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Optimizing Group Turbine And Generator Replacement Times With Life Cycle Cost Model Approach

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Abstract

This article presents a model for calculating the Economic Service Life of turbines and generators in power plants. It considers various factors such as Inspection Cost, Capital Cost, Risk Cost and Opportunity Cost to estimate the life-cycle cost. Based on historical data and experts' opinions, a probability distribution with different parameters is provided for each turbine and generator. With the new design of turbines and generators producing more electricity, they are likely to be replaced sooner based on economic considerations rather than just the manufacturer's lifespan. A cost-optimization model is developed for power plant networks to find the optimal Economic Service Life while considering constraints like limited replacements each year and replacement of both turbine and generator at the same time. The model is effectively tackled using genetic algorithms. In cases where solutions do not meet constraints, they are deliberately penalized. The results provide the minimum life-cycle cost for all units and determine the optimal lifetimes for each turbine-generator, maximizing assets' value, optimizing resources, and ensuring reliability in the system.

Keywords: cost optimization model, power plant networks, genetic algorithms, reliability

1. Introduction

Expected Service Time (EST) and Economic Service Life (ESL) represent distinct concepts concerning an asset's lifespan. EST denotes the anticipated duration for which an asset operates effectively and efficiently under normal conditions, considering factors like design, manufacturing quality, and operating environment. Conversely, ESL signifies the duration during which an asset remains economically viable, generating adequate revenue to cover operating and maintenance costs, and yielding a reasonable return on investment. Economic factors such as replacement costs, financing, and market dynamics also influence ESL. Analyzing the Life Cycle Cost (LCC) of an asset facilitates ESL estimation. LCC encompasses all expenses associated with owning, operating, and decommissioning a hydroelectric power plant throughout its lifespan. This comprehensive analysis incorporates initial capital outlays, operational and maintenance expenditures, as well as risk costs. LCC assessment plays a pivotal role in asset management, aiding in procurement decisions, ongoing management support, performance evaluation, and future investment planning (Sinisuka and Nugraha, 2013).

Hydroelectric power plants play a pivotal role in sustainable energy generation, providing clean and renewable electricity. However, ensuring their optimal performance and longevity poses significant challenges for asset managers and operators. A key part of good management is knowing when to replace important components like turbines and generators. This decision directly impacts operational efficiency, maintenance costs, and overall profitability. To address these challenges, this study proposes a novel approach leveraging comprehensive LCC analysis and optimization techniques to estimate the ESL of hydro-power plant assets.

The literature on asset management and life-cycle cost analysis provides valuable insights into optimizing the operational lifespan of various energy systems. El-Akruti et al. (2013) emphasizes the critical role of life-cycle cost analysis in engineering asset management, highlighting its importance in decision-making processes regarding maintenance, repair, and replacement strategies. Wang et al. (2018) offer a comprehensive review of evaluation, optimization, and synthesis methodologies for energy systems, underscoring the significance of such approaches in enhancing the efficiency and sustainability of thermal power plants. In the context of power generation, Sinisuka and Nugraha (2013) conducted a life-cycle cost analysis focusing on operational aspects, shedding light on the economic factors influencing decision-making in power generation facilities. Liu et al. (2023) extended this analysis to wind power systems, emphasizing the importance of economic modeling in assessing the life-cycle cost and economic viability of renewable energy sources. Moreover, Amba and Dalimi (2023) present an economic analysis of hybrid power plants, demonstrating the applicability of comprehensive cost assessments in optimizing energy generation from multiple sources. Amoussou et al. (2023) explores the technical and economic feasibility of replacing traditional thermal power plants with hybrid PV-PHSS systems, highlighting the potential for cost savings and environmental benefits.

Within the realm of hydroelectric power, Kumar, and Saini (2022) provide a detailed review of operation and maintenance practices, emphasizing the importance of proactive maintenance strategies in maximizing plant efficiency and longevity. Keck et al. (1995) discuss the significance of runner replacement in hydro-power plants, underlining the potential for enhancing energy generation through timely component upgrades. Incorporating optimization techniques into asset management, Koch et al. (2007) demonstrate the effectiveness of evolutionary algorithms in optimizing combined cycle power plants, illustrating the potential for improving operational efficiency and cost-effectiveness. Balanta et al. (2023) focus on planning and optimizing the replacement strategies of power transformers, highlighting the importance of strategic decision-making in asset management.

