Evaluating the use of Artificial Neural Networks (ANNs) to project Carbon Emissions Intensity (CEI) of energy usage at a national scale

MWGL8

11,997

Thesis submitted for consideration towards a degree of
MSc Climate Change,
Dept of Geography,
UCL (University College London)

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September 2021

Abstract

As the world takes steps to move away from fossil fuels, a number of goals have been set to reach Net Zero emissions. In this study, artificial neural networks (ANNs) are implemented to project the carbon emissions intensity (CEI) of energy use for the top 30 greenhouse gas (GHG) emitting countries. A set of development indicators such as population, foreign direct investment and gross domestic product were used as inputs to the networks using data from 1980-2014, with the sole output of CEI. The study utilised two methods, the first had each country with a dedicated cohort of 100 ANNs trained exclusively on data from that country. The second method collected countries into two groups based on if they were considered Advanced or Emerging by the International Monetary Fund (IMF), where each group had a cohort of 100 ANNs and was exposed to data from all countries belonging to that group. Cohorts were utilised alongside data augmentation techniques due to limited data availability. Quantitative and qualitative data from the Shared Socioeconomic Pathways (SSPs) were used to project forwards to 2050 for 5 developmental pathways.

The individually trained networks had varying accuracy across the countries, with some achieving a high R^2 (0.97) and some training poorly (-0.04). In contrast, the two IMF grouped networks both trained well (0.93 and 0.84 for Advanced and emerging respectively), exhibiting improvements in accuracy for the majority of the countries compared to their individual networks. For projections, the individual networks had two countries achieving zero CEI (Italy and the Democratic Republic of the Congo), however they exhibited a high degree of uncertainty. Within the grouped networks, no country reaches a CEI of zero, with France achieving the lowest CEI, closely followed by the Democratic Republic of the Congo, and other European countries. SSP1 generally presents good opportunities across all countries to lower CEI, however a number of countries perform slightly better with SSP4 and SPP5.

The number of countries failing to achieve a CEI of zero or lower could be explained by the limited data availability. As the ANNs also rely in historic data with 2014 being the last year used, they would not be able to accurately predict the inclusion of carbon capture and storage (CCS) systems, thus representing CO_2 emissions created, but not necessarily emitted to the atmosphere. It therefore highlights the importance of CCS in limiting GHG emissions, with the likely continued reliance on fossil fuels.

Main Text Word Count: 11,997

Total Word Count: 19,988

Acknowledgements

Firstly, I would like to thank my supervisor Dr. Chris Brierley, for assisting me in shaping this study, providing useful insights, ideas for explorations, and guiding me when I've been unsure in my return to academia after working for so long, enabling me to pursue my own curiosity whilst ensuring I remain focused and on track to succeed academically.

Secondly, I must thank my partner Nina, who not only has helped me throughout my studies with proof reading skills and advice, but for always being there to listen to me, providing love and support, and being empathetically enthusiastic whenever I was buried amongst code and solved the most mundane problems such as memory leaks or minor optimisation tweaks.

I would also like to thank my family and friends, for their support and encouragement, as well as my manager and work colleagues, who enabled me to return back to academia whilst continuing to work part time, and covering for me in my many days of absence.

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Acronyms

ANN – Artificial Neural Networks

ASCE - American Society of Civil Engineers

BECCS – Bioenergy with carbon capture and storage

CCS – Carbon Capture and Storage

CEI – Carbon Emissions Intensity

CMIP - Coupled Model Intercomparison Project

EKC -Environmental Kuznets Curve

FDI – Foreign Direct Investment

GDP – Gross Domestic Product

GHG – Greenhouse Gas

GNI – Gross National Income

HDI – Human Development Index

IEA – International Energy Agency

IMF – International Monetary Fund

IPCC - Intergovernmental Panel on Climate Change

MLP – Multi Layer Perceptron

MSE – Mean Square Error

NOAA - National Oceanic and Atmospheric Administration

PPP – Purchasing Power Parity

PV - Photovoltaic

R&D – Research and Development

SSP – Shared Socioeconomic Pathways

UNDP – United Nationals Development Programme

UNFCC – United Nations Framework Convention on Climate Change

WDB – World Data Bank

WESP – World Economic Situation and Prospects

Thesis Outline

Chapter 1: Introduction

A brief background on the topic of GHG emissions, machine learning and literature directly relevant to this study.

Chapter 2.1: Methods – Context

The selection of key development indices as inputs to the Artificial Neural Networks (ANNs). 5 scenarios are identified through the Shared-Socioeconomic Pathways (SSPs) and are interpreted for their impacts on the selected inputs.

Chapter 2.2: Methods - Modelling

The steps taken to define the model are described, as well as techniques to augment the datasets, reduce overfitting for improved predictions and the ensemble approach taken.

Chapter 3.1: Results – Training

The results from the training processes of the individual networks, and the grouped networks are shown, with accuracy measured through R^2 of predicted vs actual results.

Chapter 3.2: Results – Projections

Results from projecting the 5 SSP scenarios are shown for both networks types across all countries.

Chapter 4: Discussion

An overview of the results, as well as supplementary analysis to provide context on the modelling process and interpretation of change to CEI.

Chapter 5: Conclusion

The final comments on the results of the study.

1 | Introduction

1.1 Background

As the world developed following the industrial revolution, fossil fuels became the primary source of energy, resulting in an abundance of greenhouse gas (GHG) emissions to the atmosphere. The effects of these emissions are widely accepted to be both directly and indirectly changing our climate, and are contributing towards a global average temperature increase (IPCC, 2021).

GHG are a group of gases that contribute to a warming climate and the greenhouse effect. The most abundant GHG in the atmosphere is CO_2, which has recently peaked (Figure 1) at 420ppm at the Mauna Loa observatory in June (NOAA, 2021).

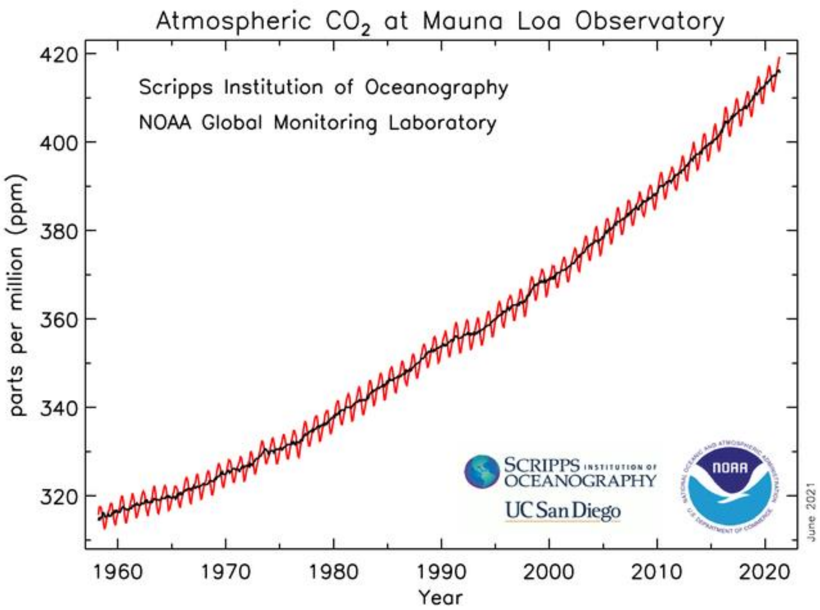


Figure 1: Measured CO_2 concentrations at Mauna Loa Observatory (NOAA, 2021)

Carbon dioxide is seen as the most dominant GHG in its contribution to global temperature increase through radiative forcing (Figure 2), in part due to the volume of CO_2 emitted into the atmosphere (NOAA, 2021).

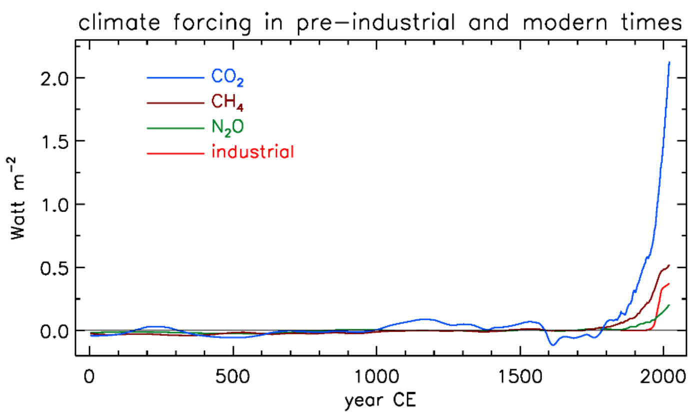


Figure 2: Radiative climate forcing by greenhouse gases during the last two millennia (NOAA, 2021)

There are a range of sources for GHGs, with the energy industry typically dominating overall emissions, followed closely by transport and industry, and the remainder falling into buildings, agriculture and other industries (Figure 3).

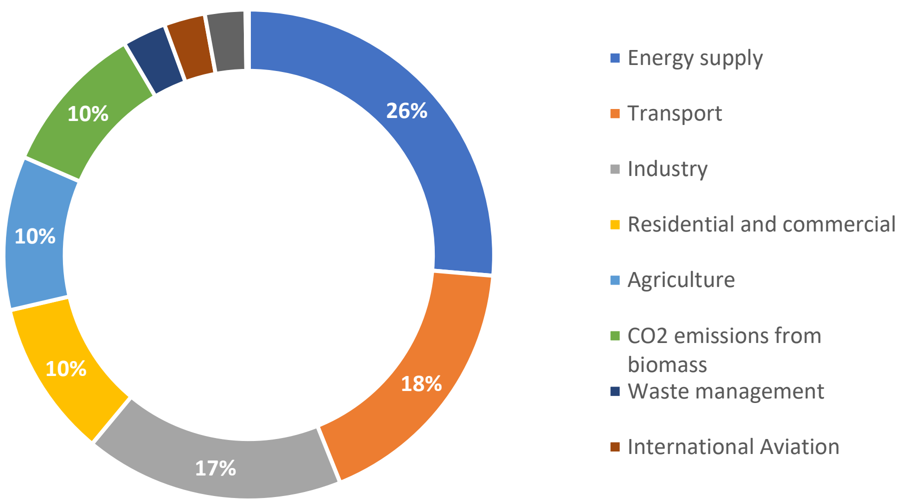


Figure 3: Sectoral breakdown of GHG emissions (IPCC, 2014)

With human caused global surface temperature increase estimated at 1.07°C (IPCC, 2021), a concerted effort is required to reduce ongoing GHG emissions and limit global temperature rise to 1.5°C. There are many predicted consequences if global temperature rise is allowed to exceed this threshold including: sea level rise, increasingly frequent extreme weather events and increased species loss (IPCC, 2017).

1.2 Net Zero Goal

In order to reach these goals, the Paris Agreement was signed in December 2015, aiming to hold "the increase in the global average temperature to well below 2°c above pre-industrial levels and to pursue efforts to limit the temperature increase to 1.5°c above pre-industrial levels" (UNFCCC, 2015). This global agreement included Nationally Determined Contributions (NDCs) from each country, an outline of their intentions to address climate change (UNFCCC, 2015). The NDCs targeted emissions reductions, but their magnitude varied between countries due to each country's individual commitments and limitations (Rogelj et al., 2016). Some NDCs included targets of reaching "Net Zero" towards the latter half of the century (Tanaka and O'Neill, 2018).

The term "Net Zero" predates the Paris Agreement, and includes references to building energy performance (Mertz et al., 2007; Torcellini et al., 2010; Sartori et al., 2012) as well as direct GHG emissions at differing scales (Kilkis, 2007; Deutch, 2020; Smith, 2021). At a national scale, countries have ambitions to become "Net Zero Carbon" through reducing their total GHG emissions, and using offsets to be able to balance any remaining emissions to zero. Countries vary in their ambition (how soon they intend to reach net zero) as well as the maturity of their intent (in the form of legislation). Table 1 presents a summary of the current state of declarations made by a total of 132 countries.

		Target Date							
		Achieved	**2030**	**2035**	**2040**	**2045**	**2050**	**2060**	**Total**
Status of Legislation	**Achieved**	2							2
	In Law					1	5		6
	In Policy Document			1	2	1	14	2	20
	Proposed Legislation						6		6
	Target Under Discussion		1				97		98
	Total	2	1	1	2	2	122	2	132

Table 1: The status of net zero targets across countries by their target date, and the maturity of their commitment. Created using data (Energy & Climate Intelligence Unit, 2021) based on currently declared commitments

So far, Suriname and Bhutan have achieved Net Zero emissions, with the latter being carbon-negative (Energy & Climate Intelligence Unit, 2021). Over 90% of countries have 2050 as their goal to reach Net Zero, however 73% of all countries with a declaration have their goal still under discussion. Although there are still three decades until that target, it introduces uncertainty in how successful the world will be in reaching their commitments.

Figure 4 demonstrates the challenges in the projected pathways to net zero, highlighting almost a 25% difference between the projected and actual value in 2017 for the emissions intensity of electricity production in the UK (UK Gov, 2017). These estimates are derived through a Dynamic Dispatch Model, taking into account various inputs from the power market such as electricity demand, price and supply. It is also capable of forward projections based on the energy market, however doesn't take into account other variables such as how renewables are becoming more accessible, which is the suggested cause of the discrepancy shown below.

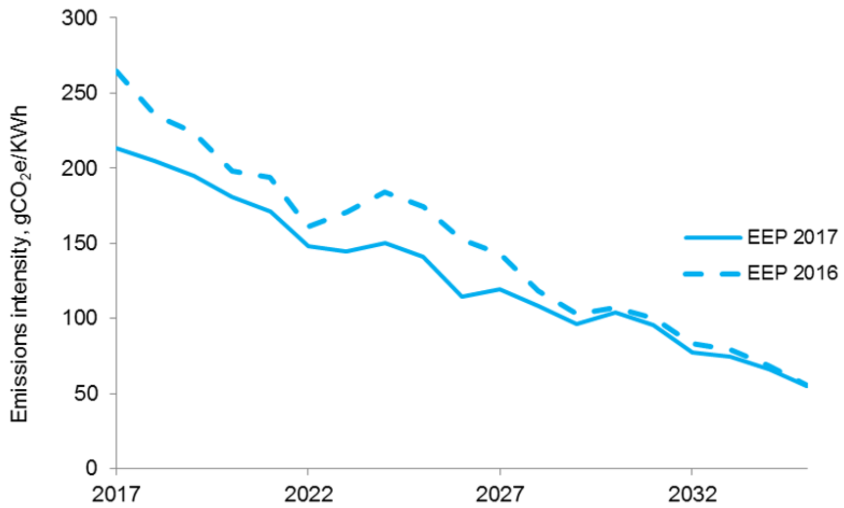


Figure 4: The UK Governments energy emissions projections from 2016 and 2017, highlighting an almost 25% reduction in 2017 from the projected value (UK Gov, 2017)

Carbon Emissions Intensity (CEI) will be the focus of this study: a measure of the volume of carbon dioxide emissions produced per unit of energy consumed. Although countries will have the goal of transitioning to Net Zero, it is likely that fossil fuels will still be used in a range of industries beyond just the energy sector (Bauer et al., 2017; van Vuuren et al., 2017). Understanding the pathway of CEI development is therefore crucial to gauge the implications for total GHG emissions. A novel route to modelling this is through machine learning, which has found success in creating accurate models (Acheampong and Boateng, 2019; Leerbeck et al., 2020). These studies, along with others investigating machine learning (Sbia et al., 2014; Shahbaz et al., 2017a) have used key development indicators as inputs into the algorithms chosen. Some are similar to those found in the Kaya identity (Mavromatidis et al., 2016; Raupach et al., 2007) such as GDP and population, but include others such as foreign direct investment or industrialisation.

1.3 Machine Learning

Machine learning is the process by which "computational methods are defined using experience to improve performance or to make accurate predictions" (Mohri et al., 2018). There is a reliance on historical data for machine learning to be successful as algorithms need sufficient training in order to provide accurate predictions.

In recent years, the use of machine learning as a modelling technique has become more popular. This is primarily driven by the increasing abundance of data, the sophistication of learning algorithms, and greater computational power. The algorithms used within machine learning can typically be categorised into six groups based on the type of problem:

- Regression: the prediction of a specific value(s)
- Classification: assigning categories to items
- Ranking: ordering items based on set parameters
- Clustering: grouping items based on common criteria
- Decision Making: learning behaviour of an agent in a specific environment
- Dimensionality Reduction: transforming the complexity of an item while preserving key identifying characteristics

There are a number of core learning methods: supervised learning, unsupervised learning and reinforcement learning (Mohri et al., 2018). Supervised learning requires sets of data that are clearly organised and labelled. The machine learning algorithms then learn the associations between the defined inputs, and can then take new inputs to make predictions on unseen outputs. Unsupervised learning takes unlabelled training data and attempts to recognise patterns or groupings in the data automatically. Finally, reinforcement learning places an agent in an environment where it is rewarded based on behaviour. The absence or presence of a reward will then train the agent to learn the desired interactions. An overview of some of these problems and learning techniques is provided in Figure 5, along with example algorithms that can be used, suitable for each problem.

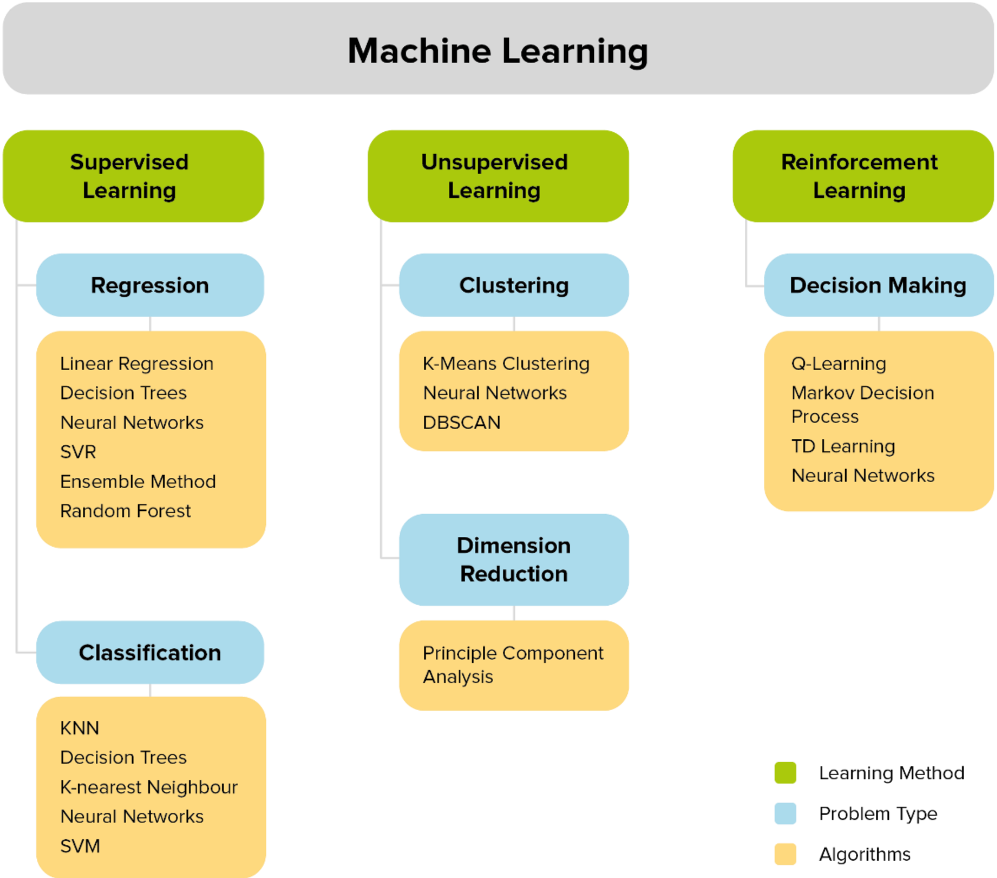


Figure 5: An overview of machine learning methods produced from multiple sources (Mohri et al., 2018; Goodfellow et al., 2016)

Artificial Neural Networks (ANNs) are considered to be quite flexible, as they can be applied to many types of problems, although they are not without fault (Dongare et al., 2012). Some pros of ANNs include:

- High flexibility with applications to both classification and regression
- Prediction speed with a trained network can be quite fast
- Scales well with large datasets in terms of height (inputs characteristics) and breadth (number of records)

However, there are drawbacks to utilising them too:

- They operate as “black boxes”, so it’s unclear how each input variable influences the output
- Training can be computationally expensive
- The training process is highly reliant on the data and has risks of underfitting and overfitting

Nevertheless, as the prediction of CEI is numeric, and as there is a wide selection of potential numeric input variables that are well defined, ANNs can provide a suitable method to model CEI through supervised regression. ANNs are an umbrella term for neural networks, of which there are several types, however they typically refer to Multi-Layer Perceptron (MLP). A perceptron is modelled after a neuron within the human brain: it takes multiple inputs, each of which have a weighting applied. The neuron processes the inputs, and applies an activation function as an output (ASCE, 2000) (Figure 6).

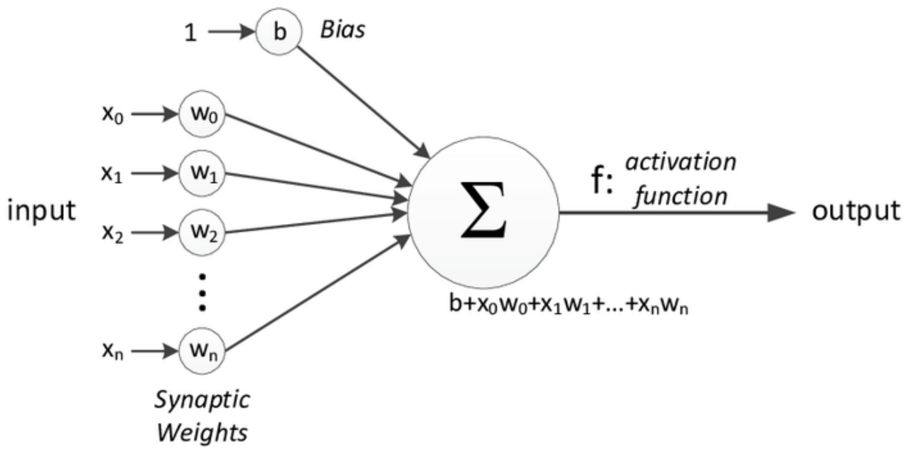


Figure 6: A schematic of a perceptron from an ANN (London and Fountas, 2021)

MLPs consist of many interconnected neurons which are arranged in layers of multiple neurons (Figure 7). The number of input neurons must match the number of entries in the training dataset, and the output neurons must match the desired output. However, in between, there is at least one hidden layer. The number of neurons can vary depending on the model, the dataset and the initial problem.

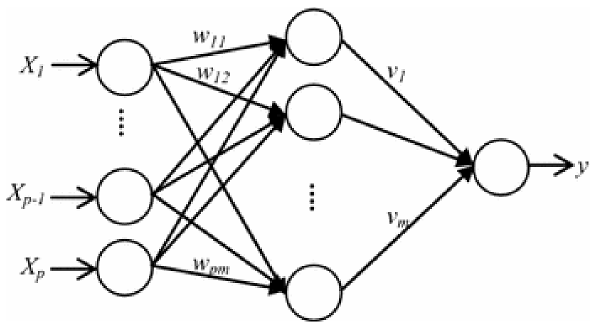


Figure 7: A schematic of an MLP with one hidden layer (Suhartono et al., 2017)

Activation functions are triggered from the output of a neuron, and there are a range that can be selected, although today, ReLU is the default function in a number of scenarios due to its efficiency.

