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Rapid Manufacture of Backup Power Energy Infrastructure for AI Data Centers

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Abstract

Artificial intelligence (AI) data centers are experiencing a lot of growth in power density, energy consumption, and uptime requirements. Federal initiatives in the United States now prioritize the rapid deployment of AI infrastructure, including backup generation systems essential to powering AI data centers (The White House, 2025). Industry reporting indicates that power-related events remain a leading cause of impactful data center outages, reinforcing the necessity of resilient backup power. This paper proposes a four-stage acceleration framework for configured generator programs: (i) AI-enabled intelligent document processing (IDP) to accelerate processing and improve the accuracy (ii) AI-enabled special engineering request processing (iii) machine learning optimization of planning bills of materials (planning BOM) to improve forecast accuracy and reduce material-related manufacturing delays, and (iv) automation of BOM-to-routing component allocations to eliminate a major manual bottleneck in ETO industrial engineering. The proposed approach integrates human-in-the-loop validation to preserve compliance and quality while reducing cycle time.

Keywords
AI data centers, Backup generators, Energy Infrastructure, AI/ML automation in manufacturing, Intelligent Document Processing.

1. Introduction
AI data centers are expanding rapidly and require high-availability power architectures. Although uninterruptible power supply (UPS) and generator systems operate infrequently, they are essential to meet stringent reliability targets and to mitigate the operational and financial consequences of downtime. At the same time, generator and critical power equipment supply chains face long lead times, especially for multi-megawatt systems, creating program delays and cost escalation. Reducing end-to-end cycle time from customer request to factory release and shipment is therefore a strategic capability for generator manufacturers and integrators supporting AI data center buildouts. Data centers – at least at the scale seen today – are relatively new actors in the energy system at the global level. Today, electricity consumption from data centers is estimated to amount to around 415 terawatt hours (TWh), or about 1.5% of global electricity consumption in 2024. It has grown at 12% per year over the last five years (International Energy Agency, 2025).

Following is some of the main reasons that cause delays in Configure to order and Engineer to Order manufacturing:

- Initial Planning Phase: The early stages of opportunity evaluation and Request for Quotation (RFQ) processing typically require substantial effort from customer-facing and business development teams. A significant portion of this time is spent locating and interpreting technical information necessary for product configuration. Critical specifications are often distributed across multiple unstructured sources—such as tender documents, email exchanges, contractual attachments, and other technical artifacts—making the extraction of relevant data labor-intensive and prone to oversight. Research on ETO environments shows that fragmented information, lack of documentation standardization, and complex early-phase requirement interpretation are major contributors to planning delays (Fortes et al. 2023), (Brundl et al. 2023), (Johnsen and Hvam 2019)

- Special Engineering Requests: Special engineering requests arise when a customer's requirements extend beyond the options supported by the standard product configuration. Such requests introduce substantial delays, as engineering teams must revisit the design, develop modifications, and integrate these nonstandard features into the established configuration framework. Peer-reviewed ETO studies confirm that non-standard customizations significantly increase engineering workload, rework, and lead-time variability, often driving substantial cost and schedule impacts (Johnsen and Hvam 2019), (Dilshan and Emese 2025), (Kanike 2023).
- Supply Chain and Material Shortages: Issues in sourcing raw materials, specialized components, or equipment can halt production. Evidence from manufacturing supply-chain research highlights raw-material unavailability, supplier delays, pandemic-driven disruptions, and global logistics instability as major causal factors behind production stoppages and missed delivery commitments (McCauley et al. 2025), (Katsaliak et al. 2022), (Chen.et al. 2023).
- Shop floor operations planning Shop-floor operations planning for configure-to-order products requires manufacturing engineers to generate the corresponding manufacturing Bill of Materials (BOM), while industrial engineers need to develop routings and perform component allocations. This phase can be time-consuming for products that have multi-operation assembly processes or large multi-level BOMs. Peer-reviewed BOM and shop-floor planning research demonstrates that increasing product complexity, multi-level BOM structures, routing depth, and lack of integrated planning tools drive significant delays in production preparation (Eichenseer and Winkler 2024), (Shurrab et al. 2022), (Brundl. et al. 2023)