Overall, the literature underscores the critical role of comprehensive life-cycle cost analysis and optimization techniques in enhancing decision-making processes, improving operational efficiency, and maximizing the economic viability of energy systems. However, there remains a gap in the literature concerning the optimization of replacement timing for turbines and generators in hydro-power plants, particularly in addressing the unique challenges posed by simultaneous replacement requirements and limited capacity constraints. This study aims to fill this gap by proposing a novel approach utilizing genetic algorithms to optimize the replacement time of group turbines and generators in hydro-power plants by estimating ESL based on a comprehensive LCC model. The LCC model incorporates various cost factors including operating and maintenance expenses, depreciated cost, and risk costs, alongside the consideration of postponed investment expenses. These costs are crucial determinants influenced by factors such as the age of the plant, technological advancements, and inspection frequency. Hydro-Québec (HQ), operating 61 hydroelectric generating stations with a capacity of 37.2 GW, faces challenges in maintaining and replacing generating units due to constraints like limited replacement capacity per year and simultaneous replacement requirements.

The rest of the article is structured as follows. Section 2 illustrates the method for computing the ESL for each asset, Section 3 shows how the model is integrated with a genetic algorithm. Section 4 provides a numerical example and presents the results. Finally, the conclusion is summarized in Section 5.

2. Financial model for LCC

Annualization is the process of converting a cost or benefit from a one-time occurrence into an equivalent cost or benefit per year. By annualizing cost, one can account for the time value of money, ensuring that the costs of a project can be compared consistently over its entire life cycle. Additionally, annualizing costs is also useful for costs that are dependent on probability, such as power outages due to sudden failures. These costs are probabilistic and can vary each year, with different probabilities of occurrence and different costs associated with each year. For example, a component with a high failure rate in its last five years of life will have a higher yearly risk cost compared to its first five years.

As previously stated, the costs included in the LCC analysis are maintenance costs, risk costs, capital costs, and investment delay costs. These costs and parameters, detailed in Table 1, represent gross estimations and are not necessarily representative of Hydro-Québec’s data. They are used solely for demonstration purposes.

Table 1. Input data.

Inflation rate	2%
Expected Service Life	40
Increase in productivity of the upgraded asset	2%
Initial Capital Cost (cost of planned replacement)	$6M
Cost of unplanned replacement	$10M
Depreciation rate	0.1
Market price (MWh)	$50
MIC	$60 k
Inspection frequency	6 years
Weibull distribution	Scale: 20 Scale: 3.7

2.1. Maintenance & Inspection Costs (MIC)

MIC in hydro power plants refer to the expenses incurred in keeping the plant running efficiently and safely over its lifetime. This includes regular inspections, repair, and replacement of equipment, as well as labor and materials costs. Every six years, in HQ, turbines and generators are inspected, and if any partial failures are found, they undergo repairs. This cost is treated as a steady, predictable expense and is spread out over the course of the year. This cost may also incorporate a probabilistic component if there is a probability of discovering partial failure at each inspection, but this is not considered in the present study. Note that the operational costs of a hydro power plant are relatively low as they generate electricity from the kinetic energy of falling water and have few fuels cost.

For example, using the data in Table 1, the MIC is calculated as $60,000, which, after considering the inflation rate, becomes $66244. This cost is then divided into six equal payments (Taking inflation into account), resulting in $11826.4 per year. The MIC for the asset's life cycle is determined by adding up all the AMIC payments over the years.

2.2. Risk Costs (RC)

RC is the cost associated with the unexpected breakdown of an asset, such as turbines or generators. It can be caused by various factors, including poor maintenance, design flaws, and wear and tear. The calculation of RC cost involves estimating the cost of replacement and the cost of any lost production or sales that result from the sudden failure. In addition, the likelihood of failure plays a crucial role in determining the RC. To calculate RC, we must first calculate the Annualized Risk Cost (ARC). The failure rate over the lifespan of an asset is used to calculate the ARC. The probability density function of an asset enables the calculation of the reliability function, cumulative failure and failure rate curve as shown in Equations (1) through (3), respectively (O'Connor, 2012.).

$$R(t) = \int_{t}^{\infty} f(t) \tag{1}$$

$$F(t) = 1 - R(t) \tag{2}$$

$$r(t) = \frac{f(t)}{R(t)} = -\frac{1}{R(t)}\frac{dR(t)}{dt} \rightarrow r(t)dt = -\frac{dR(t)}{dt} \tag{3}$$

where *R(t)* is reliability from time 0 until time t, *r(t)* is the failure rate at time *t*, *f* (*t*) stand for probability density function and *F*(*t*) is the cumulative failure until time *t*. Figure 1 displays the cumulative failure, reliability, and failure rate of an asset throughout its lifespan, using the Weibull distribution with a shape parameter of 3.5 and a scale parameter of 30 years.

