Sustainable Energy Transition:
Business Decision Support System (BDSS) for Analysing Hydrogen Consumption, Subsidies, and Gas Trade

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Preface

This capstone project serves as a culmination of our enriched journey through the Master's program in business analytics. It signifies the consolidation of knowledge and insights garnered from an array of comprehensive modules. Our journey took an exciting turn with collaboration from Accenture Ireland, significantly broadening the horizons of our project. This synergistic effort has laid the foundation for our project titled "Sustainable Energy Transition: Business Decision Support System (BDSS) for Analysing Hydrogen Consumption, Subsidies, and Gas Trade." This collaborative creation bears the collective authorship of Akhilesh Kapoor (B.E. in Computer Science), Anushka Jain (B. Tech in Engineering Physics), and Disha Raviraj Shetty (B. Tech in Electrical and Electronics Engineering).

The core objective of this capstone project is to elucidate the intricacies of operating a green hydrogen enterprise. Through this initiative, the potential of Power BI and Python as pivotal tools will be showcased, empowering policymakers, government, and institutions to craft immersive and informative simulations that shed light on the dynamics of sustainable business operations in the realm of green hydrogen.

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List of Important Abbreviations

Artificial Neutral Network	ANN
Business Decision Support System	BDSS
Business Intelligence	BI
European Union	EU
Facebook Prophet	FBProphet
Liquified Natural Gas	LNG
Multi-Layer Perceptron	MLP
Ordinary Least Square	OLS

Executive Summary

As global concerns about climate change and finite fossil fuel resources intensify, the spotlight is on environmentally friendly alternatives. Hydrogen, with its high energy density, zero emissions, and renewable production potential, emerges as a promising clean energy solution. This research presents a comprehensive decision-support framework, leveraging data science techniques and domain expertise to analyse the evolution of the hydrogen industry.

By integrating historical data and patterns within the fossil fuel sector, the project forecasts forthcoming growth and trends within the hydrogen industry. The Business Decision Support System (BDSS) places emphasis on estimating hydrogen consumption, analysing energy subsidies, and evaluating the European National Gas Pipeline Network. Given the scarcity of comprehensive data concerning hydrogen, particularly green hydrogen, innovative methodologies are essential. The utilization of LNG data enables the prediction of trends in the hydrogen market, and an examination of subsidies for electricity and gas offers insights into the progression towards sustainable energy solutions.

The European National Gas Pipeline Network is utilized to assess net consumer and supplier dynamics, facilitating the optimization of hydrogen integration and energy flow. This comprehensive tool merges data from subsidies, LNG, and pipeline networks, offering insights into hydrogen's growth potential and market trends. The BDSS aids policymakers in reducing fossil fuel dependence, generating revenue through hydrogen exports, and transitioning to greener energy.

In the wake of the global energy crisis triggered by geopolitical events, low-emission hydrogen gains prominence. The BDSS employs robust predictive models for hydrogen consumption estimation, enabling strategic decision-making and subsidy optimisation. Leveraging renewable resources, Ireland demonstrates the momentum towards green hydrogen.

Chapter 1 - Introduction

Climate change and the finite availability of fossil fuels have prompted a worldwide emphasis on finding environmentally friendly replacements. Hydrogen has the potential to be a clean energy choice with several advantages. These include a high energy density, zero emissions during use, and the utilisation of renewable resources in its production. A more sustainable energy future is possible, and the shift to hydrogen technology can help lessen the environmental impacts of burning fossil fuels now. This research aims to construct a decision-support framework encompassing global economic trends, cross-border fossil fuel trade, and the growing demand for hydrogen. The approach involves integrating advanced data science methodologies with domain expertise to anticipate the trajectory of the hydrogen industry. Historical data and established patterns in the fossil fuel sector serve as foundational elements for projecting future developments in the hydrogen market. The employed decision-support system and modelling framework seek to glean insights into the impacts of diverse economic and trade elements on the growth of the hydrogen sector. The future of hydrogen can be better understood by combining data on fossil fuel consumption, research and development spending on energy technology, electricity generation and trade, and gas trade flows. Our research aims to give decision-makers in the hydrogen industry the information they need to make educated choices about the future of the industry, including how to produce, transport, and use hydrogen.

The objective of this project is to build a holistic business decision support system (BDSS) that delves into three critical aspects of the energy landscape: hydrogen consumption estimation, subsidies on energy products, and the European National gas pipeline network. The availability of information on hydrogen, especially green hydrogen, is limited, making it challenging to analyse and predict trends in the hydrogen sector. To address this challenge, the strategy entails harnessing LNG data to predict trends within the hydrogen market. Additionally, an examination of a database detailing financial support provided by individual countries for electricity and gas is underway. Through the analysis of annual alterations in these subsidies spanning the period from 2010 to 2022, the objective is to ascertain whether nations are progressively leaning towards promoting environmentally sustainable energy sources. Leveraging the European National Gas Pipeline Network, the focus is on evaluating net consumer and supplier dynamics, enabling strategic decisions for the smooth integration of hydrogen and improved optimisation of energy flow. The tool will integrate data from subsidies, LNG, and pipeline networks to offer insights into the potential growth and market trends within the hydrogen sector.

Overall, the novel BDSS centred around hydrogen consumption estimation, energy product subsidies, and analysis of the EU national gas pipeline network offers substantial business value to countries and policymakers venturing into hydrogen technologies. By using accurate consumption estimates and optimising energy subsidies, policymakers can strategically reduce their nation's dependence on conventional fossil fuels. This helps make energy more secure and reduces negative effects. The BDSS also facilitates the identification of lucrative opportunities for revenue generation through hydrogen exports, leveraging surplus hydrogen production to tap into a growing global market. Finally, the BDSS aids in creating a transformative shift towards green hydrogen by providing insights into the existing gas infrastructure and helping policymakers strategise the transition to cleaner energy sources, aligning with international sustainability commitments and fostering a greener future.

Chapter 2 - Literature Review

The urgent need to transition from fossil-based fuels to clean renewables arises from the substantial increase in global energy demand due to population growth, economic expansion, and rapid urbanisation (UNFCCC, 2015). This necessitates global decarbonization in sectors such as transportation, industry, and electricity generation to effectively mitigate human-induced climate change, aligning with the goals of the Paris Agreement. The Paris Agreement aims to limit global warming to well below 2°C above pre-industrial levels, with an additional aspiration of striving for a 1.5°C limit (UNFCCC, 2015). In addressing these urgent environmental concerns, hydrogen production has emerged as a pivotal solution to facilitate the transition from fossil-based fuels to clean renewables. With the abundant availability of renewable energy sources, hydrogen production offers a promising pathway to meet the growing global energy demand while reducing carbon emissions. However, the variable and intermittent nature of these renewable resources presents challenges that require technical innovations to balance energy supply and demand. Additionally, exploring cost-effective production methods, research and development, policies, and the development of hydrogen infrastructure are crucial components in realising a sustainable hydrogen economy (Osman et al., 2021).

Hydrogen possesses unique properties that make it an attractive choice as an energy carrier. It is a colourless, odourless, and tasteless element with a small and light molecular structure. With its high energy content per unit mass of 143 MJ kg−1, hydrogen offers a significantly higher energy density compared to traditional liquid hydrocarbon-based fuels (Ahluwalia & Peng, 2009). Being the most abundant substance in the universe, hydrogen provides a virtually limitless resource for energy production. However, there are challenges associated with hydrogen storage and distribution. Unlike hydrocarbon fuels, which can be easily stored and transported in liquid form, hydrogen has a low density in its gaseous state. This means that larger volumes of storage are required to contain the same amount of energy. Additionally, hydrogen is not readily available in its pure form and is usually bonded with other elements, such as carbon and oxygen, which requires energy-intensive processes (Mazloomi and Gomes, 2012).

Aligned with the EU's commitment to global climate action under the Paris Agreement, the European Union strives to achieve climate neutrality by 2050. This goal, central to the European Green Deal, entails establishing a net-zero greenhouse gas emissions economy (European Commission, 2022). The EU's hydrogen strategy and REPowerEU plan aim to promote renewable and low-carbon hydrogen to decarbonise the EU and reduce dependence on imported fossil fuels. Currently, hydrogen represents less than 2% of Europe's energy consumption, mainly used for chemical production and predominantly sourced from natural gas, resulting in high CO_2 emissions. The European Commission targets the production of 10 million tonnes of renewable hydrogen with the import of 10 million tonnes by 2030 to drive the transition towards a sustainable hydrogen economy (European Commission, 2022).

As outlined in Ireland's Climate Action Plan 2023, the country has implemented its strongest climate action programme to date. Central to this plan is the commitment to increase the share of renewable electricity to up to 80% by 2030. Additionally, the plan emphasises the importance of large-scale renewable energy deployment, which will play a critical role in decarbonizing the power sector and enabling the widespread adoption of electrified technologies. Moreover, Ireland has set an ambitious goal to reduce greenhouse gas emissions by 51% by 2030, showcasing its formal and comprehensive approach to addressing climate change (www.gov.ie, 2023).

2.1 Why Green Hydrogen?

In the literature, different forms of hydrogen are commonly characterised by colour coding, such as grey, blue, green, brown, and turquoise. Grey hydrogen is created from fossil fuels such as natural gas and has a significant carbon impact, with each ton of hydrogen produced emitting around 10 tonnes of CO_2. Blue hydrogen, on the other hand, is created by combining fossil fuels with carbon capture and storage technology, which helps to decrease emissions to some extent (Dvoynikov et al., 2021).

Green hydrogen, on the other hand, is an appealing alternative due to its sustainability and environmental advantages. It is produced entirely from renewable sources, such as wind or solar energy, and hence has a substantially reduced carbon impact. Prioritising green hydrogen aligns with Ireland's objective of increasing the percentage of renewable power to up to 80% by 2030. Ireland can successfully decrease carbon emissions, enhance environmental sustainability, and accelerate the transition to a cleaner and more resilient energy system by embracing green hydrogen.

While grey and blue hydrogen has their uses, particularly in the early phases of transition or when utilising existing infrastructure, green hydrogen's long-term profitability and environmental benefits make it the better choice. Ireland's vast wind potential, both onshore and offshore, makes it an ideal candidate for producing green hydrogen from renewable electricity. With abundant offshore resources in a sea area seven times larger than its landmass, Ireland is well-positioned to embrace green hydrogen production and advance its sustainable energy goals (Consultation on Developing a Hydrogen Strategy for Ireland, 2022). Ireland can contribute to a sustainable and carbon-neutral future by taking the lead in the adoption of green hydrogen.

2.2 Renewable energy prospects in Ireland

Energy serves as the primary input to the industrial sector, forming the foundation of economic production. Economic growth and development are impossible without reliable energy supplies. It becomes crucial to maintain a harmonious balance between energy, the economy, and the ecosystem to achieve sustainable development. It is imperative to utilise energy resources without affecting the ecosystem. Renewable energy sources are widely embraced due to their perpetual nature, ability to regenerate within human lifetimes and inexhaustibility. These sources play a vital role in reducing dependence on fossil fuels and ensuring energy security amidst fossil fuel price instability. The rapid rise in energy demand is attributed to population growth, advancements in living standards, technological advancements, urbanisation, and industrialisation. Technological advancements have made energy sector investments more cost-effective and appealing, leading to increased business participation. Government subsidies and growing interest in renewable energy sources, such as wind, geothermal, solar, and hydroelectric energy production, have further contributed to the expansion of these assets.

Ireland possesses abundant renewable energy sources that power the country's energy grid. Bioenergy, solar, and wind energy offer tremendous potential for businesses and domestic consumers in Ireland. Embracing renewables enables Ireland to enhance sustainability, bolster energy security, and reduce its dependence on fossil fuels. Given its geographical location as an island at the periphery of Europe, wind power represents a particularly promising option for Ireland. Conversely, Ireland lacks substantial reserves of fossil fuels such as coal and oil, with 94% of its energy consumption relying on carbon-based fuels. Consequently, energy prices in Ireland remain comparatively low in the developed world, making it less attractive for energy-intensive industries to invest in upgraded facilities (IEA, 2022).

In Ireland, the intermittent nature of renewable energy sources poses challenges during periods of low wind speeds and sunlight. While battery storage systems provide short- and medium-term solutions, long-duration energy storage is essential for a resilient energy system with a significant share of renewables, enabling inter-seasonal supply over several months. Currently, fossil fuels are used in such scenarios, resulting in greenhouse gas emissions. To address this, green hydrogen, produced by splitting water using renewable electricity, offers a sustainable alternative to low renewable energy availability (Schütze, 2023).

To maintain grid stability, thermal generation plants relying on fossil fuels are necessary. However, the grid can be efficiently decarbonized by replacing fossil fuel with green hydrogen and synchronous condensers that use minimal grid power to sustain the grid (Schütze, 2023). Climate change is one of the world's most pressing issues. It requires a significant reduction in carbon emissions across the entire economy and a swift transition to a net-zero energy system. Ireland is committed to leading climate change. Improving plans for renewable energy will have a profound impact on the economy, investments, and the availability of clean energy for future generations. To achieve decarbonization, the Irish economy must decouple energy consumption entirely from population and economic growth.

According to the Scheer et al. (2016), Ireland's progress towards its renewable energy goals has fallen short. Ireland has an expected achievement range of 13.6% to 14.1% by 2030, below the mandatory EU target of 17%. However, policies promoting renewable energy have been implemented in Ireland and throughout the EU over the past three decades. It is estimated that renewable energies accounted for nearly two-thirds of the new capacity in 2016 globally, with further growth expected. Germany and Ireland are expected to generate over 25% of their electricity from wind energy alone by 2022, contributing over 80% of global growth in renewable power (International Energy Agency, 2021).

Ireland has established an ambitious target of 34% renewable energy share in its overall energy consumption by 2030. To reach this goal, Ireland aims to increase the proportion of renewable energy used for power generation to 70%. It also aims to generate 3.5 GW or more of offshore energy for power. In the coming years, Ireland will need to focus on developing and adopting innovative technologies to reduce greenhouse gas emissions. Decarbonization and promoting sustainable living, along with implementing intelligent and sustainable practices in food production and processing, are key priority areas for Ireland's sustainable future (Energy in Ireland Report, 2022).

	2016	2017	2018	2019	2020	2021	2030 Target
RES-E (normalised)	27.1%	30.3%	33.3%	36.5%	39.0%	36.4%	70%[17]
RES-T (weighted)	5.2%	7.5%	7.2%	8.9%	10.1%	4.3%	14%
RES-H	6.2%	6.6%	6.4%	6.3%	6.3%	5.2%	24%[17]
Overall RES	**9.2%**	**10.5%**	**10.9%**	**12.0%**	**13.5%**	**12.5%**	**34.1%**

Figure 1. Ireland's progress towards overall renewable energy share (RES) target

Figure 1. table illustrates renewable energy distribution across electricity, heat, and transport sectors. According to the Energy in Ireland Report (2022), renewable electricity currently accounts for 68% of the total renewable energy share, followed by transportation at 11% and heat at 21%. Notably, renewable electricity has contributed to renewable energy growth since 2005. The accompanying Figure 2 illustrates the annual share and quantity of renewable energy, categorised by source. Wind energy is the primary driver of renewable energy growth, constituting over half of all renewable sources. Solid biomass and bioliquids have also played a significant role in this growth trajectory.

