

Semi-Markov Reliability, Maintainability and Profit Analysis of a Raw Mill System in Cement Manufacturing

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Abstract—This paper develops a data-based stochastic reliability model for the Raw Mill system considered in a cement-manufacturing case study. The analysis uses 80 structured failure, inspection and preventive-maintenance events over 2,900.38 h. A semi-Markov and regenerative-point framework is used because the system can move among full operation, degraded operation, inspection, corrective repair, preventive maintenance and complete failure, while repair duration does not satisfy a simple exponential assumption. Inter-failure time is represented by an exponential model with an estimated rate of 0.021085 h⁻¹, whereas the Weibull distribution gives the best parametric approximation for repair time. The estimated mean time to system failure is 95.9448 h and steady-state operational availability is 0.9268. Reliability falls from 0.7205 at 24 h to 0.3238 at 96 h. Separator, Grinding and Feeding create the largest combined operational burden. Under normalized economic assumptions, long-run expected profit is 355.7148 units/h; a coordinated improvement scenario raises it to 366.1774 units/h. The results show that failure prevention, quicker restoration and condition-based intervention should be evaluated together rather than as separate maintenance decisions.

Index Terms—Raw Mill, semi-Mark

I. Introduction

Continuous cement production depends on a stable raw-meal preparation stage. The Raw Mill receives prepared material, grinds it to the required fineness, separates acceptable material, and supplies a controlled feed to the thermal line. Because the mill combines high mechanical loading, air flow, hydraulics, lubrication, electrical drives and digital control, a local abnormality can quickly become a production interruption. This makes the Raw Mill a suitable repairable, multi-state system rather than a simple working/failed component. Cement-specific stochastic studies also show that mill behaviour must be interpreted together with the surrounding production chain and its economic consequences (Gupta, 2024).

Maintenance research has long emphasized that inspection and preventive maintenance should be linked to equipment condition and failure consequences, not only to fixed calendar intervals (Barlow & Hunter, 1960; Wang, 2002). Condition-based maintenance becomes particularly valuable when degradation can be detected before a complete stoppage (Ahmad & Kamaruddin, 2012; Jardine et al., 2006). At the same time, maintenance models need to recognize imperfect and general repair, because actual restoration does not

always return a system to an exactly new condition (Kijima, 1989; Pham & Wang, 1996). These ideas are directly relevant to a Raw Mill, where wear, vibration, oil condition, motor loading and control alarms provide observable information before severe failure.

The present paper converts the thesis Raw Mill dataset into a compact journal-style analysis. It combines empirical event statistics, distribution fitting, a semi-Markov/regenerative model, RAM measures, economic evaluation and subsystem criticality. The paper also keeps an important data limitation explicit: the 80 Raw Mill observations were developed for modelling, so they should be interpreted as internally consistent model evidence rather than independently audited long-term plant statistics.

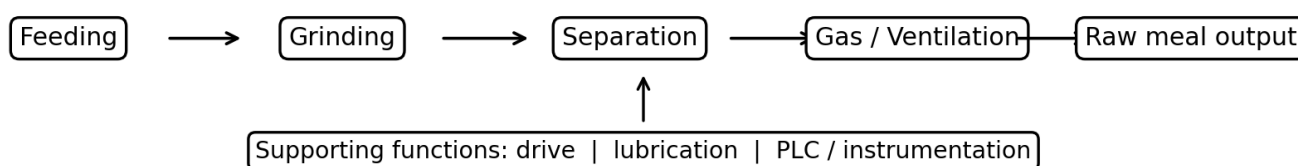


Figure 1. Functional view of the Raw Mill and its principal supporting functions.

II. Literature Background

Reliability modelling provides a useful bridge between maintenance records and operational decisions. Regenerative-point methods are appropriate when successful restoration creates a probabilistic restart of the operating cycle (Gopalan & Srinivasan, 1973). Semi-Markov formulations extend this idea by allowing state residence times to follow general distributions, which is important when field repair behaviour is not memoryless. Data-driven selection of time-to-failure distributions should therefore precede the use of a convenient mathematical model (Loui et al., 2009).

