Proceedings of ASME Turbo Expo 2011
GT2011
June 6-10, 2011, Vancouver, British Columbia, Canada

GT2011-45989

A COMPETITIVE MARKET APPROACH TO GAS TURBINE TECHNOLOGY PORTFOLIO SELECTION

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ABSTRACT

Heavy duty gas turbine developments are major endeavors which use significant resource for development. Optimization of the technology portfolio is critical to yield a competitive product-line which is robust enough to compete in a dynamic market where vantage positions bring large profits but quickly erode over time. The current research addresses some of these challenges by proposing a transparent and integrated method aimed at investigating technology portfolio selection for future gas turbine-based power plants. The value-driven methodology analyzes technology investments, and is the foundation for a strategic decision framework that facilitates the formulation of robust and competitive technology portfolio solutions. A three-step process is proposed in this paper. A market response analysis is first carried out to estimate market penetration. A technology impact and readiness level analysis is performed next and augmented with a portfolio optimization. Finally, "what-if" scenarios are investigated to assess the robustness of selected technology portfolio candidates against a set of market conditions.

INTRODUCTION

With globalization, power generation markets have greatly diversified. Some market segments are experiencing significant growth in base-load electricity demand whereas some other markets are expecting peaking demand increases related to a large portion of the electricity generated from wind and solar energy sources.

The variety of economic and geographic environments of these markets is creating a wide range of customer preferences. Markets benefiting from low natural gas prices have less interest for lowering heat rates than markets with high natural gas prices. Some markets are being strongly driven by new environmental legislations, where other markets are less impacted. Similarly, markets characterized by increasing power generation coming from renewable energy sources will assign more importance on operational flexibility than regions which are focused on increasing their base-load power capacity.

This diversity across power generation markets makes the design of new gas turbines more difficult as original equipment manufacturers (OEM) are faced with a wide variety of customer needs and economic environments (e.g., fuel price and electricity demand). Decisions related to the technology investment strategy, a key element in overall value creation for most gas turbine manufacturers, are thus characterized by high levels of complexity. The goal of this paper is to discuss a process where the technology investment decisions can be evaluated by considering customer preferences across different market segments.

TECHNOLOGY PORTFOLIO ANALYSIS

Technology portfolio optimization falls under a broader category of research defined as Research and Development (R&D) portfolio selection under resource constraints. It is characterized by the goal of determining the optimum portfolio usually under limited resources (e.g., financial and manpower). Traditionally, discounted cash flow techniques were used to estimate the business benefit of certain key technologies. Discounting cash flows enable a quantitative measure of the technology impact on the company's earnings. This approach, however, fails to capture the impact on future market shares, as well as the nonlinearities of combining several technologies in one portfolio. To address these shortcomings, several methods have been published in the literature regarding R&D portfolio optimization. They can be classified as either qualitative or quantitative methods.

Qualitative R&D portfolio optimization methods such as pair-wise comparison [2] and scoring models [3] have been widely used. These approaches usually use qualitative measurements of the goodness of each portfolio program. R&D programs are often faced with intangible terms such as intellectual property, market competitiveness, and therefore can rely on scoring models. This approach consists of qualitatively scoring the R&D programs against certain criteria and comparing the overall contribution of each program. The weighted attribute matrix [4] can then be used to consolidate each program under an overall evaluation criterion. The Analytical Hierarchy Process (AHP) is also used to compare R&D programs [5]. This approach enables the determination of the best options by performing pair-wise comparisons between each program. Visualization techniques such as risk-reward bubble charts are also used to compare R&D programs.

On the quantitative side, R&D programs have been compared using financial models where the cash flows of the program costs and revenues are discounted to obtain a Net Present Value (NPV). The shortcoming of this approach resides in the uncertainties of the R&D project outcomes and expenses. To alleviate this problem, probabilistic evaluations can be performed on each program to compute a distribution of NPV or return on investment used to compare the different R&D programs. More specifically, Monte Carlo-based net present value analyses have often been proposed where the economical impact of a technology is being varied, as well as its development cost. Hespos and Strassman [6] proposed the use of stochastic decision trees to capture the nature of the R&D investments characterized by high uncertainty and the presence of sequential decisions. The method estimates the distribution of uncertain parameters, and computes the discounted cash flow with consideration of the various options or decisions available throughout the project.

Real Options Analysis has also been proposed to capture the value of strategic investments and decisions [7], [8]. It seems to correct the deficiencies of traditional discounted cash flow analysis by recognizing the value of managerial flexibility [9]. The methodology computes the NPV of an investment through probabilistic analysis of the incoming cash flows while considering that R&D projects can be abandoned at certain decision gates of the development. This approach, similar to the stock option pricing, enables a more realistic valuation of the program based on the modeling of future managerial decisions. Carlsson et al. [10] propose a similar approach to R&D portfolio selection through the integration of fuzzy mixed integer programming.

Finally, competitive analysis is used in R&D portfolio down-selection. Used either qualitatively or quantitatively through game theory for example [11], it enables decision makers to make strategic R&D portfolio choices with consideration of the competition. This approach is integrated into the process proposed in this paper.

METHODOLOGY AND PROCESS OVERVIEW

The current research addresses some of the challenges previously mentioned, and proposes a transparent and integrated method aimed at investigating technology portfolio selection for future gas turbine power plants. The methodology analyzes technology investments using a three-step process as described in Figure 1. First, a market response analysis is carried out to estimate the market preference of existing engines as well as the market penetration of newly envisioned products. A technology impact and readiness level analysis is performed next and augmented with a portfolio optimization to generate multiple technology portfolio solutions. Finally "what-if" scenarios are created and investigated to assess the robustness of selected technology portfolio candidates against a set of market conditions.

The first step consists of a market analysis that is performed to capture the market's response to existing engines, and to assess their competitiveness. For this purpose, the market is segmented into different customer profiles, each with their own set of preferences and requirements (efficiency, reliability, grid code compliance, etc). This paves the way for the estimation of an engine's economic utility to customers. Brand choice modeling techniques are subsequently applied to transform utility results into market preference shares which in turn yield indications about future sales and revenues.

