HEC MONTRÉAL

Implementing endogenous technological learning in AD-MERGE 2.0: a comparison of two approaches

par

Maya Otomo-Lauzon

Olivier Bahn

HEC Montréal

Directeur de recherche

Sciences de la gestion

(Spécialisation Science des données et analytique d'affaires)

Mémoire présenté en vue de l'obtention

du grade de maîtrise ès sciences en gestion

(M. Sc.)

April 2024

Résumé

La transition énergétique vers des sources d’énergie renouvelable est essentielle pour contrer le réchauffement climatique. Toutefois, les coûts élevés des nouvelles technologies peuvent retarder cette transition. Par conséquent, l’étude de l’apprentissage technologique endogène (ETL) est une stratégie cruciale, notamment pour les technologies émergentes pour lesquelles on prévoit un développement considérable dans les prochaines décennies. L'ETL suggère qu'à mesure qu'une technologie mature, ses coûts diminuent en raison des effets d'apprentissage qui découlent de l'accumulation d'expérience et de l’augmentation des investissements.

Pour tenir compte des effets de l’ETL, les modèles d'évaluation intégrée (IAM) sont couramment utilisés comme cadre de modélisation. Les IAM visent à décrire les processus humains et terrestres ainsi que leurs interactions pour fournir des perspectives sur le changement environnemental et le développement durable. Parmi ces modèles, AD-MERGE évalue les effets régionaux et mondiaux des politiques de réduction des émissions de gaz à effet de serre.

Ce mémoire explore la mise en œuvre de l’apprentissage technologique endogène au sein d’AD-MERGE 2.0 en comparant deux approches distinctes : l’approche Manne-Barreto et l’approche MERGE-ETL. La première utilise une courbe d'apprentissage à un facteur en fonction de la production cumulée, tandis que la seconde utilise une courbe d'apprentissage à deux facteurs basée sur la capacité cumulée. Trois technologies de l'hydrogène sont intégrées en tant que nouvelles technologies d'apprentissage pour chaque approche. Lors de la résolution des deux modèles, des méthodes directes et heuristiques sont utilisées, puisque l'incorporation des équations ETL dans un modèle énergétique génère un problème d'optimisation non-linéaire et non-convexe.

Après avoir comparé les deux approches et avoir effectué l’analyse de leurs forces et faiblesses, l'approche sélectionnée sera intégrée dans les versions ultérieures d'AD-MERGE 2.0. Compte tenu de la crise climatique alarmante, cette étude fournit aux décideurs des outils pour comprendre l'intégration graduelle des technologies renouvelables dans le mix énergétique et leurs implications pour l'économie à long terme.

Mots clés : apprentissage technologique endogène, modèle d’évaluation intégrée, optimisation, énergie, hydrogène

Abstract

Transitioning from conventional to renewable energy sources is crucial to mitigate climate change. However, the high initial costs of new technologies can delay this transition. Therefore, studying endogenous technological learning (ETL) is a vital strategy, especially for emerging technologies expected to develop significantly in the coming decades. ETL suggests that as a technology matures, its costs decrease due to learning effects from the accumulation of experience and increased investments.

To consider the effects of ETL, Integrated assessment models (IAM) are commonly used as modelling frameworks. IAMs aim to describe human and earth system processes and their interactions to provide insights into environmental change and sustainable development. Among these models, AD-MERGE evaluates the regional and global effects of greenhouse gas emissions reduction policies.

This thesis explores the implementation of endogenous technological learning in AD-MERGE 2.0, comparing two distinct approaches: the Manne-Barreto approach and the MERGE-ETL approach. The former uses a one-factor learning curve based on cumulative production, while the second employs a two-factor learning curve based on cumulative capacity. Three hydrogen technologies are incorporated as new learning technologies for each approach. Direct and heuristic-based methods are used when solving the two models, as incorporating ETL equations into an energy model generates a non-linear and non-convex optimization problem.

After comparing the two approaches and analyzing their strengths and limitations, the preferred approach will be integrated into subsequent versions of AD-MERGE 2.0. Considering the alarming climate crisis, this study provides decision-makers with tools to understand the gradual integration of renewable technologies into the energy mix and its implications for the long-term economy.

Keywords: endogenous technological learning, integrated assessment model, optimization, energy, hydrogen

Table of contents

List of Figures

List of Tables

List of abbreviations and acronyms

1FLC: one-factor learning curve

2FLC: two-factor learning curve

AD-MERGE: MERGE with adaptation

CCS: carbon capture and storage

ETA: energy technology assessment

ETL: endogenous technological learning

GHG: greenhouse gases

GRG: generalized reduced gradient

H2: hydrogen

IAM: integrated assessment model

IEA: International Energy Agency

IPCC: Intergovernmental Panel on Climate Change

LBD: learning-by-doing

LBS: learning-by-searching

MERGE: Model for Evaluating Regional and Global Effects (of Greenhouse gas emission reduction policies)

MIP: mixed-integer programming

NLP: non-linear programming

PEM: polymer electrolyte membrane

R&D: research and development; RD&D: research, development, and demonstration

SMR: steam methane reforming

SSP: shared socioeconomic pathways

Chapter 1
Introduction

The transition from conventional to renewable energies is essential to mitigate the impacts of climate change. However, the high initial cost of new technologies makes them less commercially attractive than conventional solutions, hindering this transition. For instance, low-carbon hydrogen is a promising energy source but has yet to be cost-competitive in reaching greenhouse gas emission levels (Layzell, Young, Lof, Leary & Sit, 2020). In Canada, two critical factors influencing the adoption of hydrogen are its cost competitiveness compared to other energy sources and its potential for decarbonization (Natural Resources Canada, 2020). Therefore, endogenous technological learning (ETL) has become increasingly important, especially for emerging technologies that expect significant development in the coming decades (Mattsson, 2019). Technological learning suggests that as a technology matures, its costs decrease due to learning effects, allowing for a more accurate projection of the energy transition timeline.