This study investigates the main research question of how manufacturers can accelerate time-to-market for backup generator energy infrastructure supporting AI data centers by leveraging artificial intelligence and automation across the full value chain—including order intake, engineering, materials planning, and shop-floor production preparation. Prior research on CTO/ETO digitalization and Industry 4.0 strongly supports the need for advanced automation, intelligent planning systems, and software-based decision support to reduce lead times and improve planning efficiency (Brundl et al. 2023), (Schulze and Dallasega 2023). While the title emphasizes rapid manufacture of backup power infrastructure, this paper does not directly focus on physical manufacturing acceleration alone. Instead, it proposes an AI-enabled acceleration framework for CTO/ETO generator manufacturing, targeting key upstream bottlenecks in order intake, engineering, planning, and production preparation that collectively enable faster end-to-end delivery.

1.1 Contributions of This Paper:

This paper makes the following contributions:

- Proposes a novel four-stage AI-enabled acceleration framework for CTO/ETO generator manufacturing addressing order intake (stage 1), engineering (stage 2), planning (stage 3), and production preparation (stage 4).
- Demonstrates a practical industrial implementation of BOM-to-routing component allocation automation with quantified labor and productivity gains.
- Extends existing CTO/ETO digitalization research by integrating intelligent document processing, AI-driven engineering reuse, and ML-based planning BOM optimization into an end-to-end workflow.
- Provides a scalable architecture applicable to other industrial manufacturing domains with minor adaptations.

Among these, Stage 4 has been implemented and validated in a production environment, while Stages 1–3 are currently at design and pilot stages with expected benefits derived from literature and industry benchmarks.

2. Background

2.1 Why Backup Generators Remain Necessary

Backup generators provide continuity during grid disruptions and local power distribution failures. Increasing exposure to grid constraints and extreme weather necessitates resilient onsite power generation.

2.2 Demand Growth and Lead-Time Constraints
AI is a major driver of data center electricity growth. As new AI clusters come online, the pace of deployment stresses both the grid interconnection process and the supply chain for mission-critical power equipment. For large generators, manufacturing and delivery lead times can be many months. Data centers will use twice as much energy by 2030 (Chen 2025)

2.3 Configured-to-Order with Special Engineering (CTO+)
Generators for data centers are very big and often involve some special engineering requests in addition to Configure to Order requirements (CTO+). This type of order requires new routings and new BOMs, usually created with reference to super routing and super-BOMs.

3. Necessity of Backup Generation for AI Data Centers
AI workloads require continuous, and un-interrupted power demand. Several quantitative drivers underscore why backup generators are indispensable:

- Power Density Explosion: Next-generation AI racks require 132 kW, growing to 250–900 kW per rack by 2027 (uptime institute 2025).
- Reliability Requirements: AI facilities now target 99.99999% uptime, requiring MW-scale generator plants to support uninterrupted operations during grid disturbances (uptime institute 2025).
- Economic Impact of Downtime: A single power failure can cost >$1M per hour due to halted training and inference workloads (Kerner 2025).
- Grid Constraints: In Virginia and other hotspots, grid-connection queues stretch up to seven years, forcing data centers to rely on on-site generation (uptime institute 2025).

Given these conditions, backup generators have transitioned from secondary protection to primary enablers of time-to-power for AI-scale facilities.

4. Current Demand and Supply Chain Backlog
4.1 Growth in AI Data Center Electricity Demand
Deloitte projects that U.S. AI data center power demand will grow from 4 GW (2024) to 123 GW (2035)—a 30× increase (D. Robb 2025). Similarly, hyperscale clusters under development are approaching 2 GW per site, with early mega campus concepts exceeding 5 GW (Infinity Turbine LLC).

4.2 Generator Market Expansion
The data center generator market will grow from $1.3B in 2025 to $2.7B by 2035, with diesel retaining 56.2% market share (Grid Strategies LLC 2025). Broader global generator demand is projected to reach $13.8B by 2030(Grid Strategies LLC 2021).

4.3 Manufacturing Bottlenecks
Supply-chain shortages in large-bore engines, alternators, and copper windings have extended generator delivery times, forcing operators into multi-year procurement contracts (Amazon Web Services).