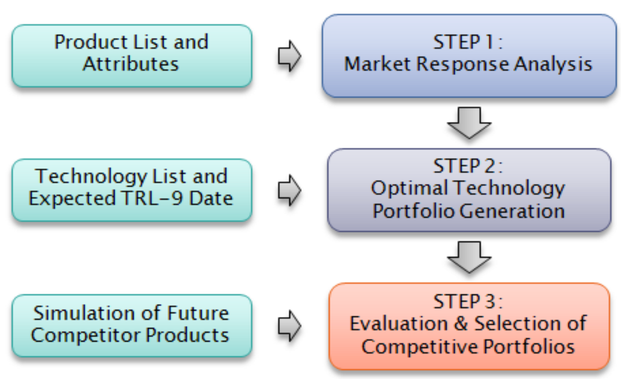

Figure 1 : Three Step Process

In the second step, the market revenue estimator is used to perform strategic technology portfolio evaluations. This is performed using technology impact forecasts on the different product attributes previously identified. These impacts are applied to the present baseline to foresee how it will evolve in the future once mature technologies are infused into a new or existing gas turbine design. Using a similar approach for the competitor's products, a new market analysis is performed which provides future expected revenues. A single or multi-objective optimization scheme is introduced at this point to select portfolios of technologies that yield the best overall market response and the best payoff for a specific manufacturer.

In the final step, the robustness of candidate portfolios is estimated. This is performed using strategic games and scenario analyses. These include tradeoff investigations between R&D expenditures and engine performance as well as timing tradeoffs between early entry into service with limited technology infusions or later production with more advanced designs.

One of the main contributions of this research effort concerns a multi-market optimization of technology portfolios while accounting for market and competitor reactions. A detailed overview of the methodology highlighting the flow of information is provided in Annex A.

STEP 1: MARKET RESPONSE ANALYSIS

The market response analysis aims at providing insights into the customer requirements as well as information regarding the market reaction to updated or new product offerings. It mimics studies performed by prospective customers during heavy duty gas turbine sale campaigns. Such studies are usually comprehensive and include technical analysis, financial analysis as well as after-sale service and guarantee analysis. The latter is beyond the scope of this paper and therefore only the technical analysis is reviewed. The market response analysis is further decomposed into four major sub-tasks as shown in Figure 2.

First, various metrics or business drivers of interest to prospective customers are identified. Second, various customer profiles or market segments representative of the whole market spectrum are selected. Third, the value of various gas turbine engines are computed for each market segments previously identified using multi-attribute utility theory. Finally the preference share for each product in each market segment is estimated using brand choice models.

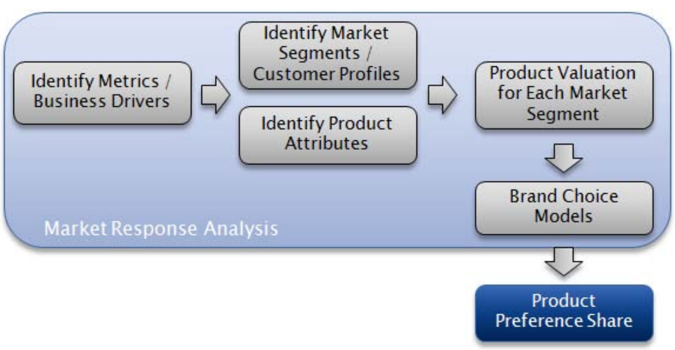

Figure 2: Market Response Analysis Process

a) Business driver identification and selection

The initial task consists in selecting a set of metrics that will be used to compare the various products offered in the market. Those metrics are ideally independent and reflect the attributes of gas turbines that matter most to customers and which customers use to compare the various engines offered to them. During design, these metrics are consequently closely monitored by manufacturers when assessing the impacts of technical choices and technology infusion. For the heavy duty gas turbine industry, the application behind this research effort, a diverse group of subject-matter experts (SME) were gathered in a workshop environment to carry out a series of voting activities. The SME's are comprised of frame designers, component technologists, gas turbine market analysts and other specialists that are instrumental to assessing the current and future gas turbine industry. Discussions and voting activities were conducted to identify business drivers and elicit information associated with them. Some of the most important drivers are mentioned in Table 1.

Table 1 : Business Driver Set

Net power	Availability
Net efficiency	Emissions
Long term program cost	Turn-down
Reliability	Ramp-up time

b) Market segment identification and selection

The next task in the market analysis consists in identifying the various customers and their requirements. To simplify and speed up the analysis, customers with similar preference profiles are lumped together in a single market segment with a market size commensurate with the size of the various customers represented. The task is then reduced to identifying and selecting a panel of market segments that is representative of the whole market spectrum. Each of these market segments has its own set of preferences and requirements and the analysis is simplified since less research effort is put into collecting the preference information. However, as fewer market segments are selected, the analysis becomes coarser and therefore some trade-offs between accuracy and effort must be made. A sample of customer profiles retained for the marketing analysis is given in Figure 3. The segmentation is made using the development status in the operating environment, the type of operations (baseload or peaker), as well as the frequency of the output.

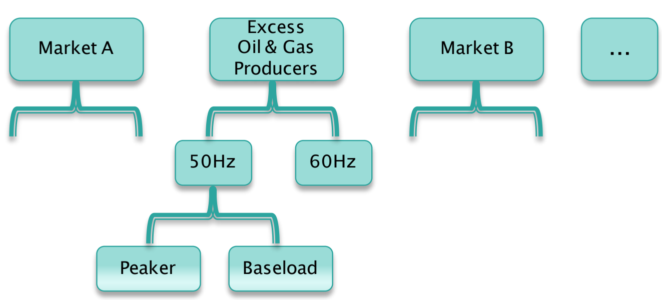

Figure 3 : Sample of Market Segmentation

c) Multi-attribute utility theory

Once the market segmentation is made, the analysis focuses on determining the preference profile for each of these markets. For this task, previous work done by Lancaster [12] in economics and the utility theory developed by von Neumann and Morgenstern [13] are used. The utility of a product measures the satisfaction that a consumer will derive from its use. Using the von Neumann-Morgenstern definition of utility, it is possible to add utilities together and therefore have multi-attribute utility models that represent the overall utility a consumer derives from the use of a good that has several distinct attributes.

