Economic risk assessment for hydro plants using computer software

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ABSTRACT: In order to decide whether an equipment upgrade, the rehabilitation or the refurbishment of any component of a hydroelectric facility is economically feasible it is essential to consider not only capital costs and benefits, but take into account the risk exposure associated with the aging equipment. Quantifying this risk exposure in terms of a cost stream hinges on a good understanding of the probability of failure as it varies over time and the consequence costs of a failure. Within an integrated, interdependent system of components, the failure probability experiences a coupling between individual components through the effect of one failure on another. Further, the costs associated with risk mitigating interventions is also coupled through the effect of outage concurrence. It is desirable that timing and type of risk mitigation interventions be selected in an optimized manner. This optimization is best accomplished by the use of a transparent and rational process in the form of a computerized algorithm. Building on and briefly recapitulating the methodology used for individual components, the present paper will discuss the methodology to calculate a coupled cost target function for a system of interdependent components. Further, the optimization algorithms used in the HydroVantage software are described. An application of the method is reported to underscore the potential benefits of the computerized method versus other less structured capital planning approaches.

1 CONTEXT

To manage hydroelectric generation assets successfully means to find the best course of action to maximize generation revenue, minimize costs such as maintenance, outages, repair or component replacements, and to maintain the value of the asset over the long term.

Given the fact that more than two-thirds of all hydro stations in North America are 40 years or older, most plant owners and operators need to deal with aging equipment. Effective tools are required to support decisions about the available options of continued operation, retirement, rehabilitation or replacement of equipment. Questions about an old piece of equipment need answer such as:

- What is the probability that it will fail?
- What would happen if it should fail?
- What should be done with the component? - Rehabilitate or replace?
- If required, when should it be rehabilitated or replaced?
- Which projects should be done first within available capital expenditure budgets?

The current approach to capital expenditure planning is mostly based on past and present performance and engineering judgment alone. Neither formal economic life cycle evaluation nor analytical optimization of intervention timing is conducted. This intuitive approach may easily result in intervention priorities being incorrectly assigned, interventions being incorrectly timed, large savings remaining unutilized or unnecessary expenditures and cost penalties being incurred.

Computerized optimization algorithms can help to translate the available technical and cost information into a format that empowers to make an informed decision. It must be noted that engineering judgement is still required - however, it is based on defined, organized and quantified information. Further, with the use of user-friendly decision support software sensitivity analyses on assumptions and estimates can be undertaken rapidly while maintaining consistency in the approach.

2 CALCULATED EQUIPMENT RISK

The risk-based methodology recognizes that exposure to risk is a real cost and has to be accounted for like any capital or Operating and Maintenance (O&M) expense. Various publications exist that deal with the application of this methodology in the hydroelectric field (de Meel et al. 1997, Bhan et al. 1998, de Meel & Donnelly 1998, de Meel & Westermann 1999, Morgenroth et al. 1999, de Meel & Morgenroth 2000, and Westermann et al. 2000). By its statistical nature, it may not affect each and every plant or component in exactly the predicted way, but if sufficient time is permitted to pass and a sufficient number of components are observed, the statistical average will represent reality well[⊕]. As a matter of definition, the risk-cost used throughout this paper is the cost arising from a failure event, directly or as a consequential associated cost, factored by the likelihood of this event occurring.

$$R = p \cdot C \tag{1}$$

Where R = Risk cost; p = probability of occurrence of failure event; and C = consequence cost that is incurred for this failure event.

Typically an initial period of early, infancy failures is followed by a period where failure is entirely random, i.e. the failure rate is constant. As wear-out of the equipment sets in, the likelihood, or probability of failure, for a component increases typically with the age of the equipment as shown in Figure 1. Most equipment exhibits this typical behavior, but the parameters describing the failure probability curve can only be determined from statistical analysis of historic data or a physics-based. capacity demand approach (Morgenroth et al. 1999).

If the piece of equipment under investigation is similar to the equipment represented by the failure probability curve and its service conditions are also similar, then application of the failure-probability curve for prediction of the future likelihood of a failure will provide a realistic estimate.

