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AN EVALUATION OF THE EFFECT OF AMBIENT CONDITIONS ON THE INTEGRATION OF INLET CONDITIONING SYSTEMS WITH INDUSTRIAL GAS TURBINE ENGINES

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ABSTRACT

All industrial power systems are influenced by ambient parameters, and power plant output fluctuates significantly with changes in ambient conditions such as pressure, temperature, and humidity. The use of an inlet conditioning system is frequently proposed to lower the temperatures at the inlet of an industrial gas turbine engine, particularly in hot and arid regions. To evaluate such a system, a robust design methodology has been developed whereby ambient operating conditions and their impacts can be modeled easily and accurately. Ambient models are developed that are specific to a given locale and consider daily and annual variations in temperature and humidity.

A robust design is one that has a high probability of meeting design goals, and at the same time, is insensitive to operational uncertainty. This paper addresses the possibility of enhancing the robustness of gas turbine engines by means of technology additions. The results of this study have been developed in part using the probabilistic analysis techniques developed at the Aerospace System Design Laboratory at Georgia Tech, and they demonstrate how differing ambient conditions can affect the decision to install an inlet conditioning system with the engine [1]. An industrial gas turbine power plant is modeled, and the ambient models are integrated with the engine model and used to predict the overall impact on power plant net revenue over a year-long period of operation. This is done at four specified locales each with widely different ambient characteristics.

Introduction

The demand for electricity is expected to grow 1.7 percent annually until 2020. This steady rise in demand, along with the prospect of climbing temperature extremes will create a need for increased peaking capacity. Combined-cycle power plants are among the most economical systems used to generate electricity, and consequently they are expected to play a major role in meeting increasing demands. These predictions, along with the large volume of combined cycle sales in recent years, have boosted research and development of performance-enhancing technologies for gas turbine engines.

With the onset of the summer months, cooling usage increases, and the demand for power escalates. At the same time, the warmer air reduces the density of air into the engine causing a reduction in available power output and efficiency. The growing demand and reduced efficiency are expected to increase the peak-to-average load ratio for utilities, thereby creating the need for power-enhancing alternatives that provide additional "peaking" capacity [2] during daytime hours in the summer.

One such power-enhancing alternative is an inlet conditioning system that reduces the temperature of the inlet air flow thereby increasing the mass flow into the engine. This can be

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done with either evaporative cooling, which mixes a water spray with the inlet air, or with a mechanical chiller that cools the inlet air utilizing a refrigerant in a closed loop mechanical heat exchange system that is driven by engine exhaust heat. Throughout the remainder of the year or at nighttime hours when temperatures are lower, the inlet conditioning system will be turned off, consequently inducing a small loss in efficiency of the system.

Given this situation, the performance of the power plant will be highly dependent on operating conditions. Hence, an inlet conditioning system may provide a significant benefit in a warm region, and at the same time degrade performance in a cooler region. As a result, the designer is faced with a situation in which the optimal design is no longer a single formula, but a variety of designs that must be tailored to the individual customer. This type of trade-off is an ever-increasing phenomenon within aerospace and power generation industries, in which system performance is often influenced by changing operating conditions. As a result, there is a need for a method that will provide the designer with the ability to easily assess the impact of operating conditions on technology performance. This method must allow the designer to forecast these operating conditions quickly and accurately, while also accounting for uncertainties. In combining these capabilities with a pre-existing decision-making methodology, the designer can deliver solutions that are tailored to individual customer.

The objective of this paper is to demonstrate how differing ambient conditions can affect the decision to install an inlet conditioning system with the engine. A two-step process is used. The first demonstrates how a probabilistic analysis, which includes ambient effects, can be used to select an optimum for a given technical design of an inlet conditioning system. The second demonstrates how an expanded use of annual ambient data can be used to investigate whether or not to use an inlet conditioning system for a specific locale. An industrial gas turbine power plant is modeled, and ambient models are integrated with the engine model and used to predict the overall impact on power plant power output, heat rate and net revenue over a yearlong period of operation. This is done at each of four specified locales.

In this study, Taguchi concepts are used in conjunction with the probabilistic analysis techniques developed at the Aerospace System Design Laboratory at Georgia Tech. Modifications to these preexisting methods were made to allow the weather model to be integrated into the analysis. Also, the study stems from a grant provided by the General Electric Company, Power Systems Division. The power plant performance and economic data presented are derived from an analysis spread sheet provided by General Electric.

Inlet Conditioning Systems

There are two options for designing an inlet conditioning system. The first mixes water with the inlet air. The water will evaporate and reduce the ambient temperature down to the wet-bulb temperature, or the lowest temperature that can be achieved by saturating the air [3]. There are several techniques that can be used to introduce water into the inlet air: SPRITS, a system commercially available from the General Electric Company, uses an array of water spray nozzles upstream of the engine inlet with the water completely evaporated ahead of the inlet. An alternative way to introduce the water is with an evaporative cooling technique that uses a wetted-honeycomb media to release water as air passes through [4, 5]. Again, the water is introduced well ahead of the engine inlet to allow full evaporation before entering the engine. A third system, SPRINT, also a system commercially available from the General Electric Company, uses spray nozzles to inject finely atomized water just ahead of the engine inlet and between compressor sections. Evaporation takes place ahead of and within the compressor, and this has a favorable intercooling effect on the compressor as well as pre-cooling of the inlet air. These inlet conditioning systems use a relatively simple concept, but their operation is greatly complicated by the fact that the maximum amount of water is dictated by the ambient conditions. If the relative humidity is already high, these systems will not be effective. In addition, if the air becomes oversaturated, the water droplets will coalesce, causing excessive corrosion and/or erosion of the compressor hardware.

A second option for inlet conditioning is the absorption chiller. This is a mechanical refrigeration system, which can utilize engine exhaust heat as the source of energy and a heat exchanger in the engine inlet to chill the inlet air. The absorption cycle uses water as the refrigerant and heat as the energy input to produce chilled water. An advantage of a mechanical chiller is that it is not limited to saturation conditions in the inlet air stream, and the air temperature can be reduced below wet bulb temperatures. A disadvantage of such a system is the increased level of complexity and investment cost. In addition, for combined cycle power plant applications, the use of the engine exhaust heat to drive the chiller reduces the energy available to produce steam for use in the steam turbine.

