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Multi-Model Approach of Global Energy Model Validation: Times and EN-ROADS Models

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Abstract Energy System Modeling tools are becoming ever-prevalent in global society to help decide factors in energy policymaking, power production methods, and means of environmental impact assessment. Energy system engineers need to be aware of the use of energy system models due to the complexity of the systems and the demand for model use in evaluating an energy system. This literature review will cover the importance of energy system models and the most recent advances in modeling technology, the accepted methods of model evaluation and validation before the use of an energy system model, and lastly, demonstrate a comparative analysis validation technique with three case studies using a multi-model approach, by applying two widely accepted global energy models. The two global energy models evaluated are the Integrated MARKAL-EFOM System (TIMES) and Energy-Rapid Overview and Decision-Support (EN-ROADS) models. The comparative analysis will be demonstrated by reviewing three base cases, whether 2.5°C average warming is achievable within the desired timeline, the projected global energy supply, and practical climate change mitigation scenarios. The comparative analysis results show that two globally accepted energy system models still predict different outcomes with the same inputs. The comparative analysis results exemplify the necessity for energy system engineers or other model users to properly benchmark and validate any model they decide to use for decision-making before accepting model results.

Keywords: *global energy and climate models, energy modeling, emission and temperature forecast, EN-ROADS, TIMES, energy policy, model validation, model calibration, and integrated assessment models*

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1. Introduction

The Earth's surface temperature in 2021 will be the sixth warmest since records began in 1880. Another analysis of global temperatures [1] reported that 2021 and 2018 were the sixth hottest years on record, with global land and sea temperatures in 2021 recorded at 1.87°F (1.04°C). Global temperature rise has been correlated with the concentration of greenhouse gases in the atmosphere. Carbon dioxide and other greenhouse gases (GHG) act like blankets, trapping some of the heat the Earth would have radiated into space. Greenhouse gases absorb energy at wavelengths from 2,000 to 15,000 nanometers. This range overlaps with infrared energy; when CO_2 absorbs this infrared energy, it vibrates and reflects the wave in all directions. About half of this energy wave goes to space, and about half returns to Earth as heat, contributing to the greenhouse effect [2].

Many scientific studies have confirmed the correlation between GHG emissions and the rise in global temperatures [3]. As shown in Figure 1, since the beginning of the industrial revolution, human activity has increased CO_2 in the atmosphere; and the global temperature has increased with increasing concentration of CO_2 or greenhouse gas produced with the extraction and combustion of fossil fuels [2].

The ice at the Earth's poles is getting smaller and smaller as it melts. Much of this melting ice contributes to sea level rise; sea levels are expected to rise by more than 10 to 32 inches (26 to 82 cm) by the end of this century, which will cause severe flooding in coastal areas. We continue to witness extreme weather conditions; for example, [4], there was a winter storm in Texas, where temperatures dropped to -13°C in February 2021, disrupting the power supply to about 3.5 million homes and businesses. In June of the same year, temperatures reached 34.8°C in Moscow, breaking that month's all-time heat record. In October, monsoon floods in a day killed about 150 people and left thousands of families homeless in India [5]. These extreme weather events and temperature fluctuations have caused enormous losses to humankind. Rising temperatures have changed the living conditions of wildlife in the affected areas. As a result of these changes, many species migrate, and some become extinct. These weather events have also increased public and governmental attention to climate change action, seeking economic, political, and legal solutions, especially in policy making.

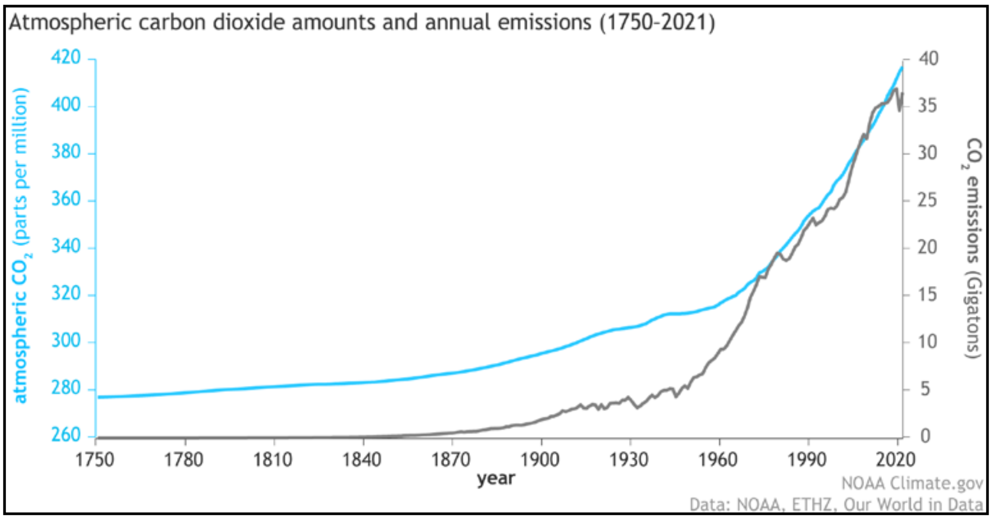

Figure 1. Historical carbon dioxide emissions and global temperature [1]

Governments and non-governmental organizations rely on robust mathematical and computer models when formulating climate protection measures and legal instruments. Energy models use mathematical concepts to describe the relationship between the sun, the environment, and human activity. Such models integrate knowledge from the natural sciences, computer science, engineering sciences such as electrical engineering, and non-physical sciences such as economics and sociology. Mathematical models can take many forms, such as dynamic and statistical models. Some models are deterministic; some are stochastic, some treat time as a discrete quantity, and some treat it as a continuous variable [6]. Some energy models combine the variables simultaneously, making them complex to understand and apply.

Global energy and climate models, also called integrated assessment models (IAM), are based on well-documented physical processes and simulate the transport of energy and materials through the climate system. Climate models, or general circulation models or GCMs, use mathematical formulas to characterize how energy and matter interact in different parts of the ocean, atmosphere, and land [7]. The construction and operation of climate models involve identifying and quantifying Earth system processes, expressing them mathematically, setting variables to represent initial conditions and subsequent changes in climate forces, and translating the equations into powerful supercomputers models. It is a complex process of iteratively solving variables like temperature [8]. A simplified global energy and climate model structure is shown in Figure 2 [9], showing variables inputs and outputs, prices, primary energy supply, energy services and materials demand, transformation, and trade data.

Most authors have to classify models into two predominant groups. First, some models focus in detail on mitigation options and climate change impacts without assessing all possible effects or summarizing them into a single metric regarding projected climate damage. Second is a high-level model that calculates carbon emission trajectories and prices to maximize global welfare [10].

A systematic review of commonly cited energy systems models both in academic literature and policy papers in the UK since 2008, identified 22 different models and showed that the MARKAL model, which later became TIMES, is commonly applied for most academic research and policy formulation in the UK energy market [11]. The MARKAL was developed in a cooperative multinational project by the Energy Technology Systems Analysis Programme (ETSAP) of the International Energy Agency [12]. MARKAL was created to ease the design of energy systems that comply with the United Nations' framework on climate change. This work presented a list of all referenced models and categorized them according to technological, mathematical description, and sectoral coverage. Hall and Buckley recommended the introduction of a classification schema for use within academia and policy, which would provide a decision-support tool for energy systems modeling.

Recently, a similar work [13] to the UK's modeling tools was carried out for publicly available tools developed by the Department of Energy (DOE). As reported, the study framed the functions and capabilities of the models. It created a methodology that stakeholders could use to determine which DOE modeling tool best suits their specific evaluation of energy storage systems (ESSs). The report focused on DOE price-taker valuation tools, including QuEST, REoptTM, DER-CAM, System Advisor Model (SAM), and Energy Storage Evaluation Tool (ESETTM). To familiarize potential users of these programs with the types of datasets needed to run these models, the author provided three example use cases. They illustrated how DOE tools could be used for storage valuations for three use-case families, which include facilitating an evolving grid; critical services; and facility flexibility, efficiency, and value enhancement. A hierarchical system was also developed to help select modeling tools. Some criteria considered in the selection system include the type of ESS (Energy Storage Systems) technology, another mix of DER resources that needed integration, stakeholders and use cases, kind of analysis, and other features and capabilities. They produced a model selection platform, which gives an overall score based on the criteria listed previously. Though the inputs of this model selection platform are subjective, the system clarifies the model selection process, which helps navigate the extensive list of energy systems models.

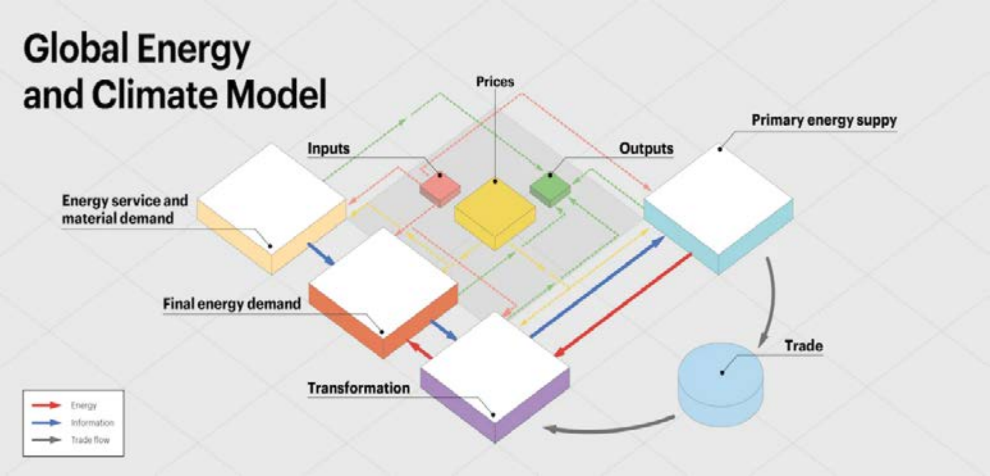

Figure 2. Structure of the internal working of a global energy and climate model [9]

In our assessment, energy modeling that contributes to system operation and engineering design is well-studied, but modeling that supports energy policy and development is less well-studied. Energy models that support policymaking are called integrated models and are the subject of our focus. The integrated model combines simplified sub-models of the global economy, agriculture and land use, climate, and energy systems. Some of these models include, examples include Global Change Analysis Model (GCAM), the Model for Energy Supply Strategy Alternatives and their General Environmental Impact (MESSAGE), the Model for Analysis of Energy Demand (MAED), the Prospective Outlook on Long-term Energy Systems (POLES), Integrated National Energy Modeling System (iNEMS), MARKAL/TIMES, and EN-ROADS.

