Life Cycle Cost Analysis of Pumping System

Subjects: Engineering, Electrical & Electronic
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The pumping system is a critical component in various industries and consumes 20% of the world's energy demand, with 25–50% of that energy used in industrial operations. The primary goal for users of pumping systems is to minimise maintenance costs and energy consumption. Life cycle cost (LCC) analysis is a valuable tool for achieving this goal while improving energy efficiency and minimising waste.

hidden Markov model life cycle cost pump

1. Introduction

Various industries worldwide depend on pumping systems for their daily operations. Optimising a pump is challenging across multiple application areas, like irrigation, water supply for the domestic sector, air conditioning systems, refrigeration, and the oil and gas industries, etc. [1]. In the world of pumps, two types of horizontal end suction centrifugal pumps are more widely used than all the others. They are the ANSI pumps designed and built to the American National Standards Institute standards and the API pump that meets the American Petroleum Institute standard 610 requirements for general refinery service. In order to handle high temperature and pressure applications of a more aggressive character, the API pump is the only option for the oil refinery business. Information on maintenance, failure, and repair times is provided for both pumps. This information has been used to demonstrate how precise predictions for life cycle costs for the pumps used in the hydrocarbon processing businesses may be made.

There is additional discussion of the fundamental ideas of LCC and its uses. In terms of global pumps, there is a need to apply LCC methodology to pumps, considering the stages of an LCC analysis, the need to identify the significant cost drivers, and the advantages of performing an LCC study. When the speed of the motor fluctuates in applications requiring variable torque, such as pumps, the torque produced by the pump likewise varies appropriately. An adaptive neuro-fuzzy inference system (ANFIS) is used in conjunction with DTC to lessen torque sags and enhance the reactivity of the control algorithm. The suggested ANFIS-based DTC has greatly reduced flux, torque, and stator current ripples compared to the conventional DTC and the fuzzy logic-based DTC. The suggested ANFIS-DTC results are verified using MATLAB simulations, and the system's performance is determined to be good when evaluated at various rotational speeds. For the PMSM to drive centrifugal pumps, a new speed control based on adaptive neuro-fuzzy direct torque control (ANFIS-DTC) has been proposed in the research [2]. Through the Matlab Simulink environment, the performance characteristics of the conventional DTC, DTC with fuzzy logic control, and DTC with ANFIS are compared in terms of stator current, electromagnetic torque, stator flux, rotor speed, and pump output pressure. Compared to traditional DTC and DTC with fuzzy logic control, the suggested ANFIS-DTC controller displays satisfactory results in removing overshoot and ripples in torque, flux, and speed.

Some statistical measurements of the mean time between failures are also provided. For pumping systems, the Hydraulic Institute presented a life cycle cost model. Initial costs, installation and commissioning expenses, energy costs, operational costs, maintenance and repair costs, downtime costs, environmental costs, and decommissioning and disposal costs are all considered in the model. An example has been used to show how to apply the methodology. The guidelines developed by Euro-pumps to assist users, consultants, and design engineers in optimising pumping systems with regard to the whole life cost were presented in the research, along with an explanation of the significance of life cycle costs. The optimal operation aims to save electricity expenses, consume maximum energy, reduce water leakage, prevent wear and tear, etc. [3]. Various optimisation algorithms are helpful for reducing electricity expenses and saving consumption of energy, such as the heuristic algorithm [4], PSO [5], ant colony, genetic algorithm [6], etc. However, if the system requires transient changes, CNN model [7] is required to optimise the system. Due to the extreme progress of technology, the costs of variable speed drives have significantly decreased, which is helpful for the pumps used in building conditioning systems. Control and optimisation of variable speed pump operation is a challenging issue. Control engineers have a great responsibility to control the robustness of the pump, improve the operating efficiency, prolong the service life, etc. [8]. An energy-efficient pump scheduling strategy can reduce maintenance and operating costs. In this way, it is possible to reduce CO_2 emissions [9]. Various researchers have conducted extensive studies on pump optimisation and scheduling. Mixed integer nonlinear programming has been used to solve the structural optimisation problem, as the problem is not convex. A binary separable program method has been developed for the optimum global system [10]. The method provides the best configuration of the pump series. The optimal pump scheduling algorithms have been introduced for the water distribution system. An energy-efficient pump scheduling strategy has enormous potential to significantly reduce pump systems’ operational and maintenance costs [11]. For instance, up to 90% of the electricity used in the water industry is consumed by pumps. Purchasing decisions for a pump and the associated system components are often based on the lowest offer rather than considering the system’s cost over its life cycle [12][13][14][15].