The intent of this study is to demonstrate how differing ambient conditions can affect the decision to install an inlet conditioning system onto an industrial gas turbine engine. It is not intended to compare the performance of different concepts. Thus, in this study, the effect of ambient conditions on two evaporative cooling schemes - SPRITS and evaporative cooling will be demonstrated. Evaporative cooling will be referred to as Ev_Cool. Power plant performance with either of these two systems is very similar, and for each of these systems there are one or more design parameters to be optimized. For SPRITS, it is the number of spray nozzles in the inlet flow path and the water pressure, and for Ev_Cool it is the thickness of honeycomb media.

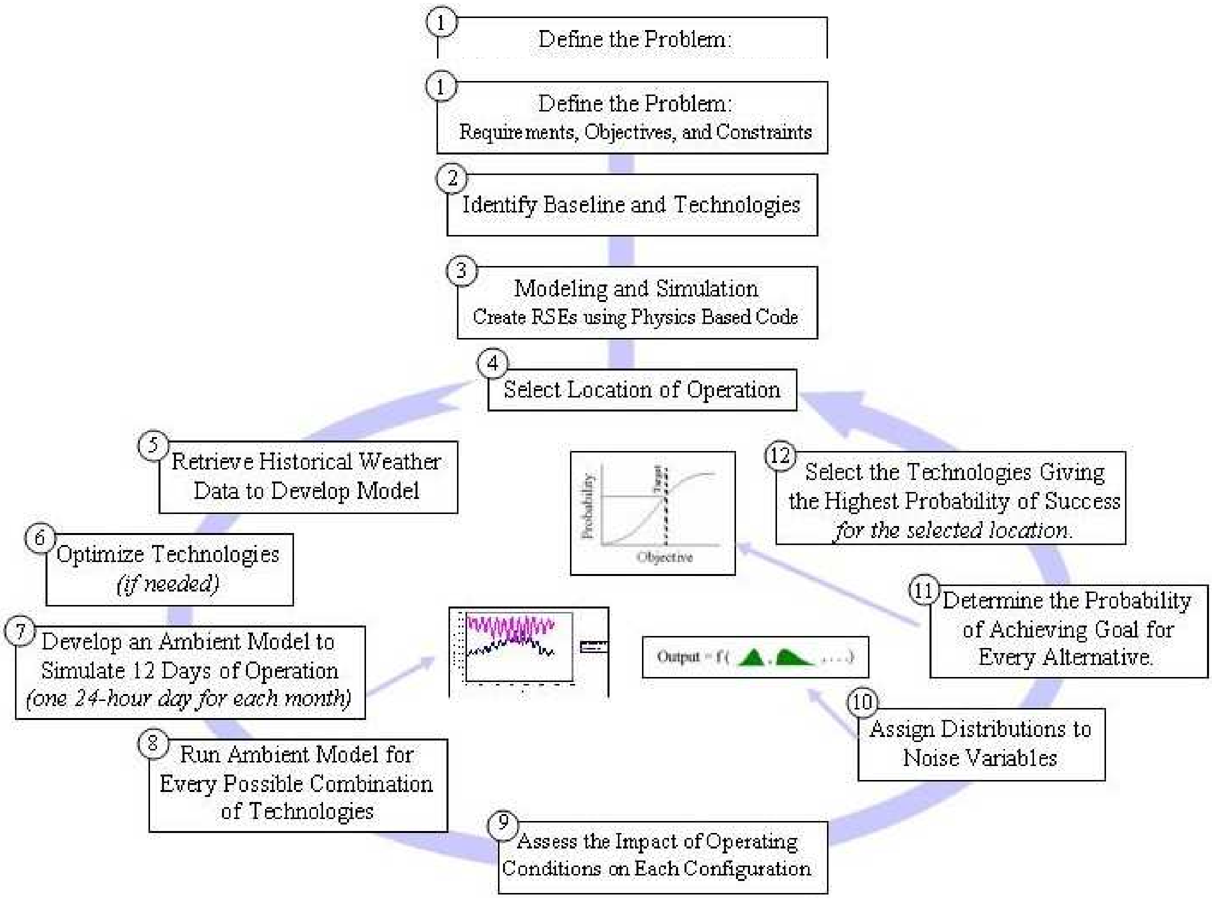

Figure 1. Method for Selecting Technologies in the Presence of Operational Uncertainty

Approach

The goal of the methodology that has been used in this study is to provide a framework where alternatives can be evaluated, and the probability of success of each alternative can be quantified on a case-by-case basis. This method is a multi-level, hierarchical approach that not only allows the evaluator to identify the most promising alternatives; it also allows the designer to adjust technology settings to achieve optimum performance. These attributes allow the method to be used as either a preliminary design tool or a technology selection tool, or both. As a preliminary design tool, the method can be used to model the operating conditions, and then optimize the design of the technology for those forecasted conditions. As a technology selection tool, the method can be used, again, to model the operating conditions, and then to select the technology that will give the customer the greatest probability of achieving a given goal. The proposed method addresses individual customer requirements using the twelve steps depicted in Figure 1.

As one can see from several of the steps defined in Figure 1, the sequence shown is not totally general - several steps are unique to this study - e.g., the selection of a location, the development of historical weather data and the development of an ambient model. However, any study which combines design and operations will require similar steps to be taken, and frequently locale and weather will be primary issues when considering operations. A brief discussion of each step is given along with results in the following section.

Results

A discussion of the methodology is presented in this section along with results. Sub-sections are given for the twelve steps shown in Figure 1.

Step 1: Define the Problem

As in any decision making process, the first step is to formulate the problem by identifying an objective. There are several tools available for formally mapping requirements based on the customer's economic or performance needs. For the example investigation described in this paper, the only objectives are to maximize the power output and net revenue generated by a combined-cycle power plant, so such tools are unnecessary.

