An Agentic AI approach to space harness component selection

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ABSTRACT

Cable and harness development for space satellite payloads is critical to mission success with implications to cost, schedule and performance. The current cable design process is error-prone and time-consuming due to necessary translation of electrical performance requirements into physical cable specifications. This cross-disciplinary communication gap introduces risk into the development phase, which can adversely impact program outcomes. In this work, we present an AI-agentic framework that bridges this gap through Large Language Model (LLM) integration with domain-specific cable design knowledge and structured parts databases. Technical specifications derived from standards documents (e.g., NEMA WC-27500, NASA EEE-INST-002) are embedded into specialized agents via Retrieval-Augmented Generation (RAG), enabling interpretation of engineering requirements and selection of compliant part numbers. The agents execute SQL queries against an organization-specific cable parts library, returning standardized components and their unique identifiers. Through conversation interaction, users provide application context and performance specifications while the agents collaboratively construct a cable Bill of Materials (BOMs), with wire and connector selections. Preliminary evaluation demonstrates successful generation of compliant part numbers from natural language queries. The extensible architecture exhibits potential for generating comprehensive BOMs, including shielding components and schematic symbols, thereby streamlining the cable design process for complex space systems.

INTRODUCTION

Cable and harness development of space systems is critical to hardware programs, however, is frequently resource constrained and receives insufficient attention relative to its importance to mission success. Space harness design is complex, requiring subject matter experts capable of rapidly understanding, interpreting, and retrieving information from NASA and military specification documents – both of which can exceed thousands of pages. Design errors or inadequately supplied requirements can result in costly rework, schedule delays, and potential mission risks. Despite this complexity, many cable design decisions follow structured decision trees that can be systematically replicated with modern Artificial Intelligence (AI) techniques.

The translation of electrical performance requirements into physical cable specifications is a persistent cross-disciplinary communication challenge. Engineers typically specify requirements in terms of signal and power, whereas cable designers must translate these into physical specifications and manufacturing constraints. This translation process is iterative, time-consuming, and prone to miscommunication across multi-disciplinary teams, introducing additional development risks. Currently, cable harness design expertise is accumulated through decades of hands-on industry experience, however, many aspects can be decomposed into discrete decisions informed by technical standards such as NEMA WC-27500 [1] and NASA EEE-INST-002 [2].

This paper investigates a multi-agent AI framework as a novel approach for enhanced cable harness part selection. Standalone Large Language Models (LLMs) are unsuitable for engineering application due to their static training data, which can lead to outdated and hallucinated outputs [3]. Agentic AI addresses these limitations by augmenting LLMs with autonomous tool-use capabilities, enabling them to access up-to-date external knowledge through databases, document retrieval, or system functions. By rooting responses with real-world data, the approach ensures accuracy, traceability, and compliance. The framework is designed to function as an assistant that collaborates with engineers, who retain oversight and decision making-authority, providing accelerated part searching and evidence-based recommendations.

The proposed multi-agent architecture distributes cable design tasks among agents that are equipped with area-specific tools and decision logic. The foundation of each agent's role is derived from part selection decision tress developed by subject matter experts. Additionally, agents access external information such as technical documentation through Retrieval-Augmented Generation (RAG) and a cable parts library through a Structured Query Language (SQL) database. This enables the framework to interpret natural language requirements to select appropriate components without additional model training. The framework provides both wire and connector parts to assist the user in in creating Bill of Materials (BOMs), enabling deterministic component filtering based on multiple criteria simultaneously. Requiring the agents to reference technical documents and utilize deterministic database integration ensures the framework yields actual, procurable parts rather than hallucinated or non-existent components, addressing the critical limitations of standalone LLMs.

The contributions of this work include an AI-agent framework for cable harness design that integrates domain-specific knowledge with RAG and SQL database systems and a demonstration of success part number generation from natural language engineering requirements. In the remainder of this work, existing work and the address gap are detailed in the Literature Review. The agentic framework and cable design context is introduced in Methodology. Preliminary investigation and results are presented in results and closing remarks and discussion for future work are in Conclusion and Future Work.

LITERATURE REVIEW

Recent advances in AI have been increasingly applied in the field of improving the process of cable harness development by using AI, however, this research has primarily fallen under categories such as cable routing, layout optimization, and operational parameter tuning. Unlike cable routing and layout tasks which are largely geometric and optimization focused, cable harness part selection involves complex decisions that require reasoning over various data sources such as vendor part availability and military specifications. This complexity makes it a promising candidate for agentic AI frameworks, which can decompose the task into specialized sub-agents to handle distinct aspects of the selection process.

