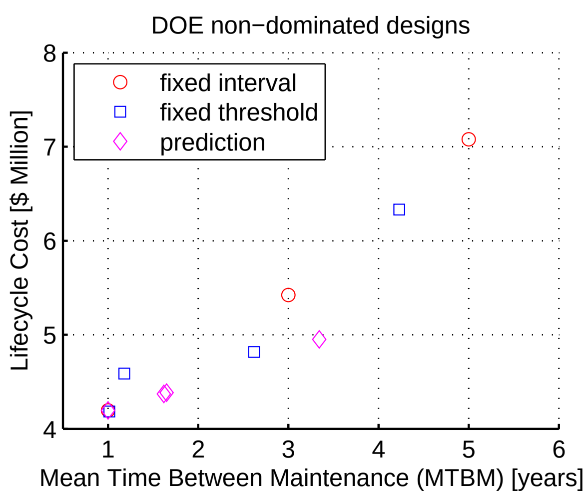

FIGURE 5. DOE NON-DOMINATED DESIGNS

be minimized, while the MTBM should be maximized to reduce the number of mechanical cleanings during the lifetime to reduce the chance of tube corrosion from excessive scraping and human error associated with opening and closing of condenser cases.

Model Evaluation The system model is evaluated using a feasible design input. The uncertainty associated with the lifecycle costs is obtained from the quasi-Monte-Carlo simulation by measuring the coefficient of variation (c.o.v.) of the simulation. By only considering the uncertainty in fouling, the c.o.v. of the lifecycle cost is roughly 2%. The results of the system model is illustrated in Table 4 in the Appendix section.

RESULTS

Design Space Exploration

The mid-fidelity model is set up in MATLAB 2011a. Full factorial design studies are performed to understanding the design space. Three levels for each of the four input variables were selected and shown in Table 1.

TABLE 1. Design of Experiment Variable Values

Number of Tubes (N_t)	6000	9000	12000
Tube Length (L)	8	14	20
Maintenance Type	fixed interval	fixed threshold	predictive
Fouling Threshold (R_{fs}), or	0.05	0.17	0.3
Clean Time	1	3	5

The average effects for the two condenser design variables (N_t and L) are computed and plotted in Figure 4. The design space exploration results suggest that for all types of maintenance strategies, low number of tubes and long tube length tend to result in lower lifecycle cost. It is also noted that using the predictive strategy resulted in lowest overall cost, and the fixed interval method the highest overall cost. Also interesting to note is the LCC with predictive maintenance increased with more tubes like the other maintenance strategies, but then seem to decrease. With more tubes, there is more surface area and therefore the condenser can tolerate higher fouling resistance without signifi-

TABLE 2. Table of Optimization Variables

Variable	Type	Unit	Bounds	Scale
N_t	Input	-	5000 – 16000	$1/10^5$
L	Input	m	5 – 25	1/10
R_{fs}	Input	m^2K/kW	0.05 – 0.3	10
MTBM	Objective	years	1 – 10	-
LCC	Objective	$ Million	3.9 – 15	-

cant degradation in performance. The tradeoff of more tubes is that flow rate through the condenser is now lower, and low flow rate promotes fouling build-up. The DOE results suggest it may be possible to always operate the condenser in high efficiency region and offset the increased capital cost.

The effects of the Mean Time Between Maintenance on the lifecycle cost is shown in Figure 5, where the design evaluations with the lowest cost for each available MTBM value (non-dominated designs) were plotted in the MTBM vs cost axes.

The graph shows that the lifecycle cost is lowest for the predictive and fixed threshold method at MTBM of around 1 years. Above this value, longer MTBM apparently resulted in higher cost. For the fixed interval strategy, the input variable clean time is the MTBM value, and thus can only take on discrete values, whereas for the fixed threshold and prediction strategy, MTBM depends on the R_f threshold value and the fouling build-up rate. The uncertainty of the simulation results is small (lifecycle cost c.o.v. around 2%, MTBM c.o.v. around 5%) and not shown in the figures.

Design Optimization

Single objective optimization was performed separately for the three different maintenance strategies with the lifecycle cost as the only objective. DOE has revealed that the fixed interval strategy has lowest lifecycle cost (LCC) at cleaning time (MTBM) of 1 year, thus leaving only two variables (N_t and L) for optimization, and both are continuous variables. For the fixed threshold strategy and predictive strategy, optimization variables include N_t, L, and the fouling resistance threshold R_{fs}, all of them continuous variables. Since all the input variables and the objective take values in significantly different order of magnitude, scaling of the variables were needed. The variables, their bounds, units, and scaling are shown in the Table 2.