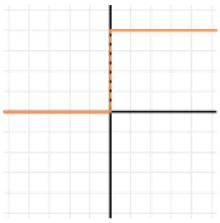
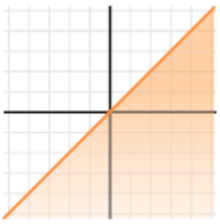
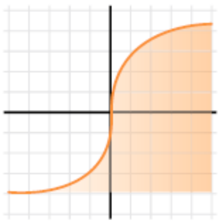
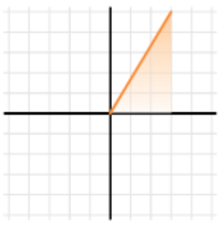
Activation Function	**Graphical Representation**	**Benefits**	**Drawbacks**
Threshold Linear		• A very simple function	• Unable to classify non-binary signals • No matter how many layers, the end network will always be a linear function of the input
Linear Linear		• Can take multiple inputs	• No matter how many layers, the end network will always be a linear function of the input
Sigmoid Non-Linear		• A smooth gradient • Clear predictions as curve is differentiable	• Has issues where very high/ low values of X have little change in prediction • Output is not zero centred, so reacts poorly to strong negative signals
Tanh Non-Linear		• Zero centred, so reacts well to neative, neutral and positive signals • Similar benefits to sigmoid	• Still has issues with vanishing gradient
ReLU (Rectified Linear Unit) Non-Linear		• Can be computationally quite efficient • It can allow for a derivative function and backpropagation	• With negative or zero inputs, the gradient becomes a function of zero, so cannot learn

Table 2: A comparison of typical activation functions

Once initialised, the network is exposed to training data of both inputs and the outputs. When the ranges of each respective variable are of different scales, datasets are typically normalised, otherwise the weights within the network could become accentuated, and generalise the input data poorly (Vabalas et al., 2019). It is important to have enough data to train the network too, although there aren’t any clear rules for a specific threshold for the starting dataset (Agatonovic-Kustrin and

Beresford, 2000; Haykin and Network, 2004). The initial dataset is typically split into two parts to represent training data used to set the weights within the network between perceptrons. The second portion is then used as validation, where the model predicts using the shown inputs, and the outputs are compared with the actual values, to evaluate the accuracy of the model. The training:validation split can vary, but a common split is 70:30 (Haykin and Network, 2004).

The model is repeatedly exposed to the training data, with validation occurring each time the entire training set has been seen once, the period of which is known as an epoch. The model repeatedly sees the data, so accuracy improves, and the model fits to the context. The number of epochs required should ideally be low, however there isn't a set rule for how many are suitable.

Fitting is the process where a model attempts to generalise a dataset, in order to make accurate predictions on unseen data. There are typically three categories to describe how well fit a model is, that can be described using bias and variance:

- Underfit (high bias, low variance) – the model has failed to generalise the training data well, and leads to poor predictions with a high error.
- Good fit (low bias, low variance) – the model has generalised the training data well, and has a low error with the validation set.
- Overfit (low bias, high variance) – the model has learned from the training data too well, likely through overexposure, and performs poorly through the validation process.

Underfitting generally occurs due to unsuitable algorithm choice, network design, insufficient data or underexposure (Narayan and Tagliarini, 2005). Overfitting can typically occur when the model is overexposed to the training data, usually through an excess number of epochs (Figure 8).

One method of improving the accuracy of results is through an ensemble approach, typically *K* -Fold Cross Validation. This process randomises the data to avoid any continuity, then divides the data into discrete sections for testing and training *K* times. Each set of data utilises different portions of the dataset, to ensure that each is unique. *K* networks are then trained using each respective dataset to measure error/accuracy, and the mean is calculated across the cohort (Figure 9). Through using this staggered approach, it decreases the impact of anomalous values, and increases the reliability of predictions (Yadav and Shukla, 2016).

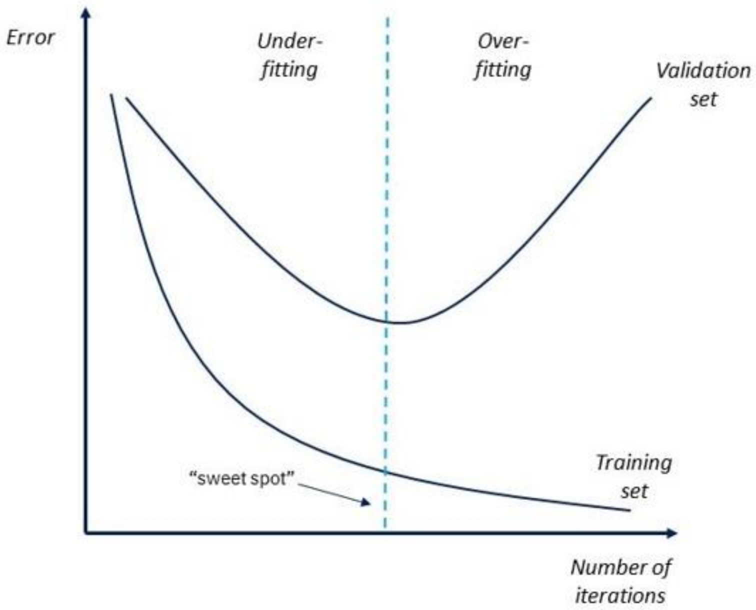


Figure 8: A demonstration of the error in training process and validation process, and where the fitting of the model is ideal (IBM, 2021)

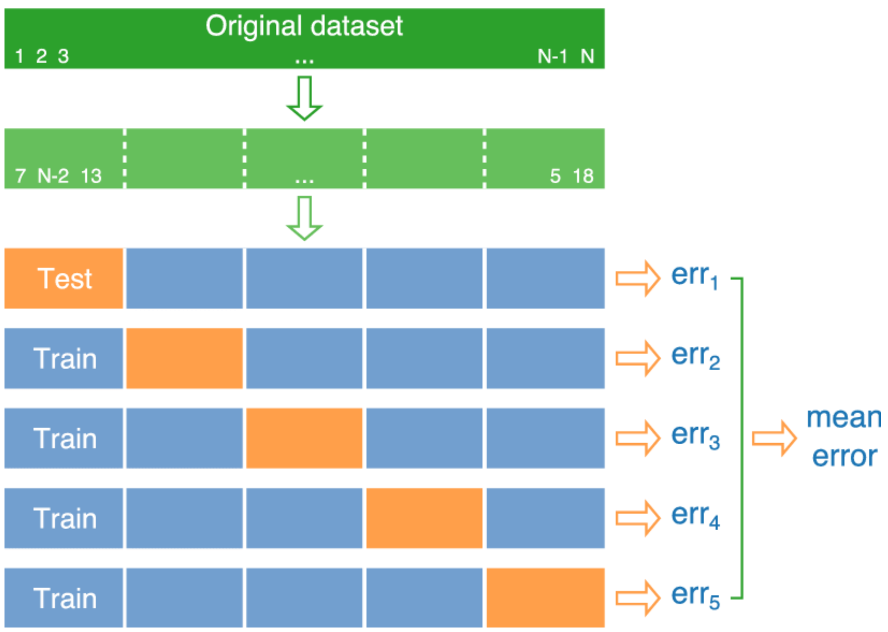


Figure 9: An Example of K-Cross Fold Validation, where K=5 and there is N data points (Fedotenkova, 2016)

1.4 Existing Literature

Applications in modelling carbon emissions with ANNs have been limited. Leerbeck et. al (2020) modelled the short-term forecasting for the CEI of power grids using machine learning. A selection of 30 input variables were identified based on data supplied from weather and electrical grid monitors in Sealand, Denmark, such as wind speed, total power generation and power imports/exports. The focus of this study was to take into account climatic factors, to provide short-term (at most 24h) forecasts for customers to be able to plan their energy loads for times when CEI was low. Some of the input variables studied directly influence the CEI of power production (e.g., % generated through renewables), and could be calculated without the use of machine learning, albeit through more complex techniques. However, despite the small regional study area, the results demonstrate the use of machine learning in successfully understanding variables that influence the CEI of power generation.

Another study (Acheampong and Boateng, 2019) used ANNs to predict carbon emissions intensity in five countries: Australia, Brazil, China, India, and USA. A selection of development indices was used in the training process such as GDP, energy use and population. Each country had a group of twenty networks trained, and the best performing network was selected for sensitivity analysis to understand which was the most influential variable. The final step of this study decomposed the networks into their weights and biases, so that the results could be utilised by further studies. This is the most promising study in literature, as it validates the use of ANNs in estimating CEI directly. One risk of this study is the selection of the "best-performing" network. Due to the small data size, the subsampling required for training means the selected network is exposed to only 115 datapoints per variable (of which only ¼ are actual datapoints due to augmentation through interpolation). Furthermore, whilst the accuracy of the network's prediction is promising, the models aren't used for forecasting.

1.5 Aims and Objectives

This study aims to construct and train effective ANNs for modelling the CEI of all energy use at a national scale. Two groups of models will be trained, the first cohort will involve a dedicated ANN for each country, trained exclusively using that country's historic data. The second cohort will group countries together based on similar characteristics, and train a smaller group of models using combined historic data. Both groups will then forecast scenarios to see a) CEI predictions from each group and b) how the predictions compare from the individual networks, and the grouped networks.

The objectives are to:

1. Determine how an ANN may be constructed and used to model CEI for various countries
2. Identify suitable input data for the training of the ANN
3. Evaluate the accuracy of the various ANNs using R^2 as a performance metric
4. Use a range of scenarios as inputs to forecast predicted carbon emissions intensity from 2020-2050
5. Evaluate the two methods of projecting decarbonisation routes

2 | Methods

2.1 Context

2.1.1 Selected Indices

The input variables for ANNs should generally characterise the modelled output, and have discernible features that the model can understand. An adequate number of predictors should be used to be able to train the model, however using too many inputs can lead to overfitting. In this study, a selection of financial and developmental indicators was selected from literature, to train the network and model the single output of CEI, summarised in Table 3.

2.1.1.1 Carbon Emissions Intensity (CEI)

As discussed previously, CEI is typically defined as the carbon dioxide emitted per unit energy consumed. It is dependent on the sources used to produce the energy, and can be highly influenced by the introduction of renewables.

2.1.1.2 Energy Consumption

With CEI directly influenced by the energy sector, the demands placed on energy would therefore be a key driver for CEI. It is well documented that energy use is closely linked to overall carbon emissions (Soytas et al., 2007; Uddin et al., 2016; Wang et al., 2016b). Energy generation has historically been dominated by fossil fuels (Kyritsis et al., 2017), with the introduction of renewables in recent decades helping to reduce CEI. However, cyclical spikes in energy demand and growing industries in developing nations still typically rely on fossil fuels (Abas et al., 2015). It has generally been found that increasing energy demand is correlated with increased carbon emission (Rout et al., 2008; Halicioglu, 2009; Jahangir Alam et al., 2012; Mulder and Scholtens, 2013; Bauer et al., 2016; Kyritsis et al., 2017). Naturally, as energy demand continues to increase with a constant CEI, total GHG emissions will rise too. This highlights the importance of reducing CEI over time, to counteract projected energy demand increases (Riahi et al., 2017a; Rogelj et al., 2018; Gidden et al., 2019) whilst minimising overall GHG emissions.

2.1.1.3 Economic Growth

It is generally understood that GDP is tied to GHG emissions (Tucker, 1995; Heil and Selden, 2001; Wang et al., 2016a), with higher GDP correlated to higher GHG emissions, although the Environmental Kuznets Curve (EKC) hypothesis adds complexity to this. Using an inverted U-Shape (Figure 10), the EKC highlights how at lower levels of economic growth, there can be increased environmental pollution and degradation due to the growth of industry. However, as the economy develops, it reaches a turning point, transitioning to a post-industrial economy, thus reducing environmental degradation (Dinda, 2004; Stern, 2004). The EKC has been documented in a number of global regions, including transitional economies (Narayan and Narayan, 2010; Tamazian and Bhaskara Rao, 2010; Apergis and Ozturk, 2015; Ahmad et al., 2017).

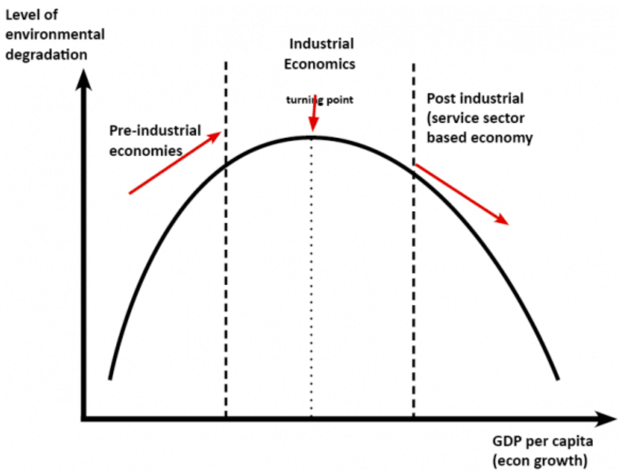


Figure 10: The Environmental Kuznets Curve with progressive stages (Pettinger, 2019)

2.1.1.4 Industrialisation

As shown in the EKC, industrialisation can play an important role in carbon emissions, with industry referring to sectoral activities of agriculture, mining, manufacturing and processing of raw materials. Studies have found that industrialisation is correlated with GHG emissions although this varies based on stages of economic development (Li and Lin, 2015). In contrast, some studies have found there to be no causative relation between industrialisation and GHG emissions (Lin et al., 2015), and rather it covaries with other key indices such as economic growth and population size. Nevertheless, it is clear that industry involves heavy use of fossil-fuel derived energy sources (Ozawa et al., 2002; Zhang et al., 2020). The metric used here is represented through Industry’s value added as a percentage of overall GDP.

2.1.1.5 Population

If population increases, so would the total GHG emissions as greater demand would be placed on existing energy infrastructure, leading to increases in absolute emissions. This has been studied in many regions (York et al., 2003; Lee and Oh, 2006; Lin et al., 2009), however it has also been found that population is an important influencer of CEI directly (Pan et al., 2019; Li and Ou, 2013).

2.1.1.6 Urbanisation

Urbanisation and CEI are typically closely tied to the development and wealth of a country too. Some studies have found the extent of this relationship varies by the stage of development. For example higher urbanisation has been found to decrease overall energy use in low-income countries, but inversely increase it in middle to high income groups (Poumanyvong and Kaneko, 2010). Other studies have found simpler relationships where increased urban area leads to higher overall carbon emissions (Sharma, 2011; Wang et al., 2014; Wang et al., 2020). There are arguments for both negative and positive impacts of urbanisation on the environment: increased urbanisation can lead to higher levels of manufacturing, consumption and energy use, whilst as the country develops, it will likely start to benefit from economies of scale, improved environmental regulations and policy and improved infrastructure. The EKC curve can also tie CEI to urbanisation (Ridzuan et al., 2020).

2.1.1.7 Foreign Direct Investment (FDI)

There is debate as to how trade and investment between countries can impact the environment. One theory is that FDI facilitates economic growth and thus could both reduce and increase carbon emissions. Studies have found that FDI tends to have an inverted-U shape relationship with carbon emissions, akin to the EKC theory (Wang et al., 2021b; Sbia et al., 2014; Song et al., 2021; Essandoh et al., 2020). However this relationship has been disputed with models that counter the inverted-U shape model (Zhou et al., 2018), furthered by the theory of Pollution Havens, that posits industrialised nations seek cheaper manufacturing sites abroad, at the cost of environmental impact (Levinson and Taylor, 2008). This is largely blamed on exploiting lax environmental regulations in certain countries, as well as other factors such as cheaper labour (Kastratović, 2019; Essandoh et al., 2020; Garsous and Kozluk, 2017). For this study, FDI is measured as foreign investment received by a country, as a percentage against its GDP.

2.1.1.8 Trade Openness

Closely related to FDI, trade openness is also contested in its relation with GHG emissions. Some studies have found that increased trade openness can reduce carbon emissions and CEI, typically through providing access to more sustainable products and technologies (Shahbaz et al., 2013; Acheampong, 2018; Wang and Wang, 2021). However other studies have found that within certain regions, increased trade can lead to higher overall GHG emissions (Ren et al., 2014; Ahmed et al., 2017; Shahbaz et al., 2017b). Trade openness is considered as the sum of import and exports of a country, as a percentage against its GDP.

2.1.1.9 Research and Development (R&D)

Technological advancement is a key factor in enabling a nation to transition away from fossil fuel energy sources as well as efficiency increases in existing energy production technologies, reducing CEI. Multiple studies have generally found that both GHG emissions and CEI are negatively correlated with increased R&D (Lee and Min, 2015; Fernández Fernández et al., 2018; Awaworyi Churchill et al., 2019; Wang and Wang, 2019) with strong correlations when R&D is focussed on "Green" technologies (Lee and Min, 2015). As a metric, the number of patents filed within the country is used to represent overall research and development.

2.1.1.10 Human Development Index (HDI)

The developed state of a country has been found to be closely tied with carbon emissions, and challenges to becoming more sustainable. Some studies identify challenges to more developed countries in moving to sustainable technologies, when compared to their less developed counterparts (Neumayer, 2012). Others have found countries with higher energy intensities typically had greater barriers to reaching a higher developed status (Pîrlogea, 2012). Importantly, it has been found that the portion renewables makeup of the overall energy mix, is closely related to human development (Yumashev et al., 2020). For this study, the development of a country is represented through Human Development Index (HDI) from the United Nations Development Programme (UNDP). The metric draws on four key factors: life expectancy, expected years of schooling, mean years of schooling and Gross National Income (GNI) per capita (PPP $) (UNDP, 2021). Whilst this does not capture all dimensions of human development (for example, inequality) and has been criticised with alternate formulations proposed as successors (Sagar and Najam, 1998; Cahill, 2005; Hou et al., 2015), it can still be a useful metric for human development and is widely used in studies across many disciplines (Yumashev et al., 2020; Akbar et al., 2020; Ataey et al., 2020; Sarkodie and Adams, 2020; Türe and Türe, 2021).

2.1.1.11 Access to Renewables

One of the primary methods of reducing CEI is through replacing fossil fuel sources with renewable energy generation (Irandoust, 2016; Emir and Bekun, 2019; Wang et al., 2021a). Excluding the opportunity to import energy from neighbouring locations, access to renewable sources is therefore a key factor in enabling a reduction in CEI. Two key studies were identified that provided potentials for renewable energy through photovoltaics (PVs) (Suri et al., 2020) and hydropower (Hoes et al., 2017).

Whilst the Earth as a whole receives varying levels of solar radiation, there can be barriers to utilising it efficiently with PVs. The study from Suri et al. (2020), takes into account the incoming solar radiation for different countries globally, but also factors that affect the potential power output. For example, the model considers scattering through clouds and water vapour, resulting in a Theoretical PV Potential. Considerations are then given to terrain accessibility, where PV sites can be situated and the efficiencies of PV modules at an optimum tilt, resulting in a Practical PV Potential. This final metric therefore provides a more realistic measure of potential solar energy generation.

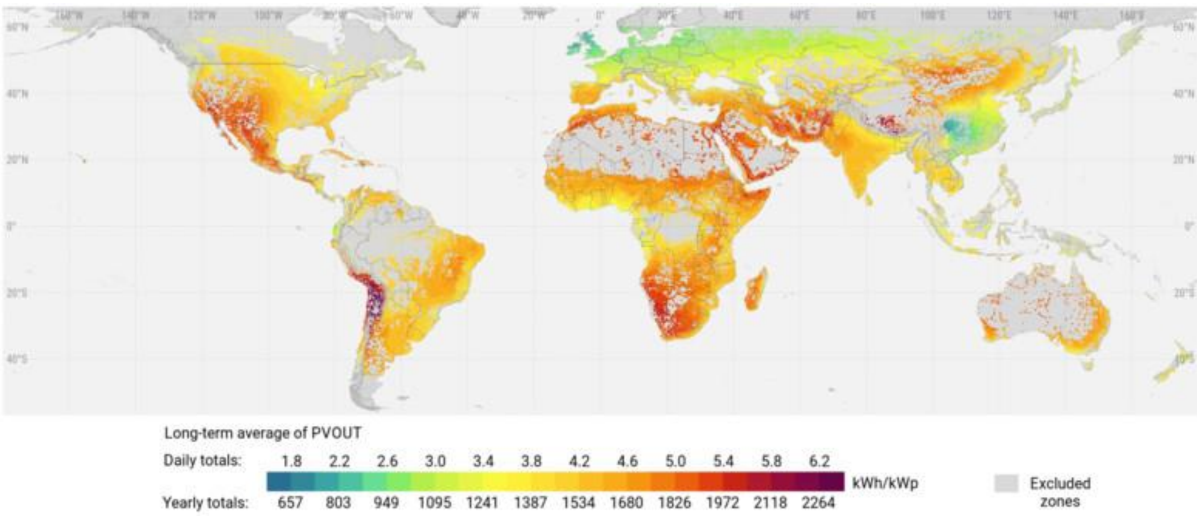


Figure 11: Map of Practical PV Potential (PVOUT) (Suri et al., 2020)

Similarly, the study by Hoes et al. evaluated multiple possible hydroelectric power plants globally, based on river slope and discharge, resulting in analysis for 11.8 million locations. These individual sites were aggregated in ArcGIS, to then result in total potential hydropower generation per country.

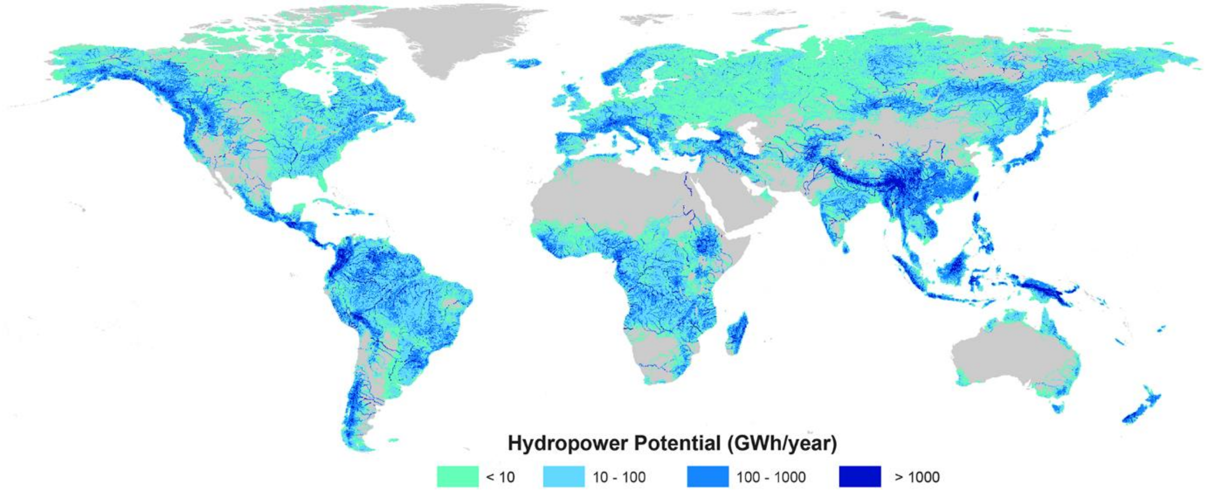


Figure 12: Global map of gross hydropower potential distribution (Hoes et al., 2017)

One limitation with the inclusion of renewables is lack of adequate data to represent wind power potential. Although wind energy is an important contributor, the hydro and solar metrics represent ~80% of today's renewable electricity generation (IEA, 2020), and so should provide adequate coverage for the requirements of this study.

2.1.1.12 Overview

All indicators were given coded terms used in this study and are summarised in Table 3. The grouped networks are exposed to some variables that an individual network would not benefit from. It is generally assumed that countries converge along the same path of development (Molina and Purser, 2013), and thus a network exposed to only one country's development, will typically produce a continuous series that grows with time. The benefit of HDI increases when a network is exposed to multiple countries, at different stages of development.

As the metric for renewable potentials have no temporal dimension, they are only included in the grouped models, where a network may be exposed to multiple countries, and thus learn the relationships. The majority of the data is sourced from the World Data Bank, which has historical records for a range of development indices of all nations.

