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ECONOMIC OPTIMIZATION OF INLET AIR FILTRATION FOR GAS TURBINES

Dale Grace
Electric Power Research Institute
Palo Alto, CA, USA

Christopher A. Perullo
Georgia Institute of Technology
Atlanta, GA, USA

Jared Kee
Turbine Logic
Atlanta, GA, USA

ABSTRACT

Selecting the appropriate level of filtration for a gas turbine helps to minimize overall unit costs and maximize net revenue. When selecting a filter type and configuration, one must consider the initial costs, operational costs, and ongoing maintenance costs for both the filter and corresponding impacts on unit performance. Calculations are complex, and a fully functional framework is needed to properly account for all aspects of the life cycle and provide an opportunity to optimize filter selection and water wash scenarios for specific plant operating conditions. Decisions can generally be based on several different criteria. For instance, one may wish to minimize maintenance costs, maximize revenue, minimize fuel consumption, etc. For criteria that can be expressed in monetary terms, Life Cycle Cost Analysis (LCCA) is a means to simultaneously consider all criteria and reduce them to a single parameter for optimization using present value arithmetic. To be practically applied, the analysis must include all the significant inputs that would have an impact on the relative comparison between alternatives, while excluding minor inputs that would unduly add to complexity.

This paper provides an integrated, quantitative, and transparent approach to life cycle cost analysis for gas turbine inlet filtration. Most prior art tends to focus either on how to perform the life cycle cost analysis (with simplified assumptions on the impact of filtration on performance), or on a specific technical aspect of filtration such as filter efficiency and performance, the impact of dust on compressor blading and fouling, or the impact of fouling on overall gas turbine performance. Many of these studies provide useful insight into specific aspects of gas turbine degradation due to fouling, but make simplifying assumptions that can lead to inaccuracies in application.

By heavily leveraging prior work, this paper provides the reader with an overview of all aspects of the functionality required to perform such a life cycle analysis for gas turbine filtration. This work also serves as a technical summary of the underlying physics models that lead to the development of EPRI's Air Filter Life-Cycle Optimizer (AFLCO) software. The software tool provides a method to account for the influence of gas turbine type, operating conditions, load profile, filtration choices, and wash type and frequency on overall life-cycle costs. The AFLCO tool is focused on guiding the user to make optimum filter selections and water wash scheduling, accounting for all the significant parameters that affect the economic outcome. Revenue and cost quantities are considered simultaneously to determine the net present value of gross revenue minus filtration and water wash costs over a multiple year analysis period. The user defines the scenarios and the software displays the net present value (NPV) and present value difference between the scenarios. The preferred configuration from an LCCA perspective is that which yields the highest present value for net revenue. The user can iterate on multiple scenarios to seek further increases in NPV. The paper provides relevant example case studies to illustrate how LCCA evaluations of inlet air filters and water wash frequency can be applied to optimize gas turbine economic performance.

The intent of the paper is to provide the user with a summary of prior work that can be integrated to provide a more holistic, complete life cycle cost analysis and describes the framework used within the AFLCO software. The underlying technical analysis in this paper can be applied to any life cycle cost analysis.

INTRODUCTION

Air filtration as applied to gas turbines is not new, and it is well known that even a minimum level of filtration significantly protects against erosion and corrosion of the compressor blading [1]. More recently, there has been a trend of installing higher efficiency level filtration in gas turbines to increase the level of compressor performance retention [2]. Recent studies have shown that increasing filtration efficiency levels to High Efficiency Particulate Air (HEPA) significantly improve long term compressor performance and unit power output [3,4].

While methods for evaluating the performance and cost benefits of higher efficiency filtration are documented, they must be considered in the context of total unit costs and revenue. When selecting a filter type and configuration, one must consider the initial costs, operational costs, and ongoing maintenance costs for both the filter and corresponding changes in unit performance that impact revenue. Calculations are complex, and a comprehensive framework is needed to properly account for all aspects of the life cycle and provide an opportunity to optimize filter selection and water wash scenarios for specific plant operating conditions. Life Cycle Cost Analysis (LCCA) is a means to simultaneously consider all quantifiable criteria and reduce them to a single parameter for optimization using present value arithmetic. To be practically applied, the analysis must include all the significant inputs that would have an impact on the relative comparison between alternatives, while excluding minor inputs that would unduly add to complexity. Multiple studies assume the gas turbine performance retention capability of upgraded filters, without data or analysis to substantiate the predictions, or without information on how to apply the result to sites other than the specific one being investigated [5,6,7,8]. Many other examples exist that evaluate the post-install impact and life cycle cost of upgrade filtration, but do not provide insight into how specific filtration choices were made [3,9]. The motivation behind creating the AFLCO software was to address these shortcomings and develop a filtration life cycle analysis method capable of predicting the cost impact of filtration for any gas turbine, filter, and operating location before installation and operation. The method should provide intelligent default assumptions, while allowing the user to customize the assumptions to a specific site, dependent on the level of available data and prior knowledge.

