

Stochastic Reliability and Economic Performance of a Rotary Kiln: A Semi-Markov and Regenerative-Point Case Study

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Abstract—This paper presents a stochastic reliability, availability, maintainability and economic analysis of a Rotary Kiln used in cement manufacturing. The model is based on 170 event records observed over 3,666 h from July to November 2025. The kiln is represented as a repairable multi-state system with normal, degraded, partial-failure, complete-failure, inspection and preventive-shutdown conditions. Estimated degradation, partial-failure and complete-failure intensities are 0.014150, 0.012920 and 0.005537 h⁻¹, respectively. The semi-Markov and regenerative-point model gives a mean time to system failure of 233.734 h, reliability of 0.9030 at 24 h and 0.6635 at 96 h, and steady-state operational availability of 0.905892. Major repairs are the main maintainability constraint: repair completion within two hours is 0.3387 for major repair compared with 0.9019 for minor repair. Complete failures generate 42.96% of event-related cost. A coordinated improvement scenario reduces failure intensities, accelerates repair, increases inspection moderately and reduces unnecessary preventive shutdowns, it raises 96-h reliability to 0.7284, availability to 0.928343 and long-run profit from INR 125,238.84 to INR 134,217.84 per hour. The results support condition-based intervention, major-repair readiness and PLC-supported early detection.

Index Terms—Rotary Kiln, semi-Markov model, reliability, maintainability, availability, clinker production, economic analysis

I. Introduction

The Rotary Kiln is the thermal core of clinker production. It must rotate continuously while sustaining high temperature, stable combustion, alignment, lubrication, refractory protection and reliable process control. A severe kiln failure stops clinker formation and also disturbs upstream raw-meal scheduling and downstream cement grinding. For this reason, kiln maintenance decisions have technical, production and economic consequences at the same time. Cement reliability studies have increasingly treated the kiln as a core component of an integrated stochastic production structure (Gupta, 2024).

Classical preventive maintenance provides an important foundation, but modern process plants require policies that respond to condition and consequence (Barlow & Hunter, 1960; Ahmad & Kamaruddin, 2012). Diagnostics, prognostics and predictive monitoring can identify deterioration before it becomes a major shutdown (Jardine et al., 2006; Peng et al., 2010). In an automated kiln, instrumentation and PLC logic are also reliability resources because sensor quality, alarms and interlocks influence fault detection and protection.

Research on PLC reliability shows that hardware-software relationships can materially affect system reliability assessment (Jiang et al., 2013).

This paper uses the Rotary Kiln chapter of the thesis to develop a self-contained journal paper. The objectives are to estimate stochastic transition rates, quantify reliability and availability, compare minor and major maintainability, evaluate event cost, identify critical subsystems and test a coordinated improvement scenario. The emphasis is on a model that remains mathematically rigorous while retaining clear operational meaning.

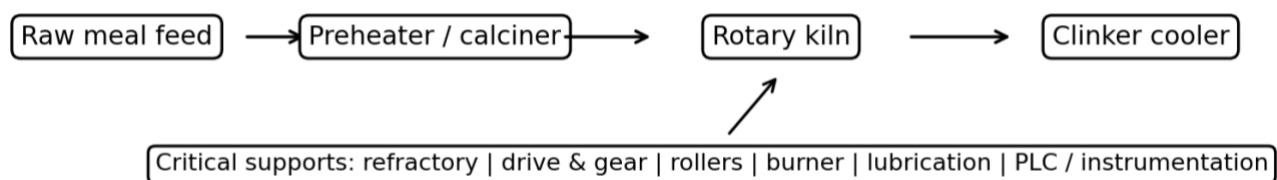


Figure 1. Process position of the Rotary Kiln and its main reliability-supporting subsystems.

II. Literature Background

Maintenance optimization research consistently shows that failure prevention, inspection and restoration should be analyzed jointly because a change in one policy can move cost or risk into another part of the system (Dekker, 1996; Wang, 2002). Imperfect-repair theory further cautions against assuming that every restoration returns a machine to a new condition (Pham & Wang, 1996). Predictive maintenance programmes use condition indicators to shift intervention from fixed schedules toward evidence-based decisions (Carnero, 2006). Risk-based maintenance adds consequence to this logic, so high-severity low-frequency events can receive appropriate priority (Khan & Haddara, 2003).