1.1 Integrated assessment models

Mathematical models can be used to support decision-making related to climate change strategies. Multiple aspects, including economics, energy systems, and climate science, are incorporated into these models to provide useful information to policymakers (Weyant, 2018). Integrated assessment models (IAM) are well-known models that aim to describe human and earth system processes and their interactions to offer insights into environmental change and sustainable development (United Nations Framework Convention on Climate Change [UNFCCC], n.d.). These models are typically categorized into top-down and bottom-up approaches (Bahn, Haurie & Zachary, 2004).

Top-down models are focused on the economy and consider energy as a subsector of the overall economy (Mattsson, 1997). These models rely on macroeconomic theory, and the economy influences the energy system indirectly. Generally, top-down models that include technological learning analyze the influence of learning on abatement activity costs and assess the energy sector's response to abatement strategies (Kahouli-Brahmi, 2008). On the other hand, bottom-up models are focused on technology and optimize the technical energy system with its environment

(Mattsson, 1997). Technological learning is usually incorporated in bottom-up models as they provide a more detailed view of the energy sector and its technological options (Bahn et al., 2004; Kahouli-Brahmi, 2008).

Top-down and bottom-up approaches complement each other, allowing for different questions to be answered. Developing hybrid models can incorporate both approaches and overcome their limitations.

1.2 Climate change scenarios

Integrated assessment models and other climate models can be adjusted to reflect different paths that may occur under various climate policies. The Intergovernmental Panel on Climate Change (IPCC) employs shared socio-economic pathways (SSP) in its sixth assessment report to provide a framework for these projections. SSP-based scenarios are designed to explore the possible impacts of different socio-economic developments on greenhouse gas (GHG) emissions under varying climate policies (IPCC, 2022). Five scenarios have been proposed to describe potential global trajectories. SSP1 describes a path of sustainability, focusing on growth and equality. SSP2 is a "middle of the road" scenario, where the world follows a path similar to historical patterns. SSP3 describes a scenario of regional rivalry, with a resurgence of nationalism and concerns about competition and security. SSP4 depicts a world of increasing inequality, where intra— and international gaps continue to grow. Finally, SSP5 focuses on fossil-fueled development, with rapid growth in the global economy and energy use. Each scenario differs in its level of technological advancement, investment, policies, and global population (Hausfather, 2018; Riahi et al., 2017).

1.3 Overview of MERGE

MERGE is a global integrated assessment model that evaluates the regional and global effects of GHG emissions reduction policies. It follows a hybrid approach and comprises four interlinked modules: an energy module (Energy Technology Assessment [ETA]), a macroeconomic module (MACRO), a climate module, and a damage module. The ETA module describes the energy sector using a bottom-up approach, whereas the MACRO module describes the economic sector using a top-down approach (Bahn, de Bruin & Fertel, 2019). The model was developed by Manne, Mendelsohn and Richels in 1995.

The figure below illustrates how the different modules interact in MERGE.

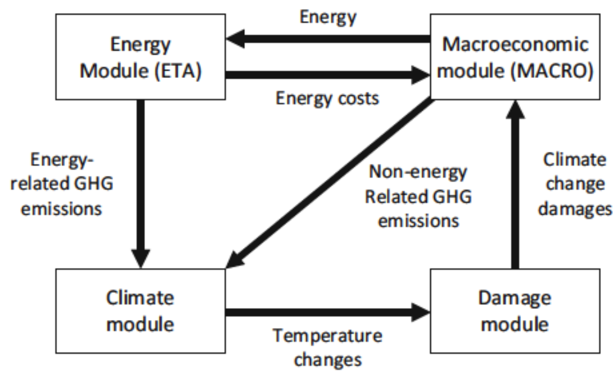

Figure 1.1*: Overview of the MERGE modules (Bahn, 2018)*

Note: From *The Contribution of Mathematical Models to Climate Policy Design: a Researcher's Perspective* by O. Bahn, 2018, Environmental Modelling & Assessment (2018) 23:691–701. Copyright 2018 by O. Bahn.

In the initial model, the years 1990 to 2050 are segmented into 10-year time steps, and then 25-year time steps are used until 2200. It distinguishes among nine geopolitical regions: Canada, Australia, and New Zealand (CANZ); China; Eastern Europe and the Former Soviet Union (EEFSU); India; Japan; Mexico and OPEC (MOPEC); the USA; Western Europe (WEUR); and the rest of the world (ROW). Like many other IAMs, MERGE maximizes the Negishi welfare, a measure of global welfare. The model is non-linear and convex and is implemented in GAMS, the General Algebraic Modeling Language. For more information on the model and its submodules, see Manne, Mendelsohn & Richels, 1995 or Bahn et al., 2019.

Versions of MERGE

In addition to the initial MERGE model (1995), a version with endogenous technological learning, MERGE-ETL (2002), has been implemented, as well as a version with adaptation, AD-MERGE 1.0 (2019), which is based on MERGE version 5.

The latest version of MERGE, currently under development, is AD-MERGE 2.0. This version is based on AD-MERGE 1.0 (2019) but has been updated and fine-tuned to reflect recent data. The original nine regions of MERGE have been divided into 15: the United States; Western Europe (WEUR); Japan and South Korea (JSK); Canada (CAN); Australia and New Zealand (ANZ); Russia (RUS); China; India; Middle East (MEA); Mexico (MEX); Africa; Other Eurasia (OEA); Brazil (BRA); Other Central America and Latin America (CLA); and Other Asia (OAS). This regional disaggregation accounts for geographical features, political coalitions, and data availability that better reflect current trends. Compared to the previous version, the base year has been updated to 2015. The time step for the first period is five years; for subsequent periods from 2020 to 2210, the time step is ten years. The model is calibrated to a newer version of the SSP2 scenario. Ongoing projects include incorporating new technologies such as hydrogen and adding a transportation sector into the existing model.