Variable	Code	Definition	Units	Usage	Reference
Carbon Emissions Intensity	CO2	Carbon emissions intensity is the volume of carbon emissions due to economic activity/economic growth. It is also defined as carbon emissions emitted per unit of energy consumed.	CO2 intensity (kg per kg of oil equivalent energy use)	Individual & Grouped	World Data Bank, 2021
Energy Consumption	ENER	Energy use refers to use of primary energy before transformation to other end-use fuels.	Energy use (kg of oil equivalent per capita)	Individual & Grouped	World Data Bank, 2021
Foreign Direct Investment	FDI	Foreign direct investment is the net inflows of investment to acquire a lasting management interest in an enterprise operating in an economy other than that of the investor.	Foreign direct investment, net inflows (% of GDP)	Individual & Grouped	World Data Bank, 2021
Economic Growth	GDP	GDP per capita the sum of gross value added by all resident producers in the economy plus any product taxes, divided by mid-year population	GDP per capita (constant 2010 US$)	Individual & Grouped	World Data Bank, 2021
Industrialisation	IND	Industrialisation refers to an increase in industrial activity. It comprises value added in mining, manufacturing, construction, electricity, water, and gas.	Industry, value added (% of GDP)	Individual & Grouped	World Data Bank, 2021
R&D	RND	The R&D covers basic research, applied research, and experimental development.	Trademark applications, total	Individual & Grouped	World Data Bank, 2021
Population	POP	Total population refers to the total number of people living in a particular geographical area. It is based on the de facto definition of population, which counts all residents regardless of legal status or citizenship.	Population, total	Individual & Grouped	World Data Bank, 2021
Trade Openness	TRD	Trade is the sum of exports and imports of goods and services measured as a share of the gross domestic product.	Trade (% of GDP)	Individual & Grouped	World Data Bank, 2021
Urbanisation	URB	Urban population refers to people living in urban areas as defined by national statistical offices.	Urban population (% of total)	Individual & Grouped	World Data Bank, 2021
Development	HDI	A summary measure of average achievement in key dimensions of human development: a long and healthy life, being knowledgeable and have a decent standard of living.	HDI range 0-1	Grouped Only	UNDP, 2021
Hydro Potential	HYD	Estimation of potential power generation given the range of sites available within the chosen country	$kWh/m^2/year$	Grouped Only	Hoes et al., 2017
Solar Potential	PV	Practical PV potential, accounting for efficiency loses and environmental variations	$kWh/m^2/year$	Grouped Only	Suri et al., 2020

Table 3: An overview of the selected variables for training in the ANNs

2.1.2 Shared Socio-Economic Pathways

The Shared Socio-Economic Pathways (SSP) are the product of a multi-disciplinary effort to understand the potential futures society could develop towards. They aren't intended to be blueprints for how the world will develop, but rather provide scenarios that consider a range of plausible socio-economic factors for global development. The data from these scenarios could then be used by the climate change research community, to understand how the environment could react to the different pathways of development (Riahi et al., 2017b). Five scenarios were identified, and alongside the datasets, narratives were created to help describe the differences between each SSP. Each SSP can also be characterised by its response to climate change in the form of adaptation and mitigation (Figure 13).

2.1.2.1 SSP1: Sustainability

Low challenge to adaptation, low challenge to mitigation

The world progresses on a more sustainable pathway. Due to a better understanding of the costs of environmental degradation, the global community mobilises collaboratively to limit climate change. Investments focus on human well-being through education and health, leading to a relatively low population and economic growth in higher-income countries. There is generally a focus on resource efficiency, lower energy demand, and international cooperation with key environmentally friendly technologies, which also helps to limit increasing inequality (Riahi et al., 2017b; O'Neill et al., 2017).

2.1.2.2 SSP2: Middle of the Road

Moderate challenge to adaptation, moderate challenge to mitigation

The pathway does not change dramatically from historical trends. Although national institutions still work towards a sustainable future, there is inequality between countries, with varying degrees of success. There are some reductions in energy and fossil fuel usage, however population growth is moderate. In low to mid-income countries, economies develop rapidly and slow as they become more established. Globally, there wouldn't be great technological innovations, and inequality persists (Riahi et al., 2017b; O'Neill et al., 2017).

2.1.2.3 SSP3: Regional Rivalry

High challenge to adaptation, high challenge to mitigation

SSP3 presents the greatest challenges. It is underpinned with a rise of nationalism that limits global cooperation due to concerns around competitiveness and increased rivalry. This individualistic intent spurs from security and protectionist ideologies in the face of environmental degradation. Policy and investments focus on regional energy and resource usage, with greater barriers to trade. Inequality is generally persistent, or worsens, particularly in developing countries. As a whole, economic growth is low, however there is an underlying dependency on fossil fuels and material intensive production. Population growth is uneven, slowing in developed countries, but remaining high in developing nations (Riahi et al., 2017b; O'Neill et al., 2017).

2.1.2.4 SSP4: Inequality

High challenge to adaptation, low challenge to mitigation

SSP4 is characterised by increasing inequality both within and across countries. Within most economies, power and capital become concentrated within a business elite. There is a disparity between developing and developed countries: generally developed countries see higher levels of education, higher economic growth and greater technological development. Global energy usage still remains reliant on fossil-fuels, however low-carbon options are introduced due to uncertainty with the market (Riahi et al., 2017b; O'Neill et al., 2017).

2.1.2.5 SSP5: Fossil-fuelled Development

Low challenge to adaptation, high challenge to mitigation

Across the globe there is economic growth, with strong competitive markets spurring technological advances and improvements to human capital. Through competition, global markets flourish with few barriers to intercountry operations. There is also a focus on improvements to health and education, and helping to limit inequality between disadvantaged demographics. Global population peaks at the mid-century, and starts to decline. All this development comes at the cost of increased reliance on fossil-fuels, with the use of new technologies to help offset environmental degradation at the small scale. At the global scale, the environmental cost is seen as an acceptable trade-off for economic growth, with solutions such as geo-engineering becoming more palatable (O'Neill et al., 2017; Riahi et al., 2017b).

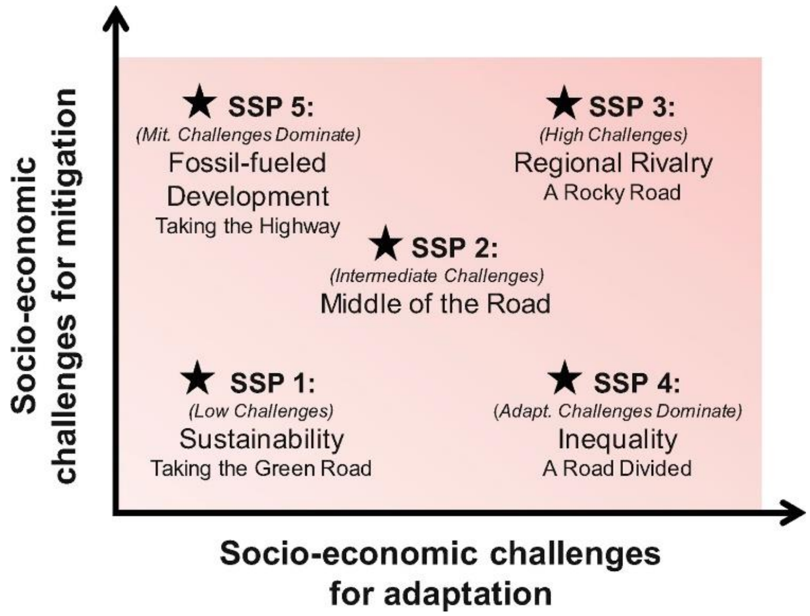


Figure 13: The 5 SSPs and their respective challenges to adaptation and mitigation (O'Neill et al., 2014; O'Neill et al., 2017)

2.1.3 Selected Countries and Groupings

Previous studies have analysed relatively small groups of countries to understand the efficacy of their approaches. In order to build on this experience, this study widens the scope to include 30 countries, selected through their overall GHG emissions (Figure 14).

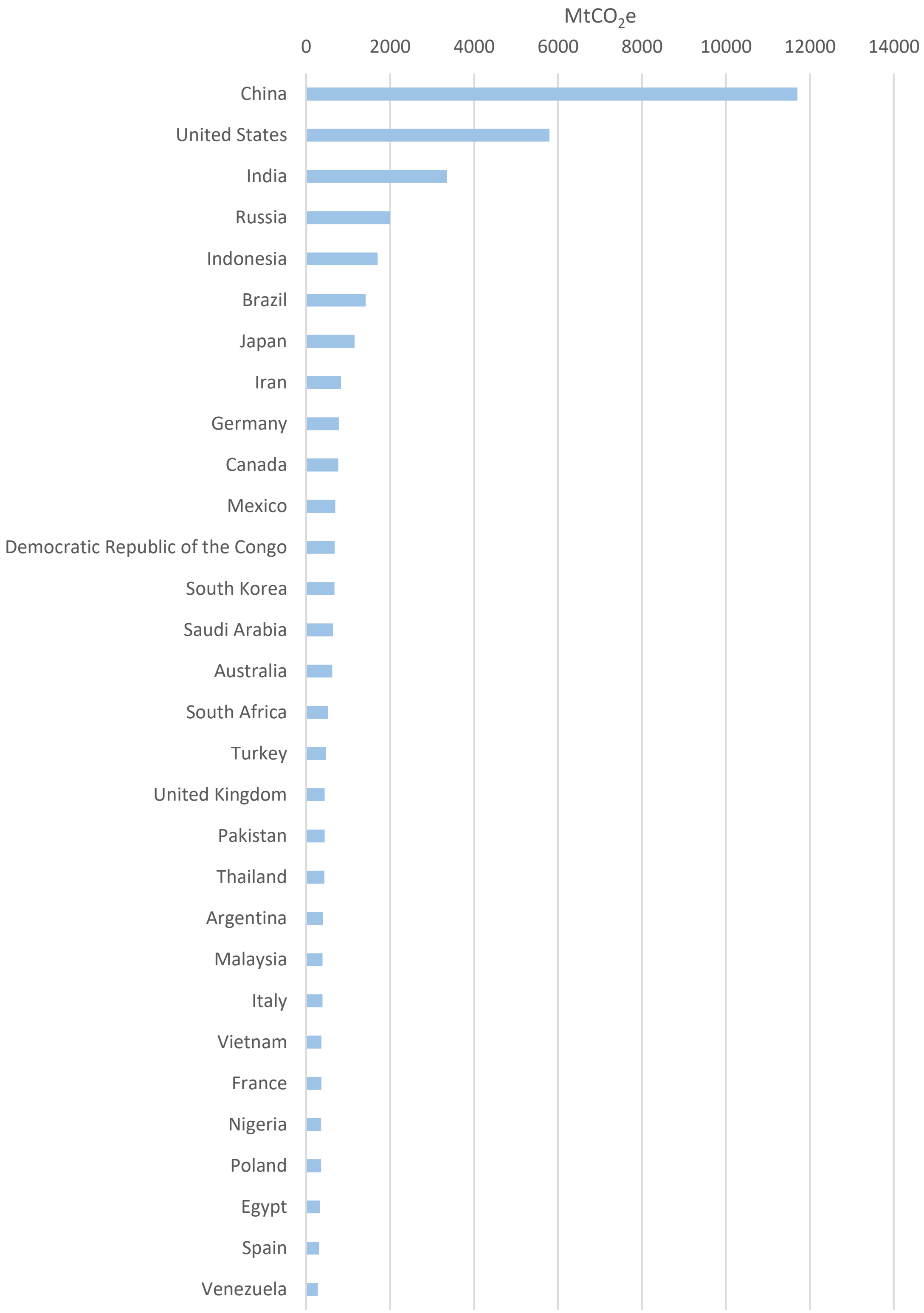


Figure 14: The selected top 30 largest GHG emitters, 2018 (WRI, 2021)

When attempting to classify these countries, both the UN and the International Monetary Fund (IMF) have methods to determine how developed a country is. Through the World Economic Situation and Prospects (WESP), the UN classified countries into three categories: Developed economies, economies in transition and developing economies (UN, 2020). The method for classifying countries is generally built around HDI (Nielsen, 2011). Initially arbitrary boundaries were setup to define countries into the 3 categories, however it has since made adjustments and no longer relies on absolute thresholds, in favour of relative boundaries (Nielsen, 2011). Typically, a country with an HDI greater than 0.8, would be classified as “Developed”.

The IMF method determines whether a country is “Advanced” or still “Emerging”, primarily based on its economic performance (IMF, 2021). There are 3 criteria taken into account:

1. Per capita income level
2. Export diversification
3. Integration into the global financial system

As an example, a country with high per capita GDPs, but with the export of a single good making up 70% of their total exports would likely not be classified as advanced. However their classification system is not solely limited to these criteria, and can take into account many other factors depending on the country’s context (IMF, 2021).

Table 4 identifies the classifications for the selected countries. Due to the differences in methodological approaches, 5 countries (Russian Federation, Saudi Arabia, Turkey, Argentina and Poland) have conflicting statuses between the institutions, classified as “Developed” by the UN, however still considered “Emerging” by the IMF.

Of the 30 countries, there is a spread across both classification systems: by the UN method, there are 15 “Developed” and 15 “Developing” countries. Using IMF’s classification, there are 10 “Advanced” and 20 “Emerging” countries. For the grouped networks, the countries were divided by the IMF categorisations, as the UN status is so closely tied to HDI.

Country	UN	IMF
China	Developing	Emerging
United States	Developed	Advanced
India	Developing	Emerging
Russian Federation	Developed	Emerging
Indonesia	Developing	Emerging
Brazil	Developing	Emerging
Japan	Developed	Advanced
Iran, Islamic Rep.	Developing	Emerging
Germany	Developed	Advanced
Canada	Developed	Advanced
Mexico	Developing	Emerging
Congo, Dem. Rep.	Developing	Emerging
Korea, Rep.	Developed	Advanced
Saudi Arabia	Developed	Emerging
Australia	Developed	Advanced
South Africa	Developing	Emerging
Turkey	Developed	Emerging
United Kingdom	Developed	Advanced
Pakistan	Developing	Emerging
Thailand	Developing	Emerging
Argentina	Developed	Emerging
Malaysia	Developing	Emerging
Italy	Developed	Advanced
Vietnam	Developing	Emerging
France	Developed	Advanced
Nigeria	Developing	Emerging
Poland	Developed	Emerging
Egypt, Arab Rep.	Developing	Emerging
Spain	Developed	Advanced
Venezuela, RB	Developing	Emerging

Table 4: Categorisation of the top 30 emitters (UN, 2020; IMF, 2021). Countries highlighted in orange have differing statuses between the institutions: considered developed by the UN, but still emerging by the IMF

2.1.4 SSPs and Projection of Indices

Of the metrics discussed previously, Population, Urbanisation and GDP all have projections directly associated with each SSP, and data is provided from the project. The units of GDP are important due to a slight variation between the SSPs and available data from the World Data Bank: the SSPs report GDP using the purchasing power parity (PPP) of the US$ from 2005. Whilst the World Data Bank has a range of reported units for GDP, the typical method to correct for PPP and inflation requires respective coefficients for each year (Turner et al., 2019), which aren't included in the SSP projections. As such, an alternate formula was derived (Equation 1) that utilised the same mechanisms as inflationary correction, but allowed the conversion of the SSPs *GDP PPP Constant US$2005* to *GDP Constant US$2010*, using the data available within the World Data Bank. Population and Urbanisation could both be utilised directly.

$$x_{2010} = \frac{\frac{z_{2005} \times p_{2005}}{c_{2005}} \times y_{2005}}{y_{2010}} \times u$$

Equation 1: Conversion of GDP PPP Constant US$2005 to GDP Constant US$2010, where x_{2010} is GDP Constant US$2010, z_{2005} is GDP PPP Constant US$2005, p_{2005} is PPP Conversion 2005, c_{2005} is GDP Current LCU 2005, y_{2005} is GDP Constant LCU 2005, y_{2010} is GDP Constant LCU 2010 and u is GDP Current US$

For the remaining indices, interpretations were made of quantitative adjustments based on the descriptions with the SSP narratives. Naturally, each of these indices has a great deal of complexity, and warrants modelling to be able to justify real world projections. However, as the nature of this study is focusing on the suitability of ANNs and the outcomes of the SSPs, and the large scope given the selected variables, countries and scenarios, simplistic and arbitrary translations were made between the qualitative descriptions and quantitative outputs. O'Neil et. al (2017) supplements the narrative descriptions with clear changes in various development indicators, a subset of which is shown in Table 5. These were used directly where possible, otherwise the parameters were inferred from the narrative descriptions, and are shown in Table 6.

SSP element	SSP1	SSP2	SSP3	SSP4	SSP5
Growth (per capita)	High in LICs, MICs; medium in HICs	Medium, uneven	Slow	Low in LICs, medium in other countries	High
Inequality	Reduced across and within countries	Uneven moderate reductions across and within countries	High, especially across countries	High, especially within countries	Strongly reduced, especially across countries
International trade	Moderate	Moderate	Strongly constrained	Moderate	High, with regional specialization in production
Globalization	Connected markets, regional production	Semi-open globalized economy	De-globalizing, regional security	Globally connected elites	Strongly globalized, increasingly connected
Consumption & Diet	Low growth in material consumption, low-meat diets, first in HICs	Material-intensive consumption, medium meat consumption	Material-intensive consumption	Elites: high consumption lifestyles; Rest: low consumption, low mobility	Materialism, status consumption, tourism, mobility, meat-rich diets

Table 5: How the SSPs affect various socio-economic development indicators (O'Neill et al., 2017)

Variable	SSP1	SSP2	SSP3	SSP4	SSP5
Energy Consumption	Low	Higher in LIC	High	Low/Medium	High
Foreign Direct Investment	High	Medium	Low	High in OECD, low in others	High
Economic Growth	High in LIC, MIC; Medium in HIC	Medium	Slow	Low in LIC, Medium Other	High
Industrialisation	Low	Medium	High in LIC, Medium Other	High in LIC, Medium Other	High in LIC, Medium Other
R&D	High	Medium	Low	High in OECD, low in others	High
Population	Low	Medium	Rich OECD, low; Others, high	Rich OECD, low; Others, high	Low
Trade Openness	Medium	Medium	Limited	Medium	High
Urbanisation	High	Medium	Low	High	High
HDI	High	Medium	Low	Low in LIC, Medium in Other	High
Hydro Potential	Constant	Constant	Constant	Constant	Constant
Solar Potential	Constant	Constant	Constant	Constant	Constant

Table 6: The interpretations for the selected parameters based on the narratives. Cells in grey either remain constant or have data provided, so extrapolation is not necessary. LIC, MIC and HIC refer to low-income, medium-income and high-income respectively

2.1.4.1 HDI

It can be assumed that most countries follow the same trajectory for HDI development (Molina and Purser, 2013). Whilst the current HDI data is noisy and temporally limited, the rate of change of HDI was plotted against HDI values to form an exponential model for how HDI changes over time. There is a general trend, demonstrating how as a country approaches a HDI of 1, the development slows (Figure 15). This allowed the creation of a formula (Equation 2) which could be adjusted to represent faster or slower HDI growth (Figure 16). Naturally this doesn't include situations where a country may lower in HDI, however it is assumed that all countries continue to grow at differing rates.

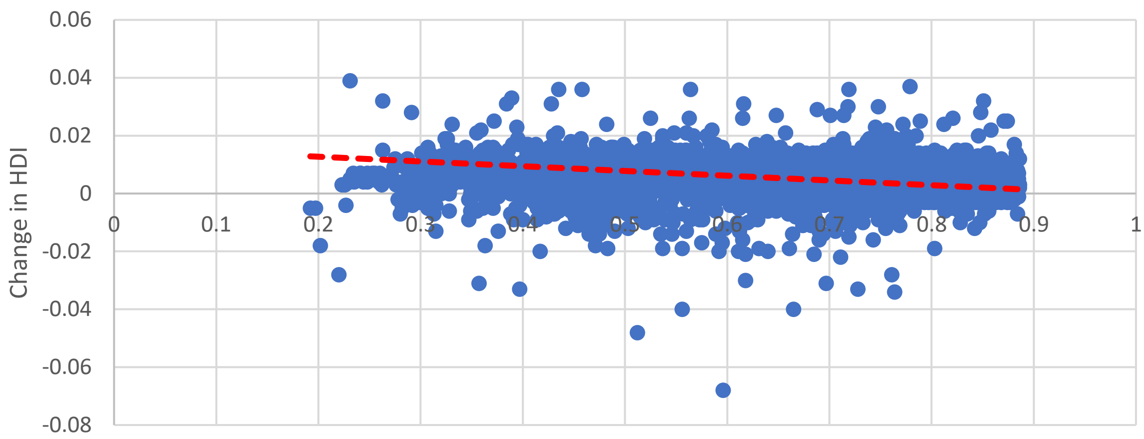


Figure 15: HDI change against HDI Value

$$x_n = 0.984x_{(n-1)} + 0.016$$

Equation 2: Formula to represent HDI Growth, where x is HDI and n is the current year

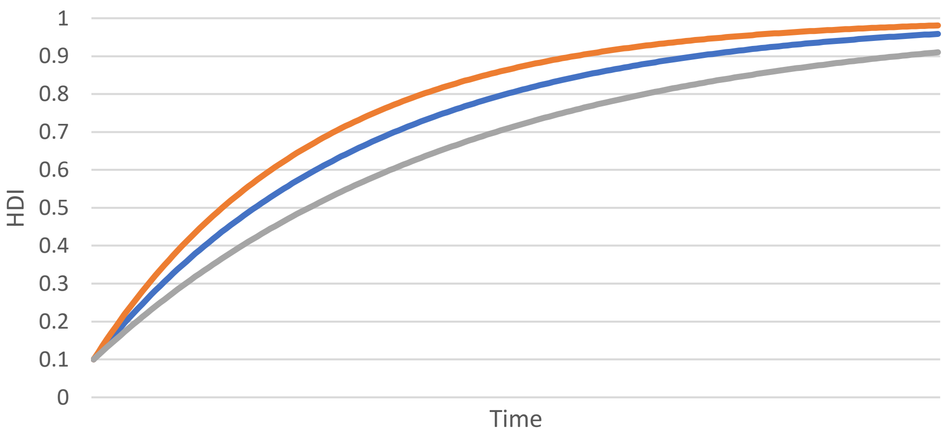


Figure 16: Example changes in HDI for three different scenarios

2.1.4.2 FDI and Trade Openness

Both FDI and Trade Openness are generally unlikely to experience continuous growth, as they are represented as a percentage against GDP, which itself will continue to grow. Therefore, targets were set conservatively based on the current spread of respective values across all countries globally, with outliers removed (Figure 17): for example, Hong Kong's trade is approximately 400% with respect to its GDP, but isn't necessarily a representative target for other countries. With these targets, the country's latest historic data could be interpolated to them linearly to 2050, providing inputs for the ANN.