The digitalization of manufacturing strengthens this approach. Cyber-physical architectures connect physical assets with monitoring, communication and analytics (Lee et al., 2015; Monostori, 2014). Remaining-useful-life and prognostic research provides methods for transforming historical and online data into maintenance information (Si et al., 2011; Peng et al., 2010). For a kiln, these capabilities are especially relevant to refractory condition, bearing temperature, vibration, gear health, lubricant condition, burner stability and abnormal PLC alarm patterns. However, as Wang (2010) notes for industrial reliability modelling, advanced information is useful only when it can be translated into a decision structure. The present stochastic model supplies that decision layer.

III. Data and Model Formulation

The observation window covers 1 July to 30 November 2025. The 170 records contain normal and degraded exposure, partial and complete failures, corrective repairs, inspections and preventive shutdowns. The model treats the kiln as one integrated repairable system composed of shell/tyres/refractory, main drive/girth gear, support rollers/bearings, burner/fuel, lubrication, cooling, and instrumentation/PLC subsystems.

Table 1. Rotary Kiln event dataset and exposure

Measure	Value
Observation period	1 July-30 November 2025
Event records	170
Normal operating exposure	3,148.21 h
Degraded exposure	102.56 h
Total operating exposure	3,250.77 h
Downtime	415.23 h
Total model exposure	3,666.00 h
Degradation events	46
Partial failures	42
Complete failures	18
Minor / major repairs	79 / 27
Inspections / preventive shutdowns	34 / 30

3.1 Rate estimation and state model

Failure and degradation intensities are estimated from event counts divided by operating exposure, while repair completion rates are estimated from repair counts divided by active repair time:

$$\lambda_k = N_k / T_{op}, \quad \mu_j = N_j / T_{rep,j} \quad (1)$$

Table 2. Estimated stochastic rates used in the kiln model

Parameter	Estimate	Unit
Degradation rate	0.014150	h ⁻¹
Partial-failure rate	0.012920	h ⁻¹

Complete-failure rate	0.005537	h^{-1}
Minor-repair completion	1.160911	repair h^{-1}
Major-repair completion	0.206754	repair h^{-1}
Inspection intensity	0.010459	h^{-1}
Preventive-shutdown intensity	0.009229	h^{-1}
Normal-state exit rate	0.042882	h^{-1}

Let S be the transient sub-generator for states that are counted as successful before complete system failure and let α be the initial state vector. First-passage reliability and MTSF are obtained from:

$$R(t) = \alpha \exp(St) \mathbf{1}, \quad MTSF = -\alpha S^{-1} \mathbf{1} \quad (2)$$

Steady-state probabilities satisfy $\pi Q = 0$ and $\pi \mathbf{1} = 1$. Total productive availability includes normal and degraded states:

$$AT = \pi N + \pi D \quad (3)$$

For exponentially represented repair completion, maintainability of repair class j is:

$$M_j(t) = 1 - \exp(-\mu_j t) \quad (4)$$

The long-run economic benchmark combines normal and degraded productive contribution with repair, inspection, preventive-maintenance and clinker-loss costs. This ensures that a technically available but degraded state has a lower economic reward than stable normal operation.

3.2 State interpretation, assumptions and verification strategy

The kiln model distinguishes conditions that have different production meanings. Normal operation is the regenerative productive state. Degraded operation remains productive but occurs under abnormal thermal, mechanical or quality conditions. Partial failure represents a more serious loss of capacity that normally requires minor corrective repair. Complete failure represents zero clinker output until major restoration is completed. Inspection and preventive shutdown are intervention states. This multi-state interpretation is important because a kiln may remain technically available while operating below its normal economic contribution, and a short inspection cannot be treated as equivalent to a long complete-failure shutdown.

