REAL-TIME OPTIMAL OPERATION DECISIONS FOR GAS TURBINES

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Abstract: The Optimizer[1] proposed in this paper addresses the problem of running a gas turbine optimally to maximize the operational profit of a power utility subject to fluctuating energy prices and changing operating conditions. The proposed optimization scheme determines the optimal load profile of a gas turbine that maximizes the operational profit generated from sale of electricity subject to fuel cost, gas turbine parts cost and other fixed costs while satisfying operational and environmental constraints. The natural formulation of this problem is both nonlinear and non-convex, which causes any real-time optimization application impossible. However, real-time optimization is key to the success of model based optimization technology, since real-time model updates either by sensor information or by user input, ensure optimization of the power plant under current plant and market conditions. To ensure real-time optimization feasibility, the non-convex problem is suitably transformed into a convex optimization problem and real time updates of input data profile of electricity price and fuel price forecasts are used

Keywords: power generation, real-time optimization, simple cycle, combined cycle, linear programming

1 . INTRODUCTION

Competition in the electricity generation market drives the operation of power utility companies to absorb fluctuations in electricity prices and fuel cost. As in any kind of optimization, optimal operation of gas turbines depends on the objective under consideration. Although there are a large number of operational degrees of freedom for profit maximization of complex power generation plants, maintenance costs and availability are two important constraints to be considered for the gas turbine owner. For this reason, a great deal of attention is being focused on understanding the various operational modes of gas turbines and their maintenance requirements. Gas turbine parts-life models have been developed by manufacturers for maintenance scheduling and operational suggestions. While these models are mostly empirical and nonlinear, they are based on laws of physics and provide operational guidelines. In such models, major factors that affect maintenance intervals and equipment life have been determined to be firing temperature, fuel type, and steam/water injection for power augmentation. For example, if firing temperature higher than the base load operation temperature is used for the operation of a gas turbine, higher power output levels are achieved, however, at the expense of the life of the equipment.

In order to understand the underlying concepts and the main hurdles encountered in this optimization problem, a specific optimization problem, similar to the general class of power system optimization problems, is considered: Given that a gas turbine has one-year parts life remaining, and that it can be taken off-line for maintenance either at the end of two months or at the end of two years—depending on the way the gas turbine is operated with base load or peak load or part loading—where does the optimum trade-off between equipment life and power production lie for generating maximum profit? Profit is obtained through the sale of electricity minus operating costs of fuel and consumption of parts life. At the end of a maintenance interval, turbine parts as well as fuel, maintenance, and other costs during the period in question. The essential point for the formulation of the optimization problem is that a meaningful optimum for such a trade-off can only be

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found by considering the operation profile for future periods (a future horizon of months, years, etc.).
In order to maximize the profit obtained until the maintenance time, it is necessary to evaluate not only the effect of today's peak-load profile on gas turbine maintenance and revenue obtained from sales, but also the effect of future load profiles on these variables. This choice of future horizon for finding a real optimum creates a dilemma for the solution of the problem. As longer horizons are chosen for the optimization solution, better optimal solutions will be found; however increasing the horizon increases the computational burden of the optimization. Note that, when a decision is made on the load profile (e.g., for 1 year), a decision also needs to be made about how often the load levels can be changed. If decisions are to be made every 6 hours, then the number of decisions (independent variables) necessary is 1 year divided into 6-hour intervals. As the horizon in consideration increases, the number of independent variables in the optimization increases. In the previous example, the independent variables would be the gas turbine load profile in each period under consideration, that is, the number of hourly load profile decisions in 1 year or 2 years, etc. As in many non-linear optimization problems, finding the optimal load profile for a future time horizon is not the only challenge for an optimizer. The models (performance, cycle, parts life) provide non-linear relations between the independent variables and dependent variables. The operational constraints such as emission constraints are also nonlinear functions of independent variables. This poses a nonlinear non-convex optimization problem. That means that generally the solution of the problem will provide local optima, not a global optimum, which may not be the best answer for the problem.

For solving such an optimization problem for real time application in a power generation plant, the following three main milestones were set and achieved.