1.4 Research problem

This study aims to incorporate endogenous technological learning into AD-MERGE 2.0, the latest version of the MERGE model. Two approaches will be employed to implement endogenous technological learning: the Manne-Barreto approach, which is more straightforward and based on a one-factor learning curve, and the MERGE-ETL approach, which is more complex and based on a two-factor learning curve. The objective is to compare the complexity of equations, the solving process, and the solution quality of both approaches. After comparing the two methods, the preferred version will be implemented permanently into the model for future works.

This thesis is structured as follows: Chapter 1 introduces the context of the study, the MERGE framework, and the research question. Chapter 2 presents a breakdown of the existing literature on endogenous technological learning. Chapter 3 describes how previous and current versions of MERGE address endogenous technological learning. Chapter 4 explains the optimization techniques used to solve non-linear and non-convex problems. Chapter 5 defines the ETL equations and how they are incorporated into the model. Chapter 6 details the data collection process used to update the characteristics of new learning technologies. Chapter 7 presents the solving results of each version of the model. Finally, Chapter 8 summarizes the study, results, and limitations and elaborates on future extensions.

Chapter 2
Literature review

This chapter discusses the concept of technological learning and its origins. It then focuses on how this concept is specifically applied to energy models and how it is modelled within them. Additionally, other learning effects and uncertainties are addressed, as well as how other energy models incorporate technological learning. Finally, it explores how technological learning impacts decision-making processes.

2.1 Technological learning

Technological learning refers to the idea that technology improvements increase over time as the technology matures. This progress can result from various effects, such as increased labour efficiency, better equipment, or knowledge transfer. Technology improvements can be measured as cost reductions, number of units produced, or overall productivity increase. This concept can be modelled as a learning curve where progress is observed with acquired experience. Several function shapes can be used as learning curves depending on the desired learning effect. Learning curves can be expressed as log-linear, sigmoid, exponential growth, or even power-law functions (Newell, & Rosenbloom, 1980; Yelle, 1979). The speed at which the learning occurs is called the "learning rate" and is usually defined in economics as the price reduction for each doubling of the cumulative production or capacity. Depending on the complexity of the task, the learning rate will vary, which will impact the steepness of the learning curve. A higher learning rate implies that the learning occurs more rapidly, making the improvements more significant. Usually, improvements are accelerated in the early learning process. After a certain number of executions, the speed at which the improvements occur decreases, eventually reaching a plateau (Ritter & Schooler, 2001). Little to no further improvement is observed during this stationary stage until additional innovations restart the learning process. This plateau is often called the "floor cost", the lowest cost a technology can attain (Rout, Blesl, Fahl, Remme, & Voß, 2009).

Learning curves can be applied in various fields, such as psychology or economics. However, in this study, learning curves refer specifically to organizational learning, which focuses on the performance of organizational units, such as manufacturing plants, and factors in the effects of technological developments (Argote & Epple, 1990). This approach differs from a limited focus on labour or behavioural learning and will be referred to as "technological learning" throughout this thesis.

Initially modelled to describe how the costs in the aircraft industry decrease with each additional unit produced (Wright, 1936), this concept, also described as the "cost-quantity relationship" (Thompson, 2010), gained significant traction in the latter half of the 20th century. Data from aircraft production during World War II enabled many industries to begin integrating learning curves into their processes (Asher, 1956; Yelle, 1979). Technological learning has since been extended to other sectors, including energy modelling, where it helps understand how technology costs can influence energy production, consumption, and environmental outcomes within the framework of integrated assessment models. New technologies typically have higher costs and sometimes greater environmental impacts than conventional technologies. However, as they mature, learning effects contribute to reducing costs and environmental impacts, making them more appealing (Thomassen, Van Passel & Dewulf, 2020).

The following figure (Ouassou, Straus, Fodstad, Reigstad & Wolfgang, 2021) shows a standard learning curve, following Wright's experience curve.

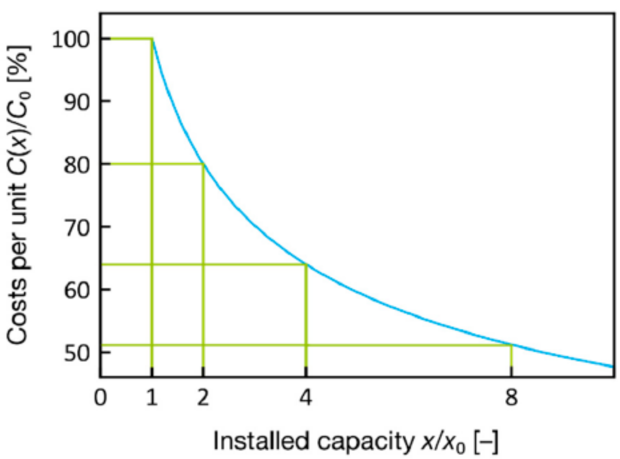

Figure 2.1*: A one-factor learning curve with a learning rate of 20%. The blue curve represents the cost per unit as a function of installed capacity. After a doubling of capacity, the cost is reduced by 20%.*

Note: From *Applying Endogenous Learning Models in Energy System Optimization* by J. A. Ouassou et al., 2021, *Energies*, 14, 4819. Copyright 2021 by Ouassou et al.

2.2 Modelling technological learning

Considering the non-negligible impact of learning on technology costs in the development of economic models or the assessment of repetitive task costs, it is essential to integrate technological learning into the equation. This integration can be modelled either exogenously or endogenously within an energy framework.

2.2.1 Exogenous versus endogenous learning

With exogenous learning, technology costs are independent of investment, economic choices, or environmental conditions. Technology costs will usually be a function of time defined before solving. This means that the cost function associated with technological advancements, which is time-dependent and already projected for the given time horizon, will begin to decrease in later years independently of the accumulated experience. Consequently, in a cost-minimization context, the model will only incorporate new technologies in later stages when their cost has significantly reduced and become financially viable. In reality, investments must be made for the costs to decrease dynamically over time (Zeyen, Victoria & Brown, 2023).