Based on the referenced prior work, filter selection is often performed in a somewhat ad-hoc manner. Performance improvement estimates may be gleaned from prior studies, the filter costs obtained from the filter OEM, and the filter lifetime estimated based on an assumed replacement schedule. The engineer or analyst performing the LCCA is even likely to follow a structured process [10]. However, there is also a need for a structured, standardized LCCA tool that provides a method for performing a filter selection analysis in a systematic and traceable manner with the intent of aiding in the filter selection process. EPRI has created the Air Filter Life Cycle Optimizer (AFLCO) software to address these industry needs [11]. This paper describes many of the key algorithms and processes within the software and provides useful example cases studies.

When constructing the AFLCO software, the authors reviewed the literature for prior work and sought to synthesize useful aspects of prior studies to develop an integrated method that encompasses several key areas:

- Lifecycle Calculation Methodology
- Impact of Ambient Conditions on Filter Loading
- Impact of Filtration Efficiency on Compressor Fouling
- Impact of Compressor Fouling on Gas Turbine Performance

Addressing the first bullet above, reference 10 provides an extremely well-defined life cycle calculation methodology which the authors adapted for the work presented herein. While the framework of Reference 10 is suitable in terms of the various factors involved in life cycle cost analysis, it makes several simplifying assumptions that make it difficult to apply to sites without existing data. For example, a calculation method is provided to calculate the impact of gas turbine degradation on fuel cost and revenue from power generation; however, no method is provided for estimating the impact of wash frequency or filtration level on degradation rates. For this reason, the authors chose to use Reference 5 as a framework and incorporated additional modeling features described in the rest of the paper.

INPUT PARAMETERS

When evaluating air filtration options, there are several major contributing factors that should be considered. Each of these are considered as user defined inputs from the perspective of creating an LCCA software tool or process.

Analysis Period

The analyst should first consider the period over which to perform the analysis. Given that the typical change out frequency of pre-filters is 6-12 months and that a final filter stage may last for 5 years, the analysis period should be long enough to account for multiple filter replacement cycles. A ten to twenty-year analysis period would account for a significant number of filter change outs, off-line water washes, and associated variation in unit performance. Thirty to forty years would be more than sufficient to account for costs over the life cycle of the project. The timestep resolution of the model over the analysis period may need to be as little as 12 to 24 hour increments if on-line water washes are modeled.

Plant Configuration

To make the results relevant to a particular unit or plant, the analysis needs to include the configuration of the plant, particularly the type of gas turbine and the bottoming cycle arrangement, if any (i.e., simple cycle, 1-on-1, 2-on-1 combined cycle). Smaller gas turbines and those with higher compressor pressure ratios have been shown to be more susceptible to fouling. The steam turbine is impacted indirectly, as compressor fouling contributes to a reduction in gas turbine mass flow which in turn reduces combined cycle output. The number of gas turbines also drives filter replacement costs on a plant-wide basis.

Operating Profile

The operating profile includes information on the service factor and type of duty (peaking, cyclic, baseload). To simplify the variation in load profile that occurs throughout the day and year, the algorithm divides the operating profile into two parts: full load and part load. Full load operation represents the maximum output that can be obtained, at the minimum heat rate, for given inlet conditions and extent of compressor fouling. At part load, the power is fixed by the grid demand; therefore, focus is on heat rate and corresponding power production costs. Variations in compressor fouling at part load do not affect the gross revenue from power production, only the heat rate. For a given overall service factor, the percentage of operating time that the unit operates at full load is defined; the remainder of the operating time is assigned as part load. The average load level at part load (as a fraction of full load rated output) must also be specified. The analysis is then carried out on these two operating regimes independently for each time step. These three parameters: average service factor, percent of fired time at full load, and average load fraction when operating at part load, can often be obtained from historical plant performance data or estimated based on the duty cycle.

Economic Parameters

Two key factors affecting the analysis are the electricity sales price ($/MWh) and fuel cost ($/MMBtu). While these factors can vary significantly, even over the course of a day, annual average values are used to reduce complexity of the analysis. These parameters set the relative value of capacity and heat rate degradation due to filter pressure drop and compressor fouling, as well as their comparison with expenses such as filter replacement and water wash. Scenario optimization may be different depending on these values.

Inflation/escalation rate and discount rate are also required. The inflation rate escalates costs and revenues into future years, whereas the discount rate brings all costs and revenues back to a single base year; its magnitude considers that a dollar could be invested elsewhere to achieve a return on investment. Both factors are necessary when considering long term financial analyses. The inflation rate can be estimated from historical data and most companies have a standard discount rate to use in these types of analyses.

Air Filtration Options

The fundamental job of the air filter is to take 'dirty' air and extract particulate matter, leaving the air exiting cleaner. There are three primary factors characterizing the performance of the filter:

- Rated filter efficiency: The ASHRAE 52.2, EN 779, or EN 1822 rating of the filter provides the effectiveness of the filter at removing particles of varying sizes.
- Filter loading: Depth loaded filters hold the particulate matter removed from the incoming air stream. As the filter loads, the pressure differential increases, impacting gas turbine performance. Eventually, the filter must be replaced. The increase in dust loading may also impact filter efficiency; this is dependent on the specifics of the particulate matter concentration and filter design.
- Operating environment: The operating environment in which the gas turbine sits influences the size and concentration of particles entering the filter. This directly influences how quickly the filter loads and the corresponding increase in pressure drop.