For example, work by Kim et al. [4] combined pre-existing pathfinding algorithms such as Jump Point Search (JPS) and A* to discover new automated methodologies for finding efficient cable paths while also avoiding obstacles, creating a new algorithm called JPS-Theta. Similarly, the work done by N et al. [5] is also meant to find efficient cable harness paths but instead leverages the use of convolutional neural networks (CNNs) and deep neural networks (DNNs) to develop harness networks from input parameters and find shortest spline paths through geometric areas while also considering the manufacturability of the specific cable parts involved. Evolutionary computation methods were used in the work conducted by Göttlicher and Wolf [6] to find a cost-minimal arrangement of cables that connects a set of connector locations while also considering the required power demands and electrical constraints such as thermal capacity, voltage drop, and power loss. While this work did not directly use language models, it demonstrated promising results in using AI methods for different aspects of cable harness design tasks.

Agentic AI was utilized in the work by Weng et al. [7] to automate the customization of cable fine-tuning in data centers. Four agents were utilized to accomplish the task, a machine learning prediction agent to estimate link quality, a live adaptation agent to perform real-time micro-tuning of DSP settings, a background explorer agent to search for superior performance profiles beyond narrow regions, and a rules agent to enforce safety, interoperability and compliance across the entire system. While the main objective of this work was to assist with cable routing and layout optimization rather than cable part harness part selection, using AI agents proved to be a promising methodology for handling cable harness design and development tasks.

While existing research demonstrated promising results for utilizing modern AI methodologies in cable design, routing, layout optimization, and operational tuning, the application of agentic AI frameworks for cable harness part selection remains largely unexplored. Furthermore, prior work has also not leveraged RAG for cable harness part selection, representing a key distinction of this research. This work seeks to address this gap by developing a multi-agent system capable of automating and optimizing the part selection process.

METHODOLOGY

The methodology of this work encompasses two parts: the cable design processes and the multi-agent framework architecture. Space cable harness part selection is a complex engineering process that requires extensive experience to accurately and effectively interpret and apply military and mission-specific specifications. The analysis of this process reveals that majority of design decisions follow predictable, well-defined decision trees that can be formalized and operationalized with AI agents. The following subsections detail cable design decision logic and the multi-agent architecture that implements this expertise.

Cable Design

For most use cases, cable parts lists are typically comprised of consistent part categories: wire, connectors, pins & backshells, shielding, solder, labels, lacing cord, jacketing, banding porch, sleeving, and adhesive. And many of these components remain constant across designs – for instance, label, solder, and lacing cord rarely change amongst application. The most critical and nuanced part of cable harness selection can be narrowed down to three main categories wire & cable, connectors & backshells, and shielding & jacketing. The parts determined in these primary categories propagate as dependencies through the cable design process – for example, banding porch and sleeving size is directly tied to connector and wire selection.

To develop the decision trees utilized in this body of work, multiple collaborative sessions were held with cable design experts to distill their domain knowledge into an agentic workflow. The initial phase focused on identifying the minimum required information for each part within a given cable category. By isolating these baseline parameters, the LLM can leverage natural language processing (NLP) to translate raw engineering requests into a structured requirement context.

To formalize this expert knowledge, these rules were mapped into a series of hierarchical decision trees. These trees serve as the logical backbone of the agentic system, translating high-level environmental, mechanical, and electrical constraints into specific component classifications. By tracing these structured decision paths, the system can systematically evaluate user inputs, eliminate incompatible materials, and converge on viable design configurations.

Once these baseline requirements are established, the system maps high-level engineering needs to suitable physical components. Wire selection, for example, requires the designer to first understand the operational environment, signal characteristics, and power constraints the cable will encounter. Through iterative dialogue, these parameters are refined until the underlying engineering needs can be mapped directly to discrete cable components. For instance, if a system engineer specifies that a cable must operate within a thermal vacuum chamber while carrying sensitive signals, the decision framework would determine that the cable requires electromagnetic interference (EMI) shielding and a jacket made of Ethylene Tetrafluoroethylene (ETFE), a high-performance fluoropolymer chosen for its low outgassing properties in vacuum environments.