Global energy models support decision-making in energy policy and development; therefore, they are always complex and far-reaching. These models are essential because they are used to make decisions that affect many people and have long-term consequences. We decided to evaluate the performance of some of these models using a pragmatic approach of comparing some of the popular models. This study attempts to validate two global energy models by applying them to similar datasets and case scenarios. We chose The Integrated MARKAL-EFOM System (TIMES) and EN-ROADS models for a few reasons:

a) These two energy models are popular all over the world.
b) Open source
c) Free and low-cost installation
d) Good dashboard
e) Publicly available well-documented user’s manual guide

Applications of global energy models such as TIMES and ENROAD include identifying the most cost-effective energy systems, identifying the most cost-effective responses to emission limits, and performing predictive analysis of long-term energy budgets under various scenarios. Notably, applications also include evaluating new technologies and priorities. Assess the impact of R&D, regulation, taxes, and subsidies, estimate greenhouse gas emissions inventories, and assess the value of regional cooperation [9].

A recent application of TIMES is the development of methods of forecasting technology developments that consider the long-term nature of technological developments, technological developments in the oil and gas and coal industries, as well as production and distribution of electricity, and the preference for hydrogen energy technology in Russia [14].

To ensure their policy impact assessments were accurate, van de Ven et al. used multi-model analysis to analyze Glasgow's climate action policy and the likelihood of gaps. They used four different models: TIMES, Global Change Analysis Model (GCAM), GEMINI-E3, and **M**od**U**lar Energy Systems **S**imulation **E**nvironment (MUSE). The short-term and long-term CO_2 emission trajectories were assessed according to national policy and pledges. The four integrated assessment models lead to different decarbonization pathways to achieve long-term goals. In addition, all the models pointed out several feasibility issues related to the cost of mitigation, the rate and technology scale, and implementation measures. This work [15] has highlighted why it is essential to properly calibrate models and decide on the type of action that is needed to validate the results.

Some of the most influential ideas about the low-carbon transition come from energy models, which approach the interaction between energy technology and policymaking differently. In any model, paying attention to combining science and policymaking is essential. The results of [16] question the political neutrality of integrated energy assessment models embedded in the interface of science and policy. They suggest future directions for building these relationships to ensure policy decisions are not technically biased. Proper calibration and multi-model testing can reveal and evaluate some of these science policy relationships.

Since most climate-related interventions have future impacts, it is essential to establish confidence in the solutions advocated and assess the certainty of delivering the required results. The European Union's ambitious Green Deal, which aims to be carbon neutral by 2050, is estimated using multi-model integrated assessment tools. The authors discussed the opportunities and challenges in creating and using an integrated assessment framework to inform the European Commission on the decarbonization roadmap [17]. With a multi-model approach, EU decarbonization pathways, modeling challenges, and consistency of results were evaluated by linking different models and modeling assumptions.

2. The Integrated MARKAL-EFOM System (TIMES) Model

The Integrated MARKAL-EFOM System (TIMES) model is a bottom-up model generator that uses linear programming to create optimized lowest-cost energy systems subject to user constraints over medium and long-time ranges. The model engine combines two systematic approaches to modeling energy: engineering and economic approaches. The model includes all steps from primary resources to the process chain that converts, transports, distributes, and transforms energy into delivering energy services demanded by energy consumers. Once all inputs, constraints, and scenarios are created, the model attempts to solve and determine the energy system that meets the energy service requirements at the lowest cost over the time range [18]. It is recognized as a powerful tool for analyzing energy scenarios that can be used to assess the impact of potential policy actions [19].

The TIMES model is suitable for modeling at a high or national level; for example, [19] used the model in modeling the energy sector of Latvia. The primary data input of the model, in this case, study, includes different elements of the power and heat sectors, thus allowing several scenarios to be analyzed for further development of these sectors. Using the TIMES model, the work confirmed that the existing tax policy of Latvia is working correctly and ensures a more significant share of renewable energy in the total primary resource consumption in the energy sector.

The TIME model is also suitable for systematically analyzing global energy issues such as Climate protection options, developing fully renewable energy systems, alternative fuels for passenger transport, and using electric vehicles [20]. These models are created to determine the optimal mix of technologies and resources that can minimize the total cost of the energy system under various user-defined constraints and opportunities.

The TIMES model has also been used to assess the impact of introducing new technology on the existing multi-regional energy system. Using TIMES evaluated the effect of using bioenergy with carbon capture and storage (Selosse & Ricci, 2014). The study shows that bioenergy with carbon capture and storage has been identified as an attractive negative emission option for achieving meaningful CO_2 emission reductions.

3. EN-ROADS Model

EN-ROADS Model is an open and fully documented online strategic energy-economy-climate simulation model. It represents the energy economy climate system at the global aggregate level, and it is based on the best available scientific evidence and tailored to match historical data and predictions from multiple sources. Users select assumptions, policies, and actions to mitigate greenhouse gas emissions through an intuitive interface and receive immediate feedback on potential energy, emissions, and climate trajectories [21]. Since its launch in December 2019, it has been used by more than 81,000 people in 86 countries. It is very functional for facilitating interactive briefings or generating scenarios. Users of this model include over 1,000 executives and over 150 elected officials, including senators, governors, legislators, and their 200 congressional staff in the United States, dozens of nonprofit executives, and foundations worldwide.

The EN-ROADS model has many uses. For example, HSBC, a global player in the financial sector, uses this tool to help employees learn about climate change, underpins HSBC's climate strategy, strengthens climate risk assessment, collaborates between businesses, and improves how the banks formulate climate policies. [22]. The 2022 Swedish general election [23] evaluated the political parties' climate proposals quantitatively. Emissions arising from proposed policies were quantified using the EN-ROADS model. Each party was then ranked by the number of megatons of carbon dioxide that would be saved compared to current levels. The model shows that the five-party proposals result in lower emissions than Sweden's planned status quo, with the Green Party (MP) proposing the most ambitious cuts.

Romania [24] used the EN-ROADS model to assess the impact of wind energy on the country's energy mix and sustainable development initiative. Their work showed that investment in wind energy is vital but must be complemented with investment in other renewable energy sources for the country to achieve its sustainable development goals.

4. Evaluating and Comparing Climate Models

Models can help us understand climate change phenomena, and valuable models are constantly being adjusted and validated. Modelers consider climate models in a variety of ways. The most common technique has always been to compare model results to observed climatological measures. Another option is adjusting parameters (such as greenhouse gas concentrations or continental locations) to determine how well the model reproduces known past climate conditions and zones that differ significantly from the current climate. Parameters are adjusted to reflect temporary increases in greenhouse gases and significant volcanic eruptions [25].

After establishing the Intergovernmental Panel on Climate Change (IPCC) in 1988, modelers introduced a series of model validation exercises. The Lawrence Livermore National Laboratory initiated the atmospheric model intercomparison project (AMIP) in 1989. AMIP required each modeling group to run the model with a specific set of "constraints" or parameters to provide a particular set of output variables in a standard format. Modelers identified biases and diagnosed their reasons by comparing model results and observed data. This task was difficult for models with hundreds or thousands of parameters [25].

Because model validation is essential, the Climate Model Diagnostics and Comparisons (PCMDI) program was established by the US Department of Energy to provide a systematic and comprehensive assessment of climate models. The World Climate Research Program (WCRP) group, which includes climate science underpinning the United Nations Framework Convention on Climate Change, also launched the Coupled Model Intercomparison Project (CMIP). Since CMIP's inception, there has been a concerted effort to make model comparison data available to scientists other than those running the models. They evaluate model performance over historical periods and quantify propagation sources in future forecasts. The main goal of CMIP is to publish multi-model output in a standardized format.

5. Significance/Scientific Merits: Model Validation and Evaluation

There is a need to validate any energy system model before use to see if the results correlate with history and if future results meet reasonable standards. According to [26], "Models are representations, useful for guiding further study but not susceptible to proof." Any energy model realizes that a model is a tool that simplifies problems allowing greater confidence in decision-making. Validation of energy system models has been in question from the first use of models, even before they became widespread in the early 2000s. In 1979 [27] and again in 1980, the National Bureau of Standards held symposiums to discuss the validation and assessment of energy models. The meetings were multi-day functions that covered everything from validation methods for any energy model to reviewing new models developed by scientists within the organization. The works [28] are essential to share due to their questions about model use for long-term predictions; they identified eight factors that must be addressed to develop large-scale modeling. The eight factors are as follows: social science models tend to have empirical factors that cannot be determined, making future predictions hard to validate; most statistical methods used for validation are based on past results assuming that the past and future will correspond; there is little agreement on what it means to predict the future, measurements of present work sometimes are not accurately making future results inaccurate, complex models are challenging to validate especially policy models, validation must be considered with the specific model, and what it is designed to do, models used to help decision making within policies should be validated differently than scientific models, and incorrect validation techniques can unfairly discredit models that have relevant results. When using any energy system model, these factors should be at the forefront of any engineer's mind. An energy system model would be incomplete without asking appropriate questions and not validating a model with adverse types of questioning. These sentiments of ensuring model validity have continued into the present, with researchers focusing on the need for certainty of the results from models and creating necessary adjustments for the future to be helpful for continued application (Pfenninger et al., 2014). Researchers from the Netherlands at the University of Groningen also echo the messages from 1970 to the present in their study of 19 used energy system models, stating the difficulties in modeling social behavior and other similar challenges [31].

Following the works of validation presented by John D. Sterman, he offers a table of questions that modelers should ask but not while building models; these questions are shown in Table 1(a) and Table 1(b). They represent ideas that any energy engineer should understand before using results from a developed model. Any modeler needs to take the time to ask the questions raised in the tables to ensure that the model they are using suits their purpose; yes, it might take some time to answer all the questions. Still, it is imperative to know whether the model will provide an appropriate response for energy systems, especially when an energy system can cover over 100 years, such as hydro or nuclear projects.

While the validation techniques presented in John Sterman's book Business Dynamics were created for building models using system dynamics, the methods used for model testing apply to any model, including the models developed for energy systems. As with any complex issue, some variables of modeling energy systems do not have mathematical equations attached to them. As environmental concerns and policy changes become more critical to an energy system, the question of how these concerns should affect the numerical results of models is presented. This paper is written not to provide answers to those questions. Still, by considering these questions as an energy engineer, better models can be created and used to influence energy system modeling. Once an engineer decides to use a model, multiple techniques can be used to test the energy system model. The types of tests in Table 2(a) and Table 2(b) here are not the only tests available to engineers, but it is an excellent places to start to ensure a suitable model.