The reduced model assumes that one dominant event or intervention describes the system at a time and that successful restoration returns the kiln to a regenerative condition. Transition behaviour is estimated from the recorded event history, while repair completion is represented by empirical class-specific rates. The model does not explicitly create separate queueing states for waiting for specialists, cranes, refractory material or spare parts. It also does not model multiple simultaneous subsystem abnormalities. These simplifications

make the state space transparent enough for analytical reliability and availability calculations, but they tend to shorten the predicted unavailable time relative to plant exposure.

Internal verification checks the mathematical structure before managerial interpretation. Estimated intensities are non-negative, state probabilities remain within valid bounds, each transition relation is normalized, reliability decreases with mission time, and maintainability increases toward one. Dimensional consistency is preserved by expressing occurrence rates per operating hour, repair completion per active repair hour, time measures in hours and economic measures in INR or INR per hour. The steady-state probabilities also sum to one. These tests are necessary because numerical agreement alone can hide an inconsistent stochastic model.

Validation then compares the analytical outputs with exposure-based measures from the 3,666-h record. The model is deliberately treated as a comparative decision tool rather than an exact digital replica of the kiln. The 2.16% availability overestimate is modest, but the larger differences in MTSF proxy and downtime show where additional states and better duration records would improve calibration. This interpretation keeps the model useful without overstating the precision that can be obtained from five months of aggregated event data.

IV. Results

4.1 Reliability, availability and downtime

The model estimates a 24-h reliability of 0.9030 and a 96-h reliability of 0.6635. MTSF is 233.734 h. Steady-state normal availability is 0.889437 and degraded availability is 0.016455, giving total operational availability of 0.905892. Empirical availability is 0.886735, so the model overestimates availability by 2.16% relative to the observed exposure. Model downtime is 94.108 h per 1,000 h compared with empirical downtime of 113.265 h per 1,000 h. The difference is consistent with reduced-state models that omit some waiting, mobilisation, spare-part and repeated restart delay.

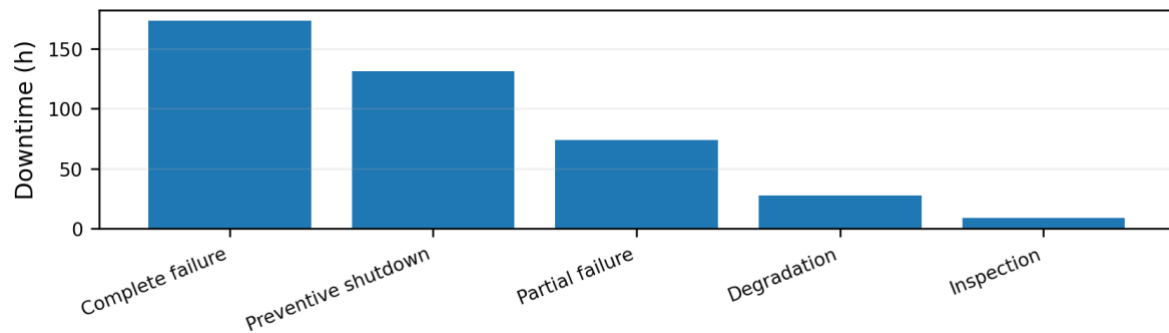


Figure 2. Downtime by Rotary Kiln event category.