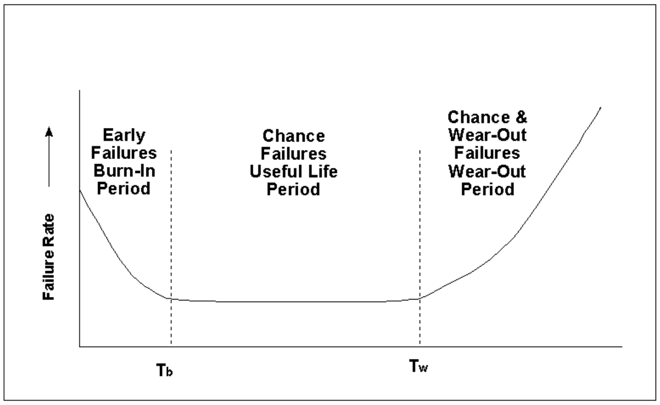

Figure 1. Typical reliability development of a component during its life

However, the actual position of a specific piece of equipment on the failure-probability curve is determined by its representative age, not its calendar age. To obtain the representative age, a condition assessment, typically expressed through a condition index, is required. To support the condition assessment and detect trends in the condition of a component traditional methods which are conducted at discrete time intervals during equipment shutdown are supplemented by modern on-line tools, such as partial discharge analysis (PDA) or air gap and vibration monitoring.

In determining the best timing for implementing a risk-mitigating intervention, one must consider the least total costs in today’s present worth. This means on the one hand that money spent on an intervention later on costs less. On the other hand, the risk (cost) increases if a risk-mitigating intervention is deferred. Figure 2 shows how this balance constitutes for a single individual component an one-dimensional optimization problem in terms of the intervention timing.

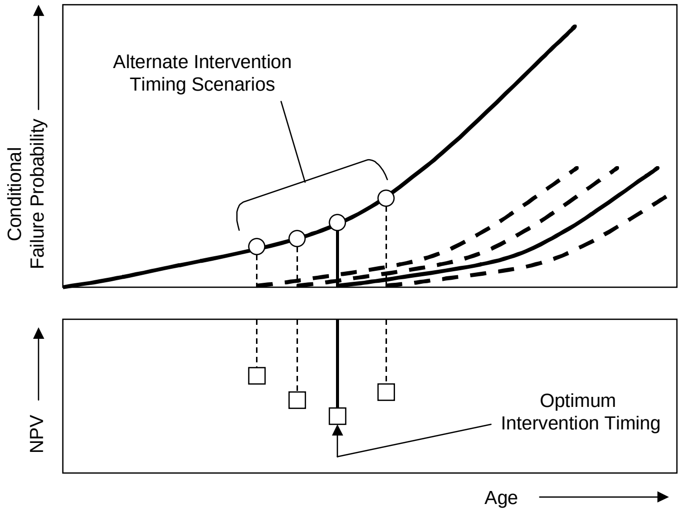

Figure 2. Application of risk concept to determine optimum timing of a risk mitigating intervention

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[⊕] Since the beginning of time, men have used elaborate rituals to determine the course of future events. They have consulted prophets, studied the stars, watched the flight of birds, sought divine revelation from a thousand and one gods. It may appear that an estimate of the average service life of the hundreds of units of presently-existing property is just another in the long history of man’s attempt to foretell the course of future events. And to the extent of forecasting remaining life, it is exactly that - an estimate. However, the result is not reached by consulting prophets or interpreting mystical patterns of tea leaves in the bottom of the cup, but by utilizing known facts and the best judgement of the people who work with this equipment on a daily basis. (Rodenburg 1995)

3 FORMULATION FOR AN INTERDEPENDENT SYSTEM

For an interdependent system the situation is more complex than just summing up all costs for the individual components in this system. Coupling effects exist which can increase or decrease the total cost arising during the study duration. These total costs are defined as

$$\mathrm{CTF} = \sum_{i=1}^{n} \mathrm{NPV}(\mathrm{annualcosts}_i) \tag{2}$$

Where CTF = Cost Target Function, annual costs_i = sum of capital intervention costs, O&M costs, benefits (negative costs) and risk costs in year i, i = counter for year starting at 1 and running to n, the end of the study duration, and NPV( ) = application of a net present value factor for the year, i:

$$\mathrm{NPV}(\mathrm{cost}_i) = \mathrm{cost}_i \cdot \frac{1}{(1+d)^i} \tag{3}$$

Where d = constant annual discount rate.