Step 2: Identify Baseline and Technologies

With the objectives defined, the next step is to identify the baseline and any technologies that might make a beneficial addition to the baseline. A "technology setting" refers to any physical parameter that may affect technology performance, and for this investigation, the technology settings that are being varied are the nozzle count and water pressure for SPRITS and the thickness of the wetted-honeycomb media for Ev_Cool. These are the technology design variables that can be changed until an optimum setting is found. Table 1 lists the three technologies, their corresponding design variables, and the range over which these settings are varied for this experiment.

Technology	Design Variables	Range of Settings
SPRITS	Nozzle Count (NC)	300 - 600
	Water Pressure (WP)	$5.5*10^6$ - $8.3*10^6$ (N/m^2)
Ev_Cool	Media Thickness (Thck)	0.0635 - 0.1143 (m)

Table 1. List of Design Variables and Setting Ranges

Step 3: Modeling and Simulation

A modeling and simulation environment is needed to assess the impact of the technology design variables. A modeling and simulation tool may consist of any combination of sizing/synthesis codes, physics-based analytical tools, or meta-models. For complex analyses, it may be beneficial to use a Design of Experiments (DoE) to create Response Surface Equations (RSEs) to model the complex system. An RSE is a form of a meta-model of the system performance in which regression equations are developed using data from the DoE that map desired output parameters from specified input parameters. A more detailed description of RSEs and DoEs can be found in the references [7, 8], and the complete process is termed Response Surface Methodology (RSM). In this study, Response Surface Equations (RSEs) were developed for power plant performance and economics, and they are used in place of a complex code.

If the system performance is truly dependent upon the operating conditions, then an adequate model must account for these conditions when computing performance outputs. This is the case in this study, and the following two steps describe the development of an "ambient model."

Step 4: Select Location of Operation

The design space exploration begins with the selection of the location of operation. For this study, an inlet conditioning system will best perform in hot, arid operating conditions in which saturation of inlet air will have the greatest effect on the temperature of the air entering the engine. However, it is equally important to consider operating conditions where the system is likely not to be beneficial - in this case cool and wet operating conditions. Four locales were selected for this study, which give a range of ambient operating conditions - Phoenix, Seattle, New Orleans and Boston.

Step 5: Retrieve Historical Weather Data

Retrieval of data is one of the easiest parts of this method. Once the information is located, the main task is simply compiling the data into a useable form. A wealth of historical weather data is available for a large number of cities in the United States [9]. For this method, historical monthly averages are used to build the weather model. In particular, this reference source provides hourly averages of ambient weather conditions by month. Thus, for every month, the average ambient conditions are given for every hour in the day. Whether the data is only taken from one year, or averaged over several years, the final model will consist of 288 data points, where each data point represents averaged ambient conditions for one hour of a given day. There are 24 data points for this day, and one day is selected for each month giving the total of 288 data points for the model. Ambient temperature and relative humidity have the most significant effects on the system, so these are the only data extracted and compiled.

If these historical weather data are plotted as a function of time, it becomes apparent that temperature and humidity are extremely dependent upon one another. Figure 2 displays a plot of these data for Phoenix, Arizona. In this plot, for the temperature line, each peak essentially represents an average noontime temperature for each month. There are twelve peaks in all, one representing each month of the year so that the first rise and fall represents a typical day in January, the second depicts a typical February day, etc.

Step 6: Optimize Technology Settings

For this investigation, it is assumed that for SPRITS the number of installed spray nozzles can be varied, as well as the water pressure through these nozzles. Likewise, for Ev_Cool, it is assumed that the manufacturer has control over the thickness of the evaporative media. These parameters are termed the "technology settings," and for this particular example, it may not be realistic to assume that the manufacturer can vary these settings for every single product sold. Nonetheless, the situation where the technology settings are treated as variables is simulated for the sake of generality. The next step is to implement a Design of Experiments (DoE) as described in Step 3. The DoE will vary

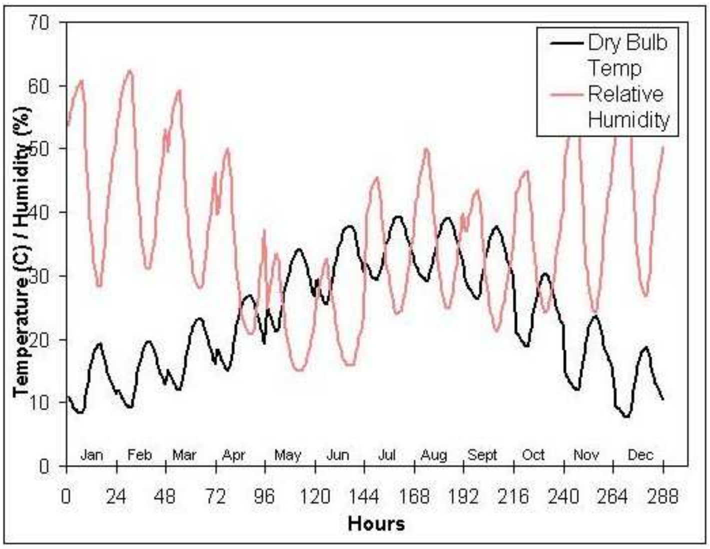

Figure 2. Plot of Annual Fluctuations in Temperature and Humidity in Phoenix, Arizona

the technology settings for the two evaporative cooling concepts, and apply the effect of operating conditions to each run of the DoE. To do this, the user has an option of either applying the ambient model with its 288 data points to each run of the DoE or to fit a distribution to the 288 data points using a program such as Crystal Ball. The latter option was selected for this phase of the study, and the distributions obtained for ambient temperature and relative humidity are shown in Figure 3. Even though the 288 data points that give ambient data for the 12 months of the year have been used, it should be recognized that in using this option any coupling between temperature and humidity, which is demonstrated in Figure 2, is being ignored. This coupling is re-introduced in a following step that computes annual energy production and net revenue.