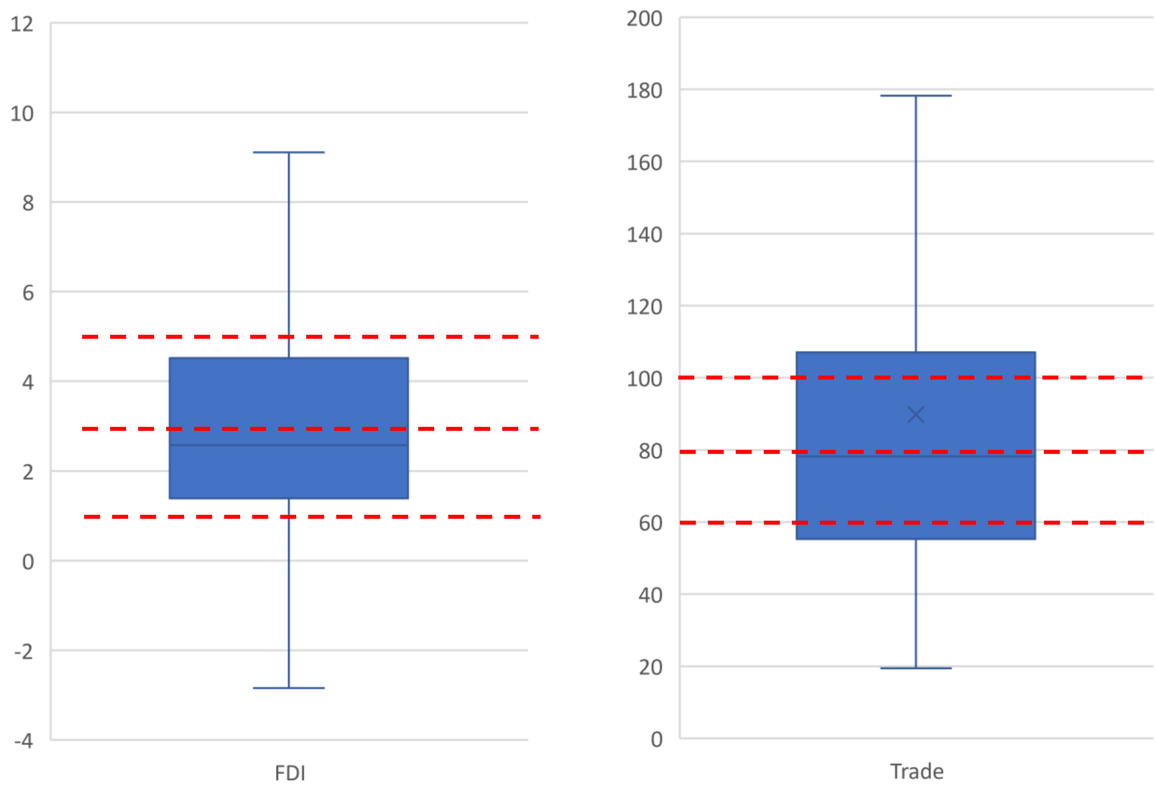


Figure 17: The spread of FDI and Trade for all countries with data available in 2014, where the red dashed lines mark the lower, moderate and upper targets for projections (WDB, 2021)

2.1.4.3 R&D, Energy Use and Industrialisation

Research and Development was assumed to continuously increase at differing rates, so a simple linear growth was applied to each country's latest historic data. Energy use was modelled linearly, broadly using the regional projections within the SSPs. Whilst these projections apply to an entire region, the growth in energy use by the mid-century was approximated, and applied linearly to each country so that each pathway had a comparable change in energy usage. Industrialisation presented the greatest challenge as each country has its trend, and the SSPs don't provide clear indication for the industrialised state. Each country was extrapolated based on the historic data, to take into account their current trajectories, and then minor adjustments were applied to represent changes from the various scenarios with limits set to prevent implausible scenarios i.e., negative values. An example of all the extrapolated indices is shown below in Figure 18 for the UK.

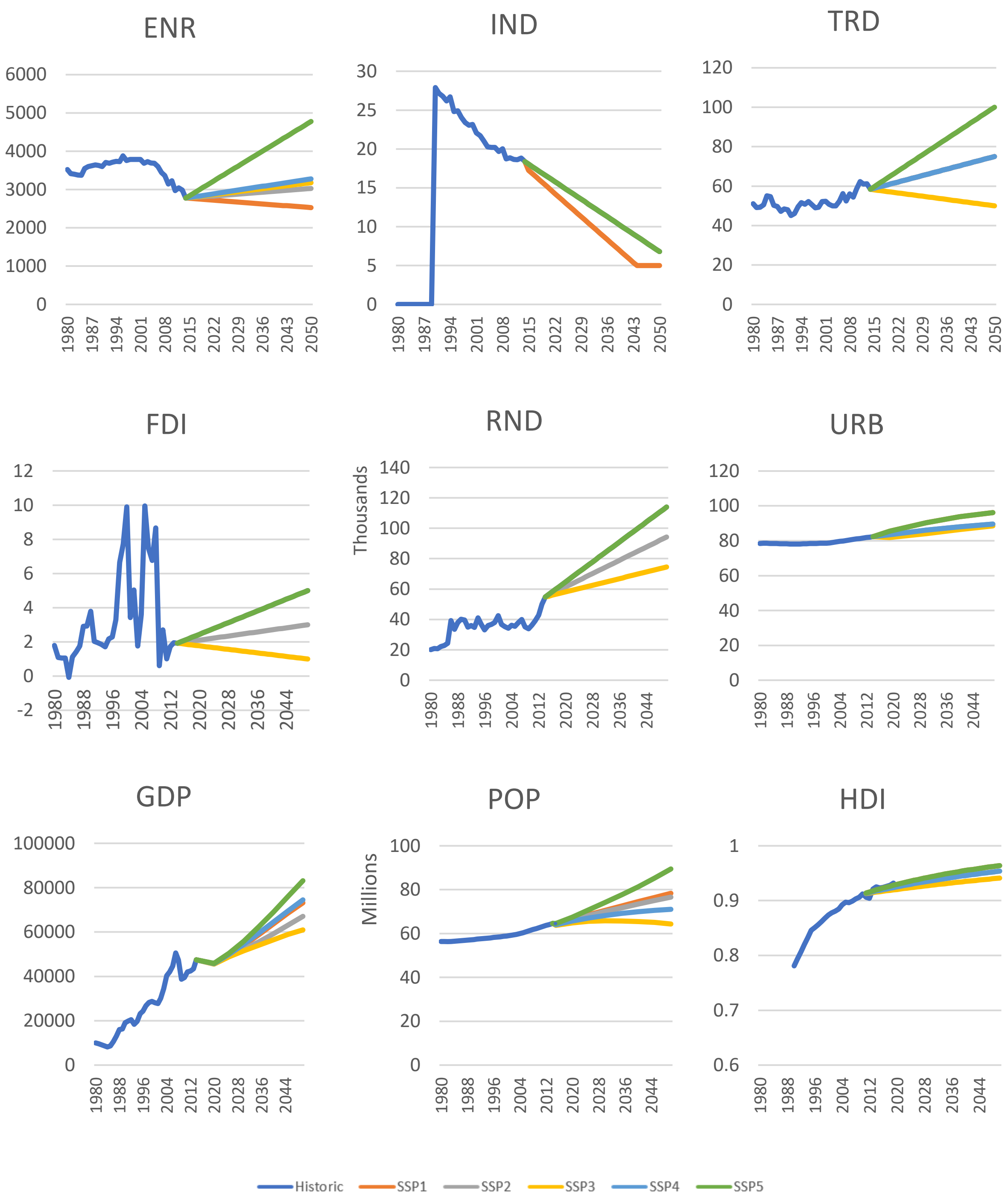


Figure 18: Extrapolated indices for the UK to 2050, overlaid on historic data

2.2 Modelling

2.2.1 ANN Design

In order to produce the model, TensorFlow (2021) and Keras (2021) were used in a Python 3.7.9 environment. As stated previously, two network styles would be used: the first would be trained with data from each individual country and use 8 input variables whilst the latter would group countries together by their IMF categories and train two networks on 11 variables. This split can be seen in Table 3. When deciding on the design of the model, there are few governing rules, as the design can be so particular to the problem it is being applied to (Judd, 1990; Rafiq et al., 2001; Haykin and Network, 2004). There can be risks such as adding too many neurons that result in overfitting, whilst too few could result in underfitting. Similarly, too many hidden layers can decrease the reliability of the network (Kanwar et al., 2019). It is generally accepted that network growing and pruning is the best method to approach optimisation (Haykin and Network, 2004). As previous studies have approached similar analyses (Acheampong and Boateng, 2019), the base design for the individual networks of 8 input neurons, 1 hidden layer with 5 neurons, and 1 output neuron was selected (Figure 19). The grouped IMF networks had the 3 additional inputs to represent the added variables (Table 3), however they featured the same 5 neuron hidden layer to form a network of 11-5-1.

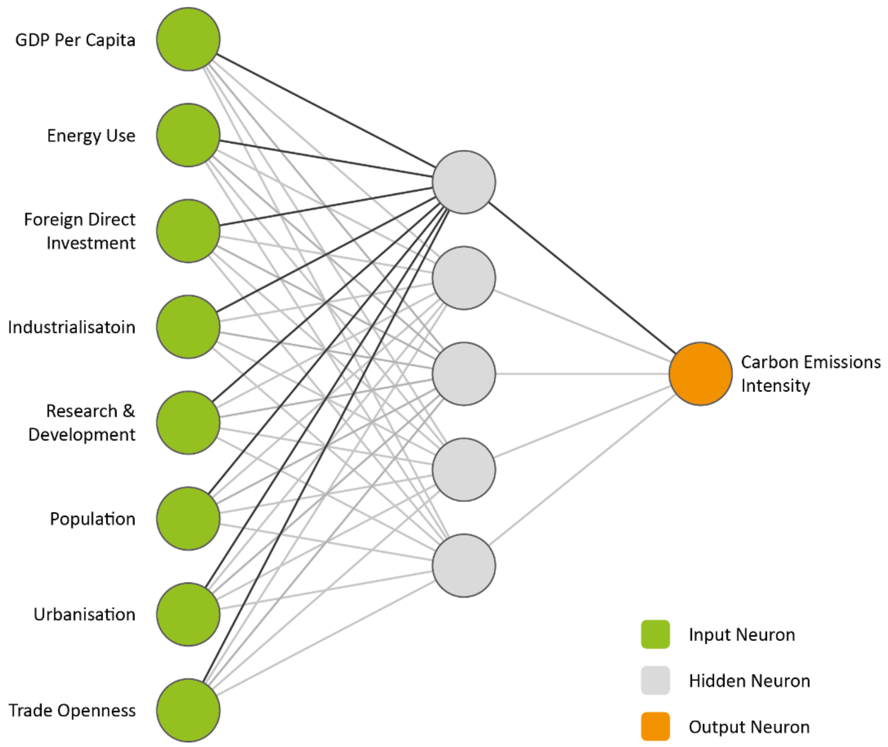


Figure 19: The representation of the ANN for individual countries

2.2.2 Data and Augmentation Techniques

Data augmentation is used to improve the amount of available data or diversity by modifying or duplicating data with the end goal of improving the training of an algorithm. The dataset from the World Data Bank provides historic values for the indices, however there are gaps for certain years. As such, the data was trimmed to the years 1980-2014 inclusive, which generally provided the most continuous series across the countries and indicators, with some exceptions such as Industrialisation (Figure 18). In cases where there were zeroes between two datapoints, a simple linear interpolation was used to make the series continuous. However, at most this only provides 35 data points per input, for each country, which is limited for machine learning applications.

There are many methods to augment datasets, however previous studies have typically utilised quadratic interpolation (Sbia et al., 2014; Shahbaz et al., 2017a; Acheampong and Boateng, 2019). This technique is generally superior to linear interpolation, as it helps to characterise trends within the data (Figure 20). Whilst it may be disadvantageous due to the accentuation from the spline, this inherently creates noise in the augmented data, which helps to limit overfitting. In line with previous studies, the annual dataset was quadrupled into an augmented “quarterly” dataset through interpolation. It is important to note, that the interpolation didn’t form actual quarterly data, through methods such as quadratic sum (Sbia et al., 2014; Shahbaz et al., 2017b) as the SSP projection data is based on annual figures.

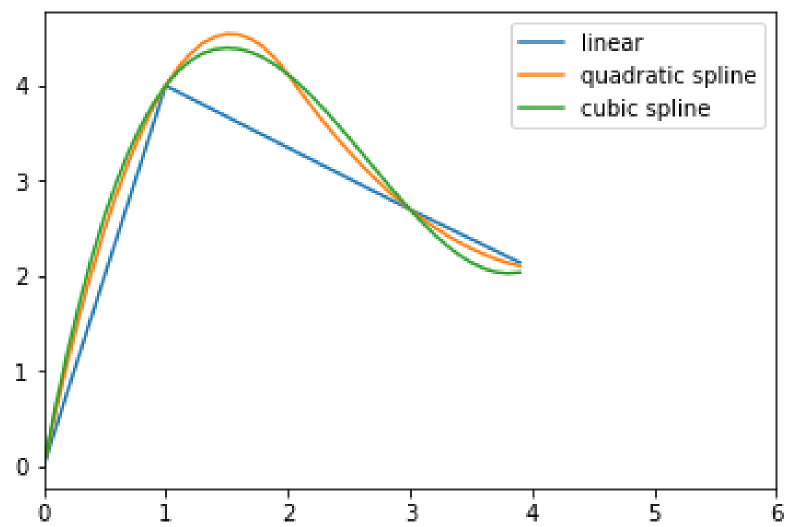


Figure 20: Demonstration of different interpolation techniques using the Scipy library (Scipy, 2020)

This interpolation technique was only applied to the data for individual countries, and not for the grouped networks. After interpolation, each individual country would have 136 data points per input, whereas the grouped networks would benefit from multiple countries, totalling 340 and 680 data points per input for “Advanced” and “Emerging” respectively, and thus should have sufficient data for training.

2.2.3 Fitting the Model

Given the precedents of using ANNs with these data types, overfitting is a risk. As risk of overfitting increases with increasing epochs, one method to limit overfitting is to employ an early stopping protocol, and limit the number of epochs (Prechelt, 1998). In order to implement early stopping, a limit on the number of allowable epochs was set that is typically higher than the expected epochs required. After each validation stage, the mean square error is calculated and reported.

The early stopping protocol monitors this “loss” value (a value representing the penalty for poor predictions), and if there isn’t any improvement in this value after a defined period, the training stops. In the implementation of this protocol, the maximum number of epochs was set at 1000, and the patience (the number of epochs without improvement) was set to 5. Once this limit has been reached, the model halts training, reloading the weights for the model from the epoch at the start of the patience period. This prevents any potential overfitting through the five epochs of patience. The loss value monitored here was Mean Square Error (MSE), which is the default loss measure for regression-based machine learning. It is calculated by the following:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \tilde{y}_i)^2$$

Equation 3: Formula for MSE, where n is the number of data points, y_i are observed values, and $\tilde{y}_i$ are the predicted values

Whilst MSE was chosen as the metric within Keras, R^2 was also used to measure the network performance with training and projections. Scikit provides an R^2 score function by comparing predicted values against actual (Scikit, 2021). The equation for this is given in Equation 4.

$$R^2 = 1 - \frac{\sum_i (y_i - f_i)^2}{\sum_i (y_i - \bar{y}_i)^2}$$

Equation 4: Calculation of R^2, where y_i is the data, f_i is the modelled data and $\bar{y}_i$ is the mean of the observed data

2.2.4 Ensemble Training & Code

For this study, 100 networks were trained per cohort, using randomised divisions of the data for each iteration (Figure 21). The use of python enabled logging of the training process through the performance and accuracy metrics such as MSE, R^2 and epochs (history.csv, error_histogram.png and r2.png), as well as saving out the weights from within the networks (checkpoints), so that each of the networks could easily be loaded up for projections as a cohort. Part of this output also included the scalers used to normalise the input and output values, a requirement for scaling the extrapolated inputs for projections, and rescaling the projected output.

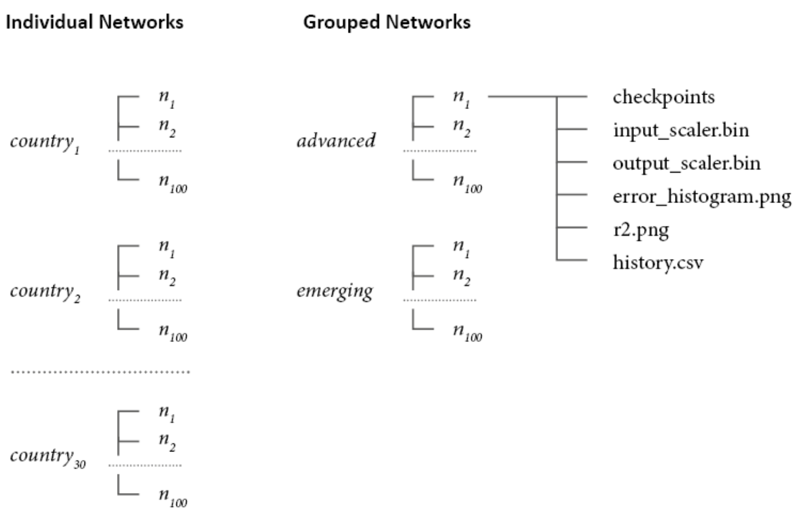


Figure 21: An overview of the code outputs, where n is a single trained network

The process of running projections then procedurally loaded up the weights of each model, processed the extrapolated inputs for SSP1-5, and recorded the collective outputs for all 100 models per cohort, alongside characteristics of the data (median, mean, standard deviation etc.), before moving to the next set of models.

All code and datasets used are available here: https://github.com/rdemello/Dissertation.

3 | Results

3.1 Training

Example outputs from the training are given below, using the data from the training history in Figure 22 and the error histogram and R^2 in Figure 23, for the 6th UK Model.

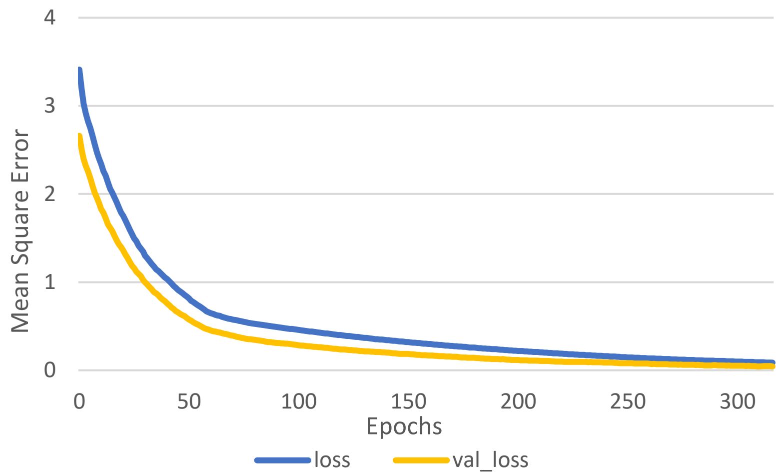


Figure 22: Training of Model 6 for the UK, demonstrating the loss for both training and validation, before stopping at epoch 317, and reverting the weights back to epoch 312

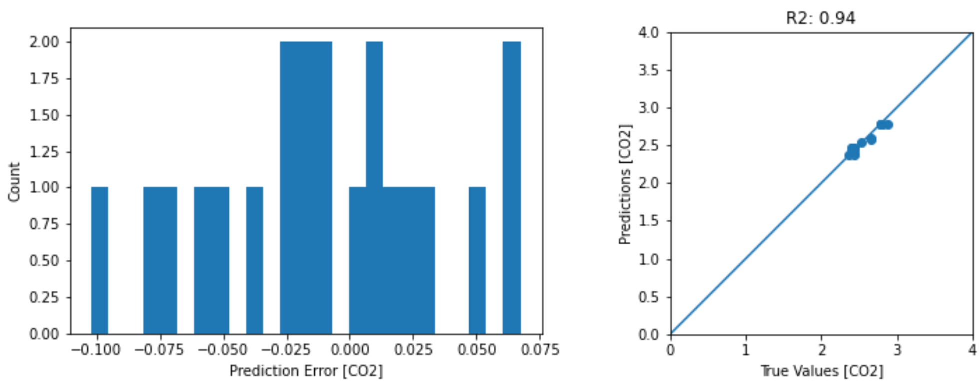
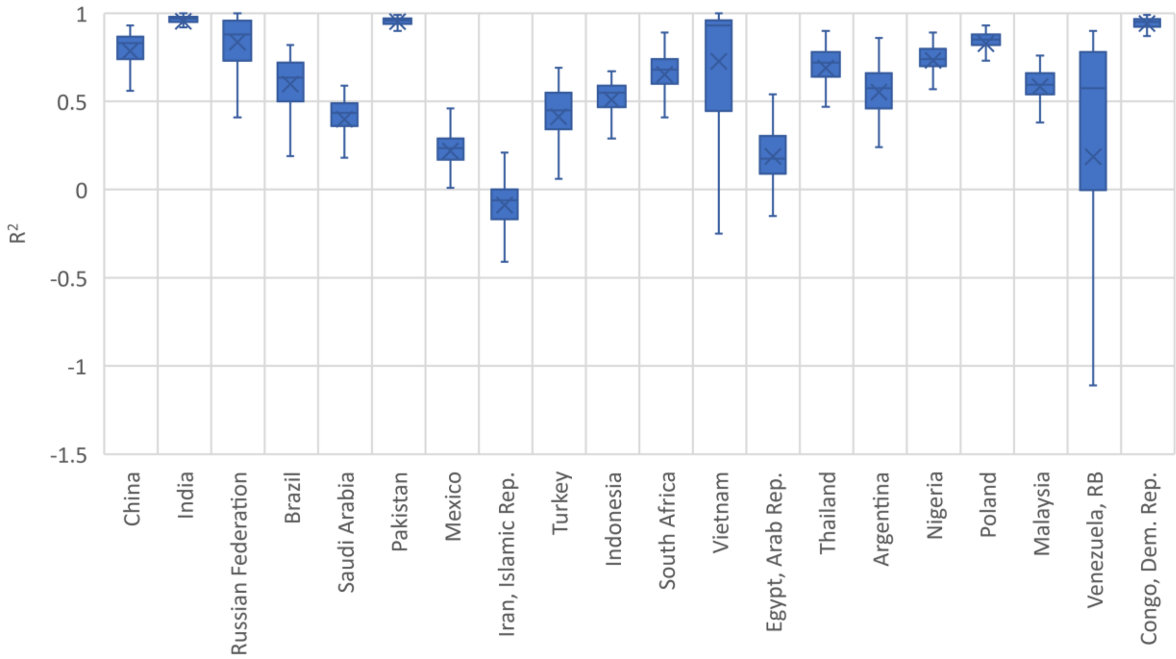


Figure 23: Automatically recorded performance metrics during validation for UK Model 6. The graph to the left shows the error spread and count, whilst the graph to the right shows the R^2

3.1.1 Individual Networks

The training of the individual networks varied on a country-by-country basis (Figure 24), with some success and some poor performance.



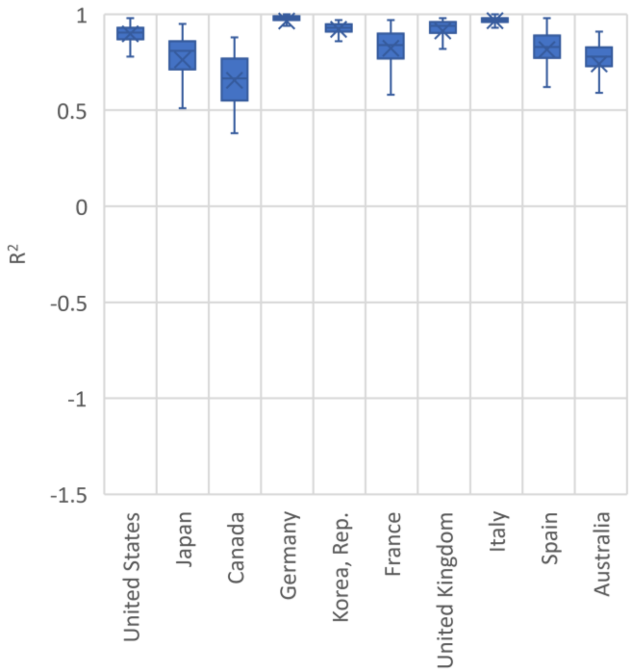
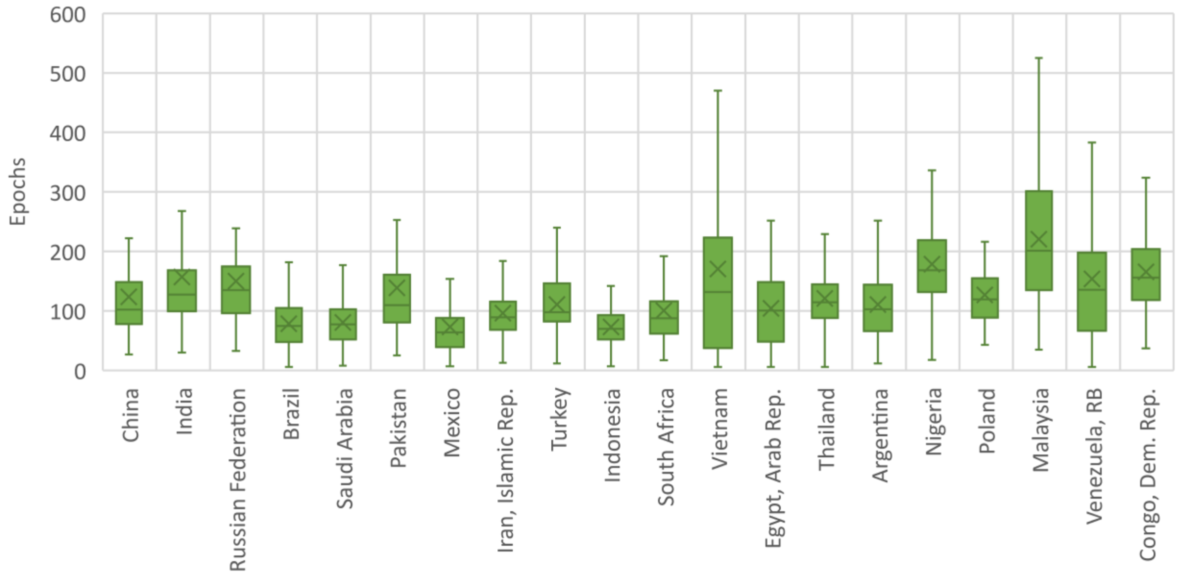


Figure 24: The R^2 performance of the individually trained networks per country. Above are the Emerging countries, and to the left are the Advanced

Some countries performed quite well such as Germany, UK and Democratic Republic of the Congo, others experienced large ranges of predictions across their networks and generally poor R^2 values. The Advanced countries had better performance than the Emerging countries. The former has a mean R^2 of 0.85, whilst the latter only managed 0.58.