Optimization was done using sequential-quadratic programming (SQP) method as well as genetic algorithm (GA) by utilizing MATLAB functions. The results of the optimization are shown in Table 3.

Both the SQP and GA results were in the same vicinity of the design space, with N_t between 6700 and 7100 and L between 12m and 14m. It was interesting to note that the optimal configurations for all three maintenance methods were very similar in the design space and resulted in similar lifecycle cost as well, between $3.9M and $4.1M. However, the MTBM values were different, with predictive method resulting in the longest MTBM at around 1.5 years, fixed threshold around 1.3 years, and fixed interval at 1 year between each maintenance.

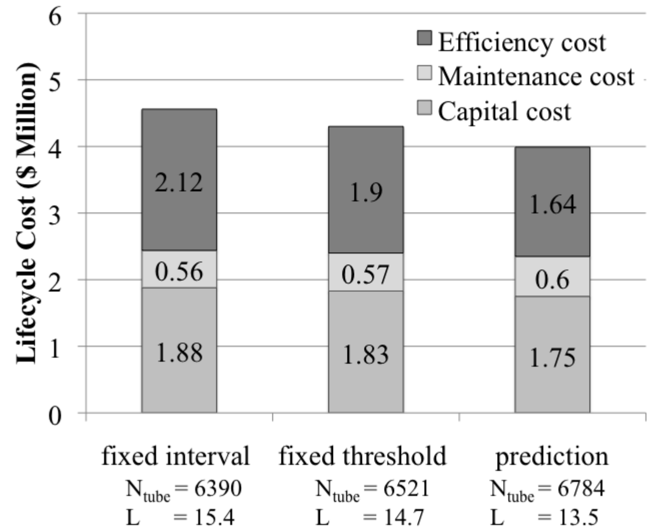

FIGURE 6. CONSTRAINED OPTIMIZATION RESULTS - COST BREAKDOWN IN $ MILLION

Next, we constrained the MTBM to be greater than 2 years. This is a realistic situation as plant operators may be interested in keeping the number of mechanical cleanings during the plant lifetime below a certain value to reduce excessive wear on the condenser due to manual cleaning. A detailed break down of the optimal configurations is shown in Figure 6.

At MTBM equal to 2 years, different maintenance strategies resulted in significantly different lifecycle costs. The breakdown of the costs also show that by using a predictive method, the plant can save significantly on the efficiency costs as expected, and also design a smaller condenser and reduce the initial capital investment.

Figure 7 shows the optimal condenser designs for different maintenance strategies in the design space along with the condenser capital expenditure contour. As suggested by the graph, the capital expenditure decreases going from fixed interval strategy to fixed threshold and to predictive strategy. Since in the model the condenser cost is directly proportional to the condenser heat exchanger area, this means that by selecting the appropriate maintenance method, a smaller condenser can be used and also result in better performance.

It should be noted that the implementation cost of various maintenance strategies are not considered in the model. In real-

TABLE 3. Table of Unconstrained Optimization Results

	Sequential-Quadratic Programming					Genetic Algorithm				
	Design Variables			Objectives		Design Variables			Objectives	
	N_t	L	R_{fs}	LCC	MTBM	N_t	L	R_{fs}	LCC	MTBM
fixed Interval	6951	12.2	-	4.11	1	6671	12.6	-	4.12	1
fixed threshold	6869	13.2	0.105	4.00	1.33	7151	12.4	0.106	3.98	1.31
prediction	7057	12.5	0.165	3.90	1.52	6835	13.4	0.161	3.93	1.44

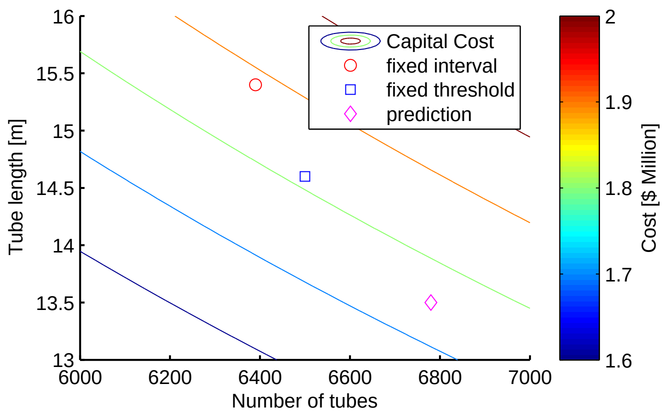

FIGURE 7. EFFECT OF MAINTENANCE ON OPTIMAL DESIGN

ity, there will be costs associated with the sensors for monitoring degradation, and processing elements for prognosis. Designers must compare the reductions in lifecycle cost to the implementation cost of maintenance strategies to make sound design decision.