4.4 Data Center Construction Timelines
Traditional hyperscale builds require 18–24 months from planning to commissioning (Wahedi et al 2023).

4.5 Power Infrastructure Delays
Grid interconnection delays (4–7 years) far exceed construction timelines, making backup power the true critical path (uptime institute 2025).

4.6 Modular Containerized Data Centers
While modular data centers can be deployed in 12–14 weeks, they still require rapid manufacture and commissioning of backup generator systems (Wahedi et al 2023).

5 Four Stage Acceleration Framework

This section describes an end-to-end framework to reduce cycle time by applying automation and AI to (i) order intake, (ii) engineering, (iii) planning and procurement readiness, and (iv) industrial engineering and production preparation. The framework is intentionally designed to preserve auditability and compliance through human-in-the-loop controls. Table 1 summarizes the status and validation level of each stage in the proposed automation framework.

Table 1. Framework stages, Techniques and Validation

Stage	Capability	AI / Method	Implementation Status
Stage 1	Automated RFP parsing and quote generation	NLP, Generative AI, CPQ integration	Discovery
Stage 2	Engineering knowledge reuse for special requests	AI similarity search, semantic retrieval models	Development
Stage 3	Planning BOM accuracy improvement	ML-based demand forecasting, supplier signal integration	Concept
Stage 4	Automated BOM-to-routing allocation	Rule-based automation with ERP integration	Implemented

5.1 Stage 1: Faster and More Accurate Intake of Configured Orders

Problem: Order intake is frequently slowed by manual extraction of requirements from RFPs, tender documents, emails, and attachments. Errors introduced at intake propagate into engineering rework, procurement churn, and production disruptions.

Approach: Recent research demonstrates that NLP-based AI systems can automate RFP parsing and proposal generation, while integrated CPQ platforms leverage machine learning for predictive quoting and dynamic price optimization, significantly improving sales efficiency and responsiveness in B2B environments (Chandramohan P. 2025). An AI-enabled intelligent document processing (IDP) pipeline: (1) ingests tender/RFP/email document sets; (2) extracts and normalizes technical attributes such as power rating, voltage, frequency, fuel type, emissions tier, enclosure rating, ambient constraints, and sound limits; (3) maps extracted attributes to a variant configuration schema to generate quotes and preliminary BOM/routing selections; (4) flags unmapped attributes as special engineering needs and routes them to an ETO workflow; (5) applies human-in-the-loop review for validation and compliance; and (6) executes multi-level availability checks (ATP/CTP) in the ERP to estimate lead time and provide a reviewable promise date. Bid preparation involves understanding tender contents, checking deviations, estimating timelines/costs, and these tasks can be supported by AI assistants that extract and structure information from tender documents (Manchanda 2021). Figure 1 demonstrates AI enables IDP workflow.

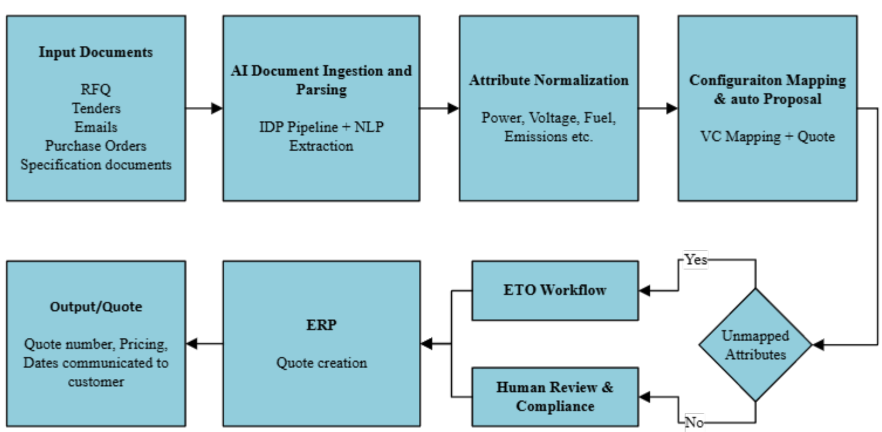

Figure 1. AI enabled IDP

Expected Benefit: Intelligent document processing enables automated extraction and integration of unstructured data into enterprise workflows, significantly improving efficiency and reducing manual effort in document-intensive processes. (Cutting, G. A., and Cutting-Decelle, A.-F.).