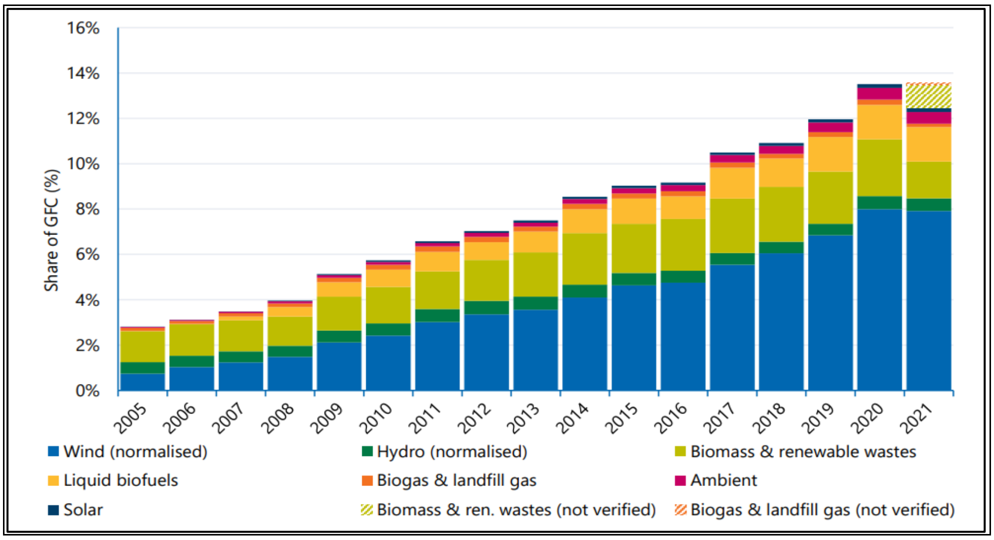


Figure 2. Renewable Energy Share (RES) of Gross Final Consumption by Source

2.2.1 Type of Energy

Wind Energy

Wind energy has consistently proven to be Ireland's most effective renewable energy source. Due to its expansive territory in the Irish Sea and Atlantic, Ireland has great potential for wind energy, making it one of the most cost-effective renewable energy sources in Europe. Ireland has installed wind turbines of 1,000MW capacity with 3,700MW of applications due to connecting to the grid power (www.kellyservices.ie, n.d.). Furthermore, advancements in grid integration technology and wind turbine development are expected in the coming decades.

The Sustainable Energy Authority of Ireland (SEAI) states that Ireland can deploy 30GW of offshore wind generation by 2050. It suggests that by 2050, Ireland can deploy 30GW of offshore wind generation. This projection is significant considering the estimated electricity demand for 2030 is around 7GW. While offshore wind is still in its early stages, Ireland's substantial onshore wind resources should be further developed. Onshore wind projects serve as an interim solution before offshore projects become operational but also contribute to decentralising renewable generation across the country.

The 2023 Climate Action Plan outlines targets for 9GW of onshore wind, 8GW of solar, and 7GW of offshore wind. In addition, it dedicates 2GW dedicated to green hydrogen production (www.gov.ie, 2023). With an anticipated electricity demand of 7GW in 2030 and limited interconnection to mainland Europe, the question arises as to how Ireland can maximise the utilisation of excess renewable energy resources. As more generators connect to the grid, curtailment levels (when renewable electricity supply exceeds demand) are expected to increase. Leveraging this surplus electricity that would otherwise end up in waste, green hydrogen production can be a viable solution. Wind power deployment may face challenges in the future due to market uncertainties related to demand and financing availability, despite successful cost-cutting efforts. To achieve ambitious goals for 2030 and beyond, new regulatory structures are crucial. Long-term visibility and robust regulatory frameworks will continue to be essential for widespread wind energy adoption. Lower-than-anticipated growth rates in wind power have been linked to legislative program gaps and changes observed in several countries, including Germany and Ireland.

Bioenergy:

Bioenergy is Ireland's primary renewable heat source. It is expected to continue replacing fossil fuels, particularly in industries and commercial sectors with high heat demand. Domestic biomass accounts for 3.5% of Ireland's energy consumption. By 2035, with a bioenergy potential of approximately 30%, this contribution is projected to increase. Bioenergy potential includes forestry, energy crops, agricultural waste, and other forms of waste (www.askaboutireland.ie, n.d.). However, biofuel refineries in Ireland have been limited due to the need for significant scale to achieve economic viability.

Solar energy:

Solar energy is the radiation energy emitted by the sun, which results from the conversion of hydrogen atoms into helium atoms. Ireland's Department of Communications, Climate Action and Environment (DCCAE) recognise the benefits of solar photovoltaic (PV) technology and its potential to diversify Ireland's energy mix. The government's commitment to investing in emerging technologies is expected to support the solar industry through the Renewable Electricity Support Scheme (RESS) and encourage a more varied energy portfolio. For solar PV, Ireland has resources such as research and development capabilities, building materials, system integration expertise, high-quality manufacturing, and experience in onshore wind.

In addition to bioenergy and solar, Ireland has potential opportunities in other energy sources. The SEAI's report (Ireland’s Solar Value Chain Opportunity, 2017) on

Ireland's Solar Value Chain Opportunity highlights the significant market potential for solar PV in the EU. Irish organisations have the potential to capture between €42 million and €216 million per year of the EU solar PV market by 2030, depending on different scenarios. Ireland's domestic PV market could reach €340 million per year. Despite the mass production of traditional crystalline silicon PV modules in China and Taiwan, Irish innovators are well-positioned to capture a share of this sizable market with components, services, and new materials. Ireland has made significant progress in achieving its energy efficiency and renewable energy goals, but it needs to expand these efforts. The growing economy and low oil prices have increased energy demand, posing challenges to meeting energy requirements.

To meet EU 2030 goals, Ireland should study other countries' achievements, invest in energy infrastructure, address challenges in data centres, energy demand, and agriculture, and learn from successful support programs for renewable technologies. Ireland has seen benefits in business, the economy, and the environment through energy efficiency and renewable energy advancements. It has also positioned itself as a model for renewable energy deployment. However, continued effort is required to reach future goals, and offshore wind has the potential to play a significant role in Ireland's renewable energy mix.

The Climate Action Plan aims to have up to 80% of electricity sourced from renewables by 2030, with wind energy playing a crucial role. Ireland is projected to have 70% of its electricity coming from renewables by 2030 (windenergyireland.com, 2022), making it a global leader in onshore wind, especially when considering Denmark's offshore wind share (about 47%). Achieving renewable energy targets depends on alternative financing methods, energy efficiency retrofits, and the ongoing implementation of Energy Efficiency Obligations on energy suppliers.

Looking ahead, despite challenges and the economic crisis, Ireland is well-positioned in the energy sector with renewable energy playing a crucial role. The government should prioritise renewable energy for electricity, heating, and transportation, leveraging the country's robust economy for a sustainable future. Demand for electricity on the east coast, grid connectivity, and shallow seas make offshore wind a promising option for Ireland's renewable energy portfolio. Ireland has a crucial role to play in the growing renewable energy industry. It's imperative to act quickly and initiate projects that stimulate demand and further expand renewable energy initiatives.

By fully embracing solutions like green hydrogen, Ireland can move towards energy independence and bring positive change. Now is the appropriate time to seize these opportunities and lead the way in creating a sustainable energy future.

2.3 Hydrogen Demand in Ireland

Hydrogen, a flourishing industry with significant economic value, witnessed a global demand of 94 million tonnes in 2021, exceeding the previous record of 91 million tonnes in 2019. This notable 5% increase in demand was mainly attributed to the recovery of the chemical sector and refining activities. Unfortunately, the prevailing challenge lies in the fact that a large portion of hydrogen supply continues to heavily rely on fossil fuels, resulting in alarming annual CO_2 emissions of around 830 million tonnes, posing severe consequences for the environment (International Energy Agency, 2021).

In Ireland, hydrogen utilisation is mainly observed in specific sectors. The Whitegate refinery in Co. Cork produces hydrogen for internal purposes. BOC, a leading provider of industrial and medical gases, supplies hydrogen to diverse industries such as aerospace, electronics, pharmaceuticals, and medical applications. BOC also facilitates the provision of green hydrogen for Bus Éireann's three hydrogen buses. Additionally, prominent technology company Intel has a substantial internal hydrogen network catering to various processes (Consultation on Developing a Hydrogen Strategy for Ireland, 2022).

In the heat sector, the focus for hydrogen in Ireland is on decarbonizing medium and high-temperature heat in the industrial sector. The National Heat Study has explored various pathways to achieve net-zero emissions by 2050. Hydrogen is primarily utilised to produce high-grade and medium-grade heat in industrial manufacturing processes. However, the use of hydrogen for space heating in buildings is limited. Other technologies like heat pumps are more widely employed. Competing technologies such as electric technologies, biomass, and Carbon Capture, Utilisation, and Storage (CCUS) are also considered for sites with significant process emissions (Consultation on Developing a Hydrogen Strategy for Ireland, 2022).

Hydrogen has potential as a fuel for various vehicle types in the transport sector. Battery-electric vehicles are the primary solution for decarbonising passenger cars and lightweight vehicles. However, challenges remain for heavy, long-range vehicles in sectors like maritime, aviation, and long-haul road freight. In these cases, hydrogen can complement electricity as a zero-carbon transport fuel. The development of hydrogen-based renewable or carbon-neutral fuels is essential to meet decarbonization targets. Aviation can benefit from hydrogen in the form of e-fuels, while hydrogen can be used to produce green ammonia for the maritime sector. Hydrogen fuel cell technology can also complement battery electric technology for heavy-duty vehicles, providing advantages for longer-distance freight movements.

In the power sector, the deployment of green hydrogen fuel with hydrogen-ready gas turbines can contribute to achieving net-zero emissions by 2050. Hydrogen can help decarbonize conventional generation during periods of low renewable electricity availability, enhancing energy security and addressing system stability challenges. Furthermore, hydrogen can play a role in the inter-seasonal storage of electricity, supporting the decarbonization of the power system. Maximising the utilisation of excess renewable electricity through electrolysis is also being considered. Co-locating electrolyser with onshore or offshore wind projects can help overcome network constraints and meet domestic or international demand for green hydrogen (Consultation on Developing a Hydrogen Strategy for Ireland, 2022).

Overall, the demand for hydrogen in Ireland is driven by its potential to decarbonise medium and high-temperature heat in the industrial sector. Also, it can serve as a transport fuel for heavy-duty vehicles and contribute to the stability and decarbonisation of the power sector.

2.4 Transportation Methods

Hydrogen delivery is a crucial component of hydrogen pathways, affecting their cost, energy consumption, and greenhouse gas emissions. There are two primary phases involved in the delivery of hydrogen from centralised production facilities to end users: transmission and distribution. The choice of delivery method is contingent on a number of variables, including the method of storage employed. There have been identified three primary methods for hydrogen delivery: gaseous hydrogen delivery, liquid hydrogen delivery, and material-based hydrogen carriers.

Transporting hydrogen as a compressed gas through pressure vessels or conduits constitutes gaseous hydrogen delivery. Transporting compressed hydrogen typically involves using tube trailers, which are high-pressure vessels. They offer infrastructure requirements that are simple and have minimal compression costs. However, tube trailers encounter obstacles in terms of storage capacity, dimensions, and production costs. Transporting hydrogen through pipelines, on the other hand, necessitates the development of an extensive infrastructure. Even though approximately 2600 km of hydrogen pipelines already exist in the United States, their extensive implementation would require substantial expansion of gas (Moradi and Groth, 2019).

Delivery of liquid hydrogen is considered cost-effective for scenarios with high demand and moderate distances. This method entails liquefying hydrogen, storing it, and then transporting it in cryogenic tanks. Compared to gaseous hydrogen, liquid hydrogen allows for greater storage capacities. North America has a limited number of liquefaction facilities at present. To meet future hydrogen demand, it will be necessary to construct additional plants with higher production rates, enhanced energy efficiency, and lower capital costs. To improve the viability of large-scale liquid hydrogen delivery, research is being conducted to develop more efficient liquefaction processes. Material-based hydrogen carriers provide an alternative delivery method. Due to low storage pressures, manageable properties at ambient conditions, and greater gravimetric density than gaseous storage, these carriers offer higher levels of safety. However, material-based carriers may not be appropriate for applications with significant demand. Due to their limited storage capacity, they are better suited for applications where smaller quantities of hydrogen gas is necessary (Moradi and Groth, 2019).

Various factors, including geographic and market characteristics, population density, and the penetration of hydrogen-consuming units, influence the selection of a hydrogen delivery method. Ongoing research and development efforts are being made to improve the efficiency and cost-effectiveness of these hydrogen delivery technologies. In order to realise the maximum potential of hydrogen as a clean energy source, further advancements in delivery methods are essential.

2.5 Previous Works

Numerous research papers delve into infrastructure and supply chain optimisation within the realm of hydrogen energy. Agnolucci et al. (2013) utilise the Spatial Hydrogen Infrastructure Planning Model (SHIPMod) to analyse the impacts of economies of scale, transport costs, and demand patterns on infrastructure optimisation. This study enhances our understanding of essential factors in efficiently planning hydrogen fuelling networks. Similarly, the work of Razmi, Babazadeh, and Kaviani (2018) concentrates on determining optimal facility configurations and, providing insights into effective hydrogen fuelling network planning.

Furthermore, De-León Almaraz et al. (2022), applying the model in Hungary, identifies an optimal hydrogen supply chain architecture that balances economic gains with reduced environmental and social costs. Their study underscores the trade-offs between economic, environmental, and social goals within the hydrogen supply chain. In line with these research directions, our strategy, as discussed with Accenture, revolves around training models to forecast hydrogen sector trends using data from fossil fuels, LNG, and electricity. For instance, the Ukraine-Russian conflict led to Europe ceasing oil purchases from Russia, consequently prompting Russia to seek new markets. India and China capitalised on this shift, stockpiling affordable Russian oil.

Our objective is to create a tool that evaluates these effects on Ireland's prospective hydrogen exportation. Given the evolving nature of hydrogen technology and its limited available information, our approach aims to provide insights into potential outcomes for Ireland. This, however, is just a glimpse of the possibilities this research offers.

2.6 Decision Support Systems (DSS)

A Decision Support System (DSS) is a computerised program used to support determinations, judgments, and courses of action in an organisation or a business (Segal, 2022). DSSs are interactive software-based systems intended to help managers in decision-making by accessing large volumes of information generated from various related information systems involved in organisational business processes (www.tutorialspoint.com, n.d.). DSSs are designed to support the decision-making process, rather than to render a decision. The hallmark of DSS is flexibility, and personal DSSs should be easy to develop (www.umsl.edu, n.d.). DSSs are adaptive over time, and they can be tailored for any industry, profession, or domain, including the medical field, government agencies, agricultural concerns, and corporate operations (Segal, 2022).

The main components of a Decision Support System (DSS) can vary slightly depending on the source, but the common components mentioned in the search results are:

- **Data Management:** The database component of a DSS stores and manages the data that is used for decision-making. It contains relevant and organised information from various sources (Olavsrud, 2020).
- **Model Management:** The software system component of a DSS includes the algorithms, models, and analytical tools that are used to analyse and process the data. It provides the computational capabilities to perform calculations, simulations, and other analytical tasks (Kukreja, 2018).
- **User Interface:** The user interface component of a DSS is the interface through which users interact with the system. It provides a way for users to input data, specify queries, view results, and interact with the analytical tools and models (Talerico, 2022).
- **Knowledge Management:** This component involves capturing and organising expert knowledge, rules, and guidelines that can be used to support decision-making. It helps in providing context and guidance to users during the decision-making process (Kukreja, 2018).
- **Decision-Making Tools:** What-if analysis, sensitivity analysis, goal-seeking, and scenario planning are just a few of the decision-making methods available in a DSS. Users are able to consider a variety of choices, weigh the pros and cons of each, and visualise the results of their selections with the use of these aids (Segal, 2022).