Therefore, when a product can be fully described by its attributes across different dimensions, it is usually easier and more transparent to use marginal utilities for each of the dimensions. In this case, the marginal utility with respect to an attribute X is defined as the utility gained or lost by the end-user from a unit increase in the value of the attribute X. Using this approach, the overall utility is computed as a weighted sum of marginal utilities. As a result, the preference profile definition needs to be done in two stages: in the first stage, the marginal utilities are defined using actual product attribute values and marginal utility curves while in the second stage, weights are assigned to the business drivers identified previously to capture their relative importance.

The marginal utility functions are established for each business driver identified and reflect the value the customer is assigning to specific levels or magnitudes of a product attribute. These functions are directly reflecting the requirements set by each market segment regarding the various product attributes and are therefore market specific. Marketing experts have provided estimates of the marginal utility curves for each business driver and for each market segment under consideration. Data points from these curves were selected to construct marginal utility functions using spline interpolation. These curves have also been normalized between zero and one and a sample of these curves is given in Figure 4. As may be observed in the sample graphs, the marginal utilities may exhibit a threshold reflecting a minimum functionality that the customer is requesting. They may also exhibit the law of diminishing returns reflecting the fact that customers see little, but still positive, interest in over-exceeding their requirements.

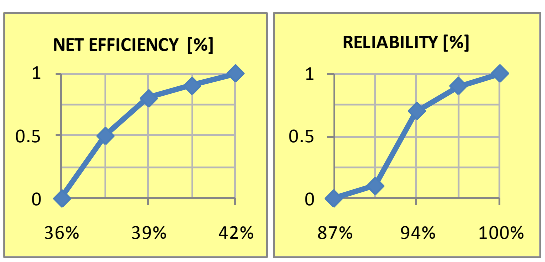

Figure 4: Notional Marginal Utility Curves

Marginal utility functions represent the level of functionality that customers expect from gas turbine engines but they do not represent the importance of the business driver to which they apply. The business driver preference profiles are tackled by assigning weights to each of them. These weights reflect the relative importance that customers from one market segment give to one metric over another metric. For instance, some market segments might be more sensitive to efficiency while other segments might be more sensitive to reliability and therefore a higher weight should be given to efficiency. Again, inputs from subject matter experts from a large frame manufacturer are used to derive weights for each attribute and for each market segment. Using this information, it becomes possible to compute the overall utility of a product for a customer from a specific market segment using Eq. 1.

$$U_j = U_j(FU_j, P_j) = FU_j^{\alpha_j} \cdot \left(1/P_j\right)^{1-\alpha_j} \qquad (1)$$

Following the work of Ader [14] regarding disruptive technologies, there is a need to separate the functionality analysis from the overall utility analysis. This is the reason why the engine price has not yet been dealt with and why this price is treated separately. In fact, the multi-attribute utility analysis carried so far is mostly based on technical attributes and may be interpreted as a functionality analysis. To yield meaningful utility results, the initial purchasing price must be taken into account. This is done using Ader's formula [15] given in Eq. 2. In this equation, the alpha power term represents the trade-off that customers are willing to make between functionality and price. Those alphas are used later to calibrate the model.

$$U_j = U_j(FU_j, P_j) = FU_j^{\alpha_j} \cdot \left(1/P_j\right)^{1-\alpha_j} \qquad (2)$$

d) Brand choice modeling

Using the utility equation described above, it is possible to estimate the utility of any heavy duty gas turbine for the various market segments as long as the gas turbine's attributes are known. For each market segment, a list of competing engines is generated and their respective utilities to the customer are computed. The next challenge is to transform these utility values into preference shares or purchasing probabilities. The preference share is different from the market share in that it does not include any advertisement effect or distribution network effect as shown in Eq. 3. For simplicity purposes, the share of voice and the share of distribution are initially assumed to be one. This assumption is not unrealistic since the research concerns large industrial power-plants and not consumer products for which the effects of availability at distribution centers and the effects of advertisement are more pronounced.

$$\begin{matrix} Market \\ Share \end{matrix} = \begin{pmatrix} Share\ of \\ Preference \end{pmatrix} \cdot \begin{pmatrix} Share\ of \\ Voice \end{pmatrix} \cdot \begin{pmatrix} Share\ of \\ Distribution \end{pmatrix} \qquad (3)$$

To perform this task, brand choice modeling techniques are used. Several brand choice models have been developed over the years. Luce [16], Lesourne [17] and McFadden [18], [19] have introduced pertinent models, some of which are more adapted to specific cases. According to Matsatsinis [20], an algorithm using the properties of utility distributions (range, skewness and kurtosis) of competing products may be used to select the most appropriate model. This algorithm is used to estimate the preference shares for the analysis.

e) Validation and calibration

Once the marketing model is complete, the verification and calibration task may be performed. The validation is done by comparing the market preference results from the marketing analysis with real-world results. It is important to keep in mind that the model developed so far yields market preference results based exclusively on technical and price analyses whereas the data available for comparison is sales data and therefore encompasses more factors. Therefore, rigorous verifications cannot be performed. However, a close investigation of the results might provide order-statistics that are compared with real world market preferences to find correlations.

Similarly, the use of the alpha coefficients in the utility equation for calibrating purposes is limited since no actual benchmark can be used for calibration. Consequently, the alpha coefficients are set to only yield market preferences that make sense and are correlated with the observed market shares.

f) Initial results

Besides market preference estimations, the marketing analysis yields indifference curves. Indifference curves are market-segment specific and represent different combinations of product attribute that have the same utility to a customer. Since these curves are defined by the levels of two different attributes, they reflect the trade-offs that customers are willing to make between the two dimensions under review without compromising the overall functionality of the product. This trade-off is described in Figure 5 for reliability and simple cycle efficiency. The graph shows a customer that values efficiency more than reliability for which a threshold may be observed. Below this threshold, any decrease in efficiency cannot be offset by improvements in reliability.