Figure 1 shows high level architecture of utilizing AI enabled intelligent document processing along as part of the RFP -> Quote -> Sales Order process.

5.2 Stage 2: Faster special engineering request processing via AI-enabled search

When a customer request cannot be fully satisfied through the standard product configurator, engineers must initiate a special engineering (SE) process to address the unmet requirements. While the configurator captures all feasible options within its predefined ruleset, any deviation—such as unique performance constraints, environmental requirements, or non-standard integrations—triggers an SE workflow.

Special engineering is inherently time-consuming, as engineers must design modifications that may alter existing assemblies, introduce new fit-form-function considerations, and frequently require the creation of new components within the bill of material (BOM). These tasks not only increase engineering effort but also extend downstream activities such as procurement, routing generation, documentation updates, and validation cycles.

To reduce this recurring overhead, we propose an AI-enabled similarity search mechanism that automatically analyzes historical SE orders to identify previous solutions that match or closely resemble the customer's new request. The system leverages natural-language understanding, vector-based retrieval, and pattern recognition to scan past engineering notes, BOM deltas, change records, and configurator exceptions.

When a close match is found, the system proactively surfaces the prior solution to the engineer-in-the-loop, enabling rapid assessment and reuse. Instead of initiating a full SE cycle from first principles, engineers can review previously validated architectures, component selections, and design documents—dramatically reducing engineering cycle time.

Incorporating AI-driven retrieval into the SE workflow transforms what is traditionally a manual, exploratory, and time-intensive activity into a structured, intelligence-supported decision process. This significantly shortens lead time, decreases engineering load, and enhances responsiveness for configured-to-order and engineered-to-order products. Figure 2 demonstrates this architecture.

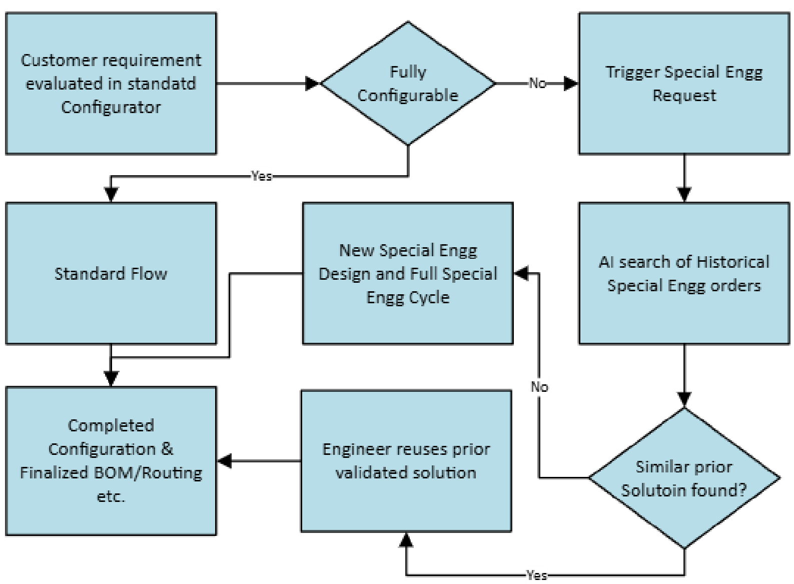

Figure 2. AI enabled Special Request processing.

Estimated savings: In the past two years, a mid-sized generator manufacturing company's special engineering group processed approximately 750 repeat orders involving similar special engineering requirements. Each order required about one hour of manual effort, including workflow management, executing BOM changes (manual adds and deletions), updating special instructions, revising cost estimates in quotes, and closing workflow tasks. Based on an internal labor rate of approximately $100 per hour, this represents an estimated annual labor savings of approximately $75,000 through automation of repeat special engineering processes. In addition to labor savings, the automation is expected to reduce manual errors, shorten order processing lead time, and improve engineering resource availability for new orders. This data is derived from internal workflow tracking and engineering time estimate.