1. Use of parts-life models already developed or under development, as well as gas turbine thermodynamics (cycle-deck) and performance models, to formulate the trade-off between equipment life and power production in a modular way.
2. Development of an innovative algorithm to solve the formulated optimization problem with respect to firing temperature (load profile) decisions in near real time for the real-time application.
3. Analysis and demonstration of the robustness of the proposed Supervisory/Optimizing Control Scheme to uncertainties.

The first milestone provided modular formulation of the simulation environment. All challenges posed by the nonlinear and non-convex nature of the problem were overcome by the development of an innovative algorithm that changed the structure of the problem into a convex problem. Once the original problem has been translated into a linear optimization problem, the novel algorithm computation time increases but only linearly with an increase in the number of independent variables, increments in the length of the horizon and for increments in the number of periods considered in the horizon. Increasing the horizon from 1 year with 6-hour decision intervals to 2 years with 6-hour intervals doubles the number of decision variables. Keeping the horizon at 1 year but reducing the decision interval from 6 hours to 3 hours also doubles the number of decision variables. However, by the merit of the new formulation, the computation time for optimization will increase only linearly in both these cases. With the third milestone, sensitivity analysis of the optimization was investigated and a robust design was achieved.
Section 2 describes the models used, Section 3 presents the formulation of the optimization problem, and Section 4 describes the algorithm that solves for optimal firing temperature (thus, load profile) for a future time horizon. In Section 5, the proposed method is adapted for a combined cycle power plant (gas turbines in operation along with steam turbines) and illustrated with numerical examples.

2 . GAS TURBINE MODELS

Models that provide power (in Mega watts, MW) production, emission levels, and parts life of the gas turbine are needed for the setting the optimal trade-off between parts life and MW production in order to achieve maximization of profit subject to operational constraints. Static Thermodynamic Cycle models (cycle-deck) that provide MW production and emission levels (e.g., NOx and CO), given ambient conditions and operating regime, are currently in use. Cycle-deck is a GE proprietary gas turbine model that provides gas turbine outputs such as MW production, emissions, and required fuel flow, when given necessary inputs such as firing temperature and ambient temperature. Since the optimization intervals are in the order of hours, a static performance model is sufficient for the problem solution. However, if the decision intervals are in seconds, then a dynamic performance model should be used because of the importance of dynamic effects. A static performance model, a GE specified model derived from GE maintenance guidelines and a performance degradation model that gives the degradation of the performance of the gas turbine as a function of time, are combined in a Matlab platform (a widely used computational platform) to solve the optimization problem. A key independent variable—firing temperature at a particular time in the horizon—can be fed into models that give the level of MW production, emissions, and consumed part life. This information is then fed into the optimization algorithm to determine the optimum turbine load profile for the future time horizon.

3 . PROBLEM FORMULATION

The optimization formulation presented in this section is applicable to a power generation plant that operates gas turbines for producing electricity. Although the focus in this section is on the optimal operation of a single gas turbine running in simple thermodynamic, the formulation can be easily extended to multiple gas turbines running simple cycle applications. The formulation can also be extended to combined cycle applications that have gas turbines in operation along with steam turbines. A preliminary analysis is presented in Section 5.

The original problem is nonlinear, non-convex optimization problem due to nonlinear, non-convex relationship of power production & fuel consumption & parts-life consumption with optimization variable firing temperature. This problem was transformed into an alternative convex optimization formulation in terms of factored hours (see definition below) that has a convex objective function. The following notation scheme is used in this section for the natural formulation of the optimization problem:

N = Future time horizon, number of long time periods before next inspection (weeks, months, years),
τ = Time period (decision interval: resolution of future horizon, e.g., for 1 hour, future horizon N with will be at 1 hour resolution).
T = Total number of shorter time periods before next inspection (hours, days)=*function of (N, τ)* (e.g., if N=52 weeks, and τ=6 hours, T=52*7*24/τ=1456)
i = index of time periods
t_i = Firing temperature in period i
m_i = Maintenance factor in period i
$f_i = m_i \tau$ = Factored fired hours spent in period i
q_i = Megawatt hours (MWh) produced in period i
ω_i = NOx produced in period i
F = Total number of factored fired hours left before next inspection
C^m = Maintenance cost per factored hour
C^f = Fuel cost per lb of fuel used
F_{flow} = Fuel spent in period i
C_i^o = Other operating costs incurred in period i
Ω_i = Limit on NOx produced in period i
P_i = Price per MWh in period i
Prf = Profit obtained from sales revenue of electricity produced minus operational costs (fuel cost and maintenance cost for the operation of gas turbines) and fixed costs

