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GRADUATE SCHOOL

MASTER THESIS

**MACHINE LEARNING-BASED PREDICTION MODEL
FOR INSTALLED WIND AND SOLAR ENERGY
CAPACITIES AMONG OECD COUNTRIES: AN LSTM
APPROACH**

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ABSTRACT

MACHINE LEARNING-BASED PREDICTION MODEL FOR INSTALLED WIND AND SOLAR ENERGY CAPACITIES AMONG OECD COUNTRIES: AN LSTM APPROACH

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The main cause attributed to the climate crisis is the consumption of fossil fuels, particularly arising from industrialization and industrial activities. To mitigate the impacts of these changes, environmental policy measures and technological innovations have focused prominently on renewable energy sources, especially wind and solar energy.

This research aims to predict installed wind and solar energy capacities using a machine learning-based model, specifically the Long Short-Term Memory (LSTM) algorithm. The analyses cover a comprehensive time series dataset, including social, economic, conventional, and renewable energy attributes, as well as various environmental policy incentives and laws. The dataset spans the years from 2000 to 2020 and encompasses 24 OECD member countries. The results reveal that the installed wind energy capacity model exhibits high accuracy in prediction performance, whereas the installed solar energy capacity model demonstrates lower accuracy compared to the installed wind energy model. This study intends to draw attention to and provide valuable insights into the predicted solar and wind capacities, aiming to contribute to discussions on energy transformation processes and policymaking.

Keywords: machine learning prediction, LSTM method, installed solar energy capacity, installed wind energy capacity, environmental policy

ÖZ

OECD ÜLKELERİ ARASINDA KURULU RÜZGÂR VE GÜNEŞ ENERJİSİ KAPASİTELERİ İÇİN MAKİNE ÖĞRENİMİ TEMELLİ TAHMİN MODELİ: BİR LSTM YAKLAŞIMI

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İklim krizinin ana nedeni olarak gösterilen fosil yakıt tüketimi, özellikle sanayileşme ve endüstriyel faaliyetlerin bir sonucu olarak ortaya çıkmaktadır. Bu değişimlerin etkilerini hafifletmek adına, çevresel politika önlemleri ve teknolojik inovasyonlar, özellikle rüzgar ve güneş enerjisi gibi yenilenebilir enerji kaynaklarına odaklanmıştır.

Bu araştırma, makine öğrenimi temelli bir model olan uzun kısa vadeli hafıza (LSTM) algoritmasını kullanarak, kurulu rüzgar ve güneş enerjisi kapasitelerini tahmin etmeyi amaçlamaktadır. Analizler, 24 OECD üyesi ülkeyi içeren geniş kapsamlı bir zaman serisi veri setini kullanarak, 2000 ile 2020 yılları arasındaki sosyal, ekonomik, geleneksel ve yenilenebilir enerji kaynakları ve çeşitli çevresel politika teşvik ve yasalarını kapsamaktadır. Elde edilen sonuçlar, kurulu rüzgar enerjisi kapasitesi modeli yüksek doğrulukta tahminleme performansı sergilerken, kurulu güneş enerjisi kapasitesi modelinin kurulu rüzgar enerjisi modeline kıyasla daha düşük doğrulukta tahminleme performansı gösterdiğini ortaya koymaktadır. Bu çalışma, öngörülen güneş ve rüzgar kapasiteleri ile enerji dönüşüm süreçlerine ve politika oluşturmaya dair dikkat çekmeyi ve değerli bilgiler sunmayı amaçlamaktadır.

Anahtar Kelimeler: Makine öğrenimi tahminlemesi, LSTM yöntemi, kurulu güneş enerjisi kapasitesi, kurulu rüzgâr enerjisi kapasitesi, çevresel politika

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Ezgi aęlar NİZAM

İzmir, 2024

TEXT OF OATH

I declare and honestly confirm that my study, titled “MACHINE LEARNING-BASED PREDICTION MODEL FOR INSTALLED WIND AND SOLAR ENERGY CAPACITIES AMONG OECD COUNTRIES: AN LSTM APPROACH” and presented as a Master’s Thesis, has been written without applying any assistance inconsistent with scientific ethics and traditions. I declare, to the best of my knowledge and belief, that all content and ideas drawn directly or indirectly from external sources are indicated in the text and listed in the list of references.



Ezgi Çağlar NİZAM

08.01.2024



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ABBREVIATIONS

LTSM Long Short-Term Memory

IWC Installed Wind Capacity

ML Machine Learning

ISC Installed Solar Capacity

ANN Artificial Neural Network

RNN Recurrent Neural Network

MAE Mean Absolute Error

RMSE Root Mean Squared Error

MAPE Mean Absolute Percentage Error

OECD Organization for Economic Co-operation and Development

AI Artificial Intelligence

TPB Theory of Planned Behavior

CSD Cross Sectional Dependence

ARDL AutoRegressive Distributed Lag

CADF Cross-Sectionally augmented Dickey-Fuller

CS-ARDL Cross-Sectional AutoRegressive Distributed Lag

PPSR Public Policies Supporting Renewables

RES Renewable Energy Sources

FiT Feed-in Tariffs

LPSP Loss of Power Supply Probability

LCOE Levelized Cost of Electricity

PCA Principal Component Analysis

RFR Random Forest Regression

DL Deep Learning

GRU Gated Recurrent Unit

LR Logistic Regression

DT Decision Tree

SVM Support Vector Machine

NB Naive Bayes

k-NN k-Nearest Neighbors

AB Ada Boost

EPSI Environmental Policy Stringency Index

Pop Population

GDP Annual Gross Domestic Product Growth

EG_Oil Electricity Generation from Oil

EG_Coal Electricity Generation from Coal

EG_Gas Electricity Generation from Gas

EG_Hydro Electricity Generation from Hydropower Energy

EG_NE Electricity Generation from Nuclear Energy

TEG Total Electricity Generation

EG_RE Electricity Generation from Renewables

SES Solar Energy Support (Auctions & FITs)

WES Wind Energy Support (Auctions & FITs)

TSP Technology Support Policies

LC_R&D Low-carbon R&D expenditures

EPS Environmental Policy Stringency

RETS Renewable Energy Trading Scheme

SL Supervised Learning

UL Unsupervised Learning

Greenhouse Gas (GHG)

1. CHAPTER: INTRODUCTION

Clean energy has become a fundamental element in shaping the future of energy production within the global obligation to fight against global climate change and transition to sustainable implementations. The Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC, AR6) highly confidently stated that continuing Greenhouse gas (GHG) emissions will increase human-made global warming and will cause the surface to get warmer by approximately 1.5 °C. According to the authorities, it is crucial to act in political commitments, laws, policies, financial strategies, and technological developments to mitigate and reverse the effects of the climate crisis (IPCC, 2023.). Since many countries and sectors have been directly affected by the climate crisis, especially in the last 50 years, governments have implemented strict policies and encouraged investments in sustainable and clean energy resources. It is an acknowledgeable fact that governmental policies have a big influence on clean energy, climate crisis, and renewable energy usage (Salem et al., 2023).

Recognizing the urgency of addressing the climate crisis, international collaboration has become essential. Two key players in this global effort are the Conference of the Parties (COP) and the Organization for Economic Co-operation and Development (OECD). COP, operating under the United Nations Framework Convention on Climate Change (UNFCCC), serves as an annual forum where countries come together to strategize and make decisions aimed at mitigating climate change impacts. Meanwhile, the OECD, comprising 38 member countries, plays a crucial role in fostering economic cooperation and sustainable development. According to the data from WorldBank (2021), the Gross Domestic Product of OECD countries constitutes approximately up to 60 percent of the global total, related to their consumption of renewable energy and main energy representing almost 50 percent. The outcome of these international gatherings is an increase in academic research and studies has emerged, reflecting the great influence of COP meetings and OECD collaborations. The important topics discussed in these meetings not only made governments act but

also caused many studies to happen. Many papers and studies are now looking at the complicated parts of climate policies (Ayugi et al., 2023), strategies for sustainable development, and how countries work together economically (Jiang and Jiang, 2023). These studies show how the decisions made in COP meetings and the teamwork from the OECD have a big impact. Particularly, the Kyoto Protocol, a milestone international agreement aimed at reducing greenhouse gas emissions, was signed during the COP-3 meeting in Kyoto Japan, further highlighting the historic significance of these international platforms (Ghezloun et al., 2013). This link between global policy formulation and academic discussions underlines the significant role these international platforms play in shaping both governmental practices and the way humanity faces big challenges nowadays.

In addition to these aspects, the negative impact of the climate crisis on health due to air pollution and rising temperatures and preventive efforts towards climate change are increasing day by day. Numerous studies are currently being conducted on the healthcare sector, which ranks among the areas extremely affected by climate change. Studies have shown that there is a direct link between climate change and air pollution and cardiovascular diseases recognized as one of the deadliest consequences. The increase in hot climates results in dust storms and wildfires which can alter the air chemistry and result in a well-known air pollution phenomenon: climate penalty (Alahmad et al., 2023). These studies coincide with the estimates of the World Health Organization that air pollution is the reason every year 7 million people lose their lives globally mostly with cardiovascular diseases (WHO, 2019). From a socio-economical view, Ike et al. (2023) have shown that econometric parameters play a key role in preventive actions regarding bad air quality and health. It is stated that their study conducted across OECD countries highlights a causal relationship between non-renewable energy consumption, household air pollution, and low-income parameters, ultimately leading to a positive effect on the health burden. Moreover, water scarcity is one of the issues that the climate crisis most deeply affects our daily lives. While extreme temperatures and water scarcity pose significant challenges on their own, the excessive rainfall patterns due to climate change have profoundly and negatively impacted the economic conditions of those living in rural areas who rely on agriculture (Anser et al., 2023).

In response to the essential quest for clean energy, as required by the climate crisis, the most crucial question for environmental policies became: What is the financial dimension of transitioning to sustainable energy resources? Since financing is a significant and undeniable factor for all actions to happen, this concern of policy markers resulted in numerous amount of studies among economists and researchers. There is a variety of subjects among these studies such as stock price evaluations of companies regarding energy generation, it is a meaningful variable to examine the impact of climate policies and energy transition on stock values for investors and governments (Qiu et al., 2023). Taxation policies of governments are examined in detail by researchers and presented estimations for further years to have an insight into the future of energy generation and financing tendencies regarding clean energy (Yin et al., 2023). Another financial issue to consider is the connection between mineral prices and renewable energy generation. Madaleno et al. (2023) observed that policymakers should consider the role and dependency on rare earth minerals for further technological improvements, trading processes, and green growth. The research from financial aspects underlines the important role of renewable energy in addressing the climate crisis. As policymakers and investors explore the dynamics of stock evaluations, taxation policies, and mineral dependencies, it becomes increasingly evident that the sustainable energy sector is not only an essential component for environmental sustainability but also a driving force shaping the economic future.

Unquestionably, the role of technological developments in green future and sustainable energy generation can not be doubted. It is an above suspicious element regarding eco-friendly and sustainable alternatives against climate crisis (Kwakwa, 2023) which has been observed by many researchers that the impact of Renewable Energy Technological Innovation on sustainable energy transition resulted in a positive effect on energy transition process (Yang et al., 2023).

On the other hand, among these technological developments, tools, and examinations to seek better strategies on environmental issues, Machine Learning (ML) stands out as a new artificial intelligence (AI) tool for its ability to learn from extensive datasets and recognize complex patterns. Therefore, it serves as a powerful tool to assess and optimize the large amount of data in the renewable energy sector. There are various implementations of a machine learning tool in clean energy areas such as measuring

air quality attributes caused by energy transition (Zhang et al., 2023), predicting clean energy stock prices under economic policy uncertainty (Sadorsky, 2022), predicting CO² levels for clean energy policy-making and climate crisis mitigation and monitorization (Kumar, 2023), new technological approaches to renewable energy generation and efficient storage (Tirth et al., 2023), studies among countries and locations according to their solar irradiance and wind speed for possible wind and solar farms (Ribeiro and Fanzeres, 2023). With the increasing integration of machine learning in the renewable energy sector, it also is used to measure the two commonly used core terminology in renewable energy: Installed wind energy capacity (IWC) and installed solar energy capacity (ISC). IWC is a measure that represents the total amount of wind power generation infrastructure that has been physically installed and is actively producing electricity. It reflects the real-world contribution of wind turbines to the energy grid. ISC also represents the total solar power generation capability that is physically implemented and operational as mentioned above (IRENA, 2023).

For the past 20 years, solar and wind energy have been rapidly growing and they have become the focus of new technological research and investments (Şahin, 2023). Even though, their share is half of the total renewable energy production (OurWorldInData, 2023), wind and solar sources are the favorite. The preference of researchers and policymakers for wind and solar sources rather than primary clean energy sources hydropower energy can be associated with large-scale projects need for extensive space and water resources contrary to faster installation and flexibility, smaller amounts of costs, more accessible for small businesses and even small communities, rapidly growing technological developments making these energy sources more accessible.

Electricity production by source, World

Measured in terawatt-hours¹.

Our World
in Data

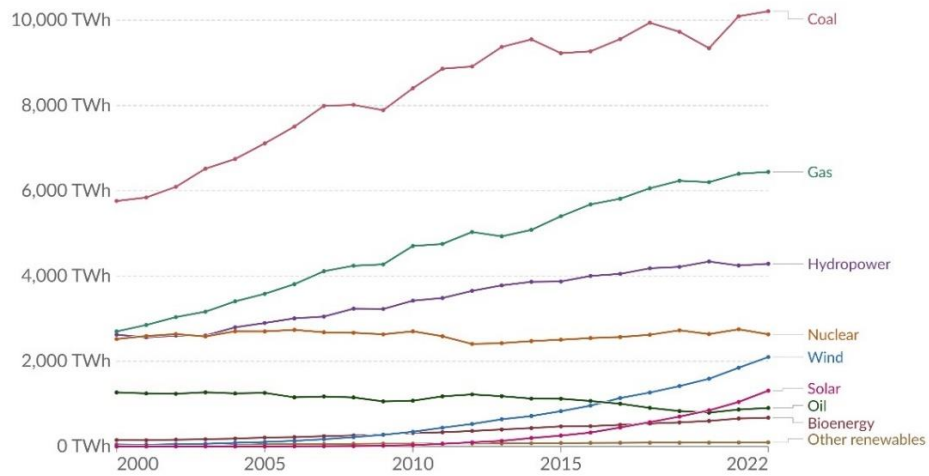


Figure 1.1. Electricity Production by Energy Source Chart

Source: Our World in Data, 2023

There are papers specifically focused on IWC and ISC using machine learning tools to forecast the trajectory of renewable energy in the future (Hoeser and Kuenzer, 2022; Şahin, 2023) but, since these terminologies and AI technology is at its beginning, there is so much to discover and to benefit in green field. Thus, the objective of this research is to make a meaningful contribution to the emerging domain of ISC and IWC by leveraging the latest advancements in AI Technologies.

2. CHAPTER: LITERATURE REVIEW

Renewable energy has a broad perspective that affects not only the energy sector but also socioeconomic and environmental dynamics. In this context, studies on OECD countries aim to understand the socioeconomic impacts and evaluate the energy transition process. Meanwhile, advanced analytical methods such as machine learning have critical importance in filling the gaps from previous works in the field of renewable energy and shedding light on future research. This category aims to investigate the current situation on renewable energy, focusing on studies conducted in the context of OECD countries, socioeconomic impacts, use of ML, and existing gaps in the literature.

The literature review is categorized into five subjects. The first topic reviews the socio-economical perspective of climate change and renewable future. The second topic examines studies conducted across OECD countries for a broader international economic and policy-making view. The third subject reviews the concept IWC and ISC in the renewable energy context. The fourth subject delves into ML models of related issues. The fifth topic notifies the existing gap in the literature and the last topic declares the aim of this study.

2.1. Socioeconomic Dimension within the Context of Renewable Energy

In the first step of the literature review, the interaction of socioeconomic factors in the renewable energy context has been investigated from different perspectives.

Pata et al. (2023), examined the role of economic policy uncertainty and geopolitical risk, as well as controlling economic growth and urbanization among G7 countries due to their leading role in both economic and political areas. In the study, socioeconomic and political variables are analyzed.

The study conducted 4 different analyses for the annual data from 2004 to 2018. First, a descriptive analysis has been conducted. Then, the presence of CSD in the panel

dataset has been analyzed whether the shock in one country affects the other countries. In the third stage, the study performs an Augmented Mean Group (AMG) method to analyze the effects of Economic Policy Uncertainty Index, Geopolitical Risk Index, GDP, and Urbanization on Renewable Energy Investments (URB). Lastly, for robustness check, Government Efficiency and Regulatory Quality variables are included as a control variable. In conclusion, the outcomes from the three models offer consistent estimations regarding the impact of Economic Policy Uncertainty (EPU), Global Policy Rate (GPR), GDP, and URB. Based on these findings, one can assert that a rise in economic well-being fosters REINV. Conversely, an escalation in EPU, GPR, and URB poses obstacles to REINV in G7 countries, with institutional quality showing no significant influence on REINV.

Shoaib and Ariaratnam (2016) investigated the usage of renewable energy sources affected communities on social and economic terms in two towns in Afghanistan. The aim of the paper is to identify whether Community-based Renewable Energies offer sustainable energy solutions in particular places such as rural areas, verify whether communities experience socio-economic development benefits from Community-based Renewable Energies (CREs), and whether these initiatives lead to enhancements in the living standards of the recipient communities.

The paper evaluates the issue in two sections; firstly, assessing the economic effects of Community-based Renewable Energies (CREs) in areas that do not have any access to dependable energy sources; and secondly, Examining the social implications of CREs and their cumulative effect on the sustainable development of these communities. The information gathered in this research is individual interviews, fostering direct interaction between the interviewer and the respondent. By using this approach, is targeted to minimize the likelihood of misunderstandings between the interviewees. The result of 140 one-on-one interviews, participants perceived CRE projects have a better social and economic impact at the household level. It is stated that projects did lead to an acceptable amount of improvements in the social conditions (59%) and economic conditions (40.6%). The variables that showed the greatest improvement among the twelve that were used to determine the socioeconomic advantages for families were personal security, family contact, children's learning environments, and choices for entertainment. Working hours for productive reasons

and cleanliness and health conditions are the two metrics that show the least improvement.

Masrahi et al. (2021) surveyed to identify the influence of socioeconomic factors on consumers' behavior in renewable energy usage via the household market in the United States. Research aims to understand the behavioral intentions of consumers towards the utilization of renewable energy in the household market in the United States and to identify the key elements and their respective contributions to this behavior. The authors conducted a survey developed by Survey Monkey software using a 5-point Likert scale. The targeted sample of the study was the people living in the United States who participated in the residential sector. The survey requires 19 variables and 6 categories such as;

- “Attitudes toward using renewable energy” has 6 types of statements.
- “Subjective norms” has 3 types of statements.
- “Perceived behavioral control” has 3 types of statements.
- “Willingness to pay” has 3 types of statements.
- “Intentions to use renewable energy” has 4 types of statements.

They have conducted 3 models to find hidden factors and determine the frequency of this behavior. Hypothesis testing has been applied to each model to reduce the complexity of the theory of planned behavior (TPB) model. In the first TPB model, 3 categories are examined: consumers' attitudes, subjective norms, and perceived behavioral control. The second model adds the willingness to pay construct into the TPB model. The last model includes all 6 categorized factors in the model. Results show that in the expanded TPB model, perceived behavioral control consistently emerges as the primary determinant of intentions, followed by subjective norms and willingness to pay. Notably, attitude toward the behavior in the extended TPB does not exhibit statistical significance in influencing intentions to adopt renewable energy. Furthermore, according to the extended TPB model, there is a positive impact of willingness to pay on the intentions to use renewable energy. Researchers indicated that the willingness to pay factor may have a significant role in predicting customers' intentions to adopt renewable energy. Moreover, these results can also provide insights

for policymakers by underlining that intentions to adopt renewable energy in the U.S. can be influenced by socioeconomic factors.

Kostakis et al. (2023) examined the correlation among detailed energy consumption, human development, openness to trade, financial expansion, urbanization, and sustainability index among OECD countries from the years 2014 to 2019. The authors confirm the direct influence of disaggregated energy sources, both fossil and non-fossil fuels, on socioeconomic sustainability using static linear methods, quantile techniques, and dynamic specifications. They used the data annually observed over six years for variables conducted from various secondary sources over the period 2014 to 2019 among OECD countries. The dependent and independent variables are listed, below.

- Global sustainable competitiveness
- Coal use per capita
- Petroleum and other liquids use per capita
- Natural gas use per capita
- Renewable energy use per capita
- Renewables and nuclear energy use per capita
- Human development index
- Real GDP growth
- Trade openness (Share of GDP)
- Urbanization population (% of the total population)

In this research, econometric panel methods are employed to address concerns like endogeneity, cross-sectional dependence (CSD), group-level heteroscedasticity, and serial correlation. The researchers utilized the generalized least squares approach to handle group-wise heteroscedasticity and serial correlation, and ordinary least squares combined with standard errors to tackle cross-section dependence as baseline models. Additionally, to ensure robustness, dynamic system generalized method of moments (sys-GMM) specifications were implemented, offering dependable outcomes in the presence of endogeneity issues and short panel data. After that, they conducted a CSD test, which is expected to be reliable in small panel datasets in econometric analysis. The results of the study implied that OECD countries are highly dependent on fossil

fuels as an economic aspect. The shift to cleaner energy sources in the transition away from oil, natural gas, and coal can mitigate sustainability degradation. While some economies may not have attained a non-fossil fuel usage level that dramatically reverses environmental harm, the promotion of alternative energy sources is crucial for enhancing socioeconomic sustainability. In essence, the empirical results affirm that energy transition serves as a valuable means to advance socioeconomic sustainability in OECD countries.

2.2. Renewable Energy Studies Among OECD Countries

The second part of the literature review presents the papers that review renewable energy studies among OECD countries in the literature.