A similar structured approach was applied to connector selection. However, in addition to environmental and power constraints, the agent must extract a broader set of connector-specific parameters. These include:

- **Physical Configuration:** Connector quantity, gender, and contact count.
- **Material Properties:** Specific shell materials and surface finishes.
- **Mechanical Design:** Connector style/type and whether backshells are required.
- **Mission Assurance:** Whether high-reliability NASA upscreening (space-grade testing and inspection) is required.

Once the agent has successfully extracted this complete set of minimum required parameters through natural language interaction, it queries the components database to return precise part numbers matching the user's exact specifications.

Wire & Cable

Cable designers typically follow military specification NEMA-27500 [1]. to determine an appropriate wire type for specific applications. This military specification is comprised of a series of tables that define various aspects of wire part numbers based on power, shielding, number of conductors, conductor size, and jacketing requirements. These tables provide a systematic decision pathway for wire selection.

Wire selection requires, at minimum, the application context and either the wire gauge (if known) or the power requirements the cable must support. For instance, if the cable must support a 10A in a thermal vacuum chamber, the designer would reference NASA EEE-INST-002 [2] to get the minimum wire AWG of 16. Then consult the 16 AWG NEMA-27500 cable to determine that they need at least M22759/44 (cross linked ethylene tetrafluoroethylene ETFE) jacketing to be sufficient for vacuum testing. Concatenating the information together would complete the wire part number M22759/44-16.

This selection process follows a decision tree where given power requirements and the application, the appropriate wire gauge and jacketing material can be systematically determined by traversing the relevant specification tables. The structured nature of the specification – organized in lookup tables with clear conditional logic – make them suitable for LLM-assisted automation. In this work, the wire current rating table shown in Fig. 6 is utilized to convert power requirements to an appropriate wire gauge selection.

Connectors

The connector selection process requires users to specify the number of contacts needed, the connector gender (male or female), connector type (e.g., D-sub, Micro_D, circular, etc.), and the wire gauge compatibility. Fig. 1 illustrates the relational database structure linking these connector characteristics. The connection selection process requires users to specify these attributes, which directly map to part characteristics that can be queried and filtered within the connect parts database. Much of this information can be derived from previously supplied wire and cable selections or inferred from application requirements.

Unlike wire selection, which requires interpretation of specification documents to determine appropriate part numbers, connector selection primarily involves filtering a structured catalog based on compatibility constraints. This deterministic filtering process – where specific attribute combinations map directly to specific part numbers – makes connector selection well-suited to a SQL database query operation. The structured nature of connector specifications, organized as discrete attributes with clear relationships, enables straightforward lookup and filtering without requiring contextual interpretation of unstructured documentation.

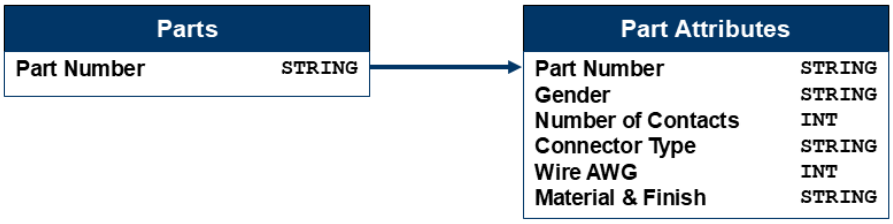


Fig. 1: Structural representation of the connector SQL parts database and associated attributes.

Agentic Framework

The multi-agent framework implements the cable design decision logic as described above, enabling user-assisted automated part selection through conversation interaction. As shown in Fig. 2, the framework determines appropriate cable parts based on application and usage specifications obtained through dialogue with the user. Cable harness parts are then selected based on the developed cable design decision tress and the external knowledge libraries. The agents are powered with the Qwen3-Coder [8] language model and agent interactions are orchestrated using LangGraph [9].