On the other hand, endogenous learning considers technology costs as a variable that varies dynamically during the optimization process (Ouassou et al., 2021). In other words, until production starts, the learning process and cost reductions will not begin. Incorporating learning curves endogenously in the model usually results in a more accurate representation of the cost function but is computationally more expensive because of the non-convexity of these curves (Bahn & Kypreos, 2003).

2.2.2 One-factor learning curve (learning-by-doing)

The previous definition of the learning curve depicts the relationship between cost and accumulated experience. When technological learning emerges from experience only, it is referred to as “learning-by-doing”. This is modelled with a one-factor learning curve, where technological learning improves and becomes more cost-effective with accumulated experience.

Learning-by-doing (LBD) adheres to a one-factor learning curve that can be defined in terms of the investment cost for the technology k (Bahn & Kypreos, 2003; Marcucci, 2012):

$$INVC_k = \begin{cases} A_k \cdot CC_k^{-b_k}, & \text{if } INVC_k \geq l_k \\ l_k, & \text{otherwise} \end{cases}$$

Where A_k is the investment cost at unit capacity, CC_k is the cumulative capacity, b_k is the learning-by-doing index, and l_k is the floor cost for technology k.

Technological learning is often described in terms of cumulative (installed) capacity in energy models. However, it can also be defined in terms of the cumulative number of units produced (Thomassen et al., 2020).

For an electric technology k, cumulative installed capacity is defined as follows (Bahn & Kypreos, 2003):

$$CC_{k,t} = CC_{k,0} + \frac{\sum_{regions,\tau}^{\tau\in[1,t]} 10 \cdot PE_{k,r,\tau}}{life_k \cdot lf_k \cdot 0.00876}$$

Where $CC_{k,0}$ is the cumulative capacity at the beginning of the time horizon, $PE_{k,r,\tau}$ is the yearly generation of electricity (TkWh) in the region r, $life_k$ is the technology’s lifetime (in years), lf_k its load factor, and 8760 is the number of hours in a year. For non-electric technologies, the formula is similar but expressed in EJ.

When expressed in terms of cumulative production, the learning-by-doing cost curve can be defined as follows (Ouassou et al., 2021):

$$C(x) = C_0 \left(\frac{x}{x_0}\right)^{b_{lbd}}$$

Where $C(x)$ is the cost of producing x units, C_0 and x_0 corresponds to values observed at time t_0, and b_{lbd} is the learning-by-doing index.

Focusing solely on learning-by-doing may not accurately capture the full extent of a particular technology's learning effects, as it does not consider research and development (R&D) expenditures (Jamasb, 2006). This limitation can result in overestimating and underestimating learning rates (Ouassou et al., 2021). Technological learning can be modelled using a two-factor learning curve known as “learning-by-searching” to achieve a more comprehensive representation of learning effects.

2.2.3 Two-factor learning curve (learning-by-searching)

In a two-factor learning curve, more investments in the research will lead to better technological progress, thus reducing technology costs. In the early stages, technological progress will likely arise from R&D expenditures rather than the accumulation of experience, as the technology is not yet commercially viable for the installed capacity to grow (Jamasb, 2006).

Learning-by-searching (LBS) can be modelled with a two-factor learning curve (Bahn & Kypreos, 2003; Magne, Kypreos & Turton, 2010; Marcucci, 2012):

$$INVC_k = \begin{cases} A_k \cdot CC_k^{-b_k} CRD_k^{-c_k}, & \text{if } INVC_k \geq l_k \\ l_k, & \text{otherwise} \end{cases}$$

Where CRD is the cumulative R&D expenditures and c_k is the learning-by-searching index.

2.2.4 Other learning effects

While using a two-factor learning curve may provide a better representation of learning effects compared to a one-factor learning curve, it still has some limitations. The transfer of knowledge from other countries or industries, called “spillover”, plays a significant role in technological progress at various levels (Lee, Kim, Choi & Koo, 2022) and is not accounted for in the previous two-factor learning curve. Spillovers can also arise from other technologies, where a group of technologies shares a common component technology that experiences learning (Anandarajah, McDowall & Ekins, 2013).

To account for technological spillovers from other regions, the investment cost function can be modified (Marcucci, 2012):

$$INVC_{k,r} = \begin{cases} A_k \cdot \left(\sum_{i \in R} a_{i,r} CC_{i,k}\right)^{-b_k} \left(\sum_{i \in R} a_{i,r} CRD_{i,k}\right)^{-c_k}, & \text{if } INVC_k \geq l_k \\ l_k, & \text{otherwise} \end{cases}$$

Where $a_{i,r}$ is the spillover coefficient from the region i to the region r.

Other learning effects that have direct and indirect effects on technical, economic, and environmental performance have also been introduced in the literature, such as learning-by-using, learning-by-interaction, learning-by-implementing and more. These learning effects can be factored in by introducing additional terms to the investment cost function (Junginger, van Sark & Faaij, 2010; Sagar & Van der Zwaan, 2006; Thomassen et al., 2020). However, including additional factors increases the complexity of the learning curve and the uncertainty related to the combination of often correlated learning rates (Ouassou et al., 2021).

2.2.5 Uncertainties when modelling ETL

When modelling endogenous technological learning in an energy system model, various uncertainties can impact the outcome of the analysis, leading to inaccurate conclusions. One source of uncertainty is the estimation of learning rates, which describe how quickly the cost reduces along the learning curve (Mattsson, 2019). Different studies in the literature show significant variability in estimated learning rates (Rubin, Azevedo, Jaramillo & Yeh, 2015). Furthermore, uncertainties may also arise when modelling technological learning regionally or globally. Economic and geographic factors specific to different regions can influence learning rates, introducing potential biases when approximating regional learning rates from global learning rates. Estimating learning rates for new technologies can also be challenging, as they often lack sufficient historical data and might follow different learning curves than conventional technologies in the early development stages (Ouassou et al., 2021). When dealing with uncertain learning rates, technological improvements can be estimated with the ratio of cumulative capacity over initial capacity (Lee et al., 2022) or by performing a Monte Carlo simulation to estimate uncertain learning rates (Kim, Koo, Lee & Yoon, 2012).