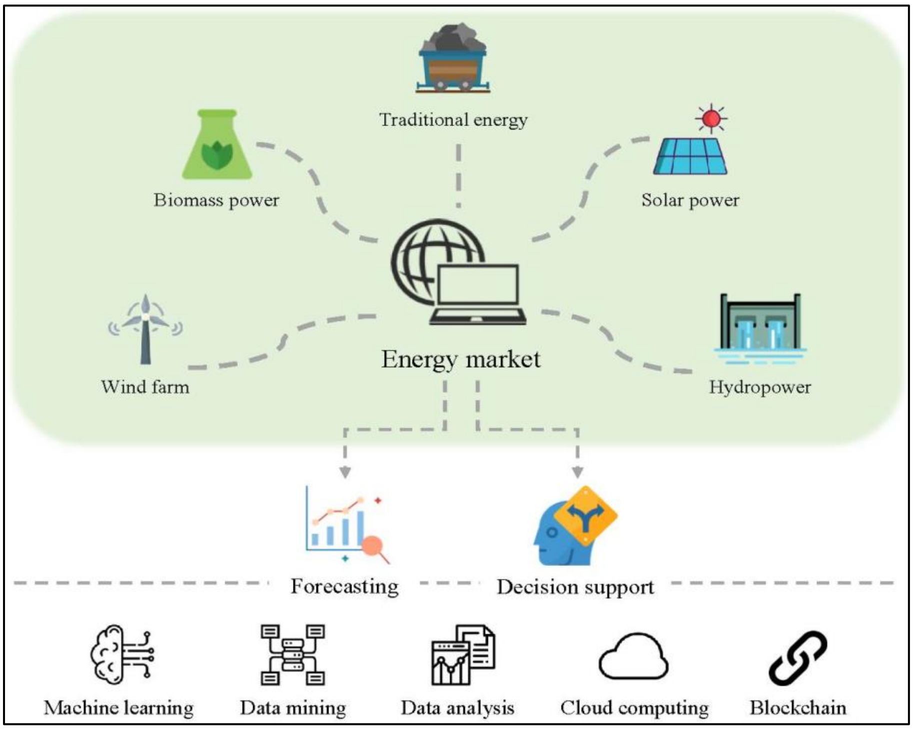


Figure 3. DSS Tool for Hydrogen Energy Market (Mdpi.com, 2023)

The benefits of using DSS in decision-making processes include:

- **Improved Decision-Making:** DSS aids decision-makers in gaining access to and analysing pertinent data, leading to a deeper comprehension of intricate circumstances. It aids decision-making by facilitating the use of facts to inform judgments and by encouraging action based on solid evidence (Wasylewicz and Scheepers-Hoeks, 2019).
- **Enhanced Efficiency:** The time and effort required for data processing, analysis, and reporting are all reduced because of DSS's automation. As a result, the likelihood of making mistakes or succumbing to biases is diminished, and decision-makers are better able to zero in on the most important considerations (Lee, 2021).
- **Scenario Evaluation:** DSS lets users run hypothetical situations to weigh the pros and cons of certain actions and determine how they might pan out. The best next step may then be determined, and the repercussions of any other possible moves can be comprehended (Lee, 2021).
- **Collaboration and Communication:** DSS allows stakeholders and decision-makers to work together by offering a forum for exchanging ideas and

information. It helps people talk to each other and makes the decision-making process more open and honest (Lee, 2021).

A Decision Support System can be useful for studying hydrogen demand in Ireland and renewable energy supply/production capability in the context of the research objectives. The levelised cost of hydrogen may be predicted with its help, along with production setup costs, renewable electricity costs, and operation and maintenance expenses. Researchers in Ireland can optimise the use of renewable energy sources and hydrogen production with the help of a decision support system (DSS).

2.7 Multiple Linear Regression

Multiple Linear Regression, an extension of Simple Linear Regression, expands its capacity by incorporating multiple predictor variables to anticipate the response variable. This regression approach holds particular importance in modelling the linear association between a sole dependent continuous variable and a spectrum of independent variables. Within its framework, it employs two or more independent variables to predict a dependent variable, achieving this through the establishment of an optimal linear relationship. It's important to note that Ordinary Least Squares (OLS) play a crucial role in Multiple Linear Regression, as it works to minimise the sum of squared differences between the observed and predicted values. In practice, the model employs two or more independent variables (X) and one dependent variable (Y), wherein Y signifies the targeted prediction. This method essentially provides a mechanism for forecasting a quantitative response, leveraging the collective influence of multiple attributes, while OLS ensures an effective fitting of the model to the data by minimising prediction errors (Yadav, 2021).

$$\mathrm{Y} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \dots + \beta_n X_n + \mathrm{e}$$

where,

$Y = Dependent\ variable\ or\ target\ variable$

$\beta_0 =$ Intercept of the regression line

$\beta_1, \beta_2, \beta_3, \dots, \beta_4 =$ Slope of the regression line which tells whether the line is increasing or decreasing

$\mathrm{X}_1, \mathrm{X}_2, \mathrm{X}_3, \dots . \mathrm{X}_n =$ Independent variable *or* Predictor variable

$\mathrm{e} =$ Error

The accuracy of this model is evaluated through significant metrics, including the coefficient of determination (R-squared) and the root mean squared error (RMSE) which provides a robust means of predicting a quantitative response by leveraging the collective influence of the target and response variable.

Ordinary Least Squares (OLS) is pivotal in this process, aiming to minimise the sum of squared differences between the observed and predicted values. Through this optimisation technique, the model calculates the coefficients for each independent variable, ensuring the line of best fit aligns closely with the observed data points. The coefficient of determination (R-squared) quantifies the proportion of the dependent variable's variance that can be predicted by the independent variables. A higher R-squared value indicates a better fit of the model to the data (Zach, 2022).

2.8 Artificial Neural Network

Artificial Neural Networks (ANNs) are a family of computational methodologies whose design is inspired by stylised models of the workings of the human brain and central nervous system. A Neural Network (NN) is a network of simple processing units called nodes or neurons (Agatonovic-Kustrin and Beresford, 2000). Signals or influences can only pass in one direction along a given connection; furthermore, the effect of the signal along an edge may be adjusted by a weight in that edge. This means NNs are weighted directed graphs (NVIDIA Developer, 2018). NNs can exhibit complex emergent global behaviour, determined. NNs are inductive, data-driven modelling tools which do not require an explicit a priori specification of the relationship between model inputs and outputs. NNs provide a very general and powerful framework for representing non-linear mappings from several input variables to several output variables, where the form of the mapping is controlled by a number of parameters (whose values may be adjusted). In the context of neural networks, the sought-after function parameters are commonly referred to as "weights," as they represent weights assigned to the edges of a graph. Learning the weights is also called training the NN. NNs can be used for a wide variety of tasks including prediction, clustering, classification and dimensionality reduction (Agatonovic-Kustrin and Beresford, 2000).

A supervised NN aims to address the function approximation problem by building up an internal model of a function which is a good fit to the training data provided

(Agatonovic-Kustrin and Beresford, 2000). The model has the form of a weighted digraph, where each node constructs a weighted sum (linear combination) of building block (or basis) functions (from the nodes of the previous level, which feed into this node) (NVIDIA Developer, 2018). The NN parameters are the arc weights, which are learned from provided training data. Then the resulting weighted sum is a sufficiently good approximation (for our purposes) to a function which fits the data well.

2.8.1 Multi-Layer Perceptron (MLP)

A Multi-Layer Perceptron (MLP) has one input layer and for each input, there is one neuron (or node), it has one output layer with a single node for each output and it can have any number of hidden layers and each hidden layer can have any number of nodes.

It is comprised of how the network transforms inputs into outputs is primarily determined by three factors: the processing occurring at the hidden and output layer nodes, the interconnections between the nodes, and the weight associated with them.

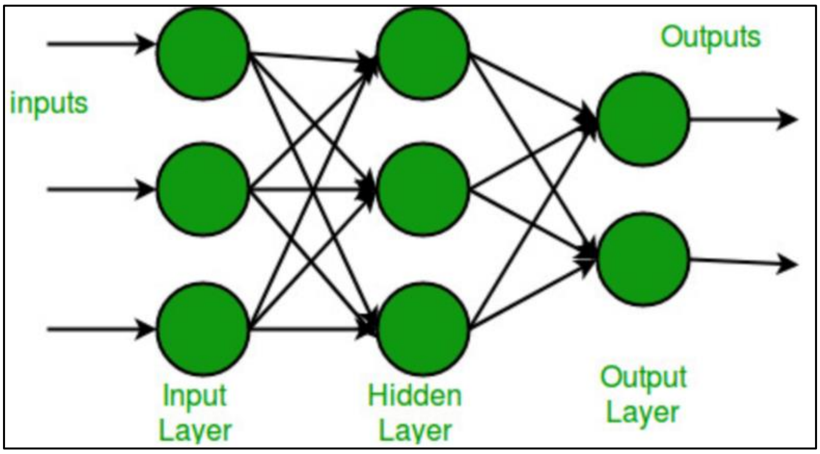


Figure 4. Single Layer Perceptron Network (GeeksforGeeks, 2021)

The activation function is represented by the threshold T. The neuron produces the value 1 if the weighted total of the inputs is greater than zero; else, the output value is 0. The perceptron can be utilised as a binary classification model with this discrete output, controlled by the activation function, defining a linear decision boundary. In order to reduce the distance between incorrectly categorised points and the decision boundary, it determines the separation hyperplane. Neurons in a Multi-layer Perceptron can utilise any arbitrary activation function, unlike neurons in a Perceptron, which must have an activation function that enforces a threshold, such as ReLU or sigmoid (Bento, 2021).

MLPs are topologically depicted as directed multipartite graphs, specifically tripartite when there are three layers. The standard architecture of an MLP is feedforward, meaning activation flows unidirectionally from input to output, resulting in directed acyclic graphs. However, recurrent MLPs are not acyclic as they involve feedback loops. The signal traveling along a connection within an MLP is amplified or dampened by multiplying it by the corresponding weight before it reaches the next node. A regression coefficient is analogous to this concept of weight.

The sum of input values directed to node j is found by multiplying each input (x_i) by its respective weight (w_{ij}), then adding them up:

The total activation fed to node j is the dot product.

$$\sum_{i=0}^{n} x_i w_{ij} = x^t w_j = x \cdot w_j$$

This multiplication process, $x \cdot w_j$, is a type of equation called bilinear, which means it behaves linearly when one part is changed while the other remains constant. In the context of MLPs, where the input data vector (x) stays the same, the function that determines the activation of neuron j can be seen as a linear relationship with the weights, represented as:

$$a(\cdot, x) : \mathbb{R}^{n+1} \rightarrow \mathbb{R} : w_j \longrightarrow w_j \cdot x$$

Processing at each node in the hidden and output layers involves passing the weighted sum of inputs through a nonlinear transfer function as given in the Figure 5.

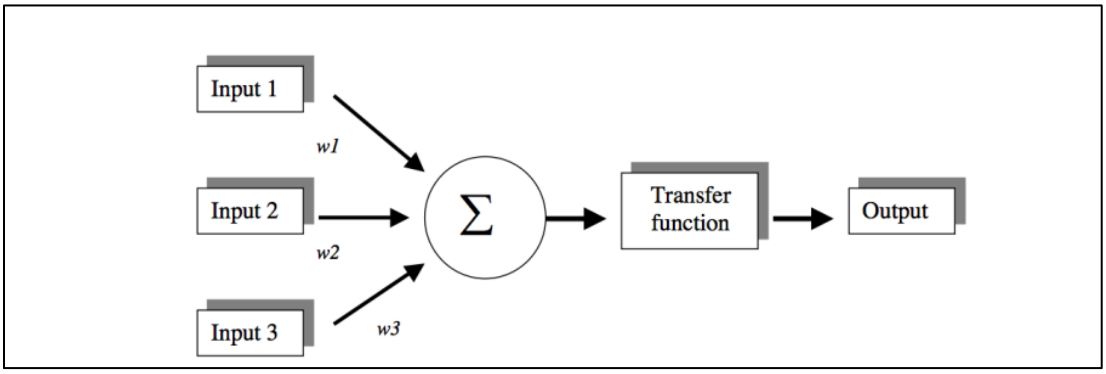


Figure 5. A Single Processing Node in an MLP (Brabazon et al., 2015).

Figure 5 illustrates a single processing node in an MLP, showing the weighted sum of inputs as well as the application of a transfer function to produce the node's output.

Various transfer functions may exist across different layers and nodes, although this is very rare. The general form of a single output y from a three-layer MLP is:

$$y = \sigma(w'_0 + \sum_{j}^{m} w'_j \sigma (\sum_{i=0}^{n} x_i w_{ij}))$$

where,

x_i *represents input* i (x_0 *is a bias node*);
w_{ij} *represents the weight between input node* i *and hidden node* j;
w'_0 *is the bias node weight fed to the output layer*;
$w'_j, j = 1, \ldots, m,$
represents the weight between hidden node j *and the output node*;
y *denotes the output produced by the network*
for input data vector $x = (x_1, \ldots, x_n)$
σ *represents a nonlinear transfer function*

A bias node functions similarly to a constant term in a regression model. The bias node's input value is commonly set to 1, adjusting automatically as its outgoing connection weights change. Determining the optimal hidden layer size is a heuristic.

MLP builds upon the original single-layer perceptron, which lacked hidden layers. While effective for patterns that can be separated with a straight line, it falls short for more complex, nonlinear patterns. To illustrate, a basic 2-layer MLP without hidden layers and just one output node, using a linear transfer function, is essentially like a linear regression model. This means the weights in the connections act similarly to regression coefficients. For instance, the equation $y = \beta_0 + \beta_1 x_1 + \beta_2 x_2$ can be depicted as shown in Figure 6.

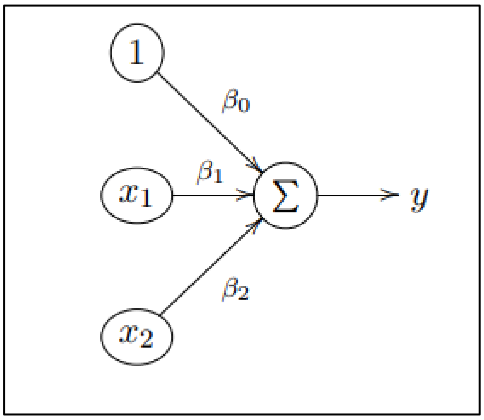


Figure 6. Linear equation $\boldsymbol{y = \beta_0 + \beta_1 x_1 + \beta_2 x_2}$ *as a node-arc structure (Brabazon et al., 2015).*

Moreover, a logistic regression model can be reinterpreted as a 2-layer MLP with a sigmoidal transfer function at the output node. When multiple layers are added, an MLP becomes a versatile tool for nonlinear regression without predefined parameters. It's worth noting that hidden layers are unnecessary if you're aiming for a linear data model. MLPs embody parallel, distributed computing. Although individual node processing is simple, their interconnections lead to emergent global capabilities, enabling intricate nonlinear mappings from input to output. Essentially, an MLP implements a function (model) $\hat{f}$ that translates input values (x) into output values (y).

MLP showcases an instance of parallel and distributed computation. This occurs because each hidden layer node functions as a local information processor, operating both independently and simultaneously alongside other nodes in its layer. It is important to note that even though the tasks that are carried out by the individual nodes are relatively straightforward, the interconnection among them creates collective capabilities that allow the network to form complex nonlinear relationships between input and output. Essentially, an MLP performs a function (model) denoted as $\hat{f}$, which translates a set of input values (vector x) into one or more output values (vector y). In more straightforward language, this relationship is denoted as y = $\hat{f}$(x).