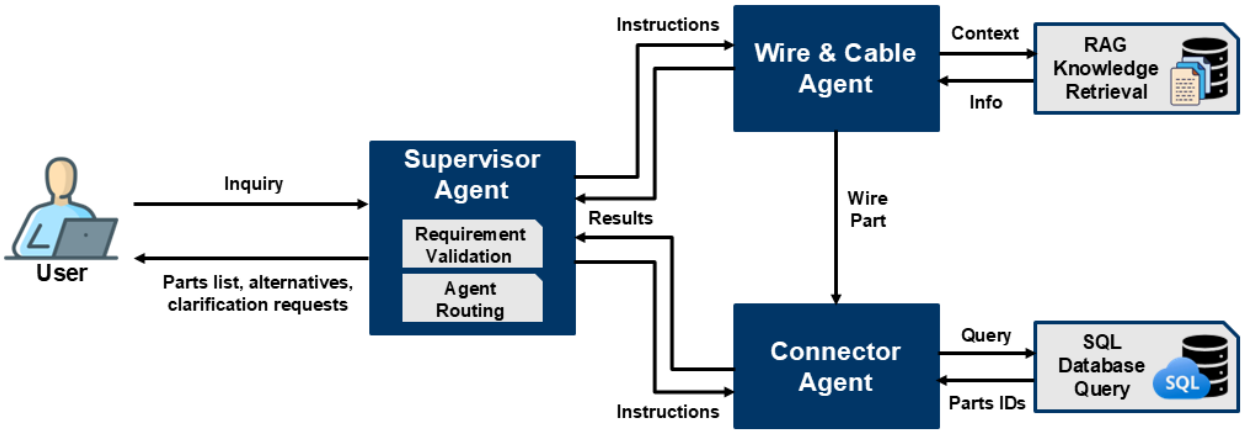


Fig. 2: Multi-agent framework architecture for cable harness part selection. The user interacts with a supervisor agent that coordinates task delegation to specialized part agents (Wire & Cable, Connector) and validates recommendation requirements. Each specialized agent is equipped with domain specific decision logic and access to external knowledge sources through RAG or SQL databases.

The framework architecture is structured such that the user interacts with the supervisor agent, whose main function is to gather sufficient context, and once collected, to plan and delegate tasks to the specialized component agents. The supervisor validates its gathered cable queries from the user against the information requirements that each individual agent would need to return an accurate result. If the user provided cable requirements are insufficient, the supervisor agent determines the minimum viable questions to ask the user. Once the supervisor determines that sufficient information has been gathered, the user's specifications are parsed to be handed off to the additional agents.

The supervisor routes tasks sequentially through the specialized cable agent, and connector agent, re-validating at each step that agent prerequisites are met. It determines which agent is best suited to complete the task based on its knowledge of each agent's capabilities and user provided cable requirements. During this process, the supervisor dynamically oversees the agent chain's output. If specific agents can be skipped because a part is not needed for the final cable, the supervisor will skip that agent call. If an agent cannot find valid parts that match user specification, the supervisor will interrupt agent calls to ask the user additional questions or suggest alternatives. Upon receiving successful results from the specialized agents, the supervisor synthesizes the information to present a generated parts list or asks the user for further clarification.

The supervisor delegates tasks to part-category specialized agents, each informed by its respective cable part decision logic and equipped with access to external information sources. These specialized agents leverage external knowledge through either RAG-based retrieval or SQL database tools. Below are descriptions of each specialized agent:

- The **Cable and Wire** agent implements the wire selection decision logic in coordination with a RAG-based retrieval system to access specification documents for wire determination. The RAG database is built by embedding document content with the Sentence Transformer embedding model [10] into a ChromaDB vector database. Unlike conventional LLMs that may hallucinate or rely on outdated training data, the RAG approach refines agent responses in retrieved specification documents, ensuring accuracy and traceability to authoritative sources. RAG-based retrieval is chosen because wire specifications involve unstructured and complex documentation that requires additional contextual interpretation. The embeddings allow for search that avoids rigid constraints of a standard database. In this work, the RAG database is populated with the NASA EEE-INST-002 [2] document (Fig. 6Fig. 6 in the Appendix A) and parsed with the Python Pillow (PIL) library.
- The **Connectors** agent implements the connector selection decision tree and accesses an SQL database that contains hundreds of commonly used parts and their respective characteristics. Given the user requirements, this agent translates them into SQL queries that filter the parts catalogue based on compatibility constraints, returning the parts that meet the provided criteria. The agent is designed for SQL database access due to how the connector specifications are inherently structured – where part specifications and compatibility naturally map to standard queries. Unlike conventional language models used in isolation, access to an organization-specific SQL database requires no retraining when new parts become available, enabling reference unique identifiers and maintain awareness of a real-time, up-to-date parts catalogue.

Each specialized agent has predefined required inputs that must be obtained from the user before it can recommend appropriate parts. When required inputs are incomplete, agents engage in iterative dialogue with the user to gather necessary information such as requested voltage, environment conditions, and connector types. Upon receiving a delegated task, each specialized agent queries its respective knowledge source, goes through the part category decision tree, and then returns its recommendations to the supervisor. The RAG retriever semantically searches the knowledge database to retrieve the relevant information, which are provided as context to the wire and cable agent. Similarly, the connector agent translates natural language requirements into SQL queries, filtering parts based on specifications.