The financial and socioeconomic effects on renewable energy and eco-growth among OECD countries are examined by various researchers. Wang et al. (2023) explored the influence of financial efficiency and ecological innovation on the utilization of renewable energy in OECD countries. This research examined the financial efficiency of 24 OECD countries, over 2001-2018 years period through an input-output perspective, employing the super-efficiency data envelopment analysis (DEA) model designed to assess the relative efficiency of peer decision-making units (DMUs) in multiple input-multiple output scenarios. This method ensures dependable financial effectiveness data. The study examines how renewable energy utilization is affected by both financial effectiveness and environmental innovation employing a combination of Fully Modified Ordinary Least Squares and Driscoll-Kraay margin of error regression analysis. This dual-method approach enhances the robustness of estimates compared to using a single regression method, offering assistance in ensuring the precision of research findings. Additionally, the research delves into varied impacts of both financial effectiveness and environmental innovation on the utilization of renewable energy in a context of OECD countries. It employs the fixed effects panel quantile regression method to enhance the dependability. Finally, utilizing the Dumitrescu and Hurlin (2012) panel causality test, study investigate the connections and impacts associated with the consumption of renewable energy, financial effectiveness, and environmental innovation. Variables are examined in the panel data are stated, below.

- Renewable energy utilization
- Financial effectiveness
- Environmental Innovation
- Energy efficiency
- Trade openness

Input and output variables for financial efficiency are stated below.

- Compensation of employees
- Credit
- Market capitalization
- Premium income
- Enhancement of value in the financial sector

As a result, economical effectiveness together with environmental innovation emerge as pivotal elements affecting renewable energy utilization. Study also identifies energy effectiveness and commerce opportunity as contributors into increased renewable energy consumption. Outcomes from panel quantile regressions with fixed effects highlight heterogeneous impacts of individual explanatory factors on the utilization of renewable energy. Especially, financial effectiveness and environmental innovation exhibit Substantial beneficial impacts on the utilization of renewable energy, underlining their further evident impact in nations where the proportion of renewable energy usage is lower. The Dumitrescu-Hurlin panel causality test indicates a mutual causation between financial effectiveness and renewable energy utilization, coupled with a one-way causal relationship from environmental innovation to renewable energy utilization. These findings aim long-term coefficients' regression findings. Experimental investigation confirms improving financial effectiveness and fostering environmental innovation contribute significantly to promoting renewable energy utilization. This positive relationship underlines the importance of expanding the consumer market, enhancing improvement of the economical field and supporting technological advancement to increase renewable energy utilization and accomplish energy conversion.

From a different perspective on this issue, Aydin and Bozatli (2023), inspected the influence of favorable and unfavorable unexpected environmental tax change on utilization of renewable energy across OECD nations. In detail, researchers examined the influence of green tax, innovative eco-friendly practices, economic expansion, and progress in financial institutions on utilization of renewable energy across the top ten OECD nations with top utilization levels. Study includes the duration between 1994-2019, utilizing information from various sources. Associated variables are stated, below.

- utilization of renewable energy
- green tax, evaluated as the percentage of GDP represented by total green taxes
- economic expansion gauged as GDP (constant 2015 US dollars)
- progress in financial institutions
- innovative eco-friendly practices, determined by patents related to eco-friendly technologies

As methodology, initially, the study assessed series stationarity, followed by the application of the cointegration test. This test enables the exploration of a durable connection, even in cases where the series displays varying levels of combination. The results of the cointegration test indicate the co-movement in both uniform and ununiform models over the extended period. Among uniformed model, researchers employed the panel AutoRegressive Distributed Lag (ARDL) method to identify the impact of green tax, innovative eco-friendly practices, economic expansion, and progress in financial institutions on utilization of renewable energy. Meanwhile, the ununiformed model indicated that study delved into the ununiformed effect of green tax on utilization of renewable energy through Nonlinear ARDL method by Yongcheol et al. (2014).

The results showed that the environmental tax is advantageous in stimulating Renewable Energy Consumption (REC) and facilitating the transition to sustainable energy. The results from panel causality also lend support to this perspective. Nonetheless, concerning ununiformed evidence, it is observed that only unfavourable changes impact utilization of renewable energy rather than favourable changes in the green tax. Additionally, the supporting information of ununiformed causality suggests

an interplay between green tax changes (both favorable and unfavorable) and utilization of renewable energy. The estimation outcomes indicate that economic expansion has a minor and unfavorable impact on utilization of renewable energy in extended periods, both in uniformed and ununiformed models. Thus, opposed to assumptions in previous papers, economic expansion only sporadically promotes utilization of renewable energy. The favorable impact of financial development and environmentally friendly innovation in encouraging utilization of renewable energy serves as a crucial guideline for policymakers.

Perone (2023) pointed out another meaningful indicator regarding the climate crisis which is the CO₂ emission level. The author examined the relationship between renewable energy production and CO₂ emissions. This paper stands out for its utilization of various renewable energy sources including biofuel, biomass, and geothermal energy in addition to solar, wind, and hydropower. The paper investigates panel data from the years 1965 to 2020 and includes 27 OECD countries. The study employs various types of variables listed below.

Independent variables:

- Biofuel energy
- Geothermal energy
- Hydropower energy
- Nuclear energy
- Solar energy
- Wind energy

Dependent variable:

- CO₂ emissions, metric tons per capita

Control Variables mainly consist of energy, population, and agricultural attributes.

The empirical methodology conducted by the authors consists of Pesaran's CD test (Pesaran, 2004), Cross-sectionally augmented Dickey-Fuller (CADF) panel unit root test by Pesaran (2007), panel unit root test by Karavias and Tzavalis, (2014), panel ARDL models (Pooled mean group, mean group, dynamic fixed effects), after that for sensitivity check fully modified ordinary least squares, dynamic ordinary least squares

by Pedroni (2001), and common correlated effects mean group estimators by Pesaran (2006) are employed, at last Granger's (1969) non-causality test has been employed. For the robustness check, Dumitrescu and Hurlin's (2012), bivariate panel causality test is employed.

The findings of the study revealed that geothermal and biomass technologies exhibit the highest efficacy in reducing carbon dioxide emissions. However, it is also stated that since these technologies are capital-intensive and financially risky, this presents a distinct financial obstacle in the near future. The second inefficiency of reducing carbon dioxide emissions in OECD countries is hydropower. Preference for hydropower stems from its relatively low production cost in comparison to geothermal and biomass generation. The third most effective energy source for reducing CO₂ emissions has been Solar energy. Wind energy follows solar with a slight decrease in emission reduction. On the contrary, effect of nuclear energy production on reducing CO₂ emissions is insignificant. Also, the results imply that biofuel has a generally limited impact on reducing CO₂ emissions. The result implies that biofuel may not be the most optimal resolution for developing sustainability and addressing climate change, especially when compared to alternatives.

Another research that utilized descriptive analysis methods among OECD countries but differs from the research motivation conducted by Cergibozan (2021), examined the energy security problem of 24 OECD countries in the context of renewable energy sources. The annual data is collected between 1985 and 2016 among OECD countries. The descriptive analysis variables are stated, below;

- Energy Security Risk Index
- Wind electricity net generation
- Solar electricity net generation
- Hydroelectricity net generation
- Biomass and waste electricity net generation
- Net generation of electricity from renewable sources
- Urban population growth
- Industrial production

- Economic integration

As the methodology, the author conducted six stages of analysis. At first, cross-sectional dependence tests by (Breusch and Pagan, 1980; Pesaran, 2004; Baltagi et al., 2012) are employed. After that, a slope homogeneity test by Pesaran and Yamagata (2008) has been conducted. A cross-sectionally augmented IPS by Cole (2006) for panel unit root test has been employed. Then, the Durbin-Hausman panel cointegration test developed by Westerlund (2007) is conducted. After identifying a sustained connection among variables, the subsequent step involves estimating long-term coefficients. The researcher employed the Augmented Mean Group (AMG) estimator, as formulated by Eberhardt and Bond (2009). The researcher applied the heterogeneous panel causality test, introduced by Dong et al. (2018), to identify causal relationships between variables.

The results indicate that while biomass, wind, hydroelectricity, and total renewable energy contribute to reducing energy security risk in certain OECD countries, these positive effects are not universally applicable across all OECD nations. Specifically, for 7, 13, 9, 5, and 9 countries, the coefficients of biomass, wind, solar, hydroelectric, and total renewable energy were found to be negative and statistically significant. Additionally, the researcher identified a unidirectional causality from biomass and hydroelectricity to energy security risk, along with a bidirectional causality between industrial production, total energy, economic integration, urbanization, wind, and energy security risk.

2.3. The Concept of Installed Wind and Solar Capacity in the Renewable Energy Context

ISC and IWC play pivotal roles in the renewable energy context, serving as key metrics that gauge the effectiveness and progress of sustainable energy initiatives. This part of the literature review delves into the concept of installed wind and solar capacity within the broader context of renewable energy.

Islam et al. (2022) emphasized the importance of mineral importing in the context of renewable energy technologies such as solar PV and wind turbines. The authors examined the responsiveness level of the mineral import demand of top mineral-importing countries within the context of renewable energy regarding ISC and IWC.

The selected 9 top mineral importing countries are Australia, Brazil, Canada, Chile, Mexico, Russia, South Africa, Ukraine, and the United States. The annual data requires the period 1996 to 2019 to eliminate the effect of Covid-19.

The authors conducted statistical analysis such as Pesaran et al.'s (2008) CD test and CADF test generated by Pesaran (2007) to examine the sequence of integration within the variables. Ultimately, through the utilization of the cross-sectional autoregressive distributed lag (CS-ARDL) approach, researchers assess both the short-term and long-term relationships among the variables within the dynamics of the co-integration. Researchers also employed the slope homogeneity test by Swamy (1970) further improved by Pesaran and Yamagata (2008) and Blomquist and Westerlund (2013) after conducting descriptive analysis.

Consequently, the leading nations in mineral imports experience a favorable increase in aggregate mineral imports in direct response to the presence of installed solar capacity. In the extended duration, the positively significant coefficient of installed solar capacity aligns with the initial assumption, implying that solar production contributes to an elevated demand for critical minerals in these leading mineral-importing countries. In the long run, the average mineral price exhibits a statistically significant negative correlation with the contrary of oil price. Also, the exchange rate has a strong negative effect on mineral flow.

The response for the IWC, positively specific factor of wind capacity underscores the presence of IWC, serving as a robust indicator of universal transitions toward renewable energy, requires minerals. Consequently, this leads to an elevation in the import quantities of these essential mineral resources. Both oil price and mineral price have slightly favorable relationship in extended time, indicating that these two terms have a complementary effect on wind generation. On the contrary, the exchange rate has been found negatively significant for wind capacity for an extended time.

Other comprehensive research was conducted by Marques et al. (2019) regarding installed capacity regarding context of renewable energy policy, economic, sustainable development. This large-scale study includes 48 countries and within the years 1997 to 2017. The paper examines the impact of various categories and subcategories of Public Policies Supporting Renewables (PPSR) on both the installed capacity and electricity generation of Renewable Energy Sources (RES) in an aggregated format.

Additionally, the study analyses disaggregated data for new RES. It examines whether the positive impact of PPSR on installed capacity results in increased deployment. Additionally, it compares the impacts of PPSR on aggregated RES, wind power, and solar PV to reveal specific technological implications. The study evaluates both short- and long-term effects, assessing the persistence of short-term impacts over time. The cross-section dependence test introduced by Pesaran (2004) was conducted, revealing the existence of cross-section dependence in all variables, excluding those involved in policies. Initial generation unit root tests, namely LLC (Levin et al., 2002), ADF-Fisher (Maddala and Wu, 1999), and ADF-Choi (Choi, 2001), were employed. Additionally, following the outcomes of the cross-sectional test, the second-generation unit root test CIPS (Pesaran, 2007) was also executed. Finally, ARDL models were employed using the Driscoll–Kraay (1998) method, which includes fixed effects, illustrating its suitability for addressing the specific characteristics identified in the data.

As a result, in the short run, the establishment of specific entities like agencies and departments responsible for energy can guide policy enhancement, licensing procedures, and the preparation of loan requests. Conversely, policy instruments designed for long-term effects primarily focus on financial support, including loans, subsidies, and tax incentives. Market-driven instruments such as certificates for environmentally friendly and conventional energy, and RPS are effective solely in the extended promotion of Renewable Energy Sources (RES). As anticipated, Feed-in Tariffs (FiT) and policy support have proven to be the most influential Public Policies Supporting Renewables (PPSR) for fostering wind power, both in both the immediate and extended periods. FiT appeals to investors by ensuring a fixed electricity price and offering priority dispatch orders. Solar, being the minimal developed RES technology in harnessing natural resources, exhibits unique characteristics. Overall, the impact of PPSR on installed capacity aligns consistently with its influence on electricity generation.

Another perspective from Biresselioglu et al. (2016), has been conducted in the context of how installed wind capacity has been influenced by economic, political, and environmental factors. The authors employed an analytical approach among 26 countries from 1997 to 2014. Furthermore, the analysis includes a robustness check by categorizing the sample of twenty-six countries into four regions. This evaluation

relies on the metrics such as Installed wind capacity (MW) and other economic and energy attributes as dependent variables. GDP per capita (current US\$) is stated as independent variables.

The empirical examination of the selected factors fostering the development of IWC was conducted through the application of the System Generalized Method of Moments (GMM) estimator introduced by Blundell and Bond (1998) and Arellano and Bover (1995). Then, the validity of the elements is analyzed using Hansen (1982).

The study concludes that carbon dioxide emissions and FDI stock have a statistically notable and positive influence on the development of installed wind capacity. Positive connection between the proportion of wind power in electricity generation and the growth of installed wind capacity is consistently observed across regions and the sample of twenty-six countries. A decrease in overall energy import reliance encourages the expansion of IWC, proving to be statistically significant, especially in Non-continental and Northern Europe. Additionally, the positive relationship between primary energy intensity, hydroelectricity consumption shares in electricity generation, and installed wind capacity development is statistically notable and corresponds with the assumptions made in the study.

Development in technology has caused a change in renewable energy technologies. Yang et al. (2022) employed an analysis of different types of wind-solar hybrid energy systems among different locations in China. The economic and power supply aspect of solar and wind resources, as well as the determination of optimal installed capacities, is examined. Researchers have chosen 36 representative sites in the regions of China, characterized by concentrated wind and solar energy resources and suitable geographical conditions. The multi-objective optimization algorithm is employed to optimize the installed capacities of components within the hybrid system, taking into account both power supply reliability and economic considerations. The objective of the optimization is to minimize both LPSP (Loss of Power Supply Probability) and LCOE (Levelized Cost of Electricity). The variables independent variables of the model are stated below.

- IWC
- PV capacity

- Solar multiple
- Thermal Energy Storage hour
- Power cycle capacity
- Electric Heater capacity
- Battery capacity
- Bidirectional inverter capacity

As the optimization process accounts for both reliability and economy, the authors employed the Non-dominated Sorting Genetic Algorithm II as a multi-objective optimization algorithm (Deb et al., 2002). It is stated that extensively utilized for addressing multi-objective optimization problems in various studies (Guo et al., 2019; Thanganadar et al., 2021; Padilla et al., 2018). The population size is set at 800, and the highest level of generation is limited to 1200 to guarantee precision in calculations. The Pareto frontier is implemented to balance the two optimization objectives.

The researchers found that the regions where solar-wind hybrid renewable energy sources are recommended to be popularized due to good economic benefits. The LCOE might be calculated as 0.1 \$/kWh with an LPSP of 10%. The optimal configuration of the system devices is notably influenced by the conditions of wind and solar energy resources, depending on distinct power supply reliability and economic criteria. Employing electric heaters with thermal energy storage and power cycle to harness surplus wind and solar power outputs proves to be an efficient strategy for significantly minimizing LPSP in an economically viable manner. For achieving elevated power supply reliability alongside favorable economic performance, it is advisable to incorporate concentrated solar power technology into the system across the majority of regions.

2.4. Machine Learning Models in Energy Literature

This section explores the varied machine-learning models that are progressively gaining significance in the energy sector. Known for their robust predictive capabilities and contributions to decision support systems, these models are effectively applied across diverse energy domains, including consumption, production, and management.

Kumar (2023), suggests employing hybrid machine learning models to predict CO2 emissions, leveraging energy, social and economic variables in his paper. The study investigated India's energy and socio-economic attributes regarding CO2 emissions and employed the real annual data from the Indian government spanning the years 1960 to 2018. The study employs a significant amount of independent variables to predict CO2 regarding improving reliability and maintaining a multidimensional approach. Paper includes independent variables that can be categorized as social, economic, energy generation attributes such as conventional and sustainable.

The hybrid model proposed relies on flexible regression and incorporates a procedure for choosing characteristics. Principal Component Analysis (PCA) has been employed to select features for reducing the dimensionality of extensive datasets, as outlined by Ringner (2008). The suggested hybrid model, combining PCA consists of 3 types of Linear Regression models Ridge Regression, Lasso Regression, Random Forest Regression (RFR) (Liu et al., 2012), ElasticNet Regression and Support Vector regression (SVR). The hybrid models are compared with machine learning and deep learning (DL) methods such as Recurrent Neural Networks (RNN) (Schuster and Paliwal, 1997), Long Short-Term Memory (LSTM) (Graves, 2013), and TabNet. The suggested hybrid model is assessed through well-known regression metrics, encompassing Mean Absolute Error (MAE), Mean Squared Error, Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and Symmetric Mean Absolute Percentage Error.

The results showed that Hybrid models demonstrate better performance when compared different machine learning and DL methods. The most effective model is suggested to be the PCA + Linear ElasticNet Regression model. It has been observed that there is an association among GDP, economic expansion, and the quantity of emissions. Since the Indian economy is reliant on energy derived from conventional methods, the increase in GDP results in an increase in energy demand which consequently leads to an increased emission of CO2. The author also stated that socioeconomic and energy factors need further assessment.

Serrano-Ar'evalo et al. (2023), investigated the clean energy transition process regarding future energy demand and clean energy production. DL models and a multi-objective Mixed-Integer Programming (MIP) mathematical model have been

developed as methodology. The proposed methodology's applicability and results are demonstrated through a case study conducted in Mexico. The data period 1965 to 2019 of annual energy demand data of Mexico is employed. Two types of DL models, namely, LSTM and Gated recurrent unit (GRU), have been developed to predict energy demand from 2020 to 2040. The LSTM method, which is an upgraded version of the RNN model, was developed by Hochreiter and Schmidhuber (1997). The GRU method is also a different type of RNN which was developed by Cho et al. (2014). The authors considered five primary conventional technologies as well as five main renewable technologies currently operational for energy production in Mexico. The conventional technologies are conventional thermoelectric, combined cycle, turboelectric, internal combustion, and turbo gas. On the other hand, clean technologies include hydroelectric, wind, geothermal, solar photovoltaic, and solar thermal. The proposed solution involves a combination of existing and new energy production, to be installed within a specified timeframe. This approach aims to reduce reliance on conventional technologies and, consequently, mitigate associated emissions. Therefore, 3 different scenarios were employed such as reaching 30%, 50%, and 70% of the renewable energy demand in 2040.

The authors determined the structure of the DL models to be a single hidden layer with 250 LSTM units. a linear regression (LR) and an artificial neural network (ANN) were constructed to contrast the outcomes obtained from LSTM and GRU. The ANN was developed with identical parameters as those used for LSTM and GRU. Also, the mathematical model's objective function aims to minimize both the overall discounted cost of the process and the total emissions produced. At last, the ϵ -constraint method was utilized to create Pareto curves and examine the trade-off between economic and environmental goals.

The findings suggest that the scenario aiming to achieve 70% of renewable energy demand by 2040 anticipates the least total cost, minimal emissions, and lower water consumption when compared to alternative scenarios. The paper suggests the adoption of clean technologies, involving a higher initial investment. Nevertheless, this choice is offset by a reduced total future cost in the presented planning, thereby mitigating the environmental impact. Across all three scenarios, it is evident that the combined cycle technology exhibits the highest thermal efficiency, potentially leading to decreased costs and emissions compared to other conventional technologies.

Izanloo et al. (2022), studied the investment decision process in the clean energy industry. Researchers conducted a hybrid methodology with statistics and machine learning algorithms for this process. A risk assessment model specifically designed for renewable energy technology (RET) investments has been developed. The model consists of 6 features that are stated below.

- Variations in GDP
- Changes in inflation
- Shifts in the production of electricity from hydropower, wind, solar PV, and biomass, individually
- Oscillations in electricity prices
- Shifts in energy demand
- Carbon dioxide emission

A dataset was generated for utilization of renewable energy such as wind, solar, hydropower, and biomass. The data set consists of 5 years of data from the period 2015 to 2019 from various countries. The countries are classified into five groups, ranging from minimal risk to elevated risk countries to invest in utilization of renewable energy or in other words, from the most favorable nation to the least favorable nation to invest. ML algorithms and a statistical method are employed corresponding to each technology of renewable energy.

As methodology, the standard deviation (STD) is employed for calculating the risk. The lowest STD indicates the lowest level of risk, while the highest deviation represents the utmost degree of risk.

Various machine learning algorithms, including Artificial Neural Network (ANN), Logistic Regression (LR), Decision Tree (DT), Support Vector Machine (SVM), Naive Bayes (NB), k-Nearest Neighbors (k-NN), Random Forest (RF), and Ada Boost (AB), were employed on each Renewable Energy Technology (RET) dataset to categorize countries based on their level of risk, spanning from the least risky country to the most risky country concerning RET investment alternatives. LR, SVM, ANN, and DT exhibited superior performance compared with different machine learning

methods. The highest precision, reaching 0.94, was achieved, while AB had the lowest accuracy at 0.24, specifically for biomass technology. LR yielded minimum and maximum Mean Squared Error values for biomass technology, and Ada Boost for hydropower technology. Additionally, the most crucial criteria influencing decision-making in RET investment were identified to the risk associated with electricity generation from Renewable Energy Technologies and the risk associated with electricity cost in each nation.

2.5. Gap in the Literature

As the global demand for sustainable and clean energy continues to grow every day, the renewable energy sector stands as the pioneer in this movement. The significant role that wind and solar energy sources play in the renewable energy sector towards a greener future is becoming increasingly evident. In this context, various studies serve as illustrative examples. Insel et al. (2022) constructed a linear regression model to determine the installed wind and solar energy capacities of Turkey and employed three scenarios of cost and investment for 2030. Perone (2023) examined the relationship between CO₂ emissions and renewable energy attributes of OECD countries and found remarkable results. Islam et al. (2022) and, Islam et al. (2023) studied the supply and demand effect of mineral demand for installed wind and solar capacities regarding the clean energy transition process in 9 top mineral-importing countries. Kumar (2023) employed a hybrid ML model to predict CO₂ emissions, leveraging energy, social and economic variables of India. Marques et al. (2019) conducted a cross-sectional analysis regarding installed capacity in the context of Public Policies Supporting Renewables and economic and sustainable development includes 48 countries. Biresselioglu et al. (2016), employed an empirical study among 26 countries in the context of how IWC has been affected economically, politically, and environmentally. Yang et al. (2022) conducted a multi-objective optimization algorithm to optimize the cost and power supply attributes for wind-solar hybrid energy systems in different locations in China. Serrano-Ar'evalo et al. (2023) also employed a multi-objective Mixed-Integer Programming model, LSTM, and Gated recurrent unit (GRU) DL models to predict future energy demand and clean energy production. Izanloo et al. (2022), developed a hybrid methodology with statistics and machine learning algorithms to improve the investment decision process in the clean energy industry.

