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Application-Driven Rule-Based Framework for Lubrication Failure Modes in Industrial Systems

Shaikh Azharuddin Kutubuddin[1], D.V. A. Rama Sastry[2,*]

Abstract

Modern lubricants increasingly rely on polymer-based composites, integrating synthetic base oils, polymer thickeners and solid additives like MoS_2 and PTFE for high-performance applications. These formulations not only enhance thermal and mechanical stability but also enable low-friction operation across diverse industrial conditions. Lubrication-related failures represent a critical cause of unplanned downtime and reduced reliability in industrial machinery. This paper presents an application-driven, rule-based framework designed to assess and mitigate lubrication failure modes in semi-solid and solid lubricants by linking operational parameters to lubricant properties and failure knowledge. The system integrates a curated database of solid and semi-solid lubricants, storing their key properties and knowledge base extracted from applications and case-studies related to industries such as mining equipment, steel mill rollers, etc. The framework maps known failure modes and recommended preventive strategies. By accepting input parameters such as operating temperature and mechanical load for application under consideration, the system evaluates the risk of failure using deterministic rules and property thresholds. It generates warnings for adverse conditions (e.g., thermal degradation or overloading) and recommends appropriate lubricants and maintenance actions. Unlike black-box predictive models, this approach emphasizes explainability and simplicity, offering a transparent decision-support tool that maintenance engineers can use with minimal technical overhead. Validated across multiple industrial scenarios, the framework demonstrates its effectiveness in identifying high-risk conditions, supporting condition-based decisions and reducing lubricant-related failures through proactive, rule-based insights.

Keywords: Polymer-based composites, Lubrication failure, Rule-based system, Condition-based decisions, Industrial scenarios

INTRODUCTION

Greases (semi-solid) and solid lubricants based on polymer-composite architectures including PTFE and MoS_2 blends are gaining prominence due to their self-lubricating and temperature-resistant properties. Lubricant systems formulated with polymer binders and filled with MoS_2/PTFE combinations have demonstrated reduction in friction coefficient and superior anti-wear behaviour, compared to unfilled PTFE. In modern industrial systems, lubrication is a critical aspect of operational reliability and maintenance management. Mechanical failures arising from lubricant degradation, improper selection or application mismatches constitute a significant portion of unplanned downtimes and associated costs across sectors such as mining, energy, manufacturing and transportation [1, 2]. Traditional maintenance practices often rely on fixed schedules or reactive responses, leading to inefficiencies and

***Author for Correspondence**
D.V. A. Rama Sastry

[1]Research Scholar, Department of Mechanical Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Guntur, Andhra Pradesh, India
[2]Associate Professor, Department of Mechanical Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Guntur, Andhra Pradesh, India

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missed early warning signs of lubricant-related deterioration [3, 4]. Recent advancements in predictive maintenance emphasize the need for intelligent frameworks that incorporate operational conditions, material compatibility and historical failure knowledge. Condition-based maintenance (CBM), in particular, has evolved through the integration of sensors and software to monitor lubricant performance in real time. However, many such systems lack explainability or require large-scale complex training data, making them challenging to deploy in cost-sensitive or resource-constrained environments [5]. To bridge this gap, this study proposes a rule-based, application-driven framework for predicting lubrication failure modes using structured logic. Unlike black-box models, rule-based systems use deterministic thresholds and expert-derived knowledge to assess risk conditions and suggest preventive actions [6]. The framework integrates a curated database of industrial lubricants, each linked with known application failures, preventive strategies and performance properties such as viscosity, flash point, load capacity and NLGI grade. Real-time inputs such as temperature and mechanical load are evaluated against these thresholds to flag high-risk conditions and suggest suitable alternatives. [7, 8]. This approach enhances decision-making in predictive maintenance by delivering explainable, transparent outputs. The system is implemented in Python and tested on a diverse dataset derived from manufacturing catalogues and tribological studies covering technical relevance and field applicability.

