Sustainable Energy Decision-Making With an RAG-LLM System

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***Abstract*— To reach the ambition of a net-zero economy by 2050, the UK aims to improve energy efficiency in all homes by 2035, targeting reductions in energy consumption and household expenses. Small and Medium-sized Enterprises (SMEs) play a critical part in this evolution but frequently face challenges in navigating the complex and fast-changing Energy sector to access essential information. Required data spanning regulatory updates, market trends, renewable energy production, and climate patterns is dispersed across multiple sources, creating inefficiencies and raising costs for SMEs pursuing sustainable Energy goals. This study addresses this information gap through a prototype Information System (IS) that consolidates diverse regulatory and environmental topics as a proof-of-concept. The proposed Energy Question Answering (QA) Assistant, based on the Large Language Models (LLMs) and Retrieval-Augmented Generation (RAG), integrates information from government, industry, and environmental sources. Using open-source technology, this tool delivers SMEs timely insights into Sustainable Energy Initiatives (SEIs) and regulatory frameworks, supporting cost-effective and informed decision-making that aligns with the UK's sustainability targets.**

Keywords—Sustainable Energy Transitions, Information System, Energy Question Answering Assistant, Large Language Models, Regulatory and Environmental Data Integration

I. INTRODUCTION

The UK's net-zero emissions ambition by 2050 includes upgrading majority of homes to Energy Performance Certificate (EPC) band C by 2035 [1]. SMEs, comprising 99.7% of the 340,000 construction firms, are crucial to achieving this target [1, 2]. Yet, many SMEs face challenges accessing critical information on Sustainable Energy Initiatives (SEIs), leading to inefficiencies and elevated costs. Successful Sustainable Energy Transitions (SETs) demand timely insights across multiple data categories: Regulatory and Environmental data, Renewable Energy Production, Market and Pricing Data, Technological Data, Climate Data, Social Demographics, Local and Regional Initiatives, Case Studies and Best Practices, as well as Financial and Economic Data [3, 4].

Each of these categories provides SMEs with essential information. Regulatory and Environmental Data outline policies, compliance requirements, and renewable energy incentives, ensuring SMEs align with regulatory expectations. Renewable Energy Production Data delivers metrics on renewable capacity and efficiency, while Market and Pricing Data highlight trends and tariffs for cost-effective investments. Technological Data presents innovations in smart energy solutions, while Climate Data provides forecasts crucial for optimizing energy production. Social Demographic Data reveal consumption behaviors by region, supporting targeted solutions. Local and District-Level Initiatives, alongside Case Studies and Best Practices, illustrate successful energy projects and strategies, and Financial and Economic Data offer insights into costs, funding options, giving SMEs a comprehensive framework for sustainable energy planning. Though broad in scope, this research focuses on Regulatory and Environmental Data as a proof-of-concept to showcase the value of an integrated IS for SMEs in the Energy sector.

The study explores how advanced open-source technologies can integrate this information to improve decision-making and ensure the IS is adaptable, with scalable upgrades and customization as organizational needs evolve. To achieve these goals, this study introduces the Energy QA Assistant, a comprehensive tool that unifies data from government reports, industry publications, and websites. By using advanced open-source technologies such as LLMs (Artificial Intelligence (AI)-based systems trained on extensive diverse datasets to understand context and produce human-like text or images [5]) and RAG (i.e., enhances text generation by retrieving relevant information from external sources [6]), the Energy QA Assistant provides SMEs with timely insights into SEIs and emerging energy trends, streamlining decision-making and operational efficiency. The Assistant simplifies information gathering, enabling SMEs to adapt proactively to policy changes and integrate sustainable technologies. Designed for flexibility and scalability, it supports upgrades and customization to meet the evolving needs of SMEs with limited resources. By leveraging open-source technologies, the QA Assistant [7] minimizes development costs, making it accessible and practical. Ultimately, it serves as a centralized and cost-effective resource that empowers SMEs to stay competitive, informed, and compliant, supporting the UK's net-zero objectives.

The paper is ordered as follows: Section 2 presents the background of the research study, establishing the foundation for our approach. Section 3 introduces the Energy QA Assistant; an IS developed using RAG with LLM. Section 4 examines the system's advantages and limitations, and Section 5 provides concluding insights.