Chen et al. (2023), conducted machine learning and artificial neural network models to predict mineral resource trends in China with indicators such as economic growth, the producer price index, market prices, and the Environmental Policy Stringency Index (EPSI).

Despite the sector's remarkable growth, there is a notable gap persists in the literature, regarding these renewable capacities and key socio-economic and environmental terms. The terminology used in studies related to the transition to renewable and clean energy processes tends to vary notably, particularly among economically robust nations, those with advanced industries, abundant natural resources, and large populations. This selection is rooted in the idea of focusing on countries that exert the most influence on global resources and the transition process itself. Consequently, OECD countries are frequently chosen due to their well-established attributes in terms of energy, environment, and socioeconomics within the context of clean energy literature.

However, despite the extensive literature on clean energy, there remains a notable gap in the realm of forecasting installed solar and wind capacities. This gap is particularly evident concerning other crucial variables, including environmental policy, renewable energy attributes, and socio-economic factors. To the best of my knowledge, no research has been conducted thus far employing machine learning models to predict installed wind and solar capacities while incorporating considerations of environmental policy, renewable and conventional energy attributes, and socio-economic factors, especially among sampled OECD countries within a complex time series data set.

2.6. Aim of the Study

This research aims to analyze the installed wind and solar energy capacities for a 21-year data set including 2000 to 2020 for 24 OECD countries. The dataset encompasses a comprehensive range of attributes related to environmental policy, energy, society, and economics. The study employs the sophisticated machine learning method, Long Short-Term Memory (LSTM). By using the first 16 years of data to train these LSTM model, the prediction performance of the obtained algorithms was tested for the last 5 years of model. Another objective of this study was to compare and demonstrate the

predictive capabilities of ISC and IWC models within the framework of diverse variables, each contributing uniquely to our study conducted among OECD countries.



3. CHAPTER: METHODOLOGY

The methodology section of this study presents a comprehensive framework encompassing the analysis and processing of the dataset. It focuses on four main aspects: "Data Set Analysis," which involves a detailed exploration of the dataset, and the subsequent implementation of "Machine Learning Models" and the "Long Short-Term Memory Method" (LSTM) and Experimentation. Each subheading contributes to the analytical process of the study, ensuring a thorough examination of the dataset, the establishment of machine learning models, and the application of the LSTM method. The detailed exploration within each subheading aims to improve the study's reliability and in dept examination of methodology conducted.

3.1. Data Set Analysis

In this section, each component of the dataset will be meticulously examined. Before presenting analytical methods, a concise introduction to contextualize each variable in detail and its significance within the scope of the study. The dataset comprises socioeconomic, sustainability and related energy attributes of OECD countries that are explained detailly, below. These countries are Australia, Austria, Belgium, Brazil, Canada, China, Denmark, Finland, France, Germany, Greece, India, Italy, Japan, Netherlands, Poland, Portugal, South Africa, South Korea, Spain, Sweden, Turkey, United Kingdom and United States. Due to the absence on data of ISC and IWC of other OECD countries, the study is limited to 24 OECD countries and dataset comprises the period 2000 to 2020.

Installed Wind Capacity (IWC) is one of the dependent variable of the model. IWC refers to the total power-generating capability of wind energy facilities. It represents the aggregate amount of energy that wind power plants operating in a specific region or country can potentially produce. Typically measured in megawatts (MW), this capacity serves as an indicator of the total energy output potential of wind energy installations, contributing to assessments of renewable energy sector growth, capacity factors, and energy demand. The dataset of IWC includes the years 2000 to 2020 for

24 OECD countries and measured in gigawatts. The dataset utilized in this study was sourced from International Renewable Energy Agency (2023) – processed by Our World in Data which is a reputable and widely recognized platform that provides comprehensive information.

Installed Solar Capacity (ISC) is the dependent variable of the model. ISC refers to the total electricity-generating capability of solar energy systems that have been installed and are operational. It represents the maximum amount of solar power that these systems can produce under optimal conditions. The capacity is measured in terms of power output, typically expressed in kilowatts (kW) or megawatts (MW), and it indicates the overall contribution of solar energy to the total power generation capacity within a specific region, facility, or country. The dataset of ISC includes the years 2000 to 2020 for 24 OECD countries and measured in gigawatts. The dataset utilized in this study was sourced from International Renewable Energy Agency (2023) – processed by Our World in Data platform.

Population (Pop) is an independent variable of the model. The data comprises the Pop of 24 OECD countries includes the years 2000 to 2020. This variable represents the demographic information, including the total number of inhabitants, within the member countries of the OECD. Employing population data from OECD countries as an independent variable enables the exploration of how differences in population size among these nations might impact or show correlations with the outcomes of renewable energy generation or behaviors in the green field of the research in the study. The dataset utilized in this study was sourced from Gapminder- Population v7 (2022) and other sources – with major processing by platform.

Annual Gross Domestic Product Growth (GDP) is an independent variable of the model. This variable refers to the percentage increase in the total value of goods and services produced by a country over the course of a year. It serves as a key economic indicator, reflecting the overall health and expansion of a nation's economy. This economic indicator plays a pivotal role in understanding the broader impact of economic conditions on the renewable energy sources and environmental sustainability. It can be observed that higher GDP growth rates might be associated with increased investment in renewable energy infrastructure, thereby revealing the complex connection between economic development and sustainable energy

utilization. The dataset utilized in this study was sourced from World Bank – processed by Our World in Data and includes the 24 OECD countries and period from 2000 to 2020.

Electricity Generation from Oil (EG_Oil) is an independent variable of the model. This variable allows an examination into how fluctuations in electricity generation from oil sources, may relate to or impact the outcomes under investigation. This variable becomes pivotal in understanding the broader implications of energy practices, such as their influence on environmental sustainability, carbon emissions, and the overall energy position within the studied countries. Analyzing changes in energy consumption through this variable can help evaluate shifts in demand for traditional energy sources. The dataset utilized in this study was sourced from Ember- Yearly Electricity Data (2023) with major processing by Our World in Data platform and includes the 24 OECD countries and period from 2000 to 2020 and measured in terawatt-hours (TWH).

Electricity Generation from Coal (EG_Coal) is an independent variable of the model which represent the total amount of electricity produced from coal sources. This variable is typically measured in terawatt-hours (TWH) and indicates the energy output derived from coal-based sources within a specific region or country. In the context of the study, using EG_Coal allows us to explore how the reliance on coal for electricity generation influences IWC and ISC and overall energy patterns and environmental sustainability within the studied countries. The dataset utilized in this study was sourced from Ember- Yearly Electricity Data (2023) with major processing by Our World in Data platform and includes the 24 OECD countries and period from 2000 to 2020 and measured in terawatt-hours (TWH).

Electricity Generation from Gas (EG_Gas) is an independent variable of the model which represents the total amount of electricity produced from gas sources, typically measured in terawatt-hours (TWH). This variable indicates the energy output derived from gas-based sources within a specific region or country. In the context of the research, data utilized from 24 OECD countries, might help to understand the generation of electricity from gas sources relate to or impact the outcomes or behaviours for EG_Gas influences environmental sustainability and demand towards conventional energy within the context of IWC and ISC. The dataset utilized in this

study was sourced from Ember- Yearly Electricity Data (2023) with major processing by Our World in Data platform and comprises period from 2000 to 2020.

Electricity Generation from Hydropower Energy (EG_Hydro) is an independent variable of the model which represent the total amount of electricity produced from hydropower sources within a specific region or country. In the context of the study, it implies that investigating the variations in the generation of electricity from hydropower sources in 24 OECD countries relate to or impact the outcomes, with ISC and IWC. For example, you might explore how the reliance on hydropower for electricity generation influences the deployment of wind and solar capacities, considering the different renewable energy sources within the context of OECD nations. The dataset utilized in this study was sourced from Ember- Yearly Electricity Data (2023) with major processing by Our World in Data platform and comprises period from 2000 to 2020. The unit of EG_Hydro is measured in terawatt-hours (TWH).

Electricity Generation from Nuclear Energy (EG_NE) is an independent variable of the model which represents the total amount of electricity produced from nuclear energy sources. The variable indicates the energy output derived from nuclear power within a specific region or country and typically measured in terawatt-hours (TWH). In the study, the impact in EG_NE utilization influences the deployment of (ISC) and (IWC) has been examined within the broader context of green energy. The dataset utilized in this study was sourced from Ember- Yearly Electricity Data (2023) with major processing by Our World in Data platform and includes the 24 OECD countries from period of 2000 to 2020.

Total Electricity Generation (TEG) is an independent variable of the model which expresses the overall amount of electricity produced in a particular region or country, typically measured in terawatt-hours (TWH). This variable indicates the aggregate energy output derived from various sources, including fossil fuels, renewables, and nuclear power. The research explores the impact of TEG on the deployment of ISC and IWC, considering the broader dynamics of green innovation across the 24 OECD countries. The dataset utilized in this study was sourced from Ember- Yearly Electricity Data (2023) with major processing by Our World in Data platform and includes the 24 OECD countries from period of 2000 to 2020.

Electricity Generation from Renewables (EG_RE) is an independent variable of the model, quantifying the total electricity output derived from sustainable sources like wind, solar, hydro, and geothermal energy. Measured in terawatt-hours (TWH), this metric reflects the collective energy contribution of environmentally friendly sources within a specific region or country. The study aims to investigate the overall electricity generation from renewable sources influences the ISC and IWC. It is important to include how changes in renewable electricity generation impact deployment of sustainable energy practices within the studied region, 24 OECD countries. The dataset utilized in this study was sourced from Ember- Yearly Electricity Data (2023) with major processing by Our World in Data platform and includes the period of 2000 to 2020.

Solar Energy Support (Auctions & FITs) (SES) is an independent variable of the model which refers to mechanisms and policies designed to promote the development of solar energy projects. These mechanisms include auctions and Feed-in Tariffs (FITs), which guarantee a fixed payment for each unit of solar energy produced. These support mechanisms aim to stimulate investment in solar energy, enhance renewable energy deployment, and contribute to sustainability goals. The data for SES, obtained from the OECD organization's website, specifically corresponds to the “Environmental Policy Stringency Index” developed by Botta and Ko’zluk (2014) and includes the period of 2000 to 2020. This index measures the strictness of environmental policies of OECD countries within the context of the regulatory environment and environmental policy stringency. The index is derived from the level of strictness exhibited by 17 environmental policy tools, predominantly focused on climate and air pollution. These environmental policy tools consist of Emission limit value sulphur, Low-carbon R&D expenditures, Solar Energy support (Auctions & FITs), Environmental Policy Stringency, Nitrogen Oxides (NOx) Tax, Sulphur Oxides (SOx) Tax, Emission limit value PM, Diesel tax, Wind Energy support (Auctions & FITs), Market based policies, Environmental Policy Stringency, Carbon dioxides (CO2) Tax, Emission limit value SOx, Non-market based policies, CO2 Trading Scheme, Emission Limit value NOx, Low-carbon R&D expenditures and Technology Support policies. The study conducted 6 environmental policy tools in accordance with the research subject. The index spans from 0 (indicating low stringency) to 6 (representing the utmost level of strictness).

Wind Energy Support (Auctions & FITs) (WES) is an independent variable of the model which refers to policy mechanisms including auctions and Feed-in Tariffs (FITs), designed to encourage and facilitate the development of wind energy projects. These mechanisms aim to encourage investment in wind energy by providing financial support and regulatory structures. In the context of the study, WES has examined to understand their impact on the ISC and IWC. The data for WES, obtained from the OECD organization's website, specifically corresponds to the “Environmental Policy Stringency Index” developed by Botta and Ko’zluk (2014) and includes 24 OECD countries and the period of 2000 to 2020.

Technology Support Policies (TSP) is an independent variable of the model which is a set of policies and measures to support and enhance technological innovation and development within the energy sector. These policies include incentives, subsidies, and regulatories designed to foster the deployment and utilization of advanced technologies within the renewable energy sector. The data for TSP, obtained from the OECD organization's website, specifically corresponds to the “Environmental Policy Stringency Index” developed by Botta and Ko’zluk (2014) and includes 24 OECD countries and the period of 2000 to 2020.

Low-carbon R&D expenditures (LC_R&D) is an independent variable of the model which indicates the financial investments into research and development activities for advancing low-carbon or eco friendly technologies and resolutions. LC_R&D variable helps to understand the financial resources dedicated to research initiatives on reducing carbon emissions and enhancement of sustainable practices. The data for LC_R&D, obtained from the OECD organization's website, specifically corresponds to the “Environmental Policy Stringency Index” developed by Botta and Ko’zluk (2014) and includes 24 OECD countries and the period of 2000 to 2020.

Environmental Policy Stringency (EPS) is an independent variable of the model. This variable measures how stringent a set of environmental policies in factors related to climate, air pollution, and other environmental concerns. In the context of the study, variations in EPS are examined to understand the impact on the ISC and IWC in the 24 OECD countries. The data for EPS, obtained from the OECD organization's website, specifically corresponds to the “Environmental Policy Stringency Index” developed by Botta and Ko’zluk (2014) and includes the period of 2000 to 2020.

Renewable Energy Trading Scheme (RETS) is an independent variable of the model that refers to a policy framework in the trading and exchange of renewable energy certificates and credits. This mechanism enables entities to purchase and sell attributes associated with renewable energy, offering a market-driven strategy to encourage the generation and utilization of renewable energy. The data for RETS, obtained from the OECD organization's website, specifically corresponds to the “Environmental Policy Stringency Index” developed by Botta and Ko’zluk (2014) and includes 24 OECD countries and the period of 2000 to 2020.

Table 3.1. Data Set Description

Data Type	Variable	Notation	Unit	Source
INDEPENDENT	Population	Pop	Number of People	Our World in Data
	Annual Gross Domestic Product Growth	GDP	US\$	Our World in Data
	Electricity Generation from Oil	EG_Oil	TwH	Our World in Data
	Electricity Generation from Coal	EG_Coal	TwH	Our World in Data
	Electricity Generation from Gas	EG_Gas	TwH	Our World in Data
	Electricity Generation from Hydropower Energy	EG_Hydro	TwH	Our World in Data
	Electricity Generation from Nuclear Energy	EG_NE	TwH	Our World in Data
	Total Electricity Generation	TEG	TwH	Our World in Data
	Electricity Generation from Renewables	EG_RE	TwH	Our World in Data
	Solar Energy Support (Auctions & FITs)	SES	0,1,2,3,4,5,6	OECD.stat
	Wind Energy Support (Auctions & FITs)	WES	0,1,2,3,4,5,6	OECD.stat
	Technology Support Policies	TSP	0,1,2,3,4,5,6	OECD.stat
	Low-carbon R&D Expenditures	(LC_R&D)	0,1,2,3,4,5,6	OECD.stat
	Environmental Policy Stringency	EPS	0,1,2,3,4,5,6	OECD.stat
	Renewable Energy Trading Scheme	RETS	0,1,2,3,4,5,6	OECD.stat
DEPENDENT	Installed Wind Capacity	IWC	GW	Our World in Data
	Installed Solar Capacity	ISC	GW	Our World in Data

Source: Author

Country	Year	Pop	EG_Oil	EG_NE	EG_Hydro	EG_Gas	GDP	EG_Coal	SES	WES	TSP	LC_R&D	EPS	RETS	EG_RE	TEG	ISC
Australia	2020	25670052	4.2	0	14.76	49.51	-0.05	133.21	6	0	2	1	2.916667	6	25.503168	250.91	17.625
Austria	2020	8907780	3.26	0	42	9.95	-6.45	0.56	0	5	3.25	4	3.305556	0	80.098274	69.19	2.22
Belgium	2020	11561716	3.14	34.43	0.27	26.78	-5.36	0.08	0	0	2.5	5	3.444444	6	26.692457	87.89	5.646
Brazil	2020	213196300	10.14	13.21	396.33	51.48	-3.88	19.53	0	0	1	2	0.888889	0	84.641174	614.37	8.290503
Canada	2020	37888704	2.58	92.65	380.93	65.32	-5.23	34.29	0	0	2.5	5	3.027778	0	68.77964	624.08	3.325
China	2020	1424929800	10.8	366.2	1321.71	252.5	2.24	4920.83	5	4	2.25	0	3.138889	0	28.24646	7735.27	253.9638
Denmark	2020	5825638	1.04	0	0.02	1.18	-1.99	3.06	1	1	2	3	3.722222	0	81.622	28.73	1.3
Finland	2020	5529468	3.39	23.29	15.88	3.99	-2.21	2.44	0	6	4.5	6	4.111111	0	52.042294	69.04	0.318
France	2020	64480052	9.77	353.83	62.59	35.28	-7.78	3.09	4	4	5	6	4.888889	0	23.761024	527.25	11.724
Germany	2020	83328990	20.42	64.38	18.72	96.38	-3.7	134.6	3	6	3.75	3	3.472222	0	44.332405	567.26	53.781
Greece	2020	10512232	4.77	0	3.34	19.23	-9	6.61	3	3	2	1	2.888889	0	36.44103	48.16	3.247
India	2020	1396387100	2.11	44.61	163.71	74.46	-6.6	1125.77	4	5	2.25	0	2.833333	5	20.205925	1562.71	39.38516
Italy	2020	59500576	14.09	0	47.55	133.7	-9.04	13.38	5	3	3	2	3.722222	0	42.039772	278.07	21.594
Japan	2020	125244760	38.19	41.86	78.81	368.19	-4.51	310.29	0	6	4	5	3.777778	0	21.324924	964.13	67
Netherlands	2020	17434562	5.79	4.09	0.05	72.55	-3.89	7.61	5	4	3.75	3	3.472222	0	26.671553	122.79	10.213
Poland	2020	38428370	4.22	0	2.12	17.29	-2.02	107.4	3	2	1.75	1	3.472222	6	17.964872	157.14	3.936
Portugal	2020	10298186	1.47	0	12.08	17.6	-8.3	2.36	0	0	1	2	2.777778	0	58.420643	51.54	1.025
South Africa	2020	58801930	1.38	11.62	1.44	0	-6.34	196.12	0	0	0	0	0.916667	0	5.7805815	221.95	5.994495
South Korea	2020	51844690	6.5	152.58	3.88	155.08	-0.71	203.47	0	0	1.5	3	3.166667	2	6.1312203	551.44	14.57479
Spain	2020	47363810	12.38	58.3	30.51	69.74	-11.33	5.52	0	0	0.5	1	2.5	0	43.81088	259.73	11.785
Sweden	2020	10368968	2.34	49.2	72.39	0.1	-2.17	0	0	0	2	4	3.833333	5	68.471825	163.79	1.417
Turkey	2020	84135430	2.13	0	78.09	70.93	1.94	104.02	6	4	3	1	2.888889	0	42.02082	305.42	6.667
United Kingdom	2020	67059470	8.22	50.85	6.68	111.22	-11.03	5.34	1	3	3	4	3.611111	6	42.8604	307.37	13.563
United States	2020	335942000	34.34	789.88	279.95	1624.17	-2.77	773.39	1	1	2	3	3.027778	5	20.315693	4043.18	73.814

Figure 3.1. ISC Dataset Structured for 2020

Source: Author

Figure 3.1. illustrates the structured dataset of ISC for the year 2020. It provides a comprehensive view of input variables and corresponding ISC values for 24 OECD countries, serving as a representative example.

Country	Year	Pop	EG_Oil	EG_NE	EG_Hydro	EG_Gas	GDP	EG_Coal	SES	WES	TSP	LC_R&D	EPS	RETS	EG_RE	TEG	IWC
Australia	2020	25670052	4.2	0	14.76	49.51	-0.05	133.21	6	0	2	1	2.916667	6	25.50317	250.91	9.457
Austria	2020	8907780	3.26	0	42	9.95	-6.45	0.56	0	5	3.25	4	3.305556	0	80.09827	69.19	3.224
Belgium	2020	11561716	3.14	34.43	0.27	26.78	-5.36	0.08	0	0	2.5	5	3.444444	6	26.69246	87.89	4.692
Brazil	2020	213196300	10.14	13.21	396.33	51.48	-3.88	19.53	0	0	1	2	0.888889	0	84.64117	614.37	17.198324
Canada	2020	37888704	2.58	92.65	380.93	65.32	-5.23	34.29	0	0	2.5	5	3.027778	0	68.77964	624.08	13.577
China	2020	1424929800	10.8	366.2	1321.71	252.5	2.24	4920.83	5	4	2.25	0	3.138889	0	28.24646	7735.27	282.11266
Denmark	2020	5825638	1.04	0	0.02	1.18	-1.99	3.06	1	1	2	3	3.722222	0	81.622	28.73	6.235
Finland	2020	5529468	3.39	23.29	15.88	3.99	-2.21	2.44	0	6	4.5	6	4.111111	0	52.04229	69.04	2.474
France	2020	64480052	9.77	353.83	62.59	35.28	-7.78	3.09	4	4	5	6	4.888889	0	23.76102	527.25	17.382
Germany	2020	83328990	20.42	64.38	18.72	96.38	-3.7	134.6	3	6	3.75	3	3.472222	0	44.33241	567.26	62.184
Greece	2020	10512232	4.77	0	3.34	19.23	-9	6.61	3	3	2	1	2.888889	0	36.44103	48.16	4.113
India	2020	1396387100	2.11	44.61	163.71	74.46	-6.6	1125.77	4	5	2.25	0	2.833333	5	20.20593	1562.71	38.5586
Italy	2020	59500576	14.09	0	47.55	133.7	-9.04	13.38	5	3	3	2	3.722222	0	42.03977	278.07	10.839
Japan	2020	125244760	38.19	41.86	78.81	368.19	-4.51	310.29	0	6	4	5	3.777778	0	21.32492	964.13	4.206
Netherlands	2020	17434562	5.79	4.09	0.05	72.55	-3.89	7.61	5	4	3.75	3	3.472222	0	26.67155	122.79	6.6
Poland	2020	38428370	4.22	0	2.12	17.29	-2.02	107.4	3	2	1.75	1	3.472222	6	17.96487	157.14	6.267
Portugal	2020	10298186	1.47	0	12.08	17.6	-8.3	2.36	0	0	1	2	2.777778	0	58.42064	51.54	5.239
South Africa	2020	58801930	1.38	11.62	1.44	0	-6.34	196.12	0	0	0	0	0.916667	0	5.780582	221.95	2.516
South Korea	2020	51844690	6.5	152.58	3.88	155.08	-0.71	203.47	0	0	1.5	3	3.166667	2	6.13122	551.44	1.635802
Spain	2020	47363810	12.38	58.3	30.51	69.74	-11.33	5.52	0	0	0.5	1	2.5	0	43.81088	259.73	27.088
Sweden	2020	10368968	2.34	49.2	72.39	0.1	-2.17	0	0	0	2	4	3.833333	5	68.47183	163.79	9.689
Turkey	2020	84135430	2.13	0	78.09	70.93	1.94	104.02	6	4	3	1	2.888889	0	42.02082	305.42	8.832
United Kingdom	2020	67059470	8.22	50.85	6.68	111.22	-11.03	5.34	1	3	3	4	3.611111	6	42.8604	307.37	24.665
United States	2020	335942000	34.34	789.88	279.95	1624.17	-2.77	773.39	1	1	2	3	3.027778	5	20.31569	4043.18	117.744

Figure 3.2. IWC Dataset Structured for 2020

Source: Author

Figure 3.2. represents the structured data set of IWC for the year 2020. It provides a comprehensive view of input variables and corresponding IWC values for 24 OECD countries, serving as a representative example.