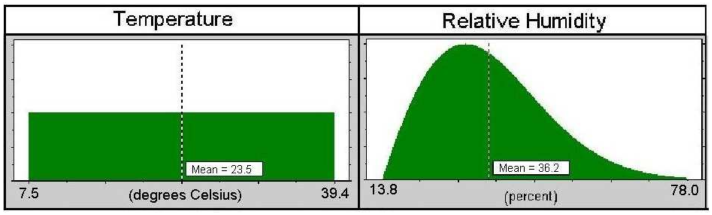

Figure 3. Yearly Distributions in Temperature and Humidity

The DoE used to establish optimum technology settings is given in Table 2. The first run in this table is included to simulate the baseline (no evaporative cooling) performance in the selected location. Also, a '0' or '1' in the table denotes whether a technology is included as part of the system. At the completion of this step the optimum technology settings (number of nozzles and water pressure for SPRITS and media thickness for Ev_Cool) are established. However, it is possible that these optimum settings will differ depending on the output result in question, e.g., for SPRITS, the optimum number of water nozzles to maximize power may be different than the optimum number of water nozzles to maximize revenue.

Run	SPRITS	NC	WP (N/m^2)	Ev_Cool	Thck (m)
1	0	NA	NA	0	NA
2	1	600	$8.27*10^6$	0	NA
3	1	600	$6.89*10^6$	0	NA
4	1	600	$5.52*10^6$	0	NA
5	1	450	$8.27*10^6$	0	NA
6	1	450	$6.89*10^6$	0	NA
7	1	450	$5.52*10^6$	0	NA
8	1	300	$8.27*10^6$	0	NA
9	1	300	$6.89*10^6$	0	NA
10	1	300	$5.52*10^6$	0	NA
11	0	NA	NA	1	0.114
12	0	NA	NA	1	0.0762
13	0	NA	NA	1	0.0635

Table 2. Yearly Distributions in Temperature and Humidity

The analysis used here is a Taguchi-type parameter design of experiments [6] consisting of two parts: 1) a design parameter matrix and 2) a noise matrix. The design parameter matrix specifies the test settings of the design parameters, and is given in Table 3. A noise matrix consists of factors that the designer cannot control. There two noise factors being considered here are temperature and relative humidity, the behavior of which is represented by the distributions in Figure 3. The complete experiment consists of a combination of the design parameter matrix and this noise matrix. Each test run of the design parameter matrix (Table 2) is crossed with multiple random values selected from the distributions for the noise variables. The analysis is applied using Crystal Ball, and the output is a series of Cumulative Distribution Functions (CDFs). Each CDF represents the distribution of results obtained by applying the temperature and humidity distributions to one run of the DoE. On each CDF, the response is plotted on the horizontal axis, and the vertical axis gives the probability of achieving a certain response. An example CDF is shown in Figure 4, which displays results from the fourth trial run of the DoE.

Mean values from the CDFs of output power for both simple cycle and combined cycle power plants are shown in Table 4. In essence, the CDF plots give the predicted variation in performance of each configuration of the complete year, and if power output was recorded an arbitrary number of times each day for an entire year, the average of the data would be close to the value given in Table 4.

Also shown are the corresponding values of the computed cost of electricity (COE). The elements that combine to give COE are fuel cost, depreciation cost and maintenance cost. In addition, the annual number of operating hours must be known because COE is expressed in /kWh. In the GE spread-sheet, the price for the complete plant, either simple cycle or combined cycle is a fixed value, fuel price is fixed, and the number of annual operating hours is fixed. Maintenance costs are not included as part of the spreadsheet analysis tool that was provided to the authors. It is understood that the technologies will most likely affect maintenance costs, but those effects have yet to be determined, so maintenance costs must be ignored for this study. The only thing that will vary the COE in this analysis is the fuel flow rate, which is computed from the power output and the heat rate. Since only relative values are meaningful in this study, this level of analysis is acceptable. In a later step in the study, variability of fuel price and number of operating hours will be introduced as noise variables. In addition the value of power will also be introduced as a noise variable so that net revenue can be computed. However, at this point, there is no sense in tracking net revenue, because the noise variables have not yet been accounted for. Thus, if there were no uncertainties, the maximum power output would equate to maximum net revenue, so there is no need to track both outputs for this step.

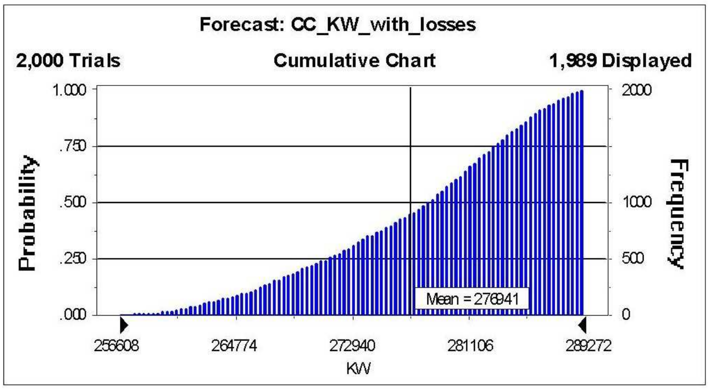

Figure 4. Example CDF of Trial 4 from the DoE

From Table 4, it is evident that the SPRITS optimum settings for nozzle count and water pressure to maximize power output are given by the 4th run, which represents the maximum possible nozzle count, and minimum water pressure. The optimum media thickness setting for the Ev_Cool is given by the 11th run, which represents the maximum possible value for the media thickness. These optimum settings are highlighted in Table 4, and the design variable settings for these optimums are given in Table 5.

Technology	Optimized Design Variable Settings
SPRITS	NC = 600 & WP = $5.52*10^6$ N/m^2
Ev_Cool	Thck = 0.1143 m

Table 4. Optimized Design Variable Settings

It is also evident from the data in Table 4 that inlet evaporative cooling will provide a significant benefit in power output and a modest reduction in COE. These settings, however, only reflect the optimum settings for the operating conditions that were modeled for Phoenix, Arizona. It is possible that the optimum settings will be different for a different region.