5.3 Stage 3: Faster Procurement Initiation via Planning BOM Optimization

Problem: For configured orders, procurement is initiated using planning BOMs derived from historical usage percentages of assemblies and materials. If these percentages are suboptimal, forecasts degrade and material shortages extend manufacturing lead time.

Approach: Machine learning is used to refine planning BOM percentage factors using historical order configurations (option combinations and volumes), seasonality and program mix shifts, supplier performance signals (lead-time variability and fill rates), and external factors (policy/regulatory changes, regional project clustering, and commodity constraints). The model outputs adjusted planning factors that improve material forecasts and inventory planning. Machine learning-based forecasting models significantly improve accuracy over traditional approaches by adapting dynamically to demand variability and market fluctuations. (Douaioui, et al. 2024).

AI-driven BOM management leverages predictive analytics and real-time data integration to improve cost estimation, optimize procurement decisions, and mitigate supply chain risks. (Ajax et al. 2025).

Effective BOM management is critical for ensuring production efficiency, and inconsistencies across BOM data can lead to delays, cost overruns, and coordination issues across engineering and production functions. (Mudunuri, L. N. R., and Aragani, 2024). Expected Benefit: Improved forecast accuracy enables earlier and more reliable procurement, increasing schedule adherence for generator builds.

5.4 Stage 4: Faster Engineering and Production via Automated Component Allocation

Problem: ETO generator orders often require new routing and new BOMs created by copying super-routing and super-BOM references. Super Routing is a routing which holds all possible operations that a finished product could go through on an assembly line. Super BOM contains all possible components that are needed to make any variation of the finished configuration. The variant configuration rules defined in ERP determine which operations and components are selected based on the customer selected configuration. Many ERP systems do not automatically copy component allocations that link BOM components to routing operations. These allocations are critical for shop-floor clarity: material handlers and assemblers need to know which parts are used at which step. Large generators can involve thousands of components in multi-level BOM explosions, making manual allocation a major engineering bottleneck.

Approach: Automate BOM-to-routing allocation using compare and update method. In this method, the new routing is compared with Super routing and assignments of all the matching components from super routing are copied over to the new routing. Typically, more than 80% of components allocation of new routing match with super routing component allocation. A bill of material can have multiple BOM explosion levels. 8-10 levels are very common in Generator BOMs. Also, any level in any such assemblies can have updates associated with Engineering change numbers and a validity date for each change. This makes the comparison difficult. However, with proper rules and programming, it can be achieved.

The automation also provides a simple user interface to perform the allocation of remaining items easily. The solution standardizes allocation logic across plants, ensuring consistency, faster onboarding of new engineers, and reduced dependency on tribal knowledge. The framework is modular and can be extended to other ETO/manufacturing environments with variant configuration, requiring minimal customization to adapt to different product structures and routing complexities. Automated allocation significantly reduces human errors in component-to-operation mapping, leading to improved shop-floor execution accuracy and reduced rework or line disruptions. By eliminating a major engineering bottleneck, the approach accelerates order release cycles and enables higher throughput in high-mix, lowvolume ETO manufacturing environments. The automated approach preserves allocation history and linkage across BOM levels and engineering changes, improving traceability for audits and compliance requirements. Figure 3 depicts high level process flow of this automation.

Measured Savings (Field Case): Automation of component allocation resulted in substantial labor savings across multiple plants and improved material movements, inventory accuracy, reduced confusion, and saved execution time. The measurement was conducted across multiple plants over a one-year period, based on observed engineering hours spent on manual component allocation activities before and after automation deployment.