Coupling arises from the fact that a failure mode can affect a subsequent consequential failure on the same or other components. Therefore, the total risk cost, which is the sum of the individual risk costs for each component's failure modes, is increased by a factor corresponding to the likelihood of any failure mode causing another failure mode:

$$R_i = (p_i + p_j \cdot p_{ji}) \cdot C_i \tag{4}$$

Where R_i = risk cost for failure mode i, p_i = probability of failure mode i individually, p_j probability of failure mode j individually, p_{ij} = probability of failure mode j causing failure mode i, and C_i = consequence costs of failure mode i.

Additionally, coupling arises from the fact that if interventions that are planned in the same year, typically some overlap of the outage time to implement an intervention mode exists. For example, if an unit is taken down to implement a generator rewind then possibly little additional outage costs arise to do refurbishment work on the turbine, transformer or, depending on the water passage configuration, even the penstock or intake gates. If individual intervention modes are outage coupled then the outage costs are directly entered into the program replacing the term:

$$\sum_{i=1}^{n} \mathrm{od}_i \cdot \mathrm{or}_i \tag{5}$$

Where i = counter that runs from 1 to n, n = total number of intervention modes for all components that concur in a given year, od_i = outage duration to implement intervention mode i in days, and or_i = daily rate for a planned outage caused by intervention mode i.

This approach of prescribing a single cost for a combination of interventions would require detailed scheduling and cost estimating for all combinations of interventions that can possibly concur. Since such a level of detail in data preparation is not practical for a large system, another more global approach to model outage concurrence coupling was introduced into the software. Expressed as a global degree of concurrence the user may enter his concurrence input on a percentage scale between 0%, and 100%. In this scale 0% is equivalent to all outages occurring sequential if implemented in the same year, and 100% to all intervention outages having a complete concurrence with only the intervention requiring the longest outage governing the total outage costs.

4 OPTIMIZATION ALGORITHMS

Optimization is a common task in many areas of technology, business and daily life. Loosely the term is used for the process of finding the best solution to a problem.

In the present context, however, the term optimization is used more specifically. It means to find the minimum value of the scalar cost target function, the total costs over a predefined period of time, which is dependent on a vector of independent values which are the times at which each intervention mode is implemented.

4.1 *Stochastic dynamic programming (SDP)*

Dynamic Programming is a classic optimization approach, particularly well suited for problems whose dimensionality is low. It has been applied to a wide diversity of topics in Operations Research, such as Water Resource Management and Power Systems Control (Wurbs 1993, Hachem et al. 1997). A similar formulation to the present one is described in Dreyfus & Law 1977, under the title of the "Equipment Replacement" problem.

The system dimensionality is determined here according to the number of interdependent components. When this number of interdependent components within the plant is relatively low, such as two or three, the Dynamic Programming approach can provide a very efficient, robust and complete resolution of the problem. Furthermore, the problem at hands is discrete, nonlinear and fundamentally stochastic, which makes it difficult for other traditional approaches to solve without making a significant number of approximations.

4.1.1 *Problem formulation*

A number of different intervention modes can be applied to every component within a plant, at various time steps. The formulation allows for finding the best combination of interventions that minimizes the overall cost over the study period. A multiple number of interventions can be applied to the component, as the choice of intervention mode at any given time step constitutes the basic discrete decision variable of the problem.

The stochastic nature of the problem is introduced by calculating the mathematical expectancy of the cost function, defined here as the product of the probability of the future failure or non failure events times their costs. All possible events can be considered in the SDP formulation, i.e., the component can fail once, several times, according to different modes, etc.

The nonlinear characteristic of the problem comes from the fact that the future probabilities of failure depend on the present decision and its cost. This is illustrated in the following paragraph.

4.1.2 *Target Function*

The stochastic cost function (SCF) can be written at time *T0*, as:

$$SCF = \sum_{i} p_{faili(T0)} \cdot C_{faili(T0+1)} + (1 - \sum_{i} p_{faili(T0)}) \cdot C_{nofaili(T0)} \qquad (6)$$

Where p_{faili} = probability of failing in mode i in the current time step, C_{faili} = cost of failing in mode i in the current time step, $C_{nofaili}$ = cost of not failing in mode i in the current time step.