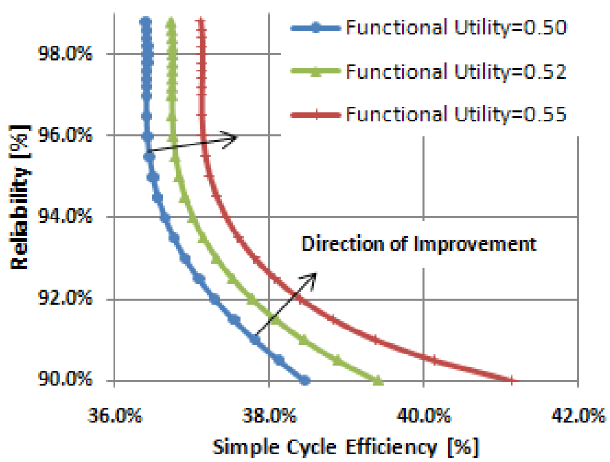

Figure 5 : Indifference Curves for Reliability and Efficiency for an Excess Oil and Gas Producer

When several curves representing different utility levels are drawn next to each other on the same graph, a utility gradient may be computed which yields information regarding the direction of improvement to best match a customer preference. This gradient-based optimization is however difficult to use when several markets are investigated since these various markets have different indifference curves and therefore different gradients as shown in Figure 6.

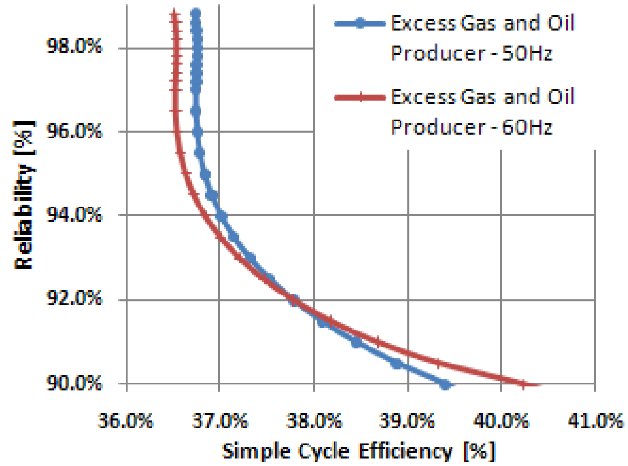

Figure 6 : Indifference Curves for two Distinct Markets

STEP 2: OPTIMAL TECHNOLOGY PORTFOLIO GENERATION AND MATURITY FILTERING

Once the market response analysis is complete, investigations regarding perturbations of the input values are possible. More precisely, investigations regarding the impact on market preference of improving the engine characteristics by a certain percentage are performed. For instance, what is the effect of using a technology improving the net efficiency by one percent? This is in essence the purpose of the second step of the analysis during which technology portfolios are generated and evaluated in order to down-select non-dominated candidates that improve market preferences the most while satisfying budgeting and readiness level constraints.

This analysis starts with a list of technologies that are assumed to be independent and compatible. These technologies are defined by their impacts on the business drivers as well as their development costs and their technology readiness levels. The process used is described in Figure 7 and is composed of three different tasks.

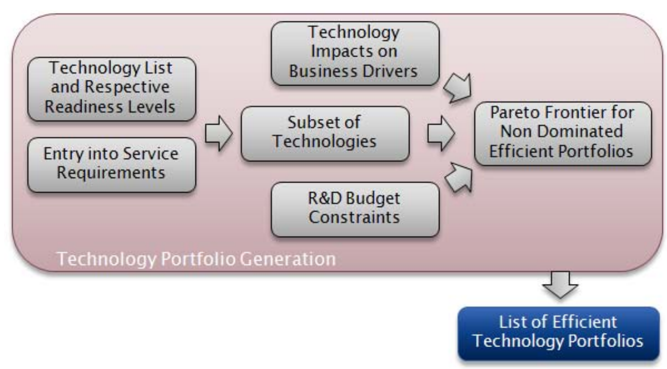

Figure 7: Technology Portfolio Selection

First, the technologies are filtered to keep only a subset of technologies that will achieve a technology readiness level of nine (TRL-9) by the time the updated gas turbine enters service. This is to ensure that the entire technology portfolio will be mature at the time-horizon under consideration. Then, technology space exploration is performed to find portfolios of technologies that yield good market performance while meeting pre-defined budget constraints. Finally, a Pareto plot of the best technology portfolios is constructed to visualize the trade-offs between extra profits and R&D costs.

a) Technology Portfolio Modeling

Once a subset of technologies that meet the entry into service timeline constraint is selected, the task is to design portfolios of technologies that yield the largest market preference while meeting the budget constraints. To quantify their impacts, technologies are assumed to be independent, compatible and their effects are described as percentage improvement or k-factors over the baseline business drivers' values. An example of an extended technology impact matrix (TIM) including development cost and projected technology readiness level nine date (TRL-9) is provided in Table 2.

Table 2: Extended Technology Impact Matrix (TIM)

	R&D Cost	TRL 9 Date	Net Power	Efficiency	Reliability	…
Tech 1	1.1M	11/2011	3%	2%	4%	…
Tech 2	0.6M	03/2013	-2%	5%	1%	…
Tech n	…	…	…	…	…	…

For simplicity, the effects are initially assumed to be additive so that a technology portfolio impact is the sum of the impacts of the technologies belonging to this portfolio. A technology portfolio is represented by a Boolean vector of size ***n*** representing the status (funded or not funded) of the ***n*** possible technologies that could be included in the portfolio as shown in Eq. 4. These vectors as well as the technology impact matrix are used to assess the extra performance of future engines over current baselines.

$$\begin{pmatrix} 1 \\ 0 \\ 1 \\ \dots \\ 0 \end{pmatrix} = \begin{pmatrix} Technology\ 1\ funded \\ Technology\ 2\ not\ funded \\ Technology\ 3\ funded \\ \dots \\ Technology\ n\ not\ funded \end{pmatrix} \tag{4}$$