Table 1(a). Questions model users should ask but do not [32]

Purpose, Suitability, and Boundary • What is the purpose of the model? • Have you identified the model boundary? Is the problem significant for coping endogenously? What essential variables and issues are exogenous or excluded? Are important variables excluded because there is no numerical data to quantify them? • What is the time horizon relevant to the problem? Does the model include the factors that may change significantly over time as endogenous elements? • Is the level of aggregation consistent with the purpose?
Physical and Decision-Making Structure • Does the model conform to basic physical laws such as the conservation of matter? Are all equations dimensionally consistent without fudge factors? • Is the stock and flow structure explicit and consistent with the model purpose? • Does the model represent disequilibrium dynamics or assume the system is always in or near equilibrium? • Are appropriate time delays, constraints, and bottlenecks considered? • Are people assumed to act rationally and optimize their performance? Does the model account for cognitive limitations, organizational realities, noneconomic motives, and political factors? • Are simulated decisions based on information the real decision-makers have? Does the model account for data flow delays, distortions, and noise?
Robustness and Sensitivity to Alternative Assumptions • Is the model robust in the face of extreme variations in input conditions or policies? • Are the policy recommendations sensitive to plausible variations in assumptions, including assumptions about parameters, aggregation, and model boundary?

Table 1(b). Questions model users should ask but do not [32]

Pragmatics and Politics of Model Use

- Is the model documented? Is the documentation publicly available? Can you run the model on your own computer?
- What data types were used to develop and test the model (e.g., aggregate statistics collected by third parties, primary data sources, observation and field-based qualitative data, archival materials, and interviews)?
- How do the modelers describe the process they use to test and build confidence in their model? Did critics and independent third parties review the model?
- Are the results of the model reproducible? Are the results "add-factored" or otherwise fudged by the modeler?
- How much does it cost to run the model? Does the budget permit adequate sensitivity testing?
- How long does it take to revise and update the model?
- Is the model being operated by its designers or by third parties?
- What are the modelers' and clients' biases, ideologies, and political agendas? How might these biases affect the results, both deliberately and inadvertently?

Table 2 (a). Energy system models validation tests

Validation Test	**Description**
Boundary Assessment	Identifying the boundary of a model can be qualitative or quantitative. Looking at the scope of what the model looks like allows engineers to determine if it will meet its needs. The qualitative boundary inspection could be whether the model considers decisions made by people, non-quantitative environmental concerns, or rules changing due to policy over time. The quantitative boundary inspection could ensure different variables in the model are not omitted or considered infinite, such as fuel resources or constant water supplies from the rain in a region. Researchers have seen that as a model's boundaries grow, the model will become more complex, and result accuracy becomes more dependent on historical data [33].
Unit Consistency	For most energy models, there is heavy use in quantitative modeling. With the difficulties in working with significant algebraic expressions, ensuring that units of conversions are inspected is necessary so no fundamental error is created. This should be one of the first tests done on any model.
Variable Analysis	Variable analysis entails checking the individual parameters of models to ensure that they affect the model as they are expected to. For example, changing the fuel amount of a natural gas power plant to zero should make power output go to zero for the given period. Another example is adjusting the period of a project without changing other parameters; will the results be the same, or will the model produce different results?
Shock Testing	Shock testing involves adjusting parameters to normal outside operations of the model. Models should be able to react to abnormal parameters correctly. For example, negative input fuel amounts into a natural gas power plant model; will the model's results respond correctly to the odd inputs?
Model Archaeology	Due to some models taking decades to develop, researchers Paul E. Dodds, Ilkka Keppo, and Neil Strachan have proposed a novel method of inspecting energy system models. Reviewing changes in energy system model versions allows engineers to see the differences between the model and its output to evaluate whether the model produces reliable results. The research presented by (Dodds et al., 2015) uses this technique on the UK MARKAL model, highlighting the validation method and how this tool can be used for other energy models.

Table 2(b). Energy system models validation tests

Validation Test	**Description**
Reproduction	Reproduction testing is a straightforward test. Can a different entity reproduce the same results following the methods used to produce the actual outcome? Robbie Morrison suggests that allowing others to see a model not only allows scientific testing validation of the model but builds public trust in the results within an energy model [35].
Assumption Checking	Assumptions can be detrimental to the results of energy system models. Understanding what is assumed within a model is imperative for adequately analyzing results. If too many inputs are assumptions such as economic factors, model results could vary drastically from natural energy systems. Researchers at NREL studied assumptions made in their renewable energy integration reports and found by changing assumptions; results could vary by up to 20% in some of their models [36]
Scenario Analysis	Scenario analysis uses past data to test a model with known results. If models cannot recreate known effects, then adjustments must be made. Energy Strategy Reviews has recommended using a three-part framework when performing scenario analysis, starting with a qualitative outline, then quantitative metrics, and finally, evaluation criteria [37]. An MIT researcher Sergey Paltsev has indicated there are benefits to scenario analysis and models built using known data. Still, he does caution that models do not provide exact solutions to specific problems, only suggestions [38].
Comparative Analysis	With the hundreds of available energy models, comparative analysis can be performed on most energy systems. Comparative analysis is when two energy system models are used with the same input data, and results are compared between the different models. This method allows for judgments to be used in deciding factors of energy systems. Comparison analysis can take a long time due to ensuring the correlation of input data to the models used. Researchers have reviewed Comparative analysis and shown that it leads to more robust and reliability of models [39].
Empirical Validation	Depending on the model boundary, it may be possible to validate a model using actual results from an energy system. Using live data from a constructed energy system, an energy model can have high accuracy percentages in future predictions. Smaller energy models, such as those for buildings or factories, continue improving based on empirical analysis [40]. For smaller energy models using empirical data, the National Renewable Energy Laboratory (NREL) has various levels of empirical validation based on errors [41]. As an energy system grows in complexity, it becomes less likely full empirical validation will be possible.

Along with the validation techniques presented in Table 2(a) and Table 2(b), many engineers have proposed frameworks and rating systems for energy system models that can be used to analyze and critique an energy system model before use; those engineering tools can be viewed in their work (Khan et al., 2017; Niet et al., 2022). An energy engineer must test the models before using them for results. Using the techniques shown and questioning a model before use makes it possible to catch calculation mistakes that could hinder future energy projects. For example, using validation techniques, researchers found 58 different energy system articles and models with errors within their findings [44]. Issues within energy models are to be expected, and it is a good thing that problems can be found. When issues are found within models, an opportunity is created; the model's creators can improve the model to produce more accurate and reliable results. Without researchers searching for faults within energy models, impressive results from large projects would not be available. When using models, it is never good for engineers to have blind trust that the results are what would happen if a system were put in place that matched the energy model.

6. ASHRAE and IPMVP Standards of Measurements

With the growth of models within engineering, there have been standards set that engineers can use to validate energy system model's inputs before use. The validation rules reviewed are the American Society of Heating, Refrigeration, and Air Conditioning Engineers (ASHRAE) Guideline 14-2014 and the International Performance Measurement and Verification Protocol (IPMVP). These two standards have been accepted by the Federal Energy Management Program of the US department of energy for their use in measurement and verification [45]. These guidelines are helping the energy industry record the pertinent data needed for modelers to have a reliable data source in energy system models, which allows the results and future predictions of models. Organizations such as ASHRAE have also recognized the importance of modeling within the global economy and offer professional development courses on how to build, evaluate and use energy models [46]. These courses help advance energy modeling by providing the most appropriate and acceptable methods to use energy models.

ASHRAE states that the document aims to "provide guidelines for reliably measuring the energy, demand, and water savings achieved in conservation projects [47]". ASHRAE guidelines fulfill this purpose with details providing the basis needed for any model of an energy system. By using the ASHRAE guidelines to inspect independent variables within an energy model, engineers can determine the validity of a model's results and determine if any critical factors of a model are missing. The guidelines offer specific approaches to energy models that follow the IPMVP outlines of whole building models, retrofit isolation, modeling, and simulations [47]. The guideline gives engineers a straightforward measurement information source to evaluate an energy system model. The IPMVP started in the early 1990s as a high-level review of best practices within the energy sector to measure performance levels. This document was created by National Renewable Energy Laboratories (NREL) researchers. The IPMVP is a similar document to the ASHRAE guidelines, even influencing the ASHRAE guideline on methods of measurement and validation on energy projects. The IPMVP focuses on measuring energy projects and efficiency on a larger scale than the ASHRAE guidelines. A handy tool for modelers in the IPMVP is the chapters on common issues with evaluation, verification, and measurement procedures [48]. The problems will allow modelers to examine energy system models for common mistakes to ensure validity before use. The IPMVP standard has become globally accepted as a trusted standard that companies will advertise that their energy system models comply with their usual [49]. The standards of measurements delivered by both ASHRAE and the IPMVP ensure energy system models use trusted measurement methods, allowing energy engineers to create or use models and their results accurately. While the standards of measures are not a validation test that can be used on all models, it is another indicator of trustworthy modeling when it can be used.

7. Evaluation Methods of En-ROADS and TIMES

A comparative analysis will be performed on two leading global energy system models to demonstrate validation tools and how to use them. Comparative analysis, as discussed in Table 2(a) and Table 2(b)**,** is when multiple energy system models take the same input data to review differences in results and then find improved methods for the models. The EN-ROADS global climate simulation and the TIMES (The Integrated MARKAL-EFOM System) models were chosen to be analyzed. These two models were chosen based on their high use in energy system modeling analysis globally, with hundreds of papers using the models available for review. The amount of data on the two energy system models allows for a thorough examination and a fitting example of how energy engineers can approach using an energy model for their desired applications. While not every validation and verification technique is used on both models, and it is not recommended to perform every method possible on one energy model, this process of verification of models should be performed before engineers begin trusting any energy system model.

EN-ROADS is a system dynamic-based model worked on since the 1990s as a partnership of many groups, including MIT, Ventana Systems, and Climate Interactive. System dynamic models have been shown to produce reliable unexpected behavior from human behaviors such as policy choices and other large-scale systems interactions (Eker et al., 2017; Bernardo & D'Alessandro, 2019; McGookin et al., 2021). The transparency that the creators of EN-ROADS have with users has been a critical development point for the model. The data available to review from the developers can begin with a historical review or "archeological review," as suggested in Table 2(a) and Table 2(b)**.** The input data for EN-ROADS can be examined thoroughly on their website, listing sources for data and techniques used for the statistical fit of input data [21]. The historical data for EN-ROADS is updated regularly so that the newest information can help enhance the future projections of the model. Once a review of previous data and history is completed, the model can be reviewed with the extensive reference guide provided by EN-ROADS. The guide covers model structures, formulations, and measurements for all topics addressed within the model [21]. The guide is a needed resource for an engineer to review the model's boundaries and assumptions to ensure the model will fit the engineer's needs.

The TIMES energy model is a newer, early 2000s model to the MARKAL energy model, which has progressed since the late 1970s. The TIMES model has been globally accepted for its transparency in model structure and its public access. Government agencies of large nations have used the model to develop their models with additional data inputs specific to their region; these regions include the United States of America, Scotland of the United Kingdom, South Africa, and Brazil (EPA, 2022; Tomaschek, 2014, Tomaschek et al., 2016 & Dodds, 2021). TIMES's massive adaptation makes it a considerable resource among energy modeling academics worldwide. The TIMES model follows EN-ROADS in providing documentation [18]. The TIMES model provides the energy system structure, formulations, and assumptions. The user guide for TIMES also goes through step-by-step processes on making a running simulation with available demo energy models.