The recursive element of Equation 6 is based on the fact that the cost of not failing in a given time step t is the cost of failing in time step t+1 times its probability, plus the cost of not failing in time step t+1, times its probability, respectively. Mathematically,

$$C_{nofail(T0)} = \sum_{i} p_{faili(T0+1)} \cdot C_{faili(T0+1)} + (1 - \sum_{i} p_{faili(T0+1)}) \cdot C_{nofaili(T0)} \qquad (7)$$

4.1.3 *State variables*

The failure costs are strictly dependent on the age of the component. On the other hand, the O&M, capital and performance benefit costs are dependent on the history of intervention on the component. Although the history of intervention affects the component age through its rejuvenation characteristics, it does not define it completely because failure can also affect the component age (e.g., through complete or partial destruction). There are therefore two state variables that define the components:

- Component age (referred to as “age state”)
- History of intervention (referred to “intervention state”)

There are quickly many possible age states to the problem, as the component can fail in succession, under different failure modes, etc. However, the number of intervention states is generally quite low (number of defined intervention modes with benefits).

4.1.4 *Resolution*

A backward Stochastic Dynamic Programming approach has been used, where the problem is optimized at each stage (time step of a year), for every possible state of the system, starting from the end of the study period. The least cost path to time step 0, for the current age of the component, provides the optimal SCF. The process is illustrated in Figure 3.

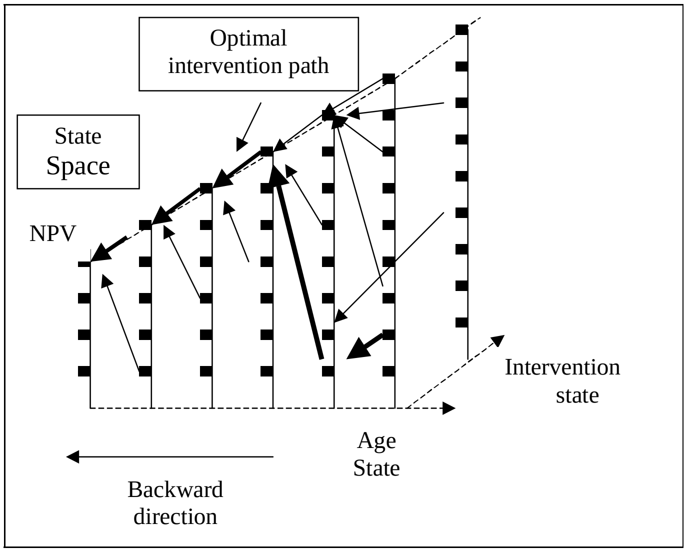

Figure 3: Search for the optimal SCF

4.1.5 *Other Considerations*

Aggregation of the age state has been found to be very effective at reducing the dimensionality of the problem and increasing performance, without a significant impact on the accuracy of the solution. Without interdependencies, a multiple failure and intervention mode problems can be solved within a fraction of a second, whereas a two interdependent component problem is generally of the order of a few seconds when aggregation of the age state variable is applied. The method provides a global optimal, which can be used to compare against the results of the Downhill Simplex approach.

4.2 *Downhill simplex*

4.2.1 *Description of Method*

The downhill simplex method (Press et al. 1992) is suitable for higher dimensional problems and uses only evaluation of the target function itself. No knowledge of its derivatives is required. Its algorithm is self-contained in that it does not require an one-dimensional optimization algorithms to perform.

This method competes mainly with directional methods in that both methods are suitable for multi-dimensional problems, don't require explicit knowledge about the target function derivatives and require data storage proportional to the square of the problem dimensionality. However, the downhill simplex has shown in the present application as well as in the application to an inverse design problem (Favaretto et al. 1998) to be superior in terms of robustness and speed.

The method is geometrically inspired and makes use of a simplex, i.e. a figure with n+1 corners or vertices for an n-dimensional problem. This figure, starting from an initial guess, reflects, expands or contracts to "roll" down the n-dimensional topography of the solution domain to converge at a minimum

4.2.2 *Solution Constraints*

The solution domain is bounded by the problem constraints. These constraints limit the implementation timing to neither reach into the past (which can in the non-Orwellian context not be changed) nor go beyond the horizon of the study duration (where it was decided in the problem definition that costs are inconsequential for the present day). However, not to implement an intervention is a valid implementation outcome and is coded with the value zero for the affected intervention mode.