2.3 Solving ETL problem in energy models

Moreover, incorporating learning curves makes the model non-linear and non-convex, which leads to increased computational complexity and higher solving times. Traditional solvers can be used but may not guarantee optimal solutions for such models. Consequently, algorithms or heuristics that can handle non-convexity are required to provide near-optimal solutions.

Two main approaches are used to integrate experience curves in energy system models (Mattsson, 2019): direct non-linear implementation and piecewise linear approximation of cumulative costs or cumulative capacity. The first approach is the most straightforward but may result only in locally optimal solutions. Piecewise linear approximation does not depend on the initial starting point of the solver and can be faster than commercial solver algorithms (Zeyen et al., 2023). Even though the piecewise linear approximation solution may not be globally optimal, it provides a lower bound to the direct non-linear approach. A post-optimization calculation of the piecewise linear solution with the continuous learning curve provides an upper bound to the optimum (Mattsson, 2019). One can be assured that the solution is accurate by reducing the gap between the lower and upper bounds.

2.3.1 How ETL is modelled and solved in other energy models

Many energy models have solved endogenous technological learning and explored various approaches. Comparing solving methods, model types, and learning curve implementations can provide a more comprehensive understanding of the modelling methods.

In the TIMES (The Integrated MARKAL-EFOM System) model, endogenous technological learning is modelled using global cumulative capacity. The cumulative cost curve is approximated using a piecewise linear approximation and includes clustered learning options to account for spillovers from other technologies (Loulou, Lehtilä, Kanudia, Remme & Goldstein, 2016). The endogenous technological learning problem is a Mixed Integer Programming (MIP) problem and is solved with solvers such as CPLEX, EXPRESS, or GUROBI. Because MIP problems are more complex to solve, technological learning is activated with an “on-off” switch using *$SET ETL ‘YES’* and is usually only applied in TIMES when necessary (Goldstein, Kanudia, Lehtilä, Remme, & Wright, 2016).

In the WITCH (World Induced Technical Change Hybrid) model, endogenous technological learning is modelled with learning-by-doing and R&D expenditures. Learning-by-doing is specific to wind and solar technologies and is defined in terms of the cumulative installed world capacity. R&D affects backstop technologies, batteries for electric vehicles, and the overall system energy efficiency. The model assumes perfect technology spillovers and learning rates are constant across countries; the model uses five-year time steps, which are assumed to be sufficient for a complete flow of technology transfer across firms. The interactions between world regions are modelled as a non-cooperative Nash game that is solved recursively. The WITCH model is solved numerically in GAMS/CONOPT (Bosetti, Massetti, Tavoni, 2007).

In the GENIE (Global ENergy system with Internalized Experience curves) model, experience curves determine investment costs endogenously. To simplify the solving complexity, only technologies with a significant potential for cost reductions are treated with experience curves, whereas other technologies are considered to have constant investment costs. The model assumes perfect spillover, where technology information transfers freely between regions without delay. Technology characteristics are identical in all regions and are described as one global learning curve (Mattsson, 1997). The model is solved with MINOS in AMPL, but since there is no guarantee of an optimal solution, global optimization techniques like simulated annealing are used to confirm the solution. Most often, the solution found by MINOS is confirmed by the ones produced by heuristic techniques (Mattsson & Wene, 1997).

In the MESSAGE (Model for Energy Supply Strategy Alternatives and their General Environmental Impact) model, technological learning is modelled endogenously, where specific investment cost is a function of the cumulative installed capacity. In an earlier version of the model, “MESSAGE III”, non-convexity is addressed with a mixed-integer programming (MIP) extension inside the linear formulation (Seebregts et al., 1998). A branch-and-bound algorithm searches the solution space along the tree of possible decisions for integer variables to find the optimal solution (Messner, 1997). The model is implemented in GAMS and solved with CPLEX. In a reduced-form version of MESSAGE studied by Leibowicz, the model is coupled with a technology market model structured as a Cournot competition. The technology market model is implemented in GAMS as a non-linear program (NLP) and is solved using CONOPT (Leibowicz, 2015).

In the REMIND (REgional Model of INvestment and Development) model, endogenous technological learning is modelled through learning-by-doing with a global learning curve and internalized spillovers for renewable energy technologies in the power sector (Luderer et al., 2015). In a recent study on REMIND, different multi-level learning approaches are studied to measure the impact of technology diffusion and the regional costs of mitigation policies (Zhang, Bauer, Yin & Xie, 2020). This study compares regionalized learning with and without interregional spillovers and multi-level learning with varying cost components. The model computes the market equilibrium as a Pareto optimal solution that maximizes global welfare or a non-cooperative Nash solution that maximizes regional welfare (Luderer et al., 2015). The model is implemented in GAMS and solved with CONOPT (Aboumahboub et al., 2020; Luderer et al., 2015).

In RICE (Regional Integrated model of Climate and the Economy), the original model is enhanced with endogenous technological learning in two versions: an R&D-driven one and an LBD-driven one (Castelnuovo, Galeotti, Gambarelli & Vergalli, 2005; Junginger et al., 2010). The learning curve is modelled as a function of installed capacity. This paper aims to compare the learning effects of both factors separately. The two versions are implemented in GAMS and are solved with basic simulations under alternative scenarios. Although the two versions result in different outputs, they lead to similar qualitative patterns. However, this paper does not explore the interaction between R&D and learning-by-doing.

The following table summarizes the implementation of endogenous technological learning in the six models mentioned above.