Natural Formulation of Optimization Problem

Formulation-1: For user specified maintenance interval

Maximize

$$Prf=\sum_{i=1}^{T}(P_i q_i(t_i) - C^f F_{flow}(t_i) - C^m f_i(t_i) - C_i^o)$$

With respect to t_i

Subject to

$$\sum_{i=1}^{T} f_i(t_i) = F$$

$$\omega_i(t_i) \le \Omega_i \qquad i=1,\ldots,T$$

Formulation-1 describes the objective function of the problem as the revenue obtained from sales of produced electricity reduced by the fuel cost and the maintenance cost in N time periods. Maintenance cost of the machine — mainly the repair or replacement cost of parts — is assumed fixed. However, this maintenance cost will be realized in N time periods. N is specified either by the user or determined by the optimizer. If N is fixed, then the objective is to maximize profit in that time interval. If N is not fixed, the objective is then to find both an optimal firing temperature profile and a value of N that maximizes average profit obtained per interval ($/weeks, months) as will be presented in Formulation-2. While the first constraint in Formulation-1 is a nonlinear equality constraint specifying the limit on the factored fired hours that can be spent in future time horizon N, the second constraint is a nonlinear inequality constraint for the NOx emission levels. In order to simplify the notation, the factored hour constraint is taken for the limiting parts; however, additional factored hour constraints for different parts of the equipment can also be used.

Formulation-2: For determining optimal maintenance interval

Maximize *Prf* =

$$\sum_{i=1}^{T}(P_i q_i(t_i) - C^f F_{flow}(t_i) - C^m f_i(t_i) - C_i^o)/N$$

With respect to t_i, N

Subject to

$$\sum_{i=1}^{T} f_i(t_i) = F$$

$$\omega_i(t_i) \le \Omega_i \qquad i=1,\ldots,T$$

Note that once Formulation-1 can be solved in a reasonable time, this solution can be done iteratively for different N values in Formulation-2 to find the optimum maintenance time. For that reason, the solution for Formulation 1 is explored in detail in Section 4.

4 . OPTIMIZATION STRATEGY

The problems described in Section 3 (Formulations 1 and 2) are transformed into linear convex optimization problems making it possible to use linear programming concepts for solution. The transformation of the optimization problem and the novel algorithm that is used to solve the problem are not discussed in detail for proprietary reasons. See (Eker & Bollapragada, 2002). However underlying concepts will be discussed in detail. The following three main user objectives were identified for proposed feasibility study.

1) Maximizing Profit for a user selected level of MW production level: This option will help the user to find the best operating condition that will allow maximizing profit while maintaining the desired level of production
2) Maximizing Profit with outage impact: This option will help the user to achieve best profit possible regardless of allowed contractual maintenance date, i.e., the user wants to know what is the best operating profile with assumed or forecasted market conditions in user selected period of time. Depending upon market conditions, when the spark spread [2] is low, this option will result in delaying the maintenance time (late outage) by suggesting lower production levels (part-loading) obeying user production constraints; however, when the spark spread is high, it will provide optimal profile that will maximize operational profit in the selected period of time even though allowed factored fired hour limit might be exceeded.
3) Maximizing Profit without any outage impact: This option will help the user to achieve best profit possible within allowed contractual maintenance scheduled period, i.e., if a gas turbine, operating continuously 24 hours/day under base-load conditions, consumes 168 factored fired hours in user selected period of time of 1 week, what will be the best load schedule for gas turbines that will consume not more than 168 hours with assumed or forecasted market conditions in that user selected period of time. Depending on market conditions, when the spark spread[2] is low, this option will result delaying the maintenance time (later outage) by suggesting low production levels (part-loading) obeying user production constraints, however, when the spark spread is high, it will provide the best profile (balancing part-load factored hour credits with peak-firing factored fired hour fees) that will not exceed the allowed factored fired hours limit set by the customer.