To achieve the lowest energy usage and cost, managers must carefully match these interdependent parameters and ensure they are maintained during working conditions [16]. A pumping system typically lasts 15 to 20 years. Some costs will be incurred initially, while others may appear at various points throughout the existence of the multiple options under consideration. Therefore, determining a current or discounted value of the LCC is conceivable and possibly even necessary to properly evaluate the various alternatives [17].

2. Background

There is a significant body of research on pumping systems’ life cycle cost analysis (LCCA). Three distinct pumps have undergone an LCC analysis using a technique based on dependability and maintainability principles, and the results have been compared. Two pumps have been chosen from the literature for analysis, and the information therein is used. The third pump is chosen from a reputable Indian pump manufacturer, and the necessary information is acquired directly from the supplier. The idea of the predicted number of failures in a particular time interval has been used to model the maintenance and repair costs [18]. A methodology for calculating the net present value (NPV), lifetime costs (LCC), energy use, and greenhouse gas emissions related to a water distribution system (WDS) pump using a process-based life cycle assessment (LCA) and an economic input-output LCA (EIO-LCA) model has been described in the research. The methodology takes into account the stages of production, usage, and end-of-life (EOL) disposal in addition to less common operations, such as discharge valve throttling, pump testing, deterioration, refurbishment, and variable speed pumping. A case study presents the technique, evaluates the effects of various operating scenarios, and establishes the relative significance of various processes [19]. A study compares and contrasts decentralised greywater reuse systems' life cycle costs and anticipated financial gains.

In comparison to the current centralised systems, the extra life cycle expenses and expected life cycle financial benefits of the groundwater pumping systems and on-site greywater reuse systems are assessed. Before the wastewater effluent is dumped into the environment, a sewer network gathers used water for treatment at a centralised wastewater treatment plant. Centralised systems refer to the traditional form of water delivery where one centralised treatment plant treats and distributes potable water to a large service area [20]. The optimal design and rehabilitation of a water distribution network are being provided using a new multiobjective formulation to minimise life cycle cost and maximise performance. The initial cost of the pipes, the cost of replacing old pipes with new ones, the cost of cleaning and lining existing pipes, the anticipated repair cost for pipe breaks, and the salvage value of the replaced pipes are all included in the life cycle cost. The resilience index has been modified for use in water distribution networks with multiple sources as the performance measure suggested in this study. In order to find a solution for the design and rehabilitation challenge, a new heuristic strategy is suggested [21]. In order to guarantee the excellent performance of chilled water pump systems and achieve the lowest annual total cost while taking input uncertainties and system reliability into account, this research proposed a reliable, optimal design method that is based on a reduced life-cycle cost. It is accomplished by optimising the number of chilled water pumps, overall pump flow capacity, and the pump pressure head [22].

The suggested approach is tested and shown using a case study. The amount of literature on the life cycle cost of wastewater treatment has significantly increased over the past two decades. The employment of several frameworks and approaches was caused by the lack of a generally accepted life cycle costing methodology. Over the past ten years, a progressive transition from conventional to environmental and societal life cycle costing has been observed. Techniques and approaches for conducting life cycle cost analysis are also changing.

Nevertheless, there is still a need for a thorough, systematic assessment of life cycle costing techniques and methodologies in wastewater treatment. A thorough and systematic evaluation offers the chance to track recent advancements in the subject and pinpoint areas that require additional study [23]. In order to effectively assess the long-term treatment performance and cost under influent fluctuations, this study uses artificial neural networks (ANNs) as surrogate models for water resource recovery facility (WRRF) models. A current facility that handles combined domestic and industrial wastewater served as the model for the five WRRFs. Even though the prediction performance (R-square) somewhat declines with increasing model complexity, the ANNs satisfactorily capture nonlinear biological processes for all five WRRFs. By using ANNs trained by simulation data from steady-state models to simulate long-term (10-year) performance with monthly influent fluctuations, the application of ANNs in WRRF models is expanded, and their effectiveness in removing phosphorus (P) and nitrogen (N) is expanded. Because enhanced biological phosphorus removal and recovery (EBPR) is more susceptible to influent characteristics altered by storm water inflow, EBPR-S has the greatest resistance. To create adequate working conditions, mine-dewatering techniques must be used to eliminate water flow into the mining area. One method of mine dewatering involves the use of pumps. Centrifugal and positive displacement pumps are primarily employed in mine dewatering operations. The primary goal of this project is to create a simple decision-support tool for choosing the most cost-effective pump type.