Sensitivity Analysis

Changes in optimal LCC to changes in the condenser design parameters are computed by changing each design variable independently while keeping the other design variable at optimal value, and re-run the optimization to find the fouling threshold R_{fs} that minimizes LCC and satisfy the MTBM ≥ 2 years constraint. The results are plotted in Figure 8.

The plots show relatively flat regions around the optimal designs for all three strategies. The LCC is more sensitive in large decreases of both variables but less sensitive to increases. This is consistent with the notion that designers should avoid undersizing the condensing, because the penalty associated with efficiency loss is significant.

The sensitivity to a few design parameters were computed using finite difference, the normalized sensitivities are plotted in Figure 9 and Figure 10.

In Figure 9, it is noted that the lifecycle cost is less sensitive to changes in scraper prices. This is because the scraper only directly affects the maintenance cost, which is a small portion of the lifecycle cost. For similar reasons, the sensitivities to material price and coal price are much higher and about equal in value. Only the sensitivities to coal price show any significant difference between different maintenance strategies, and that using the predictive maintenance strategy resulted in the least sensitivity against changes in coal price.

Figure 10 shows the sensitivity of the optimal condenser area to changes in the price parameters. This shows how the optimal design will change in changes to maintenance related parameters. Again, there is little effect on the condenser design from scraper price. The positive sensitivity in coal price means that if coal price is increased from the current value, larger condensers should be designed to compensate for the increase in efficiency cost. The negative sensitivity in condenser material price indicates that a larger condenser can be used if the material price decreases, as expected.

CONCLUSIONS AND FUTURE WORK

In this study we have demonstrated a framework for integrating maintenance in the design stage by considering the effects of system design parameters on the physics of component degradation. We used a case study of condenser design to evaluate the significance of different maintenance strategies and their effects on system design decisions. Three maintenance policies were considered: fixed maintenance interval, maintenance based on degradation threshold, and maintenance based on the prediction of future degradation. The results found show that by concurrently optimizing both the system design variables and the maintenance variables, the optimal design will change with different maintenance policies. However, depending on the values of system parameters, the effects of maintenance policies on design may vary in magnitude.

The proposed framework takes a system level approach by integrating the maintenance strategies and lifecycle analysis with the design process, and thus significantly increased the problem complexity. Efforts to reduce complexity included decoupling the uncertain degradation and maintenance models from