The analyst determines if the filter changeout occurs on a fixed schedule (i.e., every 6 months), at the end of the filter life (when it reaches its rated final pressure drop), or whichever occurs first. The analysis in AFLCO contains built-in correlations from an extensive test campaign to calculate filter pressure drop as a function of dust loading. This is described in more detail in the modeling section.

Filter Replacement Costs

The filter replacement cost is driven by the labor cost to replace, the number of filters per stage, and any initial capital cost required to accommodate the filters under consideration.

Water Wash Profile and Costs

Finally, any site considering a change in the filtration options should not do so without also considering potential changes to the water wash profile. Consideration should be given to whether washing is online and/or offline, the effectiveness of either wash type on removing built-up dust from the compressor, and whether the off-line washes are performed on a periodic basis (i.e., 4 times per year or every 2,000 hours) or as needed (i.e., when compressor efficiency degrades more than 2%). Water and detergent costs should also be considered.

ANALYSIS APPROACH AND MODELING

While many calculations are required for an air filter LCCA, refer to Reference 10 for an overview of the economic calculations required. The calculations described therein are focused on engineering calculations that are most likely to be excluded from most LCCA due to the complexity involved.

The general structure of the Air Filter Life Cycle Optimizer (AFLCO) is a time-dependent simulation that, for each timestep, first starts with a quantity or slug of air with an assumed ambient particulate matter concentration. This slug of air is passed through the filtration stages. The filter efficiency is used to remove a calculated amount of particulate which is then used to update the filter dust loading, efficiency, and pressure drop for the next time step. Once through the filtration stages, the cleaner slug of air is passed through the compressor where a deposition model is applied to determine how much of the remaining particulate is deposited on the compressor blading. Next, a performance model is used to relate the compressor dust accumulation to gas turbine performance changes. The performance is then used to estimate the economics for the current time step. Finally, any washes or filter changes are carried out and recorded in the economics or performance modules. A database of gas turbine data is used to estimate the impact of filter pressure drop on gas turbine flow rate, power output and heat rate at full load and part load.

The following sections contain pertinent details of the ambient particulate concentration module, the air filter efficiency prediction calculations, and the compressor deposit and performance model.

Ambient Particulate Matter Concentration

The concentration of particulate matter in the air must first be estimated to start the analysis. If a detailed site measurement is available, this should be used; however, in most cases the particulate loading can be estimated from publicly available data. A two-step process is required. Most air quality monitors aggregate and report the measurements as PM2.5 and PM10. PM10 reports the cumulative concentration of small particles under 10 microns in size, and PM2.5 reports the concentration for particles under 2.5 microns in size. Within the U.S. the Environmental Protection Agency (EPA) tracks PM2.5 and PM10 concentrations across many sites, and uploads that information to a public database [12]. Europe also maintains a similar database [13]. PM data is available at a fairly granular level, including city and county level data.

While these databases are useful for analyzing health impacts, a more detailed concentration profile is required for air filtration. This is because air filtration efficiency is a strong, non-linear function of particle size, as illustrated in Figure 1.

This variation is especially true for particle sizes under 2 microns, which are also the most likely sizes to cause fouling of the compressor [14]. Given the large variation, especially for lower efficiency pre-filters (e.g., MERV 8 / G4), a more detailed distribution of ambient particulate matter is required to estimate the filter dust collection efficiency as a function of particle size.

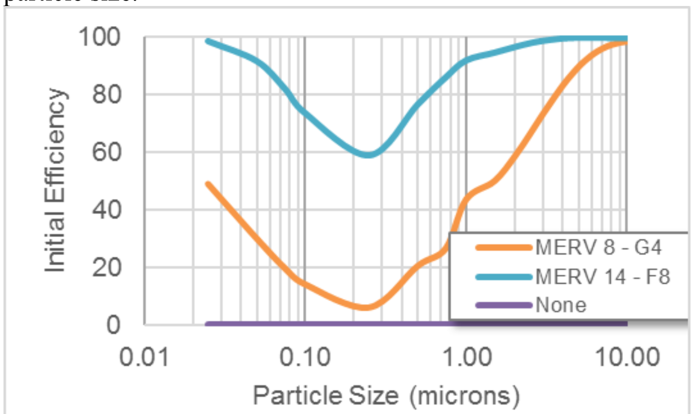

Figure 1: Example of Initial Filter Efficiency vs. Filter Rating

Estimating the fractional filter efficiency is required to predict the dust accumulated within the filter, which impacts pressure drop and life, and to identify the particulate matter concentration entering the next filter stage or compressor. The particles captured and passing through are calculated through the following equation.

$$\eta_{filter} = \frac{w_{captured}}{w_{upstream}} \quad w_{downstream} = w_{upstream}(1 - \eta_{filter})$$

This equation can be applied by multiplying a continuous function of filter efficiency and ambient particulate matter concentration; however, this level of resolution is rarely available. As a result, a binned approach is suggested which uses the filtration efficiency and average particulate concentration for a range of particle sizes. At a minimum, the particle geometric mean diameters for ASHRAE and EN testing standards are proposed as a minimum set of bins, listed in Table 1[15,16].

