JOURNAL OF WORLD SCIENCE
https://jws.rivierapublishing.id/index.php/jws
Volume 3 No. 1 January 2024
P-ISSN: 2828-8726
E-ISSN: 2828-9307

USE OF MACHINE LEARNING WITH THE LONG SHORT TERM MEMORIES METHOD AS THE BASIS FOR CLEANING AND PERFORMANCE OF STEAM TURBINE CONDENSERS FOR GAS AND STEAM POWER PLANTS

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ABSTRACT

This research focuses on the design of a bidirectional reinforced concrete slab for a 5-storey apartment building located on Jalan Pemuda, Semarang, following SNI 1726:2019 standards. The objective is to compare the results of the direct design method (DDM) using Excel with ETABS v18 software, analyzing the accuracy of traditional methods in modern structural designs. The study employed a practical approach, incorporating various design parameters such as beam dimensions, span length, dead and live loads, and material strengths (f'c and fy). The results indicate that although there is a slight difference between the methods, they exhibit similar trends. The study found that increased load leads to higher moments, while larger beams and higher concrete strength reduce reinforcement requirements. However, discrepancies between the methods were observed due to rounding errors in the DDM. The research suggests refining moment calculation techniques and enhancing software tools for more accurate slab designs. The findings are essential for improving design accuracy in both academic and professional practice, particularly for earthquake-resistant structures.

Keyword : Plate Design, Plate Calculation, Bidirectional Plate

INTRODUCTION

The increasing global demand for electricity has necessitated the enhancement of power plant efficiency. In Indonesia, the industrial sector's electricity demand is projected to grow by 38% annually, necessitating advancements in power plant operations. As part of Indonesia's Industry 4.0 initiatives, power plants must adopt digitalization and automation to optimize performance and reduce operational losses. PT PLN Indonesia Power's Priok Gas and Steam Power Plant (PLTGU Priok) operates a steam turbine condenser system where performance degradation due to fouling is a significant concern (Fenno et al., 2020; Fonna, 2019; Rosyid et al., 2020; Wibowo, 2018).

Traditional maintenance strategies employed in industrial settings typically rely on time-based or usage-based schedules (Andrae & Edler, 2015; Hu et al., 2025; Khafidli & Choiruddin, 2022; Zahara & Ilmiddafiq, 2019; Zahara & Ilmiddaviq, 2020). These approaches often fail to accurately predict the actual condition of condenser components, leading either to premature maintenance activities or to delayed interventions after performance degradation has already occurred (Lee et al., 2014). Such inefficiencies not only increase maintenance costs but also risk plant derating and unplanned shutdowns (Bergman et al., 2011; Hilmawan, 2021; Holman, 1986; Parhusip, 2018).

Recent advances in machine learning have introduced new opportunities for predictive maintenance. Long Short-Term Memory (LSTM) networks, a class of recurrent

neural networks (RNNs), have shown exceptional performance in modeling time-series data and

capturing long-term dependencies (Malhotra et al., 2015). In industrial applications, LSTM models have been successfully used to forecast equipment failures, optimize maintenance scheduling, and reduce unplanned outages (Zhao et al., 2020).

The increasing adoption of digital monitoring in industrial applications provides an opportunity for power plants to enhance predictive maintenance capabilities. The integration of real-time sensor data with artificial intelligence-driven analytics has the potential to revolutionize conventional maintenance approaches (Forghani et al., 2023; Gielen et al., 2019; Jacobson & Delucchi, 2011; Masters, 2013; Shahveran & Yousefi, 2025; Sorrell, 2014). As highlighted by Holman (1986), efficient heat transfer management is critical to maintaining optimal plant performance. Heat exchanger fouling has long been a concern in industrial systems, with researchers like Bergman et al. (2011) emphasizing the importance of timely maintenance to prevent significant thermal losses. The use of predictive modeling, including machine learning techniques, has become increasingly relevant in addressing these challenges.

This research investigates the application of LSTM to improve condenser cleaning and maintenance. By leveraging time-series forecasting capabilities, the study seeks to determine optimal maintenance schedules that maximize efficiency while minimizing operational disruptions. Previous studies have focused on regression-based approaches, but LSTM presents an opportunity to capture nonlinear temporal patterns that may not be evident in traditional models. As discussed by Kakac (2002), fouling factors vary over time, and the ability to model these variations dynamically could provide superior predictive capabilities.