The search for optimal technology portfolios is performed along two dimensions: extra market revenues (rewards) and research and development costs (efforts). On the one hand, the extra market revenues are computed as the difference between the market revenues generated by a baseline engine fleet updated with the new technology portfolio and the initial revenues generated by the current baseline engine. On the other hand, the research and development costs relate to the expenditures to bring the technologies to a mature readiness level.

b) Monte Carlo Simulation

The first approach is using Monte Carlo simulations to generate random technology portfolios. These candidate portfolios are later sorted to find non-dominated ones in the revenue-cost space. The Monte Carlo simulations are performed by sampling technology portfolio vectors: zeros and ones are randomly assigned to each and every component of the technology portfolio vector indicating whether the technology represented by this component is included. This portfolio vector is subsequently transposed and multiplied with the technology impact matrix (TIM) to yield a first order estimate of the overall improvement vector as shown in Eq. 5. The overall improvement vector represents the percentage improvement over the baseline engine's business driver. It is used to estimate the future engines' business driver values. The market performance of these newly generated engines is finally assessed using the market response analysis developed in step one.

$$[Improvement\ Vector] = [TP]^t \cdot [TIM] \tag{5}$$

A design space exploration is performed through Monte Carlo simulations and the results are displayed in Figure 8 where each red dot represents one possible technology portfolio. The graph exhibits a Pareto frontier in the reward-effort design space which highlights the border between achievable market revenues and non-achievable ones for a given level of investment outlay. The Pareto frontier is made of non-dominated technology portfolios and it encompasses three distinct regions: the lower left part of the curve ("low cost") represents low investments for limited profit portfolios, the upper right part ("high perf") represents high investments for high profit portfolios and finally balanced solutions ("balanced") may be found in-between. These three areas are used later in the paper to pick technology portfolios representative of different industrial strategies: low R&D investment, medium R&D investment and finally high R&D investment strategy.

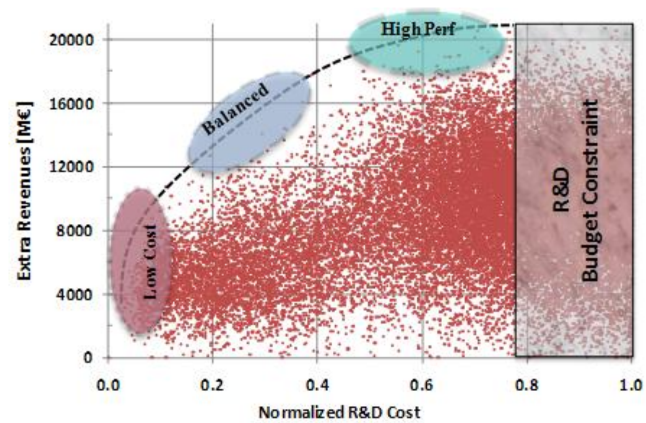

Figure 8 : Monte Carlo Simulation for Technology Portfolio Generation

The results also exhibit a horizontal plateau that represents a situation of market saturation resulting from the law of diminishing returns with which customers value functionality. This is the case when the end-customer has limited use for the added functionality past its own set of requirements, even if more technologically advanced gas turbines were proposed to the market. Consequently, the manufacturer is unable to extract additional revenues from the customers and this explains why the Pareto frontier becomes almost flat past a certain investment level.

c) Portfolio Optimization

Monte Carlo simulations may be adequate to highlight Pareto frontiers but are not efficient to find optimum portfolios due to the curse of dimensionality (which is relevant in this case with more than two hundred technologies under review). An optimization scheme is therefore needed to minimize computational expenditure. An objective function which will be maximized is designed to account for the extra profits derived from extra market revenues (MR) using the profit margin (***a***), for the technology portfolio development cost (TP_C) and for the research and development budget constraints ($R\&D_{Bud}$) as shown in Eq. 6. A factor ***q*** is introduced to specify the level of return required by the gas turbine manufacturer and a factor ***k*** is introduced in front of the penalty function to indicate how strictly the research and development budget constraint is enforced.

$$F(TP) = a \cdot MR - q \cdot TP_C - k \cdot \max(0, R\&D_{Bud} - TP_C) \quad (6)$$

Several routines are available to solve this type of optimization problem but a genetic algorithm is selected here because of the discrete nature of the technology selection process (technologies are either funded or not), the size of the problem, and its relative ease of implementation. The genetic algorithm is an evolutionary optimization process that mimics natural evolution processes by generating useful solutions using techniques inspired by natural evolution such as elitism, crossover and mutation. The impacts of a technology portfolio on the market preference and on the market revenues are estimated using the marketing analysis previously described. The revenues as well as the costs associated with developing this portfolio are then used to compute the value of the objective function. In order to perform the genetic optimization, an initial population of technology portfolio vectors is randomly generated and is subsequently used for the selection, crossover and mutation processes.

Parametrically changing the value of the factor ***q*** in the objective function will yield different portfolio solutions for a given level of return. This is quite similar to an optimization over the return on investment. In this case, the optimization will converge towards portfolios situated at the intersection (tangency point) of the highest return line and the Pareto frontier as shown in Figure 9.