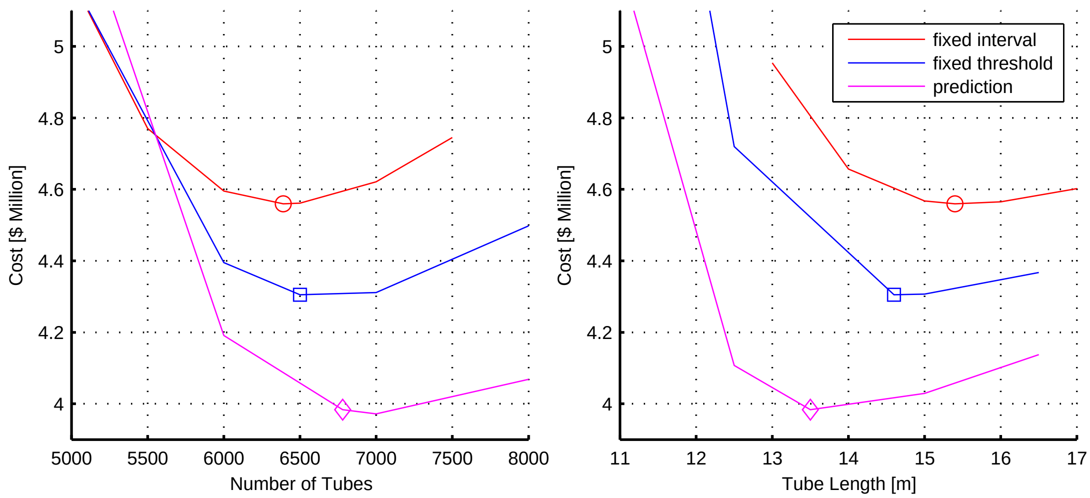

FIGURE 8. SENSITIVITY TO DESIGN VARIABLES. MARKERS SHOWING THE OPTIMAL DESIGNS

the deterministic system models, using quasi-Monte-Carlo simulations, and implementing mid-fidelity physics based models. Future research efforts should look into the effects of having multiple degrading components, which could increase the problem complexity exponentially.

In this work we have assumed a physics based mid-fidelity model is available to avoid the unnecessary long processing time of high-fidelity models. In cases when a mid-fidelity model is not available, low-fidelity models may be used with trade-offs in model precision and uncertainty. Future work could involve performing sensitivity analysis to determine how maintenance strategy changes for different design conditions. This work has neglected nonphysical conditions in systems engineering such as human factors in operation. Nonphysical conditions could be considered in future iterations of framework development.

The uncertainty in fouling resistance was assumed to be normally distributed with c.o.v. of 20%, however this had a very little effect on the lifecycle cost as shown by the low uncertainty of the lifecycle cost (c.o.v. around 2%), and therefore difficult to draw any conclusion on whether maintenance strategies affect the uncertainty in lifecycle. Future work should vary the uncertainty factors and evaluate the robustness of different maintenance methods.

An important factor neglected in this study is the selection of sensors for monitoring component degradation. The choices of sensors would affect the overall capital cost as well as the efficacy of the predictive maintenance strategies. Future work should incorporate the cost of sensor technologies and the uncertainty associated with degradation prediction. Future work should also explore different applications of the proposed framework in aerospace or electronic systems.

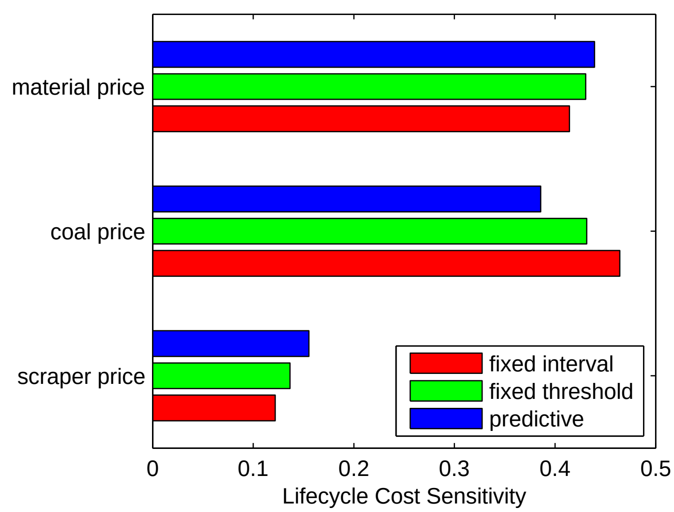

FIGURE 9. LCC SENSITIVITY TO COST PARAMETERS

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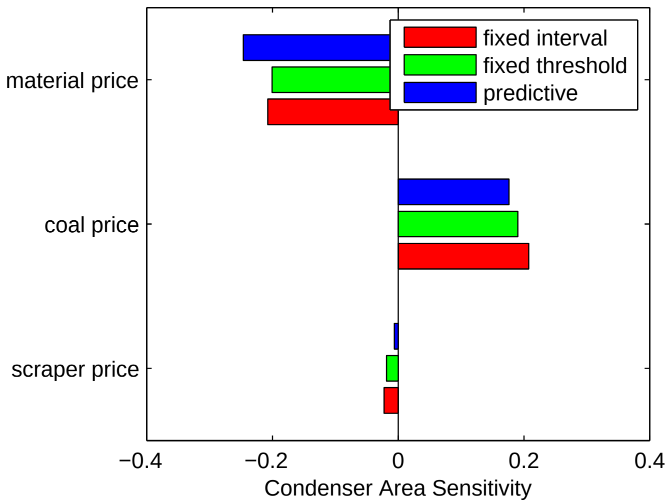

FIGURE 10. CONDENSER DESIGN SENSITIVITY TO COST PARAMETERS

ions, findings, conclusions, and recommendations expressed are those of the authors and do not necessarily reflect the views of the sponsors.