II. BACKGROUND

SETs focus on moving from fossil energy resources to renewable energy to reduce carbon emissions and enhance sustainability. Research highlights the role of media in disseminating crucial Energy knowledge and developing IS to support SETs [7]. For instance, Chen and Rowlands [8] utilized the SPEED framework to analyze 156 articles on Energy Storage (ES), revealing the Chinese government's supportive role amidst challenges. Piselli et al. [9] explored the impact of online sources on Energy Communities. Ganowski and Rowlands [10] studied national news coverage of ES, observing its impact on public acceptance. Dehler-Holland et al. [11] did media framing analysis using the German Renewable Energy Act, documenting a shift from optimism to cost concerns. Marzouki et al. [12] examined

Sustainable Development Goal 11 discussions on Twitter, highlighting reduced engagement during COVID-19 and increased focus on AI and IoT. Rommetveit et al. [13] emphasized automation and digital integration in Norway's energy practices, while Krzywda et al. [14] assessed media coverage of Poland's coal transition, revealing diverse perspectives. In the realm of Energy management, various Chatbots have been developed as ISs. Gnewuch et al. [15] presented design guidelines for developing Energy feedback agents. Suresan et al. [16] created a Chatbot for managing peak energy use, while Rocha et al. [17] established a self-reading Chatbot for tracking consumption. Fontecha et al. [18] developed GreenMoCA for smart homes, and Milano et al. [19] presented EcoBot, which encourages energy savings through persuasive strategies. Finally, Onile et al. [20] showcased a mix digital twin approach to improve user action in Energy conservation.

Studies indicate that online media sources, such as government reports, news websites, and other platforms, play a crucial role in supporting organizations that lead SETs [21, 22]. These media resources offer a broad view of the Energy landscape through integrated ISs or LLMs-based Chatbots [7]. However, many SMEs lack the Research and Development (R&D) resources to identify and implement suitable open-source solutions, which makes it tough to address their specific needs. Rapid changes in the Energy sector require regular updates to systems and datasets, creating further challenges for resource-limited SMEs. Many studies rely on a single dataset type, limiting information depth for decision-making and potentially introducing bias. For example, while government reports provide policy updates, real-time market reactions and industry innovations are often found on social media [23]. To address these limitations, a more integrated approach is necessary, combining various sources to provide comprehensive insights. Semantic enrichment techniques [21, 22] can bridge gaps by connecting policy updates with real-time market data and in-depth analysis. Using advanced semantic methods enables organizations to extract relevant insights and understand the Energy landscape in context. For a more sustainable solution, leveraging LLMs based on Natural Language Processing (NLP) provides effective capabilities for information retrieval, summarization, and sentiment analysis [23]. However, training LLMs requires substantial computational power and thousands of GPUs, with significant environmental considerations [24].

To support sustainability objectives, organizations should focus on maximizing the reusability of LLMs, opting for open-source models that can be tailored to meet specific requirements. This method advances responsible investment and helping to minimize the carbon footprint of technological advancements [25]. RAG enhances LLM performance by first retrieving relevant external information before generating text. This integration upgrades the relevance of outputs, making them more dependable in real-world applications. Recent studies [26, 27] have demonstrated RAG's effectiveness in various domains, from textbook QA to financial sentiment analysis, showcasing its versatility in ISs that support user engagement. Regardless of these innovations, the use of RAG-LLMs in the Energy sector remains principally untapped. By linking RAG with LLMs, SMEs can retrieve and process data from diverse sources, including government reports. This novel approach simplifies the implementation of sustainable QA systems, mining valuable insights for informed decision-making in SETs. The following section will outline our approach to creating an Energy QA Assistant that assists analysts in navigating the present Energy landscape.

III. Energy QA Assistant System

This section starts by describing the process of creating a dataset aimed at enhancing RAG-LLM-based IS, developed for the Energy sector to serve as an Energy QA Assistant. The adoption of a QA Assistant is assisted by existing research studies [15 – 20], which highlights its effectiveness in improving user interaction and engagement with ISs [7]. QA Assistants simplify the query and information retrieval process, providing prompt responses and expanding accessibility for users. This is particularly valuable in the Energy sector, where complex information needs to be distilled and presented in an easily understandable way [7]. Following the dataset creation, we will outline the implementation, and finally, assess the system's accuracy in producing answers to user questions.