3.2. Machine Learning Models

Machine learning (ML) is a branch of AI that focuses on developing algorithms and models that enable computers to learn from data. The ML systems are designed to learn and improve from experience unlike traditional programming, where instructions are provided for a computer to perform a task. As it is mentioned previously, ML models has become the new focus in new technological advancements. The primary reason for greater preference over traditional models is that, while traditional models have rigid assumptions, machine learning models demonstrate superior performance. ML stands out due to its exceptional performance in the field of predictive analytics by leveraging advanced algorithms to analyze historical data, recognize patterns, and make informed predictions about future outcomes. Through the identification of hidden correlations and trends, machine learning models enhance their accuracy over time, enabling organizations to make data-driven decisions and anticipate future events with a high degree of reliability. Main branches of ML includes Supervised Learning (SL), Unsupervised Learning (UL), Classification, Regression, Reinforcement Learning, Association Rule Learning (ARL) and Clustering. The visual overview of ML can be seen in Figure 3.3.

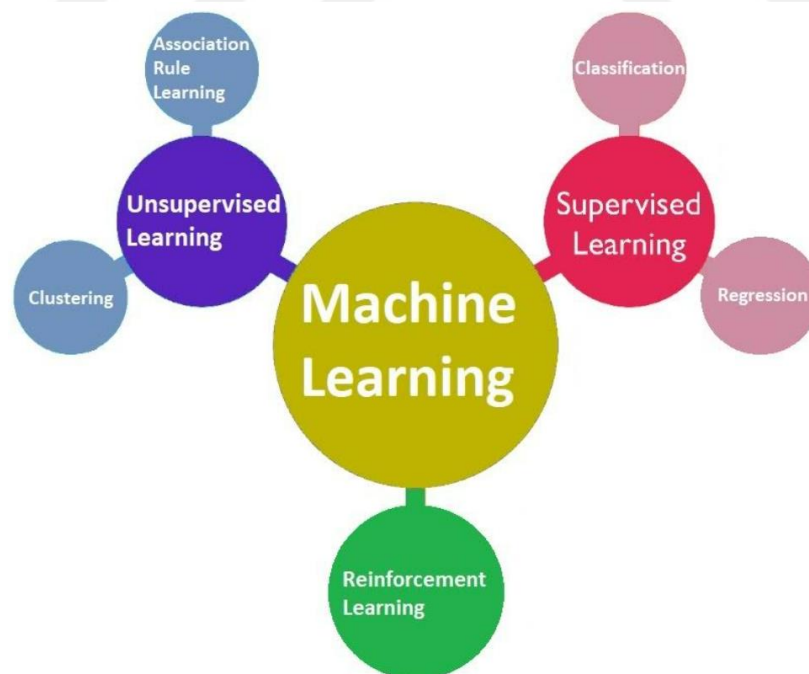


Figure 3.3 Visual Overview of ML

Source: Author

SL is a key subset of machine learning, focusing on training a model using labeled data where each dataset example includes input features and corresponding output labels. The main target in supervised learning is for the model to learn the mapping function from inputs to outputs. It is achieved through iterative predictions and comparisons with actual outputs. The model continuously adjusts its parameters to minimize the difference between predicted and actual values, enhancing its proficiency in making accurate predictions. Supervised learning is widely applied in diverse domains such as classification and regression. Classification instructs a model to categorize input instances into specific groups using labeled data. The model comprehend the connections between input characteristics and their respective category labels, enabling it to forecast the classification of novel data. Regression involves instructing a model to forecast continuous output values using labeled data, acquiring an understanding of the relationship between input features and their corresponding continuous targets. Mostly favourable algorithms for prediction and classification purposes are tree-based algorithms such as Decision Trees (DT) which make decisions by recursively splitting the dataset based on features and selecting the best feature at each split point, RF algorithm which is an ensemble learning method that trains multiple decision trees and combines their predictions to create a more robust and generalizeable model and AdaBoost algorithm which trains low-performing models, and increases the weights of misclassified examples at each stage. It combines the predictions of these weak learners to form a strong and accurate model.

UL is a branch of ML where algorithms are training on unlabeled data, with the objective of notifying patterns, relationships, or structures within the data without any guidance. ARL is a specialized subfield in UL which is concentrated on finding significant associations or rules among variables in extensive datasets. Another branch which is clustering, involves the categorization of similar data points based on specific features. One of the most popular clustering algorithm is the k-means algorithm (Ribeiro and Fanzeres, 2023). The k-means algorithm employs an iterative process to maximize similarities and optimize cluster centers. In each iteration, each data point is assigned to its nearest cluster center, and the cluster centers are shifted to the averages of the assigned data points. These steps are repeated iteratively until the cluster centers and assignments are updated, completing the clustering process. Both ARL and clustering are pivotal in extracting meaningful insights from unstructured data,

offering valuable information for tasks such as market basket analysis and data grouping.

As the study focuses on predicting ISC and IWC within labeled data, the SL approach stands out as the most suitable choice among various methodologies. Utilizing SL proves to be a robust strategy, especially when the objective is to predict complex patterns within datasets that come with labeled data. SL algorithms, like linear regression or decision trees, establish a strong basis for predictive modeling for historical data patterns and labeled outcomes. However, in situations where the prediction task involves sequential dependencies, the LSTM algorithm characterized by its specialized RNN architecture, distinguishes. LSTMs are proficient in capturing complex temporal relationships, making them well-suited for tasks such as time series forecasting or natural language processing, thereby introducing a layer of sophistication to predictive analytics.

3.3. Long Short Term Memory Algorithm (LSTM)

In this section, the principles and application areas of the LSTM algorithm is explained in detail which is the main focus of the methodology.

The LSTM is an algorithm within a domain of DL, stands out as a superior method widely employed in applications such as complex time series data processing, handwriting recognition, healthcare and video games. From a broader perspective LSTM is acknowledged as a method within the subfield of machine learning. It can be stated as LSTM is positioned within the larger framework of ML, contributing to advancements in the DL field within the enhancement in RNN structure. The LSTM algorithm is proposed by Hochreiter and Schmidhuber (1997), stands out for its innovative resolution of the gradient loss and vanishing gradient problems inherent in traditional RNN models.

A LSTM memory cell typically consists of three gates: the input gate, the forget gate, and the output gate. The input gate takes information from the current input LSTM unit, determining the inclusion of new data. Simultaneously, the forget gate plays a crucial role in deciding which information from the past should be discarded, emphasizing the LSTM's ability to filter out irrelevant historical data. Additionally, the output gate acts as the final filter, refining the information that contributes to the

ultimate output. Notably, the use of 0 and 1 in this context symbolizes a binary decision-making process: 0 indicates exclusion or forgetting of certain information, while 1 signifies the inclusion or retention of valuable data, collectively enabling the LSTM to selectively process and store essential information over time. These gate structures enable LSTM cells to effectively extract valuable information while discarding less relevant details, mitigating the issues of gradient explosion or vanishing gradient (Xu and Wu, 2023). The problem of gradient explosion refers to the scenario where gradients become extremely large during training, leading to numerical instability. On the other hand, the vanishing gradient problem occurs when gradients become extremely small, hindering the learning process as the model struggles to update its parameters effectively.

Various fields utilize LSTM algorithm applications due to its capability of processing complex datasets. The most recognized areas are natural language processing (NLP), speech recognition, handwriting recognition, healthcare, short-term traffic forecast and time series analysis and prediction (Sundermeyer et al., 2012; Bouktif et al., 2018; Zhao et al., 2017). Among other fields, LSTM outstands with its significant performance in complex non-linear time series and prediction capabilities due to its ability to capture and learn long-term dependencies in sequential data. Unlike traditional RNN's, LSTM can capture and retain information over extended sequences. Dealing with complex time-series datasets with large number of parameters can pose challenges for models, leading to the phenomenon known as "Overfitting". Therefore, it is crucial to finely tune parameters to ensure highly accurate prediction results and reduce the risk of overfitting. There are some key factors to consider to set up a LSTM model: "Number of cells" determines how many memory cells the model has, the more cells mean it can learn complex patterns, but it also requires more computing power. The "input size" is about defining the size of the input data, adjusted based on its format. If the data is a time series data set, the "time steps" command the model how many time points make up each input. The "output size" decides how many values the model predicts, adjusted according to the study. The "learning rate" influences how quickly the model learns. Dropout and regularization parameters, such as Dropout, are essential techniques for preventing overfitting by selectively deactivating neurons during training. Lastly, activation functions like sigmoid, tanh, and relu are commonly used in LSTMs to regulate the flow of information between cells.

3.4. Experimentation

In this study, the LSTM algorithm was employed to analyze a comprehensive panel time-series dataset, spanning 21 years and encompassing data from 24 OECD countries with 17 variables to predict the ISC and IWC variables.

The time series analysis was conducted using the LSTM algorithm with the Python programming language and related libraries. The following libraries were utilized for the calculations and modeling stages. These libraries includes: NumPy 1.23.5 used for numerical computations and data manipulation, Pandas 1.5.3 used for working with data frames and for data analysis, Scikit-Learn 1.2.2 used for machine learning modeling and evaluation processes, Keras 2.15.0 used as a high-level deep learning library to create the LSTM model and Matplotlib 3.7.1 utilized for data visualization process. The specified versions represent the specific library versions used in the development of this study. The model utilizes the “ReLU” activation function, undergoes 30 training cycles, known as “epochs”, with a batch size set at 50. The model's time step is configured as 1, input size as 35, and output size set to 1. Additionally, the learning rate for the model is specified as 0.001.

To evaluate the model's performance, the dataset was divided into two segments: training and testing. The model was trained on a dataset spanning 16 years, and its performance was tested on a separate 5-year dataset to validate its predictive capabilities. Later on, the performance of the model was assessed using analysis tools such as RMSE, MAE, and MAPE. The mathematical notation of RMSE, MAE and MAPE are stated below. Notation of $\hat{y}_i$ denotes actual value, y_p as prediction value, n as number of observations.

$$\text{RMSE} = \sqrt{\sum_{i=1}^n \frac{(y_i - y_p)^2}{n}}$$

$$\text{MAE} = \sum_{i=1}^n \frac{|(y_i - y_p)|}{n}$$

$$\text{MAPE} = \frac{1}{n} \times \sum_{i=1}^n \left| \frac{y_i - y_p}{y_p} \right| \times 100$$

Figure 5 illustrates the overall framework of the proposed methodology. The data is initially partitioned into distinct training and testing datasets. Following the initial parameter selection, the model undergoes the training and evaluation phases. Finally, the interpretation of prediction results concludes the process.

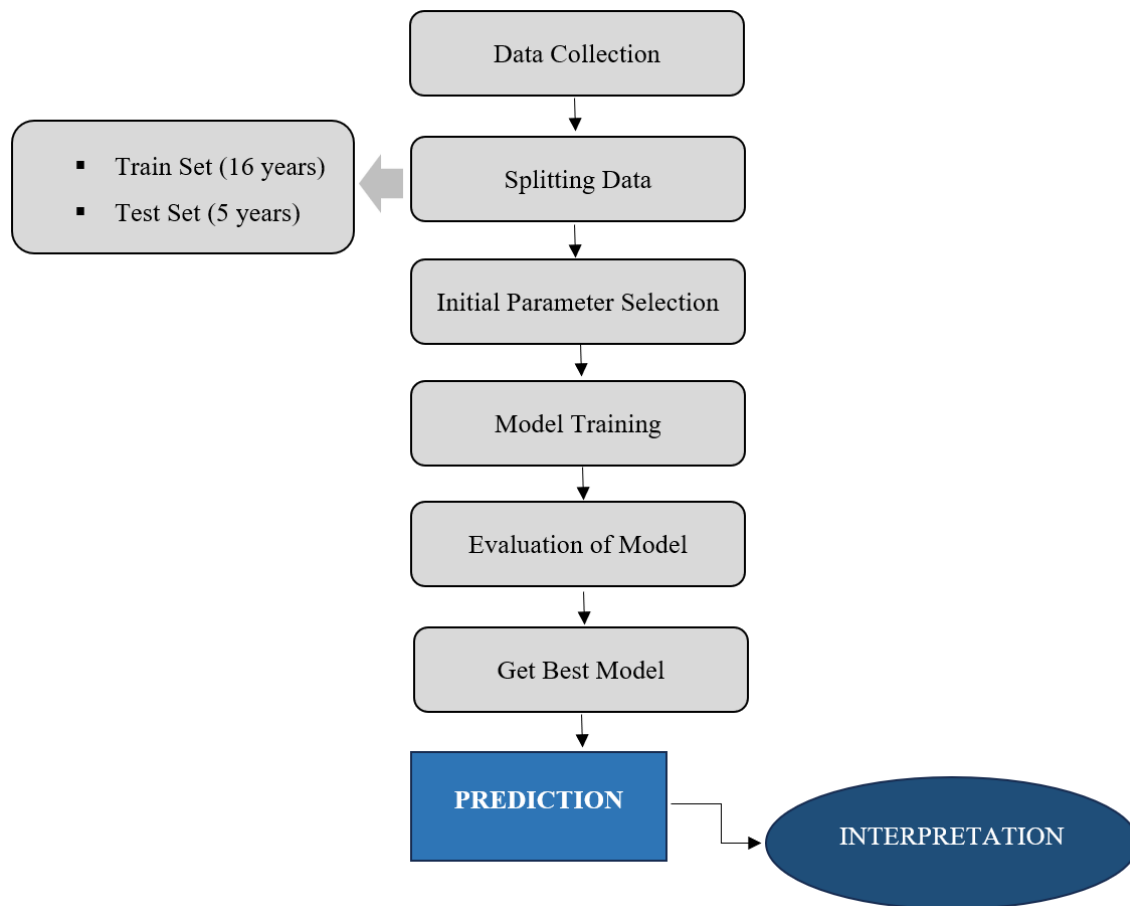


Figure 3.4. A General Overview of Proposed Methodology

Source: Author

4. CHAPTER: RESULTS

4.1. Descriptive Analysis

Descriptive analysis has been applied in this study, involving the calculation of minimum, maximum, average, standard deviation, and the number of observations for each country and variable. The purpose of this analysis is to comprehend the overall structure of the dataset, anticipate potential errors in advance, and acquire fundamental statistical insights. The outcomes of the descriptive analysis are presented in Table 3.1. through table 4.17 below.

Table 4.1. Descriptive Analysis of Pop

Country	Min	Max	Average	Median	Std.Dev.	n
Australia	19017968	25670052	22097331.2	22019166	2150501.13	21
Austria	8010425	8907780	8423233.14	8362829	284097.187	21
Belgium	10264351	11561716	10889759.1	10877948	425407.324	21
Brazil	175873710	213196300	195757021	196353500	11526670.7	21
Canada	30683316	37888704	34059809.1	33963416	2224171.13	21
China	1264099100	1424929800	1348338914	1348191400	52492172.5	21
Denmark	5340662	5825638	5562341.43	5550850	150844.92	21
Finland	5176208	5529468	5360668.52	5363279	124687.73	21
France	58665456	64480052	62084683.8	62444570	1931656.83	21
Germany	81177816	83328990	81781494.8	81514570	683374.329	21
Greece	10512232	11115089	10934305.8	11033784	196085.369	21
India	1059633660	1396387100	1236808493	1240613600	104816516	21
Italy	56966400	60322790	59080265.8	59562844	1198103.32	21
Japan	125244760	128117040	127312772	127502350	793121.811	21
Netherlands	15899138	17434562	16648530.9	16617121	479156.872	21
Poland	38428370	38662860	38564299.3	38555290	57546.1069	21
Portugal	10289833	10591341	10443581.7	10464537	111983.098	21
South Africa	46813270	58801930	52273870.1	51784930	3849432.7	21
South Korea	46788588	51844690	49285812.4	48813036	1726397.77	21
Spain	40741652	47363810	45141245	46431344	2196436.3	21
Sweden	8871042	10368968	9474884.81	9381722	485709.092	21
Turkey	64113548	84135430	73936407.9	73195350	6495831.62	21
United Kingdom	58850044	67059470	62834452.7	62760050	2755594.87	21
United States	282398560	335942000	310569233	311182850	16942162.2	21

Source: Author

A descriptive analysis of the Pop variable has been carried out for 24 OECD countries, spanning a period of 21 years. This analysis of the Population variable facilitates the observation of changes in the social aspects over time, providing valuable insights into the dynamics of these countries.

Table 4.2. Descriptive Analysis of EG_Oil

Country	Min	Max	Average	Median	Std.Dev.	n
Australia	1.45	5.66	3.490952	3.26	1.319632	21
Austria	2.84	3.7	3.321905	3.26	0.244573	21
Belgium	2.57	5.48	3.874286	3.69	0.693502	21
Brazil	9.46	32.66	15.25	13.75	5.907973	21
Canada	2.58	18.16	8.768571	6.31	5.190799	21
China	9.52	65.53	25.42238	12.13	19.35062	21
Denmark	0.97	4.99	2.02381	1.52	1.305463	21
Finland	3.39	9.19	6.01619	5.6	1.804559	21
France	9.15	12.77	11.21524	11.25	0.893804	21
Germany	18.05	25.34	22.78619	23.27	2.056715	21
Greece	4.77	10.01	7.251429	6.2	1.749003	21
India	2.11	31.09	15.23	11.35	9.153505	21
Italy	14.09	93.59	40.6119	28.39	27.12388	21
Japan	38.19	195.62	120.7786	130.85	43.47636	21
Netherlands	5.33	7.28	6.335238	6.29	0.555037	21
Poland	3.68	5.13	4.434286	4.58	0.356799	21
Portugal	1.38	11.67	4.377619	3.34	3.168181	21
South Africa	0	3.99	1.015238	0.13	1.422092	21
South Korea	6.5	30.84	17.79714	17.2	6.906728	21
Spain	12.38	30.15	20.48667	19.32	4.772061	21
Sweden	2.14	5.66	3.259048	2.94	0.913723	21
Turkey	2.07	10.5	5.535238	4.24	2.836372	21
United Kingdom	5.46	11.31	8.042857	8.22	1.602995	21
United States	34.34	135.59	68.71857	47.5	37.66728	21

Source: Author

The descriptive analysis of EG_Oil is presented in Table 4.2. This analysis enables the anticipation of the overall reliance on conventional energy sources, particularly offering insights into the specific dynamics of oil source itself. As observed, South Africa ranks as the country with the lowest average EG_Oil, in contrast to Japan, which holds the highest position.

Table 4.3. Descriptive Analysis of EG_NE

Country	Min	Max	Average	Median	Std.Dev.	n
Australia	0	0	0	0	0	21
Austria	0	0	0	0	0	21
Belgium	26.1	48.23	43.00143	46.35	6.686313	21
Brazil	4.94	15.17	13.19333	13.84	2.398029	21
Canada	69.16	101.21	87.82095	88.3	9.349419	21
China	16.74	366.2	124.2471	74.74	107.9015	21
Denmark	0	0	0	0	0	21
Finland	22.3	23.87	23.05429	22.99	0.417451	21
France	353.83	451.53	424.4857	428.52	23.14555	21
Germany	64.38	171.3	123.9405	134.93	38.46972	21
Greece	0	0	0	0	0	21
India	15.23	45.16	27.50143	23.08	10.43077	21
Italy	0	0	0	0	0	21
Japan	0	305.95	161.2795	228.01	125.5568	21
Netherlands	2.89	4.25	3.890476	3.97	0.324014	21
Poland	0	0	0	0	0	21
Portugal	0	0	0	0	0	21
South Africa	10.07	15.21	12.64524	12.66	1.452479	21
South Korea	103.52	157.16	136.0538	141.12	14.92975	21
Spain	52.76	63.71	59.06857	58.35	2.966359	21
Sweden	49.2	77.49	64.16905	65.7	6.753181	21
Turkey	0	0	0	0	0	21
United Kingdom	50.85	90.09	71.13143	70.34	11.35769	21
United States	753.89	809.41	790.6005	790.2	16.08657	21

Source: Author

The descriptive analysis of EG_NE is outlined in Table 4.3. It is evident that some of the selected countries do not utilize EG_NE. This trend may be attributed to the perceived high risks associated with nuclear plants and security concerns. The United States stands out with the highest average EG_NE rate among the countries that do utilize nuclear energy.