While ordinarily least squares linear regression produces linear response surfaces, MLPs with nonlinear transfer functions can produce complex yet smooth response surfaces in n dimensions. Adjusting weights during learning refines these surfaces to better fit the training data.

MLPs are trained using a supervised learning paradigm and follow the below approach (Brabazon et al., 2015):

1. **Forward Propagation:** Forward propagation is the process in which input data is passed through the neural network layer by layer. Each neuron computes a weighted sum of its inputs, adds a bias term, applies an activation function, and passes the output to the next layer. This process generates predictions based on the given input data (Brabazon et al., 2015).
2. **Error Calculation:** Error calculation involves quantifying the difference between the predicted outputs of the neural network and the actual target values. This difference is determined using a loss function, which measures the accuracy of the model's predictions. The goal is to minimise this error by adjusting the model's parameters (Brabazon et al., 2015).
3. **Backpropagation:** Backpropagation is the learning process in which the network identifies and corrects its mistakes. Gradients of the loss with respect to the model's parameters (weights and biases) are computed using the chain rule of calculus. These gradients indicate how much each parameter contributes to the error. The model's parameters are then adjusted in the opposite direction of these gradients using an optimisation algorithm, enabling the network to improve its predictions over time (Brabazon et al., 2015).
4. **Regularisation:** Regularisation techniques are employed to prevent overfitting and enhance the generalisation ability of the neural network. L2 regularisation adds a penalty term to the loss function based on the magnitude of the weights, discouraging overly complex models. Dropout, on the other hand, randomly deactivates some neurons during training to ensure that the network does not overly rely on specific neurons (Brabazon et al., 2015).
5. **Training Loop:** The training loop is an iterative process that drives the learning of the neural network. It involves repeatedly presenting the training data to the network, calculating errors, adjusting weights through backpropagation, and updating the model's parameters. The loop continues for a specified number of iterations (epochs) to ensure that the network gradually refines its predictions (Brabazon et al., 2015).
6. **Model Evaluation:** Model evaluation is the process of assessing the performance of the trained neural network on unseen data. After training, the

model is tested on a separate dataset to measure its ability to generalise and make accurate predictions for new inputs. This evaluation helps determine how well the network has learned and whether it can effectively predict hydrogen consumption based on the provided predictors (Brabazon et al., 2015).

These definitions aim to provide clear and concise explanations of each aspect in the context of implementing an MLP for your specific problem.

2.8.2 Facebook Prophet (FBProphet)

FBProphet is a versatile and effective time series forecasting tool that caters specifically to univariate analysis. The algorithm was developed by Facebook's data science team to predict an individual variable's behaviour over time. It provides insight into the future trajectory of a solitary variable by studying its trends, patterns, and fluctuations in depth, making univariate analysis vital for businesses and researchers. (Khare, 2023)

The data preparation process is vital for ensuring the historical time series data are formatted appropriately and ready for analysis. Addressing any missing values and arranging the data chronologically are fundamental aspects of this step. Once the data is ready, FBProphet initialises the forecasting model by considering the main components contributing to the time series data – namely, trend, seasonality, and noise. These components play a pivotal role in accurately predicting future values. (Khare, 2023)

FBProphet further refines the modelling process by breaking it down into distinct components:

- **Trend Component:** FBProphet models the overall trend present in the time series data by employing a piecewise linear regression model. This allows the algorithm to capture sudden shifts or changes in the trend over different time intervals.
- **Seasonality Component:** The algorithm effectively captures periodic patterns inherent in the data, such as weekly, monthly, or yearly cycles. FBProphet accomplishes this by utilising a Fourier series, which is a versatile approach to modelling diverse seasonal variations.

- **Holiday Effects:** FBProphet provides the flexibility to incorporate special events or holidays that might influence the time series data. These events can have a significant impact on the variable being analysed.

Once the components are defined, FBProphet fits the model to the historical data, learning the intricate relationships between the trend, seasonality, and noise components. As a result, the algorithm generates forecasts for future time points, providing valuable information about the predicted trajectory of the variable (Khare, 2023).

Among FBProphet's notable strengths is its ability to estimate forecast uncertainty. By utilising Bayesian inference, the algorithm provides probabilistic forecasts that encompass potential variability in future predictions. This aspect is particularly beneficial for decision-making processes that require a thorough understanding of potential outcomes.

To aid understanding, FBProphet also offers visualisation tools that encompass historical data, fitted trends, seasonal components, and forecasted values alongside uncertainty intervals. The visual representation enables users to better understand the forecasts (Khare, 2023).

2.9 Regularisation

Regularisation is a technique used in machine learning and deep learning to prevent overfitting and improve the generalisation performance of a model. It involves adding a penalty term to the loss function during training. This penalty discourages the model from becoming too complex or having large parameter values, which helps in controlling the model’s ability to fit noise in the training data (Jain, 2018).

In this report, three prevalent regularization techniques will be examined: Ridge, Lasso, and Elastic Net. Additionally, three extensively employed models will be discussed: Regression, and Multi-Layer Perceptron (MLP).

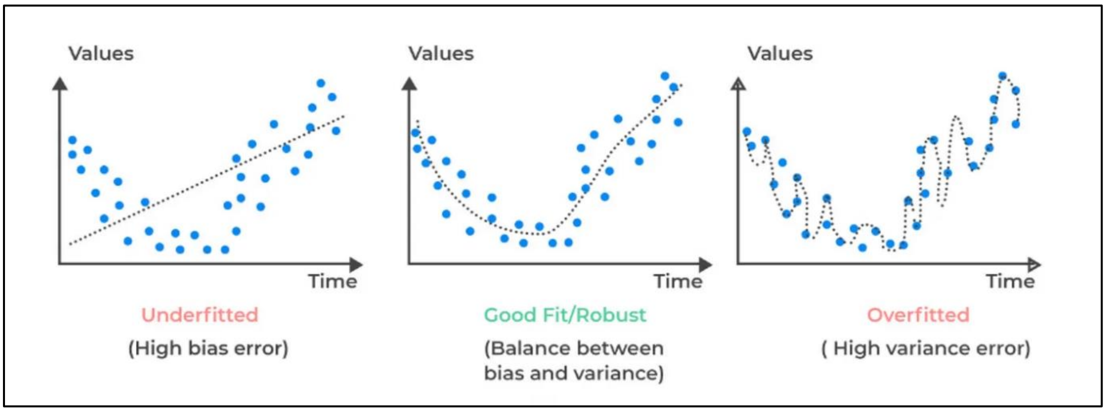


Figure 7. Regularisation (Singh, 2022)

2.10 Performance Metrics

2.10.1 Root Mean Squared Error (RMSE)

RMSE is a widely used metric to measure the accuracy of regression models. It represents the square root of the average of the squared differences between predicted and actual target values. RMSE assesses how closely the predicted values align with the true target values. A lower RMSE indicates better model performance, as it signifies smaller errors between predictions and actual values (Glen, 2022).

The selection of RMSE is based on its ability to offer a clear interpretation of the average prediction error. This enables an evaluation of the model's accuracy in forecasting housing prices.

2.10.2 R-squared (R^2) Score

R-Squared (coefficient of determination) is a statistical measure in a regression model that determines the proportion of variance in the dependent variable that can be explained by the independent variable. In other words, r-squared shows how well the data fit the regression model (the goodness of fit) (Taylor, 2020). R^2 score ranges from 0 to 1, with 1 indicating a perfect fit and 0 indicating a model that performs no better than predicting the mean of the target variable. Higher R^2 scores indicate better model performance in capturing the variance in the data.

Chapter 3 - Methodology

A pioneering analysis was executed through the integration of an all-encompassing Business Decision Support System (BDSS), encompassing Extract, Transform, Load (ETL) procedures for data amalgamation, predictive analytics for hydrogen consumption estimation, and descriptive analytics for subsidies and the pipeline network.

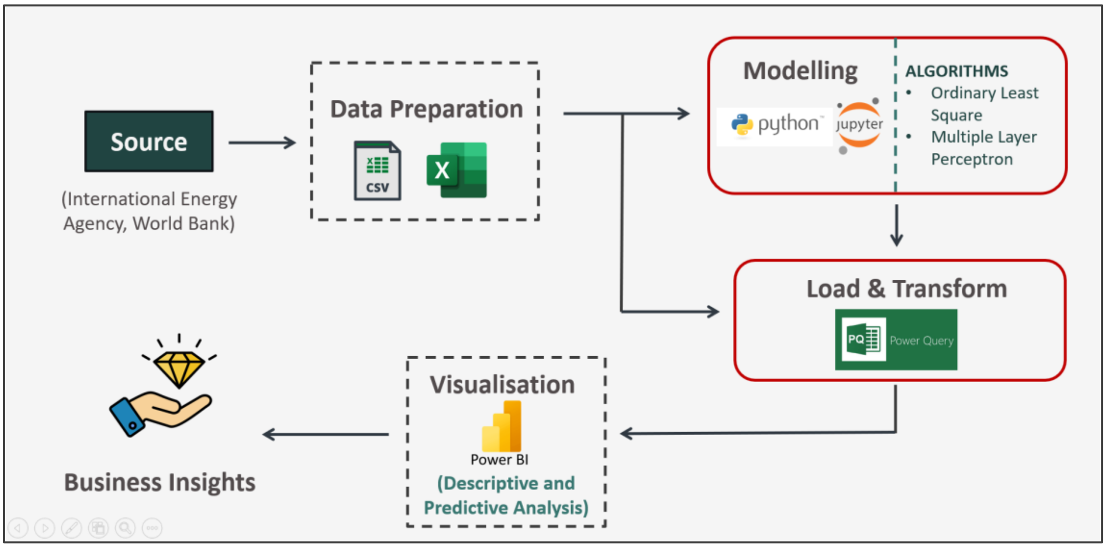


Figure 8. Process Flowchart

Figure 8 represents our approach harnessing Python for data extraction and transformation, Power Query for preprocessing, and Power BI for visualisation. The CSV datafiles, generously provided by Accenture and sourced from the International Energy Agency, formed the foundation.

Data extraction was accomplished using Python scripts to access the relevant data from CSV files. Post extraction and transformation, the refined datasets were seamlessly integrated into Power BI. This integration enabled us to design interactive dashboards and visualisations for thorough data exploration and analysis. Vital data preprocessing tasks were executed in Excel before integrating the data into Power BI. This ensured that the data was both clean and ready for use.

The methodology outlined above was consistently applied to our three datasets, resulting in the creation of three distinct dashboards within our decision support system. The subsequent sections will now provide an in-depth exploration of the particulars of each dashboard.

3.1 Energy Subsidies Dashboard

Introducing hydrogen as an energy carrier requires significant infrastructure development, including hydrogen production, storage, and distribution facilities. Subsidies can help fund and expedite the development of such infrastructure, creating a supportive ecosystem for hydrogen adoption. By subsidising electricity and gas used in hydrogen production processes, governments can promote research and development in hydrogen technologies. This can lead to technological advancements and innovations that improve the efficiency and sustainability of hydrogen production methods. Hydrogen technologies, especially in the early stages, may face higher costs compared to traditional energy sources. Subsidies on electricity and gas can reduce the overall cost of hydrogen production, making it more attractive for consumers, industries, and businesses to adopt hydrogen-based solutions.

3.1.1 Data Understanding

The IEA (2022) dataset comprises comprehensive data spanning over 41 countries, detailing subsidies in million USD allocated to various energy products including oil, electricity, gas, and coal. Covering a substantial timeframe from 2010 to 2021, this dataset offers a thorough insight into the financial support provided by nations to sustain and promote energy-related sectors. With its extensive coverage and temporal scope, the IEA dataset serves as a valuable resource for analysing trends, patterns, and changes in energy subsidies across a diverse range of countries over the past decade.

3.1.2 Data Preparation & Visualisation

No major changes were needed for visualisation since the IEA's estimations of subsidies to fossil fuels are focused on those directly used by end-users or for electricity generation (IEA, 2022). Power Query's pivot functionalities were utilized for data preparation and transformation during the project.

Visualisation enables descriptive analytics. Leveraging the subsidy-by-country database, our goal is to underscore substantial subsidies allotted by each country for electricity and gas. A line chart is utilized to visualize subsidies provided by each country across years and products. The analysis of subsidies' year-wise data spanning from 2010 to 2022 can facilitate the tracking of countries' increasing interest and commitment towards endorsing environmentally sustainable energy sources.

Furthermore, a table is presented, encompassing all values, along with a scatter plot that highlights the top 10 countries offering subsidies in energy products. Filters for year and products are incorporated for refined data exploration.

3.2 Hydrogen Consumption Estimation Dashboard

The IEA's dataset, crafted to monitor advancements in low-carbon hydrogen technology, offers a valuable resource for estimating hydrogen consumption. Covering global projects initiated since 2000 for energy and climate-change-mitigation purposes, its broad scope and historical span enable a comprehensive understanding of hydrogen usage trends. With diverse project types, a focus on climate change mitigation, and the authoritative backing of the IEA, this dataset serves as a reliable foundation for accurate hydrogen consumption estimation.

3.2.1 Data Understanding

The datasets, provided in Excel by Accenture, were sourced from the esteemed International Energy Agency repository. Our initial data collection was from the IEA Hydrogen project database, outlining low-carbon hydrogen technology advancements globally since 2000. Complementary datasets were acquired from two sources to identify variables impacting hydrogen consumption for specific countries.

1. Energy data: Ritchie, Roser and Rosado (2022)
2. GDP annual growth data: World Bank (2023)

Table 1 from Ritchie, Roser, and Rosado (2022) provides comprehensive data on various factors related to energy consumption, generation, and environmental impact for different countries over the years. It serves as predictors for analysing trends and patterns in hydrogen energy usage.

Variables	Description
Country	The name of the country
Year	The year of the data observation
Population	The population of the country (in Numbers)
Electricity Demand	The amount of electricity demand in the country (in TWh)
Electricity Generation	The amount of electricity generated in the country (in TWh)

Gas Consumption	The consumption of gas in the country (in TWh)
Greenhouse Gas Emission	The amount of greenhouse gas emissions in the country (Million tonnes of CO_2)
Low Carbon Consumption	The consumption of low-carbon energy sources in the country (in TWh)
Net Electricity Imports	The net amount of electricity imported by the country. (in TWh)
Solar Consumption	The consumption of solar energy in the country (in TWh)
Wind Consumption	The consumption of wind energy in the country (in TWh)
GDP	The country's Gross Domestic Product (annual growth %)

Table 1. Hydrogen Consumption Estimation Predictors (TWh: Tera-watt hour)

3.2.2 Data Preparation

Data preparation plays a pivotal role in the training of machine learning models, as it significantly influences the quality of outcomes. To ensure robust and accurate results, a systematic data preparation process was meticulously executed for multiple datasets extracted from diverse excel files. This process commenced by identifying pertinent datasets and collating excel files from multiple reputable sources. Subsequently, an exhaustive data preparation procedure was conducted within Microsoft Excel. This encompassed the meticulous handling of missing values and the creation of supplementary variables essential for precise hydrogen estimation.