This research aims to develop a predictive maintenance system for the PLTGU Priok Block 4 Condensor by applying the LSTM method. By analyzing operational data such as seawater flow rates, steam temperatures, and product water flow, the study establishes a health index classification system. The integration of this predictive model with the PI Vision system enables real-time monitoring, providing maintenance teams with actionable insights to schedule interventions based on actual equipment conditions rather than fixed intervals. Through this approach, it is expected that operational efficiency can be enhanced, maintenance costs reduced, and plant reliability improved, contributing significantly to the company's broader digital transformation objectives.

The efficiency of steam turbine condensers in power plants is critical for optimal power generation performance. Over time, fouling and dirt accumulation in condenser tubes degrade heat transfer efficiency, causing operational inefficiencies, increased maintenance costs, and unplanned shutdowns. Traditional time-based maintenance schedules often fail to predict the optimal cleaning time, leading either to premature or delayed interventions. This results in unnecessary costs or performance losses, highlighting the need for more accurate predictive maintenance solutions.

The rising demand for electricity and the push towards Industry 4.0 necessitate improvements in power plant efficiency, particularly in Indonesia where electricity consumption is rapidly growing. Effective maintenance scheduling is essential to avoid production losses and ensure reliability. Without predictive maintenance tools, plants risk costly downtime and reduced operational lifespan of key components such as condensers. Moreover, the complexity and variability of condenser fouling require advanced modeling techniques that can capture non-linear and temporal patterns in operational data. Implementing real-time monitoring and forecasting tools is urgent to transition from reactive to proactive maintenance strategies, thereby enhancing plant performance and sustainability.

Previous research has demonstrated the limitations of traditional maintenance approaches relying on fixed schedules or simple regression models (Lee et al., 2014). Machine learning, particularly Long Short-Term Memory (LSTM) networks, has shown promise in modeling time-series data and forecasting equipment failures with higher accuracy (Malhotra et al., 2015; Zhao et al., 2020). Studies highlight the

suitability of LSTM for capturing long-term dependencies and nonlinear trends in industrial maintenance data. Additionally, digitalization efforts integrating IoT sensors and AI analytics have been reported to improve predictive maintenance in various industrial contexts, including heat exchangers and turbines (Holman, 1986; Bergman et al., 2011). However, applications specifically targeting condenser cleaning scheduling in Indonesian power plants remain limited.

Despite advances in ML-based predictive maintenance, there is a lack of focused research on applying LSTM models for condenser cleaning optimization in Indonesian steam turbine power plants. Most existing studies do not integrate real-time operational data with predictive analytics or provide practical implementations linked to plant control systems.

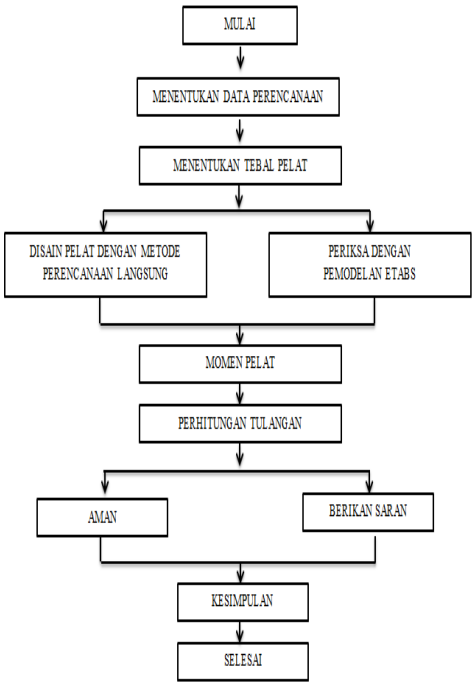
This study uniquely applies an LSTM-based machine learning model to real operational data from the Priok PLTGU Block 4 condenser, combining historical sensor data with digital monitoring platforms like PI Vision. The model predicts optimal cleaning times with high accuracy, supporting real-time decision-making and proactive maintenance. This integrated approach advances digital transformation in Indonesia's power sector.

The primary objective is to develop and validate an LSTM-based predictive maintenance system to optimize condenser cleaning scheduling at the PLTGU Priok Block 4 power plant, thereby enhancing condenser efficiency, reducing maintenance costs, and minimizing unplanned downtime.

This research provides actionable insights for power plant operators seeking to implement AI-driven predictive maintenance. The developed model improves operational efficiency, extends equipment lifespan, and supports sustainable energy production. The integration with digital platforms enables real-time monitoring and early warnings, contributing to Industry 4.0 initiatives and enhanced plant reliability.