Options 2 & 3 are more focused on finding the optimal load (MW production) schedule of gas turbines & total MW production of Combined Cycle (within user defined constraints) in a selected period of time. With Options 2 & 3, user will have the flexibility to decide on how much gas turbine life should be spent to ensure best return on their investment as well. Thus, Options 2 & 3 can be considered for plant management in order to gain profitability by means of optimal load and operating schedules. Option 1, on the other hand, focuses on finding optimal load factors (factored fired hours) of gas turbines for user desired total MW production level of Combined Cycle plants. In this option, the user already gives the total MW production to be achieved, and the optimizer returns the best load factors for gas turbines to achieve that output. Although there might be other user objectives & different user types for a power generation facility, feasibility focus is directed to the three objectives mentioned above, since they cover options for plant operators, managers and higher level of management who want to achieve the best operational modes that maximize user profits subject to variable costs of fuel, Contractual Service Agreement (CSA) cost, operational and environmental constraints.

The natural formulation of the problem as presented in Section 3, is both nonlinear and non-convex, which causes any real-time optimization application impossible. However, real-time optimization is key to the success of model based optimization technology, since real-time model updates by user inputs, ensure optimization of the power plant under current plant and market conditions. Thus, it is important to consider changes in fuel costs and electricity price along with parts life in terms of factored fired hours cost for designing a robust optimization algorithm. To simplify and make it possible to apply linear optimization techniques, the original nonlinear, non-convex optimization problem was transformed into an alternative convex optimization formulation in terms of factored hours that has a convex objective function with linear constraints. A novel algorithm based upon linear programming was formulated to solve this new transformed problem to achieve the execution speed specified by customer requirements. This transformation achieved execution speeds in the minute time frame. For comparative study, quadratic programming was applied to optimize over an approximated quadratic profit surface. However the large size of optimisation problem rendered this method infeasible for real-time implementation as the solution time was several hours.
Since the optimizer gives optimum operating set point (firing temperature profile that corresponds to gas turbine load profiles throughout future time horizon, a day, a week, a month, years etc.) by utilizing electricity forecasts, the robustness of the algorithm to uncertainties in electricity prices was investigated and illustrated by simulations. Theoretical analysis of electricity price distributions was conducted and validated with distribution fitting techniques using historical data. Using the outcome of this study, a sensitivity analysis was done using Monte Carlo simulations to achieve encouraging results. The analysis showed that, by incorporating weekly update of electricity prices to the model, the optimizer profitability predictions were near perfect results. Depending on the choice of optimization structure, mean values of expected profit with respect to uncertain electricity profiles would shift for the better compared to base load profiles. In summary, robustness of the optimization with respect to changing electricity prices was established by the following two different but practical methods:

a. Receding horizon application of optimization with continuous updates on electricity price information as conditions change in time. See (Qin &Badgwell, 1997) for an overview of receding horizon applications.

[2] Spark spreads indicate the profitability of running a power plant at various efficiency ratings, taken into account variable fuel cost & power prices

b. *Selecting only smaller time scales like a day or a week for looking ahead into future & having mid targets (tollgates) for the limiting number of factored fired hours / factored starts for that time window*

5 . FEASIBILITY WITH COMBINED CYCLE

In this section, the feasibility results with respect to two gas turbines and one steam turbine operating in a Combined Cycle will be demonstrated. Performance values for the two gas turbines are obtained from cycle-deck runs, while the resulting exhaust temperature flow and exhaust mass flows are given as inputs to a simplified Steam Cycle model (obtained from GEPS) for this feasibility study in order to obtain corresponding steam turbine output. Maintenance factors for part-load to peak-fire are obtained from parts-life model and market conditions are obtained from current public domain data.