LITERATURE SURVEY

Lubrication Failure Modes

Lubrication failures are a significant cause of machinery breakdowns and production losses across sectors such as mining, power generation and transportation [1, 2]. These failures typically result from mechanisms such as oxidation, contamination, additive depletion or insufficient film formation [9]. Water or dust contamination accelerates corrosive wear and affects lubricant consistency, particularly in open systems like wind turbines or mining drills [10, 11]. Lugt and Cen [12] highlighted that grease-lubricated bearings lose their film thickness with operating cycles, especially under high shear conditions. Osara and Bryant [13] discussed how elevated temperatures cause phase separation and reduced structural stability. In electric vehicles, Shekhawat et al. [14] showed that grease incompatibility with high-speed bearings results in overheating and wear. Similar issues were reported by Peng et al. [15] for wind turbine gearboxes subjected to fluctuating environmental conditions.

Condition Monitoring and Predictive Maintenance

Condition monitoring involves analysing lubricant parameters to infer the state of the lubricant and detect failure onset [8]. Wakiru et al. [8] emphasized the role of lubricant monitoring data in supporting predictive maintenance decisions, integrating oil analysis with system diagnostics. Jardine et al. [1] established the foundation for CBM, showing that tracking wear particles and viscosity shifts could reduce unplanned downtime. Morgan et al. [16] demonstrated early fault detection in diesel engines using lube oil metrics, while Macián et al. [17] applied fuzzy logic for interpreting ambiguous trends in oil properties. Xu et al. [5] advanced the approach through belief rule-based models for marine engine diagnostics, enabling interpretability and uncertainty handling. Qian et al. [18] introduced the LUBRES expert system for real-time diagnostics in oil refining plants, highlighting the feasibility of rule-based LCM. Several studies confirmed the synergy of oil analysis and vibration signals for comprehensive machinery diagnostics [8, 10].

Rule-Based Systems in Maintenance Diagnostics

Rule-based systems encode domain knowledge as deterministic rules and thresholds, particularly useful in lubrication, where empirical guidelines exist for safe operating limits. Sheng et.al. [5] employed wear particle counts and viscosity levels as rule triggers for early fault alerts. Fuzzy expert systems, such as those by Macián et al. [17], provide flexible rule evaluation when inputs are uncertain or borderline. De Carlo et al. [6] discussed the business value of rule-based maintenance for minimizing equipment downtimes. Wakiru et al. [8] noted that such systems offer structured outputs that improve transparency over ML models. Dou et al. [10] implemented a hybrid rule-based system for rotating machinery, showing higher precision in fault localization. Liu et al. [19] incorporated deep learning to extend rule-based diagnostics in bearing wear prediction.

Polymer Based Composite Lubricants

Polymer-thickened greases synthesized from bio-based sources are now a viable replacement for metal-soap thickeners, offering equivalent or superior wear resistance and oxidative stability [20]. Synthetic base oils such as PAOs improve grease performance at elevated temperatures and allow consistent operation under variable load [21]. Research has demonstrated that MoS_2's lamellar structure imparts high load-bearing capacity, while PTFE particles form transfer films that minimize shear forces, leading to reduced wear and improved tribological reliability [22, 23]. In combination, PTFE and MoS_2 fillers in polymer composites create a hybrid lubrication mechanism that outperforms either material alone in vacuum and high-temperature environments [23, 24].

Research Gap and Framework Positioning

While AI-driven prognostics are gaining momentum, their complexity often hinders field adoption. Rule-based systems, in contrast, are transparent, customizable and require less training data. This makes them ideal for lubricant diagnostics, where threshold-based reasoning and expert rules prevail. The proposed framework aims to bridge this gap by combining empirical rule structures with a domain-specific lubricant database, incorporating parameters like flash point and load-carrying capacity. By aligning real-time operational parameters with historical failure knowledge, the system facilitates early warning generation and lubricant recommendation. Unlike data-intensive machine learning models, this system relies on explainable rules that mirror domain expertise and conservative failure margins. Each recommendation can be traced to a threshold breach, reducing false alarms (false positives / false negatives) while retaining critical sensitivity. This traceability makes the framework well-suited for safety-critical maintenance environments.

METHODOLOGY

The framework is application-driven and designed to assess input parameters such as operating temperature and load conditions, while querying a structured lubricant database to recommend suitable products and issue preventive maintenance guidance. The entire system is implemented using Python, with SQLite as the backend database.