8. TIMES and En-ROADS Analysis 2.5-degree Celsius Case

Evaluation of whether a two degrees Celsius warming is achievable under high uncertainty, analysis with the TIMES model. The approach of this study was to use the TIMES model to evaluate the effect of the climate sensitivity parameter and to look at hedging strategies to maintain a global temperature increase to 2.5 degrees C. The concept behind the hedging strategies is that actions are taken before 2040 that will hopefully help prevent temperature increases above the target without knowing the likely climate sensitivity parameter. The metric to evaluate the outcome is the cost of implementing the hedging strategy compared to the base case without a temperature target. A perfect forecast approach is used where it is assumed that the climate sensitivity parameter is known at the start of the simulation and that various actions are taken to achieve the temperature targets.

For this comparison, we only focus on the results that the study identified as of particular interest and that fit within the range of capability of EN-ROADS. The following range of parameters of the presented cases will be used to replicate these results in EN-ROADS.

8.1. Base Cases

This analysis shows what changes to the energy system are needed to meet a 2.5 degrees C temperature target by 2200, which implies that the base case will be above the target. In the base case scenarios where no climate target is imposed but differing assumptions around the climate sensitivity parameter are used, the TIMES approach determines a warming of between 2.7 and 3.6 degrees C by 2200. It provides a trajectory for achieving that temperature.

8.2. Results 2.5-degree Celsius Case

Using the business-as-usual scenario in EN-ROADS with matched climate sensitivity parameters, there is a significant difference between the temperatures at the start and the trajectories of the temperature increase until 2100. The available version of EN-ROADS stops its simulation at 2100, but the differences in both models by that point are straightforward and can be seen in Figure 3.

An additional comparison of the different scenarios' atmosphere carbon dioxide equivalent concentration. Using the base case scenario again, this time with just one climate sensitivity was reported as 558 ppm by 2090. EN-ROADS with a similar climate sensitivity will result in 652 ppm by 2090. When plotted over time, as seen in Figure 4, there is a clear difference between the shapes of the curves. The EN-ROADS concentration has a distinct exponentially increasing concentration of CO_2 compared with the linear increase seen in the TIME's concentration.

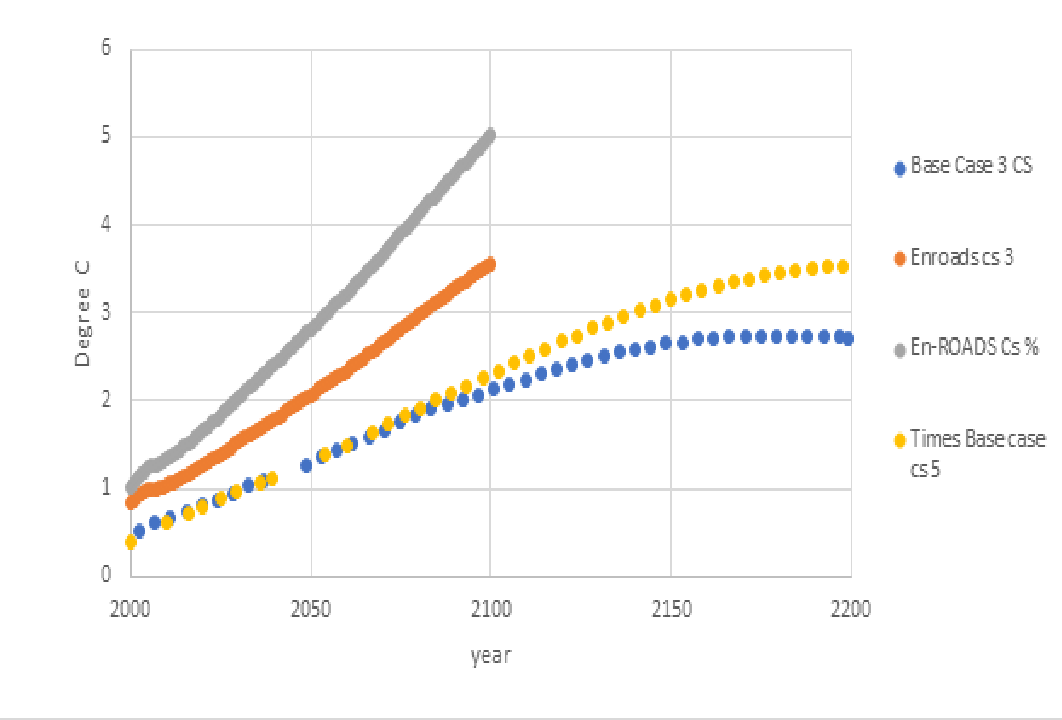

Figure 3. Business-as-usual scenario results between EN-ROADS and TIMES

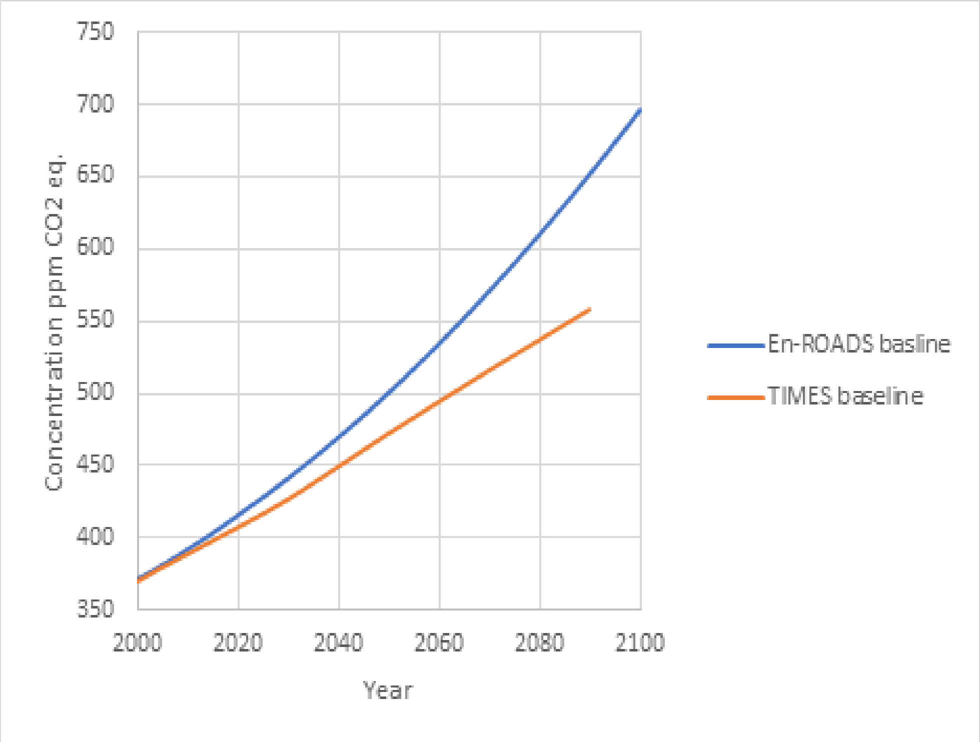

Figure 4. Atmosphere carbon dioxide equivalent concentration

Table 3. Assumptions for the perfect forecast (PF) case parameters (5-degree C)

Parameter	**2015**	**2030**	**2050**	**2070**	**2090**	**Remarks**
GHG $/ton	2	4	12	43	86	CO_2 eq
CCS %	0	0	1.1	6.6	10.9	Contribution to total GHG reduction
Afforestation %	65	43	29	26	20	Contribution to total GHG reduction
Coal EJ/year	170	90	50	30	80	
Oil and gas EJ/year	180	340	560	390	290	
Nuclear EJ/year	100	110	200	730	1280	
Hydro EJ/year	100	150	300	390	440	
Biomass EJ/year	0	0	10	10	10	
Renewables EJ/year	0	0	10	10	20	
Total EJ/year	560	700	1140	1550	2140	

Table 4. Assumptions for the perfect forecast EN-ROADS parameters (5-degree C)

Parameter	**2015**	**2030**	**2050**	**2070**	**2090**	**Remarks**
GHG $/ton	0	2.75	10.6	42.8	80.1	CO_2 eq
CCS %	0%	55%	35%	35%	45%	Contribution to total GHG reduction
Afforestation %	0%	24%	53%	56%	46%	Contribution to total GHG reduction
Coal EJ/year	157	174	134	101	83.5	
Oil and gas EJ/year	305	354	373	364	350	
Nuclear EJ/year	11.2	14	68.5	178	228	
Hydro EJ/year	0	1.44	64.7	93.2	125	
Biomass EJ/year	56.8	62.4	60.7	59.9	60.5	
Renewables EJ/year	19.2	42	46.6	60.1	88.6	
Total EJ/year	548	647	747	856	936	

8.3. Results 2.5-degree Celsius Target Case

Of the provided cases, the perfect forecast case is used for comparison with EN-ROADS. The chosen case is the 5-degree C climate sensitivity to achieve 2.5 degrees C. The key inputs to the EN-ROADS model from the study are the greenhouse gas pricing, carbon sequestration ratios, and the energy supply mix moving towards 2100. Table 3 depicts the range of assumptions that are desired to be met for the perfect forecast case and the EN-ROADS parameters developed. As shown in Table 4, the EN-ROADS case does not meet the targeted 2.5 degrees C by 2100.

8.4. Results of 2.5C Case

The differences between the TIMES and EN-ROADS results for the base case and the perfect forecast case are significant. There are some limitations in comparison, as EN-ROADS cannot match all the scenarios. Still, comparing the conditions of the base case scenario shows why there would still be no alignment even with a matched set of parameters in the perfect forecast. The base case has a lower temperature starting point than EN-ROADS and a different mode of behavior of the CO_2 concentration. The combination of these, even when including the reductions in emission-producing energy generation as shown with the perfect forecast and EN-ROADS case, will not result in an agreement.

The EN-ROADS case does not meet the targeted 2.5 degrees C by 2100 but is 4.5 C by 2100, which is a significant deviation. As with the base case, the major differences are the amount of nuclear power, hydropower, and renewables. The base case energy production breakdown in both models shows several significant differences. Specifically, the differences are mainly in the expected nuclear and biomass growth shown between Figure 5 and Figure 6. The assumptions of the rapid growth of nuclear power likely change oil and gas production and coal; those are the baseload power sources resulting in less oil and gas usage and less coal consumption. That likely leads to the differences in CO_2 concentration and, thus, temperature increase in the outcomes.