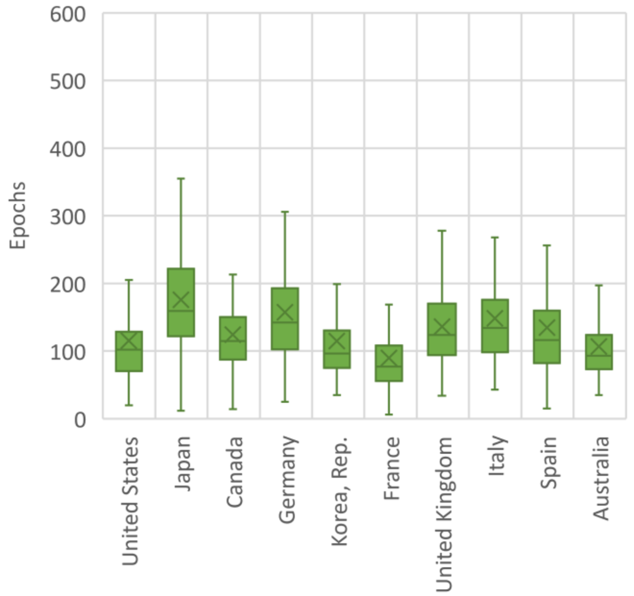


Figure 25: The number of epochs required for the individually trained networks per country. Above are the Emerging countries, and to the left are the Advanced

When reviewing the number of epochs required before the early stopping protocol was triggered, all countries are comparable with some anomalies such as Vietnam, Malaysia and Venezuela. The Emerging countries required an average of 127 epochs, while the Advanced countries required an average of 131 epochs.

3.1.2 Grouped Networks

The two sets of grouped networks generally trained well, with the Advanced countries performing slightly better with an average R^2 of 0.93, while the Emerging countries achieved an average R^2 of 0.84.

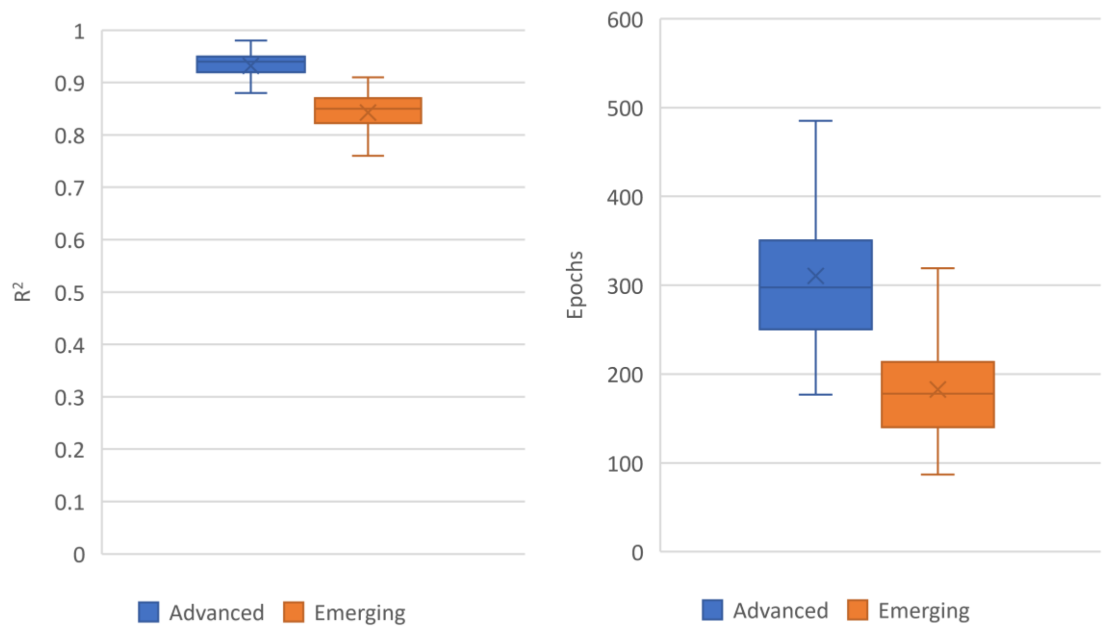


Figure 26: The R^2 performance and epochs required for the Advanced and Emerging networks

The Advanced countries required more epochs to complete their training, with an average of 310 epochs, compared to the Emerging countries, which averaged 183.

3.1.3 Comparison Between Network Types

When comparing the results from both training methods, the grouped networks generally have better R^2 for most countries (the exceptions being Germany, Italy, Democratic Republic of the Congo, India and Pakistan). The Emerging countries see the biggest improvement with an average R^2 increase of 0.24 across the 20 countries when comparing the individual networks to grouped. On the other hand, the Advanced countries see only a 0.08 improvement to R^2 by using the grouped network over the individual.

The number of epochs required for the grouped network was greater than the individual networks (with the exception of Malaysia). The individual networks for Advanced countries on average required 179 fewer epochs to train sufficiently, while the Emerging countries required 56 fewer epochs.

Country	IMF	R^2			Epochs		
		Individual	Individual Mean	Grouped	Individual	Individual Mean	Grouped
Australia	A	0.74	0.85	0.93	107	131	310
Canada	A	0.66			124		
France	A	0.82			90		
Germany	A	0.96			158		
Italy	A	0.97			149		
Japan	A	0.76			176		
Korea, Rep.	A	0.92			115		
Spain	A	0.82			135		
United Kingdom	A	0.91			136		
United States	A	0.9			116		
Argentina	E	0.55	0.58	0.84	111	127	183
Brazil	E	0.6			79		
China	E	0.79			124		
Congo, Dem. Rep.	E	0.94			165		
Egypt, Arab Rep.	E	0.19			104		
India	E	0.95			157		
Indonesia	E	0.51			73		
Iran, Islamic Rep.	E	-0.09			96		
Malaysia	E	0.58			221		
Mexico	E	0.22			73		
Nigeria	E	0.73			179		
Pakistan	E	0.95			139		
Poland	E	0.83			127		
Russian Federation	E	0.84			150		
Saudi Arabia	E	0.4			81		
South Africa	E	0.65			101		
Thailand	E	0.69			121		
Turkey	E	0.41			111		
Venezuela, RB	E	0.19			154		
Vietnam	E	0.73			170		

Table 7: The training results for the individual country networks, and the grouped networks for R^2 and epochs required. The countries individual scores are colour coded based on their values with respect to the group networks e.g. green indicates the individual networks have a better R^2 or required fewer epochs compared to the grouped value.

3.2 Projections

3.2.1 SSP Projections for Individual Networks

The 2050 results from the individually trained networks' 5 SSPs for the Advanced and Emerging countries are displayed in Figure 27 and Figure 28 respectively. The mean is shown, with error bars representing the 95% confidence interval in the mean, from the 100 networks. Only two countries have scenarios that achieve zero CEI (Italy and the Democratic Republic of the Congo). Although not true for every country, the SSP1-3 in Advanced countries generally follow the same pattern, where SSP1 has a lower CEI than SSP2, which has a lower CEI than SSP3. SSP5 generally has a lower CEI than SSP4, except for Germany, where SSP5 is larger.

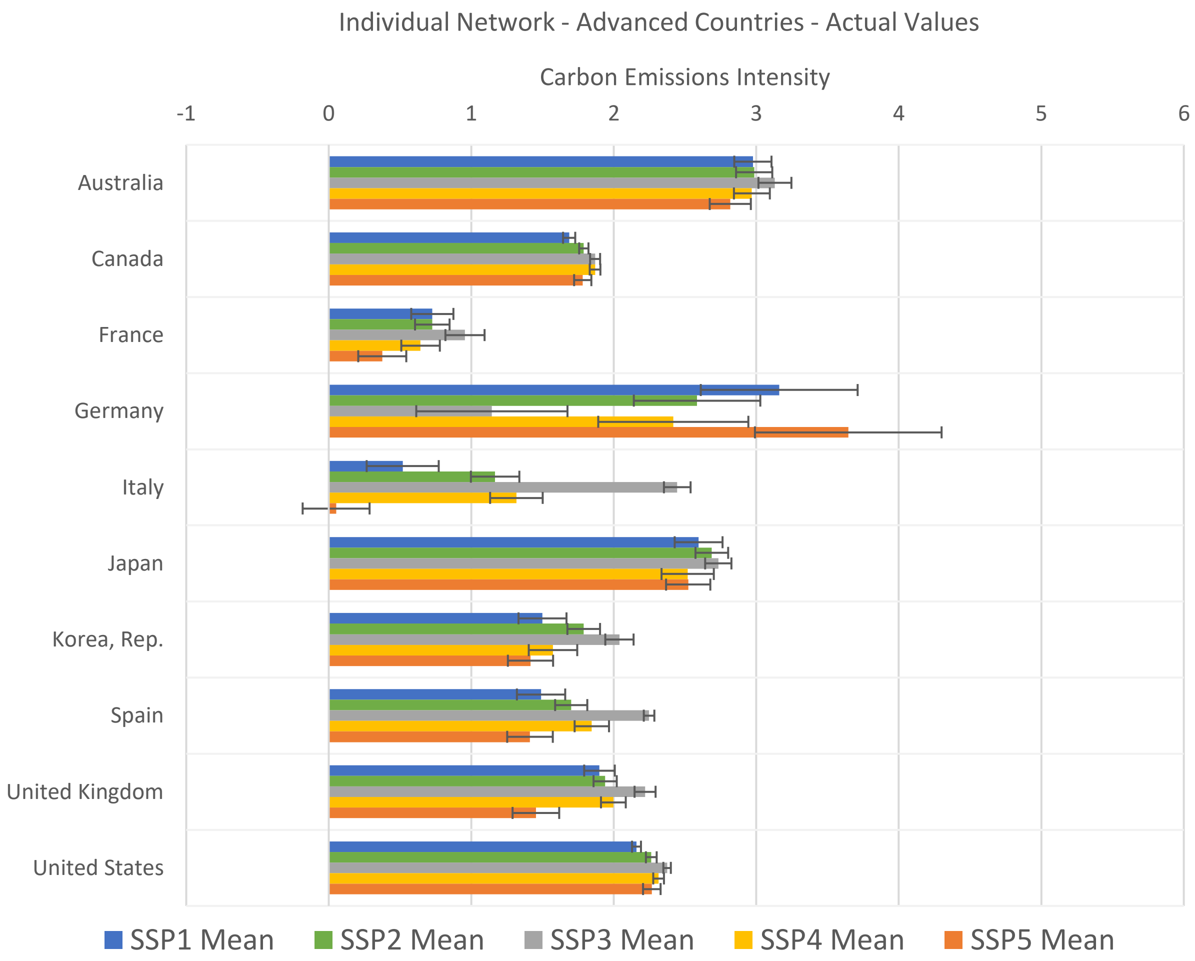


Figure 27: The mean 2050 CEI for all SSP scenarios, for the Advanced countries individually trained networks. Error bars represent the 95% confidence interval for the mean

The Emerging countries have more variation in which SSP results in the lowest CEI, although 12 of the countries have the inverse trend of the Advanced countries for SSP1-3, where SSP3 has a lower CEI than SSP2, which has a lower CEI than SSP1.

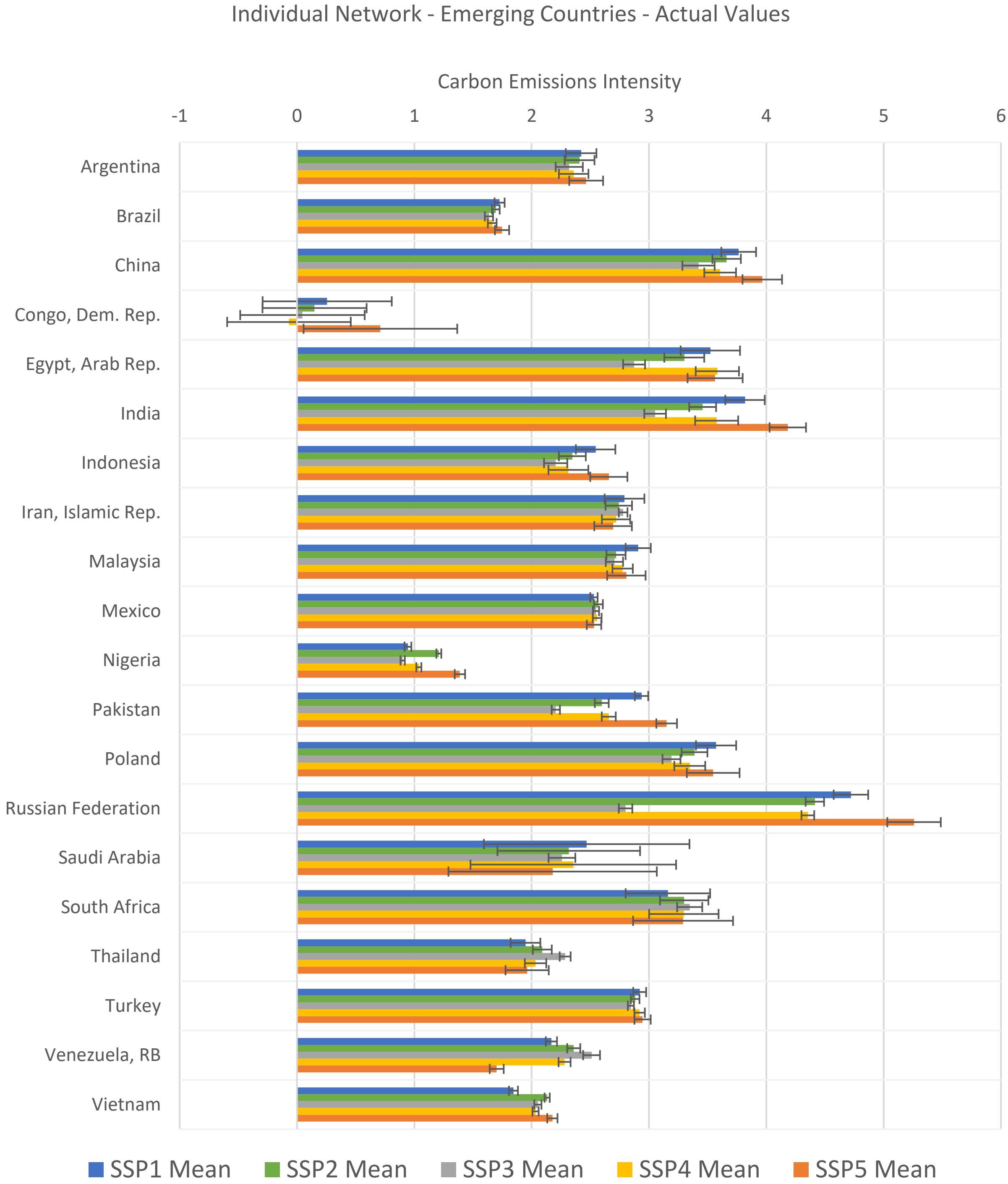


Figure 28: The mean 2050 CEI for all SSP scenarios, for the Emerging countries individually trained networks. Error bars represent the 95% confidence interval for the mean

The trajectories for the UK (Advanced) and India (Emerging) are provided in Figure 29 and Figure 30 respectively, as examples of their respective IMF groupings.

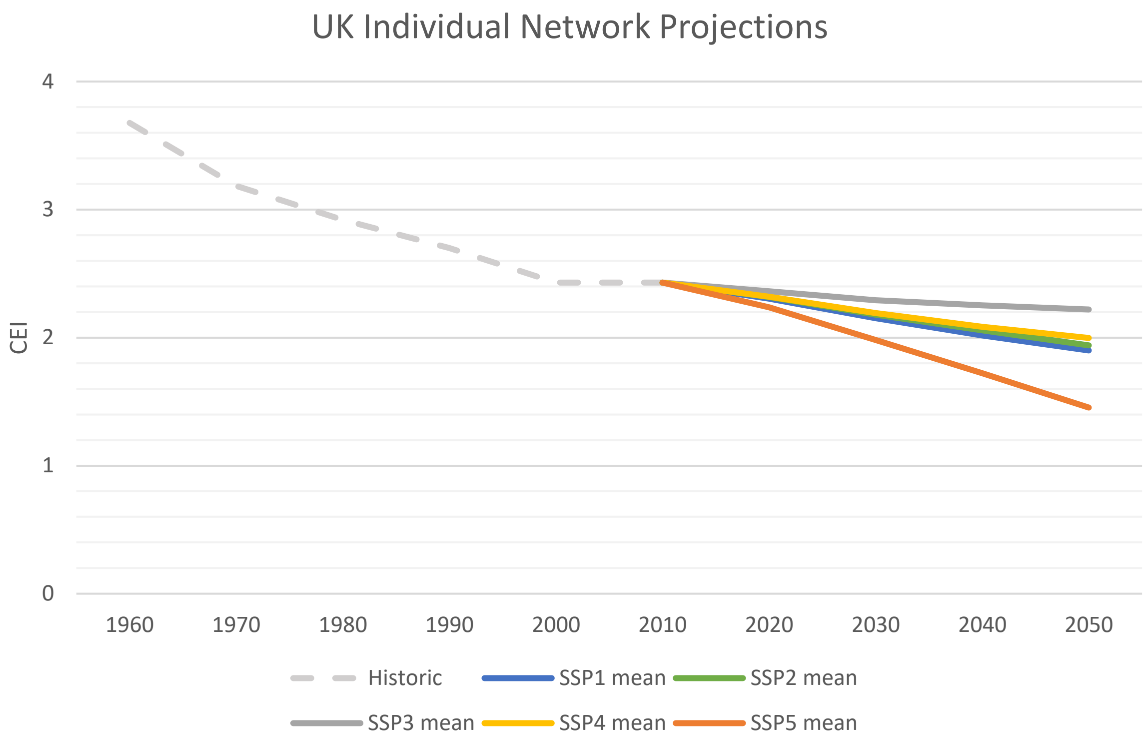


Figure 29: Projections of UK CEI for the 5 SSPs up to 2050 using the individually trained networks

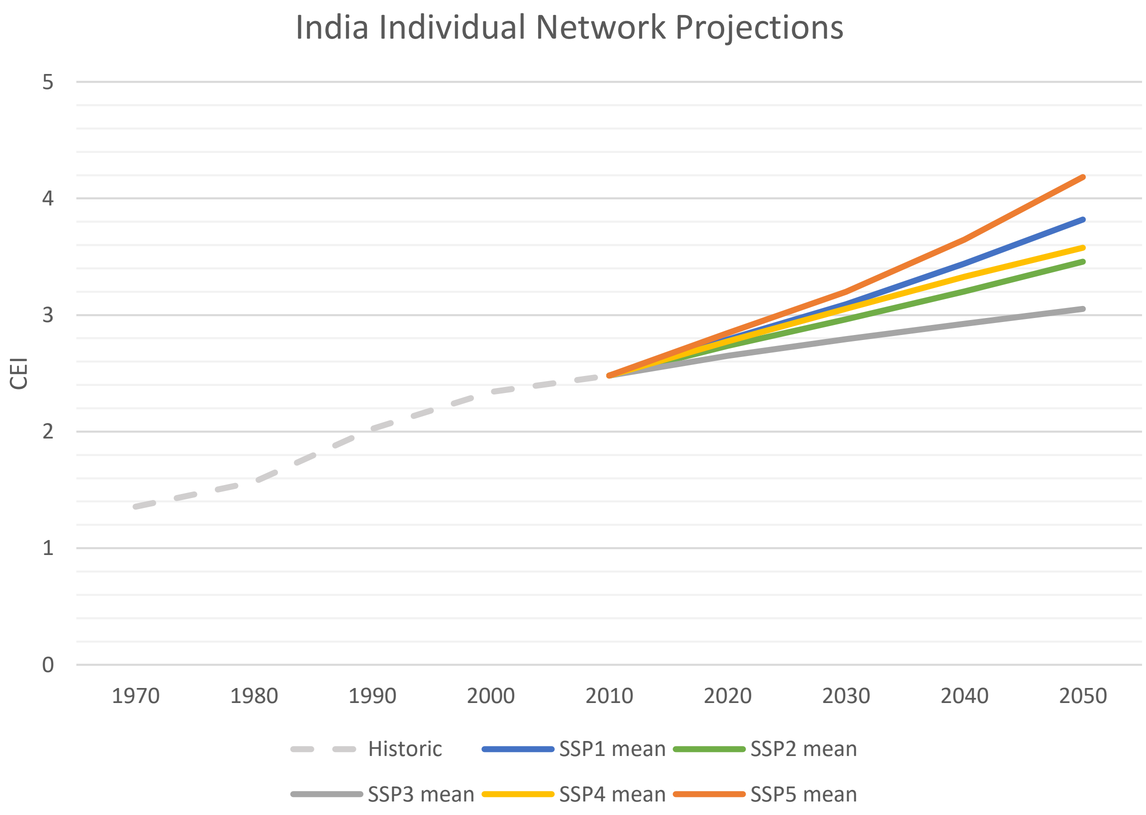


Figure 30: Projections of India's CEI for the 5 SSPs up to 2050 using the individually trained networks

3.2.2 SSP Projections for Grouped Networks

The 2050 results from the grouped networks' 5 SSPs for the Advanced and Emerging countries are displayed in Figure 31 and Figure 32 respectively. The mean is shown, with error bars representing the 95% confidence interval in the mean, from the 100 networks. No country achieves net zero CEI by 2050. Although not true for every country, the SSP1-3 in Advanced countries generally follow the same pattern, where SSP1 has a lower CEI than SSP2, which has a lower CEI than SSP3. SSP5 generally has a lower CEI than SSP4, except for Germany and the UK, where SSP5 is larger.