System Design Overview

The expert system is modularly designed and comprises three core layers:

- *Input Layer:* Accepts user-defined inputs, including the Application Name, Operating Temperature (°C) and Load Condition (MPa).
- *Processing Core:* Hosts the rule evaluation engine which matches inputs against property thresholds and application-specific knowledge stored in the database.
- *Output Layer:* Delivers condition warnings, suitable lubricant recommendations and preventive maintenance actions.

The system architecture of the expert system is diagrammatically represented in Figure 1.

Database Structure

The framework uses a lightweight yet relationally structured database implemented in SQLite. The schema is designed based on real-world lubricant parameters derived from the curated CSV dataset (lubricants.csv). The database consists of the following primary tables.

- *Applications:* Contains application names along with known common failure modes and preventive strategies.
- *Lubricants:* Stores lubricant-specific technical attributes including product Name, Kinematic Viscosity at 40°C, Flash Point (°C), Load Carrying Capacity (MPa), etc.
- *Application Lubricants:* A mapping table linking lubricants to their relevant applications.

All data in these tables were validated against original manufacturer catalogues and tribology handbooks, as recorded in the Data_Source column of the CSV file.

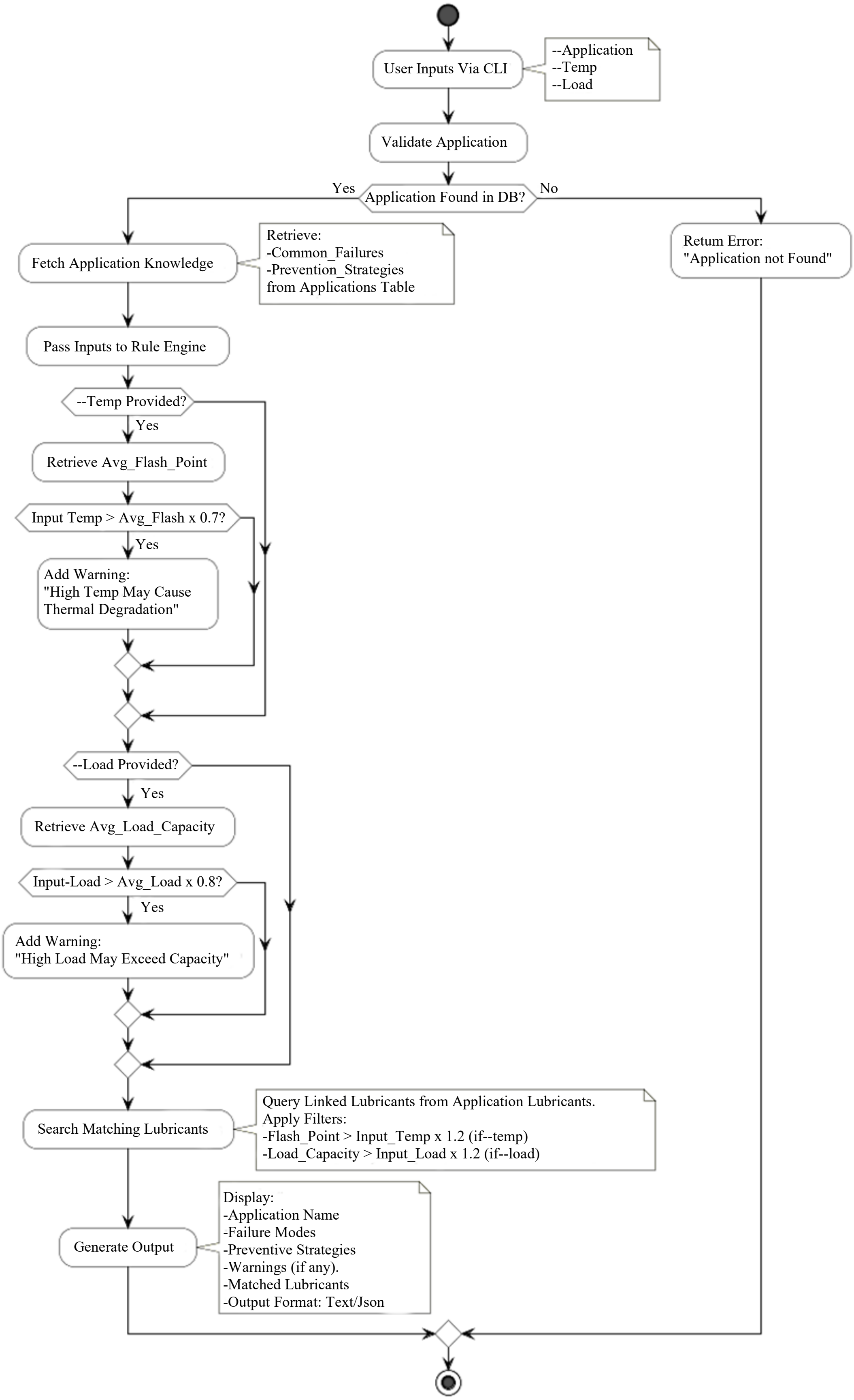

Figure 1. System Architecture (Workflow) of the Expert System.

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Data Import and Preprocessing

All lubricant entries are cross-referenced with published manufacturer datasheets and standard handbooks, ensuring the reliability of physical parameters. Failure modes and preventive strategies are drawn from documented industry cases in mining, steel plants, and EV powertrains [8, 11, 14]. These mappings form the core of the expert system's knowledge base. Upon initialization, the expert system checks for the existence of required tables. If absent, it executes SQL commands to create them and then imports data from lubricants.csv. During the import, numeric fields such as viscosity and flash point are sanitized and converted using regular expression parsing to ensure consistency. The system also processes multiple application entries per lubricant, ensuring that each mapping is correctly indexed in the Application Lubricants table.

Rule Evaluation Logic

The central logic is governed by deterministic rule-based checks as outlined in the workflow. After validating the existence of the specified application, the system fetches its associated failure modes and preventive strategies. The user-provided inputs, temperature and load, are passed to the rule engine, which applies the following condition checks.