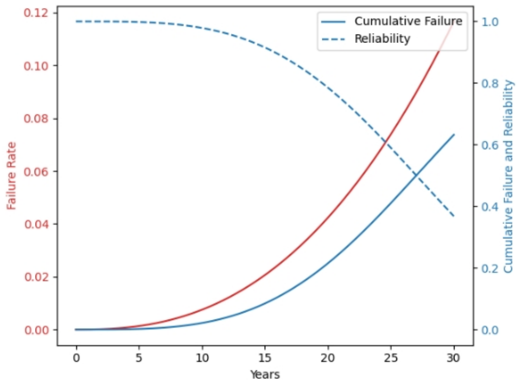

Fig. 1. The cumulative failure, reliability, and failure rate of an asset over the course of its lifetime.

By having the probability density function, the probability of failure at year t can be calculated as follows:

$$F(t-1,t) = F(t) - F(t-1) = \int_0^t f(t) - \int_0^{t-1} f(t) \tag{4}$$

Consequently, ARC can be calculated by multiplying the cost of unplanned replacement and lost production by the probability of failure for each year. The RC for the life cycle of the asset then calculated by summing up all its ARC over the years.

$$ARC\ (t) = F(0,t)\ \times Costs\ due\ to\ sudden\ failure \tag{5}$$

$$RC\ (t) = \sum_{i=0}^{t} ARC\ (i) \tag{6}$$

Given the same probability distribution and the data in Table 1, the failure rate for the year 15 is 0.020 and the cumulative failure rate by this year is 0.084. ARC for year 15 is 0.084 ×100,000k$ =8400 k$ and the RC for the lifespan of 30 years is equal to 63238 k$. Figure 2 presents the cumulative failure and ARC for the duration of 30 years.

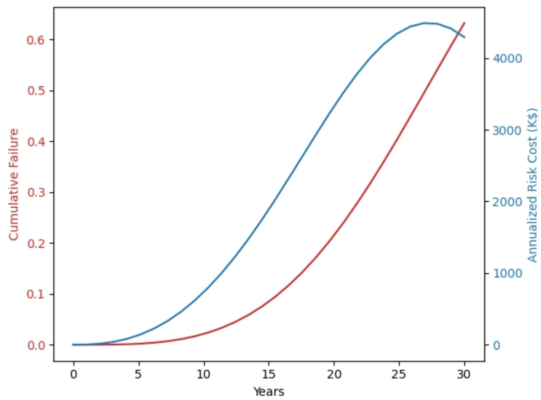

Fig. 2. The cumulative failure and the annualized risk cost.

2.3. Capital Cost (CC)

CC of an asset includes all expenses incurred in bringing an asset into use, including its purchase price, transportation, installation, and any other costs necessary to make it operational. On the other hand, the Depreciated Cost of an asset is the expense incurred for the gradual decrease in value of an asset over its useful life. This cost is typically calculated using a depreciation method such as the straight-line method, declining balance method, or sum-of-the-years'-digits method (Harrison Jr, 2014.). The purpose of calculating depreciation is to allocate the cost of the asset over the years that it is being used, rather than incurring the entire cost in the year the asset is purchased.

The CC for year T can be calculated based on depreciation rate using Equations 7.

$$CC\left(year\ (T)\right) = CC\left(year(0)\right) * (1 - Depreciation\ rate)^{Year\ (T)} \tag{4}$$

where, Salvage Value is the estimated value of the asset at the end of its useful life, which is typically zero and Expected Service Time (EST) is the number of years the asset is expected to be used which is provided by the manufacturer. For example, based on the information in Table 1, an asset with initial capital cost of 60,000 k$, depreciation rate of 0.1 and with ETS of 40 years, the CC after 10 years will be equal to 20,400 k$.