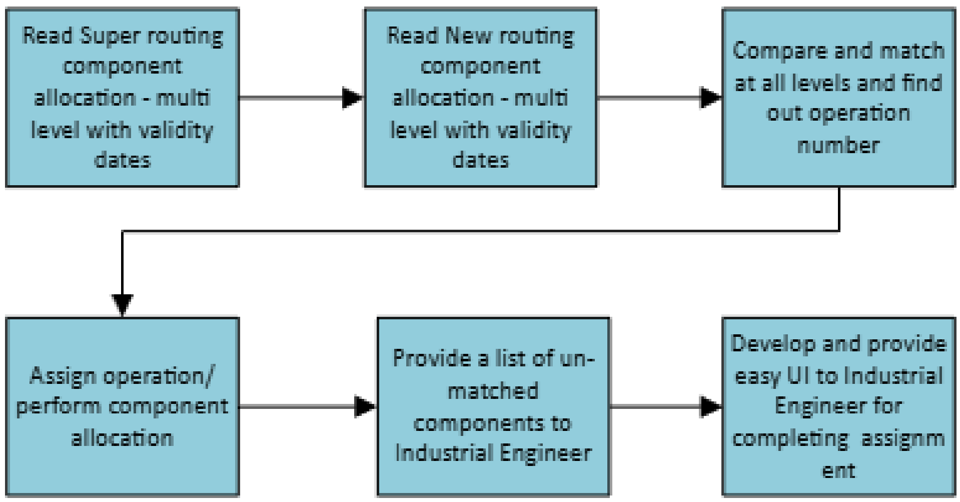

Figure 3. Component allocation process flow

The reported savings shown in Table 2 reflect actual operational data collected from industrial engineering teams.

Table 2. Annual Savings from Automated Component Allocation

Plant Type	Hours/Week	Weeks/Year	Hours Saved/Year
Small generator plant (Qty ~ 15000 units/year)	52	52	2704
Medium generator plant (Qty ~ 9000 units/year)	25	52	1300
Big generator plant (Qty ~ 4000 units/year)	15	52	780
Total hours saving per year			4784

Assuming a blended engineering cost of $100/hour, the annual savings are approximately $478,400/year. For a company operating two plants of each type, the annual savings amount to approximately $1 million.

6. Evaluation Methodology

To quantify impact, the following metrics are recommended: intake cycle time (RFP receipt to quote readiness), first-pass configuration accuracy (rework rate), forecast accuracy improvements (e.g., MAPE and fill-rate uplift), manufacturing lead-time reduction due to fewer shortages, engineering throughput (ETO release time and allocations per day), and shop-floor execution KPIs (pick accuracy, WIP aging, and line stoppages).

7. Discussion

The four-stage framework targets distinct but coupled bottlenecks. Stage 1 reduces front-end latency and prevents downstream churn; Stage 2 improves engineering response time to special requests. Stage 3 improves material readiness and reduces schedule variance; Stage 4 removes a high-effort engineering step that directly affects shop-floor execution quality. A key practical insight is that human-in-the-loop review is not optional: it is a control mechanism that enables AI acceleration while maintaining safety, compliance, and customer-specific constraints. Given the substantial financial impact of power disruptions in AI facilities, earlier power readiness delivers significant strategic value per site.

8. Conclusion

AI data center expansion increases the urgency of fast, reliable backup power infrastructure. This paper presented a pragmatic acceleration framework spanning AI-enabled intake, planning BOM optimization, and automated component allocation from BOM to routing. A field case indicates meaningful annual labor savings and operational improvements from allocation automation alone. Future work will quantify end-to-end lead-time compression across multiple product families and evaluate model generalization across plant networks and ERP landscapes.

AI data centers represent the fastest-growing class of critical infrastructure in the U.S., with federal directives now emphasizing rapid deployment of energy systems—including backup power generation—at a scale never seen before. Backup generators have shifted from auxiliary systems to mission-critical accelerators enabling time-to-compute and national AI competitiveness. By adopting AI-driven engineering automation, modular manufacturing, and error-proofed commissioning, the U.S. can close multi-month gaps in generator supply and ensure data centers receive reliable power at hyperscale speed (DOE Energy.gov).

This concept can also be applied to other Industrial manufacturing companies that produce make to order configured products.

Despite the demonstrated benefits, the current study has limitations. The validation of Stages 1–3 is based on a targeted implementation and does not yet cover the full spectrum of product variability, plant configurations, or ERP system diversity. As such, the generalizability of the framework across heterogeneous manufacturing environments requires further empirical evaluation.

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Biographies

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