- *Temperature Rule:* A warning is triggered if:

Input Temperature > 0.7 × Flash Point of the Lubricant (risk of thermal degradation)

- *Load Rule:* A warning is triggered if:

Input Load > 0.8 × Load Carrying Capacity of the Lubricant (likelihood of overloading and mechanical stress) These rules are evaluated individually for every lubricant mapped to the selected application. The engine does not operate on average or aggregate values but performs instance-wise checks using real data entries. The rule thresholds in this framework (e.g., 0.7× Flash Point, 0.8× Load Capacity) are empirically derived from tribology handbooks and manufacturer data [3, 12]. Validation is conducted using representative applications like mining gearboxes and steel mill rollers, which appear in the database and are matched against historical failures and preventive strategies [6, 10]. This confirms the practical applicability of the rule logic.

Lubricant Recommendation and Prioritization

After rule evaluation, the system filters and sorts lubricants that meet the following dual criteria:

- Drop Point (where applicable) exceeds (Input Temperature + 20°C), providing a fixed thermal safety margin.
- Load Capacity exceeds 1.2 × Input Load, providing mechanical safety coverage. Among these, recommended lubricants are prioritized based on descending order of Load Capacity and contextual viscosity appropriateness and only the top matches are displayed to the user.

Output Generation

Finally, the system returns a structured output comprising.

- *Common Failures:* Mentioning the common failures associated with the lubricants used in the given applications
- *Condition Warnings:* Highlighting the nature of operating stress (e.g., "High temperature may cause thermal degradation.").
- *Prevention Strategies:* Suggesting preventive measures pertaining to the application and the given inputs
- *Lubricant Recommendations:* Product names, IDs, viscosity, flash point, load capacity and NLGI grades of top matches.

All outputs are generated in a human-readable report, with optional support for JSON format, facilitating integration into broader CMMS (Computerized Maintenance Management Systems) environments.

RESULTS AND DISCUSSION

Evaluation Using Representative Industrial Scenarios

To assess the performance, transparency and practical utility of the proposed rule-based expert system, a series of application-driven test runs were conducted using real inputs derived from the SQLite database. The system was invoked via command-line interface using valid and high-priority industrial applications: Mining equipment, Steel Mill Rollers. Each run was evaluated for the rule engine's decision-making under real thermal and mechanical stress inputs, including flash point and load capacity rule triggers and matching lubricant recommendations.