The ANN model employs time and fitted measurements from its present and prior points as input, together with Weibull hazard rates for root mean square (RMS) and kurtosis. The output is chosen to be the normalised life percentage in the meantime. In doing so, reducing the degradation signal noise from target bearings and raising the prognosis system accuracy is possible. The feedforward neural network (FFNN) with the Levenberg–Marquardt training method is used for the ANN RUL prediction [24]. To reduce catastrophic failure events, the notion of remaining useful life (RUL) is used to predict the life span of components. It is essential to have a continuous monitoring system that records and identifies trends, as well as sources of component degradation prior to failure as customer demand for dynamically regulated systems increases. The goal of the early warning capacity is to identify, localise, and gauge the severity of defects using fault propagation and identified machine or component deterioration to forecast RUL. RUL is typically computed randomly from data on condition and health monitoring that is readily available. Remanufacturing engineers must consider a device's RUL when deciding which parts should be removed from service for remanufacturing. Using case studies, some techniques for estimating RUL, including those for automotive components, rotating equipment, aviation engines, electro-hydraulic servo valves, electronic systems, low methane compressors, bearings, etc., are examined [25]. Further research has been carried out based on support vector regression analysis, XGboost, and PSO for pump performance curve analysis. The performance prediction model has been trained on 428 samples in total, while 107 samples are used to evaluate the model's capacity to generalise, and 46 examples are used to confirm the model's ability to predict outcomes [26]. Some research based on **Table 1** describes various investigations into LCC analysis and RUL application in industrial sectors and their results.

Table 1. Various research based on LCC analysis.

Author	Research Technology	Aim of the Research	Research Outcome
Galagedarage Don, M., and Khan, F. [11]	Hidden Markov model–Bayesian networks	To predict and identify the faults	The suggested method adequately predicts all ten flaws and isolates eight of the ten defects found. The maximum acceptable noise levels for the various flaws were established, and the isolation accuracy

Author	Research Technology	Aim of the Research	Research Outcome
			changed depending on the noise level added to the testing data.
Hofmann, P., and Tashman, Z. [13]	Hidden Markov model	To detect the failure events	It is combined with a Markov mixed membership model (MMMM) and an observable Markov decision process (POMDP) for each asset to evaluate the trade-off between the risk of failure and prolonged operational hours to dynamically optimise the strategy for when and how to maintain the asset.
Waghmode, L.Y., et al. [18]	Economic input/output LCC model	To learn when the pump will end its useful life and how much energy the water distribution system uses	Refurbishing and variable speed pumping can improve a pump's overall sustainability by reducing lifetime expenses, particularly in terms of energy use and GHG emissions.
Jayaram, N., and Srinivasan, K. [20]	Multiobjective formulation	To determine the optimal design and rehabilitation of water distribution network	As novel multiobjective formulations for the optimum network design and rehabilitation, the maximisation of the least modified resilience index and the minimisation of life cycle cost have been proposed. The adjusted resilience index measures the network's ability to handle uncertainty.
Cheng, Q., et al. [21]	Robust optimal design	Calculating the uncertainties generates the cooling load distribution and hydraulic resistance distribution using Monte Carlo simulation	When uncertainties are taken into account, the annual average cooling load varies significantly. The design cooling capacity and chilled water flow will most likely be large if the design cooling capacity is designed based on the cooling load without considering uncertainties. For high accuracy and quick computing, the Markov method can be used to obtain the probability distribution of the system state.
Ilyas, M., et al. [22]	Various conventional approaches to LCC analysis	To find out the impact of LCC in wastewater treatment	The authors examined 66 studies on the LCCA of pumping systems and discovered that energy cost was the most significant factor in life cycle cost. They also found potential cost benefits from using variable speed drives and high-efficiency pumps.
Li, S., et al. [23]	Artificial neural network	Assessing water resource recovery facilities' long-term treatment performance and nutrient removal	Five different WRRF treatment options' long-term nutrient removal efficacy and cost-effectiveness have been compared using a unique methodology. Using ANN models for long-term simulation can significantly reduce the computational load