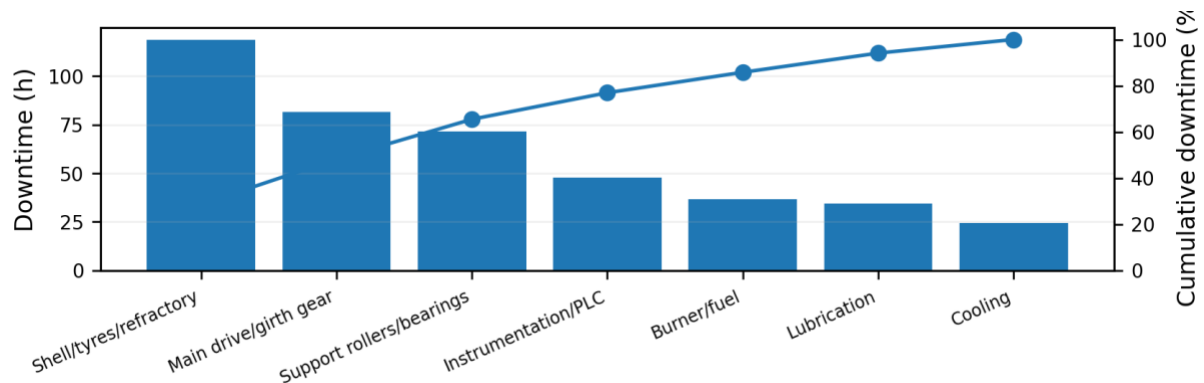


Figure 3. Subsystem downtime Pareto view for the Rotary Kiln.

Table 3. Baseline Rotary Kiln RAM results

Performance measure	Result
Reliability at 24 h	0.9030
Reliability at 96 h	0.6635
Model MTSF	233.734 h
Empirical complete-failure exposure proxy	180.598 h
Normal-state availability	0.889437
Degraded-state availability	0.016455
Model total availability	0.905892
Empirical total availability	0.886735
Model / empirical downtime per 1,000 h	94.108 / 113.265 h

Minor-repair maintainability at 2 h	0.9019
Major-repair maintainability at 2 h	0.3387
Repair-facility busy proportion	0.084264

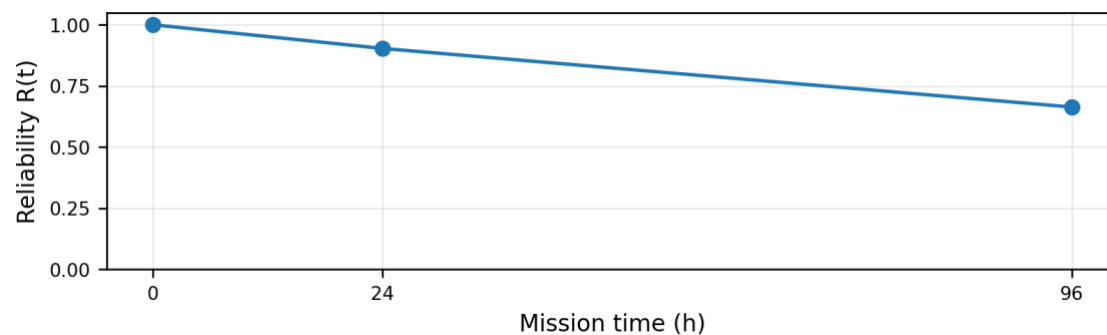


Figure 4. Rotary Kiln reliability at selected mission times.

4.2 Maintainability and maintenance resource burden

The difference between minor and major restoration is operationally important. Minor repairs accumulated 68.05 active repair hours for 79 interventions, whereas 27 major repairs accumulated 130.59 h. The probability of completing a minor repair within two hours is 0.9019, but major-repair maintainability at the same time is only 0.3387. Major repairs therefore consume much more facility time despite their lower frequency. Increasing major-repair speed improves availability more strongly than the same proportional increase in minor-repair speed. This finding supports pre-positioned critical spares, specialist readiness and standardized restart procedures.