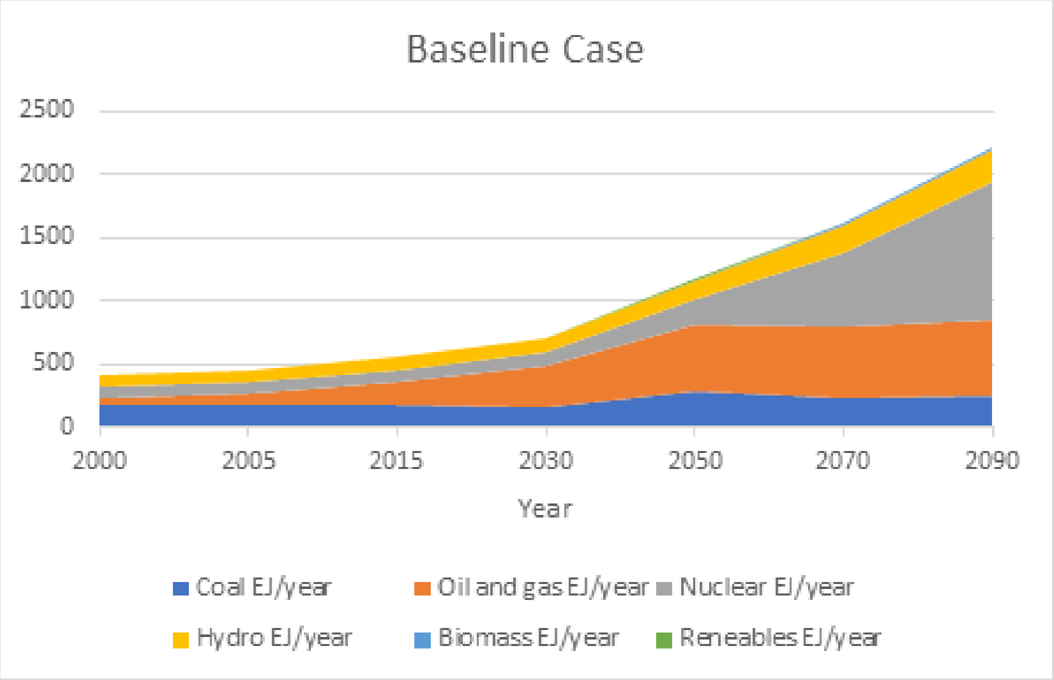

Figure 5. Baseline case energy output/year

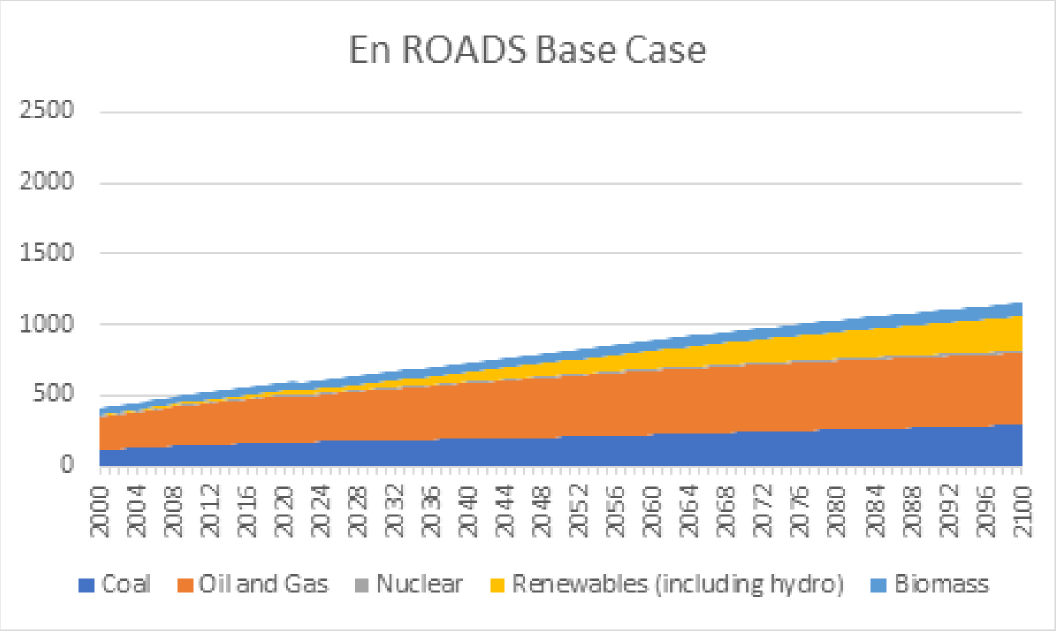

Figure 6. EN-ROADS base case energy output/year

9. Methodology: Global Energy Supply: Model-based Scenario Analysis of Resource Use and Energy Trade

This Analysis (Remme et al., 2007) aims to evaluate the long-term supply of fossil fuels relative to reserves and uses. Several cases are used to assess the energy supply under different scenarios and how that will alter the oil, gas, and coal trades until 2090. Understanding how the global energy system will change is essential to evaluate how various fossil fuel trade changes occur. This study concludes that CO_2 capture must be increased to keep coal as a viable option by implementing policies intended to protect the climate. The volume of the global coal trade will depend heavily on climate policies [57]. For natural gas, unconventional sources increase in popularity as there are more CO_2 emissions targets, likely due to replacing coal sources. The oil trade is not strongly influenced by CO_2 emissions targets [57]; this may be because transportation will still rely heavily on oil soon.

9.1. Base Case

The base case is aligned with the IPCC A2 scenario, a higher-end emission scenario where the global surface temperature increase from 2000 is about 3.6 degrees C by 2100 [58]. Some other aspects of the base case are a global GDP of \$235 by 2100 in the year 2000 USD and a population of 9.8 billion by 2100 [57]. Another assumption of the base case is increased use of nuclear after 2040 and everyday use of renewables, with coal and gas being the critical energy supplies.

Using the baseline case from EN-ROADS as a comparison with the BAS, there are some similarities and differences. The similarities are in which energy sources are the primary sources globally. In the BAS and EN-ROADS, coal, oil, and gas are much of the direct energy supply, with the remaining smaller fraction being nuclear, biomass, and others. The difference between the two cases is severalfold. First, the total magnitude of the primary energy supply in the BAS case is about 1800 EJ/year in 2090 versus EN-ROADS, where just under 1200 EJ/year are needed by 2100. Second, the amount of nuclear power assumed in BAS is much higher than in EN-ROADS, where very minimal growth of nuclear is expected. Finally, the growth shape differs where EN-ROADS takes a slowing growth rate in the primary energy supply, whereas the BAS case has an exponentially increasing direct energy supply. Both scenarios start at similar levels, but whatever aspects of the TIMES model that drove the exponential growth of energy supply likely caused the difference in total energy supply between the two models over time; these changes can be seen clearly in Figure 7 and Figure 8.

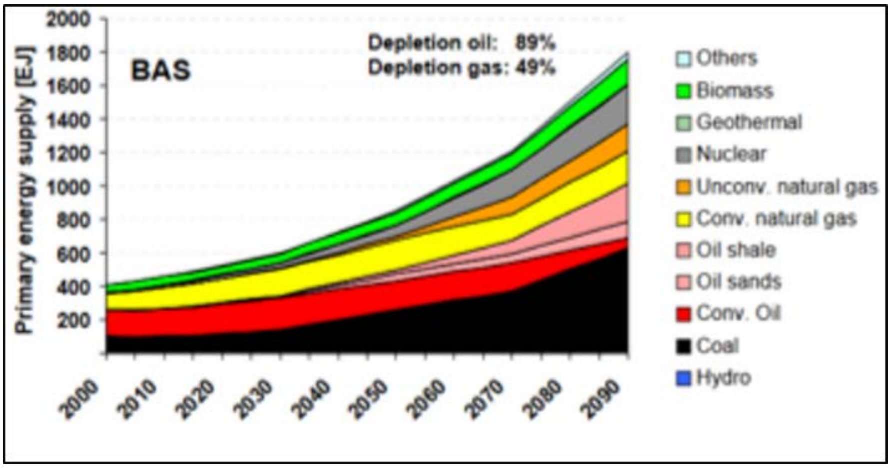

Figure 7. Base Case Energy supply [57]

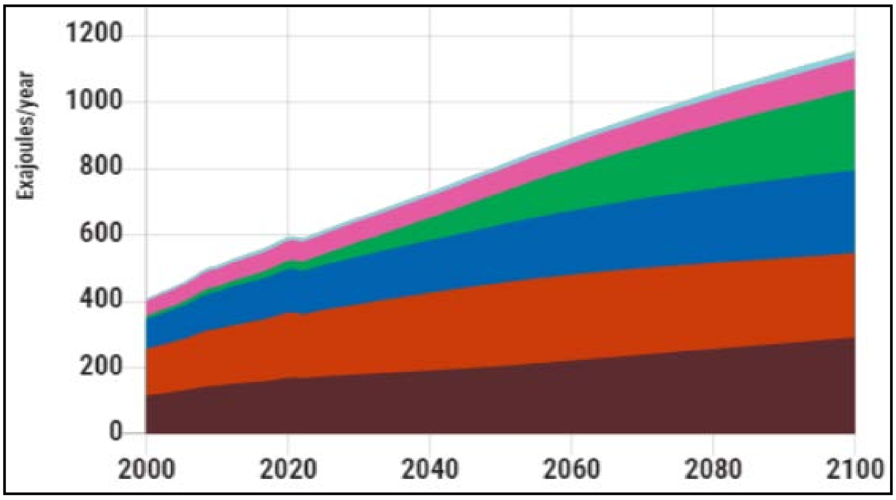

Figure 8. *Base Case EN-ROADS* [21]

10. Results from Global Energy Supply, CO_2 Case

The CO_2 mitigation case aims to reduce global annual CO_2 emissions to 18 gigatons CO_2 by 2090, corresponding to an atmospheric concertation of 550 ppm in 2090. The model develops the specifics of how this is met.

For the CO_2 Scenario, some policy choices are needed in EN-ROADS to meet the target of 18 gigatons of CO_2 emitted per year. Based on the CO_2 scenario presented in the study, the significant changes from the baseline scenario are a reduction in coal and an increase in biomass and other energy sources. There is also an overall reduction in energy production to about 1600 EJ/year [57]. Attempting to model a similar set of choices in EN-ROADS does not result in the CO_2 reduction expected. A high tax on coal and a significant incentive on bioenergy result in the 200 EJ/year reduction in energy supplied. However, the gigatons of CO_2 per year decreased from 63 Gt/year to 53 Gt/year, respectively, not nearly down to the 18 Gt/year target. Part of the issue can be seen from the CO_2 emissions starting point where EN-ROADS assumes 32 gt/year was emitted in 2000; this study adopted 20 gt/year. That 12 gt/year difference would result in a CO_2 case as replicated in EN-ROADS of 41 gt/year, which is still more than double the target. The results of the added policy changes can be seen in Figure 9 and Figure 10.

To achieve the targets of the CO_2 case, even with the shift, a final CO_2 emissions level of 30 gt/year in EN-ROADS is required. It is maintaining the high coal tax and subsiding bioenergy. Further energy efficiency and electrification in transport and buildings/industry cannot be used to influence the energy supply, as shown in Figure 11. This causes a very different primary energy mix with much less energy generated overall, partly due to increased energy efficiency (see Figure 12).