After the technology design settings have been optimized, the list of possible configurations can be reduced to include the optimum settings, and a new DoE is developed as shown in Table 5. This DoE include runs 1, 4 and 11 from the original DoE to preserve the baseline (no evaporative cooling) and the optimum settings that have been determined for SPRITS and Ev_Cool, respectively.

Step 7: Develop an Ambient Model to Simulate Twelve Typical Days of Operation

Now that optimum values have been established for the technology settings a new model is developed that will correctly couple the interaction between ambient temperature and relative humidity that has been demonstrated in Figure 2. This is a critical step because if temperature and humidity are treated as noise variables, as they were in Step 6, then any interactions between the two would be neglected, and impossible combinations of the two would be incorporated into the analysis.

The 288 data points defined in Step 5, which represent daily and annual variations in ambient temperature and relative humidity in Phoenix, are used to form the DoE. A simple script is needed to execute it for the three configurations given in Table 5. It is generally recommended that RSEs be used to approximate the results if the analysis code is complex. For this example, however, a simple Visual Basic script was written to allow the full analysis to be executed within the General Electric spread sheet.

Run	Simple Cycle Output with Losses (kW)	Combined Cycle Output with Losses (kW)	Simple Cycle Cost of Electricity (cents/kWh)	Combined-Cycle Cost of Electricity (cents/kWh)
1	167276	264465	4.24	3.21
2	176971	276756	4.16	3.17
3	176986	276850	4.16	3.17
4	177138	276941	4.16	3.17
5	176429	276153	4.17	3.17
6	176572	276252	4.17	3.17
7	176614	276267	4.17	3.17
8	175669	275233	4.14	3.17
9	175750	275333	4.17	3.17
10	175964	275427	4.17	3.17
11	176052	275907	4.18	3.18
12	175489	274976	4.18	3.18

Table 3. Mean Outputs Obtained from Taguchi Analysis

Step 8: Run Ambient Model for Every Combination of Compatible Technologies

A Taguchi analysis is again used to assess the impact of the operating conditions. Only this time, the inner array is the new, smaller DoE given in Table 5, and the outer array is the 288-run ambient model instead of the uncoupled distributions of temperature and relative humidity given in Figure 3. At this point, both power output and net revenue are determined. These outputs are recorded for every run in the DoE, giving 288 values for power output and net revenue for each configuration given in Table 5. To compute net revenue, a constant value of power of 4/KWhr is assumed along with the computed value of COE as described in Step 6. These values of power and net revenue will be used in Step 9 when increments in power and net revenue between the baseline and the baseline plus inlet conditioning technology will be computed.

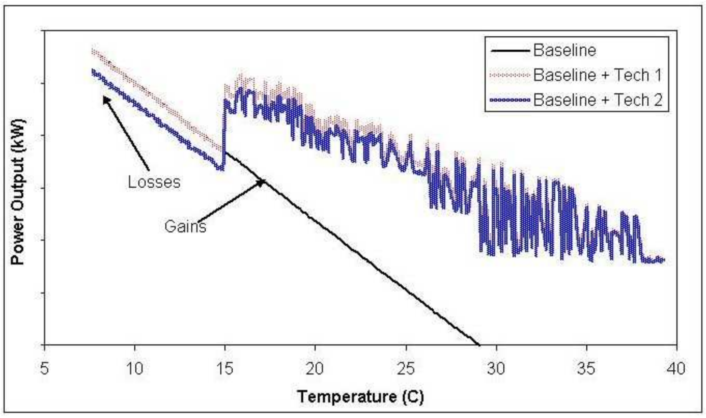

Figure 5. Power Plant Output for a Range of Temperature and Humidity Values in Phoenix, AZ

Configuration	SPRITS	NC	WP	Evap. Cooler	Thck	Original DoE Run #
1	0	NA	NA	0	NA	1
2	1	600	$5.52*10^6$	0	NA	4
3	0	NA	NA	1	4.5	11

Table 5. Optimized Design Variable Settings

Power output from each of the 288 runs is plotted against temperature in Figure 5. It is the humidity that causes the data to fluctuate when the inlet conditioning technologies are employed, implying that performance is influenced by humidity, as expected. The smooth line for the baseline indicates that the baseline output, which has no evaporative cooling, is not sensitive to changes in humidity. For those configurations with evaporative cooling, either SPRITS or Ev_Cool, any data points that occupy the space above the baseline curve (black line) represent gains. For SPRITS and Ev_Cool, a step in power output occurs at 59 degrees, when the technology is turned on. Below that temperature the evaporative coolers are turned off causing a small loss in efficiency due to the added pressure drop in the inlet. The extent of the losses and/or gains will be dictated by the amount of time that the system spends operating under or over 59 degrees. The cut-off temperature of 59 degrees is arbitrary, and it appears from these results that either SPRITS or Ev_Cool should be left on until the power output drops to the level of the baseline. For this case, which represents Phoenix, this occurs at an ambient temperature of approximately 48F.

Run	Response from Baseline Configuration	Response from Configuration with Additional Technology	Percent Difference Between Baseline and Configuration with Additional Technology
1	9360.2	9921.8	+6%
2	8992.6	9981.8	+11%
3	9147.3	8964.4	-2%
:	:	:	:
:	:	:	:
288	9487.9	10341.8	+9%

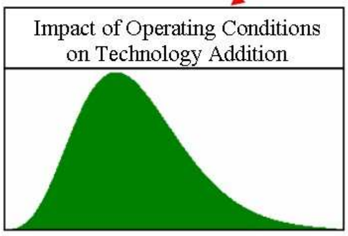

Figure 6. Method for Finding Technology Impact Distributions Due to Operational Uncertainty

Step 9: Assess the Impact of Operating Conditions on Each Configuration

Taking the percent difference between the hourly output for the baseline and the baseline plus the evaporative inlet cooling technology will give an approximation for the technology impacts. These impacts are simply estimates of the effects that a technology will have on a certain output. For this problem, this impact is quantified as a percent increase or decrease from the baseline output. However, each of these technology impacts applies only to the ambient operating conditions for which it was found. Unlike most technology selection methods that assume that only the technology has a direct impact on the output, this method accounts for the direct impact of operating conditions on the technology performance. In other words, the actual impact of a technology is determined by the ambient conditions in which it is operating.