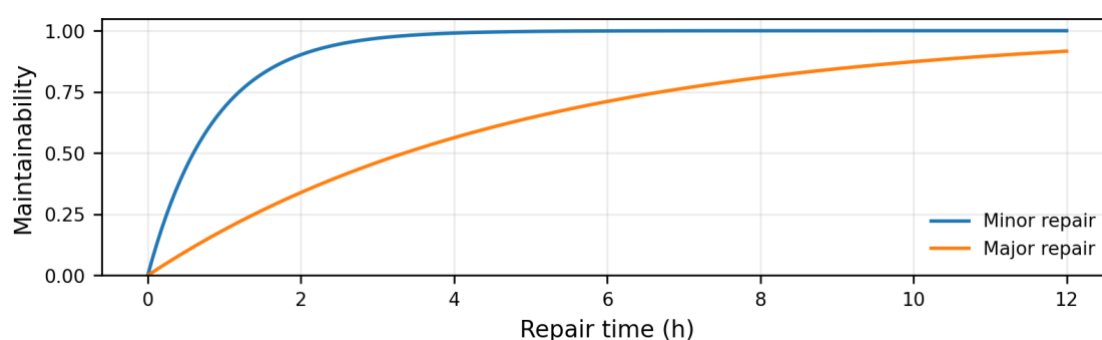


Figure 5. Minor- and major-repair maintainability based on estimated completion rates.

4.3 Economic burden of interruption

The observation-period gross productive contribution is INR 577.959 million. Direct repair and maintenance cost is INR 63.040 million and clinker production-loss cost is INR 55.794 million, leaving a net contribution of INR 459.126 million. The calibrated long-run benchmark is INR 125,238.84/h. Complete failure is the largest event-cost category: only 18 complete failures account for 173.66 h downtime, 23,574.66 t clinker loss

and 42.96% of all event-related cost. Preventive shutdowns account for another 31.47% of cost. Planned shutdowns should therefore be optimized, not eliminated, because their purpose is to prevent much more expensive unplanned failure.

Table 4. Baseline economic result for the Rotary Kiln

Economic component	Observation-period INR	INR/h
Normal-operation contribution	566,677,800	154,576.60
Degraded-operation contribution	11,281,600	3,077.36
Gross productive contribution	577,959,400	157,653.96
Direct repair and maintenance cost	63,040,230	17,195.92
Clinker production-loss cost	55,793,600	15,219.20
Total event-related cost	118,833,830	32,415.12
Net contribution	459,125,570	125,238.84

4.4 Sensitivity and critical subsystem results

Sensitivity analysis changes one parameter by 20% while keeping the others fixed. A 20% increase in complete-failure intensity reduces 96-h reliability to 0.6128, MTSF to 195.868 h, availability to 0.899127 and profit to INR 122,071.75/h. Faster major repair raises profit by 0.705%, compared with 0.306% for faster minor repair. Excessive preventive-maintenance intensity reduces profit by 2.245% because planned downtime consumes productive time. The normal-operation contribution has the largest direct economic sensitivity, while complete-failure intensity is the most important stochastic reliability driver.

Table 5. Selected +20% sensitivity results

Changed parameter	R(96)	MTSF (h)	Availability	Profit INR/h	Profit change
Degradation rate	0.6481	221.103	0.902559	123,037.84	-1.757%
Partial-failure rate	0.6675	237.313	0.903481	124,154.21	-0.866%

Complete-failure rate	0.6128	195.868	0.899127	122,071.75	-2.529%
Minor-repair rate	0.6626	233.034	0.908506	125,621.96	+0.306%
Major-repair rate	0.6635	233.734	0.911917	126,122.08	+0.705%
Inspection rate	0.6647	234.827	0.905733	125,245.80	+0.006%
Preventive-maintenance rate	0.6661	236.099	0.899766	122,426.76	-2.245%