RESULTS

The agentic framework was evaluated through a series of representative queries spanning wire selection, connector specification, and multi-component cable design scenarios. Performance was assessed based on three criteria: (1) accuracy of part number generation against expert validation, (2) appropriateness of clarifying questions when information was insufficient, and (3) quality of explanations provided to users. Results are organized by agent type, with each subsection demonstrating the agent's decision-making process through representative use cases. To assess accuracy and reliability, all agent-generated recommendations were reviewed by cable design subject matter experts in space hardware development.

Wire & Cable Agent Performance

The Wire and Cable agent was evaluated using queries representing common engineering scenarios requiring wire specification. Two representative cases are presented: a bench test application (Example 1) and a thermal vacuum environment (Example 2), both validated by experienced cable designers.

Example 1 (top) in Fig. 3 illustrates the agent's response to a power-constrained query. When the user requested wire capable of supporting 10A without specifying environmental conditions, the agent appropriately identified the missing information and asked for clarification. Upon receiving confirmation of bench test usage, the agent correctly recommended M22759/11-16 along with a brief description to explain its decision. Subject matter experts validated the M22759/11 designation as appropriate, confirming that silver-coated copper conductors with extruded polytetrafluoroethylene (PTFE) insulation meet requirements for the specified application and validated that 16 AWG wire would be suitable to meet the provided power requirement.

Example 2 (bottom) in Fig. 3 presents a similar query to Example 1, however, instead the application environment is switched to a thermal vacuum chamber. This case also displays the agent interactions when not enough information was provided, therefore, the agent's follow-up responses include a contextual summary, and questions communicate its currently contextual understand and the gaps. The agent's recommendation of M22759/44-16 was validated as acceptable by subject matter experts, as this wire's cross-linked insulation ensures high thermal stability, eliminates insulation cold flow, and prevents melting during testing in intense thermal vacuum environments.

Notably, the user requested that only some of the conductors needed to be shielded, therefore the agent provided both M22759/44-20 (unshielded) and M27500-20-SCN23 (shielded) options. The agent's performance is validated as acceptable by cable designers as acceptable, confirming that both the wire gauge selection for 5A current and the nickel-plated shielding meet requirements for low earth orbit (LEO) environments. Additionally, the agent provides a breakdown of the constituent pieces that make up the provided part, enabling the user to understand the agent's reasoning behind the recommendation. This explainability feature allows users to request further clarification – for example, asking why 20 AWG was recommended – prompting the agent to reference the specification table (Fig. 6) and cite the source, thereby promoting transparency in the decision-making process.