Author	Research Technology	Aim of the Research	Research Outcome
		costs under stochastic influence characteristics	while maintaining acceptable accuracy, making it easier to couple complicated process models.
Aktaş, Ali Burak [27]	Decision support tool	Utilising LCC analysis, this evaluates centrifugal and positive displacement pumps in mine dewatering operations and creates a program as a decision assistance tool	Since LCC focuses on overall costs rather than the initial capital investment cost of the systems, it can be utilised as a decision-support tool. The total cost of the centrifugal pump is more than the positive displacement pump.
Saon, S., and Hiyama, T. [28]	Artificial neural network	Predicts the remaining useful life of rotary machine	CBM prioritises a machine's precise RUL to boost dependability and reduce maintenance expenses. This research recommends utilising ANN to provide a more accurate estimate RUL of a bearing failure. In this case, the ANN model's input is the Weibull hazard rates of RMS and kurtosis from the current and prior points. The output, which is the normalised life percentage, is also chosen.
Salunkhe, T., et al. [24]	Various conventional methods	To predict the remaining useful life of mechanical components	Model-based approaches are employed when there is a chance that the system could be mathematically modelled. When it is impossible to create a mathematical model of the system, data-driven approaches are applied.

significant thered to d. A time- [18][19][20][21][22][23][27][29][30]. Operating costs are the labour expenses related to running a pumping system. Depending on the complexity and duty of the system, these vary substantially. A pump must be efficiently and routinely serviced to obtain the best performance [31]. Unexpected downtime and lost production costs account for a sizeable portion of the total LCC and can have an impact comparable to those of energy and replacement part costs. Most of the time, the price to dispose of a pumping system will not change substantially based on its design [32]. A life cycle cost analysis (LCCA) is an economic evaluation method used to compare different alternatives over the life cycle of an asset. In the case of a pumping system, an LCCA would compare the costs of various pump systems over their expected lifespan, including initial purchase, maintenance, energy, and replacement costs. The application of artificial intelligence (AI) in pumps can significantly improve their energy efficiency, reduce maintenance costs, and prolong their lifespan. It is seen that with AI applications, most of the costs are reduced, and it becomes possible to save energy.

There can be a distinction when a system includes disposal arrangements as a component of its operational arrangements. A total life cycle cost analysis (LCCA) is the methodology for evaluating bridge intervention solutions that are presented in the study [32][33]. Life cycle cost (LCC) analysis involves assessing the total cost of owning and operating a system or equipment throughout its life cycle, including acquisition, operation, maintenance, and disposal. Various types of research show in **Table 2** that LCC analysis can be performed to compare the costs associated with using pumps in AI applications and without AI applications [34][35].

Table 2. Various results based on LCC analysis.

LCC Analysis Components	Pumps in AI Application	Pumps without AI Application
Acquisition cost	Due to specialist pumps that are compatible with AI systems, there could be greater initial costs.	In AI applications, pumps are compared based on kind, capacity, and manufacturer.
Operation cost	Due to AI optimisation, there could be potential energy savings and lower operating expenses.	Due to a lack of AI optimisation, there will be greater energy consumption and possibly higher operating costs.
Maintenance cost	Due to AI-enabled proactive repairs and predictive maintenance, maintenance expenditures may be reduced.	Higher maintenance costs due to scheduled maintenance or reactive repairs without AI.
Efficiency and performance	Real-time optimisation and adaptive control have improved performance and efficiency.	Lower efficiency and suboptimal performance level.