For the cost target function itself no constraints exist in that both positive and negative values are permissible. In the latter case the benefits of a capital plan outweigh its costs.

4.2.3 *Solution Strategy*

To get started the algorithm needs an initial guess of the geometry and a set of basis vectors for the solution space. Since any multi-dimensional optimization problem is plagued by the nagging question whether the optimum found is truly global or only local it is good practice to use as much information about the problem as can be obtained.

Knowledge that can be obtained at relatively cheap computational cost is the best timing of an intervention for the one-dimensional problem of a single individual intervention mode. Further, it is known that the outage concurrence coupling of intervention modes always yields a less expensive cost target function than an equivalent uncoupled system.

Therefore, this information is used to construct the initial simplex placing its vertices on points in the domain that represent individual optimum timing and outage concurrence points.

4.3 *Comparison of optimization methods*

Marked differences between the two approaches exist. While the dynamic programming approach deals with the stochastic values of risk costs according to their true nature the downhill simplex method uses a pseudo-deterministic approximation.

What is the advantage of the former approach, i.e. an accurate model of all possible paths through time, for a system of one or two components becomes its downfall for models of higher dimensionality. This is where the approximate nature of the downhill simplex is more advantageous.

For the user it translates into the following profile for the two approaches (see Table 1)

Table 1. Comparison of Downhill Simplex and Stochastic Dynamic Programming optimization approach

	Downhill Simplex	SDP
Stochastically Accurate	No	Yes
Suitable for Individual Components	Yes	Yes
Suitable for Larger Coupled Systems	Yes	No
Able to Optimize Intervention Mode and Timing	Timing only	Yes

5 APPLICATION

The application for the HydroVantage model described above varies broadly. Potential uses include:

- Devise a risk-based capital expenditure (CapEx) plan for a whole plant or individual components
- Review an existing CapEx plan from a risk-based perspective
- Demonstrate viability of a rehabilitation or upgrade project
- Prioritize competing projects
- Determine optimum timing for a viable project
- Determine the optimum intervention mode for a component at risk
- Determine costs of deferring or anticipating an intervention (if overruling reasons exist to do so)

Similarly, the potential user group is diverse:

- Operating or maintenance staff
- Maintenance manager
- Station/plant manager
- Engineering staff
- Asset manager

The following application example was carried out on behalf of the station management to review the 20-year CapEx plan developed by the owners' head office engineering group and asset managers.

5.1 *Plant description*

The utility-owned plant, built in the mid 1950's, consists of two units with a combined installed capacity of 60 MW which deliver a total of about 280 GWh of electricity per year.

The equipment to be modeled was selected in a screening process outside the actual software using general and specific outage statistics. The model components were selected to include the equipment that posed the greatest risk exposure. The generating equipment including windings, excitation system, bearings, turbine regulation, runner and governor as well as the transformer and parts of the water conveying system of one unit were part of the model. Figure 4 depicts a diagram of the modeled components as well as their failure modes and intervention modes.

5.2 *Application of individual component optimization*

In an initial analysis step components were analyzed on an individual basis without considering their interdependencies. Table 2 shows a comparison between the existing CapEx plan and that devised from a single component risk-based analysis.

The largest difference between the existing and risk-based plan can be realized by introducing benefit driven interventions into the CapEx schedule. This shows most prominently for the intervention modes "upgrade" on the turbine and remove on the inlet valve. Between these two components a difference of about $ 3.25 M can be realized. However, the changes in timing on the risk driven interventions (exciter replacement, turbine overhaul and governor replacements) are in themselves attractive and a difference of about $ 1.85 M can be realized there. The benefit driven and risk driven amounts are not exactly cumulative, because of an overlap in components and for a comprehensive intervention schedule solution a fully interdependent model needs to be consulted.

5.3 *Application of interdependent system optimization*

5.3.1 *Effect of failure coupling*

To investigate the effect of interdependencies of failure modes, or failure coupling, alone the components whose failure modes had a chance of inducing other failure modes were grouped together and modeled. These groups can be identified in Figure 4 as being linked by dashed lines.