2.4. Opportunity Cost (OC)

Opportunity cost is the cost of not investing in a particular project or asset and is a measure of the lost potential benefits of an investment. In HQ, the overall improvement in turbine performance results in new designs being more efficient and powerful compared to older ones. This enhancement occurs gradually over the span of decades. The cost of not replacing the outdated generating unit with the new and improved one is calculated as the difference in the anticipated revenue or gain that the new unit could bring compared to the old one.

Consider an aging 40-year-old generating unit producing 50,000 MWh annually, generating $2.5 million in revenue at $50/MWh. The upgrade version is available after 40 years of set up of the last one, boosts output by 2%, reaching 51,000 MWh annually. This generates $2.55 million revenue annually. It means that failing to take advantage of this opportunity would result in a loss of $1 million after 20 years. This cost would prompt the replacement of the asset sooner to take advantage of the opportunity and convert the cost into profits.

2.5. Total cost and ESL

In this section, we create a visual representation of the total cost of the asset over a 30-year span, utilizing the information presented earlier in the examples and in Table 1. The costs taken into account include inspection costs, risk costs, capital costs, opportunity costs, and the total cost, all adjusted for a 2% inflation rate. In figure 3, the X-axis represents the time in years, and the Y-axis represents the cost in dollars. The graph provides a clear picture of the costs over time, allowing for easy comparison and analysis of cost trends. The point in time when the total cost reaches its minimum is referred to as the economic service life of the asset. In the given example, the minimum total cost occurs at year 13 and is equal to $4.01 million. This information is important in making decisions about when to replace the equipment, as operating it beyond its economic service life may lead to higher costs.

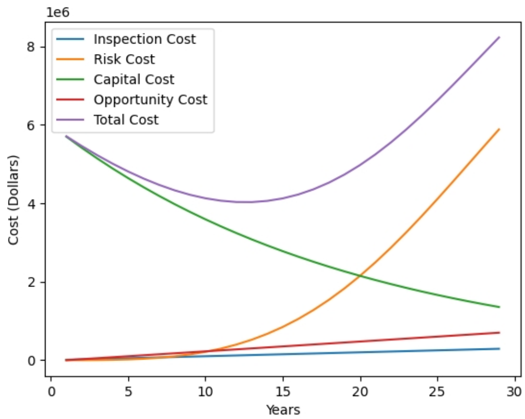

Fig. 3. A visual representation of all costs over 30 years.

3. Model description and Genetic Algorithm

Each power plant in HQ comprises several generating units, the two primary and expensive components of which are the turbine and generator, each possessing its own set of characteristics such as probability distribution and initial capital cost. By utilizing this methodology, the estimated economic Service Time for each group of turbines and generators can be calculated. However, the implementation of the plan may be affected by restrictions within the hydro power plant network, leading to the need to adjust the replacement schedule for the generator units from the original estimate. With limited replacement windows available per year and the simultaneous replacement requirement of turbines and generators, and external constraints may cause variation in the replacement date. As such, an optimization model is required, with the ESL for each turbine and generator as the variables and the objective being to minimize the total cost for the entire system. The model is then developed and solved through the use of Genetic Algorithms.

3.1. Mathematical Model

In optimizing the replacement schedules for turbines and generators within our system, we aim to minimize the total costs while adhering to various operational constraints. Equations 8 through 13 present the objective function and constraints governing the optimization model.

$$Min\,(\sum_{i=1}^{GTA} CC(x_i) + CC(y_i) + \sum_{i=1}^{GTA} RC(x_i) + RC(y_i) + \sum_{i=1}^{GTA} OC(x_i, y_i) + \sum_{i=1}^{GTA} IMC(x_i, y_i) + \sum_{i=1}^{GTA} P1_i + \sum_{i=1}^{GTA} (P2T_i + P2A_i) + P3) \tag{8}$$

Subject to:

$$(x_i - y_i) \times M1 = P1_i \quad \forall\, i = 1, 2, \ldots, GTA \tag{9}$$

$$\big((MS(i) + x_i) - D_i\big) \times M2 = P2T_i \quad \forall\, i = 1, 2, \ldots, GTA \tag{10}$$

$$\big((MS(i) + y_i) - D_i\big) \times M3 = P2A_i \quad \forall\, i = 1, 2, \ldots, GTA \tag{11}$$

$$\text{Let C} = \{i = 1, 2, \ldots, GTA \mid C_i = x_i + MS(i)\}\text{: (CountRep (C)} - T) \times M_4 = P3 \tag{12}$$