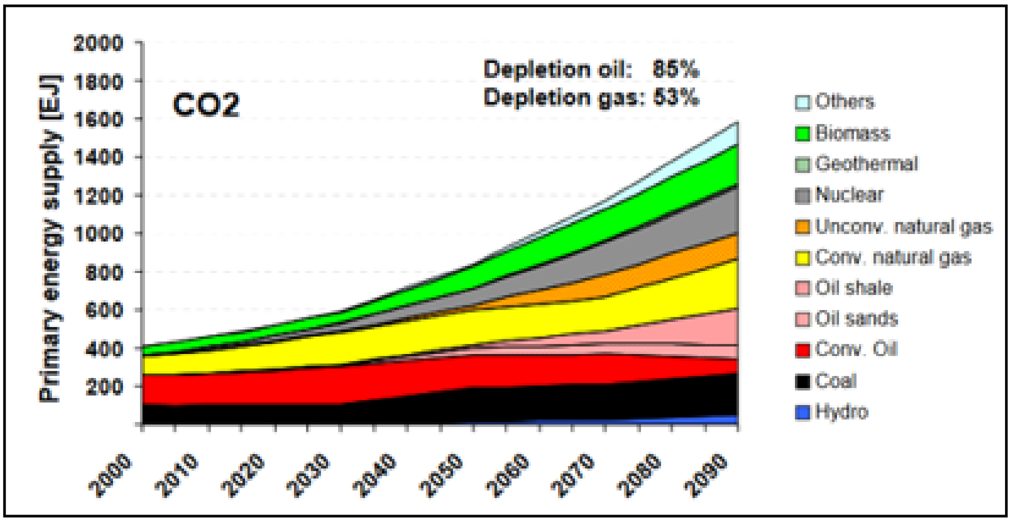

Figure 9. CO_2 Case Energy supply [57]

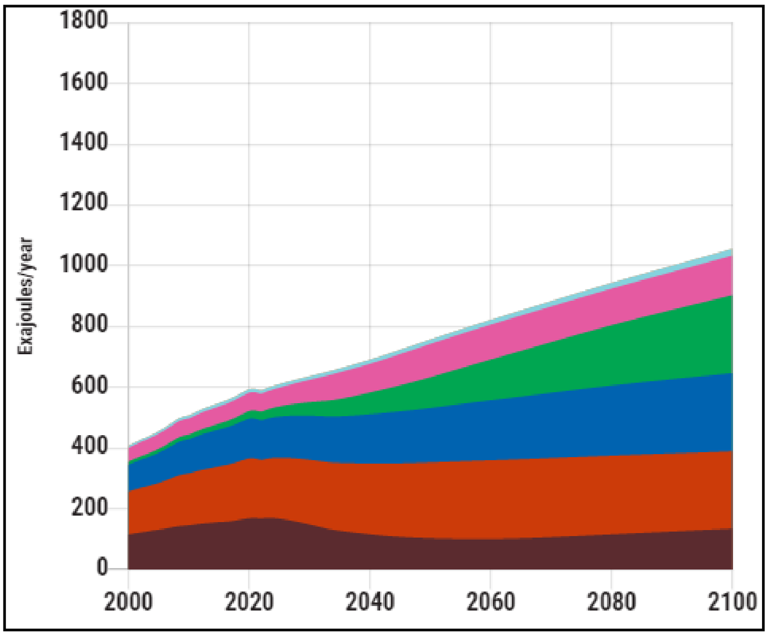

Figure 10. CO_2 Case in EN-ROADS Energy supply [21]

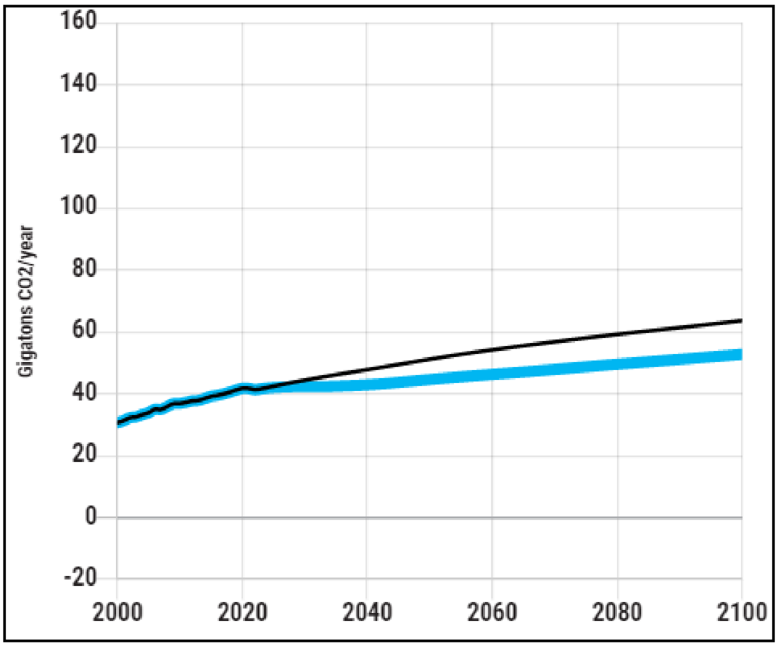

Figure 11. CO_2 Emissions with the CO_2 policies in EN-ROADS [21]

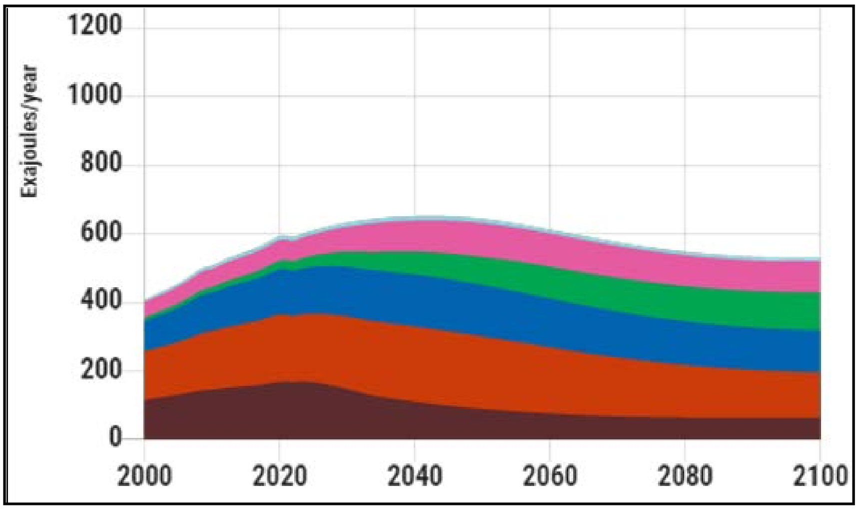

Figure 12. Attempt to Match CO_2 emissions from Study in EN-ROADS

This approach better matches the shape of the CO_2 emissions curve as provided in the study, shown in Figure 13, compared to Figure 14.

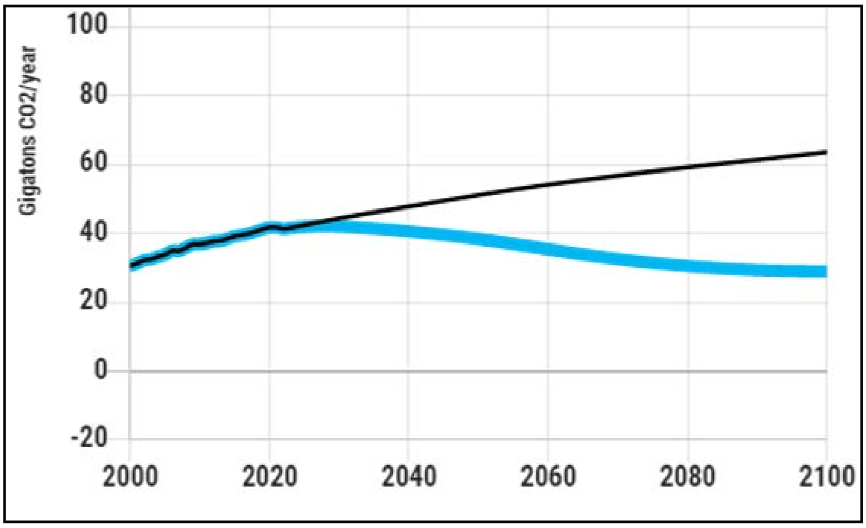

Figure 13. CO_2 emissions of the matched case

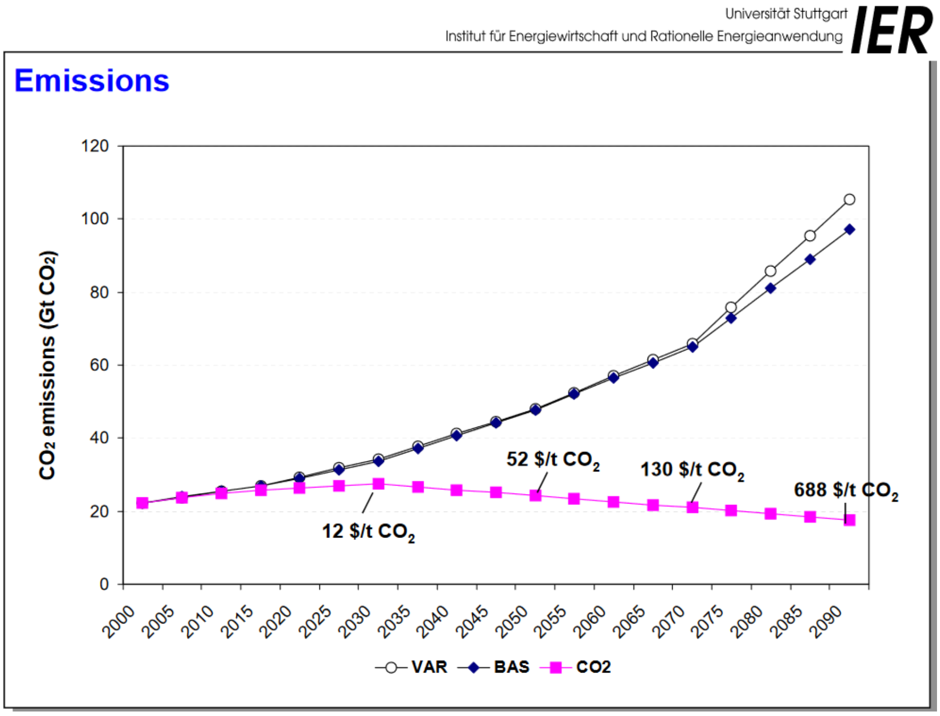

Figure 14. CO_2 emissions from the CO_2 Case from [57]

11. Results of Global Energy Supply Analysis

There are apparent differences between EN-ROADS and this study that result in a primary energy mix that is not aligned. This lack of alignment makes comparisons of the results challenging, but some areas can be compared. The shape of the CO_2 emissions curve to meet the policy target is similar for both models, although the magnitude of the change needed is different. Similarly, the changes to the primary energy supply are identical in some ways, but as with the CO_2 emissions, the magnitude of these changes and the assumed rate of energy production growth differ.