A. Energy Dataset Development

To create a dataset crucial for developing an IS that leverages RAG with LLMs for decision-making in SETs, we performed an in-depth literature review [7 - 20]. This review acknowledged critical data related to SEIs, including Regulatory and Environmental Data, Renewable Energy Production, Market Pricing, Technological Data, Climate Data, Social Demographics, Local and District-Level Initiatives, Case Studies, Best Practices, and Financial and Economic Data. For the proof-of-concept, we focused specifically on Regulatory and Environmental Data. This category encompasses various sources, including Government Websites, Energy and Environmental Standards Organizations, Environmental Data Portals, Carbon Emissions Data, Climate Reporting, Energy Incentive Databases, and Sustainability Compliance Platforms (see Table 1). To ensure that the information is both current and relevant, we relied on three key sources: news websites, government reports, and industry publications. Each Energy-related topic significantly contributes to providing valuable insights for experts involved in driving SETs, thereby supporting decision-making in this crucial area. The dataset (see Table 1), serves as the foundation for developing our Energy QA Assistant, an integrated IS designed to assist SMEs in making sustainable Energy-related decisions.

B. Energy QA Assistant Implementation

To facilitate SMEs with a dynamic tool for investigating SEIs and the broader Energy landscape, we implemented the Energy QA Assistant (see Fig. 1), an AI-powered system designed to handle Energy-related queries. The core of this system is built using LLMs. After evaluating several existing LLMs [28 – 32], we chose to customize Llama 3.2 (developed by Meta [33]) due to its superior performance with extensive datasets. While other models are available, we tailored Llama specifically for the Energy sector by integrating RAG technology. This enables the QA Assistant to efficiently extract and deliver relevant answers based on Energy-related datasets, including government regulations, carbon emissions, and sustainability reports. The development process began by installing key libraries like Langchain [34], Sentence-Transformers [35], and FAISS [36]. We used PyPDFLoader [34] to prepare documents, breaking them into manageable chunks with a CharacterTextSplitter, and then generated embeddings for each chunk using the HuggingFace -

TABLE I. KEY TOPICS IN REGULATORY AND ENVIRONMENTAL DATA FOR SETS

No.	Topic	Description	Example of data
1	Government and Regulatory Websites	These platforms provide essential access to energy policies, laws, and regulations for compliance with energy standards.	• UK Department for Energy Security and Net Zero: Offers updates on policies, regulations, and net-zero initiatives. Website*: gov.uk/government/organisations/department-for-energy-security-and-net-zero*
2	Energy and Environmental Standards Organizations	These organizations develop and maintain standards for energy efficiency and environmental sustainability. They provide guidelines that help industries and organizations align with best practices.	• British Standards Institution (BSI): Develops and publishes standards, including energy management and environmental practices. Website: *bsigroup.com/en-GB/* • UK Environmental Agency: Sets regulations and standards for environmental protection and sustainability in the UK. Website: *gov.uk/government/organisations/environment-agency*
3	Environmental Data Portals	These portals offer datasets on environmental conditions, energy use, renewable generation, and climate data, supporting energy forecasting and sustainable planning.	• UK Government Data: The official government portal for public sector data, including environmental datasets. Website*: data.gov.uk* • Environment Agency Data Services: Provides access to environmental data. Website*: environment.data.gov.uk* • Defra (Department for Environment, Food & Rural Affairs) Open Data: Offers datasets related to agriculture, fisheries, biodiversity, and environmental protection. Website*: defra.gov.uk/statistics*
4	Carbon Emissions Data and Climate Reporting	Platforms and databases that track carbon emissions and climate-related metrics. They are used to monitor the environmental impact of energy systems.	• UK Greenhouse Gas Emissions: This official government inventory provides comprehensive data on greenhouse gas emissions in the UK. Website*:gov.uk/government/collections/uk-greenhouse-gas- emissions-statistics* • Department for Business, Energy & Industrial Strategy (BEIS): BEIS publishes annual reports on UK greenhouse gas emissions.Website*:gov.uk/government/organisations/department-for-business-energy-and-industrial-strategy* • Carbon Trust: The Carbon Trust provides resources, reports, and tools to help businesses and organizations measure and reduce their carbon emissions.Website*: carbontrust.com*
5	Energy Incentive and Subsidy Databases	These databases list financial incentives, subsidies, and tax breaks for energy efficiency and renewable adoption, aiding cost-effective energy decisions.	• GOV.UK - Energy Grants and Funding: Provides information on various grants and funding opportunities for energy efficiency and renewable energy projects. Website*:gov.uk/government/collections/find-energy-grants-for-you-home-help-to-heat* • Ofgem - Renewable Energy Guarantees of Origin (REGO): Information on the REGO scheme, which certifies the renewable origin of electricity. Website*: ofgem.gov.uk/environmental-and-social-schemes/renewable-energy-guarantees-origin-rego*
6	Sustainability Reporting and Compliance Platforms	These platforms aid organizations in reporting sustainability practices, ensuring compliance with energy and environmental regulations.	• UK Government - Streamlined Energy and Carbon Reporting (SECR): Outlines energy use and carbon emissions by the UK companies. Website*: gov.uk/government/publications/environmental-reporting-guidelines-including-mandatory-greenhouse-gas-emissions-reporting-guidance*

embedding model. These embeddings were stored in FAISS for efficient retrieval. The environment was configured with the Langchain-Ollama package [34], enabling smooth interaction between the Llama model and the retriever via a RetrievalQA chain. Users can submit their queries, and the system processes these inputs to deliver precise responses. The QA Assistant's scope can be further refined by adjusting topics or data formats [7], ensuring that it provides targeted and relevant answers to a variety of Energy-related questions.