$$x_i \;\&\; y_i \quad Integer \tag{13}$$

The objective function (Eq. 8) is the sum of Capital Cost $[CC(x_i), CC(y_i)]$, Risk Cost $[RC(x_i), CC(y_i)]$, Opportunity Cost $OC(x_i, y_i)$, Inspection Maintenance Cost $IMC(x_i, y_i)$, and penalties resulting from constraint violations. In constraint (9), the replacement date of turbine and generator of each group should be performed at the same time. In Case of having different replacement date for Turbine and generator of each group *i*, the penalty $P1_i$ will be added to the objective function. Constraints (10) and (11), the replacement date of group i should be after date D_i. $P2T_i$ and $P2A_i$ will be added to the objective function if these constraints are not met. In constraint (12), each year only T number of group can be replaced. CountRep (C) tallies yearly replacements, moreover, T denotes the maximum number of GTA replacement at each year. $P3$ represents the penalty imposed for surpassing the maximum allowable number of replacements each year. Lastly, x_i & y_i which represent the lifetime of turbine and generator in group *i*, respectively, should be integer.

3.2. Genetic Algorithm (GA)

GA has been widely used to find the optimal solution of highly complex practical problems (Popov, 2005). In this study, to solve the explained model, a GA has been implemented. GA establishes a searching technique by combining the idea of survival of the fittest and an interbreeding population. The strings and the best interbreed are ranked to produce new strings, which are closer to the optimal solution for the problems. Different aspects of GA, such as objective function, crossover, and mutation, are discussed below.

Objective function

The objective function takes the solution encodings as input, then produces a result that quantifies how good that solution is. Due to the constraints provided above, penalty functions are also used to penalize solutions by increasing the total cost based on their degree of constraints' violation. This penalty function also allows the algorithm to search out of the feasible area and on the frontier.

Crossover and mutation

To produce off-springs for the next population, crossover and mutation operations are used. In the crossover, more than one parent is selected, and one or more off-springs are produced using the genetic material of the parents. Here, two types of crossovers named 'single point' and 'multi-point' are used. In the single-point crossover, to create new offspring, a random crossover point is chosen and the tails of its two parents are swapped. Double-point crossover is a modification of one-point crossover in which two segments are exchanged to produce new offspring. Figure 3 shows a double point crossover. To maximize diversity and avoid premature convergence into a local optimal solution, the mutation operator is used. In mutation, we select one or more random bits and flip them. Figure 4 shows a solution before and after mutation.

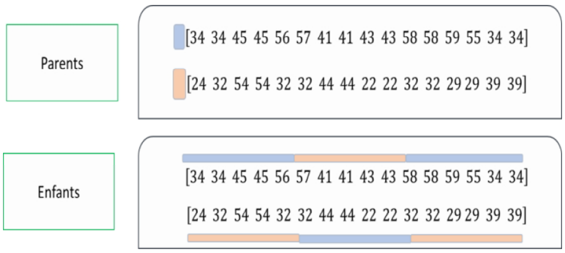

Fig.3. Double-point crossover operator.

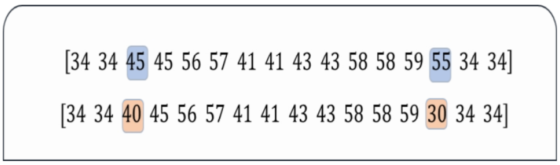

Fig.4. Mutation operator.

4. Results

This section examines six power plants that have had various groups of turbines and generators installed at different years. Each power plant's combination of turbine and generator follows a different probability distribution. For example, Power Plant A, which was installed in 2011, has four GTA combinations where the turbines follow a Weibull distribution with a shape parameter of 80 and scale parameter of 5, while the generators have 67 and 4.6 as their scale and shape parameters, respectively. The replacement cost and initial capital cost for the turbines and generators for each power plant are assumed to be the same. There are no plans to upgrade the design of power plant A. Details about all the GTA for each power plant can be found in Table 2.

A genetic algorithm was used to model to find a solution, considering a 10-year time frame for upgrading the turbines and a price of 40$ per MWh increase in productivity due to the upgrades. The constraints were that replacement actions must begin after 2030, with a maximum of two GTA replaced per year. The results, shown in

Table 3, list the costs for each GTA in each power plant, with the overall cost for the entire network being 29.98 million dollars. Figure 4 displays the Life Cycle Cost for the first GTA in Power Plant A.