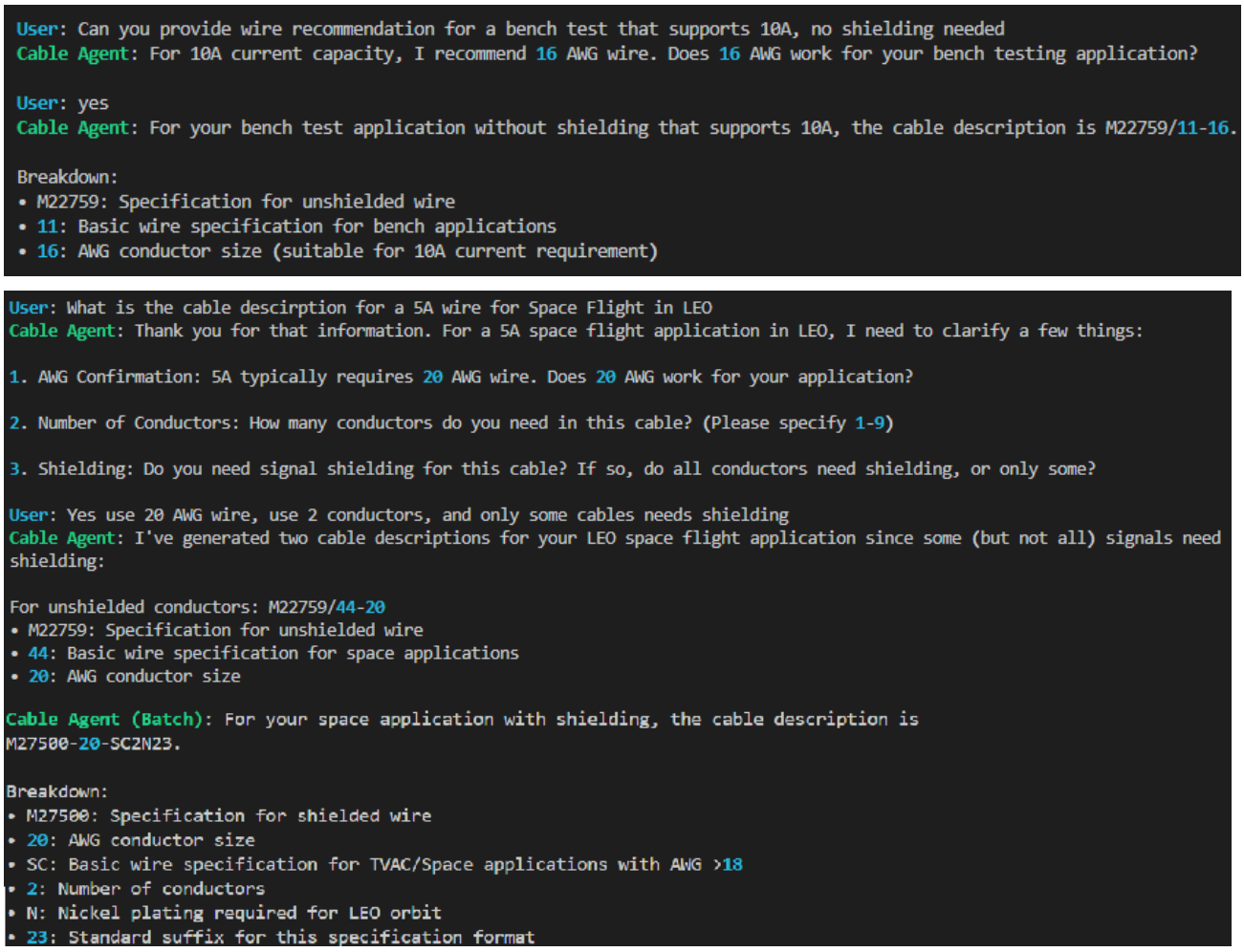


Fig. 3: Wire and Cable agent responses for two scenarios. Example 1 (top) shows the agent interaction for a simple bench test with direct part recommendation. Example 2 (bottom) demonstrates the agent interaction for a space environment application, where the agent required additional information from the user before determining the appropriate wire part.

Multi-Agent Framework Performance

In this demonstration, the full multi-agent architecture consisting of supervisor, wire & cable, and connector agents is utilized to create a BOM of the wire and connector parts. After the supervisor validates user given cable requirements, the wire agent successfully determined the part number and passed the information to the connector agent. The connector agent's initial performance revealed important design considerations for ambiguous requirements. When presented with the query "I need a cable that can support 5A and has two 9-position DSUB connectors for a bench test," the agent successfully matched the technical specifications (current capacity, contact count, connector type) but failed to interpret the cost-sensitivity implied by "bench test." As shown in Fig. 4, the agent recommended high- reliability parts (M24308/2-

521 and M24308/3-335) appropriate for flight hardware rather than cost-effective alternatives suitable for a lab environment. Although the resulting BOM was found to have minor technical inaccuracies compared to the ideal parts list gathered by an engineer, the multi-agent system's cohesive operation in gathering tailored parts demonstrates promise with further tuning.

Bill of Materials - Cable Assembly

Item	Part Number	Qty	Description
Cable/Wire	M22759/11-24	1	Wire assembly, 9 conductors, 3.0 ft
Connector - End 1 (PLUG)	M24308/2-521	1	9 pin DSUB connector
Connector - End 2 (RECEPTACLE)	M24308/4-335	1	9 pin DSUB connector

Fig. 4: Multi-agent framework generated BOM for a cable parts selection. Specialized agents work collaboratively under supervisor agent coordination to produce a complete parts list for a wire and connector cable assembly.

This limitation stemmed from the ambiguity inherent in contextual descriptors like "bench test," which can indicate different performance requirements depending on organizational context and user intent. Rather than attempting to encode assumptions about cost-performance tradeoffs, which could introduce systematic bias or errors, a conversational approach was implemented. Additionally, instead of providing a single answer, the agent was redesigned to provide multiple options to the user with high-level information rather than a single recommendation, enabled users to make informed trade-off decisions. While pricing data would be impractical to maintain in the database due to market volatility, the agent was equipped with knowledge of factors influencing connector cost to provide qualitative cost guidance.