Global energy and emissions scenarios for effective climate change mitigation—Deterministic and stochastic cases with the TIAM model

This study examined the feasibility of achieving the EU 2 degree C target. A baseline scenario was developed to match the business-as-usual case [59]. The second case focused on an optimized energy system to achieve a 2-degree C warming target.

11.1. Baseline

The baseline case GDP growth is the driving factor for much of the energy consumption over the next 80 years, and a planned GDP growth rate for the world economy is assumed to be 3.8% from the year 2000 to the year 2020, 2.3% from 2020 to 2050, and 1.7 from 2050 to 2100. This can be compared with the EN-ROADS base case gross world product (GWP) growth, as shown in Table 5 (Syri et al., 2008).

EN-ROADS baseline case has a lower growth rate than planned in the study, but this can be adjusted to some extent, but the economic growth slider results in the following comparison in Table 6.

Table 5. GWP for both baseline cases of EN-ROADS and the study [21,59]

	GWP growth rate	
Year	ENROADS Baseline	Study Baseline
2000 to 2020	2.2	3.8
2020 to 2050	2.0	2.3
2050 to 2100	1.4	1.7

Table 6. Adjusted EN-ROADS GWP to get closer to Study [59]

	GWP growth rate	
Year	ENROADS - Matched Growth	Study
2000 to 2020	2.2	3.8
2020 to 2050	2.2	2.3
2050 to 2100	1.8	1.7

Based on the above growth rates of the GWP, the resulting CO_2 emissions from the energy supply with the base case economic assumptions were presented for the model. The result was a CO_2 emission level in pentagrams CO_2 equivalent to gigatons of about 60 gigatons of CO_2 from a starting point of 28 gigatons CO_2 emitted, as shown in Figure 15.

The baseline EN-ROADS results in a very similar CO_2 emission level of 63 gigatons emitted but with a higher GWP growth rate, including the CO_2 emissions increase to nearly 80 gigatons per year. The study reports that the atmospheric CO_2 concentration in the baseline scenarios would be 610 ppm which is lower than the EN-ROADS estimate of between 700 and 750 PPM, depending on the GDP growth. The lower atmospheric concentration, in part, drives the difference in the global temperature increase in both models. The Baseline scenario in the study estimates a 3-degree C rise, while EN-ROADS estimates a 3.7-degree C increase, as shown in Figure 16.

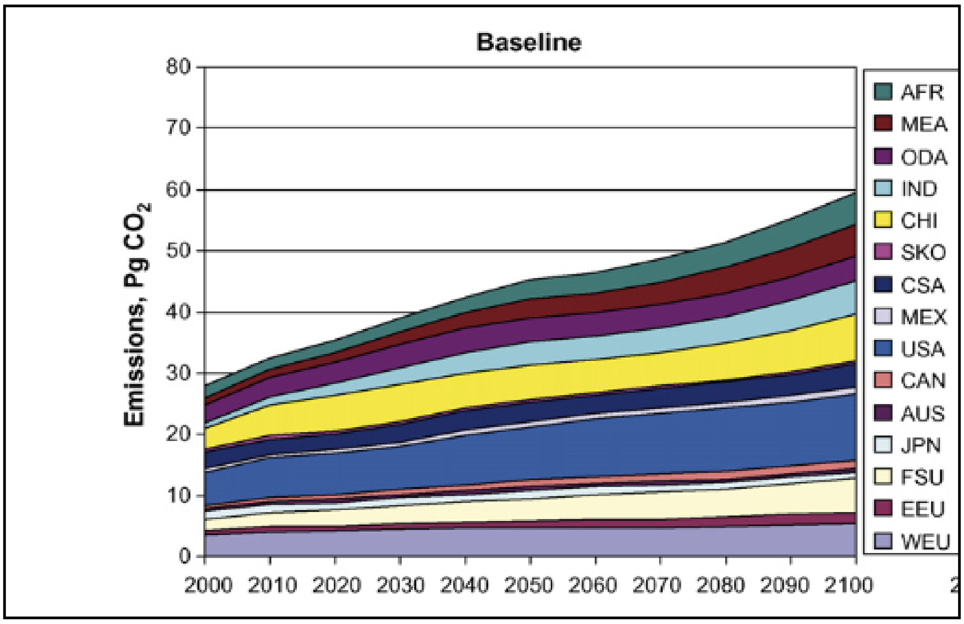

Figure 15. Study baseline emissions [59]

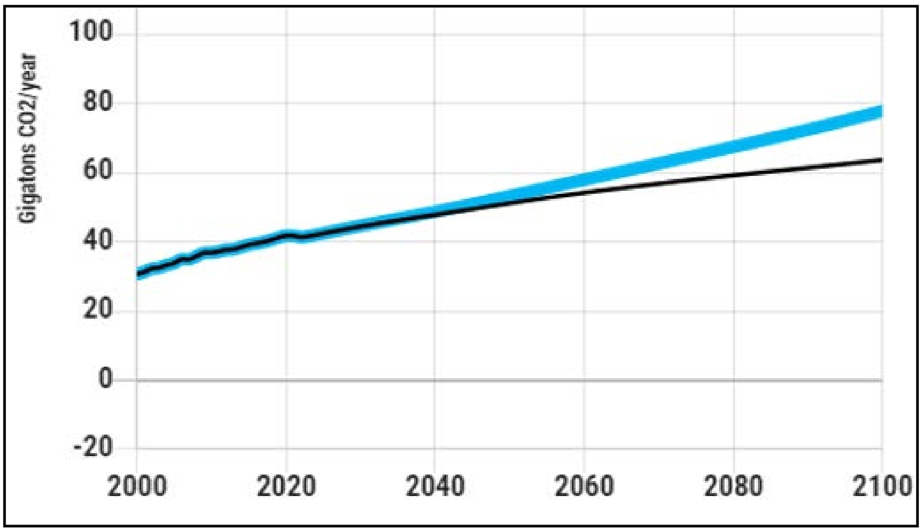

Figure 16. EN-ROADS CO_2 emissions for the adjusted GWP (blue) and baseline (black) [59]

The assumed limitations in Figure 17 on the global model's various energy resources control the optimization outcome.

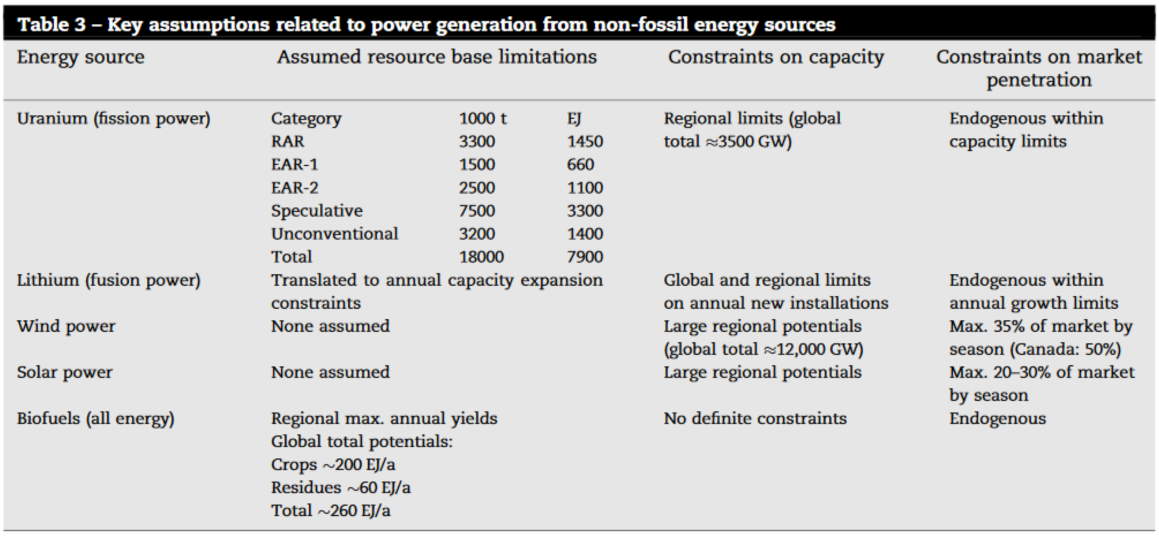

Table 3 – Key assumptions related to power generation from non-fossil energy sources

Energy source	Assumed resource base limitations			Constraints on capacity	Constraints on market penetration
Uranium (fission power)	Category	1000 t	EJ	Regional limits (global total ≈3500 GW)	Endogenous within capacity limits
	RAR	3300	1450		
	EAR-1	1500	660		
	EAR-2	2500	1100		
	Speculative	7500	3300		
	Unconventional	3200	1400		
	Total	18000	7900		
Lithium (fusion power)	Translated to annual capacity expansion constraints			Global and regional limits on annual new installations	Endogenous within annual growth limits
Wind power	None assumed			Large regional potentials (global total ≈12,000 GW)	Max. 35% of market by season (Canada: 50%)
Solar power	None assumed			Large regional potentials	Max. 20–30% of market by season
Biofuels (all energy)	Regional max. annual yields Global total potentials: Crops ~200 EJ/a Residues ~60 EJ/a Total ~260 EJ/a			No definite constraints	Endogenous

Figure 17. Limitations on resources used in the 2-degree C optimization [59]

12. Results of Climate Change Mitigation

The optimization, with these limits in place, was run to achieve a target of 2 degrees C increase by 2100 in the study. Some critical areas noted as changes from the baseline emissions were an 11.8 gigaton CO_2/year removal from carbon capture technologies in 2100 and an afforestation policy which reduced emissions by an additional 7.7 gigatons CO_2 in 2080. This can be replicated in EN-ROADS with high afforestation and technological carbon removal growth, resulting in about 20 gigatons of anthropogenic carbon removals, shown in Figure 18.

Another greenhouse gas emissions change noted in the 2 degrees C optimization was the reduction of methane emissions of 36% by the year 2100 as compared with the baseline. Additionally, N_2O emissions were decreased by 15% relative to the baseline in the same timeframe [59]. Using EN-ROADS, a similar amount of methane can be reduced with methane reduction policies, resulting in a 20% reduction of N_2O emissions on an equivalent scale to the study [21].