***Table 2.1**: Comparison of the implementation of ETL in other energy models*

Model	**Type of model**	**1 or 2-factor learning curve**	**Language**	**Solving method**
TIMES	Bottom-up	2FLC	GAMS	Mixed-integer programming (CPLEX, EXPRESS, or GUROBI)
WITCH	Hybrid	1FLC (wind, solar) 2FLC (backstops)	GAMS	Non-linear solver (CONOPT)
GENIE	Bottom-up	1FLC	AMPL	Non-linear solver (MINOS) and simulated annealing
MESSAGE	Bottom-up	2FLC	GAMS	Mixed-integer programming (CPLEX)
REMIND	Hybrid	1FLC	GAMS	Non-linear solver (CONOPT)
RICE	Hybrid	1FLC (LBD only) 1FLC (R&D only)	GAMS	Simulation

2.4 Decision-making with ETL

Technological learning can have a significant impact on political decisions. When making choices, governments must consider their unique national circumstances, including existing energy infrastructures and resource availabilities. The data must be reliable as it influences the evaluation of energy costs and mitigation scenarios. For instance, when considering the adoption of new hydrogen-based energy sources, the Government of Canada bases its decision on cost competitiveness and its potential for decarbonization. However, decision-making becomes more complex when multiple objectives are pursued, such as preserving existing economic activities and developing new industries while minimizing greenhouse gas emissions.

Moreover, the choice of technology must be accepted by politicians, industries, and the public. Accurate learning rates are vital as they significantly influence the evaluation of energy costs and mitigation scenarios. Therefore, having precise data is essential when considering alternative strategies, long-term consequences, and risks. Depending on the government's risk behaviour, uncertain learning rates and cost differences can influence the decision to support a technology. Variables such as costs, timing, regional implications, public receptivity, and energy security will all impact the decision process. Therefore, incorporating technological learning in decision tools can be beneficial in evaluating different pathways and the impact of each decision on the economy and the environment.

To summarize, technological learning refers to the idea that technological costs reduce over time as a technology matures. Various types of learning curves, including one-factor and two-factor learning curves, can be used to model endogenous technological learning. Estimating learning rates and computational complexity can result in uncertainties and challenges when incorporating learning curves into energy system models. Additionally, technological learning can influence mitigation efforts for climate change during political decision-making processes.

Chapter 3
ETL in MERGE

3.1 ETL in previous versions of MERGE

Endogenous technological learning has been a topic of interest in energy modelling for decades. Although it was not initially included in the first version of MERGE, it has been added and modified in subsequent versions.

- MERGE (1995)

Endogenous technological learning is not considered in the first version of MERGE. Instead, technological learning is specified exogenously over time (Kypreos, 2005). It is assumed that generating costs of energy technologies decline at a rate of 0.5% per year due to autonomous technological progress.

- MERGE-ETL (2002)

The first implementation of endogenous technological learning in MERGE was introduced by Bahn and Kypreos in 2002. In this version, called “MERGE-ETL”, six electric (solar photovoltaic, wind turbine, new nuclear designs, integrated coal-gasification with combined cycle, gas fuel cell and gas turbine combined cycle) and two non-electric (hydrogen from solar photovoltaic and hydrogen from biomass) technologies are subject to learning, which follows a two-factor learning curve in terms of the cumulative capacity. This formulation assumes global technological learning without spillover, as there is no technological distinction between regions. In their study, Bahn and Kypreos compare several types of learning: a one-factor learning curve, a two-factor learning curve with exogenous or endogenous R&D investments, and a two-factor learning curve with knowledge stock formulation. Because of the non-convexity caused by the increasing returns mechanism, a heuristic iterative approach in three steps is used to solve the model (Bahn & Kypreos, 2003).

The following figure shows the solving loop of MERGE-ETL as described by Bahn & Kypreos (2002).

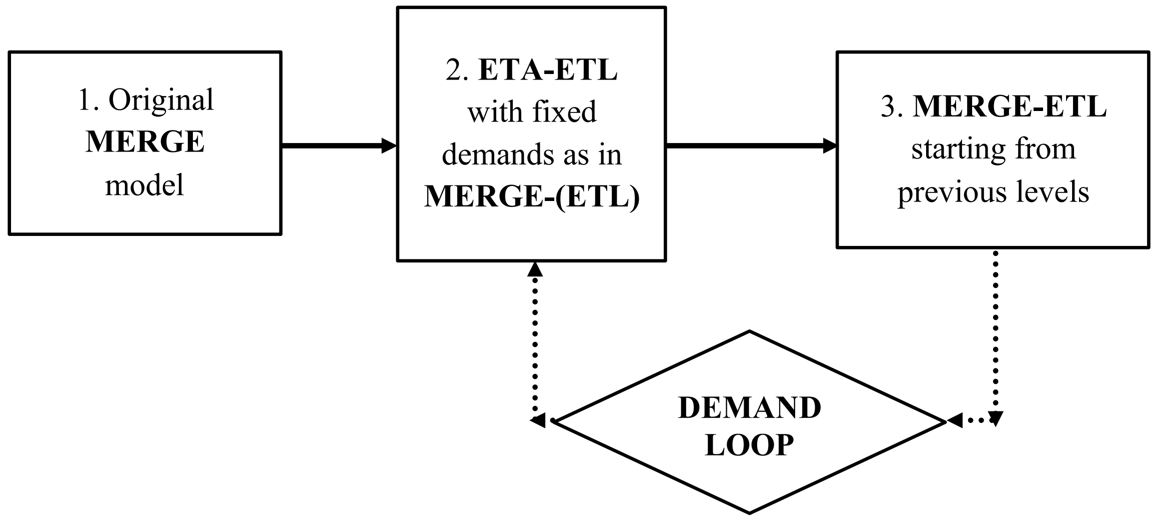

Figure 3.1*: An iterative procedure to solve MERGE-ETL*

Note: From MERGE-ETL: An Optimisation Equilibrium Model with Two Different Endogenous Technological Learning formulations by O. Bahn and S. Kypreos, 2002, PSI Report, 02(16). Copyright 2002 by Bahn & Kypreos.