METHOD

The location of the research is located on Jalan Pemuda Semarang



RESULTS AND DISCUSSION

Structural material data

- Compressive strength of concrete,
  Fc' + 30 Mpa
- Steel melting stress for bending reinforcement
  Fy = 280 Mpa

Floor Plate Data

Length of the span of the direction plate x, Lx = 3.00 m length of the span of the floor plate, h = 125 mm

Plate moment coefficient for:

TWO DIRECTIONS, Because Ly/Lx < 2Field x,

Clx = 31 Field y

Cly = 19 Fields x

Ctx = 69 Focus y

Cty = 57 Focus x

Floor Plate Load

1. Beban Mati (Dead load)
   QD = 4.32 Kn/ m^2
2. Living Burden
   QL = 1.92 kn/ m^2
3. Factored planning load
   Qu = 8,256 kn/ m^2
4. Plate moment due to factored load

Momen Lapangan Arah x (Mulx)	2,303 kNm/m
Momen Lapangan Arah y (Muly)	2,510 kNm/m
Momen Tumpuan Arah x (Mutx)	5,127 kNm/m
Momen Tumpuan Arah y (Muty)	7,529 kNm/m

Plate repetition

Data-data :

- Width of the plate reviewed 1 m wide
- Plate thickness h = 125 mm→
- Selimut beton dc = 20 mm →
- Diameter of the reinforcement used 10 mmØ
  Ly/Lx = 1 (plate coefficient)

Effective thickness of floor plate,dx=h-dc-() $^{\emptyset}/_{2}$

= 125 – 20 - () $^{10}/_{2}$

= 100 mm

Effective thickness of floor plate,dy = h - dc - () $^{\emptyset}/_{2}$

= 125 – 20 – ()$^{10}/_{2}$

= 90 mm

For : Fc' ≤ 28 Mpa, 1 = 0.85 β

Form factor of concrete stress distribution, 1 = 0.85 β

TEBAL (mm)	Frame		Mu	ØMn	As Perlu	As Pakai	Tulangan
			kNm	kNm	mm2	mm2	
125	ARAH X	Lapangan bawah	23,0	28.7	500	628	D10 - 100
		Tumpuan atas	-51.2	64,0	500	628	D10 - 100
	ARAH Y	Lapangan atas	25.1	31.3	450	628	D10 - 100
		Tumpuan bawah	-75.2	94.1	450	628	D10 - 100

Plate deflection control

- Modulus of elasticity of concrete, Ec = 25742 Mpa
- Modulus elastisitas baja tulangan, Es =200000 Mpa
- Average load (unfactored) on the plateQ = QD + QL
  = 4.32 + 1.92
  = 6.24 N/mm
- Span length, Lx = 3000 mm
- Maximum allowable deflection limit, Lx / 240 = 12,500 mm
- Moment of inertia crutto plate cross-section, lg = 162,760.416 mm^3
- Modulus keruntuhan lentur beton, fr = 3,384 Mpa
- Nilai modulus ratio elastis, n = 7,769 mm
- Neutral line distance to the top side of the concrete, c = 4.879 mm
- The moment of inertia of the cross-sectional crack that is transformed into concrete is calculated as follows:
  Icr = 1/3 * b * + n * As (d – c c^3)^2
  = 1/3 x 1000 x + 7,769 x 628,000 $4{,}879^3$
  $(125 – 4{,}879)^2$
  = 44183959.66 mm
- Yt = 62.5 mm
- Momen retak, Mcr = 9984525,788 Nmm
- Maximum moment due to load (without load factor), Ma = 7020000.2 mm
- Effective inertia for deflection calculation, Ie =385352881 mm
- Elastic deflection due to dead load and live load, = 0.66 mmδe
- Floor slab reinforcement ratio, p = 0.006
- Time dependence factor for dead load, value: (> 5 year term), value:
  = 2
  = 1,522
- Long-term deflection due to skeletal and shrinkage, g = 1.01 mm δ
- Lendutan total

$\Delta$to = e + g $\delta\delta$
= 0.66 + 125
= 1.67 < 12.5

CONCLUSION

The results of the moment calculation using the langsung design method do not fully align with those from the ETABS v18 software, though the difference is minimal. The direct design method involves rounding moment coefficients, which impacts the final result, while ETABS v18 analyzes the entire structure, yielding more precise results. The study found that as load increases, the resulting moment also increases, and that larger beam sizes reduce moments under the same load. Additionally, higher f'c values reduce the reinforcement area needed. However, some combinations cannot be calculated due to limitations in the quadratic equation. Future research could focus on refining moment calculation methods, addressing discrepancies between design approaches, and improving the accuracy of the direct design method by eliminating rounding errors. Further studies could explore the effects of varying load conditions, beam size, and plate thickness, as well as optimizing reinforcement design based on material strength. Investigating alternative calculation methods or software enhancements to resolve limitations in the quadratic equation would also be beneficial.

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