There will be 288 of these percent differences to describe the overall impact each technology. In other words, values for power output and net revenue have been obtained for every hour in the 12-day model for all three configurations. The overall impact of the operating conditions on the technology may then be modeled by fitting a distribution to the 288 differences. These distributions capture the variations of the technology impacts as they fluctuate with operating conditions. Figure 6 outlines the procedure used to generate a distribution on a technology impact for an arbitrary response, such as power output or net revenue. Net revenue is being computed at each of the 288 runs, and since net revenue is an integrated parameter over the 288 runs, this percent impact represents the annual impact a technology will have on the net revenue. These technology impacts are essentially noise variables, because there is a certain level of uncertainty associated with weather trends, as well as new technologies and the analyses used to model them. Even the most complex code can not precisely predict how these new technologies will affect downtime, part corrosion, and therefore revenue. Therefore, these technology impact distributions account for the fact that technology impacts are a function of operating conditions, with an associated uncertainty.

The resulting technology impact distributions are given in Figure 7. From these results alone, one can make a general comparison of the relative performance of the technologies. However, these results do not give the complete picture, because net revenue, which is dependent on some additional noise variables, has not yet been calculated.

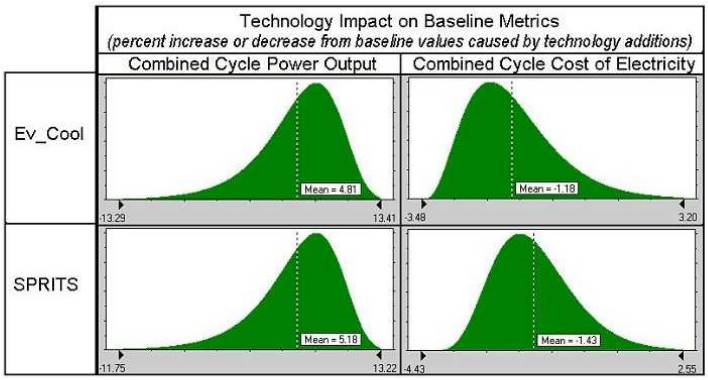

Figure 7. Actual Distributions of Percent Differences Caused by Technology Impacts

Step 10: Assign Distributions to Noise Variables

Some additional noise variables that affect the outputs of power and net revenue are the value of energy, fuel cost, hours of operation, and maintenance costs. These parameters all have an associated uncertainty, and they are introduced into the analysis to make it more robust.

It is likely that, based on historical data, the designer has a good estimate for each of these values, and these historical data may be used to fit a distribution to variables such as fuel cost and the base value of energy.

The assigned distribution for hours of operation, value of energy and fuel cost are shown in Figure 8. Judgment was used in selecting the ranges and type of distribution for value of energy, fuel cost and annual hours of operation. The uncertainty related to maintenance effects is assumed to be accounted for with assumed distribution of operating hours. It is presumed that an experienced designer would have both experience and data to support the estimate of these parameters and their distributions. The distributions that were generated in Step 9 for increments in power output and net revenue are also included among the noise variables since there is some uncertainty associated with the technology impacts. It is important to remember that these power and net revenue distributions represent the effect of the coupled variations in ambient temperature and relative humidity both daily and annually.

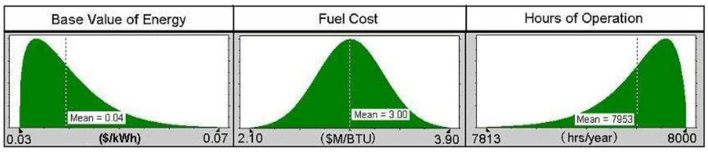

Figure 8. Uncertainty Distributions Assigned to Noise Variables

Step 11a: Determine the Probability of Achieving the Goal for Every Alternative

To complete the probability analysis, a Taguchi analysis is used to apply the noise distributions from Step 10 to the reduced DoE from Step 6, and again, the end result is a collection of CDFs. These CDFs are the culmination of thousands of random trials where the values of each of the noise variables are randomly selected from the uncertainty distributions from Step 10. The output values are extracted from each of these trials, giving a histogram where the vertical axis is the frequency of occurrence, and the horizontal axis is the range of values of the selected output. If this histogram is converted to a CDF, the vertical axis will give the probability of achieving a specified value for the output. An example showing the CDFs for power output is shown in Figure 9 for the Baseline, the Baseline + SPRITS and the Baseline + Ev_Cool.

To re-iterate the steps that have been taken to reach this point, which is the end of the probability analysis, include the following steps:

1. In Step 6, the 288 point ambient model was run to produce a distribution of ambient temperature and relative humidity. These distributions were applied independently (and thus temperature and humidity are not coupled) to a DoE that included the Baseline, several combinations of design parameters for the Baseline + SPRITS and several combinations of design parameters for the Baseline + Ev_Cool (Table 2). This DoE was evaluated, and the results were to establish technical designs for the use of SPRITS and Ev_Cool that maximize power output. From this result, a single design was established for each of these two inlet conditioning options. These designs were combined with the Baseline to create a reduced DoE (Table 5).
2. The reduced DoE is then coupled with the ambient model that includes the 288 ambient data points as outlined in Steps 7, 8 and 9. The results are distributions of increments in power output and net revenue. These increments are the difference between the Baseline and the Baseline plus the inlet conditioning technology. The coupled effect of ambient temperature and relative humidity are included in this step.
3. The reduced DoE is now run by itself, but with distributions applied for the noise parameters of value of energy, fuel cost and annual hours are operation. In addition the distributions of incremental power output and net revenue from Step 9 are applied. The result is a mean value for power output and a mean value for net revenue. Annual net revenue is computed as the product of the net revenue mean value and the value of annual hours of operation.