Economic maintenance studies further show that the best technical policy is not always the least-cost or most profitable policy. Optimization models must balance failure loss, planned intervention, repair resources and productive time (Dekker, 1996; Eti et al., 2006). Predictive programmes can improve this balance when monitoring information is reliable and actionable (Carnero, 2006; Peng et al., 2010). Risk-based scheduling similarly gives priority to events with larger operational consequences rather than to frequency alone (Khan & Haddara, 2003). Wang (2010) argues that industrial maintenance models are most useful when the mathematical structure remains connected to actual operating decisions. These studies provide the conceptual basis for integrating reliability, maintainability and profit in the present model.

III. Data and Method

The Raw Mill dataset covers 1 July to 29 October 2025 and represents seven subsystems: Feeding, Grinding, Separator, Drive, Ventilation, Lubrication, and PLC/instrumentation. Events were classified by state before the event, post-event intervention, failure category, and downtime and production loss.

Union-based downtime was used for empirical availability so that overlapping intervals were not counted twice.

Table 1. Profile of the Raw Mill dataset

Measure	Value
Observation horizon	2,900.38 h
Total events	80
Failure-related events	62
Scheduled PM events	18
Inspection-indicated events	7
Complete failures	10
Recorded event downtime	453.68 h
Union-based downtime	435.40 h
Empirical availability	0.8499
Recorded production loss	80,646.8 t

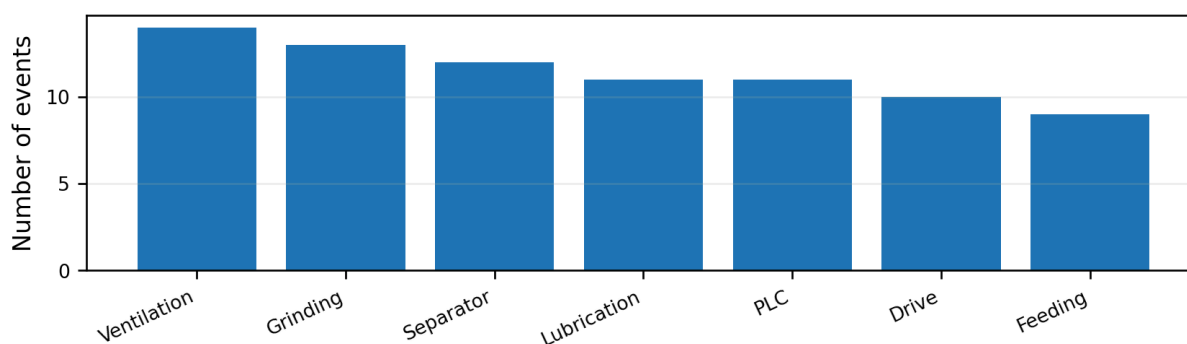


Figure 2. Subsystem-wise frequency of Raw Mill events.

Table 2. Subsystem-wise event frequency, downtime and production loss

Subsystem	Events	Downtime (h)	Mean DT (h)	Loss (t)
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Ventilation	14	60.78	4.341	10,790.6
Grinding	13	74.71	5.747	12,175.0
Separator	12	82.77	6.898	15,103.7
Lubrication	11	60.41	5.492	10,988.5
PLC/instrumentation	11	58.10	5.282	10,951.3
Drive	10	53.15	5.315	9,646.5
Feeding	9	63.76	7.084	10,991.2

3.1 Semi-Markov formulation

Let X_n denote the state entered at the n^{th} transition and T_n the transition time. The embedded chain identifies the next state, while the semi-Markov kernel retains the state-dependent holding-time distribution. For states i and j , the kernel can be written as:

$$Q_{ij}(t) = P\{X_{n+1} = j, T_{n+1} - T_n \leq t \mid X_n = i\} \quad (1)$$

Reliability is defined as the probability of avoiding the corrective-failure set up to mission time t . Its integral gives mean time to system failure (MTSF):

$$R(t) = P(TF > t), \quad MTSF = \int_0^\infty R(t) dt \quad (2)$$

For the fitted Weibull repair approximation, maintainability is:

$$M(t) = 1 - \exp[-(t/\eta)^\beta] \quad (3)$$

Long-run productive availability includes full and degraded operation, $AT = AF + AD$. Economic performance is expressed as operating reward minus intervention, downtime and production-loss costs:

$$\Pi = C_0AF + C_1AD - Cr_1nr_1 - Cr_2nr_2 - C_{ini} - C_{pmn}pm - Cd_{(1-AT)} - Ct_\ell \quad (4)$$