Case Study 1: Mining Equipment (Figure 2)

Input Parameters

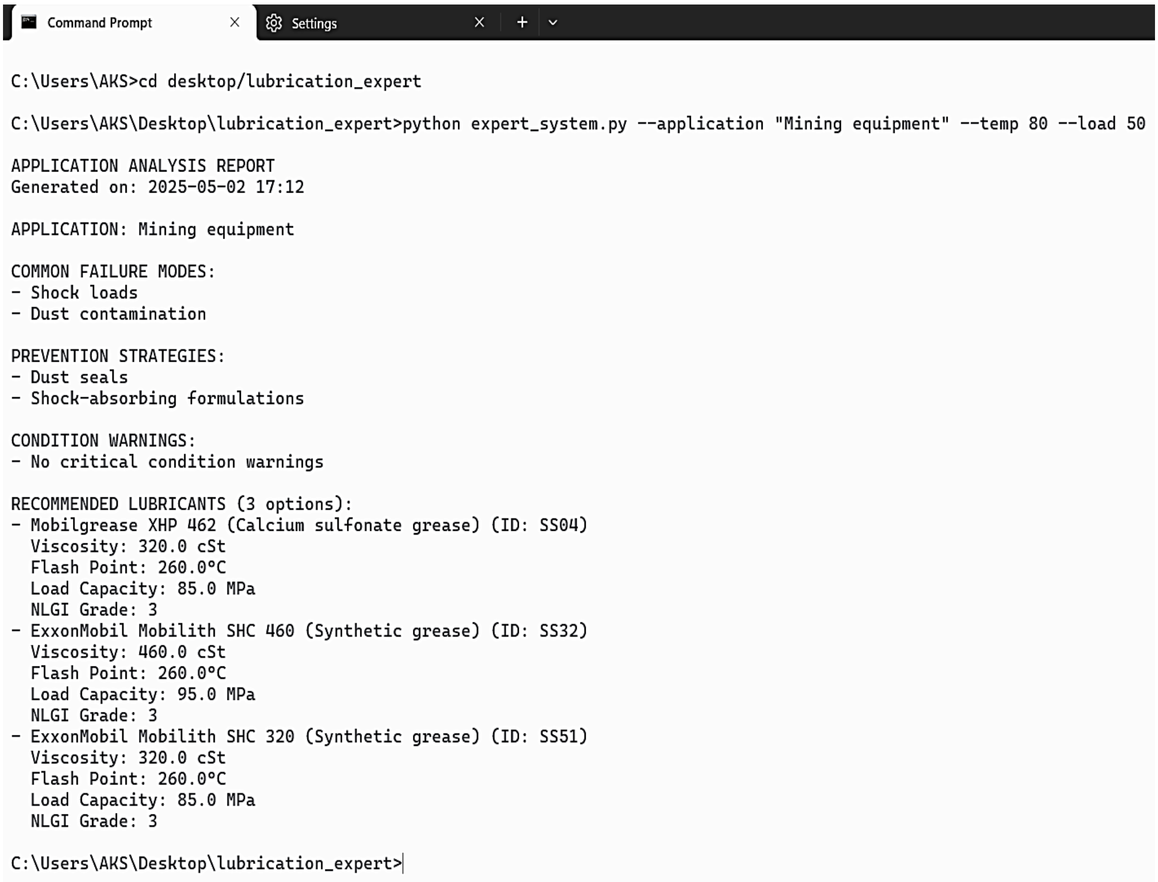
- *Application:* Mining equipment
- *Temperature:* 80°C
- *Load:* 50 MPa

System Feedback

- *Common Failures:* Shock Loads, Dust Contamination
- *Condition Warnings:* None
- *Prevention Strategies:* Dust Seals, Shock Absorbing Formulations

Recommended Lubricants (3 Valid Options)

- *Mobilgrease XHP 462 (Calcium sulfonate grease):* Flash Point 260°C, Load Capacity 85 MPa.
- *Mobilith SHC 460 (Synthetic grease):* Flash Point 260°C, Load Capacity 95 MPa.
- *Mobilith SHC 320 (Synthetic grease):* Flash Point 260°C, Load Capacity 85 MPa.