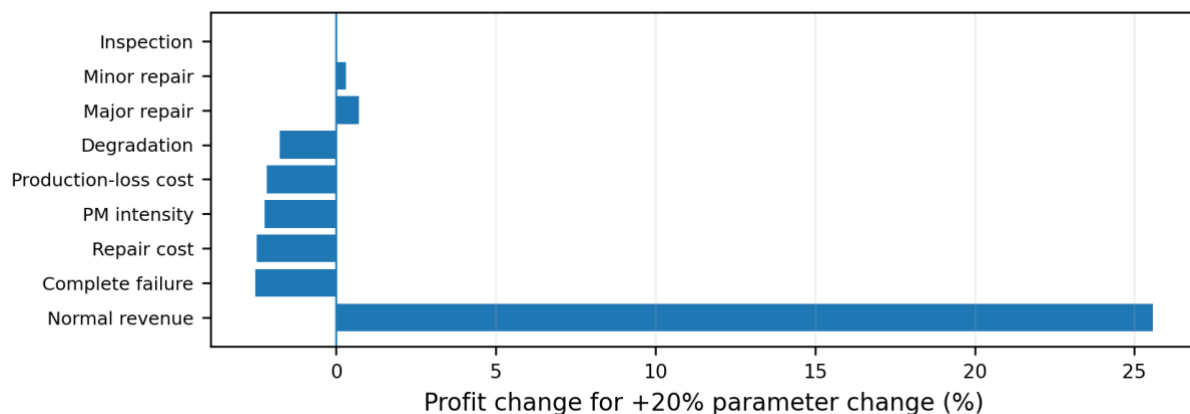


Figure 6. Profit sensitivity to a 20% increase in selected model parameters.

Subsystem analysis reinforces the sensitivity result. Shell/tyres/refractory contributes 118.83 h downtime, followed by main drive/girth gear at 81.57 h and support rollers/bearings at 71.40 h. Together, these three subsystems account for 65.46% of downtime. Instrumentation/PLC increases the cumulative contribution to 76.94%. Thus, thermal integrity, alignment, drive health, bearing condition and reliable detection deserve the strongest maintenance attention. This is consistent with consequence-based maintenance practice (Khan & Haddara, 2003) and with the growing view that industrial control and monitoring systems are integral to production reliability (Jiang et al., 2013; Lee et al., 2015).

4.5 Recommended operating scenario

A coordinated scenario was evaluated rather than changing only one parameter. Degradation, partial-failure and complete-failure rates are reduced by 20%; minor- and major-repair rates are increased by 20%; inspection intensity is increased by 10%; and unnecessary preventive-shutdown intensity is reduced by 10%. The scenario increases R(96) by 9.79%, MTSF by 29.44%, availability by 2.48% and long-run profit by 7.17%. This combination is operationally meaningful because it balances prevention, detection, restoration and planned downtime instead of maximizing a single measure.

Table 6. Baseline and recommended Rotary Kiln operating scenario

Measure/parameter	Baseline	Recommended	Change
Degradation rate	0.014150	0.011320	-20%
Partial-failure rate	0.012920	0.010336	-20%
Complete-failure rate	0.005537	0.004430	-20%
Minor-repair rate	1.160911	1.393093	+20%
Major-repair rate	0.206754	0.248105	+20%
Inspection intensity	0.010459	0.011505	+10%
Preventive-shutdown intensity	0.009229	0.008306	-10%
Reliability at 96 h	0.6635	0.7284	+9.79%
MTSF	233.734 h	302.539 h	+29.44%
Availability	0.905892	0.928343	+2.48%
Long-run profit	INR 125,238.84/h	INR 134,217.84/h	+7.17%

4.6 Cut-off points and model validation

Break-even analysis was used to distinguish mathematical limits from practical operating targets. The calculated profit cut-offs are far from the baseline: degradation intensity reaches a zero-profit threshold at 0.287233 h⁻¹, complete-failure intensity at 0.077260 h⁻¹, the major-repair completion rate has a theoretical minimum of 0.000494 h⁻¹, and preventive-maintenance intensity has a maximum break-even value of 0.127498 h⁻¹. These values should not be used as recommended settings. Operating close to a break-even boundary would expose the kiln to severe production risk and profit volatility. A wide safety margin is therefore necessary, which is consistent with maintenance-optimization studies that distinguish mathematically feasible policies from robust industrial policies (Dekker, 1996; Wang, 2002).