The final result of this process for Phoenix is given in Table 6. First compare the mean power output with that given in Table 4, which are results from Step 6 (runs 1, 4 and 11 of Table 4). The final result gives only a slight reduction in power output. The more important result from Table 6 is annual net revenue, and the advantage of using an inlet conditioning system is clearly shown. The SPRITS system shows a slight advantage over Ev_Cool.

The procedures outlined above account for all the design variables and noise variables in the system, and they follow the accepted practice of applying probabilistic analyses. However, the three step procedure outlined above is not typical. The goal was to find a way to introduce the variability in daily and annual ambient conditions while preserving the coupling between ambient temperature and relative humidity.

Another way to preserve this coupling is to continue to run the ambient model even after all noise variables have been introduced. This model requires 288 runs, and it could be prohibitive

Mean Output	Simple Cycle Power Output [kW]	Combined Cycle Power Output [kW]	Simple Cycle Annual Revenue [$M]	Combined Cycle Annual Revenue [$M]
Baseline	167833	264118	-4.2119	14.8777
Baseline + SPRITS	176912	276927	-3.5283	16.3145
Baseline + Ev_Cool	175903	275605	-3.6448	16.097

Table 6. Forecasted Outputs for Phoenix, Arizona

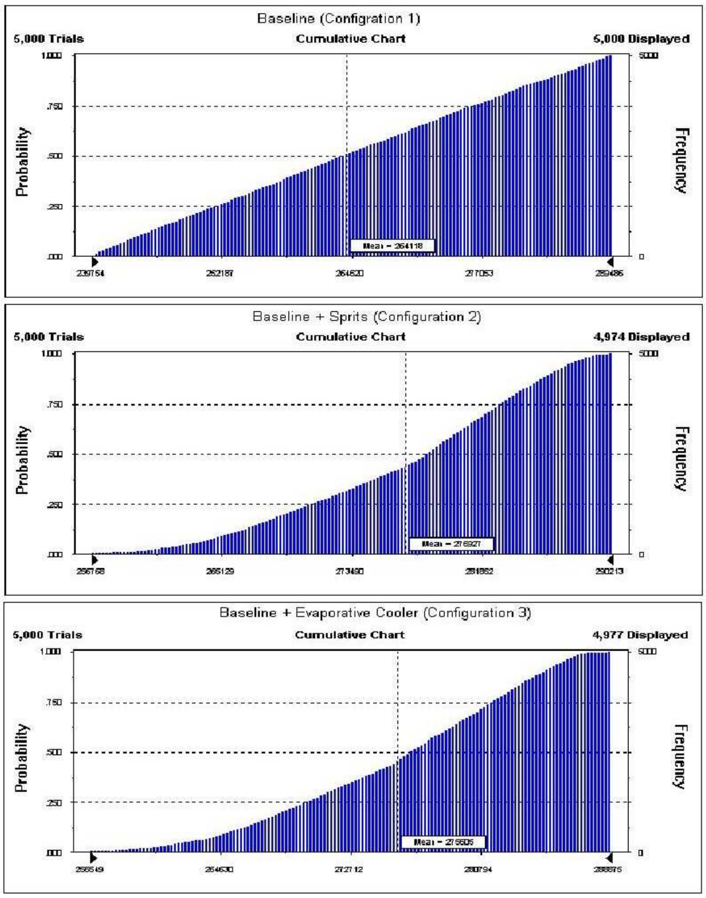

Figure 9. CDFs for Output Power Derived from Step 11a

if the analysis code being used was extensive and required a lot of computer time. For this study, this is not the case, and an alternative, essentially non-probabilistic procedure is outlined in Step 11b below.

Step 11b: Determine the Probability of Achieving the Goal for Every Alternative

Rather than extracting CDFs, it may be more logical to determine annual totals for energy output and net revenue, rather than mean values. This can be done by converting the hourly values (obtained using the 288 runs from the model) to daily values, then monthly values, and finally, yearly values. To do this, each 24-run set (used to represent one month) may be summed to find the average daily output for the corresponding month. Each daily value should then be multiplied by the number of days in the corresponding month to give the monthly value for the output. Then, all twelve monthly values should be summed to find the yearly values for the outputs. This method of computing annual energy and net revenue is preferred if the evaluator would like to have more control over uncertainty variables. For example, it has been indicated that the base value of energy is affected by demand, and it is commonplace for power providers to vary the price of energy depending on the hour of the day and the season [4]. If the model is executed using these values, then the assumed distribution for the base value of energy need not be applied. By coupling uncertainty variables in this way, the evaluator can reduce some of the uncertainty in the final design.

The results from this method are given in Table 7. Note that the difference between 'GT OutPut' and 'SC OutPut' is that 'GT OutPut' does not account for the auxiliary losses in Simple Cycle energy output due to the presence of the technologies, and 'SC OutPut' does. Also, the annual cost of electricity (COE) for a simple cycle (SC COE), and for a combined cycle (CC COE) were obtained by multiplying the output at each data point by the corresponding cost of electricity (not the value of energy) and then summed to find the annual values as previously described. None of the noise variables outlined above were applied at this point. The following constant parameters are assumed: value of energy – 4/kWh, cost of fuel – $3/MBtu, annual hours of operation - 8000. However, it is planned to introduce variability and probability of these parameters into future studies. As described above, it is straight forward to apply a variable energy value along with the 288 run ambient model and to a apply distribution to fuel cost. More research is required to intelligently apply a probabilistic model of maintenance requirements to account for variability in annual hours of operation. It is interesting to compare values for annual net revenue between Table 7 and Table 6. The rankings remain the same for the three alternatives, but the annual revenues are higher in Table 7. This reflects the use of a constant value for annual utilization (8000 hours) rather than using the distribution of utilization given in Figure 8. From this comparison, one can get a feel for the impact of forced outages might have on the economic viability of the power plant.