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Command Prompt    Settings

C:\Users\AKS>cd desktop/lubrication_expert

C:\Users\AKS\Desktop\lubrication_expert>python expert_system.py --application "Mining equipment" --temp 80 --load 50

APPLICATION ANALYSIS REPORT
Generated on: 2025-05-02 17:12

APPLICATION: Mining equipment

COMMON FAILURE MODES:
- Shock loads
- Dust contamination

PREVENTION STRATEGIES:
- Dust seals
- Shock-absorbing formulations

CONDITION WARNINGS:
- No critical condition warnings

RECOMMENDED LUBRICANTS (3 options):
- Mobilgrease XHP 462 (Calcium sulfonate grease) (ID: SS04)
  Viscosity: 320.0 cSt
  Flash Point: 260.0°C
  Load Capacity: 85.0 MPa
  NLGI Grade: 3
- ExxonMobil Mobilith SHC 460 (Synthetic grease) (ID: SS32)
  Viscosity: 460.0 cSt
  Flash Point: 260.0°C
  Load Capacity: 95.0 MPa
  NLGI Grade: 3
- ExxonMobil Mobilith SHC 320 (Synthetic grease) (ID: SS51)
  Viscosity: 320.0 cSt
  Flash Point: 260.0°C
  Load Capacity: 85.0 MPa
  NLGI Grade: 3