References

1. Zaman, K. Life Cycle Costs (LCC) for wastewater pumping systems. In Proceedings of the Water Environment Federation, New Orleans, LA, USA, 24–28 September 2016.
2. Arun Shankar, V.K.; Umashankar, S.; Padmanaban, S.; Paramasivam, S. Adaptive neuro-fuzzy inference system (anfis) based direct torque control of pmsm driven centrifugal pump. IJRER 2017, 7, 1437–1447.
3. Tutterow, V.; Hovstadius, G.; McKane, A. Going with the Flow: Life Cycle Costing for Industrial Pumping Systems; Lawrence Berkeley National Lab. (LBNL): Berkeley, CA, USA, 2002.
4. Maksimova, S.; Shkileva, A.; Verevkina, E. Life cycle cost and energy conservation for water system pumping station reconstruction. E3S Web Conf. 2020, 164, 01002.
5. Mohanty, A.R.; Pradhan, P.K.; Mahalik, N.P.; Ghosh Dastidar, S. Fault detection in a centrifugal pump using vibration and motor current signature analysis. Int. J. Autom. Control. 2012, 6, 61–76.
6. Fella, G.; Gallipoli, G.; Pan, J. Markov-chain approximations for life-cycle models. Rev. Econ. Dyn. 2019, 34, 183–201.
7. Mohamed, S.E.-D.N.; Mortada, B.; Ali, A.M.; El-Shafai, W.; Khalaf, A.A.M.; Zahran, O.; Dessouky, M.I.; El-Rabaie, E.-S.M.; El-Samie, F.E.A. Modulation format recognition using CNN-based transfer learning models. Opt. Quantum Electron. 2023, 55, 343.

8. Patil, R.B.; Kothavale, B.S.; Waghmode, L.Y.; Pecht, M. Life cycle cost analysis of a computerised numerical control machine tool: A case study from Indian manufacturing industry. J. Qual. Maint. Eng. 2020, 27, 107–128.
9. Chen, Y.; Yuan, J.; Luo, Y.; Zhang, W. Fault Prediction of Centrifugal Pump Based on Improved KNN. Shock. Vib. 2021, 2021, 7306131.
10. Arun Shankar, V.K.; Subramaniam, U.; Padmanaban, S.; Holm-Nielsen, J.B.; Blaabjerg, F.; Paramasivam, S. Experimental Investigation of Power Signatures for Cavitation and Water Hammer in an Industrial Parallel Pumping System. Energies 2019, 12, 1351.
11. Peng, L.; Han, G.; Sui, X.; Pagou, A.L.; Zhu, L.; Shu, J. Predictive approach to perform fault detection in electrical submersible pump systems. ACS Omega 2021, 6, 8104–8111.
12. Don, M.G.; Khan, F. Process fault prognosis using hidden Markov model–bayesian networks hybrid model. Ind. Eng. Chem. Res. 2019, 58, 12041–12053.
13. Soualhi, A.; Clerc, G.; Razik, H.; Guillet, F. Hidden Markov models for the prediction of impending faults. IEEE Trans. Ind. Electron. 2016, 63, 3271–3281.
14. Hofmann, P.; Tashman, Z. Hidden markov models and their application for predicting failure events. In Proceedings of the International Conference on Computational Science, Amsterdam, The Netherlands, 3–5 June 2020; Springer: Cham, Switzerland, 2020; pp. 464–477.
15. Zhou, Z.J.; Hu, C.H.; Xu, D.L.; Chen, M.Y.; Zhou, D.H. A model for real-time failure prognosis based on hidden Markov model and belief rule base. Eur. J. Oper. Res. 2010, 207, 269–283.
16. Zhao, W.; Shi, T.; Wang, L. Fault diagnosis and prognosis of bearing based on hidden Markov model with multi-features. Appl. Math. Nonlinear Sci. 2020, 5, 71–84.
17. Ocak, H.; Loparo, K.A. A new bearing fault detection and diagnosis scheme based on hidden Markov modeling of vibration signals. In Proceedings of the 2001 IEEE International Conference on Acoustics, Speech, and Signal Processing, Salt Lake City, UT, USA, 7–11 May 2001; Volume 5, pp. 3141–3144.
18. Hashim, Z.S.; Khani, H.I.; Azar, A.T.; Khan, Z.I.; Smait, D.A.; Abdulwahab, A.; Zalzala, A.M. Robust liquid level control of quadruple tank system: A nonlinear model-free approach. Actuators 2023, 12, 119.
19. Nault, J.; Papa, F. Lifecycle assessment of a water distribution system pump. J. Water Resour. Plan. Manag. 2015, 141, A4015004.
20. Dutta, N.; Kaliannan, P.; Paramasivam, S. A comprehensive review on fault detection and analysis in the pumping system. Int. J. Ambient. Energy 2022, 43, 6878–6898.
21. Jayaram, N.; Srinivasan, K. Performance-based optimal design and rehabilitation of water distribution networks using life cycle costing. Water Resour. Res. 2008, 44.