It was found that the failure coupling, which can be viewed in some way as a secondary or consequential damage cost associated with a failure mode, is small enough to generally not affect the intervention schedule significantly. Only for one intervention mode, the transformer replacement, was a different optimum intervention time by one year determined. The associated total net present value of all costs over the entire study duration, short NPV, could only be compared directly between individual analysis and failure-coupled analysis where the failure coupling remains within a single component as is the case for the generator and transformer. In Table 3, the difference refers to the difference in NPV between failure coupled and individual intervention mode optimization The small difference relative to the absolute value of NPV confirms that the failure coupling is in deed minor.

However, this application may be peculiar in that the components which may be subjected to expensive failure modes such as the water conveyances or civil structures are outside the scope of components that were analyzed. To account for these failures their costs are factored into the risk costs of failure modes of the components which are part of the scope, i.e. the costs are treated implicitly. Therefore, it can be asserted that in a model that includes such components explicitly within its scope a strong failure coupling may be present.

5.3.2 *Effects of Outage Coupling*

A further increase of sophistication in the model is the coupling of intervention modes through their outage concurrence. The recommendations to the Owner's were derived from these results.

Interdependency between intervention modes, or outage coupling, arise from the fact that implementing multiple interventions simultaneously saves on outage time. Typically and also in this application the high value of outage costs relative to costs for material and labor create a strong outage coupling in the simulation.

Unlike failure coupling, which increases only the computational time that is required for each combination in the intervention schedule, the outage coupling increases the number of combinations of intervention modes that form an intervention schedule. This affects computational time much more dramatically than failure coupling through increasing the dimensionality of the optimization problem. For this reason, a step-wise solution strategy was adopted where outage interdependencies were investigated first in pairs, then in groups of three, four, five and finally for all 13 relevant intervention modes.

From the pair-wise model runs, it can be learned that the concurrence of outages results in a strong affinity between intervention modes. Over and above the net gains from an optimization of the individual modes, up to 30% improvement relative to the NPV for single optimization can be gained. For three to five simultaneous intervention modes, this percentage rises to 150%.

For high problem dimensionality, 13-dimensional in the present application, it can never be proven rigorously that a global minimum of the NPV costs has been found because above about five intervention modes, the complete mapping of the solution domain becomes too computationally expensive. Therefore, various optimization start simplices were tried and compared based on intuition and previous lower-dimensional results. With such a solution strategy high confidence in the global validity of the found minimum NPV cost can be assured, in spite of the lack of complete rigor.

As shown in Table 4, NPV cost savings between the CapEx intervention schedule and the risk-optimized schedule amount to about $3.87 million or 115% of the total NPV for the existing capital plan.

6 CONCLUSIONS

Traditionally, risk costs are not considered in CapEx planning quantitatively in the form of risk cost stream forecasts. However, to translate engineering concerns over reliability of aging equipment into a financially tangible form the inclusion of risk costs is deemed an appropriate, consistent and transparent approach. The inclusion of these stochastic risk costs allows for a more realistic model on which to base decisions.

To compute risk costs, applicable and adequately researched failure probability curves need to be available which represent the equipment under investigation and for the life stage they are in.

Components can be analyzed in an individual, component-by-component fashion and these results already help to make better decisions than to decide by judgement and intuition alone. However, to reap the full benefit of a risk-based optimization analysis it is far superior to consider interdependencies arising from failure and outage concurrence coupling.

Significant savings are typically found between an existing traditionally prepared CapEx plan and one based on risk principles. For the presented application the difference in total costs reached a level where the revision of the CapEx schedule was worth more than the initial plan itself.

The HydroVantage model is a unique tool for the complex risk analysis of a system of interdependent components of a hydroelectric power plant that supports capital planning decisions. Easy access to the model is insured by providing it as an internet-based user-friendly application.

7 FUTURE WORK

Various improvements and enhancements to the presently offered features are planned as the software matures and its use becomes more wide spread. Some of the more significant are:

A major value of the software stems from the quality of the failure probability and component specific cost data that is provided as “default” values. To maintain the underlying data base a mechanism needs to be created to feed back information that resides with each individual user. Web-enabled polling software is planned for integration with the HydroVantage model.