This heuristic comprises three steps. First, the original MERGE model is initially solved without technological learning (step 1). The demands of electric (E) and non-electric energy (N) are fixed and are used as starting levels for the ETA-ETL submodule. The ETA-ETL model contains the ETA equations of MERGE and the equations related to endogenous technological learning. This submodule corresponds to the bottom-up part of the MERGE model in which technological learning occurs. With the inclusion of the ETL equations, the resulting model ETA-ETL becomes non-convex. The total cumulative cost curve is then linearized by defining a piece-wise linear approximation, and the model is solved using mixed-integer programming (step 2). Once the ETA-ETL model is solved, the energy demands E and N are again fixed and used as starting levels for the MERGE-ETL model. The latter includes the complete set of equations in MERGE with the ETL equations and is solved using a direct non-linear solver (step 3). Once the MERGE-ETL is solved, the demands E and N are again fixed. Steps 2 and 3 are repeated until the new demands stop varying within a given margin. Because the initial MERGE model in step 1 is convex, the solution is global. The solutions of step 1 and step 2 serve as starting points for solving ETA-ETL and MERGE-ETL, which generally yield a reasonable approximation of the global optimum's location. Therefore, the final solution is assumed to be global after all iterations.

- MERGE with learning-by-doing (2004)

Endogenous technological learning is simplified and reimplemented in the original MERGE model. This version follows Manne and Barreto's mathematical formulation, in which endogenous technological learning is modelled using a one-factor learning curve using cumulative production (Manne & Barreto, 2004). Two learning technologies, "LBDE" and "LBDN", representing electric and nonelectric learning-by-doing technologies respectively, are modelled. In this version, LBD is a parameter that is turned on or off in the input file. Since there are only two learning technologies, the model is solved with CONOPT3 and Manne and Barreto reported that the solution is equivalent to the output provided by the global solver BARON (Branch-And-Reduce Optimization Navigator).

Manne and Barreto's formulation (2004) of learning costs associated with a technology k at time period t:

$$\text{Learning cost}_k = \sum_k incl_k * P_{k,t}\left[\frac{CP_{k,t}}{CP_{k,0}}\right]^{lr_k}$$

Where $incl_k$ is the initial learning cost, $P_{k,t}$ is the production of energy, $CP_{k,t}$ is the cumulative global production, and lr_k is the learning rate.

- MERGE-ETL for Switzerland (2012)

In 2012, Marcucci applied MERGE-ETL to the Swiss energy system. This formulation of MERGE-ETL compares several endogenous technological learning scenarios with different spillover levels between regions. This version follows Bahn and Kypreos's mathematical formulation for the two-factor learning curve but includes exogenous spillovers. The model is solved using Bahn and Kypreos's iterative heuristic.

- AD-MERGE 1.0 (2019)

In AD-MERGE (Bahn et al., 2019), endogenous technological learning still follows Manne and Barreto's formulation without significant changes. LBD can be switched off depending on the scenario and the model is solved using CONOPT3.

3.2 Methodology

This thesis aims to explore the implementation of endogenous technological learning in AD-MERGE 2.0. To achieve this, two approaches are compared: the Manne-Barreto approach (2004), which uses a one-factor learning curve with learning-by-doing in terms of cumulative production, and the MERGE-ETL approach (2002), which uses a two-factor learning curve in terms of cumulative capacity.

1. Manne-Barreto approach

   Starting from the formulation that is already in AD-MERGE 1.0 (using a one-factor learning curve), more learning technologies are added: instead of having only *LBDE* and *LBDN*, one electric technology, one non-electric technology, and three hydrogen technologies are incorporated into a new set of technologies subject to learning-by-doing. This implies adding initial learning costs, learning rates and initial cumulative production for each technology. The data is also updated using a 2015 base year and updated regions. This model is then solved using a direct non-linear solver.

2. MERGE-ETL approach

   The one-factor learning curve is defined in terms of the cumulative capacity (instead of the cumulative production in Manne-Barreto's approach), and a second factor is incorporated into the learning curve. The two-factor learning curve is applied to the same five learning technologies as in the Manne-Barreto approach. This allows the R&D expenditures to be included in the technology costs. This implies introducing new learning parameters, R&D expenditures for each technology, and equations to compute the cumulative capacity. New data is incorporated to reflect the 2015 base year with updated regions. The model is then solved using the iterative heuristic approach described in **Figure 3.1** on page 18.

Once the two approaches are implemented, the solutions are compared. Based on the quality of the solution, the solving time, the complexity of the equations, the data availability, and other factors, recommendations are made for the preferred implementation. The preferred approach will be kept in future versions of AD-MERGE 2.0.

Chapter 4
Optimization techniques for solving non-convex, non-linear problems

Optimization problems can be solved using many algorithms, depending on the problem type. As mentioned, incorporating endogenous technological learning in energy models brings non-convexity into a non-linear model due to the increasing returns linked to the accumulation of experience. While a conventional non-linear solver can generate a feasible or even optimal solution, there is no guarantee that this solution is global. Obtaining a local optimum could be acceptable in some instances, but in the case of scenario analysis in energy models, a global optimum is usually preferred for better decision-making. Finding the global optimum usually requires more calculations for each iteration, which increases solving time. However, when the local optimum is estimated to be "good enough", one can decide to use this solution instead of the global one to avoid dealing with high solving complexity. For both the Manne-Barreto and MERGE-ETL approaches, an appropriate solving technique is needed to address the non-convexity.

4.1 NLP algorithms

Conventional non-linear solvers can be used even if they do not guarantee global optimality, as they can still generate reasonable optimal solutions. Initially, AD-MERGE 1.0 was solved using CONOPT3, and early versions of AD-MERGE 2.0 are solved using CONOPT4, as it provides a better solution in reduced computation time. Even if a global solution is not found, it can still be considered an acceptable solution for the decision-maker's needs.

- CONOPT

CONOPT is a generalized reduced gradient (GRG) algorithm designed to solve large and sparse non-linear models (GAMS, 2024b). CONOPT is a local solver and, therefore, is not best suited for non-convex models, as it is not developed to test for convexity.