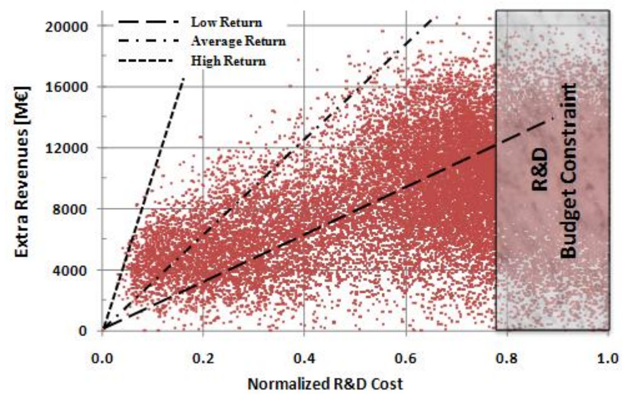

Figure 9 : Candidate Portfolio Solutions

STEP 3: EVALUATION AND SELECTION OF COMPETITIVE PORTFOLIOS

The remaining question concerns the tradeoff between solutions that lie on the efficient frontier identified in the second step. As mentioned previously, superimposing return on investment lines allows the down-selection of a few technology portfolios candidates but several other portfolios lying on the Pareto frontier and yielding slightly lower return on investments might be worth looking at. The analysis carried so far is static in that it assumes that only one manufacturer is implementing technologies into its design while the competitors are sitting idle. This assumption needs to be relaxed as competitors will be either acting or reacting to new information that becomes available by improving their product-line. The third step addresses this issue and helps assess which technology portfolios are most robust with regards to the behavior of competitors. The process to perform this analysis is outlined in Figure 10.

Competitive intelligence is first gathered to assess what the state of the competition will be for a specific investment horizon. Thus, general performance and cost estimates of competing engines are collected. Using this information, different scenarios are generated and subsequently used to perform a game-theoretic analysis that yields the best (expected return) and most robust solution.

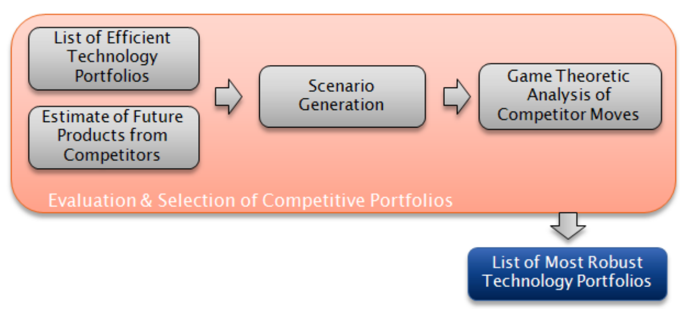

Figure 10 : Evaluation and Selection of Competitive Portfolios

a) Uncertainty regarding the competition

It is usually possible for manufacturers to guess what the other competitors are developing since most of the manufacturers are exchanging information with their customers. However, even though manufacturers have rough estimates regarding future competing products, there is uncertainty regarding this data. For this reason, a probabilistic approach is used and future product characteristics are described with probability distributions. Distributions are described by their shape, minimum, maximum and their most likely value. These are displayed for three attributes in Table 3.

Table 3 : Notional Future State of the Competition

Forecasted Improvements	Net Power	Efficiency	Long Term Program Cost	…
Min	+2%	+1%	-1%	…
Most Likely	+13%	+.3%	-5%	…
Max	+16%	+5%	-11%	…
Distribution Type	Triangular	Triangular	Triangular	…

b) Scenario generation for the competition

It is impractical to sample the previous distribution to generate new scenarios because of the dimensionality of the problem. Nonetheless, each of these scenarios might have significant market share implications and an approach to analyzing these future scenarios is warranted in order to mitigate some of the competitive risks.

One approach is to use these distributions to generate a limited number of scenarios that may be representative of the whole scope of possibilities achievable by competitors. The attributes' distributions are therefore collapsed into a four-point probability mass function describing four possible outcomes. One scenario simulates a competitor that delays the introduction of a performance improvement package and continues to offer its current engines. The three remaining scenarios represent the three upper quartiles of the attribute distributions. The attribute values retained for each of these scenarios are the expected value of the quartile they represent. These quartiles might be represented in a chart similar to a box and whiskers chart as shown in Figure 11. The figure also highlights the performance gap between what is currently achieved and what needs to be achieved in the future to remain competitive in a specific market.

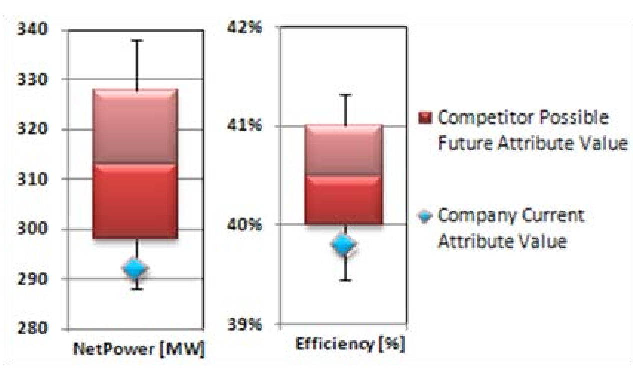

Figure 11 : Notional Chart for Performance Gap between Current Company Baseline and Forecasted Competitor Engine

c) Technology portfolio down-selection for the company

Once several scenarios have been identified for the competition, a couple of technology portfolios that could be developed by the company must be selected to assess their respective competitiveness. Using the Pareto frontier of non-dominated technology portfolio generated earlier, three technology portfolios are sampled. Each of them falls within one of the previously identified area: low cost for limited performance improvements, high cost for substantial performance improvements and finally a tradeoff between development cost and performance achievements. The different scenarios identified for the company and its competitor are summarized in Table 4.

Table 4 : Scenario Definition: Impact on Product Attributes

Player	Various Strategies	Net Power	Efficiency	Long-Term Program Cost	Description
Competitor	Scenario 0	0%	0%	0%	No product update
	Scenario 1	6%	2%	-2%	Small improvements
	Scenario 2	13%	3%	-5%	Medium improvements
	Scenario 3	14%	4%	-10%	Large improvements
Company	Scenario a	3%	2%	-3%	Low Cost Technology Portfolio
	Scenario b	3%	2%	-10%	Balanced Technology Portfolio
	Scenario c	4%	2%	-10%	High Performance Technology Portfolio

d) Dynamic games and "what-if" scenarios

Many advances have been made over the past few years in the field of decision-making and new innovative approaches and algorithms have been proposed in the field of game theory. Game theory presents a means of approaching problems involving competitors and decision-making using a rational argumentation. A game is a model of a competitive situation, and game theory is a set of mathematical methods for analyzing these models and selecting optimal strategies. Even without complete knowledge of an opponent's decisions or resources, game theory is useful for enumerating the decisions available, and evaluating these options, or "moves" in a game sense. When a competitor's investment decisions are contingent upon the other's moves, a wait-and-see approach may not always be advisable and thus a more rigorous game theoretic approach is necessary. It is a helpful tool in valuating strategic decisions because it includes a means of understanding or predicting the way in which competitors will behave and further provides an equilibrium strategy with values for those decisions.