Table 4.4. Descriptive Analysis of EG_Hydro

Country	Min	Max	Average	Median	Std.Dev.	n
Australia	11.68	18.34	15.24333	15.72	1.722316	21
Austria	33.21	43.85	38.90048	38.36	2.751818	21
Belgium	0.2	0.46	0.331905	0.32	0.064235	21
Brazil	265.2	428.33	360.8895	370.91	44.7538	21
Canada	329.99	390.64	365.0476	371.97	18.29223	21
China	222.41	1321.71	735.8667	688.04	375.3958	21
Denmark	0.01	0.03	0.021905	0.02	0.006016	21
Finland	9.59	17.11	13.80762	13.4	2.00636	21
France	45.74	72.62	59.22857	58.88	6.596049	21
Germany	17.67	23.12	20.27333	20.15	1.606314	21
Greece	2.1	7.47	4.549524	4.48	1.356936	21
India	68.54	163.71	115.8029	115.78	27.84768	21
Italy	32.82	58.55	43.95905	44.2	6.353431	21
Japan	73.27	93.66	81.92381	81.55	5.452096	21
Netherlands	0.05	0.14	0.093333	0.1	0.022657	21
Poland	1.67	2.92	2.194286	2.15	0.265981	21
Portugal	4.73	16.15	10.75333	11	3.554515	21
South Africa	0.67	2.87	1.332857	1.19	0.608713	21
South Korea	2.12	4.85	3.503333	3.6	0.703437	21
Spain	18.32	42.3	29.77143	28.26	7.498823	21
Sweden	53.54	79.06	67.26571	66.16	6.753112	21
Turkey	24.01	88.82	49.54143	46.08	16.81252	21
United Kingdom	3.23	6.68	5.130952	5.14	0.834032	21
United States	208.14	312.93	265.2148	263.88	21.73076	21

Source: Author

The descriptive analysis of EG_Hydro for period of 21 years is presented in Table 4.4. The table highlights the significance of EG_Hydro as a valuable renewable resource, with a notable high utilization across most countries. China emerges with the highest average EG_Hydro among the selected countries, while Denmark exhibits the lowest average utilization of EG_Hydro.

Table 4.5 Descriptive Analysis of EG_Gas

Country	Min	Max	Average	Median	Std.Dev.	n
Australia	15.25	52.48	38.46571	44.01	11.82639	21
Austria	5.32	14.35	10.08857	9.95	2.164168	21
Belgium	15.78	30.84	22.67667	22.08	3.82133	21
Brazil	3.84	77.75	35.58762	27.51	23.93124	21
Canada	33.66	65.32	48.3719	46.92	11.24387	21
China	4.19	252.5	94.94381	77.73	85.82096	21
Denmark	1.18	9.94	5.771905	6.67	3.254318	21
Finland	3.3	13.85	8.525714	9.82	3.523002	21
France	11.51	40.5	24.00048	21.88	8.092159	21
Germany	52.49	96.38	75.81143	78	13.21083	21
Greece	5.92	19.23	11.33143	10.88	3.760325	21
India	55.93	118.03	78.42048	74.46	17.7302	21
Italy	93.66	172.77	131.5667	129.84	23.22932	21
Japan	211.93	433.09	314.8443	301.79	83.14292	21
Netherlands	45.76	75.33	59.48952	57.53	7.816685	21
Poland	0.93	17.29	6.203333	5.16	4.24685	21
Portugal	6.83	18.89	12.32619	12.58	3.761713	21
South Africa	0	3.74	0.617143	0.01	1.146325	21
South Korea	28.18	155.17	94.32857	100.62	41.78791	21
Spain	20.18	120.8	66.80905	64.04	27.05755	21
Sweden	0.1	2.91	0.765238	0.6	0.612247	21
Turkey	46.54	120.58	84.31429	92.48	22.12077	21
United Kingdom	95.84	176.22	139.1676	143.36	24.91517	21
United States	614.99	1624.17	1035.674	987.7	320.4145	21

Source: Author

The results of the descriptive analysis for EG_Gas are presented in Table 4.5. This analysis serves as an indicator of the dependence on conventional energy sources, particularly gas. It is notable that the United States stands out as the country with the highest average utilization of EG_Gas, whereas South Africa ranks as the country with the lowest average EG_Gas utilization among others.

Table 4.6. Descriptive Analysis of GDP

Country	Min	Max	Average	Median	Std.Dev.	n
Australia	-0.05	4.22	2.770952	2.73	0.971838	21
Austria	-6.45	3.73	1.237619	1.65	2.36436	21
Belgium	-5.36	3.72	1.383333	1.69	2.012025	21
Brazil	-3.88	7.53	2.116667	1.92	3.080603	21
Canada	-5.23	5.18	1.818571	2.33	2.225617	21
China	2.24	14.23	8.691905	8.49	2.544774	21
Denmark	-4.91	3.91	1.225238	1.49	1.995456	21
Finland	-8.07	5.77	1.460476	2	3.012998	21
France	-7.78	3.92	1.000952	1.66	2.410305	21
Germany	-5.69	4.18	1.123333	1.18	2.369996	21
Greece	-10.15	5.79	-0.10048	0.6	4.727471	21
India	-6.6	8.5	5.832381	6.8	3.340242	21
Italy	-9.04	3.79	-0.0419	0.78	2.816889	21
Japan	-5.69	4.1	0.584762	1.37	2.216979	21
Netherlands	-3.89	4.2	1.300476	1.96	2.110136	21
Poland	-2.02	7.06	3.578095	3.84	2.068704	21
Portugal	-8.3	3.82	0.471905	1.63	2.875889	21
South Africa	-6.34	5.6	2.24381	2.7	2.666184	21
South Korea	-0.71	9.06	3.89381	3.16	2.235042	21
Spain	-11.33	5.25	1.222381	2.73	3.737896	21
Sweden	-4.34	5.95	2.121429	2.31	2.430309	21
Turkey	-5.75	11.2	4.791429	5.76	4.368334	21
United Kingdom	-11.03	4.09	1.212381	2.16	3.26959	21
United States	-2.77	4.08	1.85381	2.28	1.759697	21

Source: Author

The findings of the descriptive analysis for GDP are represented in Table 4.6. The results of GDP represents the economic landscape of countries, carrying implications for policy formulation and investment decisions. Notably, China stands out with the highest average GDP growth rate, while Greece exhibits the least growth in average GDP rate among the countries examined.

Table 4.7. Descriptive Analysis of EG_Coal

Country	Min	Max	Average	Median	Std.Dev.	n
Australia	133.21	174.86	160.0238	164.21	12.4797574	21
Austria	0.56	8.44	4.690952	4.92	2.352821508	21
Belgium	0.08	12.92	4.900476	4.2	3.946338146	21
Brazil	8.96	26.17	15.7219	11.67	6.591576154	21
Canada	34.29	109.21	76.47952	76.85	23.11409039	21
China	1060.26	4920.83	3114.269	3233.6	1302.24751	21
Denmark	3.06	25.31	13.99095	15.46	6.391893229	21
Finland	2.44	19.25	9.737143	8.5	4.461112129	21
France	3.09	27.51	18.50619	21.67	7.698370916	21
Germany	134.6	304.63	265.2314	275.21	42.78755605	21
Greece	6.61	35.54	27.89	31.11	8.64534152	21
India	390.23	1198.86	737.1033	642.97	288.8456215	21
Italy	13.38	49.14	37.46714	39.74	9.35060487	21
Japan	202.75	341.72	285.3686	280.01	42.64924258	21
Netherlands	7.61	39.39	25.22238	24.61	6.306217491	21
Poland	107.4	147.01	134.1395	134.97	8.75925766	21
Portugal	2.36	15.23	12.15524	12.9	3.421645246	21
South Africa	181.67	231.74	211.3567	212.74	14.16353781	21
South Korea	107.49	240.49	183.7514	203.47	43.82394794	21
Spain	5.52	81.18	51.63667	48.71	22.37644483	21
Sweden	0	2.85	0.840476	0.65	0.742842353	21
Turkey	31.42	111.36	63.29714	56.38	26.10097606	21
United Kingdom	5.34	148.85	97.14762	119.95	49.28436942	21
United States	773.39	2016.46	1640.94	1755.9	385.8818538	21

Source: Author

The outcomes of the descriptive analysis for the variable EG_Coal are outlined in Table 4.7. These results provide insights into the energy security policies of the respective countries and offer the opportunity to observe the utilization of conventional energy sources, specifically EG_Coal, over a 21-year period. Notably, China emerges with the highest average utilization of EG_Coal, while Sweden exhibits the lowest average utilization among the selected countries.

Table 4.8. Descriptive Analysis of SES

Country	Min	Max	Average	Median	Std.Dev.	n
Australia	0	6	3.095238	3	2.844376	21
Austria	0	5	2	2	1.81659	21
Belgium	0	0	0	0	0	21
Brazil	0	0	0	0	0	21
Canada	0	6	1.619048	0	2.155834	21
China	0	5	1.761905	0	1.997618	21
Denmark	1	5	1.619048	1	1.116969	21
Finland	0	0	0	0	0	21
France	0	6	3.095238	3	1.868282	21
Germany	1	4	2.904762	3	1.044259	21
Greece	0	6	3.190476	3	2.204973	21
India	0	4	2.095238	2	1.300183	21
Italy	0	6	3.428571	4	2.203893	21
Japan	0	6	2.142857	0	2.833473	21
Netherlands	0	5	2.619048	3	1.856777	21
Poland	0	3	0.285714	0	0.902378	21
Portugal	0	6	2.095238	2	2.119074	21
South Africa	0	5	0.571429	0	1.468722	21
South Korea	0	5	1.428571	0	1.748469	21
Spain	0	4	1.52381	2	1.327368	21
Sweden	0	1	0.142857	0	0.358569	21
Turkey	0	6	2.142857	1	2.104417	21
United Kingdom	0	6	1.238095	1	1.729299	21
United States	0	2	0.761905	1	0.538958	21

Source: Author

The results of the descriptive analysis for the variable SES are presented in Table 4.8. The findings suggest a significant improvement in policies related to SES between the years 2000 and 2020. While some countries still lack SES related energy policies, overall advancements in the SES aspect are apparent. The table indicates considerable variation in renewable energy supporting policies concerning solar energy among the selected countries.

Table 4.9. Descriptive Analysis of WES

Country	Min	Max	Average	Median	Std.Dev.	n
Australia	0	0	0	0	0	21
Austria	1	5	3.190476	4	1.327368	21
Belgium	0	0	0	0	0	21
Brazil	0	5	1	0	1.843909	21
Canada	0	6	1.47619	0	1.939563	21
China	0	4	1.619048	2	1.499206	21
Denmark	1	3	1.52381	1	0.601585	21
Finland	0	6	2.333333	0	2.536402	21
France	1	4	2.809524	3	0.980767	21
Germany	1	6	3.238095	3	1.578124	21
Greece	0	5	2.809524	3	1.470342	21
India	1	5	2.095238	2	1.261141	21
Italy	2	6	3.619048	3	1.43095	21
Japan	0	6	2.571429	0	3.042555	21
Netherlands	0	6	3.52381	4	2.040075	21
Poland	0	2	0.285714	0	0.717137	21
Portugal	0	4	1.52381	1	1.40068	21
South Africa	0	6	0.714286	0	1.820518	21
South Korea	0	3	1.095238	0	1.338087	21
Spain	0	3	1.238095	1	1.261141	21
Sweden	0	0	0	0	0	21
Turkey	0	6	2.904762	3	2.385472	21
United Kingdom	0	6	1.47619	2	1.83355	21
United States	0	2	0.809524	1	0.601585	21

Source: Author

The outcomes of the descriptive analysis for the variable WES are displayed in Table 4.9. The analysis reveals that a majority of the selected countries have improved their renewable energy policies related to WES over the 21-year period. This conclusion suggests a growing trend in the development of energy security policies specifically focused on wind energy.

Table 4.10. Descriptive Analysis of TSP

Country	Min	Max	Average	Median	Std.Dev.	n
Australia	0.5	4	1.702381	2	0.95072	21
Austria	1	4	2.488095	2.5	0.920177	21
Belgium	1	2.5	1.642857	1.5	0.391882	21
Brazil	0	1.25	0.630952	1	0.510019	21
Canada	1	4.75	2.345238	2	1.333408	21
China	0	2.25	0.845238	0.5	0.853215	21
Denmark	1	4	2.47619	2.5	0.921632	21
Finland	1.5	4.5	3.22619	3	1.015212	21
France	1.5	5.25	3.857143	4	1.136253	21
Germany	1	3.75	2.511905	2.75	0.784523	21
Greece	0.5	3	1.928571	2	0.87014	21
India	0.25	2.25	1.047619	1	0.625595	21
Italy	1.5	4	2.809524	2.75	0.84744	21
Japan	3	6	3.892857	3.5	1.038543	21
Netherlands	1	4.75	2.77381	3	1.066257	21
Poland	0	1.75	0.666667	0.5	0.6341	21
Portugal	0.5	2.75	1.452381	1.25	0.812477	21
South Africa	0	2.75	0.321429	0	0.818317	21
South Korea	0	4	2.059524	1.75	1.158946	21
Spain	0.5	2.75	1.238095	1.25	0.717967	21
Sweden	1	2	1.511905	1.5	0.290217	21
Turkey	0.5	3	1.761905	2.25	0.889087	21
United Kingdom	0.5	3.25	1.607143	1.75	1.116835	21
United States	1	3	1.75	2	0.564579	21

Source: Author

The results of the descriptive analysis for TSP are presented in Table 4.10. The findings suggest that energy security-related TSPs are widely supported by each of the selected countries. Despite improvements observed in every country over the 21-year period, Japan stands out with the highest level of TSP. This finding could serve as a meaningful indicator reflecting the intersection of industrialization, technological advancements, and energy policy-making.

Table 4.11. Descriptive Analysis of LC_R&D

Country	Min	Max	Average	Median	Std.Dev.	n
Australia	1	5	1.857143	1	1.152637	21
Austria	1	4	2.380952	3	1.116969	21
Belgium	2	5	3.285714	3	0.783764	21
Brazil	0	2	0.761905	0	0.995227	21
Canada	2	5	3.142857	3	0.963624	21
China	0	0	0	0	0	21
Denmark	1	6	3.380952	3	1.43095	21
Finland	3	6	5.285714	6	1.007118	21
France	2	6	4.761905	5	1.044259	21
Germany	1	3	1.952381	2	0.497613	21
Greece	0	1	0.857143	1	0.358569	21
India	0	0	0	0	0	21
Italy	2	3	2.095238	2	0.300793	21
Japan	4	6	5.428571	6	0.74642	21
Netherlands	2	5	2.47619	2	0.749603	21
Poland	0	3	1.047619	1	1.023533	21
Portugal	1	2	1.095238	1	0.300793	21
South Africa	0	0	0	0	0	21
South Korea	0	4	2.857143	3	1.276155	21
Spain	1	2	1.095238	1	0.300793	21
Sweden	2	4	2.952381	3	0.589592	21
Turkey	1	1	1	1	0	21
United Kingdom	1	4	1.857143	2	0.910259	21
United States	2	5	2.714286	3	0.717137	21

Source: Author

The outcomes of the descriptive analysis for LC_R&D are detailed in Table 4.11. The findings suggest an overall improvement in the LC_R&D variable across the majority of selected countries during the 21-year period. As an additional observation, countries heavily reliant on conventional energy sources, particularly those highly industrialized, tend to exhibit relatively lower LC_R&D results. China serves as a notable example illustrating this trend.

Table 4.12. Descriptive Analysis of EPS

Country	Min	Max	Average	Median	Std.Dev.	n
Australia	0.833333	3.527778	2.32672	2.694444	0.80713	21
Austria	1.888889	3.305556	2.694444	2.944444	0.482407	21
Belgium	1.555556	3.444444	2.588624	2.666667	0.567484	21
Brazil	0.166667	0.888889	0.53836	0.555556	0.278399	21
Canada	0.722222	3.611111	2.505291	2.638889	0.903723	21
China	0.222222	3.138889	1.601852	1.305556	1.111192	21
Denmark	1.888889	4.222222	3.37037	3.666667	0.746821	21
Finland	2.083333	4.111111	3.240741	3.194444	0.631071	21
France	1.666667	4.888889	3.453704	3.694444	0.95607	21
Germany	1.777778	3.472222	2.904762	3.027778	0.43987	21
Greece	1.388889	3.055556	2.297619	2.583333	0.614331	21
India	0.916667	2.833333	1.781746	1.694444	0.579637	21
Italy	1.777778	4.055555	3.128307	3.472222	0.837972	21
Japan	2.694444	4.055555	3.338624	3.222222	0.472518	21
Netherlands	1.555556	3.75	2.850529	3.111111	0.71067	21
Poland	1.138889	3.472222	2.451058	2.777778	0.754457	21
Portugal	1.305556	2.916667	2.382275	2.388889	0.47935	21
South Africa	0.194444	1.833333	0.716931	0.861111	0.441799	21
South Korea	0.888889	3.611111	2.743386	3	0.809326	21
Spain	1.472222	2.833333	2.27381	2.388889	0.430984	21
Sweden	2.166667	3.833333	3.322751	3.444444	0.419387	21
Turkey	0.777778	2.888889	1.940476	2.388889	0.842646	21
United Kingdom	1.333333	3.861111	2.776455	2.888889	0.819537	21
United States	1.222222	3.027778	2.068783	2.027778	0.679314	21

Source: Author

The results of the descriptive analysis for the variable EPS are outlined in Table 4.12. The overall findings suggest that each selected country has witnessed an improvement in EPS values over the 21-year period. France particularly stands out as the most stringent country in addressing environmental and sustainability issues. However, it can be noted that, on average, the selected countries performed below average in terms of the EPS variable units.

Table 4.13. Descriptive Analysis of RETS

Country	Min	Max	Average	Median	Std.Dev.	n
Australia	0	6	2.714286	3	1.764734	21
Austria	0	0	0	0	0	21
Belgium	0	6	2.285714	2	2.492847	21
Brazil	0	0	0	0	0	21
Canada	0	0	0	0	0	21
China	0	0	0	0	0	21
Denmark	0	0	0	0	0	21
Finland	0	0	0	0	0	21
France	0	0	0	0	0	21
Germany	0	0	0	0	0	21
Greece	0	0	0	0	0	21
India	0	5	1.571429	2	1.719635	21
Italy	0	2	0.571429	0	0.676123	21
Japan	0	1	0.380952	0	0.497613	21
Netherlands	0	0	0	0	0	21
Poland	0	6	2.666667	3	2.057507	21
Portugal	0	0	0	0	0	21
South Africa	0	0	0	0	0	21
South Korea	0	2	0.571429	0	0.74642	21
Spain	0	0	0	0	0	21
Sweden	0	6	4.095238	5	2.047065	21
Turkey	0	0	0	0	0	21
United Kingdom	0	6	3.285714	3	2.326862	21
United States	1	5	2.809524	3	1.209093	21

Source: Author

The outcomes of the descriptive analysis for the variable RETS are presented in Table 4.13. The findings suggest that the majority of the selected countries do not currently employ the RETS variable. Notably, Sweden stands out as the highest RETS-utilizing country among the selected nations. It is important to note that these results should be complemented with additional variables for a more comprehensive interpretation.

Table 4.14. Descriptive Analysis of EG_RE

Country	Min	Max	Average	Median	Std.Dev.	n
Australia	7.804379	25.50317	12.28554	9.63576	4.88284	21
Austria	60.69584	81.46706	71.63891	71.16139	6.118258	21
Belgium	1.268269	26.69246	10.36024	7.042102	8.512466	21
Brazil	74.04187	90.13077	84.13584	84.80723	4.484998	21
Canada	59.32876	68.77964	63.62868	63.89192	2.860207	21
China	15.03627	28.24646	20.10877	18.95812	4.223918	21
Denmark	15.47222	81.622	41.16032	31.97839	22.25953	21
Finland	22.66889	52.04229	36.09628	33.5005	8.111975	21
France	9.647984	23.76102	14.54826	13.62401	3.693538	21
Germany	6.197798	44.33241	20.35644	16.8385	11.583	21
Greece	5.538809	36.44103	17.74028	13.76922	9.712176	21
India	11.69511	20.20593	15.70839	15.63753	2.020853	21
Italy	15.53335	43.49769	27.74965	25.84002	10.30604	21
Japan	9.389759	21.32492	12.85365	11.12724	3.560394	21
Netherlands	3.322519	26.67155	10.47557	9.536809	5.677472	21
Poland	1.4999	17.96487	7.817639	6.929936	5.511815	21
Portugal	17.86488	60.75828	41.35496	39.13345	12.50265	21
South Africa	0.526721	5.780582	1.908964	1.033007	1.752599	21
South Korea	1.037825	6.13122	2.606948	1.724968	1.700858	21
Spain	13.82602	43.81088	27.86037	29.60479	9.719276	21
Sweden	43.37839	68.47183	54.89611	55.79701	5.726274	21
Turkey	17.35666	43.68044	27.36892	26.40008	6.818977	21
United Kingdom	2.500196	42.8604	14.0623	6.909292	12.90694	21
United States	7.513206	20.31569	12.05344	10.54769	3.777137	21

Source: Author

The results of the descriptive analysis for the variable EG_RE are outlined in Table 4.14. Findings imply that EG_RE improved in 21 years period of each examined country. Brazil outstands as the highest average EG_RE value among other selected countries. It is important to note that these results should be complemented with additional variables such as TEG for a more comprehensive interpretation.

Table 4.15. Descriptive Analysis of TEG

Country	Min	Max	Average	Median	Std.Dev.	n
Australia	198.16	250.91	230.8624	230.84	14.82131	21
Austria	58.06	70.86	64.13143	64.49	3.356572	21
Belgium	68.12	92.87	82.94238	83.07	6.293556	21
Brazil	323.17	618.66	485.0605	510.78	100.9683	21
Canada	572.37	644.88	610.3533	612.27	24.49745	21
China	1355.6	7735.27	4297.117	4187.31	2065.379	21
Denmark	28.73	46.16	35.45524	36	5.090906	21
Finland	67.13	85.6	73.54048	70.98	5.811227	21
France	527.25	576.45	559.5481	565.72	14.54404	21
Germany	567.26	646.01	613.1886	619.95	23.86112	21
Greece	48.16	62.92	56.17381	57.12	4.418506	21
India	571.39	1621.91	1023.177	937.47	359.5301	21
Italy	269.15	312.5	289.7052	287.58	11.72026	21
Japan	964.13	1082.17	1011.97	1005.92	32.01305	21
Netherlands	89.39	122.79	106.5119	105	9.464009	21
Poland	142.49	169.93	157.3933	158.38	8.08206	21
Portugal	43.38	59.13	49.83571	49.48	4.60463	21
South Africa	196.47	246.81	230.0405	235.99	14.7934	21
South Korea	272.52	562.28	444.7929	477.69	97.44614	21
Spain	220.92	310.67	274.8605	274.94	22.87042	21
Sweden	135.39	168.42	153.6671	153.03	9.43829	21
Turkey	122.19	305.42	214.3362	211.06	62.71313	21
United Kingdom	307.37	395.46	363.3119	373.08	27.8286	21
United States	3727.57	4201.55	4023.272	4052.31	123.4039	21

Source: Author

The outcomes of the descriptive analysis for the variable TEG are presented in Table 4.15. The findings indicate that China possesses the highest average TEG among the selected countries, whereas Denmark exhibits the lowest TEG value. It is important to note that these results should be complemented with additional variables such as EG_RE for a more comprehensive interpretation.