Table 1: Suggested Binning of Ambient Particle Concentrations

Standard	Geometric Mean Diameter (μm)	Particle Size Range (μm)
ASHRAE	0.35	0.3-0.4
	0.47	0.4-0.55
	0.62	0.55-0.7
	0.84	0.7-1.0
	1.14	1.0-1.3
	1.44	1.3-1.6
	1.88	1.6-2.2
	2.57	2.2-3
	3.46	3.0-4.0
	4.69	4.0-5.5
	6.2	5.5-7.0
	8.37	7.0-10.0

Once the bins are determined, a procedure must be put in place to map the reported PM2.5 and PM10 recorded values from the mentioned databases to the binned concentrations in Table 1. This requires assumed distributions for PM2.5 and PM10.

Filter Efficiency and Pressure Drop Predictions

ASHRAE and EN test standards provide efficiency and pressure drop information for different air flow rates and stages of filter dust loading. Air flow vs. pressure drop (resistance) is typically measured for a new and clean filter. Efficiency as a function of particle size is measured at various stages of dust loading. For each stage of dust loading, the pressure drop is also measured at a nominal flow rate. Six stages of dust loading are measured, one clean, one at end of life, and four in between. If the assumption is made that the change in pressure differential due to an increase or decrease in flow rate is independent of increase in pressure differential due to dust loading, then the following equations can be used to predict filter pressure drop as a function of dust loading and flow rate.

$$dP_{Filter} = dP_{Flow} + dP_{Fouling}$$

Where:

$$dp_{Flow} = f(dP_{initial}, Airflow, Rated\ Airflow, Filter\ Rating)$$
$$dp_{Fouling} = f(DustLoad, Filter\ Rating)$$

The above equations are functions of the filter rating. This is not required, but is suggested if test data is available for a wide variety of filters. For the AFLCO model, a test campaign was conducted and a regression surface using an artificial neural network was used to create the functional relationships from the entire test data set. For this reason, dP_{Flow} is a function of both the current airflow and the rated airflow. This allows normalization across various filter ratings, sizes, and manufacturers to create a general model. In essence, the % rated flow and filter rating are used to estimate the change in pressure drop relative to the rated flow. This change is then added to $dP_{initial}$ to calculate dP_{Flow}.

To estimate $dP_{Fouling}$ another neural network was regressed against the dust loading and filter rating. To standardize data across different filter manufacturers and filter dust capacities, the dust loading was normalized to values between 0 and 5. Zero represents a new and clean filter, five represents one that is fully loaded, and values in between are based on the actual dust loading, calculated in the equation below.

$$DustLoad = \frac{Dust_{TestState}}{Dust_{EndofLif}} * 5$$

The resulting regression allows prediction of $dP_{Fouling}$ from the filter initial rating and current dust load status. A snapshot of this is shown in Figure 2, where changes in the DustLoad and initial MERV will predict the overall impact on pressure drop. This equation can then be used to predict the impact of filter dust loading, and thereby increased pressure drop, on gas turbine power output on a time-series basis.

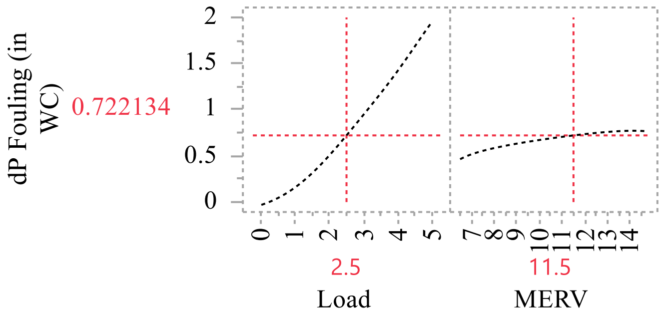

Figure 2: ANN Regression of Filter dP

While generalizing test data to predict pressure drop is straightforward, creating a general filter efficiency regression (such as shown in Figure 1) is more difficult due to the non-linearity of the filter efficiency curve. At a high level, the regression predicts particle removal efficiency as a function of initial filter rating, current dust loading state, and the geometric mean diameter of the particle. To create a stable regression, a binning of particle sizes is necessary, essentially creating a piecewise curve. The functional form is shown below.