Presently the model formulation represents explicitly only intervention modes that affect the component reliability. However, a class of interventions acts not on the component itself, but rather mitigate the failure risk by giving early warning of failure or by reducing the consequence costs or outage exposure, such as monitoring equipment and provision for spare parts at site. A more realistic formulation for such intervention modes is currently in progress.

Component interdependencies exist not only through failure and outage concurrence coupling, but also in some cases through benefits coupling. Such a coupling exists when the benefits for an intervention on one component are conditional on intervention on another component. An example for such a benefit coupling would be a runner upgrade It provides for a higher turbine capacity which may be constraint by the generator capacity and conditional upon a generator stator rewind. Formulations that allow for this type of coupling are presently under development.

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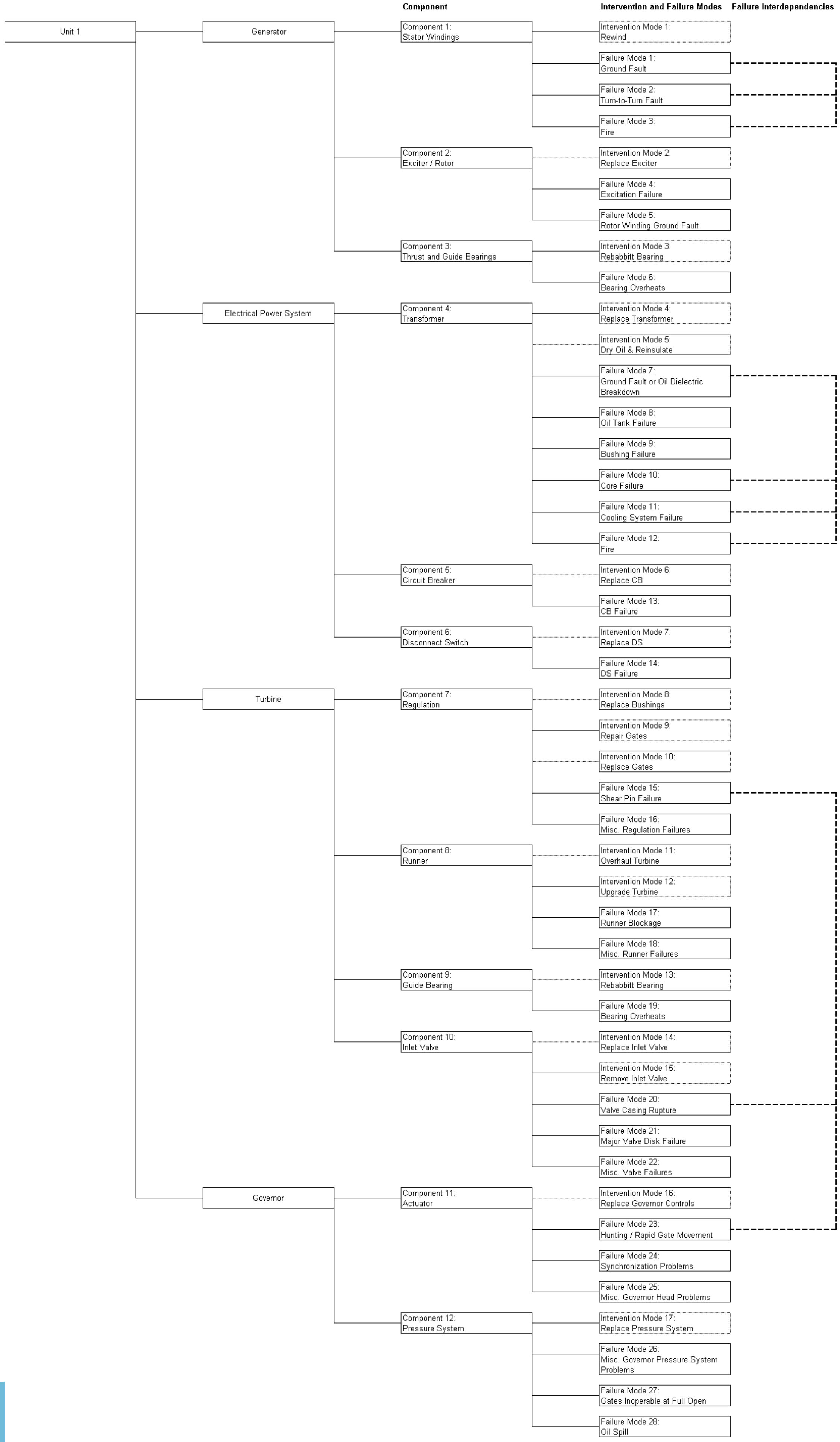