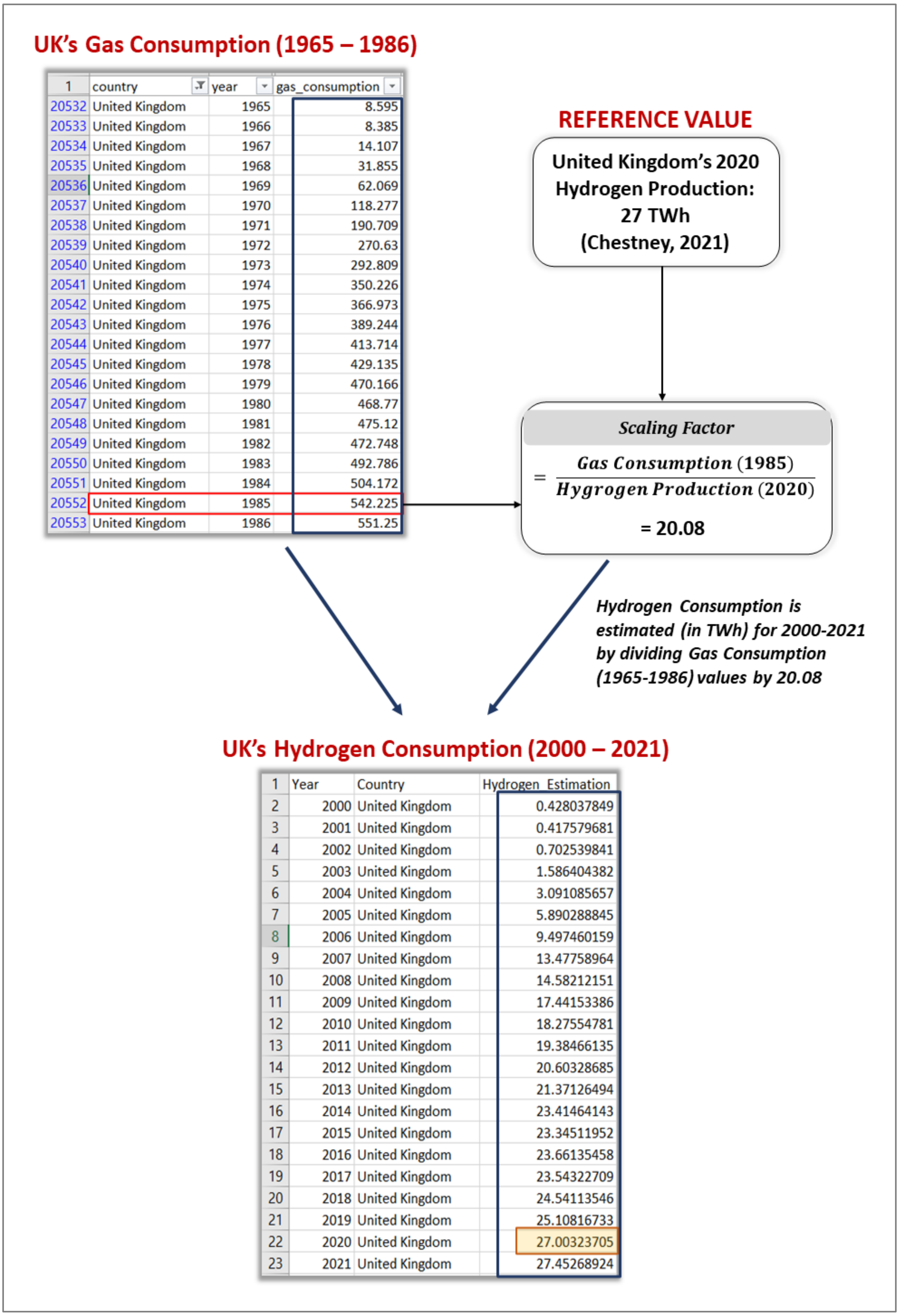
Our data manipulation approach adhered to a structured methodology, encompassing the following steps:

- **Streamlined Data Manipulation via Excel's Power Query:** Excel's Power Query functionality was utilised to optimise intricate data manipulation tasks, thereby enhancing accuracy and maintaining uniformity.
- **Integration of GDP Annual Growth with Energy Data:** The integration of GDP Annual Growth and Energy data was executed using the VLOOKUP function. This process seamlessly replaced the annual growth percentage with million USD, thereby transforming the dataset's information context.

- **Generation of GDP Forecast Data:** Projections for GDP from 2022 to 2040 were forecasted using Excel's Linear forecast function. This allowed us to gain insights into GDP trends for various countries beyond the present timeframe.
- **Scaling of LNG Consumption Dataset for Enhanced Hydrogen Estimation (2000-2021):** In the absence of a dedicated dataset detailing hydrogen consumption spanning the years 2000 to 2021, a systematic methodology was employed. This method involved cross-referencing the hydrogen consumption data of each respective country for the year 2021, or the nearest available year, in order to establish a scaling factor. Subsequently, this scaling factor was applied to the liquefied natural gas (LNG) consumption records from the period between 1965 and 1986. This adjustment effectively rendered the data appropriate for the estimation of hydrogen consumption. The procedural flow for the United Kingdom's case is visually represented in Figure 9, exemplifying the systematic approach. Analogously, this process was replicated for other nations as well. The scaling factors utilised for various countries are listed in Table 2.

Country	**Hydrogen Consumption in 2021 (TWh)**	**Time period (LNG)**	**Scaling Factor**
United Kingdom	27 (Chestney, 2021)	1965-1986	20.08
United States	330 (Shearman & Sterling LLP, 2021)	1965-1987	13.26
Germany	55 (www.bakermckenzie.com, 2021)	1965-1988	10.6
France	29.7 (www.businessfrance.fr, 2023)	1965-1989	9.68
China	825 (Global Hydrogen Flows, 2022)	1965-1991	0.158
India	231 (Global Hydrogen Flows, 2022)	1965-1992	0.261
Ireland	0.363 (Tracey, 2023)	1978-1999	96.21
Norway	277.2 (FUEL CELLS AND HYDROGEN OBSERVATORY Chapter 2 2021 Hydrogen supply and demand, 2021)	1977-1998	0.1425
World	3102 (IEA, 2022)	1965-1990	5.29

Table 2. Hydrogen Consumption Scaling for World and 8 countries



1	country	year	gas_consumption
20532	United Kingdom	1965	8.595
20533	United Kingdom	1966	8.385
20534	United Kingdom	1967	14.107
20535	United Kingdom	1968	31.855
20536	United Kingdom	1969	62.069
20537	United Kingdom	1970	118.277
20538	United Kingdom	1971	190.709
20539	United Kingdom	1972	270.63
20540	United Kingdom	1973	292.809
20541	United Kingdom	1974	350.226
20542	United Kingdom	1975	366.973
20543	United Kingdom	1976	389.244
20544	United Kingdom	1977	413.714
20545	United Kingdom	1978	429.135
20546	United Kingdom	1979	470.166
20547	United Kingdom	1980	468.77
20548	United Kingdom	1981	475.12
20549	United Kingdom	1982	472.748
20550	United Kingdom	1983	492.786
20551	United Kingdom	1984	504.172
20552	United Kingdom	1985	542.225
20553	United Kingdom	1986	551.25

1	Year	Country	Hydrogen_Estimation
2	2000	United Kingdom	0.428037849
3	2001	United Kingdom	0.417579681
4	2002	United Kingdom	0.702539841
5	2003	United Kingdom	1.586404382
6	2004	United Kingdom	3.091085657
7	2005	United Kingdom	5.890288845
8	2006	United Kingdom	9.497460159
9	2007	United Kingdom	13.47758964
10	2008	United Kingdom	14.58212151
11	2009	United Kingdom	17.44153386
12	2010	United Kingdom	18.27554781
13	2011	United Kingdom	19.38466135
14	2012	United Kingdom	20.60328685
15	2013	United Kingdom	21.37126494
16	2014	United Kingdom	23.41464143
17	2015	United Kingdom	23.34511952
18	2016	United Kingdom	23.66135458
19	2017	United Kingdom	23.54322709
20	2018	United Kingdom	24.54113546
21	2019	United Kingdom	25.10816733
22	2020	United Kingdom	27.00323705
23	2021	United Kingdom	27.45268924

Figure 9. UK's Hydrogen Estimation Process Flow

To uphold the dataset's integrity and cohesiveness, a meticulous approach was employed to address missing values:

- **Rectification of Missing Values:** Numerical variables containing missing values underwent a systematic replacement with '0', thereby ensuring uniformity for subsequent analyses.
- **Refinement of Countries with Incomplete GDP Values:** Countries characterised by incomplete GDP values were judiciously excluded from the dataset, bolstering the dependability of the data.
- **Exclusion of Countries without Hydrogen Consumption Data (2000-2021):** To maintain data coherence, deliberate omission was made of countries lacking documented hydrogen consumption data for the period 2000 to 2021.
- **Data Cleansing of the Country Column:** All extraneous entries within the country column were scrupulously eliminated to align the dataset precisely with our analytical objectives.

3.2.3 Modelling using Regression

In the modelling phase, the algorithm was implemented using Python within Power Query (Refer Appendix for Code). Employing Multivariate analysis encompassing multiple linear regression with Ordinary Least Squares (OLS), the objective was to predict the hydrogen consumption trend spanning from 2022 to 2040, based on actual data from 2000 to 2021. The accuracy of predictors for the target variable was ensured through the utilisation of the correlation matrix and p-value method.

Correlation Matrix

A correlation matrix provides insights into how variables are related to each other (wagavkar, 2021). In the context of our hydrogen consumption prediction problem, the correlation matrix will help to understand the relationships between the predictors (input features) and the target variable (hydrogen consumption). The provided correlation matrix allows for several inferences to be drawn:

- **Strong Positive Correlation with Target Variable (Hydrogen Consumption):** Variables including electricity demand, electricity generation, gas consumption, greenhouse gas emissions, and low carbon consumption exhibit robust positive correlations with the target variable hydrogen consumption, each having an approximate value of 0.99. This signifies that higher values in these variables are associated with increased hydrogen consumption.

- **Low to No Correlation:** Variables Year and 'net_elec_imports' display minimal to negligible correlation with most other variables, including the target variable, with a correlation coefficient approximating 0.

Based on the identified correlations, the study contemplates the selection of predictors with pronounced positive correlations. Techniques such as feature selection or regularisation are being explored to elevate the model's predictive performance for hydrogen consumption estimation.

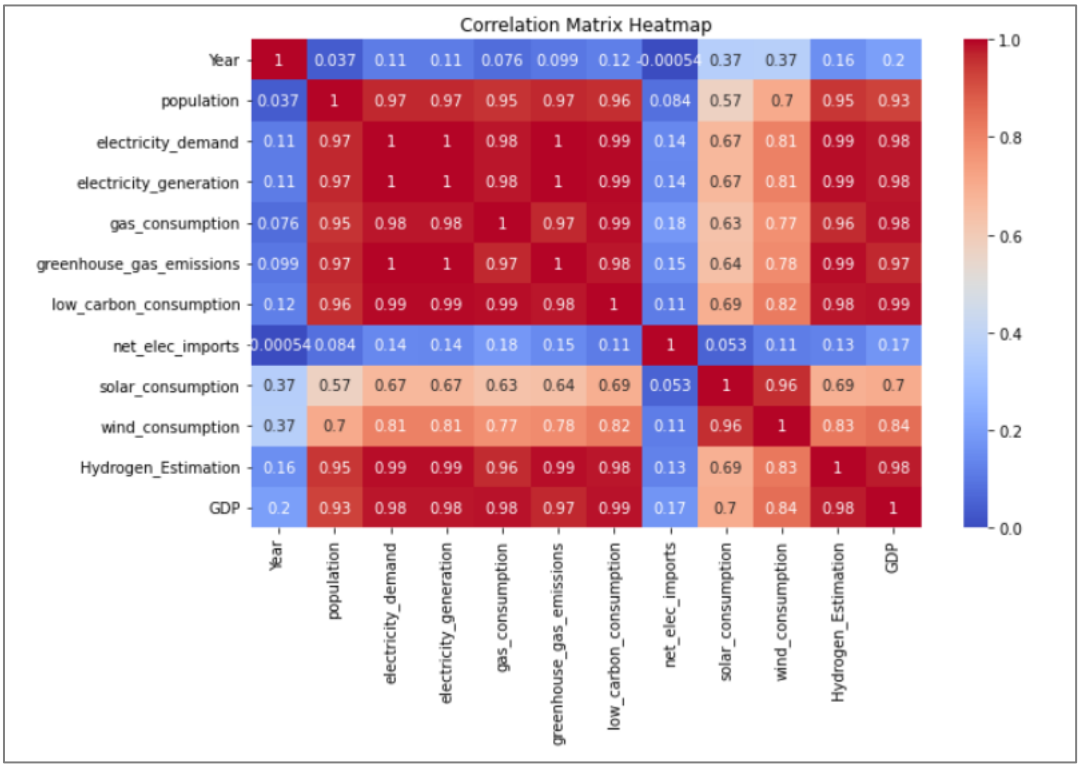


Figure 10. Correlation Matrix Heatmap for Predictors

p-value:

The p-value assumes a pivotal role in statistical analysis by assessing the significance of predictors within a regression model. It quantifies the likelihood that a predictor's coefficient is zero, implying its insignificance in relation to the target variable. A lower p-value typically signifies a predictor's statistical importance and substantive impact on the target variable (Saxena, 2020).

The regression analysis conducted yields crucial insights into the significance of predictors for hydrogen consumption prediction. Notably, variables such as electricity generation, gas consumption, greenhouse gas emissions, and low carbon consumption exhibit robust statistical significance (p-values < 0.001), indicating their substantial influence on hydrogen consumption. These variables are anticipated to exert considerable impact on hydrogen consumption dynamics. Furthermore, electricity demand demonstrates significance (p-value = 0.021), suggesting its role in influencing hydrogen consumption patterns.

In contrast, predictors like net electricity imports, solar consumption, wind consumption, and GDP display elevated p-values, implying a comparatively weaker impact on hydrogen consumption. The population predictor also demonstrates significance (p-value = 0.001), underlining its contribution to hydrogen consumption trends. While the year predictor possesses a p-value of 0.821, indicating limited influence, the constant term holds statistical significance, representing a baseline hydrogen consumption level.

Predominantly, predictors with p-values below the conventional significance threshold of 0.05 are generally acknowledged as statistically significant within the model.

Predictors	**p-value**
Year	0.8206
Population	0.0006
Electricity Demand	0.0206
Electricity Generation	0.0000
Gas Consumption	0.0000
Greenhouse Gas Emissions	0.0000
Low Carbon Consumption	0.0000
Net Elec Imports	0.0613
Solar Consumption	0.5971
Wind Consumption	0.1028
GDP	0.9479

Table 3. p-values of the predictors

Additionally, GDP data for 2022 to 2040 was forecasted, enriching the dataset with these predictions as predictors. The dataset was partitioned into two subsets:

- Training Data: Years <= 2021.
- Test Data: Years > 2021.

Linear regression was performed individually for each country, entailing the construction and fitting of models on the training data, followed by predictions on the test data. The model's performance evaluation employed key metrics, namely R-squared (R^2) and Root Mean Squared Error (RMSE) Value, for assessing accuracy on a per-country basis, thereby facilitating a comprehensive appraisal of predictive capabilities.

Regularisation Technique - A regularisation technique was applied, with the alpha value employed to determine the optimal level for predicting accuracy metrics such as R^2 and RMSE for each country.

3.2.4 Modelling using MLP (Multi-layer Perceptron)

In this phase, specialised techniques are employed to project future trends for a specific country. Firstly, values of different predictors from 2022 to 2040 are forecasted using Facebook Prophet time series analysis. The dataset is bifurcated into two segments:

- Training Data (Year <= 2021)
- Test Data (Year > 2021)

Subsequently, these projected values are applied to estimate forthcoming hydrogen consumption (the primary focus) using MLP regression methodology. Finally, the actual and estimated hydrogen consumption values for that country from 2000 to 2040 are plotted. The model's performance evaluation utilises key metrics such as R-squared (R^2) and Root Mean Squared Error (RMSE) Value, ensuring a comprehensive assessment of predictive accuracy for each country.

