Maximizing Efficiency:

How AI and Knowledge Graphs Revolutionize Spare Parts Optimization

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It is imperative for asset intensive industries to operate cost efficiently to sustain profits even when commodity prices are low, and as they face increasing pressure to decarbonize. Optimizing the holding of spare parts is a key contributor to profitability, and frees cash from the balance sheet. Cekap is developing a state-of-the-art solution for spare parts optimization using a fusion of Artificial Intelligence (AI) and Knowledge Graph (KG) technologies.

Understanding the Optimization Scope

Spare parts availability is crucial for maintaining equipment uptime. Under-stocking risks halting operations and making emergency orders for parts. On the flip side, over-stocking ties up capital and store space, and risks obsolescence when technology advances. Both sides of the optimum impact profits and cash flow negatively. In the past, the lack of sensor data and AI based analytics required companies to either hold high levels of safety spares, or make emergency orders for corrective maintenance if they didn't. The explosion of sensor data and AI models now allow advanced warning of potential failures, but that only addresses part of the optimization challenge. The other part is the ability to access corporate knowledge on the configuration of a facility, past failures to diagnose the fix, and alternate suppliers in case the primary one has a stockout for the required part(s).

Leveraging AI for Spares Optimization

The foundation for the abovementioned unaddressed information is the creation of a detailed asset register and bills of material (BOMs), and access to failure and repair data. The use of image and text AI technologies, called Semantic AI, make this possible at a fraction of the time and cost of manual processes.

1. **Asset Register:** Semantic AI locates relevant documents such as P&IDs, SLDs and data sheets, then extracts key information such as tag IDs and attributes of equipment, instruments and valves, and how they are connected, to create a detailed asset register.
2. **BOMs:** Semantic AI locates relevant documents such as part lists, cross sectionals and SPIR, then extracts the parts data in them, codifies the data in accordance with a company's naming convention for CMMS upload, and organizes this into Single Equipment BOMs.
3. **Failures:** Semantic AI locates and analyzes failure reports and their corresponding work orders, FMEA and LORA to support diagnosing problems, understanding historical use of spares and lead times for spares delivery.

Numerous case studies exemplify the tangible benefits of integrating AI into spare parts optimization strategies. For instance, a leading manufacturer implemented AI-driven demand forecasting models, resulting in a significant reduction in excess inventory and stockouts. By accurately predicting demand fluctuations and optimizing reorder points, the company achieved substantial cost savings while maintaining high service levels. Similarly, an FPSO (Floating Production Storage Offtake) vessel had to replace lost production with spot oil purchases when equipment on its facility failed and its team could not find the critical documents needed to make the fix. The company utilized our Asset BOT software to develop its ISO 14224 compliant asset register and BOMs to avoid such costly downtime again.

Augment Spares Optimization with Knowledge Graphs

Knowledge graphs are a powerful tool for organizing data to capitalize on how it is linked. At its core, a knowledge graph is a semantic network that connects highly separated data into a unified whole. Unlike traditional databases, which store information in tabular formats, the lattice format of knowledge graphs enables very efficient traversals between data points, identifying data significance and communities. We are currently using these capabilities to:

1. Prune a forest of Single Equipment BOMs from an equipment class to form Equipment Class BOMs. For example, a mix of BOMs for centrifugal, reciprocating and cavity pumps would be pruned to form a Pump Class BOM. This aggregation of common parts supports reducing Economic Order Quantity (EOQ) computation.
2. Using a graph data science technique to identify equipment inter dependencies as part of an Equipment Criticality Analysis (ECA) study.

Implementation Considerations

Implementing AI and KG in spare parts optimization requires the following:

1. **Human-in-the-Loop (HITL) software architecture:** No AI works perfectly. This is especially true when dealing with legacy data produced by different genres of software, printers, and scanners. A human should be able to interact with the AI software at critical junctures in a workflow to review and remediate AI outputs.
2. **AI metrics:** There are two considerations. First, the user needs to understand how to choose between precision, recall or a combination of them (F1 score) in order to know which to emphasize at different points in the workflow. Second, since AI is used for large data sets the user must understand the basics of statistical quality control since human quality control of the entire data is impossible.
3. **Graph technologies:** Users need to understand the concept of a knowledge graph and the applicability of different graph data science algorithms in spares optimization.

4. **Use of spares optimization models:** Users need to understand which AI and KG outputs should feed into different spares optimization models such as ABC, XYZ and EOQ.
5. **In-house or outsource:** While spares optimization software will likely be operated by in-house users for the most part, it may be that the initial setup of an asset register, BOMs and so forth would be outsourced to a specialist vendor because of the number of personnel needed and the problems likely to be inherent in legacy data. If outsourcing is the option for the setup, then it is necessary to verify the vendors competency in the above-mentioned points.

Conclusion

The landscape of AI and KG is transforming rapidly. The advent of ChatGPT and alternate Large Language Models is just one example of this. It is imperative that the solution your company chooses has the ability to incorporate any relevant advances into its spare's optimization solution. That requires deep in-house capabilities in AI, KG and asset integrity management.

The foundation your company builds with a detailed asset register, BOMs and so forth, have applicability beyond spares optimization. For example, it can also be used for fast, intelligent preparation of work orders.

The volume of facility data is growing at an exponential rate. Using data-driven decision-making across your company including for spares optimization is not an option–it is an imperative.