Connector Agent Performance Refinement

To address the limitations identified in initial testing, the connector agent was redesigned with two key improvements: (1) proactive clarifying questions to disambiguate contextual requirements, and (2) presentation of multiple options with comparative analysis to support informed user decision-making.

Fig. 5 demonstrates this new approach using Micro-D connector selection. When the user specified "I need 2 Micro-D's, 1 plug and 1 receptacle, 9 contacts each," the agent recognized that critical selection criteria (class rating, environmental requirements, cost constraints) were unspecified. Rather than making assumptions, the agent engaged in structured dialogue, asking targeted questions while providing contextual information to guide the user's responses.

The refined agent's output includes multiple viable options, each accompanied by:

- Technical specifications: contact count, gender, wire gauge compatibility
- Performance characteristics: NASA up-screen status, class rating
- Comparative analysis: key differences between options including availability

This approach enables engineers to make informed tradeoffs based on program-specific priorities while maintaining accurate part selection. By providing comparative information as opposed to prescription recommendations, the agent supports engineering judgement while reducing specification lookup time.

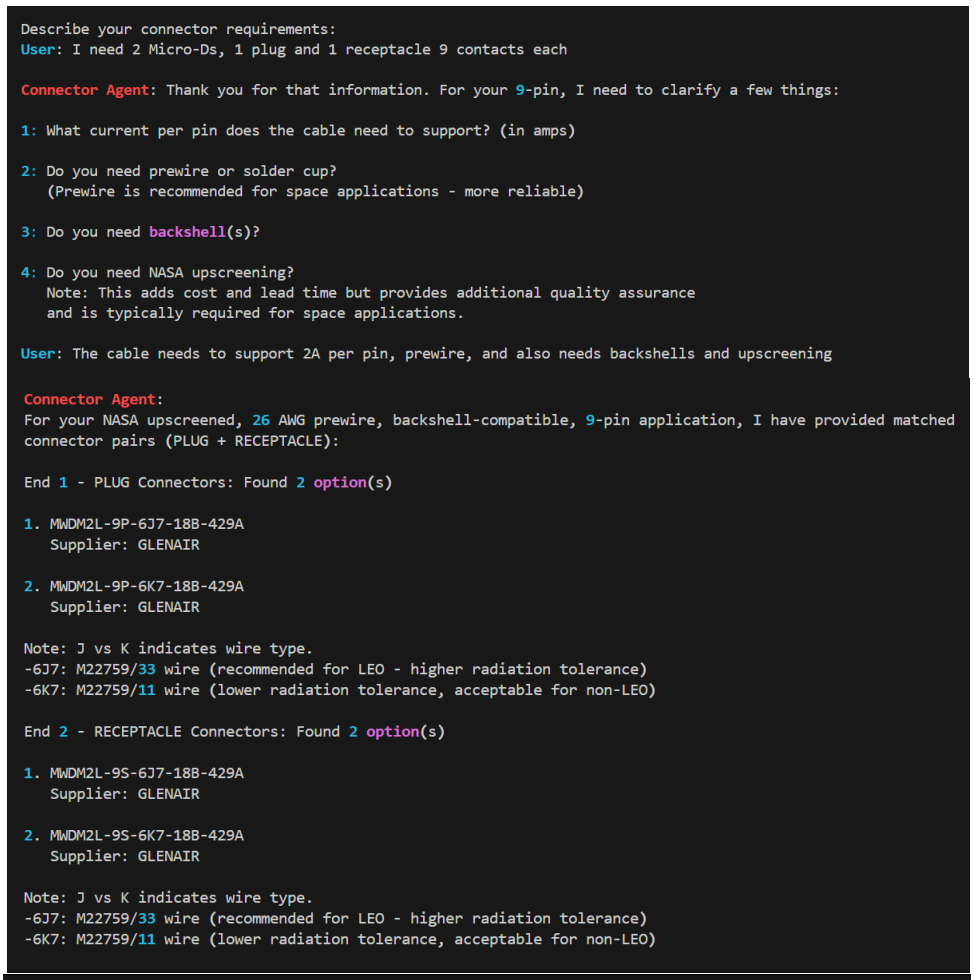


Fig. 5: Refined connector agent interaction demonstrates iterated dialogue for requirement gathering. The agent gathers user requirements and generates an ordered list of connector part recommendations pulled from the parts catalogue.