3.2.5 Visualisation

Within our dashboard, a comprehensive visualisation is presented, elucidating the hydrogen consumption trends across ten distinct countries. This encompassing representation includes both historical actual data spanning from 2000 to 2021 and our forward-looking forecasting projections extending from 2022 to 2040.

3.3 European National Natural Gas Pipeline Network Dashboard

In the future, when hydrogen exportation occurs, it will be facilitated either through trucks or pipelines. Therefore, by examining pipelines as a potential solution, insights can be gained into the movement of LNG between countries and the evolving nature of trade. This analysis is intricate to model using machine learning without a reference for understanding how energy is physically transferred, as both gases adhere to the same fundamental principles of physics, despite hydrogen's greater complexity.

3.3.1 Data Understanding

The Gas Trade Flows (GTF) data service has been meticulously structured to enhance transparency within the natural gas markets. This complimentary service draws upon a data collection system meticulously established by the IEA, with a primary focus on comprehensively encapsulating the European natural gas network. This encompassing network includes both physical pipeline flows and LNG, meticulously documented through entry points. The dataset is meticulously enriched with precise details encompassing entry border points, the distinct names of countries functioning as both entry and exit points for various segments of the intricate route, and meticulously quantified gas flow values expressed in Million-meter cube per hour (Mm^3/h). The temporal scope of the dataset spans from October 2008 to March 2023, thoughtfully organised in a systematic monthly format.

3.3.2 Data Preparation

The dataset (GitHub, n.d.) underwent enhancement through the incorporation of geographical coordinates for all countries, a strategic augmentation aimed at harnessing the capabilities of the iconmapv3 extension within Power BI. This deliberate enrichment not only provides a visually engaging representation of data but also offers spatial context to the gas trade dynamics.

The utilisation of the iconmapv3 (www.icon-map.com, n.d.) extension in Power BI delivers distinct advantages for insights and analysis. It empowers analysts to geographically visualise gas trade flows, depicting both entry and exit points with precision.

For dataset preparation, a comprehensive set of measures have been meticulously crafted and integrated, aimed at offering a nuanced understanding of the gas trade dynamics. This includes the determination of the "Net Consumer or Net Supplier Status," calculated through a structured variance analysis approach. Moreover, the "Net Consumer or Net Supplier Value" has been meticulously calculated to quantify the extent of consumption or supply disparities. These refined measures have been thoughtfully implemented to enhance insights and facilitate informed decision-making within the domain of gas trade analysis.

3.3.3 Visualisation

Upon selecting a specific country, the DSS enables analysts to visually determine the country's role as either a net supplier or consumer within the intricate trade flow network, with a comprehensive overview of total gas flow measured in Mm^3/h. This functionality is accompanied by the flexibility to seamlessly toggle between entry and exit point analyses, providing insights into whether the country functions as a gas entry or exit point.

The column chart component showcases an array of countries intrinsically linked to the selected country, depicting both the origins and destinations of gas flow. This dynamic visualisation elucidates the countries through which gas flows into and out of the selected nation.

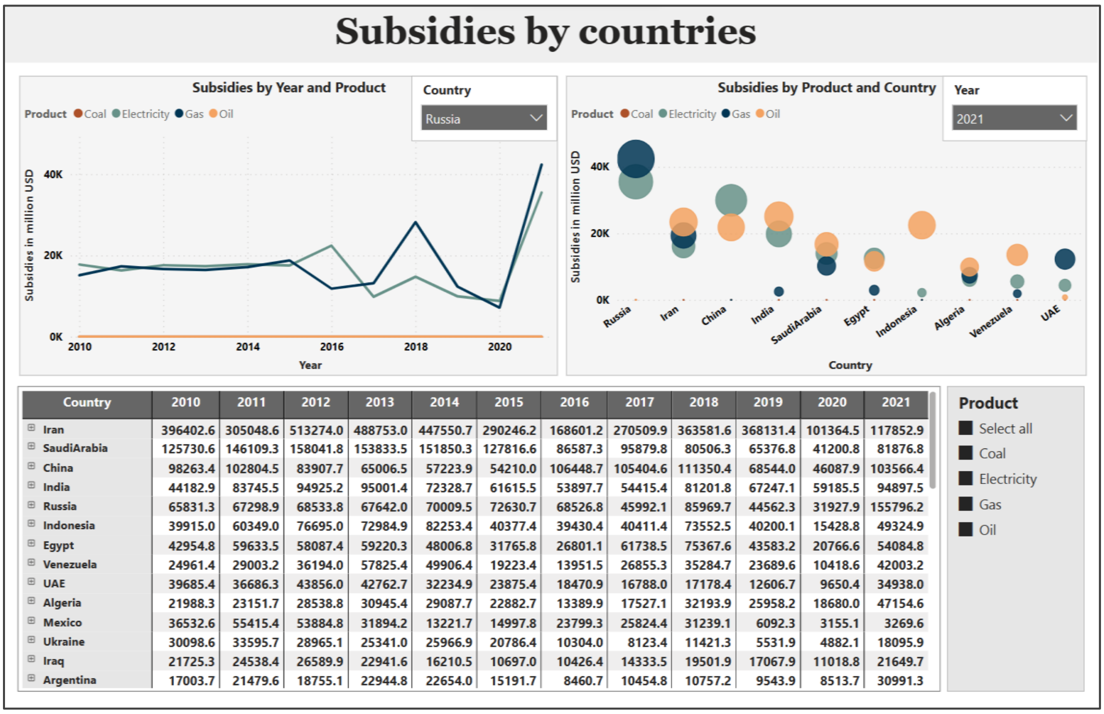
Additionally, the integration of the iconmapv3 feature elevates the visualisation capabilities by illustrating the interconnectedness of countries within the trade route. This spatial representation further enriches the analysis, offering a holistic understanding of the complex web of gas trade dynamics and fostering nuanced insights for well-informed decision-making.

Chapter 4 - Result & Inference

Please find the link to the dashboard - [Capstone_Dashboard - Power BI]

4.1 Energy Subsidies Dashboard

Energy Subsidies Dashboard (Figure 11) was utilised for descriptive analytics. Insights are derived from the subsidy by country database, revealing noteworthy allocations of subsidies for electricity and gas. Our focus was identifying top 10 countries (Scatter Plot from Figure 11) heavily investing in these sectors, indicating their interest in hydrogen production and its potential benefits. This suggests that these nations are actively exploring hydrogen's opportunities for their economies. Top 10 countries investing heavily in electricity and gas in 2021 can be seen in Table 4.



Country	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Iran	396402.6	305048.6	513274.0	488753.0	447550.7	290246.2	168601.2	270509.9	363581.6	368131.4	101364.5	117852.9
SaudiArabia	125730.6	146109.3	158041.8	153833.5	151850.3	127816.6	86587.3	95879.8	80506.3	65376.8	41200.8	81876.8
China	98263.4	102804.5	83907.7	65006.5	57223.9	54210.0	106448.7	105404.6	111350.4	68544.0	46087.9	103566.4
India	44182.9	83745.5	94925.2	95001.4	72328.7	61615.5	53897.7	54415.4	81201.8	67247.1	59185.5	94897.5
Russia	65831.3	67298.9	68533.8	67642.0	70009.5	72630.7	68526.8	45992.1	85969.7	44562.3	31927.9	155796.2
Indonesia	39915.0	60349.0	76695.0	72984.9	82253.4	40377.4	39430.4	40411.4	73552.5	40200.1	15428.8	49324.9
Egypt	42954.8	59633.5	58087.4	59220.3	48006.8	31765.8	26801.1	61738.5	75367.6	43583.2	20766.6	54084.8
Venezuela	24961.4	29003.2	36194.0	57825.4	49906.4	19223.4	13951.5	26855.3	35284.7	23689.6	10418.6	42003.2
UAE	39685.4	36686.3	43856.0	42762.7	32234.9	23875.4	18470.9	16788.0	17178.4	12606.7	9650.4	34938.0
Algeria	21988.3	23151.7	28538.8	30945.4	29087.7	22882.7	13389.9	17527.1	32193.9	25958.2	18680.0	47154.6
Mexico	36532.6	55415.4	53884.8	31894.2	13221.7	14997.8	23799.3	25824.4	31239.1	6092.3	3155.1	3269.6
Ukraine	30098.6	33595.7	28965.1	25341.0	25966.9	20786.4	10304.0	8123.4	11421.3	5531.9	4882.1	18095.9
Iraq	21725.3	24538.4	26589.9	22941.6	16210.5	10697.0	10426.4	14333.5	19501.9	17067.9	11018.8	21649.7
Argentina	17003.7	21479.6	18755.1	22944.8	22654.0	15191.7	8460.7	10454.8	10757.2	9543.9	8513.7	30991.3

Figure 11. Energy Subsidies Dashboard

Insights are garnered through descriptive analytics using the subsidy by country database, revealing noteworthy allocations of subsidies for electricity and gas. Our focus was identifying top 10 countries heavily investing in these sectors, indicating their interest in hydrogen production and its potential benefits. This suggests that these nations are actively exploring hydrogen's opportunities for their economies.

Country	Gas Subsidies in 2021 (in million USD)	Electricity Subsidies in 2021 (in million USD)
Russia	7,163.2	35,509.2
Iran	19,355.4	16,148.9
China	-	29,968.3
Saudi Arabia	10,241.7	13,971.8
India	2,517.1	19,829.3
United Arab Emirates	12,266.5	4,410.6
Egypt	2,933.9	12,489.7
Algeria	7,417.5	6,263.1
Uzbekistan	8,777.0	3,447.4
Argentina	5,470.1	6,187.0

Table 4. Top 10 Countries in gas and electricity subsidies in 2021

The inference from this descriptive analytic highlight the purpose of subsidies for electricity and gas. They play a crucial role in promoting clean and sustainable energy solutions like hydrogen. These subsidies strategically accelerate the adoption of hydrogen-based technologies, breaking initial barriers. The reasons for providing these subsidies include:

- **Facilitating Transition:** These subsidies encourage countries to adopt hydrogen, positioning them as leaders in a sustainable energy shift. Strategic policies and investments enable them to tap into hydrogen's potential, driving cleaner, more secure, and economically robust futures.
- **Economic Growth:** Supporting hydrogen technologies enhances economic growth by creating new industries, job opportunities, and innovation. Subsidies stimulate private sector involvement, fostering economic resilience.
- **Environmental Benefits:** Subsidies drive the development of low-carbon technologies, reducing greenhouse gas emissions and pollution. This aligns with international climate commitments and bolsters countries' sustainability goals.

- **Energy Security:** Hydrogen reduces dependency on fossil fuels, enhancing energy security and resilience against supply disruptions. Subsidies promote self-sufficiency in energy production.
- **Technological Advancement:** Financial support accelerates research and development in hydrogen-related technologies, spurring breakthroughs and establishing technological leadership.
- **Global Competitiveness:** Countries investing in hydrogen gain a competitive advantage in emerging global hydrogen markets, fostering international collaboration and trade.

In conclusion, the descriptive analytics from our BDSS emphasises that subsidies for electricity and gas propel the transition to hydrogen, offering multiple benefits that extend beyond energy to economic, environmental, and strategic advantages.

4.2 Hydrogen Consumption Estimation Dashboard

A dashboard snippet (Figure 12) has been attached, illustrating the actual hydrogen consumption values from 2000 to 2021 and the projected values from 2022 to 2040 for the United Kingdom. These projections have been generated through the utilisation of both OLS (a linear regression model) and MLP (a neural network model). Similar visual representations for other countries are also accessible within the decision support system.

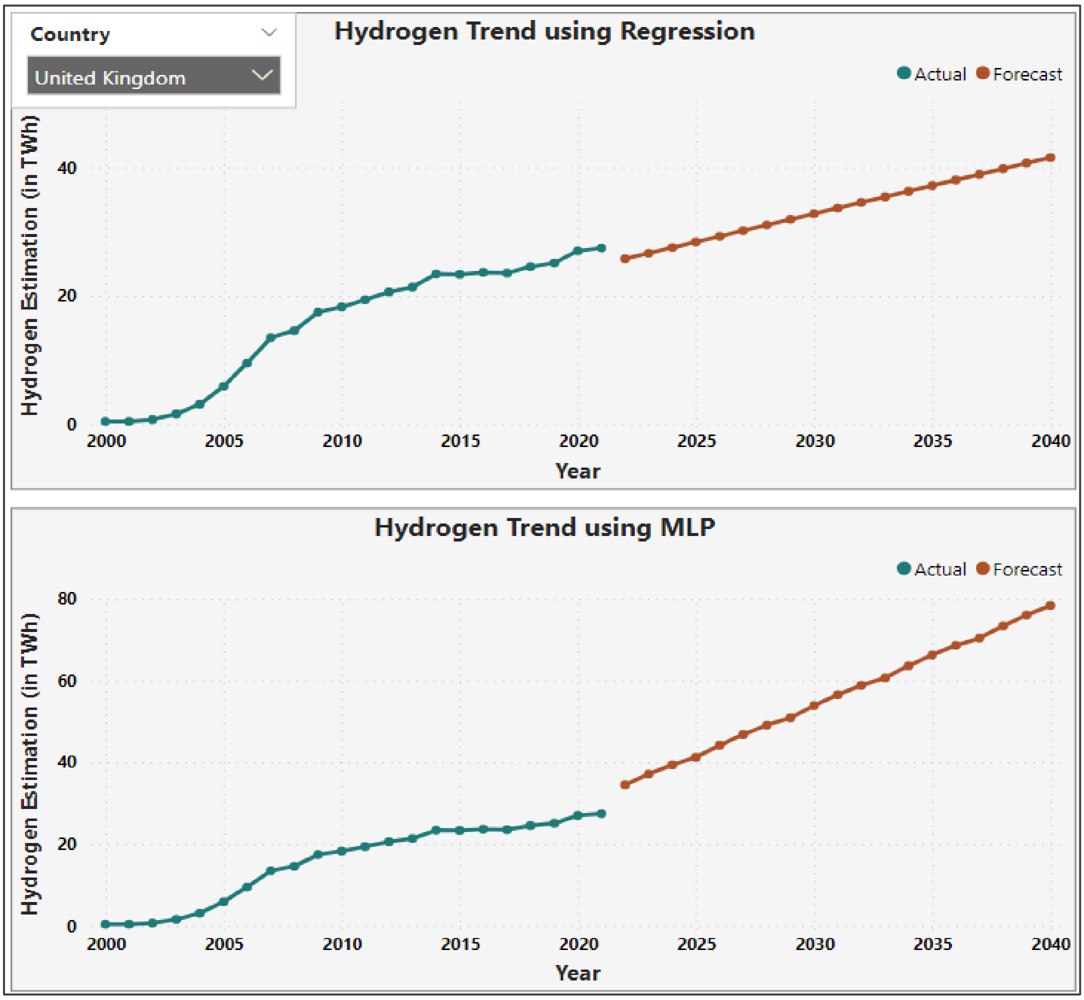


Figure 12. Hydrogen Consumption Estimation for the United Kingdom

Year	Actual Values (in TWh)	Year	OLS Predicted Values (in TWh)	MLP Predicted Values (in TWh)
2000	0.4280	2022	25.7705	32.9626
2001	0.4176	2023	26.6485	35.7210
2002	0.7025	2024	27.5266	38.2694
2003	1.5864	2025	28.4046	39.6933
2004	3.0911	2026	29.2825	42.6855
2005	5.8903	2027	30.1605	45.4555
2006	9.4975	2028	31.0386	48.0033
2007	13.4776	2029	31.9166	49.4272
2008	14.5821	2030	32.7945	52.4200
2009	17.4415	2031	33.6725	55.1900
2010	18.2755	2032	34.5505	57.7353

2011	19.3847	2033	35.4286	59.1592
2012	20.6033	2034	36.3065	62.1520
2013	21.3713	2035	37.1845	64.9202
2014	23.4146	2036	38.0625	67.4637
2015	23.3451	2037	38.9406	68.8876
2016	23.6614	2038	39.8185	71.8805
2017	23.5432	2039	40.6965	74.6487
2018	24.5411	2040	41.5745	77.1920
2019	25.1082			
2020	27.0032			
2021	27.4527			

Table 5. UK Hydrogen Consumption actual and predicted value using OLS and MLP

The linear pattern (Figure 12) and tabulated information (Table 5) regarding hydrogen consumption (measured in TWh) through multi-linear regression and Multi-Layer perceptron (neural network model) illustrate the factual data encompassing the timeframe from 2000 to 2021, alongside our anticipated projections extending from 2022 to 2040.