Table 7. Economic cut-offs and internal validation checks

Item	Model value	Comparison / interpretation
Degradation-rate profit cut-off	0.287233 h ⁻¹	Baseline 0.014150 h ⁻¹ ; large safety margin
Complete-failure profit cut-off	0.077260 h ⁻¹	Baseline 0.005537 h ⁻¹ ; severe failures must remain well below limit
Minimum major-repair rate	0.000494 h ⁻¹	Baseline 0.206754 h ⁻¹
Maximum PM intensity	0.127498 h ⁻¹	Baseline 0.009229 h ⁻¹ ; excessive PM eventually becomes uneconomic
MTSF validation	233.734 h vs 180.598 h proxy	Model +29.42%
Availability validation	0.905892 vs 0.886735	Model +2.16%
Downtime validation	94.108 vs 113.265 h/1000 h	Model -16.92%

Internal validation checked probability normalization, monotonic reliability, increasing maintainability and dimensional consistency. The largest practical discrepancy is the optimistic treatment of unavailable time. MTSF is also higher than the empirical complete-failure exposure proxy. These differences do not invalidate the comparative model, but they show where calibration is most needed: waiting for specialist labour, spare-parts mobilisation, overlapping abnormalities, repeated testing and controlled thermal restart. The availability difference is relatively modest, while the MTSF and downtime gaps warn against presenting the model as an exact forecast of future plant performance. The appropriate use is comparative decision analysis under clearly stated assumptions.

V. Discussion

The kiln results show why reliability, availability and economics should not be interpreted separately. Complete failures are less frequent than minor events, but they dominate downtime and cost because clinker production falls to zero and major restoration is slow. In contrast, repair acceleration does not necessarily change first-passage MTSF after failure has occurred, but it can materially improve availability and profit.

This separation between failure prevention and restoration effectiveness is central to sound repairable-system analysis (Pham & Wang, 1996; Wang, 2010).

The results also support condition-based maintenance rather than excessive calendar-driven shutdowns. Inspection is economically small near the baseline, while complete failures are expensive. Therefore, earlier and better diagnosis has a strong practical justification when it prevents escalation. Condition-based maintenance research similarly emphasizes the value of monitoring and prognostics in selecting the right intervention time (Ahmad & Kamaruddin, 2012; Jardine et al., 2006). At the same time, maintenance optimization warns against over-intervention because planned maintenance can create avoidable unavailability (Dekker, 1996; Wang, 2002).

The role of PLC and SCADA information should also be viewed broadly. Alarm rationalization, sensor calibration, logic backup, event synchronization and historical trending can reduce diagnostic delay and false trips. In a cyber-physical manufacturing environment, this information layer links the physical kiln to decision support (Lee et al., 2015; Monostori, 2014). Prognostic and remaining-life methods can strengthen that link, especially for bearings, refractory condition and rotating equipment, provided their outputs are used with clear maintenance rules (Peng et al., 2010; Si et al., 2011).

VI. Practical Implications and Limitations

The practical priority is to prevent complete failure while improving major-repair readiness. Refractory thermography and thickness measurement, drive and girth-gear vibration/oil/alignment checks, roller and bearing temperature trending, lubrication control, and critical-spare readiness should be formalized. PLC alarms should be rationalized and sensors calibrated so that condition evidence can trigger planned action before a severe event. These steps are consistent with predictive and risk-based maintenance principles (Carnero, 2006; Khan & Haddara, 2003).

The analysis is limited by a five-month observation period and a reduced state structure. Rare catastrophic events, ageing, seasonal effects and long-term refractory deterioration cannot be established from this duration. Waiting for specialists, spare-part delays, overlapping abnormalities and repeated restart activities are only partly represented. The model therefore gives slightly optimistic availability and should be recalibrated when longer verified histories are available. Future work can connect high-frequency SCADA variables with interpretable stochastic models and digital production architectures, rather than replacing the state model with an opaque prediction layer.

VII. Conclusion

The Rotary Kiln is a high-consequence repairable system in which failure severity is more important than event frequency alone. The semi-Markov/regenerative analysis estimates MTSF at 233.734 h and operational availability at 0.905892. Major-repair maintainability is substantially lower than minor-repair

maintainability, and complete failures account for the largest share of downtime and cost. The coordinated scenario improves reliability, MTSF, availability and long-run profit simultaneously by reducing severe failure intensity, accelerating restoration and controlling unnecessary preventive shutdowns. The principal managerial message is therefore clear: protect refractory and rotating components, strengthen major-repair capability, and use PLC/SCADA condition information to intervene before degradation becomes complete failure.

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