Figure 4. List of components, failure modes, their failure coupling and intervention modes included in analysis

Table 2. Comparison of existing CapEx plan and risk-based one using only individual component analyses

Component	Intervention Mode	Existing 20-year CapEx		Risk-Based Analysis		Difference in NPV
		Year	NPV	Year	NPV	
Generator Stator Winding	Rewind	2011	$ 2146 k	2009	$ 2145 k	$ 1 k
Exciter /Rotor	Replace	2001	$ 642 k	2017	$ 509 k	$ 133 k
Thrust and Guide Bearing	Rebabbitt	n/a	n/a	don’t	$ 323 k	n/a
Transformer	Replace	2010	$ 829 k	2009	$ 826 k	$ 3 k
	Overhaul	now	$ 1152 k	2004	$ 1123 k	$ 29 k
Circuit Breaker	Replace	don’t	$ 166 k	don’t	$ 166 k	$ 0
Disconnect Switch	Replace	now	$ 146 k	now	$ 146 k	$ 0
Turbine Regulation	Replace Bushings	n/a	n/a	now	$ 359 k	n/a
	Overhaul Gates	2011	$ 451 k	don’t	$ 265 k	$ 186 k
	Replace Gates	2011	$ 292 k	don’t	$ 265 k	$ 27 k
Turbine	Overhaul	2011	$ 1316 k	don’t	$ 46 k	$ 1270 k
	Upgrade Runner	2011	($ 1504 k)	now	($ 4007 k)	$ 2503 k
Guide Bearing	Re-babbitt	don’t	$ 169 k	don’t	$ 169 k	$ 0
Inlet Valve	Replace	don’t	$ 400 k	2002	$ 141 k	$ 259 k
	Remove	don’t	$ 400 k	now	($367 k)	$ 767 k
Governor Actuator	Replace	2008	$ 337 k	don’t	$ 151 k	$ 186 k
Governor Pressure System	Replace	2008	$ 304 k	don’t	$ 19 k	$ 285 k

Table 3. Comparison of risk-based individual component analysis and only failure coupled analysis

Component	Intervention Mode	Individual Analysis		Failure Coupled Analysis		Difference in NPV
		Year	NPV	Year	NPV	
Generator Stator Winding	Rewind	2009	$ 2145 k	2009	$ 2203 k	$ 58 k
Transformer	Replace	2009	$ 826 k	2008	$ 836 k	$ 10 k
Turbine Regulation	Replace Bushings	now	$ 180 k	now	n/a	n/a
	Replace Gates	don’t	$ 265 k	don’t	n/a	n/a
Turbine	Upgrade Runner	now	($ 4007 k)	now	n/a	n/a
Inlet Valve	Remove	now	($ 367 k)	now	n/a	n/a
Governor Actuator	Replace	don’t	$ 151 k	don’t	n/a	n/a

Table 4. Comparison of existing CapEx with failure and outage concurrency coupled risk-based analysis

Component	Intervention Mode	CapEx Schedule	Optimum Intervention Schedule
Generator Stator Winding	Rewind	2011	2009
Exciter / Rotor	Replace	2001	2009
Thrust and Guide Bearing	Rebabbitt	don’t	don’t
Transformer	Replace	2010	2009
Circuit Breaker	Replace	don’t	don’t
Disconnect Switch	Replace	now	now
Turbine Regulation	Replace Bushings	don’t	now
Turbine Upgrade	Runner	2011	now
Guide Bearing	Rebabbitt	don’t	don’t
Inlet Valve	Remove	don’t	now
Governor Actuator	Replace	2008	don’t
Governor Pressure System	Replace	2008	don’t
Total NPV		$ 3348 k	-($ 518 k)