3.2 Distribution fitting and parameter estimation

Exponential, Weibull, gamma and lognormal distributions were fitted by maximum likelihood. Kolmogorov-Smirnov, Anderson-Darling and Akaike information criteria were used to compare candidates. Inter-failure time was adequately represented by an exponential distribution. Repair time did not support a simple exponential assumption; the Weibull approximation had shape $\beta = 1.7904$ and scale $\eta = 5.5702$ h. Because β is greater than one, repair completion becomes more likely as restoration progresses. The thesis

therefore retains a general/empirical repair-time view in the semi-Markov kernel and uses the Weibull form as a practical numerical approximation.

Table 3. Selected distribution and stochastic parameter results

Quantity	Selected/estimated result	Interpretation
Inter-failure time	Exponential; $\lambda = 0.021085 \text{ h}^{-1}$	Mean fitted interval = 47.426 h
Repair time	Weibull; $\beta = 1.7904$, $\eta = 5.5702$ h	Best parametric repair approximation
Complete-failure intensity	0.003448 h^{-1}	Lower than total failure intensity
Equivalent repair completion	0.201508 h^{-1}	Baseline equivalent completion rate
Inspection initiation	0.002413 h^{-1}	Detection/inspection pathway
PM initiation / completion	$0.006206 / 0.123288 \text{ h}^{-1}$	Planned intervention pathway

3.3 State interpretation, assumptions and verification strategy

The state structure is intentionally more detailed than a binary working/failed representation. Full operation is the regenerative starting condition. Degraded operation remains productive but represents reduced performance or an abnormal condition that may require monitoring. Inspection is treated as a short diagnostic state. Corrective repair represents restoration after ordinary failure, while preventive maintenance represents planned intervention. Complete failure is separated because it has a different operational consequence and restoration pathway. This separation is important because the same event count can produce very different downtime and output effects depending on the state entered after the event.

Several assumptions are needed to keep the model identifiable from the available records. The next transition is assumed to depend on the present state and not on the complete earlier history, while the holding-time distribution may be state dependent. Successful restoration returns the system to a regenerative operating condition. Only the dominant intervention associated with an event is represented at one time. Repair support is represented through equivalent completion rates for baseline probability calculations, although the general repair-time kernel is retained conceptually. These assumptions produce a tractable

model, but they also explain why model downtime is lower than the interval-union downtime obtained directly from the event record.

Verification is therefore performed at two levels. Mathematical verification checks that every transition probability is non-negative, each transition-matrix row sums to one, reliability begins at one and decreases with time, maintainability begins at zero and increases toward one, and steady-state probabilities are normalized. Data consistency checks compare composite transition proportions with the observed intervention categories. For example, the reconstructed model reproduces 52 corrective-repair events, 18 preventive-maintenance events and 10 complete-failure events out of the 80 cycles. These checks confirm that the algebraic structure is internally consistent even when the simplified state model cannot reproduce every hour of observed downtime.

The distinction between verification and external validation is important for interpretation. The model should not be read as a precise forecast of future Raw Mill performance from a short synthetic record. Instead, it provides a controlled baseline for asking comparative questions: What happens if failure intensity is reduced? How much availability is gained from faster restoration? At what point does extra preventive maintenance consume too much productive time? Such questions are exactly where stochastic reliability models are most useful, because they translate operational changes into measurable effects on mission reliability, productive availability, intervention workload and economic return.

IV. Results

4.1 Reliability, availability and maintainability

The baseline model gives an MTSF of 95.9448 h. Reliability decreases from 0.7205 at 24 h to 0.5377 at 48 h and 0.3238 at 96 h. This pattern shows that an uninterrupted four-day mission has a much lower survival probability than a one-day mission. Faster repair does not directly increase first-passage MTSF once the failure state has already been reached; its strongest effect is on availability and economic loss. This distinction is consistent with repairable-system theory and avoids treating reliability and availability as interchangeable measures (Kijima, 1989; Wang, 2010).