$$Size\ Bin = f(ParticleSize) \begin{cases} 0.3\ to\ 1.0 \rightarrow 1 \\ 1.0\ to\ 3.0 \rightarrow 2 \\ 3.0\ to\ 10.0\ \rightarrow 3 \end{cases}$$

$$FilterEff = f(Filter\ Rating, DustLoad, SizeBin, GeometricMeanDiameter)$$

The outcome of this regression is a non-linear response surface capable of predicting filter efficiency for any particle size as the filter loads. An example of this is shown in the following charts: Figure 3 to Figure 5. Each of these plots shows the sensitivity of the point selected in cross hairs to the input parameters. The rightmost plot shows the actual filter efficiency curve. As expected, increasing the initial rating will increase the efficiency at a given diameter. Figure 3 shows the efficiency curve for a new filter with a MERV 8 (G4) rating. As the MERV rating is increased to 10, the filter efficiency will increase, as shown in Figure 4. Finally, as MERV is increased to 15, the efficiency has increased substantially and has also changed shape relative to the MERV 8 filter. This level of granularity allows for more accuracy in estimating the concentration of particles at varying sizes that eventually make it through the filtration stages and into the compressor.

A general model such as this can be applied to any test set of filter data to create a general filter performance model. This can then be reused in a variety of analyses including those with a time-series dependency since filter efficiency and pressure drop are regressed to continuous functions of filter state and flow rate. When combined with the predicted ambient particulate matter concentration, the concentration of dust entering the compressor can be estimated and used to predict the performance impact of fouling.

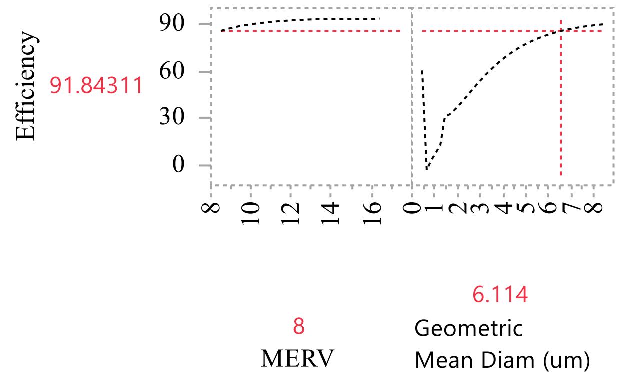

Figure 3: Predicted Filter Efficiency – MERV 8 (G4)

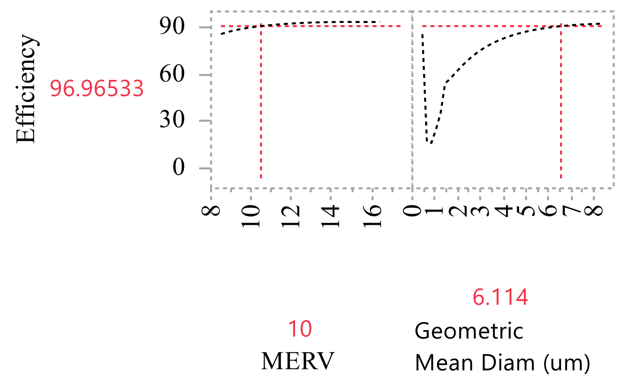

Figure 4: Predicted Filter Efficiency – MERV 10

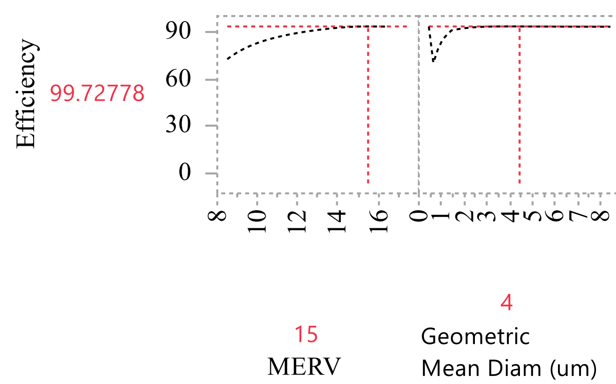

Figure 5: Predicted Filter Efficiency – MERV 15

Compressor Fouling Model

Using the methods above for ambient particulate concentration and filtration efficiency prediction, the amount and concentration of particulate matter entering the compressor can be estimated. The challenge is then predicting (a) how much of the incoming particulate matter is deposited on the blades and (b) how much this impacts performance. A wide range of studies addressed one or the other of these issues, but none addressed both issues in a wholly integrated manner suitable for this level of general analysis. The problem is therefore deconstructed into its two constituent parts using appropriate studies from the literature.

Estimating the deposition of dust within the compressor requires knowledge of the incoming mass concentration vs. particle size, the distribution pattern within the compressor, and the tendency for dust to stick to compressor blading. The incoming concentration can be calculated using the methods described above. The distribution pattern within the compressor and the propensity of dust to be deposited on compressor blading can both be estimated from prior work.

The first parameter to estimate is the fraction of incoming particles that are deposited on the compressor blading. Many technical papers address this, but most require comprehensive information on particle velocity and blade geometry, and tend to be suitable only for CFD simulations [17,18]. For performing an LCCA, a more simplified approach suitable for generalizing to many gas turbines is required. Here the work of Suman et al. is used to estimate the fraction of incoming particles that stick to each stage of the compressor [19]. Suman applies higher fidelity models to estimate particle deposition on blading and stators, but reduces this down to a damage index vs. particle size, shown in Figure 6. The damage index represents the fraction of incoming particles that stick to the suction and pressure side of the compressor blade. A critical aspect of Suman's work is the assumption that the incoming air is first filtered using typical filter levels found in gas turbines; this makes the results directly applicable to the LCCA analysis. The results are further simplified for the current work by assuming a single value for both the pressure side and suction side over a range of particle sizes. A value of 2.0 was selected based on calibration of the model with field results.