Table 4.16. Descriptive Analysis of IWC

Country	Min	Max	Average	Median	Std.Dev.	n
Australia	0.033	9.457	2.664381	1.864	2.555719	21
Austria	0.05	3.224	1.468405	1.015828	1.087402	21
Belgium	0.014	4.692	1.335857	0.912	1.409	21
Brazil	0.022	17.19832	4.310115	0.927	5.968447	21
Canada	0.139	13.577	5.680952	3.967	5.162321	21
China	0.341	282.1127	69.86825	29.63348	84.80479	21
Denmark	2.39	6.235	4.092542	3.8018	1.245429	21
Finland	0.038	2.474	0.66474	0.197	0.85643	21
France	0.038	17.382	6.420769	5.912	5.831737	21
Germany	6.095	62.184	31.2819	26.903	17.67691	21
Greece	0.226	4.113	1.525976	1.298	1.122104	21
India	0.941	38.5586	15.98487	13.184	12.75867	21
Italy	0.363	10.839	5.54742	5.794	3.903496	21
Japan	0.084	4.206	2.095048	2.294	1.249908	21
Netherlands	0.447	6.6	2.494333	2.237	1.594592	21
Poland	0.004	6.267	2.331592	1.108	2.459045	21
Portugal	0.083	5.239	3.099889	3.796	2.023086	21
South Africa	0.00316	2.516	0.583261	0.01016	0.896243	21
South Korea	0.007	1.635802	0.540229	0.382	0.532581	21
Spain	2.206	27.089	16.80836	20.693	8.057669	21
Sweden	0.209	9.688	3.259524	2.017	3.09732	21
Turkey	0.019	8.832	2.541698	1.32	2.968808	21
United Kingdom	0.412	24.665	8.710776	5.4212	8.414805	21
United States	2.377	117.744	44.94692	39.135	37.3073	21

Source: Author

The outcomes of the descriptive analysis for the variable IWC are presented in Table 4.16. The results suggest a notable trend in the IWC variable over the 21-year observed period for each selected country. China stands out with the highest average IWC value, while South Africa exhibits the lowest average IWC value among the selected countries.

Table 4.17. Descriptive Analysis of ISC

Country	Min	Max	Average	Median	Std.Dev.	n
Australia	0.026148	17.625	3.748451	1.099341	4.956823	21
Austria	0.005	2.22	0.519421	0.0888	0.675746	21
Belgium	0.001	5.646	1.732895	1.0069	1.869612	21
Brazil	0.000036	8.290503	0.799651	0.000854	2.051726	21
Canada	0.007	3.325	1.076524	0.221	1.321779	21
China	0.033515	253.9638	44.99247	1.0218	77.77017	21
Denmark	0.001	1.3	0.359353	0.007	0.455761	21
Finland	0.002	0.318	0.042905	0.007	0.083796	21
France	0.007	11.724	3.611007	1.044	4.194866	21
Germany	0.114	53.781	21.46167	18.007	19.70661	21
Greece	0.001	3.247	1.150529	0.202	1.310065	21
India	0.001084	39.38516	6.813971	0.065362	12.35377	21
Italy	0.019	21.594	9.179938	3.5967	9.481886	21
Japan	0.33	67	16.89757	3.599	22.61868	21
Netherlands	0.013	10.213	1.485476	0.09	2.716997	21
Poland	0	3.936	0.316667	0	0.900034	21
Portugal	0.001	1.025	0.266524	0.134	0.315843	21
South Africa	0	5.994495	1.149205	0.001977	1.94003	21
South Korea	0.004	14.57479	2.669533	0.65	4.180868	21
Spain	0.01	11.785	3.302476	3.873	3.1735	21
Sweden	0.003	1.417	0.15519	0.011	0.33878	21
Turkey	0.0001	6.667	1.06331	0.0057	2.176477	21
United Kingdom	0.002	13.563	4.080296	0.095	5.583736	21
United States	0.0185	73.814	15.5423	2.04	22.6411	21

Source: Author

The results of the descriptive analysis for the variable ISC are presented in Table 4.17. Findings indicate an increase in ISC among each selected OECD countries over 21 years period. The highest average ISC value is from China and the lowest average ISC value is from Finland.

4.2. Prediction Results

This section delves into the model's forecasts along with insightful interpretations, offering a comprehensive understanding of the analytical outcomes.

Table 4.18. Overall Performance of Prediction Models

Variables	# of observations in test data set	RMSE	MAE	MAPE
IWC	118	7.433	2.496	9.536
ISC	118	16.827	4.690	19.897

Source: Author

Table 4.18. indicates the overall performance with RMSE, MAE and MAPE values of the ISC and IWC model among number of 118 observations of 24 countries in test data set. The application of the LSTM algorithm involves 118 observations instead of 120, owing to its inherent moving logic. In the dataset for Australia and Japan, a testing period of 4 years has been conducted, while the remaining countries have been subjected to a testing period of 5 years. Interpreting the analysis of RMSE reveals a notable divergence in performance between IWC and ISC predictions. The IWC model demonstrated superior prediction results compared to the ISC model. Likewise, the MAE and MAPE results underscore a substantial performance gap in predictions between IWC and ISC. Particularly, MAPE proves to be a valuable tool in regression analysis, providing an accessible means to comprehend overall performance. The IWC model exhibited an overall difference of 9.536% from the actual values, indicating a successful prediction performance of 90.464%. In contrast, the ISC model displayed a larger difference of 19.897% from the actual values, resulting in a successful prediction performance of 80.103%.

In addition for the overall assessment of the panel dataset's performance, Table 4.19. provides the interpretation of the model's prediction accuracy for the IWC variable on a country-based level. Similarly, Table 4.20. offers insights into the interpretation of the ISC variable's prediction performance at the country level.

Table 4.19. IWC Prediction Performance by Countries

Countries	# of observations in test dataset	RMSE	MAE	MAPE
Australia	4	0.623	0.449	5.967
Brazil	5	1.562	1.471	10.395
Portugal	5	0.689	0.346	6.607
India	5	4.991	4.910	14.396
Finland	5	0.090	0.056	2.394
Denmark	5	1.201	0.699	11.539
United Kingdom	5	2.714	2.690	12.798
Italy	5	1.145	1.007	10.182
United States	5	6.669	6.283	6.802
China	5	34.694	30.619	14.516
France	5	1.971	1.920	13.217
Netherlands	5	0.405	0.403	8.608
South Korea	5	0.229	0.221	15.892
Sweden	5	1.174	1.169	15.264
Germany	5	3.022	2.942	5.102
Austria	5	0.237	0.236	7.805
Belgium	5	0.220	0.215	6.672
Turkey	5	0.864	0.833	12.043
Canada	5	0.725	0.563	4.308
Poland	5	0.911	0.831	14.311
Spain	5	0.419	0.366	1.557
South Africa	5	0.316	0.240	10.865
Greece	5	0.079	0.069	2.113
Japan	4	0.569	0.566	16.106

Source: Author

IWC model's prediction performance was analyzed across 24 OECD countries, revealing significant variations in prediction accuracy, with an overall error rate of 9.536%. To gain a comprehensive understanding of these results, a country-specific examination was conducted. Notably, the model exhibited its best performance in Spain, Greece, and Finland, with an average error rate of 1.9%, while it struggled the most in Japan, South Korea, and Sweden, showing an average error rate of 10.3%. Impressively, the model demonstrated robust performance for IWC, achieving a forecasting accuracy of over 90%.

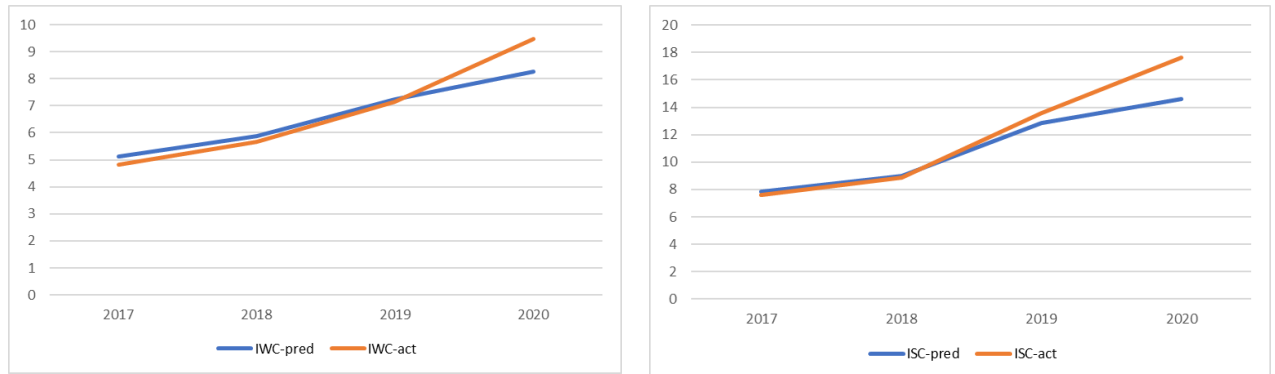
Table 4.20. ISC Prediction Performance by Countries

Country	# of observations in test dataset	RMSE	MAE	MAPE
Australia	4	1.552	1.015	6.688
Brazil	5	0.684	0.563	19.355
Portugal	5	0.217	0.208	28.202
India	5	4.162	3.701	18.646
Finland	5	0.074	0.051	32.555
Denmark	5	0.308	0.247	23.592
United Kingdom	5	3.463	3.457	26.746
Italy	5	4.384	4.320	21.257
United States	5	9.285	8.982	19.243
China	5	80.360	72.782	40.800
France	5	2.678	2.649	27.306
Netherlands	5	1.640	1.520	30.558
South Korea	5	1.684	1.413	14.012
Sweden	5	0.091	0.088	25.500
Germany	5	7.640	3.975	7.540
Austria	5	0.263	0.251	18.030
Belgium	5	0.508	0.247	4.499
Turkey	5	1.040	0.819	18.645
Canada	5	0.297	0.275	8.953
Poland	5	0.275	0.234	33.674
Spain	5	0.433	0.289	3.010
South Africa	5	0.428	0.421	11.751
Greece	5	0.749	0.687	24.037
Japan	4	4.135	3.353	7.871

Source: Author

The prediction performance of the ISC model across 24 OECD countries has been examined and is presented in Table 21. Notably, there is a significant variation in the prediction accuracy of ISC among these countries. Spain exhibits the minimum MAPE value at 3.01%, while China has the maximum MAPE value at 40.80%. Our understanding suggests that predicting ISC may pose greater challenges in countries with vast land areas, diverse geographical attributes, and notable variations in solar exposure angles during different seasons, with China being a notable example. The model demonstrated its optimal performance in Spain, Australia, and Belgium, with an average error rate of 4.73%. Conversely, its performance faced more challenges in China, Finland, and Poland, resulting in an average error rate of 35.67%. This underscores the influence of geographical and environmental factors on the ISC

prediction accuracy, with notable disparities between countries. As a final analysis, the prediction performance of ISC and IWC are visualized as a across studied countries. The corresponding figures are presented below.



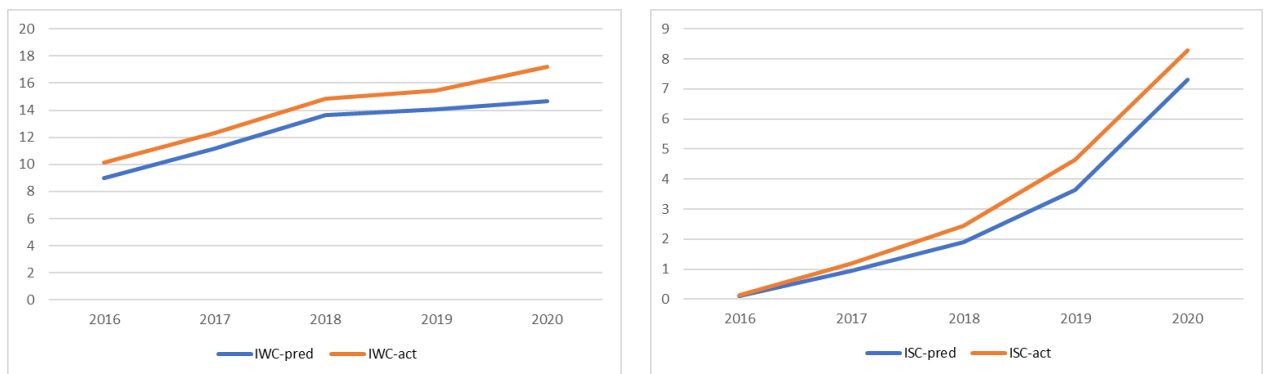
a. IWC

b. ISC

Figure 4.1. Prediction and Actual Results of Australia for IWC and ISC

Source: Author

The model demonstrates superior performance in predicting IWC and ISC for Australia, as illustrated in Figure 4.1. The deviation between predicted and actual values becomes noticeable after the year 2019. Based on our understanding, we attribute this performance decline to the global impact of the Covid-19 pandemic.



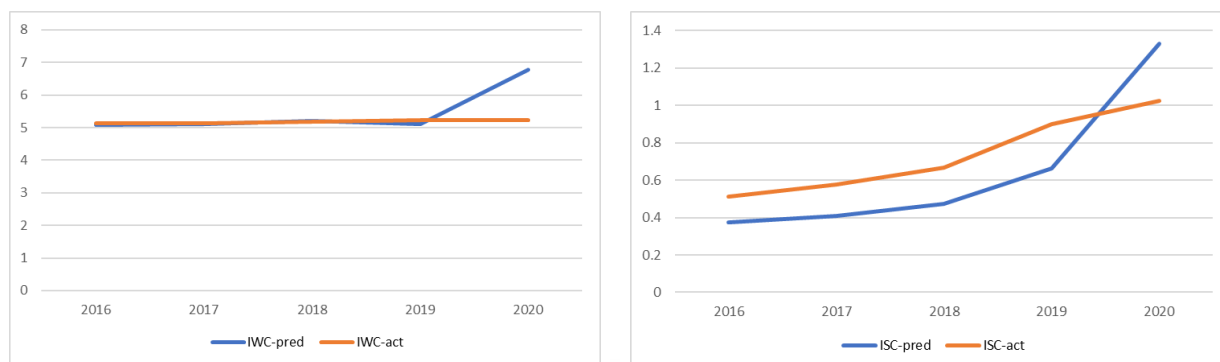
a. IWC

b. ISC

Figure 4.2. Prediction and Actual Results of Brazil for IWC and ISC

Source: Author

The model exhibited good predictive capabilities for IWC and ISC in the context of Brazil, as depicted in Figure 4.2. Comparable levels of success were achieved for both ISC and IWC predictions. The corresponding illustration suggests that the models for both ISC and IWC in Brazil performed well.



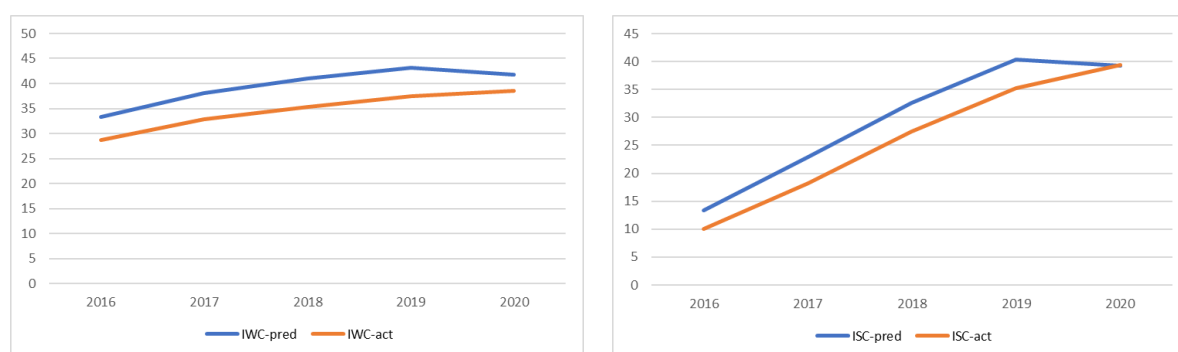
a. IWC

b. ISC

Figure 4.3. Prediction and Actual Results of Portugal for IWC and ISC

Source: Author

As illustrated in Figure 4.3., the model exhibited excellent predictive performance for Portugal's IWC until the year 2019. The overall performance for ISC was reasonably satisfactory until the year 2019. However, post-2019, the model projected elevated values for both ISC and IWC. This deviation in predictions could be attributed to the influence of the Covid-19 pandemic.



a. IWC

b. ISC

Figure 4.4. Prediction and Actual Results of India for IWC and ISC

Source: Author

The model exhibited robust predictive capabilities for both IWC and ISC in the context of India, as illustrated in Figure 4.4. It can be inferred that the model's performance progressively enhances over time, with notably superior results observed for the years 2019 and 2020.



Figure 4.5. Prediction and Actual Results of Denmark for IWC and ISC

Source: Author

As depicted in Figure 4.5., the IWC model exhibited superior predictive capabilities for Denmark until the year 2019. In contrast, the predictive performance of the ISC model was below average, except for the years 2018 and 2019.

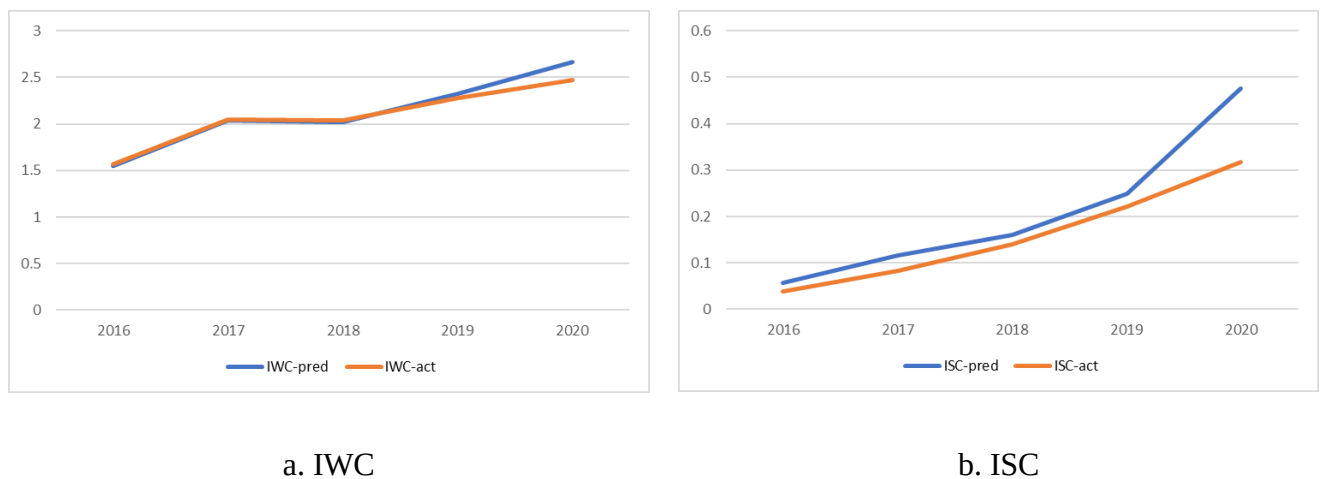


Figure 4.6. Prediction and Actual Results of Finland for IWC and ISC

Source: Author

The IWC model demonstrated exceptionally accurate predictions for Finland, as evidenced in Figure 4.6. The predictive performance of ISC for Finland was also highly accurate, with the exception of the year 2020. As depicted in Figure 11, the ISC value was slightly overestimated compared to the actual value.



Figure 4.7. Prediction and Actual Results of Italy for IWC and ISC

Source: Author

The model developed for predicting IWC of Italy exhibited a noteworthy improvement in predictive performance over time, specifically in year 2020, as depicted in Figure 4.7. Meanwhile, the predictive performance of the ISC model can be considered as average. As a general review, IWC model performed more accurately compare to ISC model.

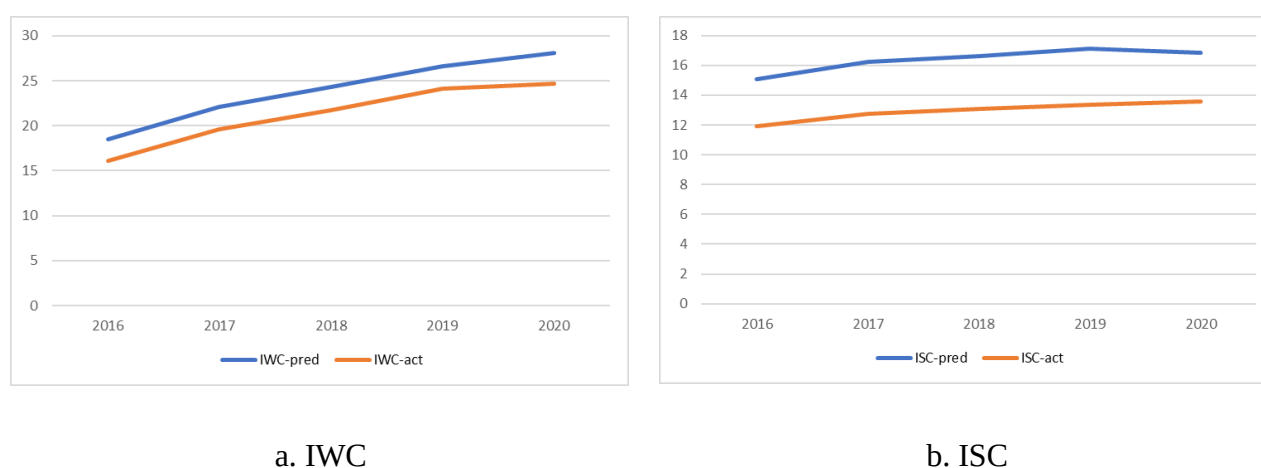


Figure 4.8. Prediction and Actual Results of United Kingdom for IWC and ISC

Source: Author

The predictive performance of both IWC and ISC for the United Kingdom is presented in Figure 4.8. The IWC model exhibited slightly better performance compared to the ISC model. However, it's important to note that both models achieved an average level of prediction accuracy.