A prototype optimizer was developed using linear programming techniques. A GUI was built to display the common data needed in combined cycle applications. User is required to enter inputs such as start date of the future time horizon in consideration (as in days, weeks, months, etc.), compressor inlet conditions, market data (electricity price, fuel cost), and to select the optimization objective (options 1, 2 or 3). Other user inputs include minimum MW constraints, peak-firing limit, and average factored fired hour cost. The results (suggested optimal load profiles for gas turbines and resulting steam turbine output and customer impact) are calculated and displayed in the GUI. Several simulations were run with different turbine operating conditions and market conditions. In one of the example cases, the market conditions were selected such that the optimization results stressed part-load operation due to lower electricity price and higher fuel cost. Some of the test case simulation results are as follows.

Option 1: Maximize Profit for user desired Combined Cycle (CC) MW output - In this option, user enters the desired Combined Cycle MW output as 380 MW for the next hour of operation. The optimizer determines the best way to produce 380 MW from the two gas turbines and steam turbine by optimizing over the generated profit surface as shown in Figure 1. This profit surface is generated using performance values and market conditions data with respect to factored fired hours spent for each gas turbine. Factored fired hour that corresponds to load of gas turbines and the corresponding fuel cost are incorporated in the profit analysis. There are many ways to generate total 380 MW in the combined cycle, denoted by vertical lines in Figure 1. However there are only 2 maximum profit conditions (same efficiency was assumed for gas turbines accounting for the symmetric optimal points for the two gas turbines), that correspond to minimum fuel consumption points denoted by two multicoloured thick lines in Figure 1. The fuel flow surface generated for this problem is as shown in Figure 2.

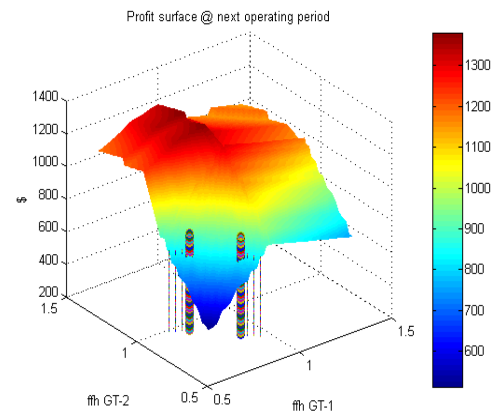

Figure 1. Profit Surface of 2 Gas Turbines

For gas turbines having different efficiencies, depending on the difference of efficiencies, life and fuel consumption trade-off will be more dominant resulting in one unique optimal operating condition. The suggested gas turbine output and corresponding MW output factored fired hours & fuel consumption difference from base-load conditions is displayed in GUI shown in Figure 3.

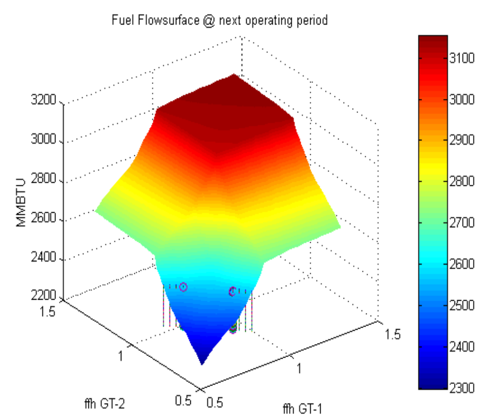

Figure 2. Fuel Consumption Surface of 2 GTs.

The optimizer determined the best way to operate for user desired 380 MW. However as clearly seen profit surface in Figure 1, although user has selected 380 MW, the profit at that hour could have been increased if more MWs were generated. This possibility leads to other remaining options, which enable user to achieve the best MW schedule in given future time horizon in order to maximize profit.