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APPENDIX

The appendix includes some of the details about the case study power plant model that were not included in the main body of the paper. Design requirements for the power plant include the following: the designed maximum power output is 100MW, the condenser will be cooled with seawater having an annual average temperature of 25C. The fuel source is steam coal. The results of model evaluation with a feasible design is also shown here in Table 4

Power Cycle Model For simplicity, a simple Rankine cycle with a single stage turbine is used. In real power plant designs multiple turbine stages are usually used with many preheaters and reheat loops to increase cycle efficiency. Since our case study is aimed to demonstrate the effect of maintenance on the condenser, the power cycle is kept as simple as possible with only five components: the boiler, the turbine, the condenser, the cooling water pump for condenser, and the feed water pump. Design inputs for the power cycle include the temperature and pressure of the boiler exit, the rated pressure of turbine exit (condenser shell pressure), and the rated cooling water flow rate. The power cycle module also takes the condenser duty as an input, which is an output from the condenser design module. The power cycle module takes all inputs and look up the temperature, pressure, enthalpy and entropy values at the inlet/exit of each component using a steam table. If the condenser exit condition is sub-cooled liquid, the condenser duty is higher than required, and the cooling water flow rate is decreased below the rated value, if the condenser exit condition contains vapor, the condenser duty is lower than required, and the turbine exit pressure is raised above the rated value. This ensures the condenser exit is always saturated liquid for best cycle efficiency. Then the feed water flow rate can be calculated in order to satisfy the 100MW output requirement. The output of the power cycle contains the actual turbine exit (condenser shell) pressure, cooling water flow rate, feed water flow rate, auxiliary power requirement (calculated from cooling water pump), and cycle efficiency. In this model, the boiler exit pressure, temperature, and rated turbine exit pressure are kept constant at 80bar, 480C, and 0.1bar respectively.

Condenser Design Model The condenser design module computes the condenser heat duty based on the inlet conditions and geometry using the log-mean-temperature-difference (LMTD) method. We assume the condenser is a one pass X-type shell and tube heat exchanger, the tubes are 70-30 Copper-Nickel alloy with 17cm ID and 19cm OD, installed in triangle arrangements with tube spacing of 25cm. The tube side pressure drop is dominated by friction loss due to tube roughness and fouling build-up. Shell side pressure drop is neglected. Inputs to the condenser design module include the length of tubes (L), the

TABLE 4. Design Evaluation of System Model

Power Plant Model		Lifecycle Model						
N_t	7000	Strategy	fixed interval		fixed threshold		prediction	
L [m]	15	Interval [year]	2		-		-	
		R_{fs} [m^2K/kW]	-		0.2		0.2	
Capital cost [$M]	2	MTBM (μ [year] & c.o.v.)	-	-	2.66	5.6%	1.71	4.8%
Condenser area [m^2]	6267	Cleaning cost (μ [$M] & c.o.v.)	0.612	0	0.459	5.5%	0.719	4.9%
		Efficiency cost (μ [$M] & c.o.v.)	1.99	2.1%	2.23	3.3%	1.29	1.3%
		Lifecycle cost (μ [$M] & c.o.v.)	4.61	0.9%	4.69	1.6%	4.02	0.9%

number of tubes (N_t) the fouling resistance (R_f), and the hot/cold side inlets temperature, pressure, and flow rate, obtained from the output of the power cycle module. The outputs of the module include the calculated heat duty, the cooling water velocity, and the tube side pressure drop.

Degradation Model The fouling resistance increases over time following the asymptotic curve described in Equation 2. The fouling resistance increases the flow resistance in the condenser tubes, resulting in more power drawn by the coolant pump. Fouling also decreases the heat transfer coefficient of the condenser, and thus the flow rate of the coolant need to be increased. Once the maximum coolant flow rate is reached, additional fouling will result in pressure rise in the turbine back pressure, and severely lower the power production efficiency.

Economic Model Some of the constants used to calculate the lifecycle cost is listed below: for calculating the capital cost of the condenser, the price for heat exchanger tubes (70-30 Copper Nickel alloy) is $20/kg. For calculating operation cost, the scraper price is $3.5/piece. The price for steam coal is $90/ton, the average energy density for steam coal is 25MJ/kg, and the capacity factor of typical coal fire power plant is 0.7.