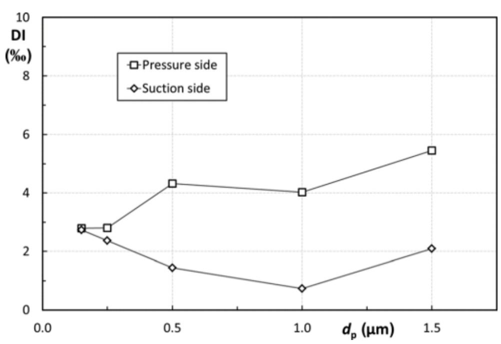

Figure 6: Damage Index vs. Particle Size

Once the deposition rate per blade is known, a distribution amongst stages must also be assumed. Prior work suggests that particulate dust loads proportionally from the first stage up through the sixth stage [20]. For the LCCA, a triangular distribution is assumed, using a fully linear distribution of dust from stage 1 to 6 when fully fouled. It is further assumed that dust first loads the stages equally, then proportionally to the front stages. As the compressor loads, the incoming particulate matter only deposits on the earlier stages until the compressor is fully fouled. Table 2 shows the maximum proportional amount of dust that would be found on a fully fouled compressor.

The incremental loading by compressor stage is modeled mathematically by mapping the loading to a fouling index. Table 3 shows the fraction of dust normalized to a completely fouled compressor vs. stage and fouling index which ranges from 0 (clean) to 6 (fully fouled). The compressor fouling model produces the expected behavior with more rapid fouling and impact on performance initially, followed by a reduced rate of drop in performance over time as the compressor fouls.

To calculate the rate of deposition on each stage, particles larger than 2 microns are assumed to not contribute to fouling of the compressor. Then, the 2% of the incoming particulate matter concentration can be deposited on each stage, unless that stage has reached its respective maximum dust loading, as given in Table 3.

Table 2: Dust Distribution in Fully Fouled Compressor

COMPRESSOR STAGE	MAXIMUM PERCENTAGE DUST
1	29%
2	24%
3	19%
4	14%
5	10%
6	5%

Table 3: Stage Dust Loading vs. Fouling Index

	Stage						
Fouling Index	**1**	**2**	**3**	**4**	**5**	**6**	**Total**
0	0%	0%	0%	0%	0%	0%	0%
1	5%	5%	5%	5%	5%	5%	29%
2	10%	10%	10%	10%	10%	5%	52%
3	14%	14%	14%	14%	10%	5%	71%
4	19%	19%	19%	14%	10%	5%	86%
5	24%	24%	19%	14%	10%	5%	95%
6	29%	24%	19%	14%	10%	5%	100%

Gas Turbine Performance and Compressor Fouling

Using the previously described compressor deposition model, changes to compressor performance can be estimated, and then be correlated to changes in gas turbine flow rate, power output, and heat rate using conventional cycle analysis.

Physically, particulate matter deposited onto the compressor blading changes the aerodynamic shape and increases surface roughness. This leads to reduction in efficiency and mass flow rate. Several studies have examined the impact of dust loading on surface roughness and efficiency, but studies of this level require information about flow velocities and compressor characteristics. A more simplified model is adapted for the filter LCCA. Tarabin describes a model that predicts the change in stage performance as a function of both the fouling degree and the unit size [21]. Smaller units with lower mass flow and units with higher pressure ratio have greater impact on performance due to fouling. Tarabin presents an "index of sensitivity to fouling" (ISF) which can be used to estimate the impact of a fouling increment on stage performance. The equation is shown below:

$$ISF = \frac{\dot{m}\Delta T_{stg}}{(1 - r_h^2)D_c^3} * 10^{-6}$$
$$where\ r_h = Compressor\ Hub\ Radius$$
$$where\ D_c = Compressor\ Diameter$$

$$where\ m = base\ load\ mass\ flow$$
$$where\ \Delta T_{stg} = Temperature\ rise\ per\ stage$$

All of these parameters are known or are easily estimated for common, large frame gas turbines. For simplification, the delta temperature per stage is assumed equal, and each stage has equal polytropic efficiency. This assumption could be easily refined if better data were available. Once ISF is known for a unit, changes in stage performance can be estimated from the ISF and two empirical constants provided in Reference 21. The two equations below are used to estimate the change in the work done by the compressor rotor (k_H) and the increase in pressure loss across the compressor stator within a single stage for a single increment of fouling (k_p).

$$\Delta k_H = mISF$$
$$k_p = 1 + nISF$$

The fouling model presented in Table 3 is used to estimate the fouling index for each stage by multiplying k_H and k_p by the fouling index for that stage. Once stage performance changes are estimated, a stage stacking model is used to modify the performance of each stage by lowering work done per stage or increasing stator pressure loss according to the coefficients calculated above. Morini provides a good discussion on stage stacking models [22]. Trade-off studies from Meher-Homji are used to relate the change in compressor performance to unit mass flow, power output, and heat rate [23].