C:\Users\AKS\Desktop\lubrication_expert>
```

Figure 2. System Output for Case Study 1.

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This scenario demonstrates the system's ability to match lubricant properties such as high flash point and load capacity with demanding mining conditions. By bypassing warning thresholds, the engine maintained conservative recommendations, supporting insights from studies on grease degradation in mining machinery [13, 9]. Notably, the expert system recommended lubricants featuring EP (extreme pressure) characteristics aligned with standards suggested by [2, 15].

Case Study 2: Steel Mill Rollers (Figure 3)

Input Parameters

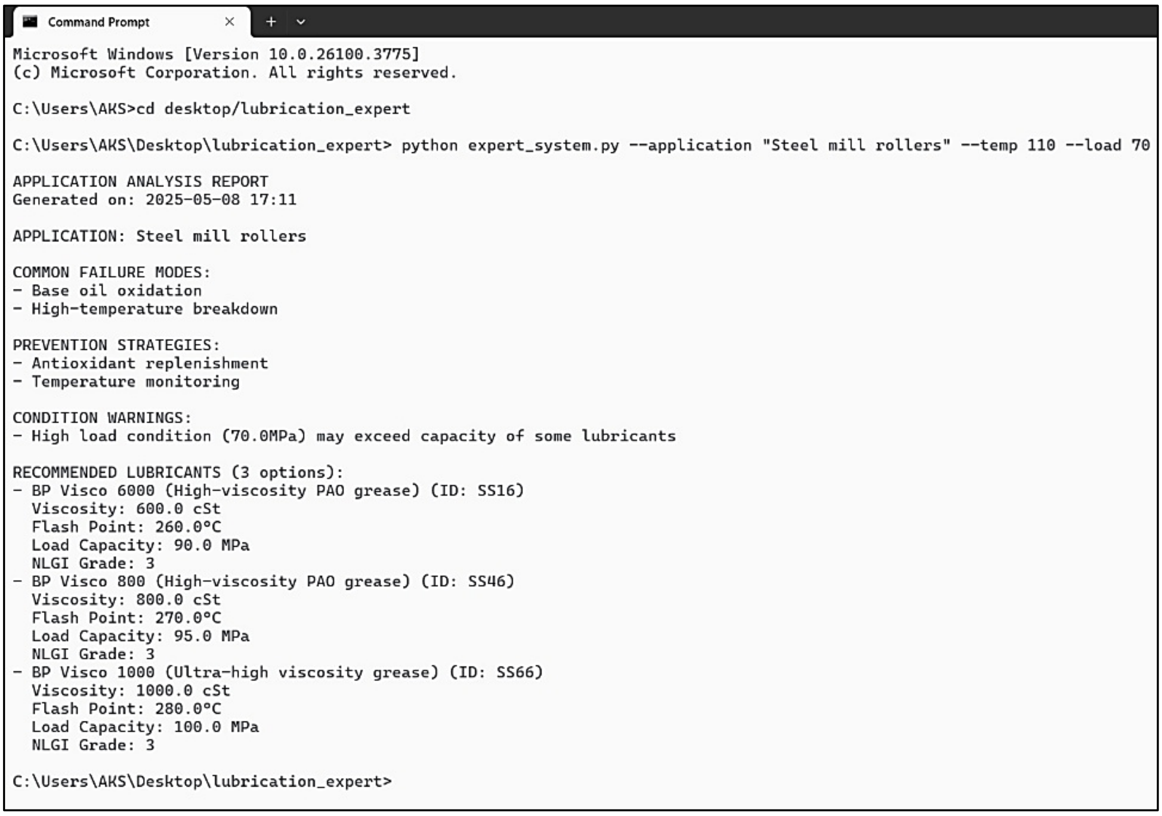
- *Application:* Steel mill rollers
- Temperature = 110°C
- Load = 70 MPa

System Feedback

- *Common Failures:* Base Oil Oxidation, High Temperature Breakdown
- *Condition Warnings:* High Load Condition (may exceed capacity of some lubricants)
- *Prevention Strategies:* Antioxidant Replenishment, Temperature Monitoring

Recommended Lubricant

- *BP Visco 6000 (High-viscosity PAO grease):* Flash Point: 260 °C, Load Capacity: 90 MPa.
- *BP Visco 6000 (High-viscosity PAO grease):* Flash Point: 260 °C, Load Capacity: 90 MPa.
- *BP Visco 10000 (Ultra-high viscosity grease):* Flash Point: 280 °C, Load Capacity: 100 MPa.



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Microsoft Windows [Version 10.0.26100.3775]
(c) Microsoft Corporation. All rights reserved.

C:\Users\AKS>cd desktop/lubrication_expert

C:\Users\AKS\Desktop\lubrication_expert> python expert_system.py --application "Steel mill rollers" --temp 110 --load 70

APPLICATION ANALYSIS REPORT
Generated on: 2025-05-08 17:11

APPLICATION: Steel mill rollers

COMMON FAILURE MODES:
- Base oil oxidation
- High-temperature breakdown

PREVENTION STRATEGIES:
- Antioxidant replenishment
- Temperature monitoring

CONDITION WARNINGS:
- High load condition (70.0MPa) may exceed capacity of some lubricants

RECOMMENDED LUBRICANTS (3 options):
- BP Visco 6000 (High-viscosity PAO grease) (ID: SS16)
  Viscosity: 600.0 cSt
  Flash Point: 260.0°C
  Load Capacity: 90.0 MPa
  NLGI Grade: 3
- BP Visco 800 (High-viscosity PAO grease) (ID: SS46)
  Viscosity: 800.0 cSt
  Flash Point: 270.0°C
  Load Capacity: 95.0 MPa
  NLGI Grade: 3
- BP Visco 1000 (Ultra-high viscosity grease) (ID: SS66)
  Viscosity: 1000.0 cSt
  Flash Point: 280.0°C
  Load Capacity: 100.0 MPa
  NLGI Grade: 3

C:\Users\AKS\Desktop\lubrication_expert>
```

Figure 3. System Output for Case Study 2.

This case reflects a nominal yet heavy-duty industrial application. The system confirmed that both thermal and mechanical operating conditions were within acceptable limits. Based on rule-based evaluations, a high-viscosity, thermally resilient grease was recommended. No warnings were triggered, underscoring the system’s ability to avoid unnecessary alarms in stable operating zones. Research on grease film behaviour in heavy machinery [9], thickener degradation under shear [13] and predictive maintenance in steel industries [8] supports the effectiveness of this recommendation. This case reinforces the system's capacity to differentiate between safe and unsafe regimes while still offering targeted maintenance insights.