There exist specific rules when constructing games. Two pioneers in this field, Smit and Trigeorgis [21], assert that *"following the rules of game theory can help reduce a complex strategic problem into a simple analytical structure consisting of four dimensions"*. These dimensions are the players, the actions available to them, the timing of these actions and finally the payoff structure of each possible outcome.

The time required for the research, development, testing, and evaluation of gas turbine engine technologies is an important factor that affects the competitive analysis process. In many cases, the estimated maturity timeframe is uncertain due to unforeseen changes in technical developments, financial constraints, or market demands. As a result, manufacturers will typically introduce their products into the market at different times. The competitive analysis must therefore account for the advantages and disadvantages of entering a market as a leader or as a follower.

In game theory, a solution concept is a formal rule for predicting how the game will be played. The most commonly used solution concepts are equilibrium concepts, of which the Nash equilibrium is the most widely used. *"The Nash equilibrium is a profile of strategies such that each player's strategy is an optimal response to the other players' strategies"* [22]. This solution concept can be viewed as a robust solution that minimizes the potential loss in payoff to each player. The Nash equilibrium is computed by performing a search in the action space and determining iteratively if the conditions for Nash equilibrium have been met. The resulting strategy profile for each player helps identify what paths of the branch in the decision tree are best responses to the actions most likely taken by the competition.

e) Technology portfolio selection with two competitors

In this part of the paper, promising technology portfolio previously identified will be reviewed in a duopoly setting with two manufacturers. A leader, the competitor, is moving first and has four strategic options for the coming years as described in paragraph c, Table 4. Having some intelligence regarding the possible strategic moves of its competitor, a follower may answer by offering the three different technology packages also identified in paragraph c, Table 4. One is a low cost technology package (with limited reward), one is a tradeoff between cost and performance (balanced reward) and finally the last one is a high performance technology package (with high reward). Competitive frameworks such as this one are best described by their extensive form representation as shown in Figure 12.

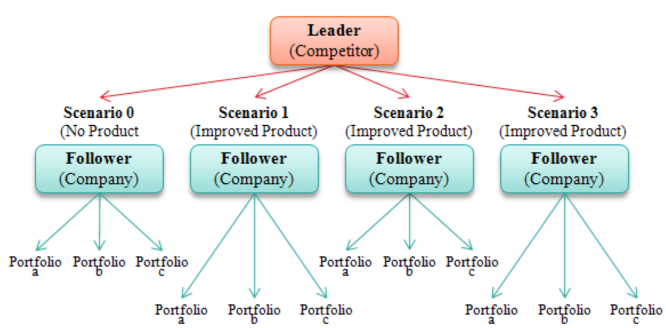

Figure 12 : Decision Tree in a Duopoly Environment

This structure, also called a decision tree, specifies the order in which players make decisions and the information available to them at the time of their decision. The game theoretic process is then implemented to analyze the different branches and to identify robust strategies. For clarity purpose, the payoffs for each outcome of the tree are presented separately in Table 5.

Table 5: Normalized Strategy Payoff (Extra Profits)

Normalized Payoffs		FOLLOWER (Company)					
		Low Cost Technology Portfolio		Balanced Technology Portfolio		High Performance Technology Portfolio	
LEADER (Competitor)	Scenario 0	-0.06	0.26	-0.14	1.00	-0.22	0.62
	Scenario 1	0.10	0.16	<u>0.05</u>	<u>0.84</u>	0.07	0.78
	Scenario 2	-0.43	0.07	-0.31	0.63	-0.31	0.61
	Scenario 3	0.25	0.58	-0.75	0.66	-0.76	0.64

To solve for an equilibrium solution, a backward induction process is used and this yields Nash equilibrium. The process to find the equilibrium solution is reviewed in more details in Annex B and yields the equilibrium where the competitor selects the Scenario 1 and the company selects the balanced technology portfolio.

f) Technology portfolio selection with two competitors and imperfect information

In this part, a more realistic setting is addressed in that the follower does not wait for the leader to start offering updated products to finish the development of technology portfolios. Instead, the follower has some beliefs regarding the moves of the leader and uses these beliefs to form its own strategy. These beliefs might be formed with data and intelligence gathered in the market. As a result, the follower knows which states are possible but it does not know with certainty which path the leader has chosen. Some likelihood probabilities must be assigned to the different strategic moves of the leader. The various technology impacts and moves are the same as in the previous example.

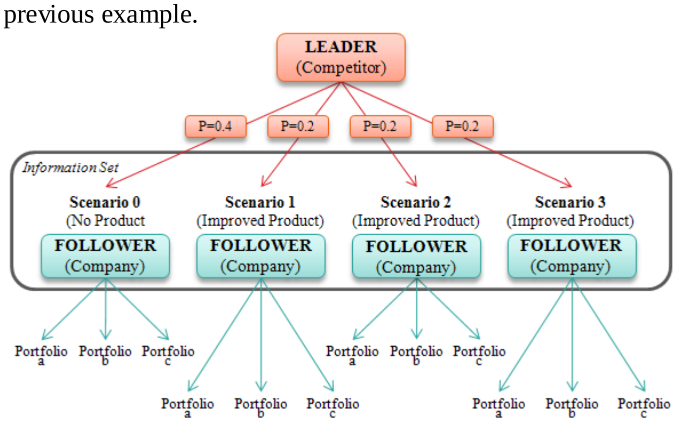

Figure 13 : Decision Tree in a Duopoly with Imperfect Information

To solve for the equilibrium solution, backward induction in conjunction with expected payoff values is used. This accounts for the fact that the leader tries to out-guess the follower and anticipate its move. The results are presented in Table 6 and these are different from the first example results because the follower cannot observe the move of the leader.