MODEL SETUP AND CALIBRATION

The AFLCO program contains two main analysis loops. The inner loop calculates the changes in GT performance as the unit operates and accumulates dirt in the filters and the compressor. This analysis is repeatedly performed over fixed duration time steps that are a function of a user-defined filter changeout schedule. There is an outer loop that executes the inner analysis loop, and then collects the unit performance metrics over that time step to translate them into the life cycle cost. For each time step, the compressor performance portion of the tool uses the specified ambient conditions to look up the particle size distribution. The default particle size distributions are estimated using average EPA reported PM10 and PM2.5 emissions. Next, using the flow rate of the compressor calculated from unit type and average load conditions, the amount of dirt that accumulates on the compressor blading is calculated. The previously described empirical correlations are used to estimate the percentage of particles up to 2 microns that are deposited on the blade. Once the mass deposited on the blade is known, the change in compressor performance can be calculated using the described compressor fouling model. The result is an estimated change in compressor efficiency and flow rate which can be used to estimate average heat rate and power output over the time step. The dust mass accumulation over the time step in the compressor and each filter stage is saved as an input to the next time step.

The AFLCO was calibrated to field studies performed by the authors and others, described in References 3 and 4. Calibration was performed by adjusting the particle deposition rate on the compressor and the rate at which the pre-filter efficiency changes due to dust loading. Results are described in the next section.

CASE STUDY EXAMPLES

Two case studies are performed to demonstrate the capabilities provided by an integrated analysis that considers ambient conditions, unit operating type and profiles, and filter and water wash characteristics. The first case study verifies AFLCO trends against a similar systematic study available from the literature. The second case study demonstrates the advantages of using an integrated analysis which considers, in a predictive manner, the direct impact of changing filtration options on compressor performance. Without this coupled analysis, the analyst would be forced to make gross assumptions on filter impact.

Verification of Trends

The combined sub-models were used in a time-varying simulation to estimate the degradation of a compressor over the course of a year. This was compared to trends presented in Reference 3 to see if the model reflects real world experience. The simulated unit was run at full load at 100% service factor to identify the impact of differing filtration options on power output and compressor efficiency degradation over the course of a year. The results are shown in Figure 7 and compare favorably to the results presented in Reference 3. Although it was not possible to account for all parameter variations including ambient conditions and operating unit health, the trends in direction and magnitude provide confidence in the predictive capability of the method presented.

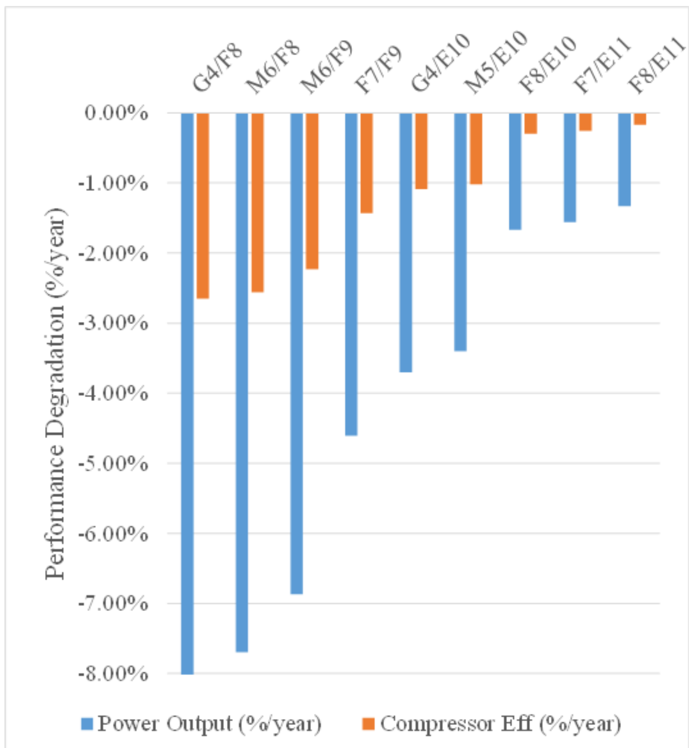

Figure 7: Simulated Performance Degradation

Case Study: Water Wash Schedule and HEPA Filtration

A study was undertaken to demonstrate the value of the predictive algorithms to aid in filter selection while considering associated changes in off-line water wash schedules to optimize for net present value. The integrated EPRI software tool, the Air Filter Life Cycle Optimizer, was used to perform the analyses. A 10-year period was analyzed with major pertinent assumptions listed in Table 4.