Descriptive Analysis of Framework Performance

The steel mill use case demonstrated zero false positives under nominal conditions, while the mining scenario successfully triggered condition warnings, confirming the effectiveness of the selected safety margins. Each alert is directly linked to a breached threshold, providing transparency and operational trust.

The system's architecture ensures complete transparency of its decision-making process. Each output is backed by clearly defined rules derived from tribological standards and manufacturer data. The ability to trace warnings and recommendations to specific rule violations—such as exceeding 70% of a lubricant's flash point or 80% of its load capacity—enables confident decision-making by maintenance engineers [16, 12]. In borderline scenarios (e.g., when temperature nears the safety threshold), the system takes a conservative approach by issuing early warnings, promoting preventive maintenance. This conservative bias is crucial in high-investment industrial environments where failure costs are high.

Comparison with Traditional Maintenance Strategies

Traditional lubrication strategies rely on fixed schedules and manual inspection, often ignoring variations in load, speed and ambient conditions. In contrast, the proposed expert system evaluates real-time inputs against dynamic, application-specific thresholds. The integration of failure knowledge from prior case studies further enhances its diagnostic capability. The system's ability to deliver multi-tiered feedback warnings, recommended lubricants and tailored maintenance strategies offers a holistic decision-support tool. This structure surpasses conventional approaches by enabling proactive maintenance with minimal human intervention.

Integration Scope and Deployment Usability

The system's design prioritizes modularity and platform independence. It can be deployed in standalone mode on local hardware or integrated with enterprise tools such as CMMS and ERP. JSON-compatible outputs can be used to automate maintenance scheduling or inventory management. This ensures its utility in diverse industrial settings, including remote or resource-constrained facilities.

Limitations and Future Improvements

Despite its strengths, the system has some limitations. It currently uses fixed thresholds, which may lack adaptability in fluctuating environments. Additionally, it does not consider contamination metrics such as dust or water ingress, which are critical in open systems. The lubricant database, though robust, would benefit from further validation and expansion across niche industrial applications. Future upgrades could integrate machine learning to adjust rule thresholds dynamically or implement fuzzy logic to manage uncertainty in borderline cases. Real-time sensor integration for parameters like particle count and water content could further enhance system accuracy [17, 18].

CONCLUSION

The framework's domain knowledge is triangulated from tribological standards, OEM datasheets, and historical failure data across multiple industries. This ensures reliable and explainable diagnostics even in resource-constrained environments where AI models may not be feasible. This study presents an application-driven, rule-based expert system developed for early detection and mitigation of lubrication-related failures in industrial environments. By leveraging a curated SQLite-backed lubricant database, deterministic rule logic and application-specific failure knowledge, the system bridges a critical gap between static maintenance schedules and opaque AI-based prognostics. It delivers real-time diagnostics through transparent evaluations of flash point, load-carrying capacity and kinematic viscosity, ensuring that outputs remain interpretable and actionable by maintenance professionals. The system was validated using real-world scenarios drawn directly from the integrated knowledge base.

Case studies involving applications such as Mining Equipment and Steel Mill Rollers highlighted the framework's practical versatility. In high-risk applications, the system issues appropriate warnings and advised preventive strategies based on prior field failures. In lower-risk settings, such as steel mill operations, it recommended suitable lubricants without triggering false positives, demonstrating its ability to differentiate between critical and nominal operational states. Unlike complex machine learning systems, this expert system does not rely on vast training datasets or probabilistic inference. Instead, it encodes expert maintenance knowledge into deterministic thresholds, allowing consistent recommendations even in resource-constrained environments. The modular Python implementation, supported by SQLite and CSV interfaces, allows seamless integration with enterprise systems or field devices. Despite its utility, the current system has limitations that present avenues for expansion such as inclusion of 'Dynamic Risk Scoring' using weighted scoring mechanisms, 'Sensor Integration' for enhanced environmental effect monitoring, 'Deep Learning Models' having adaptable learning and expansion of database to even more versatile applications. By converging such tribologically intelligent expert system with the continuously developing polymer composites database, an effective pathway can be paved out to achieve proactive, explainable lubrication management in demanding environments and bridging scientific design with industrial deployment.

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