C. System Evaluation

To evaluate the Energy QA Assistant's performance, we chose Precision, Recall, Accuracy, and F1 score as evaluation metrics [5, 7]. Our focus was on assessing the quality of information in the Assistant's responses, based on relevance and completeness. For systematic evaluation, we defined Information Components (ICs) [5, 7], which include elements like organizations, individuals, topics, locations, and dates [5]. Precision measures the fraction of relevant ICs among all retrieved components, reflecting the system's ability to exclude irrelevant data. Recall evaluates the system's ability to retrieve all relevant ICs, while Accuracy measures the percentage of correctly identified ICs. The F1 score provides a balanced performance metric. To apply this approach, we developed questions based on an Energy dataset, focusing on simple queries that involve multiple ICs. A varied set of 100 questions was compiled from sources such as news articles, government websites, and industry publications to ensure broad coverage of Energy topics and an impartial evaluation of the system's response capabilities. To ensure consistent and reliable answers, we configured the LLM with minimal creativity and prioritizing accuracy.

Our evaluation had two phases: first, we tested the Energy QA Assistant with the Llama3.2 model without RAG functionality. We used the Llama3.2 model to optimize computational efficiency. The results (see Table 2) show a significant improvement in the Energy QA Assistant's performance when RAG is integrated with the Llama3.2 model. Precision increased from 39% to 93%, and Recall improved from 36% to 95%, indicating that the model with RAG retrieves relevant information more accurately and comprehensively. Accuracy also saw a notable boost from 40% to 96%, reflecting a much higher overall correctness in response generation. The F1 score rose from 37% to 94%, showing the importance of the efficacy of RAG integration in enhancing the Assistant's capability to present reliable and complete answers to user questions.