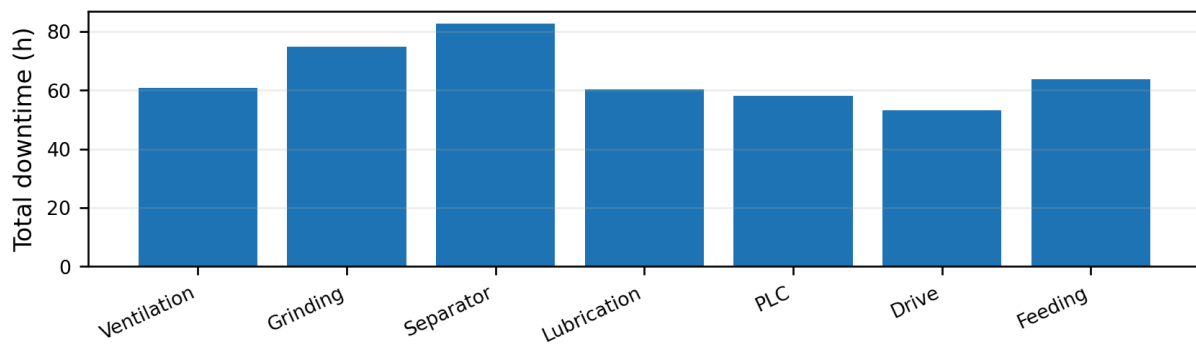


Figure 3. Total Raw Mill downtime by subsystem.

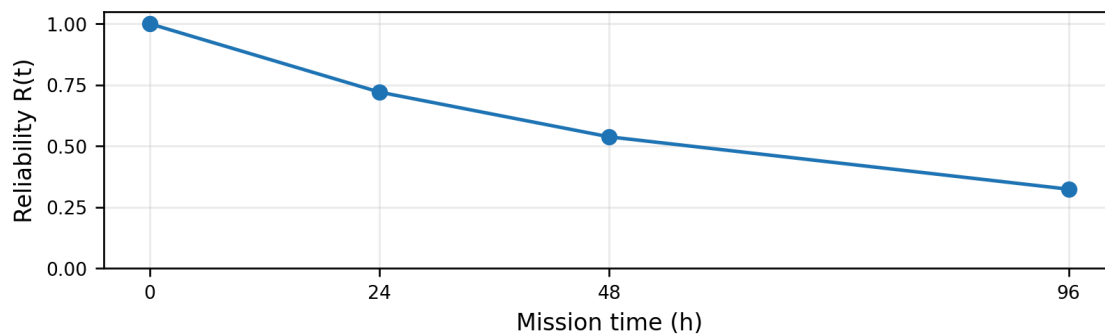


Figure 4. Mission reliability of the Raw Mill at selected operating times.

Table 4. Baseline reliability, availability and maintainability results

Measure	Result	Meaning
MTSF	95.9448 h	Expected time to corrective system failure
R(24)	0.7205	24-h mission reliability
R(48)	0.5377	48-h mission reliability
R(96)	0.3238	96-h mission reliability
Full-capacity availability	0.4634	Long-run full operation
Degraded availability	0.4634	Long-run reduced-capacity operation
Total operational availability	0.9268	Full + degraded productive time
Corrective repair busy proportion	0.0492	Fraction of long-run time in corrective repair

M(8)	0.8522	Repair completion within 8 h
M(12)	0.9808	Repair completion within 12 h