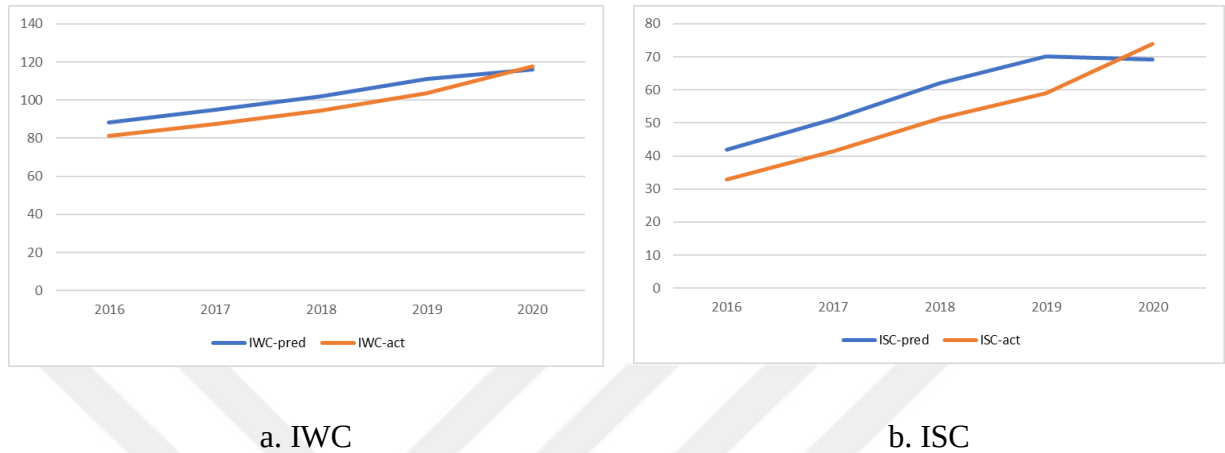


Figure 4.9. Prediction and Actual Results of United States for IWC and ISC

Source: Author

The predictive performance of both IWC and ISC for the United States is illustrated in Figure 4.9. The interpretation of the prediction performance for IWC is notably accurate, especially in the year 2020, indicating an upward trend in the model's performance. Both models attained a comparable level of prediction accuracy, with a slightly lower accuracy observed in ISC compared to IWC.

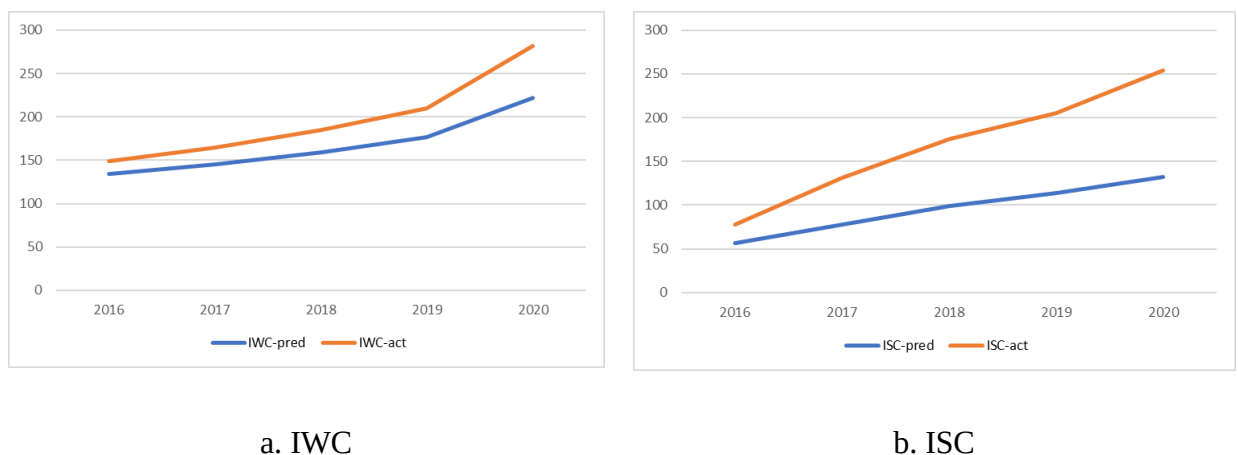


Figure 4.10. Prediction and Actual Results of China for IWC and ISC

Source: Author

Figure 4.10. illustrates the prediction performance of China for IWC and ISC values. A declining trend is noticeable in the prediction performances for both ISC and IWC values. However, in comparing the models, the IWC model yielded more accurate results than the ISC model. Furthermore, the predicted values underestimate the actual results for both models.

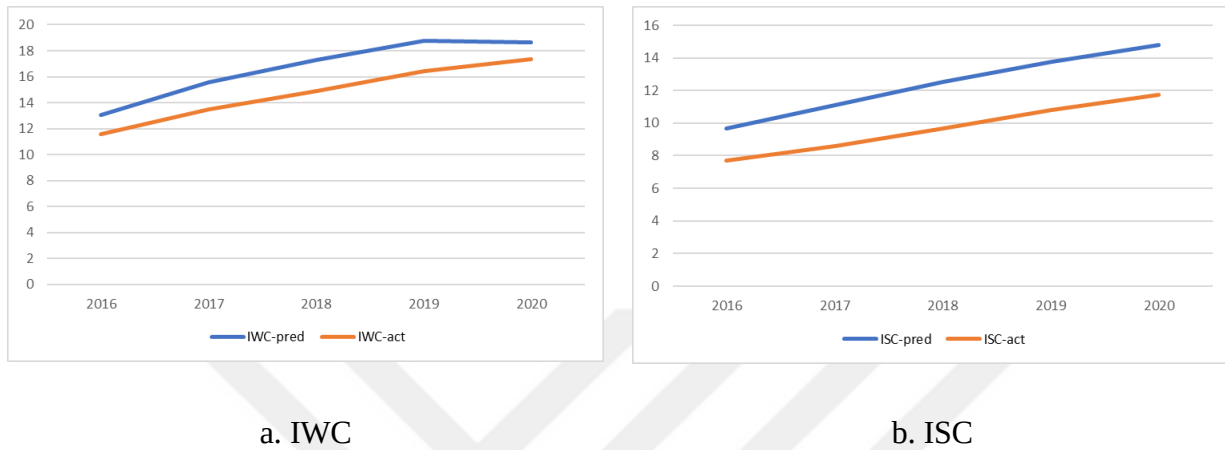


Figure 4.11. Prediction and Actual Results of France for IWC and ISC

Source: Author

The predictive performance of IWC and ISC for France is represented in Figure 4.11. It is evident that both models overestimated the predictions when compared to the actual results. Moreover, the IWC model for France exhibited a generally good prediction performance, slightly outperforming the ISC model.

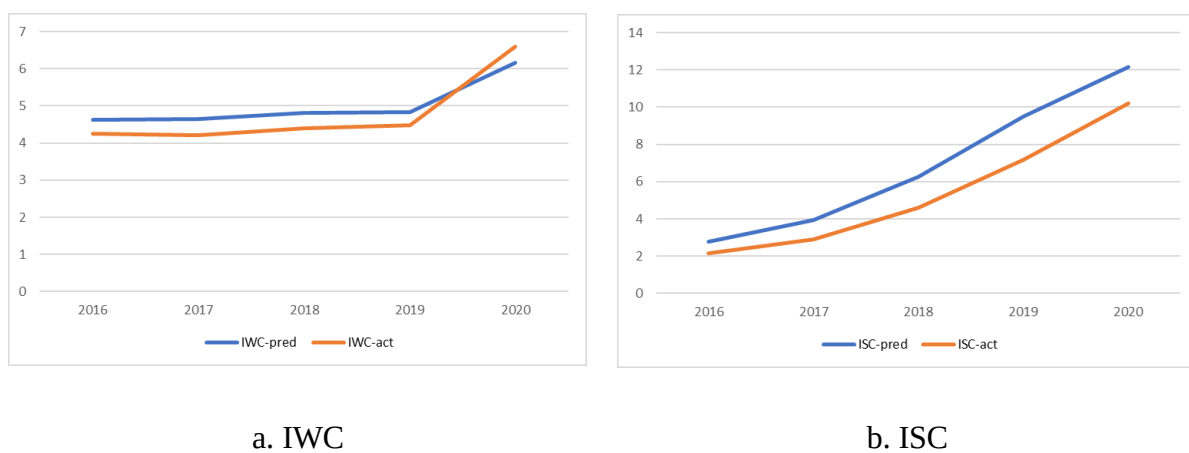


Figure 4.12. Prediction and Actual Results of Netherlands for IWC and ISC

Source: Author

Figure 4.12. illustrates the prediction performance of the Netherlands for IWC and ISC values. It is evident that both models demonstrated strong prediction capabilities for the Netherlands. Generally, both ISC and IWC models tended to overestimate actual results, with the exception of the prediction result for the year 2020 in the IWC model. Furthermore, the IWC model presented a slight performance advantage over the ISC model.

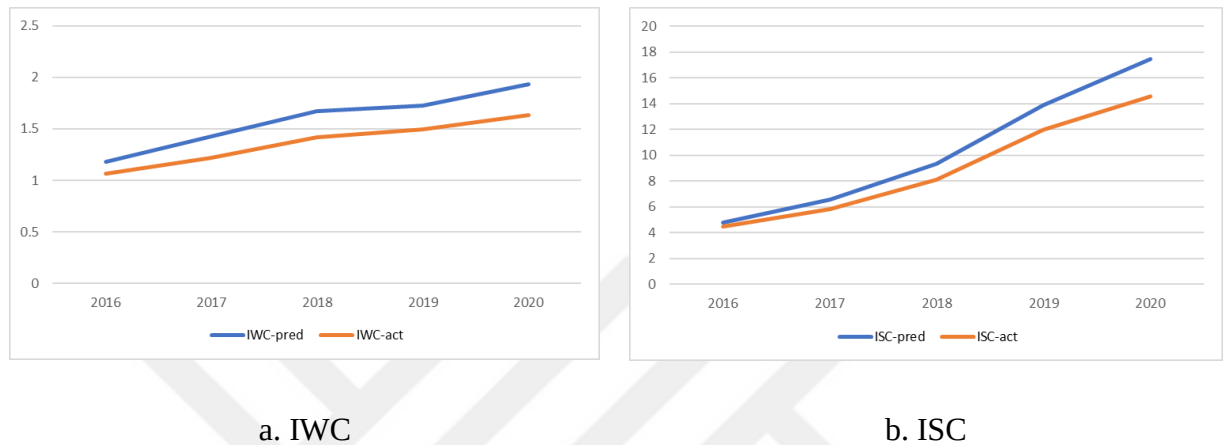
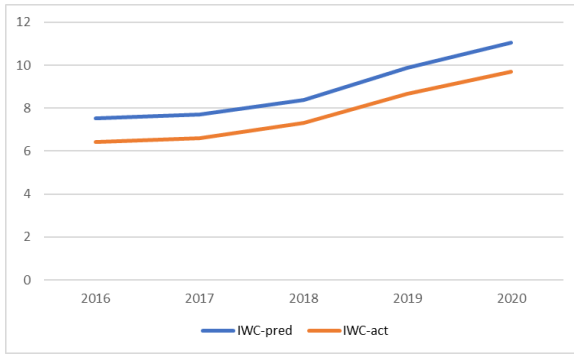


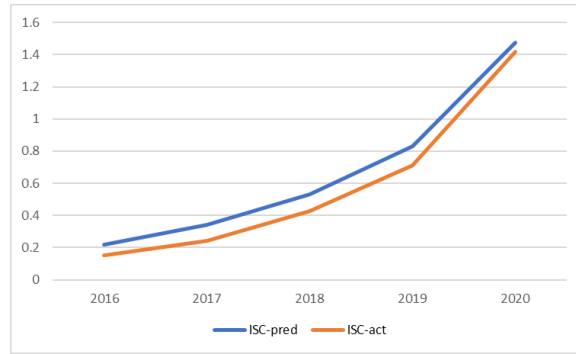
Figure 4.13. Prediction and Actual Results of South Korea for IWC and ISC

Source: Author

The predictive performance of IWC and ISC for South Korea is exhibited in Figure 4.13. In a broad overview, both ISC and IWC models tended to overestimate the actual results. The IWC model exhibited superior performance compared to the ISC model. In a more detailed analysis, the ISC model displayed a noticeable and unfavorable trend over the sampled years. In contrast, this unfavorable trend was not observed in the performance of the IWC model.



a. IWC

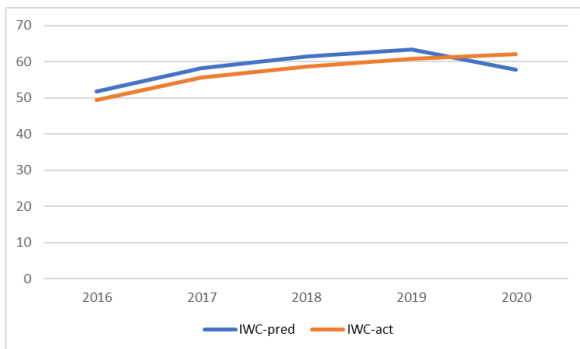


b. ISC

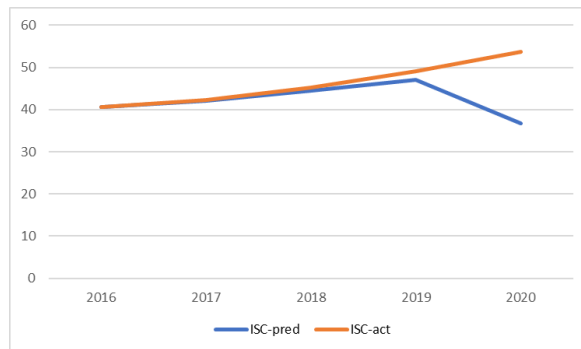
Figure 4.14. Prediction and Actual Results of Sweden for IWC and ISC

Source Author

The predictive performance of IWC and ISC for Sweden is presented in Figure 4.14. It is apparent that both ISC and IWC models tended to overestimate the actual values. The ISC model, however, displayed superior performance, showing an increasing trend in accuracy over subsequent years. In comparison, the IWC model exhibited slightly less accurate prediction performance compared to the ISC model.



a. IWC



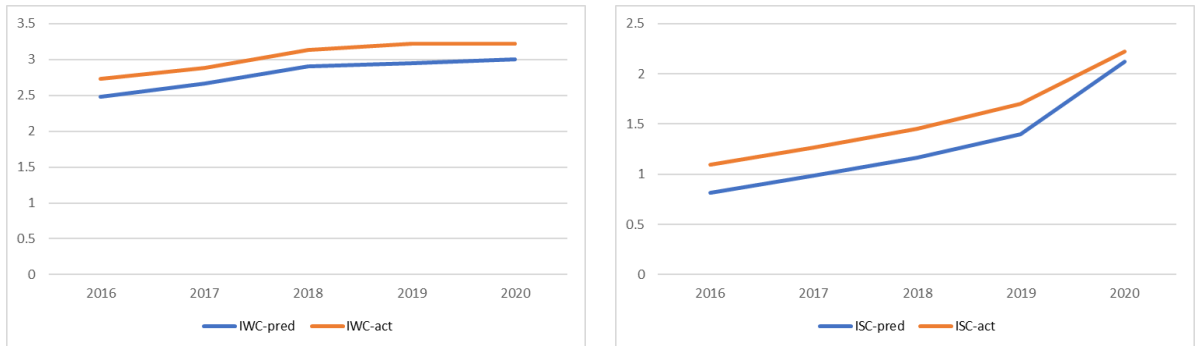
b. ISC

Figure 4.15. Prediction and Actual Results of Germany for IWC and ISC

Source: Author

The predictive performance of IWC and ISC for Germany is presented in Figure 4.15. Both the ISC and IWC models exhibited highly accurate performance in Germany,

particularly the ISC model. However, this superior performance showed a decline after the year 2019 for both models. Based on our understanding, we attribute this performance decline to the global impact of the Covid-19 pandemic.



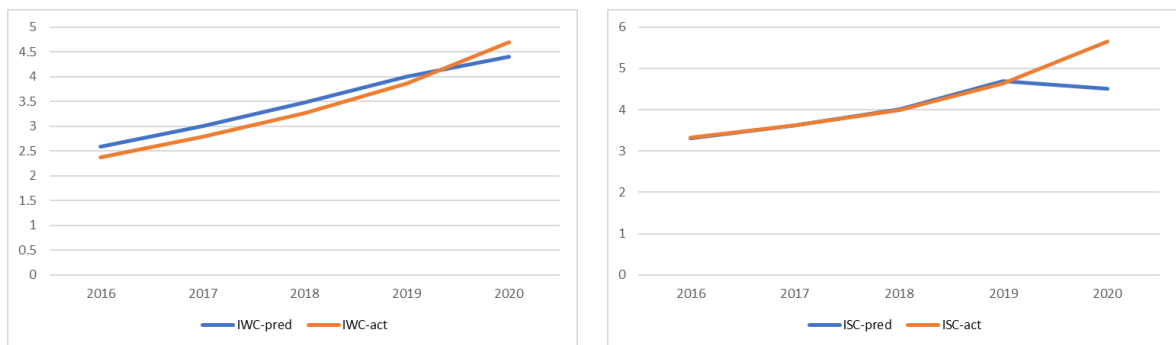
a. IWC

b. ISC

Figure 4.16. Prediction and Actual Results of Austria for IWC and ISC

Source: Author

The performance analysis of ISC and IWC for Austria is presented in figure 4.16. In a comprehensive evaluation, both ISC and IWC models exhibited strong predictive performances. Furthermore, each model underestimated values in comparison to the actual results. Notably, it is essential to highlight the favorable performance trend observed in ISC, particularly evident in the years 2019 and 2020.



a. IWC

b. ISC

Figure 4.17. Prediction and Actual Results of Belgium for IWC and ISC

Source: Author

The predictive performance of IWC and ISC for Belgium is presented in Figure 4.17. It is notably apparent that both ISC and IWC models exhibited superior predictive performances, with particular emphasis on the exemplary performance of the ISC model. However, it should be noted that predictions from the IWC model were slightly overestimated compared to actual results until the year 2020. In our assessment, the Covid-19 pandemic is considered a potential factor contributing to the observed performance decline in both ISC and IWC models.

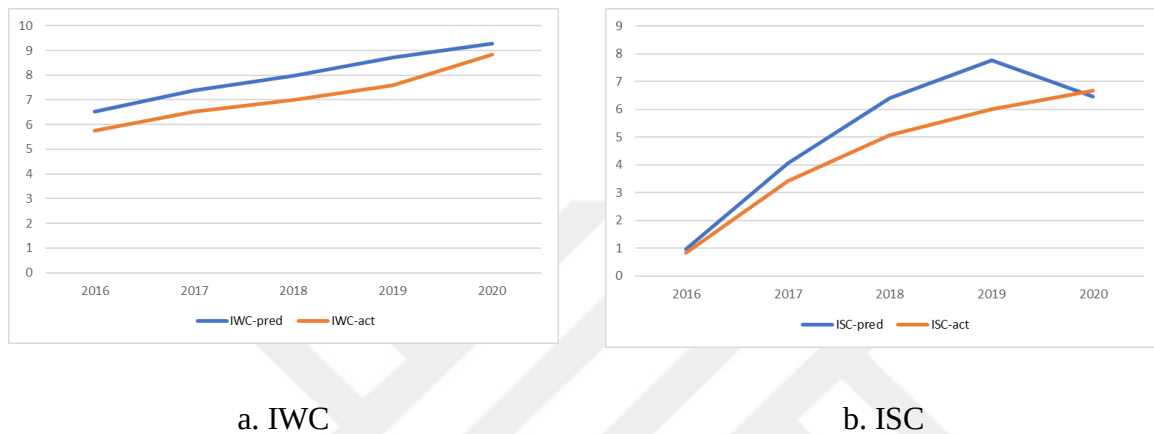
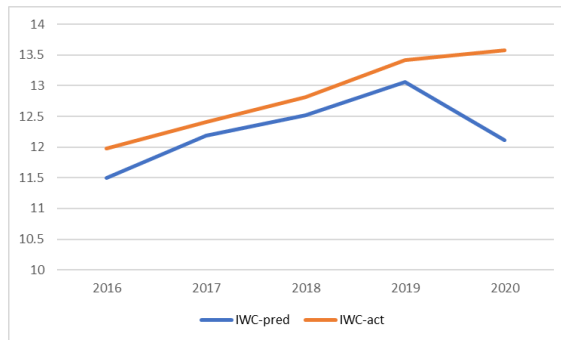


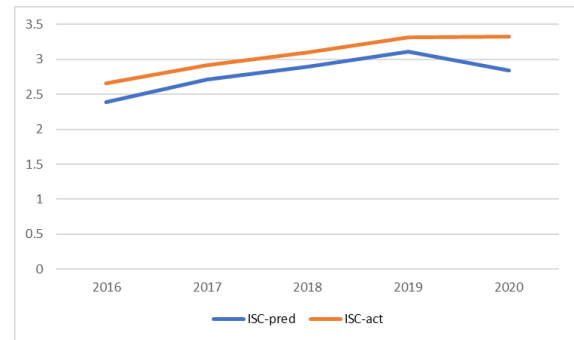
Figure 4.18. Prediction and Actual Results of Turkey for IWC and ISC

Source: Author

The predictive performance of IWC and ISC for Turkey is presented in Figure 4.18. In a broad context, both models demonstrated strong performance. As a comparison between models performance, IWC exhibited a slightly higher level of accuracy than the ISC model. Additionally, ISC model improved performance in years 2019 and 2020.



a. IWC

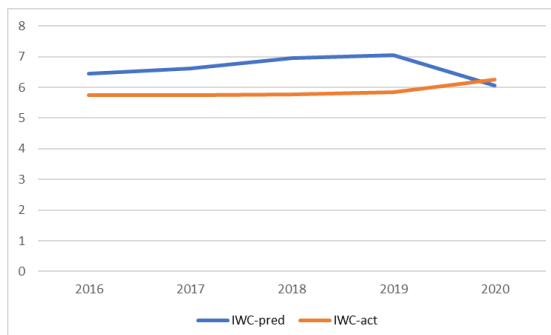


b. ISC

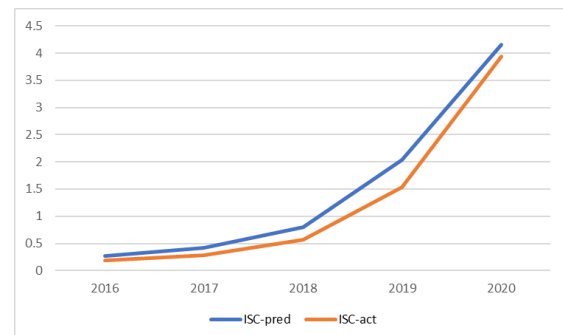
Figure 4.19. Prediction and Actual Results of Canada for IWC and ISC

Source: Author

The performance analysis of ISC and IWC for Canada is presented in figure 4.19. The ISC model displayed accurate performance up until the year 2020, while the IWC model exhibited intermediate accuracy during the same period. Both the ISC and IWC models consistently underestimated the actual values for Canada. The decline in the predictive performance of both models in the year 2020 is hypothesized to be linked to the global Covid-19 pandemic.



a. IWC



b. ISC

Figure 4.20. Prediction and Actual Results of Poland for IWC and ISC

Source: Author

The predictive performance of IWC and ISC for Poland is presented in Figure 4.20. The ISC model presented progressively superior predictive performance, consistently increasing in accuracy over time. Simultaneously, the IWC model delivered upper

intermediate results, notably improving its accuracy in the year 2020. It can be affirmed that both the ISC and IWC models demonstrated accurate prediction performance; nevertheless, the ISC model's performance stands out as particularly outstanding.