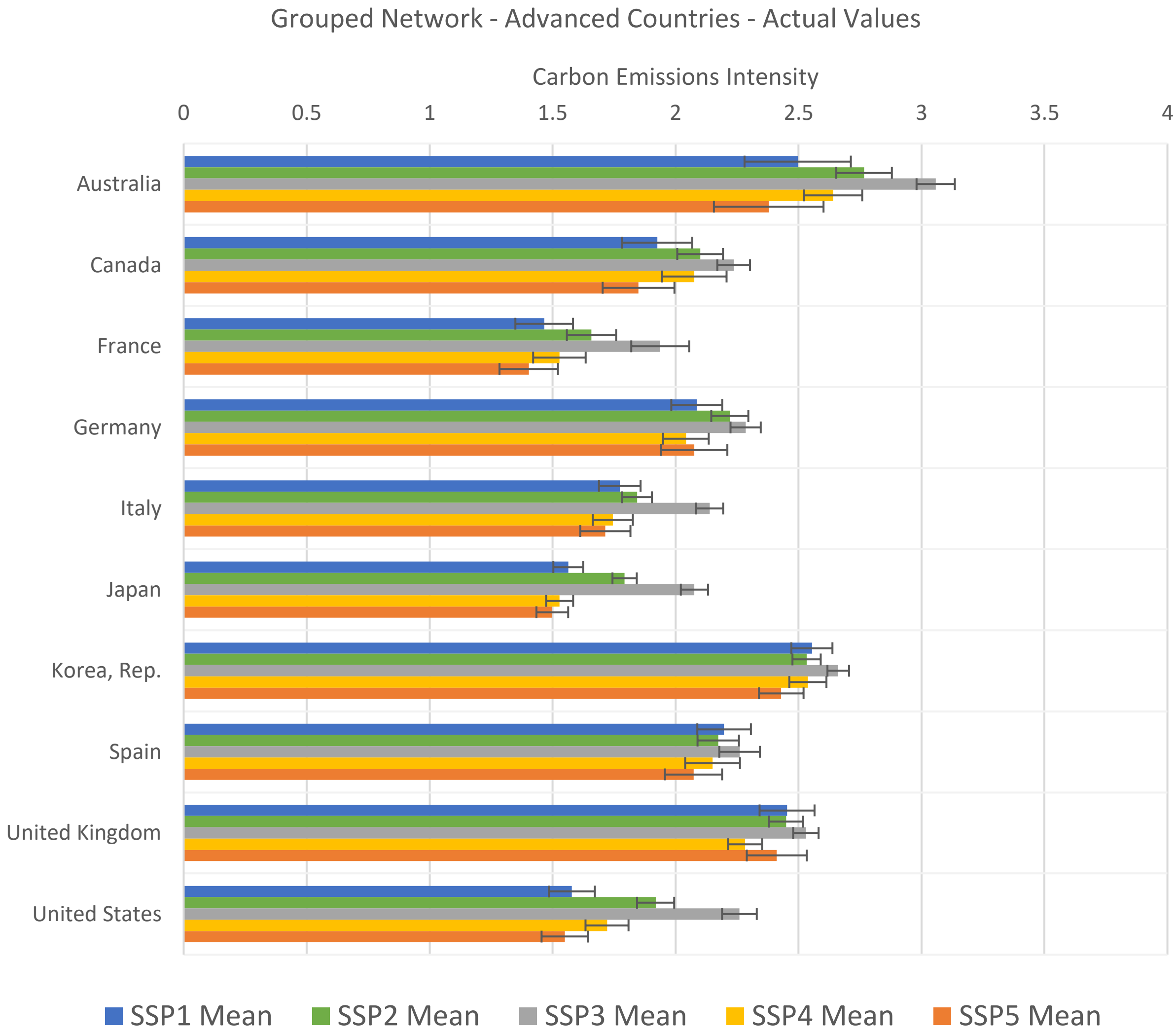


Figure 31: The mean 2050 CEI for all SSP scenarios, for the Advanced countries grouped trained networks. Error bars represent the 95% confidence interval for the mean

The Emerging countries have more variety in which SSP results in the lowest CEI, although 16 of the countries have the same trend of the Advanced countries for SSP1-3, where SSP1 has lower CEI than SSP2, which has lower CEI than SSP3.

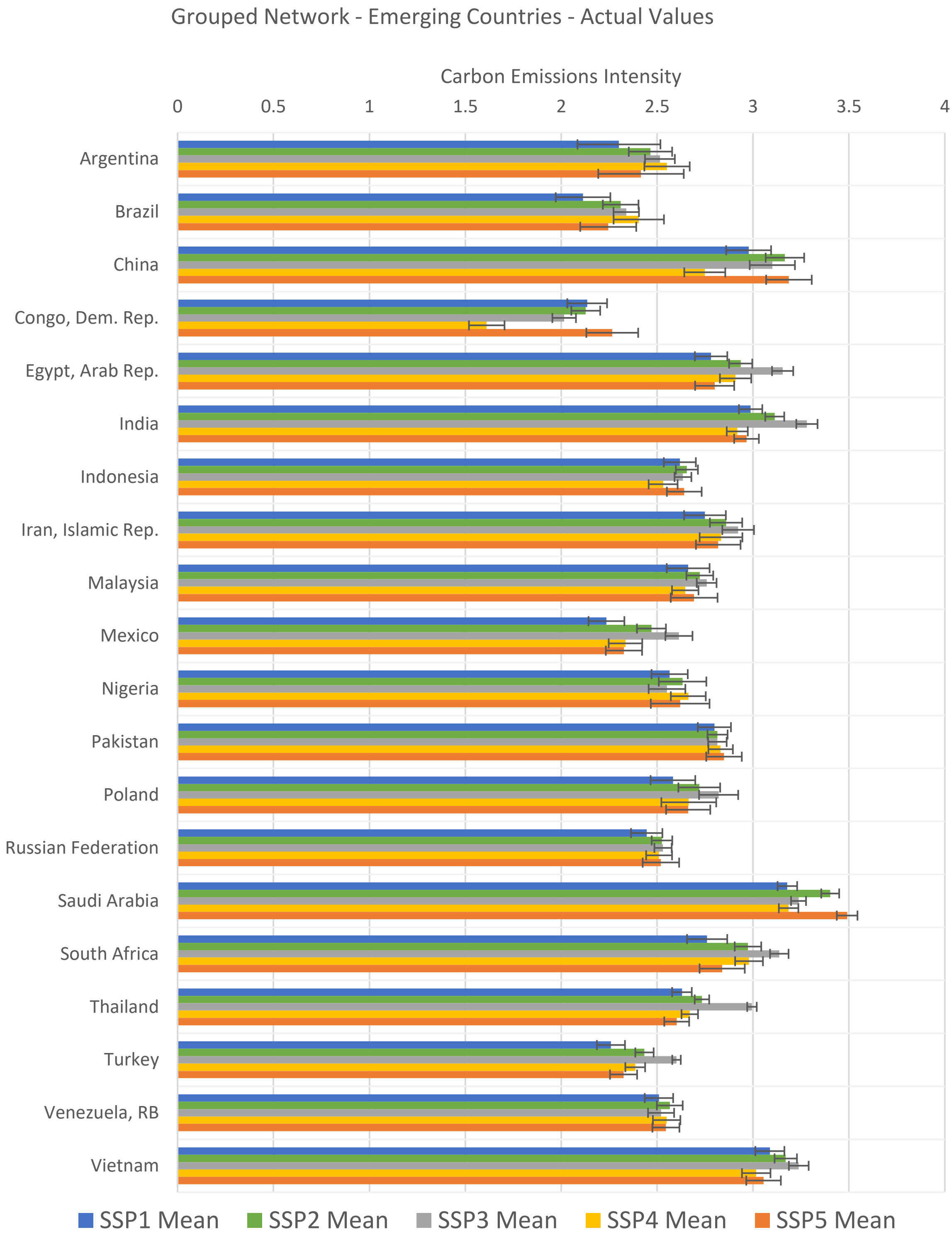


Figure 32: The mean 2050 CEI for all SSP scenarios, for the Emerging countries grouped trained networks. Error bars represent the 95% confidence interval for the mean

The trajectories for the UK (Advanced) and India (Emerging) are provided in Figure 33 and Figure 34 respectively.

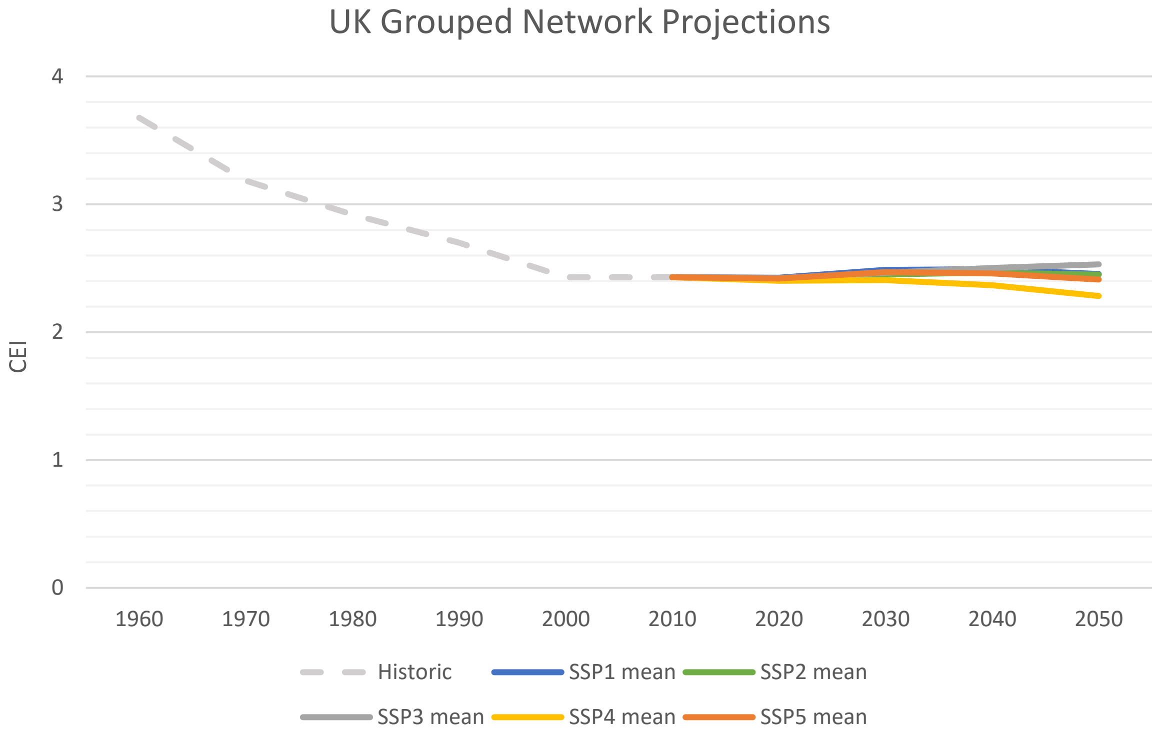


Figure 33: Projections of UK CEI for the 5 SSPs up to 2050 using the grouped trained networks

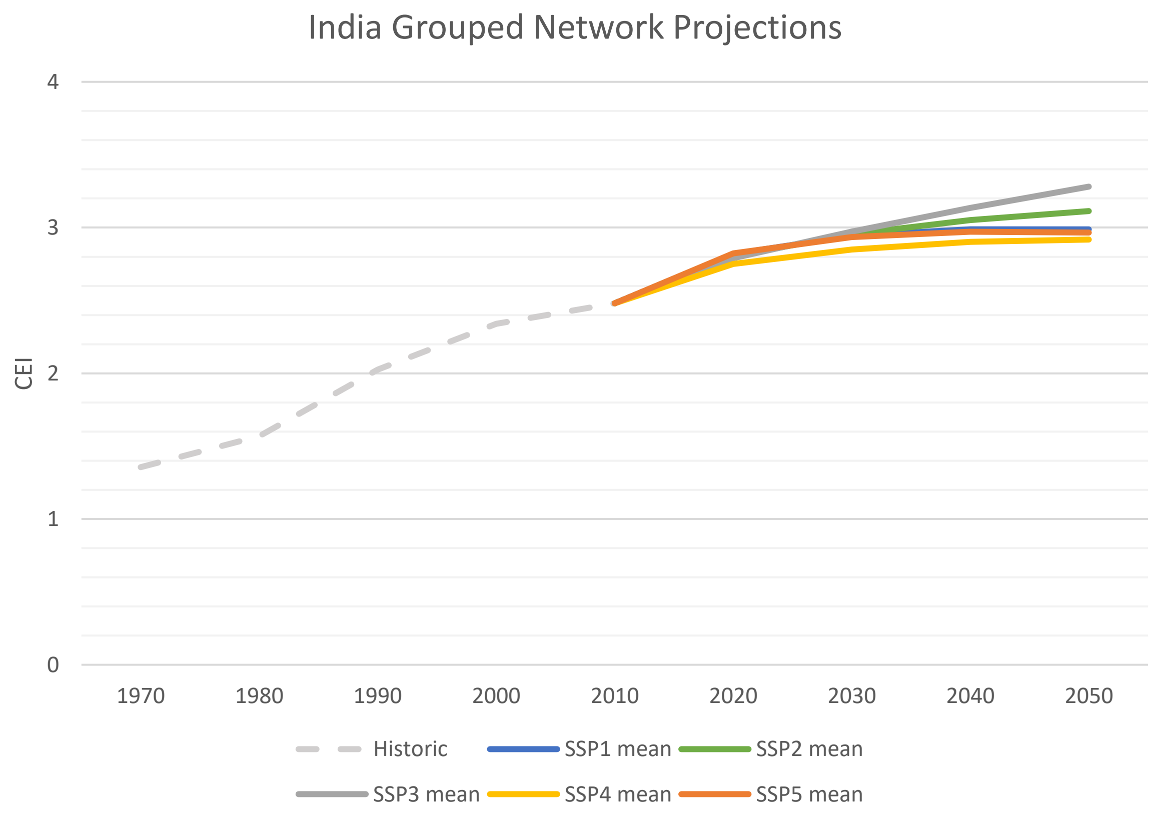


Figure 34: Projections of India's CEI for the 5 SSPs up to 2050 using the grouped trained networks

3.2.3 Comparison of Networks

The absolute value change from 2020 to 2050 is shown for all countries, projections and network types. In general, the Advanced countries see decreases in CEI whilst the Emerging countries see increases in both network types.

Country	Individual					Grouped				
	SSP1	SSP2	SSP3	SSP4	SSP5	SSP1	SSP2	SSP3	SSP4	SSP5
Australia	-0.11	-0.10	0.01	-0.11	-0.23	-0.54	-0.30	-0.05	-0.43	-0.66
Canada	-0.22	-0.14	-0.07	-0.08	-0.18	-0.09	0.06	0.16	0.02	-0.19
France	-0.37	-0.38	-0.20	-0.44	-0.65	-0.21	-0.04	0.18	-0.17	-0.27
Germany	0.58	0.20	-1.08	0.06	1.07	-0.24	-0.14	-0.12	-0.30	-0.25
Italy	-1.17	-0.77	0.27	-0.64	-1.58	-0.37	-0.40	-0.20	-0.49	-0.41
Japan	0.12	0.22	0.27	0.08	0.07	-0.85	-0.70	-0.51	-0.94	-0.89
Korea, Rep.	-0.57	-0.35	-0.14	-0.52	-0.66	0.25	0.22	0.33	0.24	0.14
Spain	-0.45	-0.40	0.01	-0.29	-0.53	-0.02	0.02	0.07	-0.01	-0.11
United Kingdom	-0.40	-0.38	-0.14	-0.32	-0.78	0.03	0.03	0.11	-0.12	-0.01
United States	-0.19	-0.11	-0.03	-0.07	-0.12	-0.72	-0.43	-0.15	-0.62	-0.75
Advanced Mean	-0.28	-0.22	-0.11	-0.23	-0.36	-0.28	-0.17	-0.02	-0.28	-0.34
Argentina	0.03	0.02	-0.05	-0.01	0.06	-0.14	-0.01	0.06	0.06	-0.09
Brazil	0.07	0.05	0.01	0.03	0.09	0.02	0.19	0.27	0.27	0.07
China	0.38	0.27	0.08	0.23	0.53	-0.27	-0.11	-0.14	-0.42	-0.13
Congo, Dem. Rep.	0.20	0.07	-0.03	-0.12	0.63	1.12	1.23	1.22	0.93	1.18
Egypt, Arab Rep.	0.52	0.36	0.05	0.55	0.55	-0.23	-0.11	0.08	-0.11	-0.23
India	1.03	0.72	0.40	0.80	1.34	0.17	0.31	0.49	0.17	0.14
Indonesia	0.45	0.27	0.15	0.24	0.56	0.04	0.11	0.14	0.04	0.04
Iran, Islamic Rep.	-0.03	-0.07	-0.04	-0.08	-0.11	-0.18	-0.11	-0.07	-0.11	-0.15
Malaysia	0.11	-0.04	-0.05	0.00	0.05	-0.14	-0.06	0.01	-0.13	-0.13
Mexico	-0.07	-0.05	-0.07	-0.05	-0.08	-0.33	-0.17	-0.06	-0.25	-0.29
Nigeria	0.02	0.22	0.00	0.11	0.28	0.91	1.07	1.13	1.10	0.90
Pakistan	0.92	0.64	0.34	0.65	1.12	0.36	0.42	0.49	0.45	0.37
Poland	0.18	0.05	-0.04	0.01	0.16	-0.43	-0.30	-0.22	-0.36	-0.35
Russia	1.21	1.39	0.32	0.93	1.57	-0.12	-0.05	-0.04	-0.06	-0.08
Saudi Arabia	-0.34	-0.47	-0.54	-0.46	-0.56	-0.10	0.08	-0.03	-0.09	0.08
South Africa	-0.19	-0.08	-0.04	-0.08	-0.10	-0.42	-0.25	-0.11	-0.25	-0.39
Thailand	-0.27	-0.15	-0.01	-0.17	-0.25	-0.12	-0.01	0.23	-0.03	-0.15
Turkey	0.09	0.06	0.03	0.09	0.11	-0.25	-0.11	0.04	-0.13	-0.21
Venezuela, RB	-0.63	-0.47	-0.40	-0.52	-1.05	-0.10	-0.06	-0.09	-0.07	-0.10
Vietnam	-0.40	-0.18	-0.20	-0.22	-0.22	0.41	0.53	0.65	0.41	0.37
Emerging Mean	0.16	0.13	0.00	0.10	0.24	0.01	0.13	0.20	0.07	0.04

Table 8: The absolute value change in CEI from 2020 to 2050 for all countries, SSPs and network types. Colour scale used shows magnitude of change

For the individual networks, the countries with the greatest reduction of CEI was Italy, whilst Russia, Pakistan and India had the greatest increases in CEI. On the other hand, Japan had the greatest reduction in CEI from the grouped networks, while the Democratic Republic of the Congo and Nigeria both experienced the largest increases within the grouped network. As discussed, the order of CEI reductions across the SSPs vary between the two network types. Few countries see the same magnitude of change between the two network types, with some countries experiencing large discrepancies.

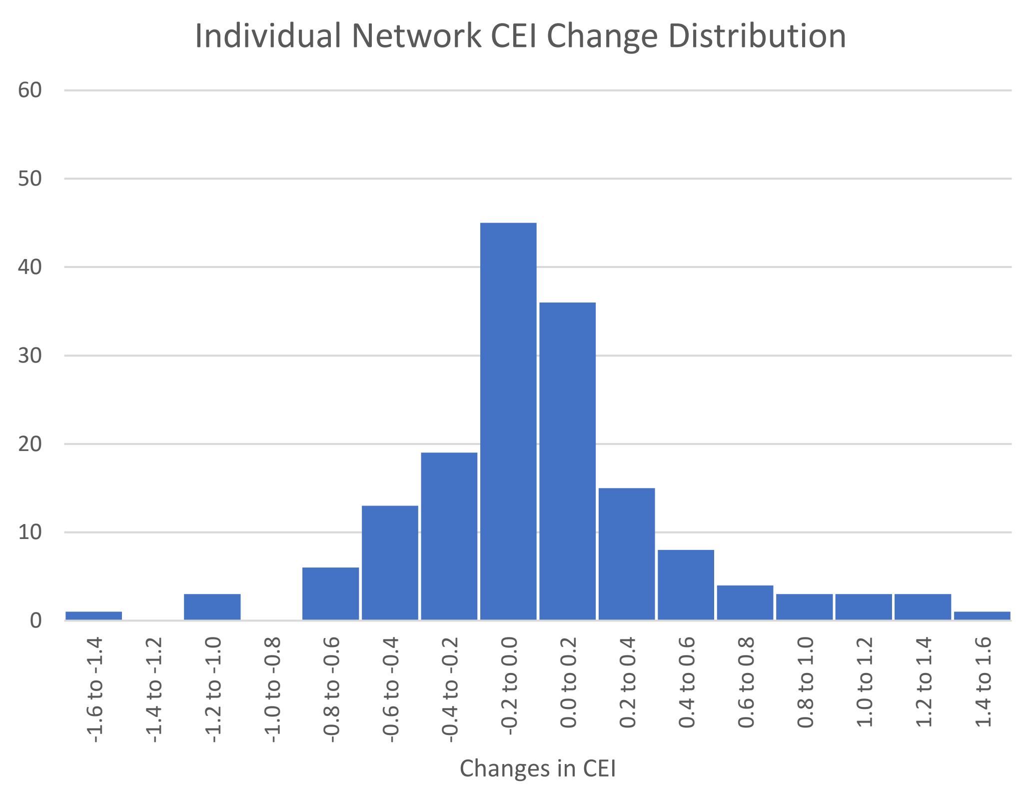


Figure 35: The distribution of CEI changes for all SSPs from 2020 to 2050 for the individually trained networks

When looking at the overall distributions for projected changes in CEI for Individual and Grouped networks (Figure 35 and Figure 36 respectively), the majority of projections experience minimal changes to CEI. The changes in CEI for the Individual networks are slightly more varied with a wider spread, whilst the Grouped network projections are generally more focused towards the centre of the distribution.

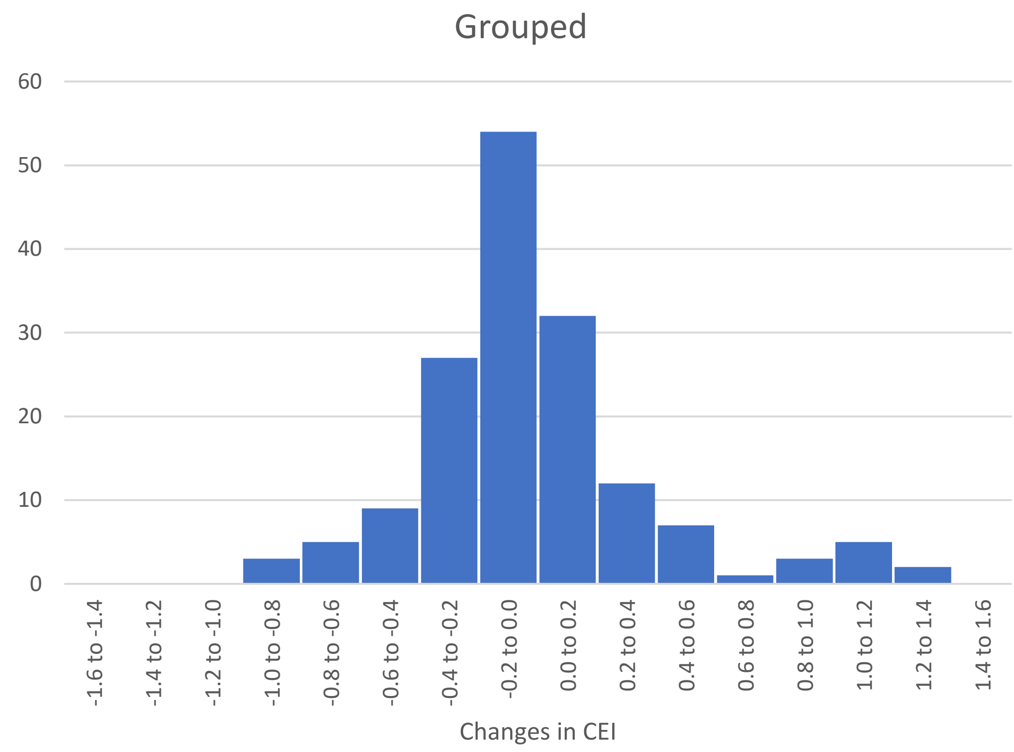


Figure 36: The distribution of CEI changes for all SSPs from 2020 to 2050 for the grouped trained networks

4 | Discussion & Limitations

4.1 Discussion

4.1.1 Performance of Individual Networks in comparison to Grouped

The individually trained networks generally performed poorly in comparison to the grouped networks, where grouped networks achieved better R^2, at the cost of more epochs. One contributing factor is likely the aforementioned data availability for the two training datasets. The data augmentation for the individual networks likely means that there is reduced variety and complexity in comparison to either of the grouped networks, resulting in fewer epochs for the ANN to generalise the data. Furthermore, the individual country datasets are subject to localised disruptions that aren't typically captured by the selected variables. For example, Venezuela experienced substantial change through the past decades with the rise and fall of Chavez, leading to uncertainty (Solimano, 2005; Dachevsky and Kornblihtt, 2017; Briceño-Ruiz, 2019; Bull and Rosales, 2020). This turbulent period likely makes it challenging to identify relationships and generalise the data, when there can be unpredictable behaviour in some indicators (Figure 37).