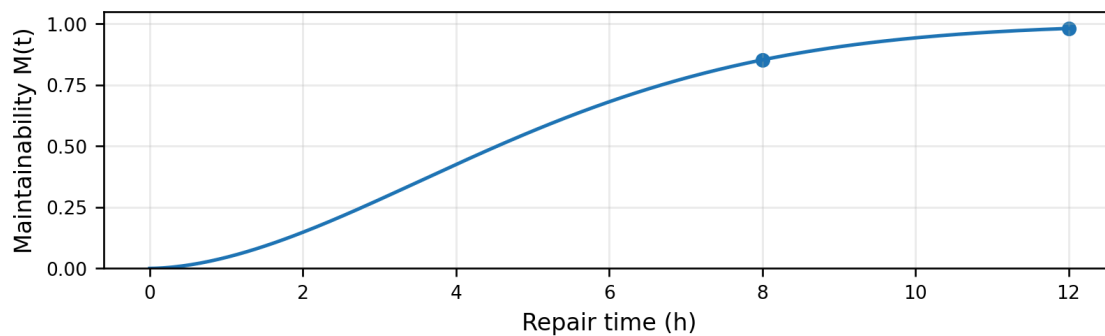


Figure 5. Weibull maintainability curve used for the Raw Mill repair approximation.

Model availability is higher than the empirical interval-union value. Over the 2,900.38-h horizon, the model gives availability 0.9262 and downtime 214.15 h, compared with empirical availability 0.8499 and downtime 435.40 h. The difference is not hidden: it indicates that exact degraded-state residence, waiting time, repair-resource constraints and repeated restart effects are not fully represented. The model is therefore best used as a transparent baseline for comparative decisions rather than as a substitute for continuously observed plant-state history.

4.2 Economic results and sensitivity

The economic model uses normalized monetary parameters because audited plant revenue and cost records were not available for the Raw Mill dataset. The purpose is therefore comparative: it shows which technical changes improve the reward-cost balance. Downtime and production-loss penalties are the largest controllable cost components, while direct inspection and maintenance-event costs are comparatively small. This result supports proactive maintenance cultures that target avoidable interruption rather than simply reducing maintenance spending (Eti et al., 2006).

Table 5. Baseline Raw Mill reward-cost result

Economic component	Units/h	Value over 2,900.38 h
Operating reward	370.7030	1,075,179.47
Minor repair cost	0.4154	1,204.78
Major repair cost	0.1598	463.38
Inspection cost	0.0224	64.87

Preventive-maintenance cost	0.1150	333.63
Downtime cost	7.3243	21,243.13
Production-loss cost	6.9514	20,161.70
Total expected cost	14.9882	43,471.50
Long-run expected profit	355.7148	1,031,707.96

Normalized sensitivity shows that combined corrective-failure intensity has the strongest negative effect on MTSF (sensitivity -1.0472). Corrective-repair and PM-completion rates improve availability, whereas excessive PM initiation reduces operating availability. A coordinated scenario that reduces failure-related rates by about 20% and improves restoration rates by about 20% increases modeled profit from 355.7148 to 366.1774 units/h, or about 2.94%. This supports a condition-based policy rather than indiscriminate fixed-frequency maintenance (Ahmad & Kamaruddin, 2012; Jardine et al., 2006).

4.3 Subsystem criticality and maintenance priorities

Frequency alone gives an incomplete view of Raw Mill risk. Ventilation has the largest number of events, but Separator has the largest cumulative downtime and production loss. Feeding has only nine events yet the highest mean downtime per event. A combined criticality index based on normalized frequency, total downtime, mean downtime and production loss therefore produces a more useful priority view. Such consequence-based prioritization is consistent with risk-based maintenance practice (Khan & Haddara, 2003).

Table 6. Integrated subsystem criticality and suggested maintenance focus

Rank	Subsystem	Criticality	Primary focus
1	Separator	95.77	Vibration/current monitoring, vane cleaning, rotor balance
2	Grinding	86.21	Bearing/roller condition and hydraulic pressure
3	Feeding	78.52	Blockage control, belt alignment, rapid spares
4	Ventilation	76.54	Fan vibration, airflow, damper condition
5	Lubrication	75.46	Oil pressure/temperature, oil analysis, filters

6	PLC/instrumentation	73.96	I/O health, sensor calibration, logic backup
7	Drive	68.63	Motor current, alignment, gearbox oil/bearings