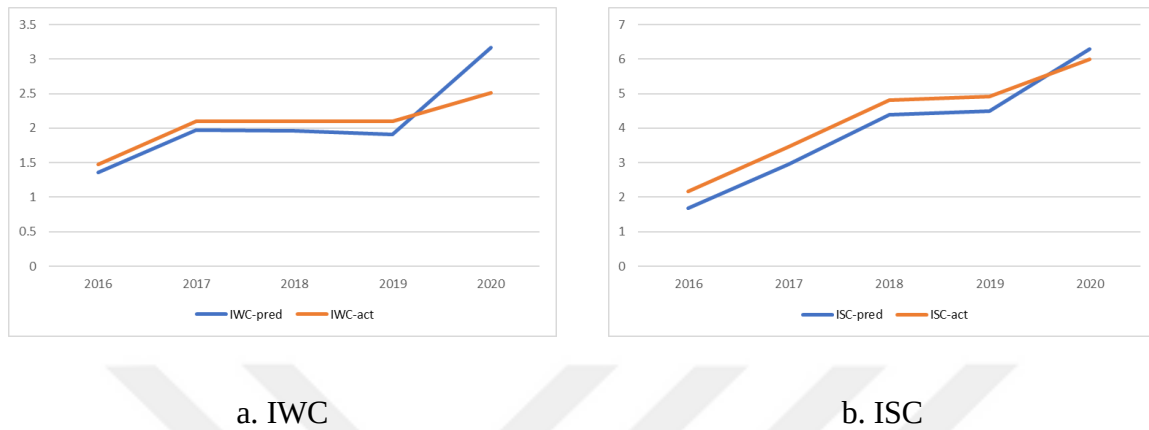


Figure 4.21. Prediction and Actual Results of South Africa for IWC and ISC

Source: Author

The predictive performance of IWC and ISC for South Africa is presented in Figure 4.21. The IWC model demonstrated highly accurate performance until the year 2020. The ISC model performed accurately with an increasing trend in accuracy. As an overview, both ISC and IWC models performed accurate results.

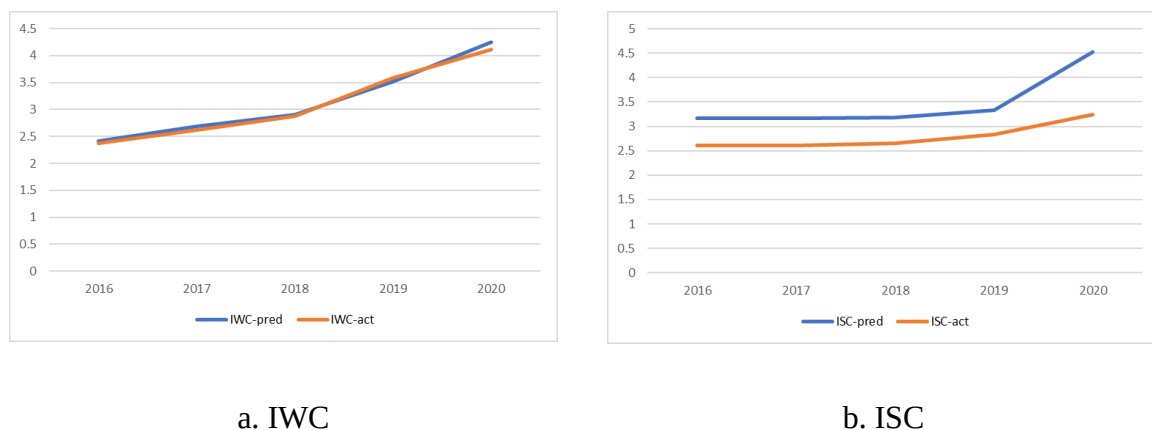


Figure 4.22. Prediction and Actual Results of Greece for IWC and ISC

Source: Author

The performance analysis of ISC and IWC for Greece is presented in figure 4.22. The IWC model exhibited remarkably accurate performance, ranking as the second-best

among the sampled countries. Conversely, the ISC model presented an above-average performance, accompanied by a decrease trend in accuracy.

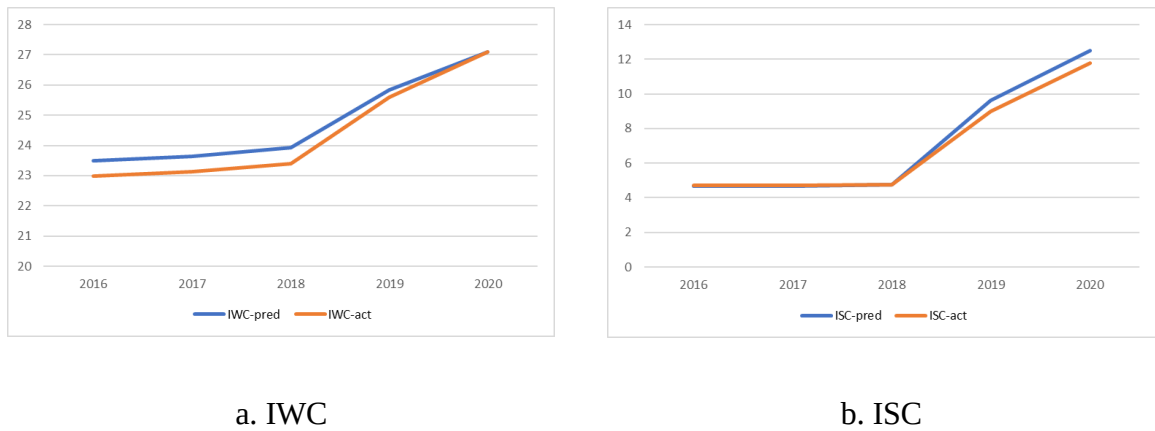


Figure 4.23. Prediction and Actual Results of Spain for IWC and ISC

Source: Author

The predictive performance of IWC and ISC for Spain is presented in Figure 4.23. The performance accuracy of both the ISC and IWC models stands out as the highest among the sampled countries. Furthermore, the illustration highlights a notably outstanding increasing trend in the accuracy of the IWC model. It is also noteworthy to emphasize that the ISC model demonstrated superior performance, particularly during the years 2016, 2017, and 2018.

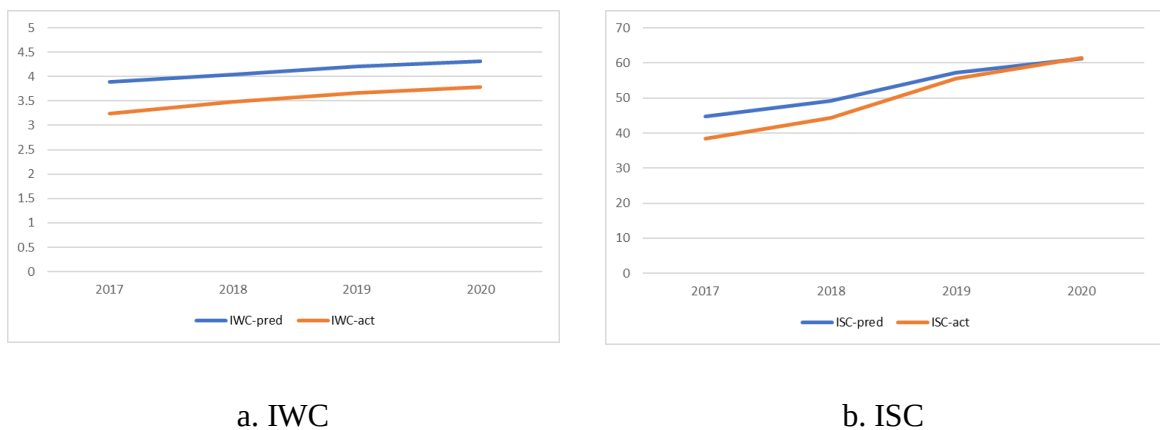


Figure 4.24. Prediction and Actual Results of Japan for IWC and ISC

Source: Author

The predictive performance of IWC and ISC for Japan is illustrated in Figure 4.24. In a comprehensive review, the ISC and IWC models exhibited above-average accuracy in their performance. Notably, the ISC model displayed a discernible upward trend in achieving high performance accuracy. However, it is worth noting that the performance accuracy of the IWC model is comparatively lower when contrasted with the ISC model's performance.



5. CHAPTER: DISCUSSION

The onset of the 20th century witnessed significant strides in industrialization, marking the inception of a climate crisis that has evolved into a pressing global concern over the past six decades. Technological researchers, developers, the industrial and financial sectors, academic communities, experts in healthcare, environmental policymakers, and governments regard this issue with utmost seriousness, fostering global collaboration to address the multifaceted challenges it presents. This climate crisis revealed the harmful effects of conventional energy consumption, underlining the crucial importance of embracing clean and sustainable energy practices for a brighter future. Policy makers and governments collaborated regularly to discuss and strategize on mitigating the impacts of climate change. Among the prominent international organizations, COP, and OECD, operating under the UNFCCC, play pivotal roles in these collective efforts. As an illustration of the significant outcomes of such gatherings, the renowned Kyoto Protocol was signed during the COP-3 meeting held in Kyoto, Japan (Ghezloun et al., 2013). The environmental policies and strategies formulated in these forums strongly emphasize the imperative of mitigating greenhouse gas emissions. This is achieved by reducing the consumption of conventional energy sources and concurrently increasing the utilization of renewable energy resources. Hydropower is recognized as the leading renewable energy resource and remains the primary source of electricity among renewable options. Over the past two decades, solar and wind energy have emerged as increasingly dominant trends, surpassing hydropower in their growth trajectory (Our World in Data, 2023). The rising prominence of solar and wind energy, in contrast to hydropower, can be attributed to several factors. Hydropower, as one of the earliest renewable energy resources, relies significantly on geographical features, including favorable climate conditions, proximity of water sources, and topography. The construction of hydropower facilities is financially burdensome, given the substantial installation and execution costs, and often involves a prolonged installation phase. These factors impact governmental

decisions on renewable energy investments, despite hydropower being a highly efficient renewable energy resource. In contrast, solar and wind energy facilities demonstrate effortless and rapid installation processes, requiring considerably lower financial support compared to hydropower plants. With ongoing technological advancements, the efficiency of solar and wind energy generation, as well as their storage capacities, is rapidly increasing (Tirth et al., 2023). Governments, policymakers, and investors stand to gain from these technological strides and research findings. The escalating trend in the adoption of renewable energy, especially from wind and solar sources, has prompted governments to introduce incentives and supportive policies and for researchers to explore and contribute into a new field. For these reasons, this study investigated the installed solar and wind energy related gap in the energy literature aiming to make a meaningful contribution to green field.

The study focuses on commonly used indicators of installed solar and wind energy performance, referred to as ISC and IWC, as the dependent variables. The model incorporates 15 distinct independent variables: Pop, GDP, EG_Oil, EG_Coal, EG_Gas, EG_Hydro, EG_NE, TEG, EG_RE, SES, WES, TSP, LC_R&D, EPS, and RETS. These independent variables can be categorized based on their attributes, covering socioeconomic conditions, conventional energy utilization, renewable energy utilization, electricity generation (both total and renewable-only), and, finally, environmental policy implementations encompassing financial incentives, renewable support policies, and low-carbon regulations. The model has employed 21 years of panel time series data set for 24 OECD countries. The preference to study OECD countries is grounded in the idea of concentrating on nations that exert the greatest influence over global resources and the renewable energy transition process due to their strong economical attributes. The decisions, regulations, and strategies formulated during these annual meetings profoundly impact lives worldwide, particularly in the realms of energy, environment, and economics within the context of the clean energy literature. Following an extensive literature review, it is evident that the ISC and IWC variables have been examined across diverse countries, encompassing various variable types (Perone 2023; Insel et al. 2022). However, these studies often focus on individual countries rather than analyzing multiple countries collectively (Kumar, 2023). While being a prominent topic in the literature, there still exists a gap in studies that utilize time series panel datasets. To the best of our knowledge, there has been no

development of prediction models that encompass a time series panel data for OECD countries, integrating a comprehensive range of variables such as socioeconomic conditions, both conventional and renewable energy utilization, total and renewable electricity generation, various environmental policy implementations, and low-carbon regulations. Therefore, the primary aim of this study is to incorporate these diverse attributes into prediction models for ISC and IWC, employing a 21-year of panel time-series data set. The goal is to interpret the model results, offering insights for forecasting the clean energy transition process, guiding investments in greenfield projects, and policy-making for governments. Numerous researchers have explored prediction models related to ISC and IWC, employing various ML methods (Kumar, 2023; Serrano-Ar'evalo et al., 2023; Izanloo et al., 2022). ML models have gained prominence in recent technological advancements due to their exceptional performance, especially in prediction models. These models harness advanced algorithms to analyze historical data, discern patterns, and offer insightful predictions about future outcomes. We scrutinized the main subcategories of ML methods to identify the optimal algorithm for our model. After an in-depth examination of forecasting methodologies aimed at selecting the most suitable approach, our analysis points to the LSTM algorithm, within the SL subcategory, as the optimal approach. LSTM algorithm is a modified RNN architecture that yields better performance compared to traditional RNN models (Hochreiter and Schmidhuber, 1997). The LSTM method distinguishes itself as a superior approach extensively utilized in applications, particularly for processing complex non-linear time series data. As the model involves a complex time-series panel dataset encompassing 24 countries over a span of 21 years, the selection of this algorithm as the optimal method is justified. The time series analysis was executed using the LSTM algorithm within the Python programming language, with the following libraries: NumPy 1.23.5 for numerical computations and data manipulation, Pandas 1.5.3 for working with data frames and conducting data analysis, Scikit-Learn 1.2.2 for machine learning modeling and evaluation processes, Keras 2.15.0 as a high-level deep learning library to construct the LSTM model, and Matplotlib 3.7.1 for data visualization. The model incorporates the ReLU activation function, undergoes 30 training cycles (epochs) with a batch size set at 50. The time step is configured as 1, input size as 35, and output size is set to 1. Furthermore, the learning rate for the model is specified as 0.001. To assess the model's effectiveness,

the dataset was partitioned into two segments: one for training, spanning 16 years, and another for testing, covering 5 years. The model underwent training on the former to develop its predictive capabilities, and its performance was subsequently evaluated using analytical tools, including RMSE, MAE, and MAPE.

First, a descriptive analysis has been conducted on the panel dataset to reveal key insights of various statistics for each country and variable, including minimum, maximum, average, standard deviation, and the number of observations. Analyzing the average values of the sampled countries reveals China's notable leadership, with the highest values in Pop, GDP, EG_Coal and EG_Hydro utilization, as well as TEG. Of utmost significance is the finding that China holds the highest IWC and ISC values among the studied countries. These findings strongly suggest a robust correlation between elevated levels of income, population, and industrialization, and the increased demand for energy generation. Considering the global shift towards renewable energy sources and advancements in greenfield technologies, it becomes logical to address these increased energy needs through the utilization of three primary renewable resources: hydropower, solar, and wind. Meanwhile, Brazil stands out with the highest average EG_RE values, despite not leading in the other renewable resource categories. This could be interpreted as an indication that Brazil predominantly meets a significant portion of its energy demand through renewable resources although it does not notably distinguish itself among the sampled countries with the largest industries globally. The United States stands out with the highest average utilization of EG_NE and EG_Gas. This outcome could be interpreted as a preference for a more risk-tolerant yet efficient choice in renewable energy, particularly Nuclear Energy. This preference may be rooted in the confidence in high technological advancements addressing security concerns associated with nuclear energy, along with the utilization of natural gas resources. Japan stands out with the highest average EG_Oil value, TSP, and LC_R&D policy. This outcome may be attributed to Japan's highly dependence on imported energy resources, particularly EG_Oil, to sustain its highly industrialized economy. Furthermore, Japan has shown a tendency to decrease nuclear energy production following events like the Fukushima nuclear disaster. Consequently, the country has excelled in implementing technological support and R&D policies, especially in the green field, as part of its strategic efforts to address energy challenges. Italy excels in average SES and WES policies, suggesting a growing environmental policy emphasis

on wind and solar energy within the country. This implies a strategic approach fostering sustainable practices and harnessing renewable energy sources in Italy's overall policy framework. France distinguishes itself with the highest average EPS value, suggesting a strong likelihood of the country's active participation in global environmental agreements. Additionally, Sweden demonstrates the highest average RETS value, indicating a proactive approach in promoting incentives for trading and investments related to renewable energy. An additional insight derived from the analysis of IWC and ISC datasets reveals that the sampled countries placed a greater emphasis on WES policy compared to SES policy. This observation also coincides with both ISC and IWC datasets. As a final observation regarding the datasets, it is noteworthy that both ISC and IWC demonstrate a distinct upward trend during the observed years, spanning from 2000 to 2020.

The model's predictive performance was assessed using regression tools such as RMSE, MAE, and MAPE. An extensive evaluation was conducted based on 118 observations for both IWC and ISC models to gauge the overall predictive capabilities of the model. The IWC model performed overall for 24 countries with 90.464% accuracy. To go into a more detail for IWC, the model demonstrated optimal performance in Spain, Greece, and Finland, achieving an average error rate of 1.9%. Conversely, it faced challenges in Japan, South Korea, and Sweden, where the average error rate reached 10.3%. The ISC model showed a notable deviation of 19.897% from the actual values, yielding a commendable prediction accuracy of 80.103%. The ISC model presented its best performance in Spain, Australia, and Belgium, achieving an average error rate of 4.73%. On the other hand, it encountered greater difficulties in China, Finland, and Poland, leading to an average error rate of 35.67%. It is worth emphasizing that both ISC and IWC models demonstrated exceptional accuracy in Spain. Another crucial point to highlight is that both ISC and IWC models experienced a notable decline in prediction performance post-2019. As this performance decline was observed across multiple countries, we attribute this variation to the impact of the Covid-19 pandemic. Hence, many studies choose to limit their time series datasets to mitigate the influence of the Covid-19 impact (Kostakis et al., 2023; Wang et al., 2023; Aydin and Bozatli, 2023; Islam et al., 2022).

The performance disparity between IWC and ISC models revealed several insights. The ISC model exhibited approximately 10% lower accuracy compared to the

predictive performance of the IWC model. We interpret this outcome as an indication that solar energy studies perform better when the model exclusively focuses on attributes associated with solar energy. Moreover, we emphasize the importance of constructing ISC models on a country-specific basis. Consequently, the literature has been re-reviewed with a focus solely on incorporating studies related to ISC models. Many studies on solar energy have been discovered to be constructed on a single-country basis (Song et al., 2023; Shi et al., 2023). The literature review strongly supports our proposition regarding the construction of ISC models.

Lastly, the model provides valuable insights for policymakers, researchers, and investors by highlighting the economic, social, political, energy generation, and environmental dimensions associated with the deployment of various variables. The study stands out due to its ISC and IWC predictions model, sampled among OECD countries and spanning 21 years of complex time series dataset. Given that OECD countries play a pivotal role in shaping the future of environmental, social, political, financial, technological and security domains, this research aims to contribute to a greener and more sustainable future.

6. CHAPTER: CONCLUSIONS AND FUTURE WORK

The study employed machine learning technology to construct a predictive model for ISC and IWC values, crucial indicators in assessing renewable energy utilization. The accurate prediction of these values holds significance in the context of addressing the emerging climate crisis. Numerous studies have been dedicated to this subject, with governments globally convening in meetings and formulating regulations and policies. Gaining global insights is a matter of great importance, impacting every individual in economic, social, political, and environmental dimensions. Hence, the meticulous selection of optimal variables and methodologies for precise predictions becomes crucial in addressing such issues. For these reasons, this study sampled 24 OECD member countries, incorporating socioeconomic, conventional, and renewable energy attributes, along with diverse environmental policy variables. A comprehensive model is constructed by integrating the LSTM algorithm, spanning 21 years of a complex dataset. Both ISC and IWC models exhibited high accuracy, with the model demonstrating superior performance in predicting IWC.

The main limitation of this study is the inadequacy in the ISC and IWC datasets, stemming from the fact that data for these variables is not available for the majority of the 38 OECD member countries due to the relatively recent history of solar and wind energy plant development, which commenced in the late 1990s. Furthermore, the dataset for the EPSI of OECD member countries is limited up to the year 2020. Consequently, the study focuses on 24 countries and spans the years from 2000 to 2020.

In future studies, enhancing the ISC model could involve the incorporation of additional variables directly related to solar energy, such as solar radiation angle, sunshine duration, and meteorological information. It is also recommended to construct separate ISC models, as focusing on solar energy analysis independently may enhance overall performance. Lastly, as part of future work, the model could benefit from updates with datasets covering the years 2024 and 2025.

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