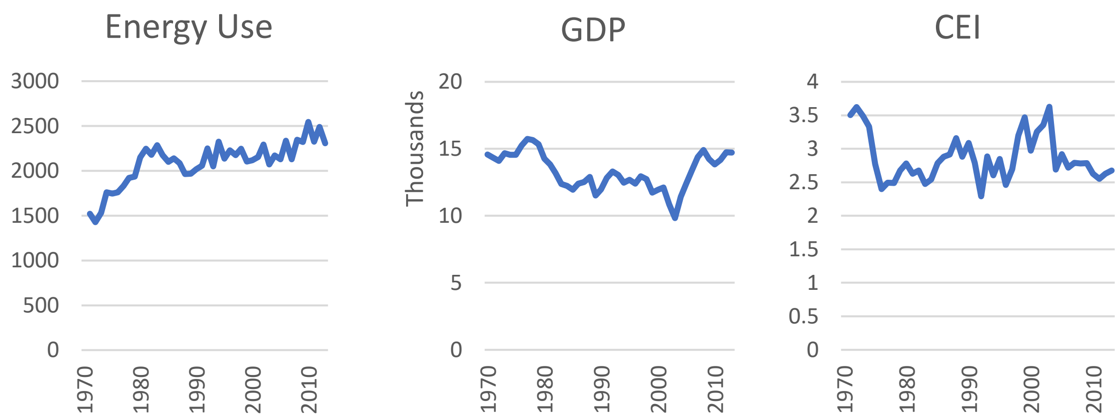


Figure 37: Historical data for select indices of Venezuela. While energy use per capita has a general increasing trend, GDP per capita and CEI are more unpredictable

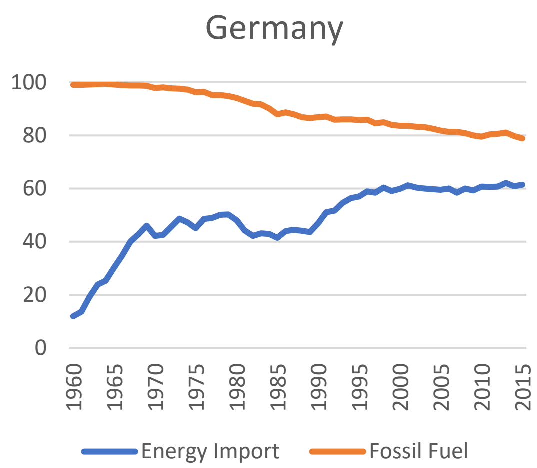
This unpredictability is likely what led to a wide range of R^2 values across the cohort (Figure 24), as the partitioning for training/validation will result in randomised divisions for the training, potentially amplifying the unpredictability of the data. This partitioning effect can be seen with Vietnam, where there is a large spread of performance across the 100 networks, but it is heavily weighted at the upper ranges of performance, with a mean R^2 of 0.73.

Countries such as Iran and Egypt trained poorly (R^2 of -0.09 and 0.19 respectively), however their performance was consistent across each respective cohort with relatively small ranges. This indicates that while both countries have experienced developmental instability through revolution (Dehesh, 1994; Mansour, 2008; El-Said and Harrigan, 2014; Abdelkader, 2017; Engo, 2021), the networks are consistent in their poor characterisation of the dataset. It highlights that whilst the historic data may have unpredictable behaviour, the selected indices may not be the most suitable to generalise CEI for these countries.

In contrast, grouping the countries improved accuracy for 24 countries, and worsened for 5 (Russia's accuracy was the same under both types). The increased accuracy was likely due to the larger size of the dataset, as well as the added complexity of exposure to multiple countries.

4.1.2 Interpretation of SSP Projections

When looking at the predictions from the individual networks, countries generally had 2050 CEI projections that were close to one another for the SSPs. Few countries reach a zero CEI, however those that do are potentially anomalous. The countries that performed the best in validation (Italy and Germany) had uncharacteristic projections in comparison to the rest of the group, with large error bars, a possible sign of overtraining (see 4.1.3). Furthermore, Germany displays uncharacteristic behaviour for the Advanced countries, where SSP3 projects the biggest improvement in CEI across the scenarios. Germany imports 63.4% of its energy, of which the majority is fossil fuel based (Eurostat, 2021). Therefore, a scenario with increased regional rivalry and concerns around security of resources may lead to reductions in trade around energy, and forces Germany to rely on domestic energy production, which would have to be through renewables. However, Italy is also a large consumer and importer of energy, yet presents SSP3 as an overall increase in CEI. Studying the energy imports and fossil fuel usage as percentages of total energy use, reveals the inverse of what is expected from SSP3 (Figure 38). As Germany has become more reliant on imports, its fossil fuel usage has declined over time, whereas Italy's fossil fuel usage and energy imports are closely coupled. This may demonstrate the benefits of ANNs in interpreting multiple sets of data to make predictions beyond the direct contributors, such as how technology and GDP could be influential. However, as discussed, predictions of Germany have high uncertainty and are uncharacteristic of the remainder of the group.



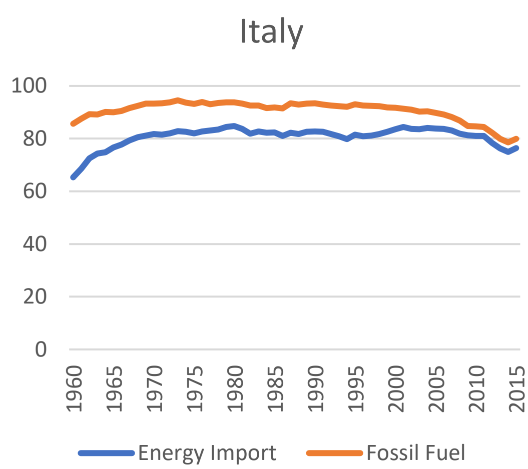


Figure 38: The percentage energy imported of total energy use, and percentage of fossil fuel sources used of total energy production for Germany and Italy

Similarly, the Democratic Republic of the Congo and Saudi Arabia demonstrate large uncertainty in their respective projections. A number of the emerging countries exhibit the same trend as Germany, where SSP3 has lower CEI projections than SSP1, which is unexpected as SSP1 has a lower challenge to both adaptation and mitigation in comparison to SSP3. This may be a weakness of the individually trained networks, and limited data availability. It is also important to remember that R^2 across the 30 countries isn't ideal: the advanced countries have an average of 0.85, however the emerging was far lower at 0.58, and so results from these models will not be entirely accurate. Two countries that did achieve good accuracy were India and the UK (0.95 and 0.91 respectively), and their trajectories were examined with respect to the historic data in Figure 29 and Figure 30. Here, the future projections follow historic trajectories, with the SSPs offering differing pathways of growth and decline in CEI for India and the UK respectively.

The grouped networks present projections that are closer in spread across SSPs as can be seen from the India and UK projections (Figure 33 and Figure 34), where projections follow the same trajectories, but are more closely aligned. The countries follow similar characteristics, with SSP2 and 3 never offering the lowest reductions in CEI. SSP1 carries the most success, the best scenario for 13 countries, followed by SSP5 that is the optimum for 12 countries and SSP4, the best for 8 countries: Egypt and Indonesia have multiple scenarios that result in the same CEI change by 2050. However, out of all these scenarios, no country achieves a CEI of zero.

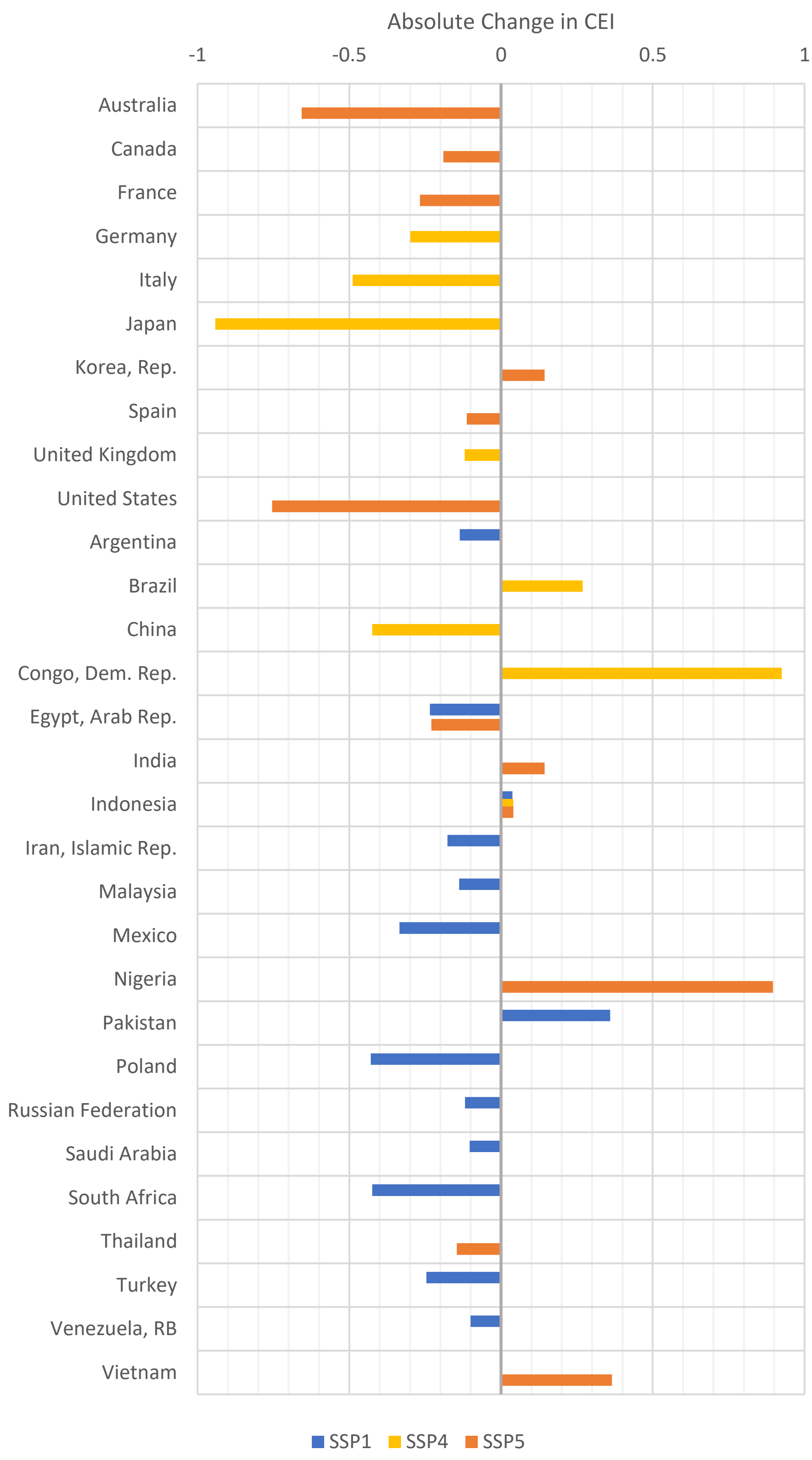


Figure 39: Absolute change in CEI with the best performing SSP for each country

SSP4 and SSP5 offered the best reductions for all the Advanced countries modelled, whereas 13 of the 20 Emerging countries modelled benefit the most from SSP1 (Figure 39). As SSP1 presents the lowest barriers to adaptation and mitigation, it would follow that it presents the best opportunity to reduce CEI, particularly for emerging countries that would rely on technology transfer, reduced consumption and greater global mobility to reduce emissions. However, the Advanced countries specifically benefit most from SSP4 and SSP5, scenarios that generally promote competitiveness between countries, giving those which are highly developed clearer pathways to reducing their environmental impact. It is also noteworthy that SSP1 still presents good opportunities for the Advanced countries, typically being the second-best scenario. However, it seems the advantage provided by the more developed economies results in the competitive scenarios causing greater reductions in CEI.

4.1.3 Uncertainty in Projections compared with Historic Coverage

There is generally large variance in the 95% confidence interval across SSPs and countries. Although the models have a high R^2, there is an increase in uncertainty when projecting forward. This can be seen in Figure 40, where the modelled mean and min/max from the 100 models generally fits well around the historic data. However, moving towards the projections for 2020 and 2030 based on SSP1, the uncertainty increases, although confidence around the mean is still generally good. One cause of this may be due to the ensemble method, where a single model may only be exposed to 70% of the historic data, and validated against the remaining 30%, the randomisation across the 100 models means the collection is exposed to all historic data. The SSP assumptions then result in the cohort utilising data never seen before, which increases variance. This is one of the challenges with the limited data availability - larger datasets would likely have more variety through the training, and give the network more complexity to understand. It may be improved too, through additional data augmentation techniques, although most techniques still rely on the core data which is augmented, and so have limitations to their application (Aftab and Siddiqui, 2018; Balabanov and Granath, 2020).

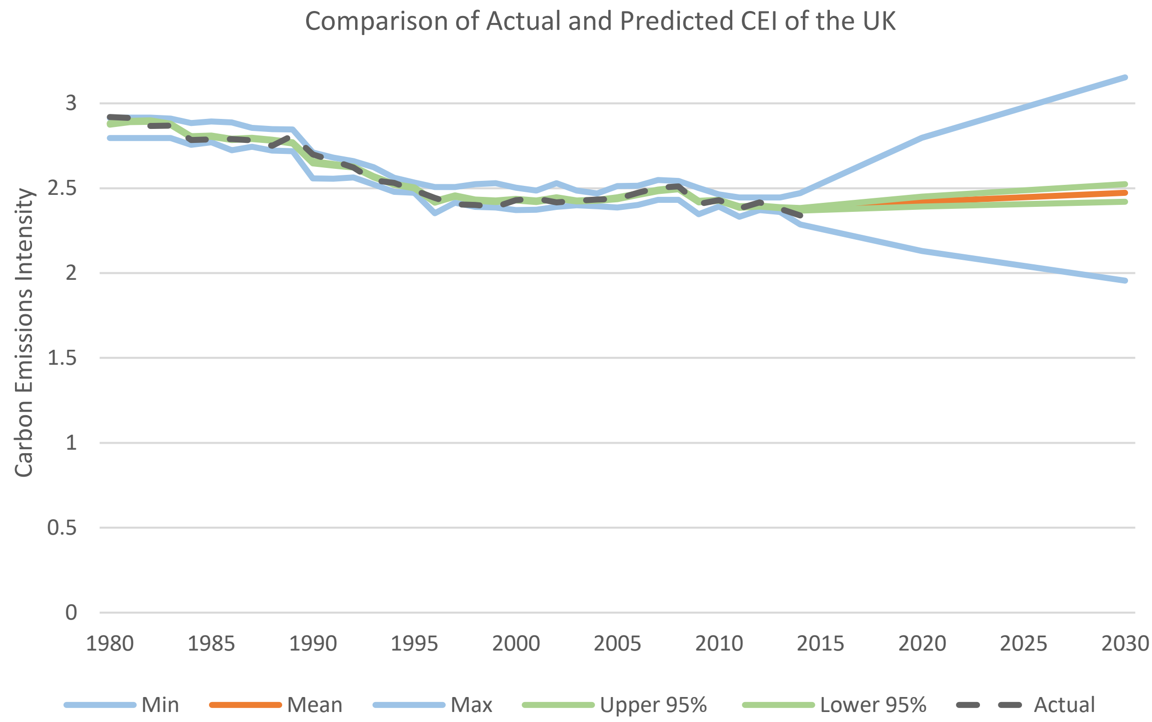


Figure 40: Comparison of the historic UK CEI data, modelled historic data and SSP1 projections. Blue represents the min and max across all models, orange is the mean of the cohort, and green are the lower and upper bounds of the 95% confidence interval for the mean. Dashed grey is historical data used for training.

4.1.4 Influence of Missing/Zero Data

Although data was trimmed to avoid gaps in recorded values, some variables still have gaps in their historic data, as seen in the UK Industrialisation (Figure 18). For countries with missing data nested between data points, interpolation was carried out. Individual country networks were trained before and after this interpolation, and the changes in accuracy were recorded (Table 9). There is a mixed response to removing the zeros: whilst five countries see some minor improvements, three see no change and four see reductions in accuracy. Note, this process was only an interpolation and not an extrapolation, and so some countries still have some zero data. The changes in R^2 show that the presence of zero data is generally not influential in degrading the performance of the individual networks. This can be corroborated with Figure 41, where no correlation can be seen with missing data and the performance of predictions across the 30 countries.

Country	IMF	Original		Filled Zeros		Change in R2
		Total	R2	Total	R2	
Argentina	Emerging	0%	0.51	0%	0.55	0.04
Congo, Dem. Rep.	Emerging	20%	0.94	17%	0.94	0.00
Egypt, Arab Rep.	Emerging	6%	0.26	0%	0.19	-0.07
Indonesia	Emerging	4%	0.51	1%	0.51	0.00
Iran, Islamic Rep.	Emerging	1%	-0.09	0%	-0.09	0.00
Nigeria	Emerging	11%	0.69	3%	0.73	0.05
Pakistan	Emerging	1%	0.96	0%	0.95	-0.01
Saudi Arabia	Emerging	12%	0.36	3%	0.40	0.04
South Africa	Emerging	0%	0.68	0%	0.65	-0.02
Turkey	Emerging	0%	0.34	0%	0.41	0.08
Venezuela, RB	Emerging	3%	0.35	1%	0.19	-0.17
Vietnam	Emerging	10%	0.70	10%	0.73	0.03

Table 9: Countries with missing data, the % missing and R^2 value (rounded to 2 d.p.) for the trained networks using the original dataset, and the filled dataset. Change in R^2 from before and after interpolation is colour coded where green represents improvement and red represents diminishment of accuracy.

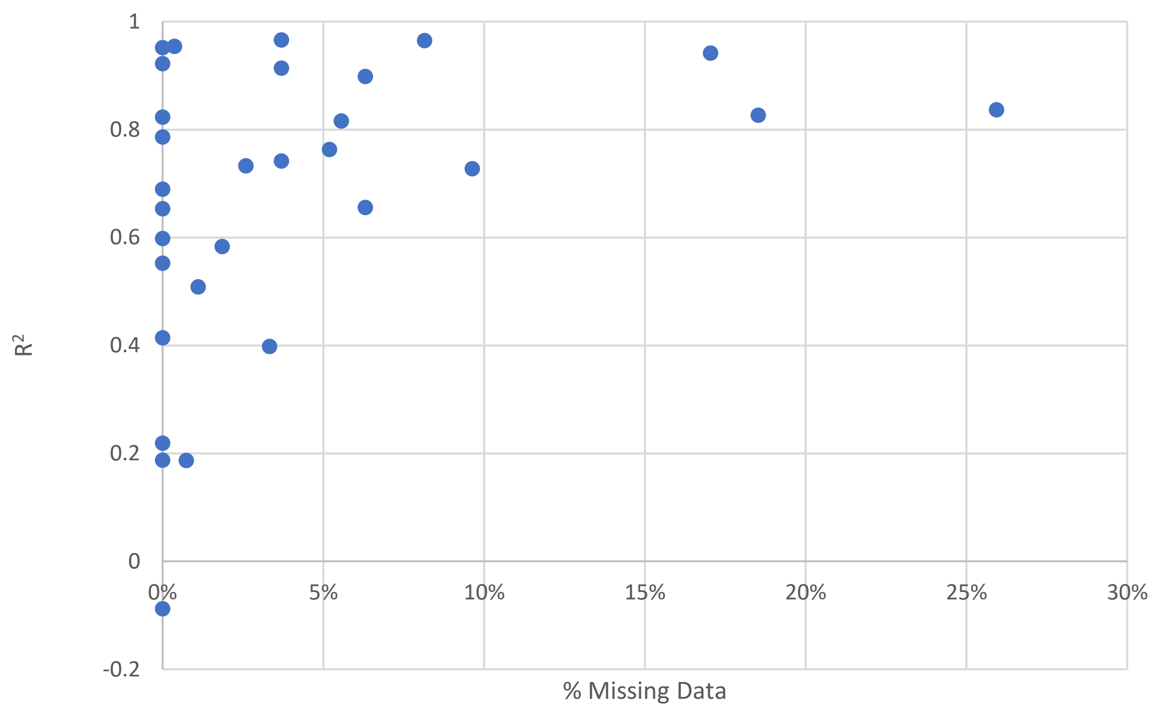


Figure 41: Plot of the average R^2 for each country against the percentage missing data

4.1.5 Approaches to Grouping Countries

As discussed previously (2.1.3), the IMF classifications were selected as the grouping method, however other groupings were tested, along with a single globalised group (Figure 42). The single global group of 30 countries performs the worst (0.67 R^2). Using the UN classifications, the network of the Developing countries trains very well, whereas the Developed countries generally train poorly with a wide range. The primary difference between the UN and IMF classifications, is the migration of Russia, Saudi Arabia, Turkey, Argentina and Poland from the Developed group, to the Emerging group (Table 4). Another reason the IMF rankings may perform so well is the reliance of financial-related metrics as inputs into the network, meaning countries with similar financial statuses will likely have similar relationships between the variables for better generalisation.

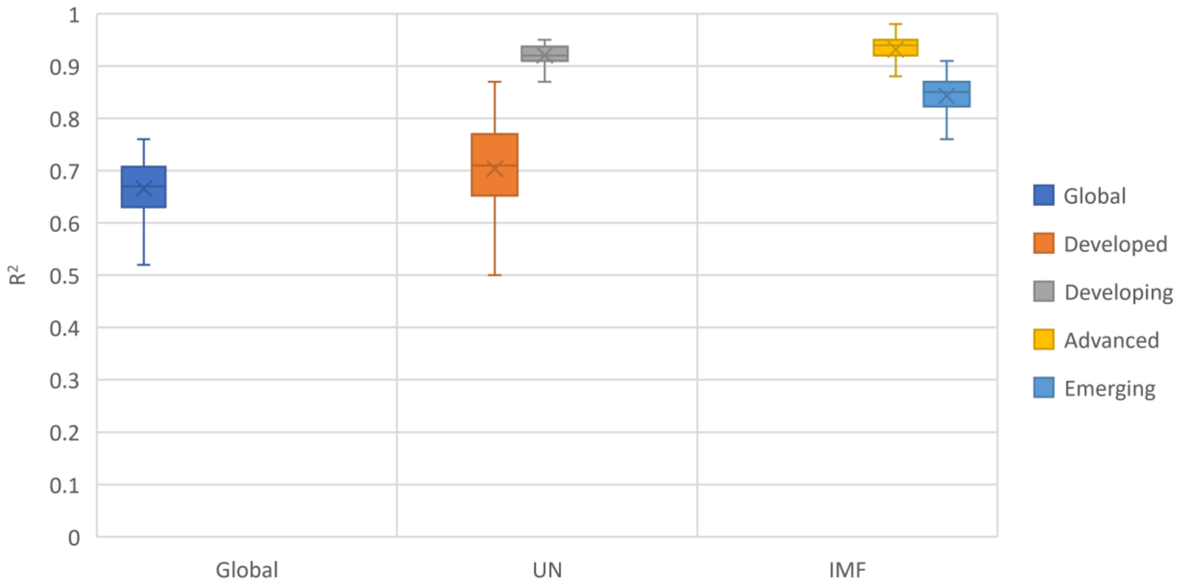


Figure 42: Different grouping types for the 30 countries, and the associated accuracy of the validation

4.1.6 Structure of Networks

In order to ensure that the network design was suitable, multiple designs were created, trained, validated for a selection of countries (China, USA, Russian Federation, India, Japan and the UK), and evaluated using the R^2 method (Figure 43).