Table 4: Major LCCA Case Study Assumptions

Operating Profile		
Service Factor	80	%
Operating Hours per Year	7,008	hours
Percent Time at Full Load	80	%
Percent Time at Part Load	20	%
Average Load at Part Load	60	% of Rated GT Load
Economic Parameters		
Average Electricity Sales Price	40	$/MWh
Average Fuel Cost	$3.00	$/MMBTU
Spark Spread at Full Load (calculated)	$22.73	$/MWh
Inflation/Escalation	2.0	%
Present Value Discount Rate	10.0	%
Unit Information		
GT Type	7FA.05	-
Configuration	2-on-1	
Total Plant output	693	MW

The unit was assumed to operate in the northeastern U.S. in an urban environment, setting the assumed ambient particulate concentration. Three filtration scenarios were initially considered as shown in Table 5. Nominal water and detergent costs were assumed. Downtime to perform off-line water wash was assumed to impact total operating time each year. Initial results of the LCCA are shown in Table 6.

Table 5: Case Study Filtration and Wash Assumptions

	Scenario 1	Scenario 2	Scenario 3
Pre-filter Rating	MERV 8 – G4	MERV 8 – G4	MERV 8 – G4
Final Filter Rating	MERV 14 – F8	MERV 16 – E10	ISO 25 E – E12
Final Filter Cost	$120 Each	$150 Each	$230 Each
Pre-filter changeout	Every 12 months or at End Of Life		
Final Filter Changeout	End Of Life (Based on filter dP)		
Wash Frequency	Offline – Every 3 months. No online wash		

Table 6: LCCA Results - Fixed Wash Schedule

	Scenario 1	Scenario 2	Scenario 3
Power Produced (NPV)	$1.745 B	$1.773 B	$1.775 B
Fuel Costs (NPV)	($1.148 B)	($1.176 B)	($1.179 B)
Water Wash Costs (NPV)	($383,493)	($383,493)	($383,493)
Estimated Downtime Per Offline WW (hours)	12	12	12
Estimated Revenue Loss Per Offline WW	($82,143)	($82,130)	($81,947)
Filter Change, Installa-tion, and Capital Costs (NPV)	($1,360,999)	($1,449,259)	($1,685,336)
Total Val-ue of Net Revenue (NPV)	$595,512,174	$595,328,844	$593,757,390
NPV Per Calendar Year	$59,551,204	$59,532,871	$59,375,726
NPV Per Operating Hour	$8,498	$8,495	$8,473

The results are presented as net present value which accounts for the time varying value of money using the assumed inflation and discount rates. The example shows that upgrading from F8 to E10 filtration somewhat counter-intuitively reduces NPV of the plant. Further upgrades to HEPA filtration in case 3 (E12) reduced NPV due to reduced power output and increased heat rate resulting from increased pressure drop and a slight increase in filter costs. In this scenario, the optimum solution appears to be to maintain lower efficiency F8 filtration. However, the off-line water wash schedule should also be optimized within each scenario. If the machine is washed frequently, there is no advantage to advanced filtration since preventative maintenance is performed through water washes. Using the integrated AFLCO analysis, the study is repeated where the number of washes per year is varied to maximize NPV over the analysis period. In the NPV calculation, it is assumed that power production revenue is reduced by the power that is not produced while the unit is being washed; this assumption can be changed in the software.

The number of scheduled, offline washes per year is varied using the same operating assumptions; the resulting NPV over the 10-year period is shown in Table 7. The number of offline washes that maximize total NPV is shown in bold type.

Table 7: Total NPV - Optimizing Off-line Wash Schedule

Washes Per Year	F8	E10	E12
0	$594,381,677	$595,822,766	**$597,190,330**
1	$596,010,814	**$597,943,484**	$596,317,033
2	**$596,442,529**	$597,063,094	$595,458,158
3	$596,121,846	$596,191,530	$594,606,814
4	$595,512,174	$595,328,844	$593,757,390

Several interesting trends emerge. First, for all three scenarios, the original analysis, which assumed the plant washed 4 times per year, shows that the offline wash frequency was too frequent from an economic perspective. The extra downtime resulting from washing decreases plant profitability from lost generating revenue. The configuration with F8 filtration can be washed twice per year to optimize NPV, upgrading to E10 allows a reduction to one wash per year, and E12 HEPA filtration allows for elimination of frequent washing. Even more striking is that by optimizing the wash schedule, the increase in NPV enabled by upgrading the filters increases to almost $2,500,000. This should emphasize the importance to the reader of considering not only the direct impact of filtration on NPV, but of accounting for the shift in wash schedule on performance of the unit. Conducting such an analysis is extremely difficult without an integrated model that couples cost and performance of the ambient environment, gas turbine, and filtration.

CONCLUSIONS

An economic optimization of inlet air filter selection and water wash schedule requires a comprehensive calculation framework, accounting for all the major costs and performance impacts that affect net revenue of the unit or plant. This paper described an LCCA approach that included modeling ambient air dust concentration and sizing, dust capture and filter performance, compressor fouling, gas turbine and combined cycle performance, and net present value accounting. These concepts were implemented in the AFLCO software tool to assist electric utilities in their selection and optimization of filtration and water wash scheduling.

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