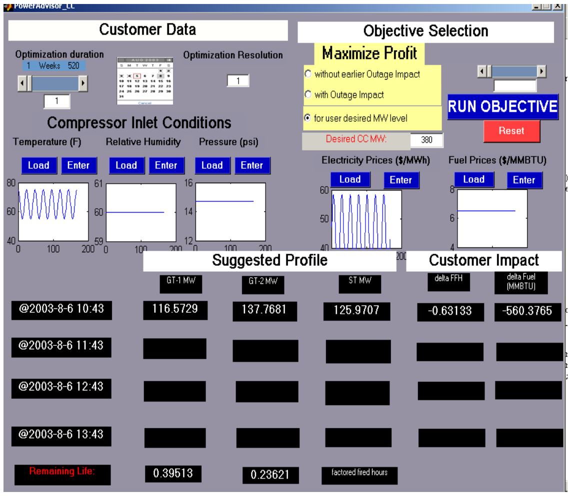

Figure 3. CC Optimization results for Option 1

Option 2: Maximize Profit with outage impact – As a specific example of Option 2 of maximizing profit with outage impact (earlier or later) over 1 week into future by finding out the optimal MW schedule for the CC plant with same market data as Option 1, the best MW load profile for that week into future was obtained as shown in Figure 4. Base-loading the turbines would have consumed 168 factored fired hours in 1 week, however, the optimal MW schedule given by optimization suggested more profit for less factored fired hours as seen in Figure 4. Remaining life numbers in the figure suggest approximately 120 factored fired hours for GT-1 and 130 factored fired hours for GT-2 and additional profit of $ 6000.

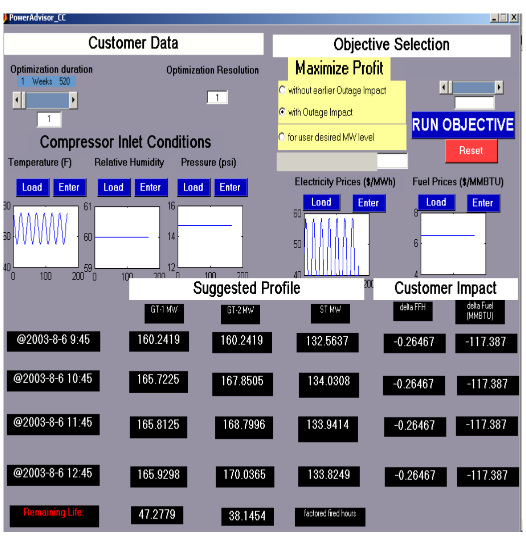

Figure 4. CC Optimization results for Option 2

Option 3: Maximize Profit without earlier outage impact - This option, as mentioned before, is to prevent any earlier outage impact while maximizing the profit for the customer. When same market conditions as in Option 2 are simulated, results same as Option 2 are obtained since the profit is maximized without any early outage as seen in Figure 4. However, in this option, user is free to change the limits of the factored fired hours to manage the life of their gas turbines as they wish for that chosen time period as a way of utilizing this tool in a robust way.

6 . CONCLUSION

The objective of the our research was to investigate the feasibility of an advanced optimization and control scheme that met the following criteria:

- Suitability for closed-loop optimization.
- Ability to find the optimal trade off between gas turbine maintenance costs and electricity production.
- Ability to perform optimization using a robust algorithm.

As discussed in this paper, these objectives were met with a novel formulation and optimization strategies. Simulation study was conducted to demonstrate real-time optimization capability using Pentium III 833 MHz desktop.
Although the focus here was on single & multiple gas turbine operation with firing temperature as the key variable, other variables such as steam augmentation and inlet chilling can be incorporated in the same framework. Preliminary analysis of the applicability of these ideas to both simple cycle & combined cycle applications were demonstrated. Maximization of operational profit for power-plant owners competing in fluctuating market & operation conditions, considering the most important variable costs, fuel & maintenance, is feasible with our novel approach. Robustness to uncertainties can be achieved by both receding horizon application with frequent model updates & optimization for shorter time scales with mid-targets on utilization of gas turbine life.

7 . ACKNOWLEDGEMENTS

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REFERENCES

Eker, S.A, and S. Bollapragada, "*Process for Optimally operating an energy producing unit and an energy producing unit*", USPO Application No. 10/301,693 , 2002.

Qin, S.J, and T.A. Badgwell, "*An overview of industrial model predictive control technology*," Fifth Int. Conf. on Chem. Process Control, AIChe Symp. Series, 1997, vol. 316, no. 93, pp. 232ff.