Table 2: Input data of six power plant generations.

Power plants	Tur. Gen.	Probability Distribution	Increase in productivity (MWh)	Sudden Replacement Cost	Initial Capital Cost	Set up date	Number of GTA
A	T	Weibull (80, 5)	0%	10 M$	6 M$	2010	4
	G	Weibull (67, 4.6)		8 M$	4 M$	2010	
B	T	Expo. (0.008)	1%	10 M$	6 M$	2013	3
	G	Expo. (0.087)		8 M$	4 M$	2013	
C	T	Gamma (40, 2)	1%	10 M$	6 M$	2014	3
	G	Gamma (45, 1.3)		8 M$	4 M$	2014	
D	T	Expo. (0.007)	1%	10 M$	6 M$	2020	2
	G	Expo. (0.001)		8 M$	4 M$	2020	
E	T	Weibull (75, 4)	0%	10 M$	6 M$	2000	1
	G	Weibull (70, 5)		8 M$	4 M$	2000	
F	T	Expo. (0.006)	1%	10 M$	6 M$	1982	2
	G	Expo. (0.001)		8 M$	4 M$	1982	

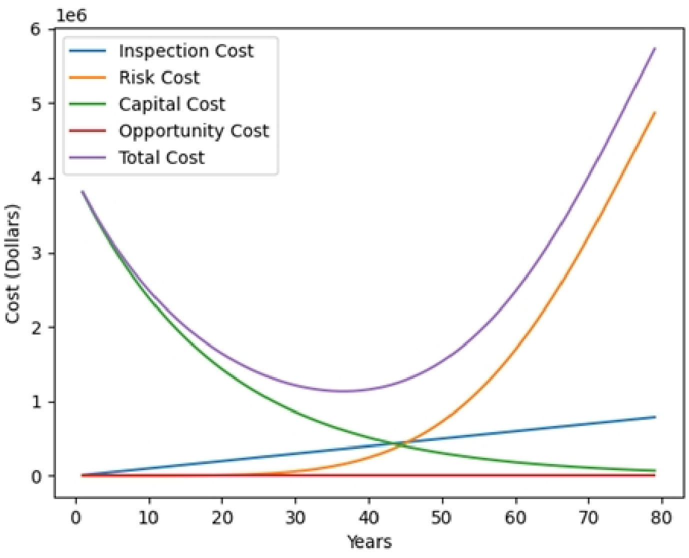

Fig.5: LCC for the first GTA in plant generation (a).

Table 3: Results obtained by GA.

Power plants	Tur. Gen.	ESL	Replacement Date	Capital Cost (M$)	Inspection Cost (M$)	Opportunity Cost (M$)	Sudden Replacement Cost (M$)	Sum (M$)
A	T	**35**	2045	0,997	0,35	0	0,159	1,506
	G	**35**	2045	0,664			0,394	1,408
B	T	**23**	2036	1,844	0,23	0,336	1,681	3,937
	G	**23**	2036	1,229			1,19	2,831
C	T	**17**	2031	2,509	0,17	0,126	0,684	3,426
	G	**17**	2031	1,673			1,571	3,476
D	T	**32**	2052	1,162	0,32	0,44	2,007	3,709
	G	**32**	2052	0,775			0,252	1,567
E	T	**33**	2033	1,104	0,33	0	0,368	1,802
	G	**33**	2033	0,736			0,184	1,25
F	T	34	2032	1,049	0,34	0,48	1,845	3,474
	G	34	2032	0,699			0,32	1,599

5. Conclusion

In conclusion, this paper presents a life-cycle cost model that estimates the economic service life for turbines and generators in power plants. The model considers various factors such as the capital cost, cost of inspection, and risk costs in its calculations. The study uses historical data and experts' opinions to calculate a probability distribution for each turbine and generator to determine the optimal lifetimes for each turbine-generator unit and help maximize the assets' value. The replacement schedule for the units in the hydro power plant network may face restrictions and adjustments due to various constraints, including limited replacement windows, simultaneous replacement of turbines and generators, and external limitations. To address this, an optimization model was developed with the aim of minimizing the total cost for the entire system. The model was solved using Genetic Algorithms with the optimal replacement time for each turbine and generator as the variables. This approach provides a solution that effectively balances the constraints and optimizes the system's cost.

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