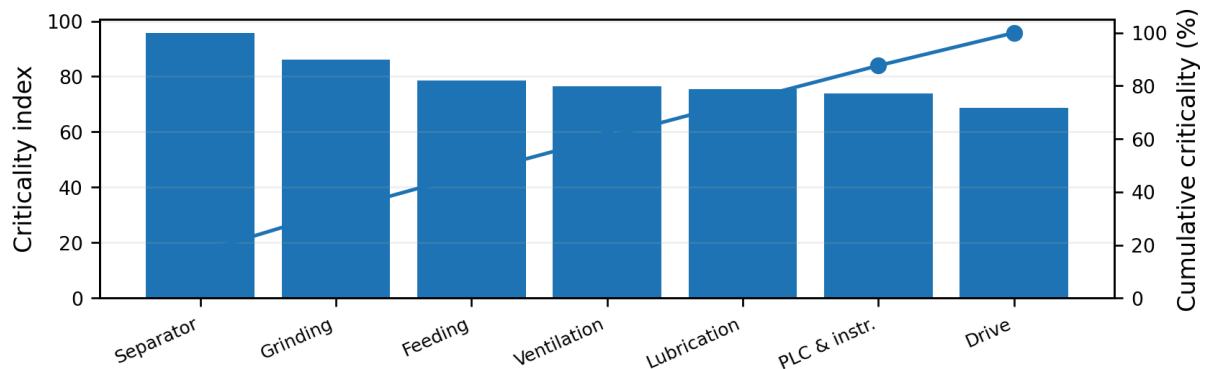


Figure 6. Pareto-style view of Raw Mill subsystem criticality.

V. Discussion

Three findings are especially important. First, repair-time behaviour is not well described by a constant exponential completion rate. This justifies the semi-Markov formulation and is consistent with the broader literature on general and imperfect repair (Kijima, 1989; Pham & Wang, 1996). Second, the largest maintenance opportunity is not simply the most frequent failure category. Separator, Grinding and Feeding emerge because downtime and production consequences matter together with occurrence. Third, faster restoration and better condition information can improve availability even when all failures cannot be eliminated. This is the practical logic behind condition monitoring, diagnostics and prognostics (Carnero, 2006; Peng et al., 2010).

The model also provides a useful economic warning. More preventive maintenance is not automatically better. Planned work occupies productive time, so intervention should be triggered by meaningful evidence of deterioration. Classic maintenance optimization and more recent condition-based approaches both emphasize this trade-off (Dekker, 1996; Wang, 2002). For the Raw Mill, useful indicators include vibration, motor current, oil pressure and temperature, airflow, hydraulic pressure and PLC alarm history. These variables can support earlier detection while avoiding unnecessary shutdowns.

VI. Practical Implications and Limitations

A practical Raw Mill reliability dashboard should combine event intensity, downtime, production loss, repair duration and condition signals. Separator and Grinding deserve immediate technical attention; Feeding requires faster recovery planning; Lubrication, Ventilation and PLC/instrumentation need systematic monitoring. Critical spares and standard repair procedures should be linked to the events that create long restoration time, not only to the most expensive components.

The main limitation is the data basis. The Raw Mill observations were developed for modelling and cover only about four months. Exact degraded-state residence time, waiting periods, repair-resource constraints and audited cost records were not available. The model consequently overestimates availability relative to the union-downtime calculation. Future validation should use multi-year PLC/SCADA histories, work-order details and verified economic data. Predictive signals can then be connected to the stochastic model, but the resulting policy should remain interpretable and operationally testable (Jardine et al., 2006; Wang, 2010).

VII. Conclusion

The Raw Mill can be represented effectively as a repairable multi-state system in which failure prevention, restoration and planned maintenance interact. The semi-Markov/regenerative model estimates an MTSF of 95.9448 h and steady-state productive availability of 0.9268. Repair time is better represented by a Weibull/general distribution than by a strict exponential law. Separator, Grinding and Feeding carry the largest integrated criticality, although the maintenance burden is distributed across all major subsystems. The economic analysis further shows that reduced failure intensity, quicker repair and control of downtime-related production loss are more valuable than simply minimizing direct maintenance cost. The model is most useful as a decision framework that can be recalibrated as higher-quality operating records become available.

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