22. Cheng, Q.; Wang, S.; Yan, C. Robust optimal design of chilled water systems in buildings with quantified uncertainty and reliability for minimised life-cycle cost. Energy Build. 2016, 126, 159–169.
23. Kouadri, A.; Hajji, M.; Harkat, M.-F.; Abodayeh, K.; Mansouri, M.; Nounou, H.; Nounou, M. Hidden Markov model based principal component analysis for intelligent fault diagnosis of wind energy converter systems. Renew. Energy 2020, 150, 598–606.
24. Saon, S.; Hiyama, T. Predicting remaining useful life of rotating machinery based artificial neural network. Comput. Math. Appl. 2010, 60, 1078–1087.
25. Salunkhe, T.; Jamadar, N.I.; Kivade, S.B. Prediction of Remaining Useful Life of mechanical components-a Review. Int. J. Eng. Sci. Innov. Technol. 2014, 3, 125–135.
26. Rubab, S.; Kandpal, T.C. A financial evaluation of renewable energy technologies for water pumping in rural areas. Int. J. Ambient. Energy 1998, 19, 211–220.
27. Aktaş, A.B. Comparative Life Cycle Cost Analysis of Centrifugal and Positive Displacement Pumps for Mine Dewatering. Master’s Thesis, Middle East Technical University, Ankara, Turkey, 2015.
28. Patel, A.; Swathika, O.V.G.; Subramaniam, U.; Babu, T.S.; Tripathi, A.; Nag, S.; Karthick, A.; Muhibbullah, M. A Practical Approach for Predicting Power in a Small-Scale Off-Grid Photovoltaic System using Machine Learning Algorithms. Int. J. Photoenergy 2022, 2022, 9194537.
29. Dutta, N.; Palanisamy, K.; Subramaniam, U.; Padmanaban, S.; Holm-Nielsen, J.B.; Blaabjerg, F.; Almakhles, D.J. Identification of water hammering for centrifugal pump drive systems. Appl. Sci. 2020, 10, 2683.
30. Dutta, N.; Subramaniam, U.; Padmanaban, S. Mathematical models of classification algorithm of Machine learning. QScience Proc. 2019, 1, 3.
31. Luo, H.; Zhou, P.; Shu, L.; Mou, J.; Zheng, H.; Jiang, C.; Wang, Y. Energy performance curves prediction of centrifugal pumps based on constrained PSO-SVR model. Energies 2022, 15, 3309.
32. Ranawat, N.S.; Kankar, P.K.; Miglani, A. Fault Diagnosis in Centrifugal Pump using Support Vector Machine and Artificial Neural Network. J. Eng. Res. EMSME Spec. Issue 2021, 99, 111.
33. Ranganatha Chakravarthy, H.S.; Bharadwaj, S.C.; Umashankar, S.; Padmanaban, S.; Dutta, N.; Holm-Nielsen, J.B. Electrical fault detection using machine learning algorithm for centrifugal water pumps. In Proceedings of the 2019 IEEE International Conference on Environment and Electrical Engineering and 2019 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe), Genova, Italy, 11–14 June 2019; pp. 1–6.
34. Gao, X.; Pishdad-Bozorgi, P.; Shelden, D.R.; Hu, Y. Machine learning applications in facility life-cycle cost analysis: A review. In Proceedings of the Computing in Civil Engineering 2019: Smart

Cities, Sustainability, and Resilience, Atlanta, Georgia, 17–19 June 2019; pp. 267–274.

35. Alshathri, S.; Hemdan, E.E.-D.; El-Shafai, W.; Sayed, A. Digital twin-based automated fault diagnosis in industrial IoT applications. Comput. Mater. Contin. 2023, 75, 183–196.