Country	OLS R-Squared	OLS RMSE	MLP R-Squared	MLP RMSE
Germany	0.8964	5.3161	-14.1927	3.3709
UK	0.9924	0.7721	-0.4778	1.4935
India	0.9168	39.3398	0.6721	34.4978

Table 6. Performance Metric for OLS and MLP

The analysis in Table 6 reveals compelling insights into the performance of Ordinary Least Square (OLS) and Multiple Layer Perceptron (MLP) models in predicting Hydrogen Estimation for different countries. OLS emerges as the superior predictor for most countries, showcasing higher R-squared values, signifying better explanatory power, and lower RMSE, indicative of reduced prediction errors.

In the evaluation process, the sklearn library has been employed to appraise the model's performance, with a primary focus on the R^2 value, a critical metric. The R^2 value, also known as the coefficient of determination, usually falls within the range of 0 to 1. This range signifies the proportion of variance in the dependent variable that the model accounts for. Interestingly, our analysis has led to a unique scenario where the calculated R^2 value is negative. According to sklearn's documentation (scikit-learn.org, n.d.), a negative R^2 value in this context indicates that the model's predictive abilities are performing even worse than a basic horizontal line, which would simply predict the mean of the dependent variable for all instances. This observation highlights a significant disparity between our model's predictions and the actual data points. Notably, this negative R^2 value serves as a clear indicator that our current model is insufficient in effectively capturing the inherent patterns and fluctuations within the dataset. Moreover, it's worth mentioning that while the R^2 value for the MLP model is negative, the R^2 value for the OLS model is positive. This distinction underscores that the OLS model provides a better fit for our dataset compared to the MLP model, indicating its superior ability to capture the underlying trends and relationships present in the data.

Notably, the United Kingdom (UK) stands out in its predictive capabilities, excelling both with OLS and MLP. This suggests that the models effectively capture the intricate relationships influencing hydrogen consumption trends in the UK. The utilisation of both modelling techniques appears to enhance the accuracy of predictions, underscoring the significance of a comprehensive approach to estimation.

Examining the forecasting trend of hydrogen consumption data from 2022 to 2040 offers countries a valuable tool for making informed decisions in several critical areas.

- **Energy Planning:** Understanding the projected trends in hydrogen consumption can aid in long-term energy planning. Countries can assess the expected demand for hydrogen and strategise investments in production, distribution, and infrastructure accordingly.
- **Policy Formulation:** Insights from the forecasting trend can guide policy decisions related to energy transition and sustainability. Governments can tailor policies to incentivise the adoption of cleaner energy sources, potentially reducing carbon emissions and supporting climate goals.
- **Investment Strategies:** Businesses and investors can utilise the projected hydrogen consumption trends to make informed investment decisions. Whether in hydrogen production technologies, supply chain development, or research initiatives, this data can help allocate resources more effectively.

4.3 European National Natural Gas Pipeline Network Dashboard

The two figures (Figure 13 & 14) depict the dashboard for Germany (among several countries) as both entry point and exit point analyses. The analysis of Germany's Natural Gas Pipeline Network highlights its dual role as both a significant importer and exporter of natural gas within Europe. It serves as a key hub for gas trade, facilitating energy exchange among connected nations. This underscores Germany's pivotal position in promoting cooperation and energy security within the region.

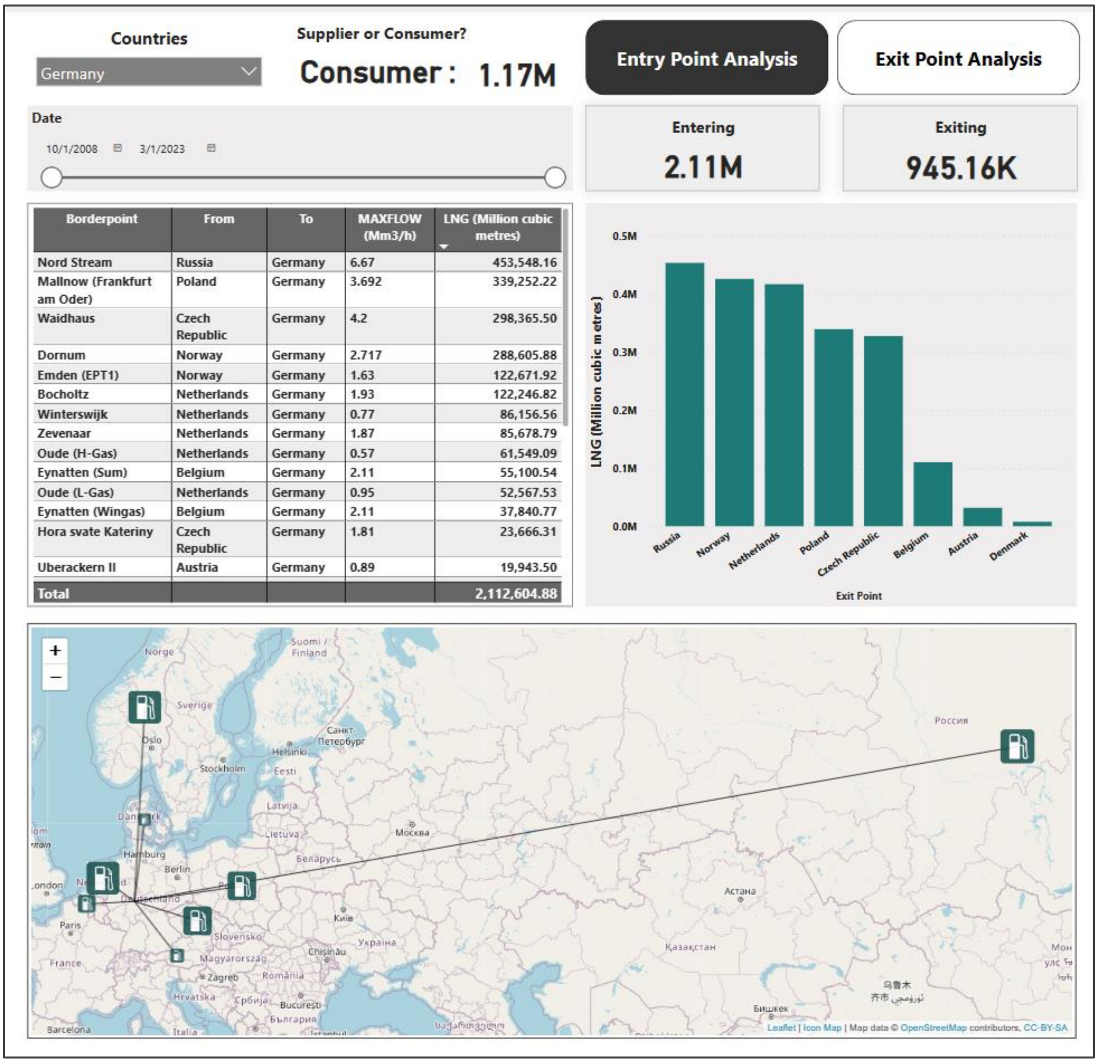


Figure 13. European National Gas Pipeline Network - Entry Point Analysis

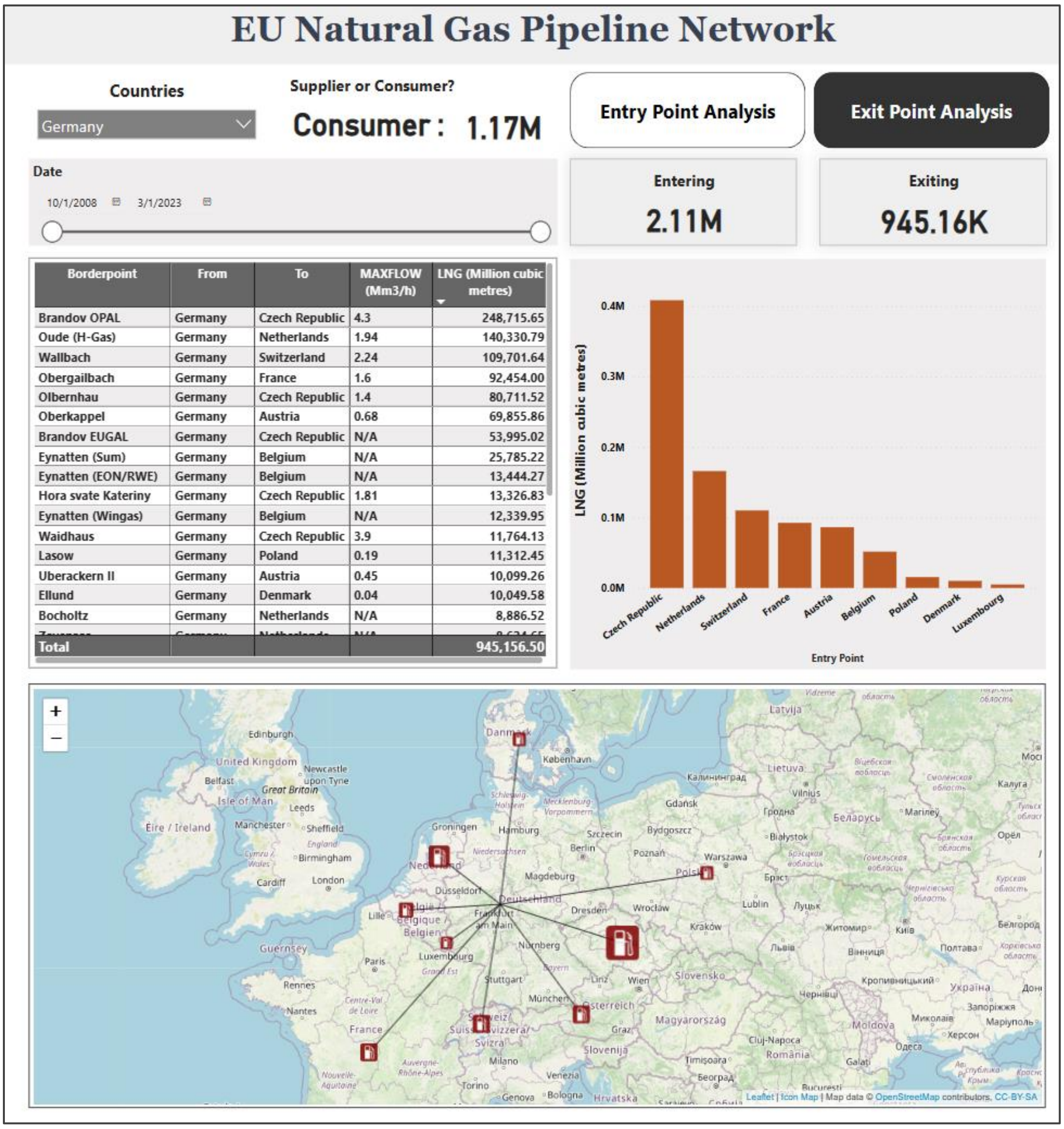


Figure 14. European National Gas Pipeline Network - Exit Point Analysis

Analysing the EU gas pipeline network provides a structured approach to understanding its implications for hydrogen production. This analysis unveils critical insights that can be categorised as follows:

- **Consumer-Supplier Dynamics:** Studying the network helps identify nations that are substantial consumers and those with access to natural gas resources. This combination indicates the potential for hydrogen production through various methods.
- **Utilising Existing Infrastructure:** Countries with surplus natural gas can strategically consider repurposing existing infrastructure for hydrogen production. This approach capitalises on established systems and minimises logistical challenges.

- **Proximity and Logistics:** The proximity of countries to consumers and established transportation routes offers an advantage in hydrogen production. This reduces logistical complexities and streamlines the distribution process.
- **Strategy for Gas-Importing Nations:** For countries reliant on gas imports, devising well-thought-out strategies for hydrogen sourcing becomes imperative. These nations can leverage the analysis to plan their hydrogen production approach.
- **Infrastructural Alignment:** The analysis effectively informs whether the necessary infrastructure, resources, and market conditions align favourably for hydrogen production. This evaluation empowers countries to make educated decisions about their prospects in the emerging hydrogen economy.

In essence, by assessing the dynamics between consumers and suppliers within the gas pipeline network, the hydrogen production potential based on natural gas accessibility becomes evident. This evaluation allows surplus gas nations to leverage existing infrastructure, thus minimising barriers to production. Conversely, countries heavily reliant on gas imports can strategise their hydrogen-sourcing approach. The comprehensive analysis considers infrastructure, resources, and market conditions, offering invaluable guidance for informed decisions in shaping a resilient hydrogen economy.

Supplier Countries	**LNG (Million cubic meters)**	**Consumer Countries**	**LNG (Million cubic meters)**
Russia	1674172.288	**Germany**	1167448.375
Norway	1489734.773	**Italy**	949412.472
Belarus	512143.571	**France**	615414.657
Algeria	276845.677	**Turkey**	609265.311
Netherlands	239494.180	**United Kingdom**	439108.885

Table 7. Top 5 Suppliers & Consumers from Jan 2022-Mar 2023

The provided Table 7 offers insights into the top 5 countries in LNG (liquefied natural gas) pipeline networks operating within Europe during the period from January 2022 to March 2023. The data highlights the exchange of LNG volumes between countries within this network.

Notably, Norway emerges as a significant LNG supplier, contributing 131,969.33 million cubic meters to the pipeline network. Following closely, Russia supplies 53,490.641 million cubic meters of LNG. On the consumer side, Germany takes the lead with an intake of 127,489.166 million cubic meters, showcasing its substantial demand within this specific pipeline network. Italy and France also feature as significant consumers, utilising 80,472.468 million cubic meters and 51,958.555 million cubic meters of LNG, respectively.

It's important to note that the terms "consumer" and "supplier" pertain specifically to this pipeline network. The data underscores the intricate energy relationships within this network, as various countries collaborate to meet their energy requirements. This snapshot provides valuable insights into the regional dynamics of LNG distribution, which plays a crucial role in ensuring a consistent and reliable energy supply for these specific European nations.

Chapter 5 - Conclusion

The global energy crisis sparked by the Russia's invasion of Ukraine has accelerated the momentum. Many governments, particularly in Europe, are looking at low-emission hydrogen as a way to reduce dependency on fossil fuels. It offers opportunities to simultaneously contribute to decarbonisation targets and to enhance energy security. Both the OLS and MLP models exhibit strong predictive capabilities for Ireland's hydrogen consumption estimation, with the OLS emphasising a high R-squared and low RMSE, and the MLP excelling in low RMSE despite a negative R-squared. After predicting the vales of hydrogen consumption until 2040, Ireland can analyse its situation with similar countries and work on providing appropriate/suitable subsidies on electricity and gas to lower the hydrogen production costs. Furthermore, with the availability of an abundance of wind and solar energy, Ireland can generate electricity using these renewable resources, which in turn should lower electricity costs (even for the general public and not just for winter months) to produce more hydrogen, thus accelerating the momentum towards green hydrogen. Analysis of gas flow dynamics reveals Germany's role as a significant consumer, indicating its potential as an export destination for Ireland's surplus hydrogen.