Limitations

While results demonstrate promising performance, several limitations were identified that require further development. The Wire and Cable agent occasionally requires multiple iterations to extract complete environmental specifications when users provided vague or ambiguous descriptors. Additionally, the current implementation is validated for single-conductor and simple multi-conductor configuration; further evaluation is needed for complex wire topologies, such as shielded twisted-triples or quad configurations.

The connector agent is currently focused on Micro-D connectors, and while accurate within its domain, requires expansion to cover the full range of connector families and related backshells used in space applications. Additionally, the system has not yet been tested on edge cases involving conflicting requirements or non-standard applications that may require engineering judgment beyond specification compliance.

Furthermore, while subject matter experts validated recommendations for the test cases presented, systematic evaluation across a broader range of scenarios is needed to establish reliability and failure modes. The current work is limited to straightforward queries and performance on complex, multi-constrained problems that are representative of actual program scenarios remain to be addressed.

CONCLUSION & FUTURE WORK

This work presents a multi-agent AI-enabled architecture for automated cable harness part selection. LLM powered agents are structured with decision tree logic derived from experience designs and equipped with external knowledge through RAG and SQL parts database access. By grounding recommendations with specification documents and organization-verified parts classification, the framework mitigates hallucination risks inherent in standalone LLMs.

The preliminary evaluations demonstrate successful wire and connector selection for engineering scenarios, with recommendations validated by experience cable designers. The modular architecture enables updates to specification databases and part catalogue without LLM model retraining. The conversational interactions allow the agents to handle incomplete requirements through iterative dialogue, and multi-option outputs support informed engineering decision-making as opposed to full automation.

While the preliminary results are promising, transitioning the framework from a demonstration environment to reliable program incorporation needs additional development and validation. Establishing reliability will require evaluation across comprehensive test scenarios that cover diverse cable configurations, environment conditions, and constraint combinations. Additionally, a formal verification process must be established to validate agent recommendations to meet both application and program requirements. The system is meant to function as an engineering assistant that aids users in cable design by providing evidence-based trade-off analysis and rapid specification look-up, and not as an autonomous decision-maker. Thus, recommendations require review and approval before program incorporation.

Future work will also expand the framework to cover additional cable design components and integrate with organizational enterprise systems. Planned additional agents include: backshell and shielding selection (utilizing organization algorithms for bundle dimension calculations), cable notes generation (applying logic-based reasoning to specifications), and pictorial drawing generation. Integration with existing design software via application programming interfaces (APIs) will enable direct import of generated parts list the drawings, facilitating automated cable drawing generation in accordance with ASME Y14.5 [11] standards, and creating an end-to-end workflow from requirements to production-ready documentation.

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APPENDIX A – WIRE CURRENT RATING CHART

Wire Size (AWG)	Single Wire Current (I_{SW}) (Amps)	Remark
30	1.3	1. Current ratings are based on wires at +70ºC in a hard vacuum (10^{-6} to 10^{-9} torr). 2. When wires are bundled, the max design current for each individual wire shall be derated according to: For $1 < N \leq 15$: $I_{BW} = I_{SW} * ((29 – N)/28)$ For $N > 15$: $I_{BW} = (0.5) * I_{SW}$ Where: N = number of wires I_{BW} = current, bundled wires I_{SW} = current, single wire 3. Deratings listed are for Teflon® insulated wire (Type TFE) rated for +200ºC a. For 150ºC wire, use 80% of value shown in table. b. For 135ºC wire, use 70% of value shown in table. c. For 105ºC wire, use 50% of value shown in table. 4. Dielectric withstanding voltage rating required: at least two times the highest application voltage. 5. Derating values listed apply only to single round conductors on helically wound bundles. See EEE parts engineer for derating information for ribbon cable and flat conductors.
28	1.8	
26	2.5	
24	3.3	
22	4.5	
20	6.5	
18	9.2	
16	13.0	
14	19.0	
12	25.0	
10	33.0	
8	44.0	
6	60.0	
4	81.0	
2	108.0	
0	147.0	
00	169.0	

Fig. 6 Wire current rating table from NASA-EEE-INST-002 [2]. Table is embedded in the Cable & Wire agent's RAG database for knowledge reference on wire gauge selection based on power requirements.