Table 6 : Payoff and Equilibrium with Imperfect Information

Anticipated Move of **FOLLOWER**		**LEADER** Move Given Expected Follower Move	
Follower Possible Moves	Follower Expected Payoff	Leader Possible Moves	Leader Payoff
Scenario a	0.20	Scenario 0	0.02
Scenario b	0.79	Scenario 1	0.05
Scenario c	0.65	Scenario 2	-0.31
		Scenario 3	-0.75

CONCLUSION AND FUTURE WORK

The research carried out so far has led to the development of a transparent methodology that allows the creation of technology portfolios that meet both research and development budget constraint and minimum return on investment threshold set by management. Moreover, the proposed approach allows for the down-selection of technology portfolios that are robust with regard to changes in the competitive landscape. Some of the main results of this work include the realization of market saturation when the customer has no use of the extra functionality offered.

Some aspects of the analysis will be improved and new research areas will be investigated in the future. One area of improvements concerns the design of technology portfolios. Presently the technologies are assumed to be independent and compatible. This will be relaxed and another filtering layer will be added to tackle incompatible technologies. Similarly, refinements regarding nonlinear impacts of bundled technologies will be made to get more relevant results.

Another area of improvements concerns the optimization scheme. At this time, the optimization scheme uses a single objective genetic algorithm which converges to a single point solution. In the future, a multi-objective genetic algorithm will be used to yield Pareto frontiers [23] that are both more accurate and broader in their spectrum.

Finally, more realistic games with more than two competitors and accounting for opportunity costs when a market player delays its move will be investigated next.

ACKNOWLEDGMENTS

The authors would like to thank the sponsor, *Siemens Energy*, for the help received while conducting the research.

NOMENCLATURE

$\boldsymbol{a}$: Attribute level
$A_{i,j}$: Attribute level
$f_{i,j}$: Marginal utility function
FU_j : Functionality
$\boldsymbol{i}$: Product attribute index
$\boldsymbol{j}$: Market segment index
$\boldsymbol{k}$: Penalty function factor
$\boldsymbol{q}$: Return level factor
U_j : Overall utility
$\boldsymbol{\alpha_j}$: Functionality-price tradeoff coefficient
$\omega_{i,j}$: Attribute relative weight

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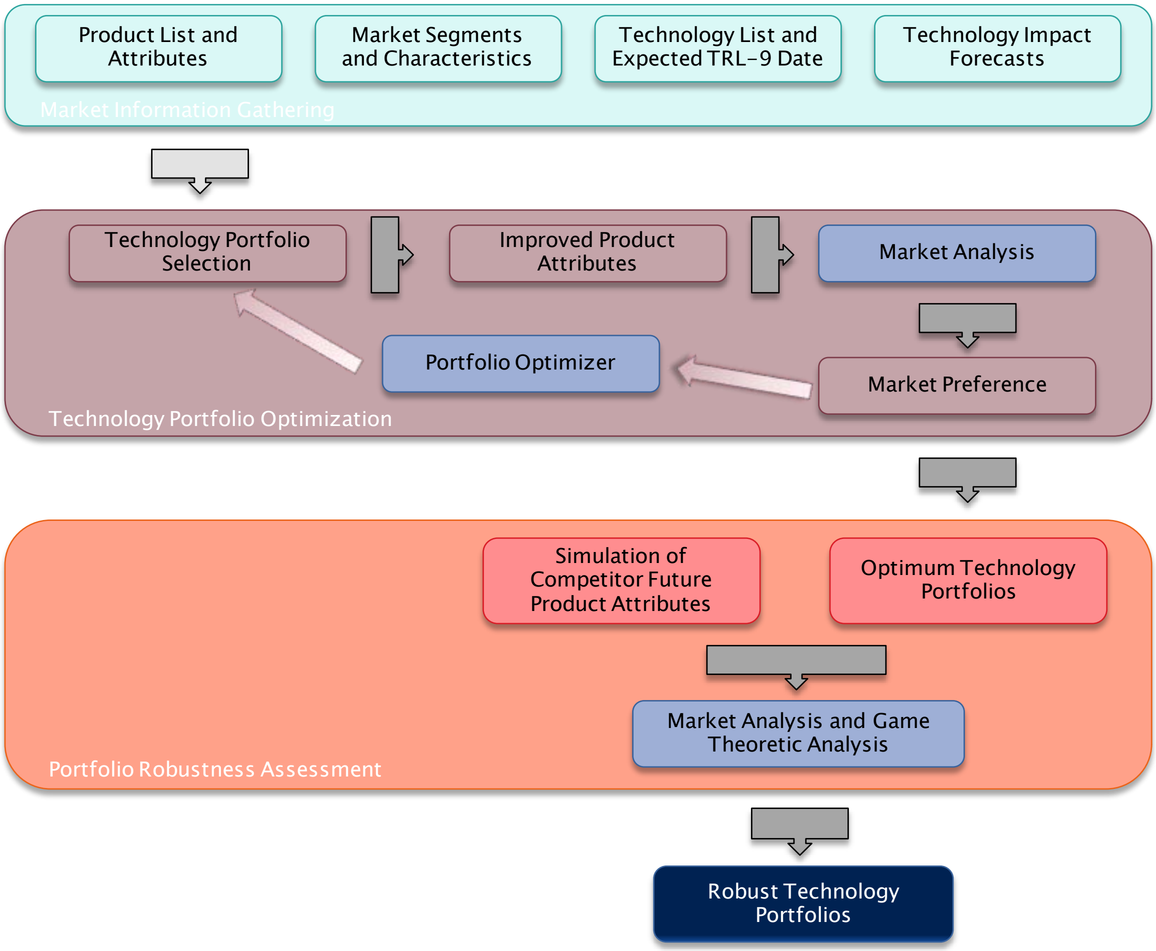
ANNEX A : Process Flowchart



ANNEX B : Extensive Representation of Competitive Situation