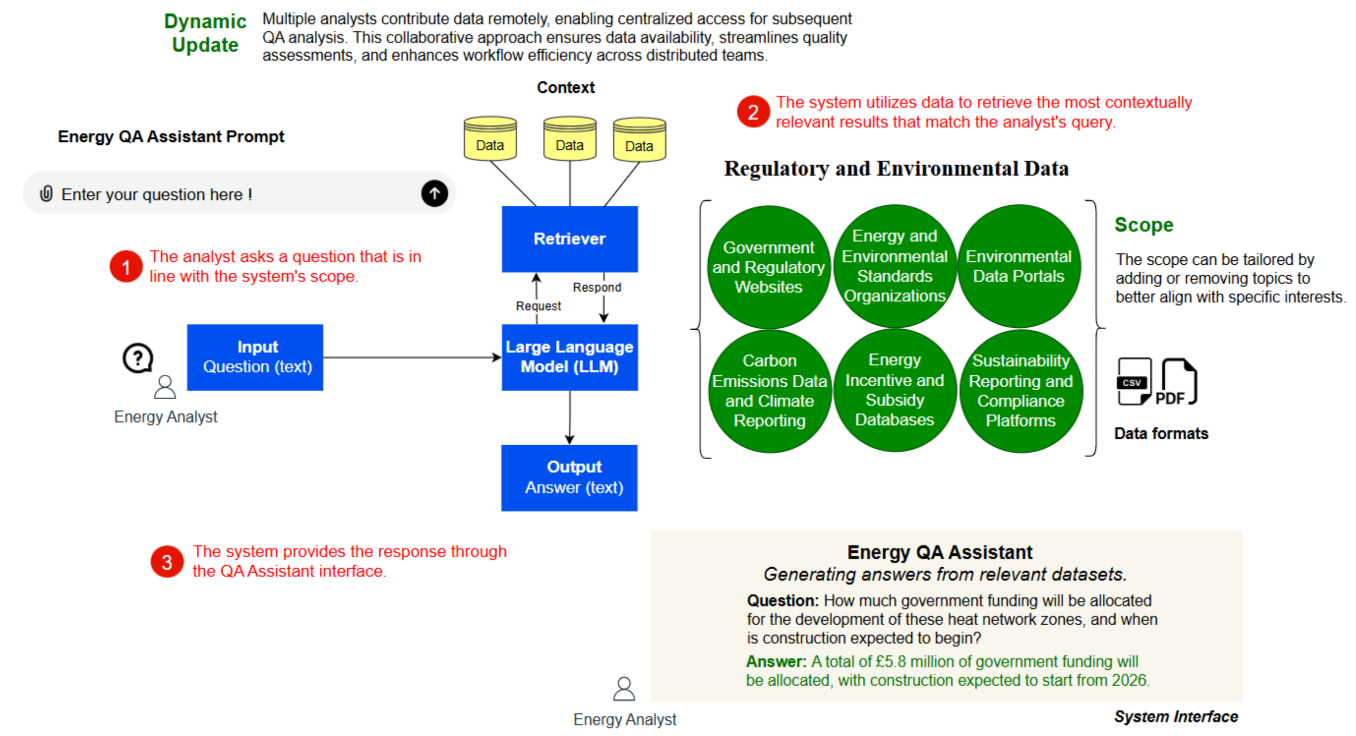

Fig. 1. Building an Energy QA Assistant Using LLM and RAG through Diverse Dataset Integration

TABLE II. USER QUERY RECORDS AND SYSTEM-GENERATED RESPONSES FOR RAG WITH LLM EVALUATION

No	Question	Answer
1	What is the purpose of the strategic spatial plan being developed for the UK's energy infrastructure?	The plan aims to speed up the transition away from fossil fuels and accelerate the growth of clean energy industries in the UK by providing long-term certainty and stability for investors.
2	Who is responsible for developing the strategic spatial plan for energy in Great Britain?	The newly formed National Energy System Operator (NESO) has been tasked with creating a strategic spatial plan for energy by 2050, covering land and sea.

TABLE III. COMPARATIVE PERFORMANCE EVALUATION OF ENERGY QA ASSISTANT WITH AND WITHOUT RAG INTEGRATION

No	Model	Precision (%)	Recall (%)	Accuracy (%)	F1-score (%)
1	Energy QA Assistant without RAG using Llama3.2	39	36	40	37
2	Energy QA Assistant with RAG and Llama3.2	93	95	96	94

IV. DISCUSSION

A vast array of information regarding diverse components of SEIs exists across different media channels, which are crucial for driving SETs. To effectively lead Energy transition efforts, SMEs require access to up-to-date information on government policies, funding options, and available support programs. However, many SMEs struggle to find integrated Energy-related ISs. The implementation of an IS involves several costs, including initial hardware and software expenses, ongoing maintenance, IT personnel salaries, and training. Current Energy-related ISs aggregate news headlines and social media data but lack the comprehensive information required for informed decision-making. To fill this gap, the study proposes an Energy QA Assistant based on a RAG framework and an LLM, acting as an integrated IS tailored to the regulatory and environmental aspects of Energy.

The proposed system suggests substantial benefits over current solutions by effectively handling a wide range of Energy-related information, supporting various media types, and enabling seamless integration of additional datasets. Its straightforward implementation leverages RAG with LLM technology, making it cost-effective and resource efficient. By automating data retrieval and analysis, this system minimizes the need for large hardware investments, thereby lowering operational expenses and enhancing adaptability. While the integration of RAG technology allows SMEs to stay updated, the quality of the generated information still hinges on the accuracy of the external datasets. The research acknowledges limitations, including the need for more extensive system evaluation and the constraints of relying on a single model family. Further exploration of other language models and adjustments to the LLM's creative capabilities are recommended to enhance the system's performance by providing accurate and relevant responses for SMEs navigating the Energy landscape.

V. CONCLUSIONS

SMEs are central to the UK's net-zero goal by 2050, especially in reducing energy use and costs through home upgrades by 2035. However, many SMEs lack essential knowledge on SEIs, resulting in inefficiencies and higher costs. Access to the latest SEI information, including regulatory and environmental data, is vital, yet current systems often fail to integrate diverse sources, hindering SME support. Our study presents an advanced LLM-powered

Energy QA Assistant with RAG integration, designed to deliver SMEs timely insights from government, regulatory, and environmental data sources, along with carbon emissions, climate reporting, and energy incentives. Adaptable to additional Energy areas like renewable production, market data, and best practices, the system demonstrated marked improvement in Precision, Recall, Accuracy, and F1 scores with the RAG-enhanced Llama3.2 model. While results show RAG's effectiveness in improving response quality, future research should address efficiency and scalability to optimize SME support for sustainable Energy goals.

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