Now looking at the evolution of the global electricity supply for electricity generation can be compared to EN-ROADS as long as it is assumed that most Oil consumption is used for transportation, not electricity generation. The total electric generation is about 84 PWh/year, about 302 EJ/year of electricity production. The mix is heavily dominated by nuclear, hydro, and wind power, with other small sources and fossil fuels remaining below about 72 EJ/year, or 20 PWh/year, over the next 80 years. EN-ROADS, with a similar set of energy sources, has about 10 P PWh/year of these fuel sources, including carbon capture and storage. One of the main differences between EN-ROADS and the study is the amount of nuclear power, which, even with maximum subsidies for nuclear, remains a small fraction in EN-ROADS, as seen in Figure 19.

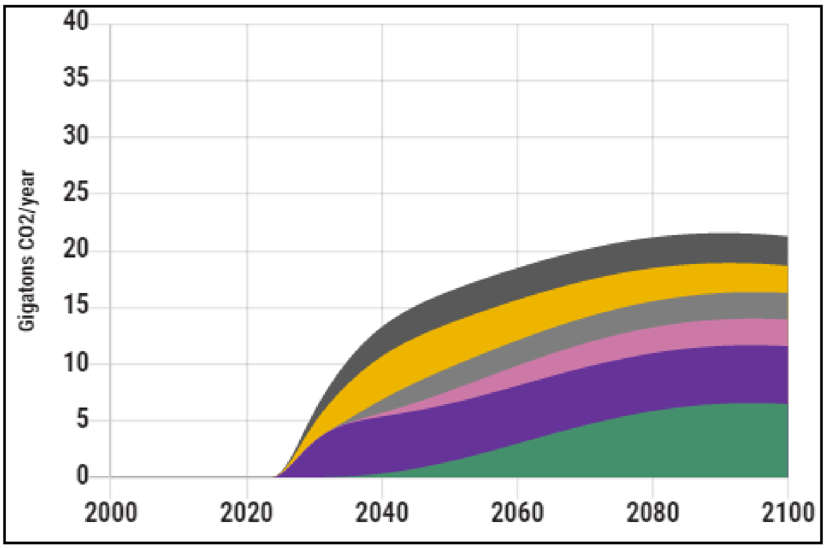

Figure 18. EN-ROADS anthropogenic carbon removal, green is afforestation, and the remainder is technological removal [21]

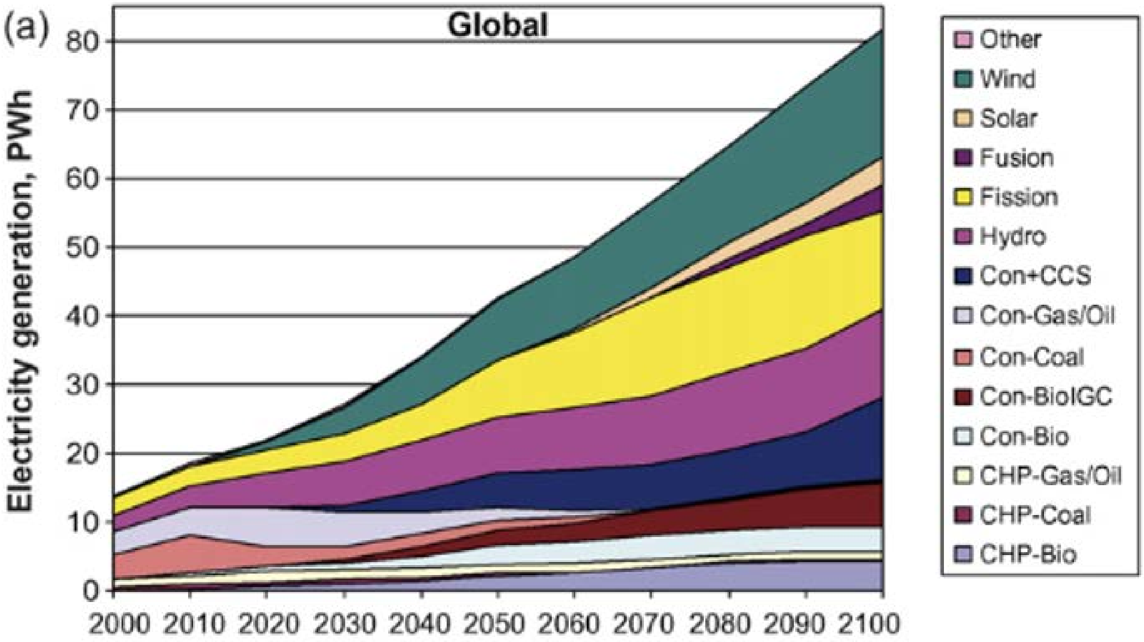

Figure 19. 2 degree C global energy supply [59]

This energy mix and the previously mentioned carbon capture and other greenhouse gas reduction results in a CO_2 emission trend that is similar for both models. There is a difference in the order of magnitude and where the emissions turn around to increase, but in general, the results of both models agree, as shown in Figure 20 and Figure 21.

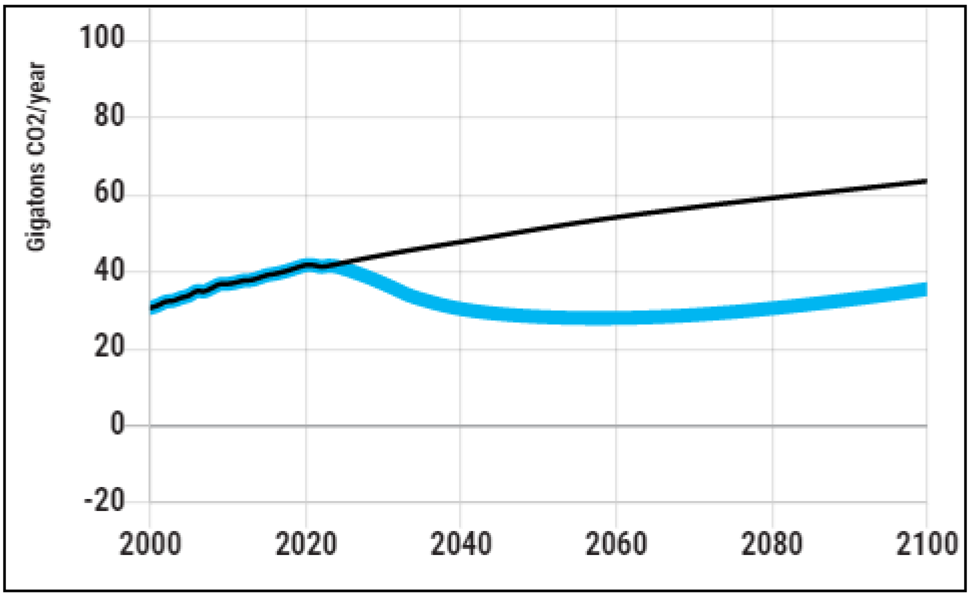

Figure 20. EN-ROADS CO_2 Emissions for a matched 2 Degree C Case [21]

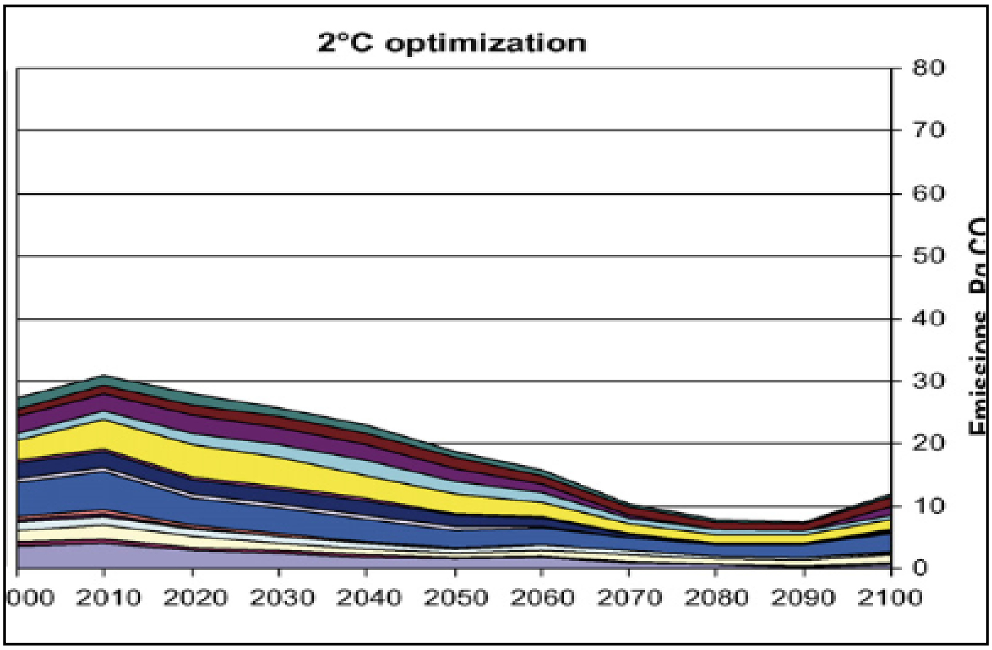

Figure 21. CO2 emissions from 2 degrees C case [59]

Table 7. CO_2 emissions for different climate sensitivity parameters

	GT CO_2/year in 2100	
Climate Sensitivity	(Syri et al., 2008)	EN-ROADS
1.5 C	57	Lower than Min
2 C	Not studied	72.5
3 C	15	35.6
4.5 C	Target not met	8.6
5 C	Not studied	2.5
6 C	Target not met	Higher than max
3 C (deterministic)	12	35.6

Another variable examined in the study was the climate sensitivity parameter relative to the 2 C scenarios and its impact on global CO_2 emissions. In this case, as the climate sensitivity parameter changes, various sliders in EN-ROADS will have to be increased or decreased to maintain the 2 C target, as shown in Table 7. The previous scenario, which met the 2-degree C target, was run using a climate sensitivity parameter of 3 C.

13. Conclusion

This literature review analyzed the new energy system modeling and validation techniques advances. A study of validation techniques was presented, and new novel validation techniques, such as model archeology, were discussed. After validation techniques that energy modelers can use were reviewed, a demonstration of the comparative analysis was completed on three different energy scenarios. The results of the comparative analysis are discussed below.

There are apparent differences between the outcome of the TIMES model and EN-ROADS. In the various analysis, two areas stick out. One is the difference in how CO_2 concentration and global temperature are related, which is a complex interaction and makes some sense as an area where there may be disagreement. Another is the global CO_2 concentration, which also has the potential for errors due to the complex nature of the carbon cycle [60]. Finally, another area of difference is the energy supply's growth rate, where the TIMES models are often more exponential than EN-ROADS. These differences make for some challenging comparisons but also help to identify areas of focus that may be worth investigating to understand what is driving the differences.

Our case study results demonstrated the importance of validating and benchmarking models before making critical decisions. The results of the EN-ROADS model gave higher temperatures and concentrations of CO_2, meaning investment decisions such as carbon sequestration could be over-capitalized. TIMES model results showed lower temperatures and CO_2 concentrations. This means that climate protection investments based on the results of this model may not be appropriate and adequate.

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