This initial exploration is a crucial step towards achieving improved transparency in the Hydrogen market and understanding its dynamics. In essence, the journey towards a greener energy landscape is marked by multifaceted approaches that interweave predictive modelling, strategic policy interventions, and renewable energy integration. By embracing these strategies, countries can position themselves at the forefront of the sustainable energy movement, contributing to global decarbonization goals while securing a more resilient energy future.

The future scope of the Business Decision Support System (BDSS) holds tremendous potential for expansion and enhancement. With the availability of additional data, the system can venture into a range of promising avenues to further amplify its capabilities. The neural network model (Multi-Layer Perceptron) could undergo rigorous refinement, resulting in heightened performance levels. By incorporating data from diverse countries, the model's predictive scope could extend to encompass their respective hydrogen consumption trends. The integration of a robust date hierarchy within the hydrogen data would facilitate intricate seasonal analysis, providing deeper insights into consumption patterns for more effective production and distribution strategies. Furthermore, the inclusion of hydrogen consumption estimates from a broader array of countries, particularly for the year 2021, could enhance the LNG dataset's applicability to hydrogen-related insights. This comprehensive approach would unveil the interplay between hydrogen consumption and LNG trade, shedding light on substitution effects and their implications for the energy sector. Accessing subsidy data for energy products across EU countries would enable a comprehensive assessment of how subsidies influence policy decisions and industrial practices in favour of cleaner energy sources, offering guidance for sustainable energy initiatives. Integrating critical mineral prices, like Nickel and Zirconium, would facilitate economic analysis and accurate price forecasting, enabling informed investment decisions and strategic planning by illuminating the cost dynamics of hydrogen production technologies. Leveraging the enriched dataset, the BDSS could assess the impact of various policy interventions on hydrogen consumption, trade, and production, empowering governments and organisations to design impactful policies for a smoother transition to cleaner energy sources. Lastly, integrating real-time data sources would enhance the BDSS's ability to provide timely insights and predictions, supporting stakeholders in making swift decisions in the dynamic energy landscape.

Appendices

1. Importing Important Libraries

```
# Importing required packages here
import numpy as np
import pandas as pd
from prophet import Prophet
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.preprocessing import StandardScaler
from sklearn.neural_network import MLPRegressor
import matplotlib.pyplot as plt
import statsmodels.formula.api as smf
import statsmodels.api as sm
import seaborn as sns
import warnings
from IPython.display import display, HTML
warnings.filterwarnings("ignore")
```

2. Correlation Matrix HeatMap Generation

```
# Loading the dataset
data = pd.read_csv('Hydrogen_Consumption_Dataset.csv')

# Calculate the correlation matrix for predictor variables
correlation_matrix = data.corr()

# Print the correlation matrix
print("Correlation Matrix:")
print(correlation_matrix)

# Create a heatmap for the correlation matrix
plt.figure(figsize=(10, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.title("Correlation Matrix Heatmap")
plt.show()

# Display the correlation table
correlation_table =
correlation_matrix.unstack().sort_values(ascending=False)
print("Correlation Table:")
print(correlation_table)
```

3. p-Value

```
# Loading the dataset
data = pd.read_csv('Hydrogen_Consumption_Dataset.csv')

#Splitting the dataset into predictors (X) and response
variable (y)
drop_col = ['Country','Key','Hydrogen_Estimation']

#Creating dataset of predictors and target variable
X = data.drop(drop_col, axis=1)
y = data['Hydrogen_Estimation']

X = X.loc[data['Year'] <= 2021]
y = y.loc[data['Year'] <= 2021]

#Adding a constant column for the intercept term
X_1 = sm.add_constant(X)

#Fitting the multiple regression (OLS) model and generating
the model summary
model = sm.OLS(y, X_1).fit()
summary = model.summary()
print(summary)

print("\n" + "*" *100 )

#Creating a DataFrame of significant predictors with p-values
less than 0.05
significant_predictors =
pd.DataFrame(model.pvalues[model.pvalues < 0.05], columns=['p-
value'])

# Displaying the significant predictors
if not significant_predictors.empty:
    display(HTML('<h3>Predictors with p < 0.05. For these
predictors, we can reject the null hypothesis H0 : βj =
0</h3>'))
    display(significant_predictors)
else:
    print("No predictors with p-values less than 0.05 were
found.")
```

4. OLS: Regression Model

```
# Splitting the data into training and test sets for model
accuracy
train_check_data = data.loc[data['Year'] <= 2021]
test_check_data = data.loc[(data['Year'] > 2017) &
(data['Year'] <= 2021)]

# Performing linear regression for each country
countries = data['Country'].unique()
print(countries)
i = 0

# Initializing an empty DataFrame to store the final results
final_df = pd.DataFrame()
```

```python
for country in countries:
    print(country)
    filter_data = data[data['Country'] == country]

    X = ['electricity_demand', 'electricity_generation',
'greenhouse_gas_emissions', 'low_carbon_consumption', 'GDP']

    # Splitting the data for the current country
    train_country =
train_check_data[train_check_data['Country'] == country]
    X_train = train_country[X]
    y_train = train_country['Hydrogen_Estimation']

    # Creating and fitting the linear regression model using
OLS while adding a constant intercept term
    X_train = sm.add_constant(X_train)
    model = sm.OLS(y_train, X_train).fit()

    # Testing the data for the current country
    test_country = test_check_data[test_check_data['Country']
== country]
    X_test = test_country[X]
    y_test = test_country['Hydrogen_Estimation']

    # Making predictions on the testing set and adding a
constant intercept term
    X_test = sm.add_constant(X_test)
    predictions = model.predict(X_test)

    #Calculating the RMSE & R-squared using the fitted model
    rmse = np.sqrt(mean_squared_error(y_test, predictions))
    r2 = model.rsquared

    #Printing the results for the current country
    print('Country:', country)
    print('Coefficients:', model.params)
    print('R2:', r2)
    print('RMSE:', rmse)
    print()

    #Creating a new DataFrame with only the desired columns
    new_df = filter_data[X].copy()

    #Splitting based on the desired index positions
    train_df = new_df.iloc[0:22]
    test_df = new_df.iloc[22:41]

    for response in X:
        predictors = 'GDP'
        f = '{} ~ {}'.format(response, predictors)
        model_b = smf.ols(formula=f, data=train_df).fit()

        # Adding the forecasted values as a new column to the
new_df DataFrame
        new_df.loc[22+i:, response] = model_b.predict(test_df)
```

```
    # Extracting the 'Hydrogen_Estimation' column from the
'data' DataFrame
    hydrogen_estimation_column =
filter_data['Hydrogen_Estimation']

    # Concatenating the 'Hydrogen_Estimation' column with the
'new_df' DataFrame
    new_df = pd.concat([filter_data[['Year', 'Country']],
new_df, hydrogen_estimation_column], axis=1)

    # Splitting based on the desired index positions
    train_df = new_df.iloc[0:22]
    test_df = new_df.iloc[22:41]

    # Assuming you have the 'Hydrogen_Estimation' column in
the 'data' DataFrame
    #and the 'new_df' DataFrame with all the predictors
(except 'Hydrogen_Estimation')
    # Specify the response variable (Hydrogen_Estimation) from
the data DataFrame
    response = 'Hydrogen_Estimation'

    # Getting the feature matrix (predictors) from the new_df
DataFrame
    predictors = new_df.drop(columns=[response, 'Year',
'Country'])

    # Creating the formula for the linear regression model
    f = '{} ~ {}'.format(response,
'+'.join(predictors.columns))

    # Fitting the model to the data
    model_b = smf.ols(formula=f, data=train_df).fit()

    # Predicting the values for 'Hydrogen_Estimation' using
the fitted model and the new_df data
    new_df.loc[22+i:, response] = model_b.predict(test_df)

    # Appending the results to the final_df DataFrame
    final_df = pd.concat([final_df, new_df])

    # Printing the updated 'new_df' DataFrame
    print(new_df)

    # Creating a DataFrame for plotting with 'Year',
'Hydrogen_Estimation', and the predicted values
    plot_df = new_df.copy()

    # Plotting the actual and predicted values with 'Year' on
the x-axis
    plt.figure(figsize=(10, 6))
```

```
    # Plotting the actual values (index 0 to 21) in blue with
'Year' on the x-axis
    plt.plot(plot_df['Year'][:22], plot_df[response][:22],
'bo', label='Actual (Year 2000 to 2021)')

    # Plotting the predicted values (index 22 to 40) in orange
with 'Year' on the x-axis
    plt.plot(plot_df['Year'][22:], plot_df[response][22:],
'ro', label='Predicted (Year 2022 to 2040)')

    # Adding labels and legend
    plt.xlabel('Year')
    plt.ylabel('Hydrogen_Estimation')
    plt.legend()

    # Adding title with the country name
    plt.title(f'Hydrogen Estimation in {country}')

    # Show the plot
    plt.show()

    i += 41
    print("i:", i)
```

5. MLP: Artificial Neural Network Model

- Forecasting predictors using FBProphet Method

```
#Loading the data
data = pd.read_csv('Hydrogen_Consumption_MLP_Dataset.csv')

#Performing linear regression for each country
countries = data['Country'].unique()
print(countries)
i = 0

#Listing of variables for forecasting
forecast_variables = ['electricity_demand',
'electricity_generation',
'gas_consumption','greenhouse_gas_emissions',
'low_carbon_consumption']

#Initializing an empty DataFrame to store all forecasted
values
all_forecast_data = pd.DataFrame()

for country in countries:
    print(country)
    filter_data = data[data['Country'] == country]

    #Initializing an empty DataFrame to store forecast data
for this country
    country_forecast_data = pd.DataFrame()
```

```
    #Looping through each variable and perform forecasting
    for var in forecast_variables:
        #Extracting the relevant columns for Prophet
        X = ['Year', var]
        new_df = filter_data[X].copy()

        #Preparing the data for Prophet
        prophet_data = new_df.rename(columns={'Year': 'ds',
var: 'y'})

        #Initializing and fitting the Prophet model
        model = Prophet()
        model.fit(prophet_data)

        #Generating future dates till 2040 (yearly frequency)
        future_dates = pd.date_range(start='2022-01-01',
end='2040-01-01', freq='YS')
        future_dates = pd.DataFrame({'ds': future_dates})

        #Predicting the variable for future dates
        variable_forecast = model.predict(future_dates)

        #Converting 'ds' column to year column only
        variable_forecast['ds'] =
variable_forecast['ds'].dt.year

        #Creating a table with forecasted values
        forecast_table = variable_forecast[['ds',
'yhat']].copy()
        forecast_table.columns = ['Year', var]

        #Concatenating forecast_table with
country_forecast_data
        country_forecast_data =
pd.concat([country_forecast_data, forecast_table], axis=1)

        #Plotting the actual and forecasted values for the
variable (optional)
        plt.figure(figsize=(10, 6))
        plt.plot(new_df['Year'], new_df[var], label='Actual',
color='blue')
        plt.plot(forecast_table['Year'], forecast_table[var],
label='Forecast', color='red', linestyle='dashed')
        plt.xlabel('Year')
        plt.ylabel(var)
        plt.title(f'Actual and Predicted {var} for {country}
using Prophet')
        plt.legend()
        plt.show()

    #Adding the 'Country' column to country_forecast_data
    country_forecast_data['Country'] = country

    #Concatenating country_forecast_data with
all_forecast_data
    all_forecast_data = pd.concat([all_forecast_data,
country_forecast_data], axis=0)
```

```
#Reseting the index of the final DataFrame
all_forecast_data.reset_index(drop=True, inplace=True)

#Getting the DataFrame with only the unique columns
new_df_1 = all_forecast_data.loc[:,
~all_forecast_data.columns.duplicated()]

#Adding 'Hydrogen_Estimation' column with null values
new_df_1['Hydrogen_Estimation'] = np.nan

#Selecting relevant columns from the original dataset
selected_columns = ['Year','Country','electricity_demand',
'electricity_generation', 'gas_consumption',
                   'greenhouse_gas_emissions',
'low_carbon_consumption']

#Concatenating filtered_data with new_df_1
concatenated_df = pd.concat([data[selected_columns],
new_df_1], axis=0)

#Assuming your DataFrame is named df
concatenated_df.to_csv('filename.csv', index=False)
```

- Using forecasted values of predictors and fitting MLPRegressor Model

```
#Creating dataframe copy to perform Multi Layer Perceptron
algorithm
mlp_df = concatenated_df.copy()

#Splitting the dataset into predictors (X) and response
variable (y)
drop_col = ['Country','Hydrogen_Estimation']

# Creating dataset of predictors and target variable
X = mlp_df.drop(drop_col, axis=1)
y = mlp_df['Hydrogen_Estimation']

#Scaling features of the dataset
scaler = StandardScaler()
X_scaled = pd.DataFrame(scaler.fit_transform(X),
columns=X.columns)

#Initializing an empty DataFrame to store all forecasted
values
all_forecast_data = pd.DataFrame()

#Looping through each country and performing forecasting
countries = mlp_df['Country'].unique()

for country in countries:
    filter_data = mlp_df[mlp_df['Country'] == country]
    train_data = filter_data[filter_data['Year'] <= 2021]
    test_data = filter_data[filter_data['Year'] >= 2022]
```

```
    #Splitting data into training & test for model accuracy
    test_check_data = filter_data[(filter_data['Year'] > 2017)
& (filter_data['Year'] <= 2021)]

    #Prepareing training data for MLP regression
    X_train =
train_data.drop(['Hydrogen_Estimation','Country','Year'],
axis=1)
    y_train = train_data['Hydrogen_Estimation']
    X_train_scaled = scaler.fit_transform(X_train)

    #Initializing the MLP regressor
    mlp_model = MLPRegressor(hidden_layer_sizes=(100,),
max_iter=1000, random_state=42)

    mlp_model.fit(X_train_scaled, y_train) #Training the model

    #Preparing the test data (without 'Hydrogen_Estimation')
    X_test =
test_data.drop(['Hydrogen_Estimation','Country','Year'],
axis=1)
    X_test_scaled = scaler.transform(X_test)
    #Forecasting 'Hydrogen_Estimation' for the test period
    y_forecast = mlp_model.predict(X_test_scaled)

    #Preparing the test data (without 'Hydrogen_Estimation')
    X_test_check =
test_check_data.drop(['Hydrogen_Estimation','Country','Year'],
axis=1)
    X_test_check_scaled = scaler.transform(X_test_check)
    y_test_check = test_check_data['Hydrogen_Estimation']
    y_check_forecast = mlp_model.predict(X_test_check_scaled)

    #Calculating the RMSE & R-squared using the fitted model
    rmse =
np.sqrt(mean_squared_error(y_test_check,y_check_forecast))
    r2 = r2_score(y_test_check,y_check_forecast)

    #Printing the results for the current country
    print('Country:', country)
    print('Coefficients:', model.params)
    print('R2:', r2)
    print('RMSE:', rmse)
    print()

    #Adding the forecasted values to the test_data DataFrame
    test_data['Hydrogen_Estimation'] = y_forecast

    #Concatenating the training and test data back together
    forecast_data = pd.concat([train_data, test_data])

    #Concatenating forecast_data with all_forecast_data
    all_forecast_data = pd.concat([all_forecast_data,
forecast_data], axis=0)

# Print the final DataFrame with forecasted values for
'Hydrogen_Estimation'
print(all_forecast_data)
```

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