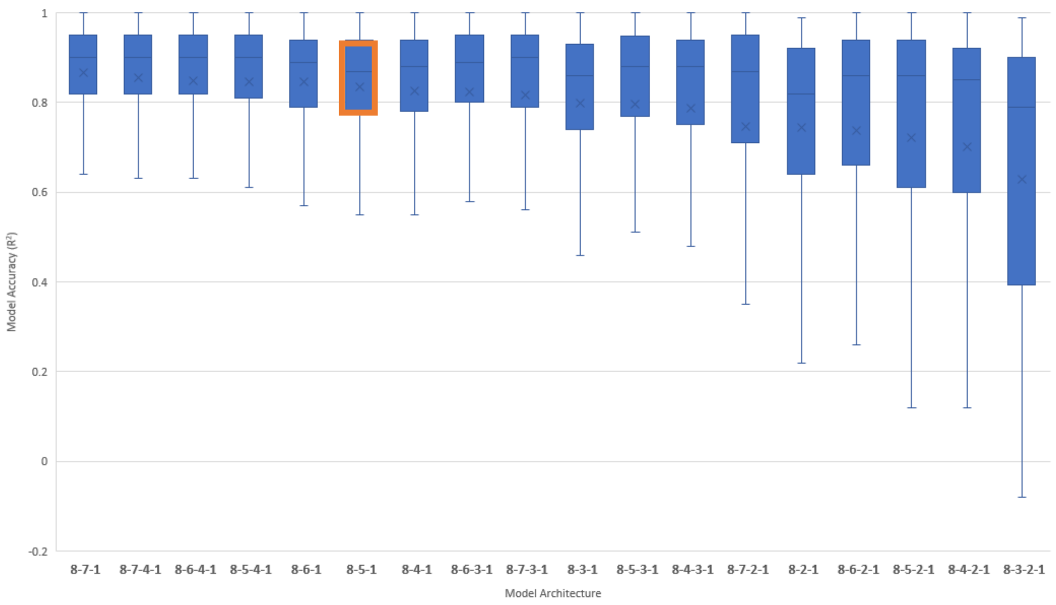


Figure 43: Performance of different ANN Architecture's prediction accuracy, using R^2 as a metric. Selected design highlighted in orange

As the number of neurons increases, so does the prediction accuracy, however the difference between the 8-5-1 setup, and the best performing architecture 8-7-1 is minimal (mean R^2 of 0.84 and 0.87 respectively). As such, the 8-5-1 network setup (Figure 19) was utilised, as there is risk that these minor improvements in the accuracy are achieved alongside overfitting. For simplicity, the grouped networks with 11 inputs, used the same intermediary architecture as the individual networks. While there may be some benefit to applying a similar parametric technique to the architecture design for the grouped networks, given the prediction capability of the 11-5-1 network, it was deemed acceptable to utilise.

4.1.7 Grouped Network Convergence

As seen in Figure 35 and Figure 36, the grouped networks tend to have a smaller spread of CEI changes, and there may be concern that the grouped networks are unifying the various countries to the same generalisation, so that in the long term, results converge towards the same CEI predictions.

Figure 44: Projections of CEI values for China, USA, Russia, India and Japan, for all SSPs up to 2100

In order to test this, a selection of countries (China, USA, Russian Federation, India, Japan and the UK) were projected forward to 2100 with their respective Advanced and Emerging networks (Figure 44). It can be seen that the network doesn't converge, but rather the SSPs follow their own pathways, with increasing range in their distribution (although this may be related to increasing uncertainty such as in Figure 44).

4.1.8 Comparison with Existing Projections

Phase 6 of the Coupled Model Intercomparison Project (CMIP6) projected various GHG emissions for SSP1-5 in combination with Reference Concentration Pathways (RCPs) (O'Neill et al., 2016) for global CO_2 atmospheric concentrations. The projections are summarised at different spatial scales; however, they do not reach the clarity for individual country predictions. Furthermore, it can be challenging to derive the same units found in the WDB as those that are given in the CMIP results. However, a proxy CEI (P-CEI) was derived (Figure 45): total CO_2 emissions from the energy sector was divided by total energy demand for the world, for a number of SSP/RCP combinations. By their nature, the RCP targets are highly influential in CO_2 emissions, however this derivation still provides some useful insights. For example, SSP3 generally leads to a high P-CEI, while SSP4 and SSP5 have ranges of possible outcomes, with the potential to reach low P-CEI.

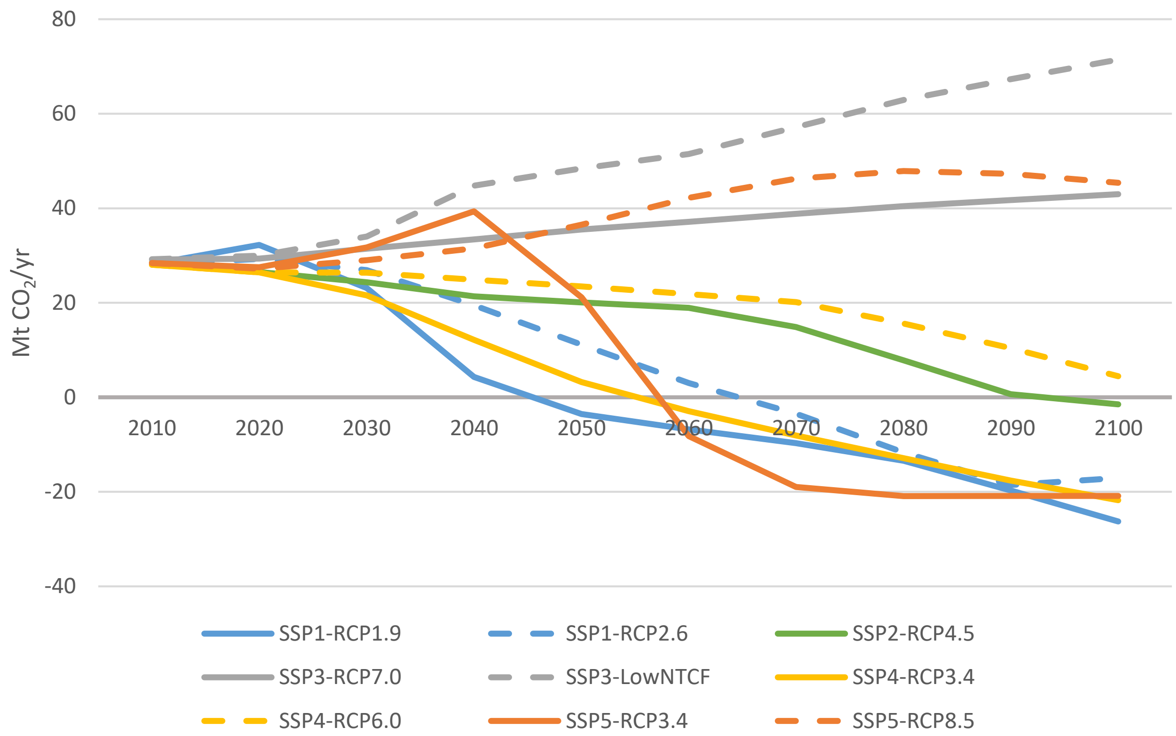


Figure 45: Global projected CO_2 emissions per Energy created

It also demonstrates that a number of scenarios are capable of reaching negative P-CEI driven by negative emissions in the energy sector. It is well noted that a number of these scenarios rely on technologies such as carbon capture and storage/utilisation (CCS/U) or energy production such as bioenergy with CCS (BECCS). As the ANNs rely on historical data, it therefore means that it has not been exposed to innovative technologies such as CCS and cannot predict this integration (see 4.2.1 Limitations and Future Work). As such, it is challenging to draw a direct comparison between P-CEI and CEI, as even with technologies such as BECCS, CO_2 is still produced.

Turning to other literature, other studies have found similar outcomes, with a continuous reliance on fossil fuels, even under SSP1. Van Vuuren et al. (2017) projected the global energy mix for SSP1-3 (Figure 46). While SSP1 sees a reduction in CEI to 2100, it isn't on the same scale as those predicted in CMIP due to the exclusion of CCS systems. They go on to identify in their study that CCS systems are critical to stabilising emissions and reaching reduction targets (van Vuuren et al., 2017).

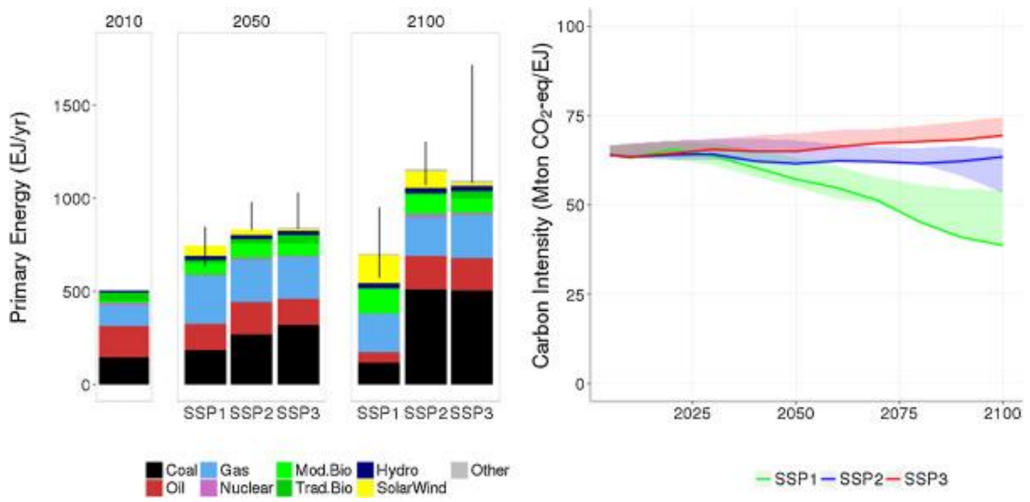
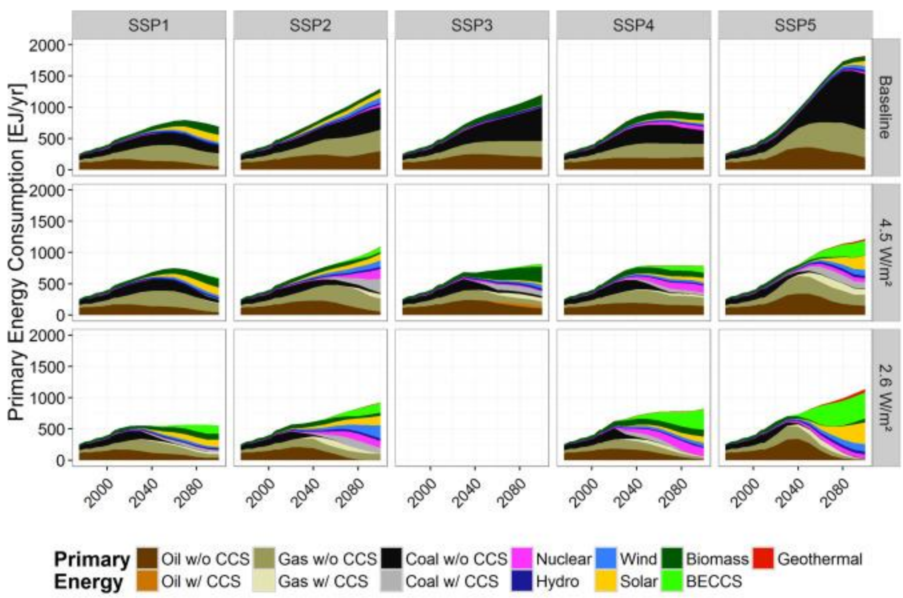


Figure 46: Projections for energy usage and carbon intensity for SSP1-3 (van Vuuren et al., 2017)

(A)



(B)

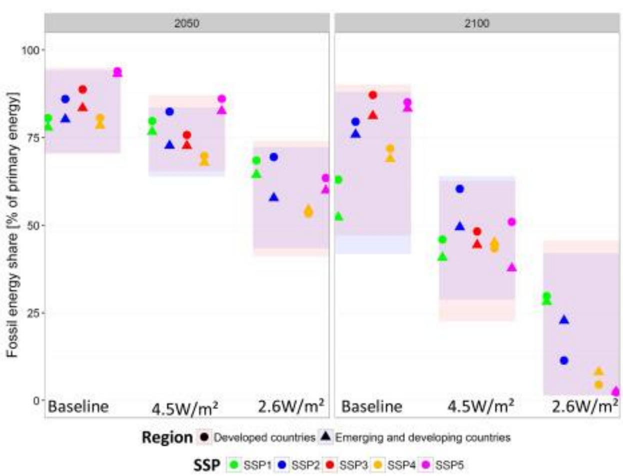


Figure 47: (A) Energy demand projections and contributions from different sources up to 2100 for SSP1-5 and 3 RCPs. (B) The percentage contributions from fossil fuels for each scenario (shaded boxes represent range of possible scenarios) (Bauer et al., 2017)

Similarly, Bauer et al. (2017) projected energy demand across multiple SSP/RCPs and the percentage contributions from fossil fuels (Figure 47). They found across all scenarios by 2050, fossil fuels still contribute at least 50% of total energy usage. By 2100, some scenarios under RCP2.6 get close to zero, however the baseline scenarios are still at or above 50% reliance on fossil fuels. Both of these studies highlight similar trends, a continuous reliance on fossil fuels, even into the period where CMIP6 projects negative CO_2 emissions.

4.1.9 Extended Projections

The reductions in CEI across countries broadly show limited change over the next 30 years, and so the UK and India were projected forward to 2100 (Figure 48 and Figure 49 respectively), as the SSPs provide data for this extended range, and the remaining indicators can follow the same extrapolation pathways. Across the SSPs for both the Advanced and Emerging network, there is a downward trend in CEI in the latter half of the century, with the only exception being SSP3 for India. This is likely due to the regional rivalry where the emerging countries may stay heavily reliant on fossil fuels for extended periods, in comparison to the UK, where SSP3 is consistent, but begins to dips from 2060 onwards.

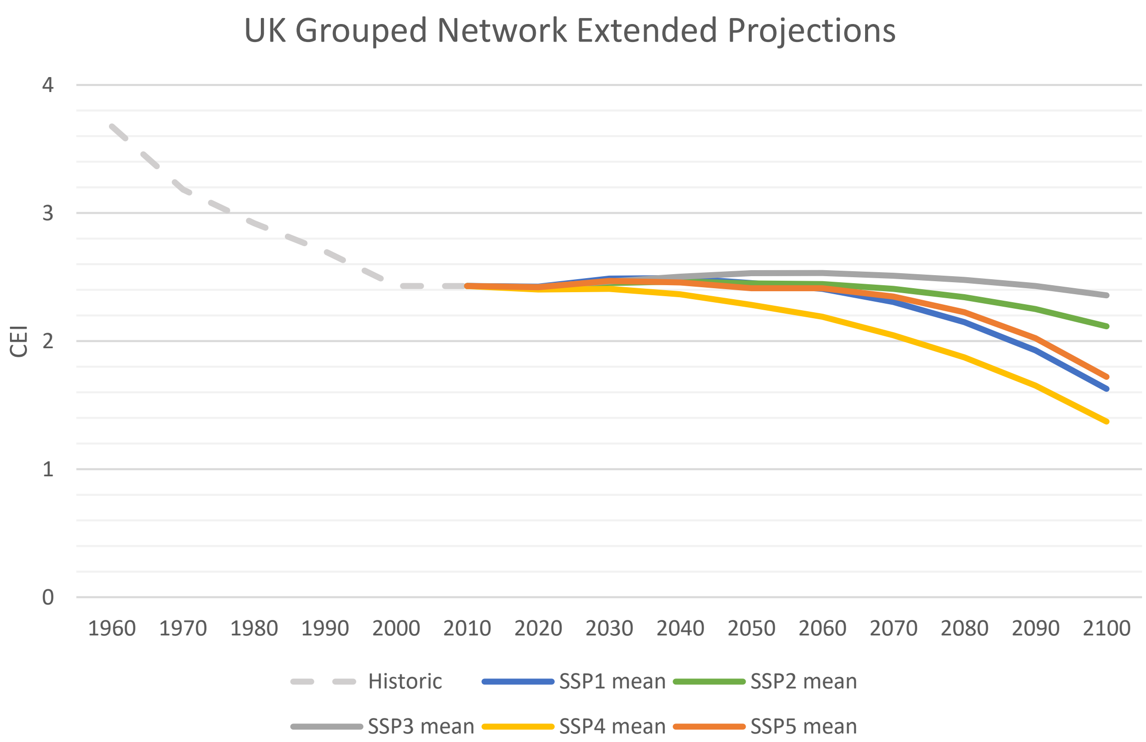


Figure 48: Mean projected CEI for the UK using the grouped network up to 2100

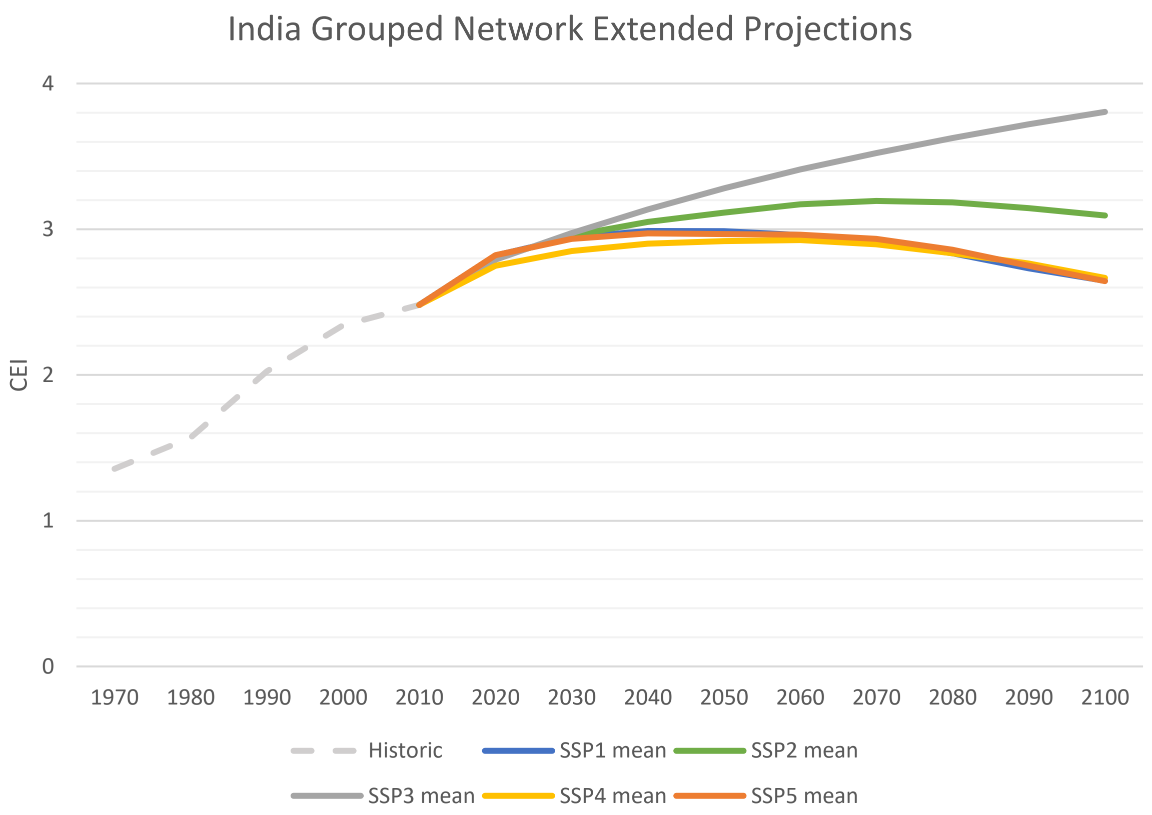


Figure 49: Mean projected CEI for India using the grouped network up to 2100

4.2 Limitations and Future Work

4.2.1 Limitations of this Study

As discussed, one of the main limitations of this study is the data availability. Although the WDB has indices tracking back to 1960, there were numerous gaps in the early years of the records, but also in the latest years too, resulting in the data having to be trimmed considerably. Although the data augmentation aided in achieving acceptable accuracy in some of the individual networks, it's clear the grouped networks generally performed better, likely with the help of the added data available from aggregation of similar countries.

Another limitation is the definition of CEI in this study, and its inability to model CCS systems. The CEI modelled here could be described as representing all CO_2 created from the energy consumed, rather than the CO_2 emitted directly to the atmosphere. It is one of the main drawbacks to machine learning models: there generally needs to be a precedent for the models to characterise, and so it can be challenging to model innovation and new technologies. As CCS technologies become integrated into the energy production industries, it would then be valuable to revaluate the selected input variables. A conservative approach was selected for this study, where inputs were identified based on existing literature, however it is common in approaches to machine learning to start with an excess of variables, and prune to those which are most influential. This technique would be particularly useful for remodelling CEI in the coming years, in order to understand what variables could represent the impact of CCS, along with some of the political changes that could be influencing poor performance of some countries.

4.2.2 Future Implications

There are two key implications from this study. Firstly, it validates the use of ANN as a useful modelling technique within this context. As more data is captured over time and added to the training set, it will likely strengthen the prediction capability of the models. This will be particularly true for the introduction of CCS and other innovations, as this will give flexibility in what is being modelled, such as capability of modelling CO_2 emissions into the atmosphere. It would also be valuable to investigate newer machine learning techniques such as random forest, as they may have performance benefits.

It has also made clear the importance of carbon capture technologies. The results from this study and others (Bauer et al., 2017; van Vuuren et al., 2017) have demonstrated an underlying reliance on fossil fuels across all scenarios. Technologies such as CCS and other carbon sequestration techniques are therefore vital in reaching Net Zero. The IPCC has already illustrated the necessity of BECCS (IPCC, 2017) in minimising global temperature rise, and it is clear that even under the best scenarios, it is a challenge to move away from fossil fuels entirely.

5 | Conclusions

In conclusion, the individually trained networks per country were generally surpassed in accuracy by the grouped networks, potentially due to the increased data available for training, although a number of individually trained networks performed adequately too. The countries that performed poorly with their individual networks, may have other external factors influencing the input data, such as experiencing revolutions (e.g. Egypt, Venezuela and Iran) that are not captured directly in the input data.

When running the SSP1-5 projections, nearly all countries have changes in their CEI by 2050, however no country reaches a CEI of zero. The grouped networks projected scenarios had a narrower range of outcomes, in comparison to the individual networks, where there was more variety. On average, the Advanced countries see reductions across SSP1-5 in CEI, while the Emerging countries see increases in CEI across SSP1-5. For most countries SSP1 provides the best route to reducing CEI, whilst SSP4-5 provides opportunities for a selection of countries, particularly those classified as Advanced. However, the ongoing reliance on fossil fuels makes it clear that technologies such as CCS are vital to be able to limit CO_2 emissions from future energy use.

6 | Auto-Critique

This topic was chosen out of interest from my professional experience, speaking with colleagues and other members from the construction industry, there is a perceived gap between the science of climate change and more tangible targets and actions that they can undertake. At the time of formulating the research outline there was little previous research into the specifics of CEI, the paper by Acheampong and Boateng (2019) being the most relevant, and also very recent. It highlighted the opportunity to explore further, and expand into projecting CEI too.

The training process resulted in models that had the capability to predict accurately, and also provided notable differences between the individual and grouped networks. Although the aims and objectives were fulfilled, there were many additional avenues that could have been explored. For example, studies previously had evaluated the sensitivity of different input variables in relation to CEI, and with a larger pool of countries in this study, some relationships and trends may have been identifiable.

The selection of CEI itself can also be seen as restrictive, particularly when CEI can be used to describe electricity or energy intensity. If data was available for the former, it would be expected that CEI would reach zero, however as the WDB focused on all energy use, it accounts for the usage of fossil fuels for travel and industry, resulting in much higher values. However the overarching barrier to aligning results to the commonly spoken goal of Net Zero is the lack of CCS representation. In the coming decade, as CCS installations come online, datasets should start to represent this interaction, and how it would be possible to reach zero CEI. It is an inherent weakness of machine learning techniques, that are so reliant on historic data, and can struggle to adequaltely represent disruptive/innovative technologies. Another area of potential study is to have a broader approach to this problem, and see how different machine learning algorithms can approach projecting CEI.

Finally, the limited variation in some of the SSP predictions for CEI could also be explained by the lack of data. The pruning required to ensure adequate coverage for training meant the latest year used was 2014. It could be argued that the past few years have been where the more significant steps have been made to limit climate change, which may not have been fully captured in the training process. If nothing else, the study has highlighted the usefulness of ANNs, but also warrants revisiting in the future, where more data is available, particularly for years where efforts to decarbonise our built environment could be better represented.

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