Configuration	GT OutPut	SC OutPut	CC OutPut	SC COE	CC COE	SC Rev	CC Rev
	KW-hr/year	KW-hr/year	KW-hr/year	$M/year	$M/year	$M/year	$M/year
No Inlet Cond.	1337824545	1337824545	2115305557	56.652	67.902	-3.139	16.710
Baseline+SPRITS	1424505949	1424320032	2223248974	59.133	70.383	-2.160	18.547
Baseline+Ev_Cool	1416227035	1416227035	2215242518	59.052	70.302	-2.402	18.308

Table 7. Annual Output Values for Phoenix

Step 12: Select the Technologies with the Highest Probability of Success

Whether the full probabilistic method (Step 11a) or the method that integrates energy and net revenue over the full year (Step 11b) is used, the advantage of an inlet conditioning system integrated with either a simple cycle or a combined cycle power plant in Phoenix is clear. Note from Table 7 that the annual revenue for the simple cycle power plant is negative. This is to be expected since the assumed value of power is 4/kWh and the COE for the simple cycle power plant is 4.24/kWh (see Table 4). Although the SPRITS system gives slightly improved results over Ev_Cool, the differences is energy production and net revenue is slight.

Additional Results

Though it is intuitive that temperature and humidity will have a significant effect on these example systems, it is still possible that there exists one optimal solution that should be employed for all operating conditions. Even so, this method can still be used to forecast the outputs that each customer can expect for the given operating conditions. Whatever the case may be, this methodology is applied to the same problem for drastically different operating conditions. The previous example demonstrated that the technologies are, in fact beneficial in a region with hot and arid operating conditions. Intuitively, it is evident that technology performance will be degraded in a cooler, more humid region, such as Seattle, Washington. The extent of the impact of operating conditions on technology performance is demonstrated by executing the method for some alternate locations. In addition to Phoenix (hot and arid), Seattle, New Orleans, and Boston were chosen as locations representative of a cool and humid locale, a hot and humid locale, and a moderate locale, respectively.

Table 8 gives a comparison of the results for combined cycle power output and annual revenue from each of the four selected locations. The results shown in this table reflect those found using part (a) of step 11. In Table 8, Phoenix, the driest and hottest city is to the left, and the other cities are ordered by decreasing temperature and/or increasing humidity. From this table, it is evident that as temperatures fall, and humidity levels rise, the inlet conditioning technologies impart smaller and smaller benefits to the baseline design. At the same time, the baseline performance is better in the cooler, more humid regions, which may even make the technology additions unnecessary in the first place. One must also consider the unwanted byproducts of technology additions, such as increased maintenance and downtime. If the potential benefits do not outweigh the potential drawbacks, then the technology additions can not be justified and one should not opt to implement those technologies. This appears to be the case for New Orleans, Boston, and Phoenix, for which the technologies give only small improvements over the baseline.

Mean Output	Phoenix	New Orleans	Boston	Seattle
	Combined Cycle Power Output [kW]			
Baseline	264118	268661	268956	273890
Baseline + SPRITS	276927	268714	268980	273904
Baseline + Ev_Cool	275605	268715	268974	273883
	Combined Cycle Annual Revenue [$M]			
Baseline	14.8777	15.497	15.623	16.231
Baseline + SPRITS	16.3145	15.508	15.629	16.233
Baseline + Ev_Cool	16.097	15.506	15.626	16.230

Table 8. Comparison of Results from Several Locations

Conclusions

This paper presented a systematic approach for identifying and modeling coupled operational uncertainties, and forecasting those effects on system performance. Two objectives are stated in the Introduction. The first was to be able to select an optimum for a given technical design for an inlet conditioning system, e.g., determine an optimum for the number of flow nozzles and water pressure for the SPRITS system. The second objective was to demonstrate how annual ambient data can be used to determine whether or not to install an inlet conditioning system for a specific locale.

For the first objective, this study illustrates a procedure using probabilistic methods that integrates annual ambient variations into the analysis. For the SPRITS system, an optimum was found for the number of spray nozzles and the water pressure, and for the Ev_Cool system an optimum was found for the media thickness. But in reality, these are rather weak examples of the procedure because there was little variation in results as the design parameters were varied. Nonetheless, the process does work, and for more significant problems where output parameter variability is greater, the definition of an optimum design would be more meaningful.

Once optimum designs were established, an expanded use of ambient data, which coupled the effects of ambient temperature and humidity on an hourly and annual basis, was successfully used to demonstrate the effectiveness of using an inlet conditioning system in a combined cycle power plant for specific locales. A critical step taken to meet this objective was to establish a method for defining ambient temperature and humidity for a specific locale. These two parameters are highly coupled, and it is important to preserve this coupling in the analysis procedure. This was achieved, and as a result much of the uncertainty related to power plant operation with varying ambient conditions is removed.

Four locales were investigated - Phoenix, Seattle, Boston and New Orleans, and it was determined that only in Phoenix does an inlet conditioning system show a clear advantage. In the other three locales, high humidity exists, and in the case of Seattle there are consistently moderate temperatures. The result is that inlet conditioning systems show little or no advantage in terms of mean power output, annual energy production or annual net revenue. However, this conclusion must be must be qualified somewhat. With the advent of deregulation, the value of energy has become very volatile, particularly in hot summer months when the demand is highest. High ambient temperature is also a condition that favors inlet conditioning so long as humidity is also not high. In this study, a relatively narrow distribution in the value of energy was used in one procedure and kept constant in a second procedure. It is possible that an inlet conditioning system would prove to be more of an advantage if a broader range of the value of energy was applied to the analysis. It is the intention to continue this research, and to have energy models that include realistic variations in demand and value of power for specific locales.

To summarize, this research is focused on enhancing existing methods to capture the effects of operational uncertainty, specifically, the trends in ambient weather conditions. This paper illustrates how to model these coupled ambient trends, and how to integrate this model with other tools in order to optimize design settings, select promising technologies and/or forecast system performance at a given locale. In a more general sense, the method enables a consideration of coupled noise variables. The results demonstrate the need for a more accurate depiction of operating conditions early in the design, and increased flexibility in the final design of systems that operate in volatile markets.

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