CONOPT4 is the latest version of the CONOPT algorithm. It has been developed and tuned for models where CONOPT3 cannot provide an adequate solution or ends in a locally infeasible solution. It can accommodate larger non-linear models with more than 100,000 variables and constraints. With the updated formulation of learning-by-doing with five learning technologies, AD-MERGE 2.0 has over 75,000 constraints with more than 123,000 variables. Therefore, CONOPT4 is more suitable than CONOPT3.

Because CONOPT cannot guarantee the finding of all optimal solutions in a non-convex model, it can miss crucial optima in the solving process. Using a solver, like Knitro, that is designed to solve non-convex models can be an alternative.

- KNITRO

Artelys Knitro is an optimization software library primarily designed to find local solutions of large continuous non-linear models (Artelys, 2023). It can solve non-linear and non-convex problems. While Knitro cannot guarantee to find the global optimum, a multi-start algorithm can be used to provide better optimality. For NLP problems, Knitro provides four different algorithms, such as barrier methods, active set methods, or sequential quadratic programming methods, that can run separately or parallelly (GAMS, 2024c). For the solving of AD-MERGE 2.0 with Knitro, a version with and without multi-start is tested as it increases the chances of finding the global optimum.

To increase the chance of finding the global optimum, solvers specifically designed to solve non-linear models at global optimality, like BARON, can be used.

- BARON

The Branch-And-Reduce Optimization Navigator (BARON) is a global optimization software for many types of problems that can solve non-linear and non-convex problems to global optimality (Sahinidis, 2023). BARON uses branch-and-reduce, cutting planes, heuristics, and domain reduction techniques. Many options can be used with the solver to increase the chances of finding the global optimum. For example, setting the number of branch-and-reduce iterations, using a multi-start heuristic, or changing the branching selection strategy. For the solving of AD-MERGE 2.0 with BARON, the model is executed with and without specifying the number of branch-and-reduce iterations. When specified, the number of iterations is set to unlimited through the *maxiter* option. Unlike CONOPT and Knitro, BARON can guarantee to provide a global optimum. In addition, similar to Knitro, BARON can handle non-convexity.

For license availability purposes, the versions of AD-MERGE 2.0 solved with BARON and Knitro are running on the NEOS server hosted by the University of Wisconsin-Madison.

4.2 Heuristics

Heuristics can also be used to solve non-convex problems and reduce computation time. In several models with endogenous technological learning, piecewise linear approximation has been used to solve the model and find a global optimum (Seebregts, 1999). This transforms the problem into a mixed-integer programming problem and can simplify the mathematical complexity of the linearized submodule and improve the solution's quality. However, compared to a direct approach, solving endogenous technological learning by a heuristic-based method requires additional steps, and the overall number of equations and constraints is greater. Compared to general NLP solvers, this heuristic can provide, with few uncertainties, that the optimum is global. However, the solving time will usually be longer.

The heuristic used by Bahn and Kypreos is implemented for solving AD-MERGE 2.0 with ETL. In GAMS, the solvers MIP and CONOPT4 are used throughout the solving loop.

Chapter 5
Modelling ETL in AD-MERGE 2.0

This chapter presents the equations of the two approaches in the GAMS code and details the steps to run the code. The equations have been incorporated into the version of AD-MERGE 2.0 extracted on February 19th, 2024. Modifications made to the general model after this date are not included.

5.1 Manne-Barreto approach

The Manne-Barreto approach is implemented in two files: a data file containing sets and parameters, and a main file containing the equations.

- Data file

In the data file, several sets and parameters related to learning technologies are incorporated. In addition, exogenous costs reductions are removed. The following sets contain the learning technologies.

```
SETS
    lbdet(et)    Electricity technologies with learning-by-doing
                 /igcc/

    lbdnt(nt)    Nonelectric technologies with learning-by-doing
                 /rnew/

    lbdht(ht)    Hydrogen technologies with learning-by-doing
                 /electrolysis, coal-h2-CCS, gas-h2-CCS/;
```

Note: Hydrogen technologies with learning are neither electric nor nonelectric. They belong to a separate category, "LBDH." This is because their production function is PH instead of PN or PE. For electric and non-electric learning technologies, the data related to *igcc* and *rnew* have not been updated since their initial implementation as learning technologies. These technologies should eventually be updated for a more accurate output. They are kept in the model to provide a framework for future learning technologies.

The following sets contain the technologies without learning.

```
SET
NLBDE(ET)  index of ET technologies without learning;
NLBDE(ET)=ET(ET)-LBDET(ET) ;

SET
NLBDE_nonvre(et) interserction of nonvre(et) and NLBDE(et);
NLBDE_nonvre(et) = NLBDE(et) * nonvre(et);

SET
NLBDN(NT)  index of NT technologies without learning;
NLBDN(NT)=NT(NT)-LBDNT(NT) ;

SET
NHT(ht) hydrogen technologies without learning
/coal-h2,gas-h2/;
```

The following parameters contain the technology characteristics for learning technologies (electric, non-electric and hydrogen, respectively).

```
PARAMETERS
    inlce(LBDET)   initial learning cost - $ per thousand kwh
    cpe0(LBDET)    initial cumulative production - tkwh
    lrne(LBDET)    learning parameter;

TABLE LBDETP(LBDET , *)  LEARNING BY DOING PARAMETERS - ELECTRIC TECHNOLOGIES

        inlce    cpe0   lrne
IGCC     50.0     1    -.0893;


PARAMETERS
    inlcn(LBDNT)   initial learning cost - $ per GJ
    cpn0(LBDNT)    initial cumulative production - GJ
    lrnn(LBDNT)    learning parameter;

TABLE LBDNTP(LBDNT , *)  LEARNING BY DOING PARAMETERS - NONELECTRIC TECHNOLOGIES

        inlcn    cpn0   lrnn
RNEW     6.0      1    -.1520;

PARAMETERS
    inlch(LBDHT)   initial learning cost - $ per GJ
    cph0(LBDHT)    initial cumulative production - GJ
```

```
    lrnh(LBDHT)    learning parameter;

TABLE LBDHTP(LBDHT , *)  LEARNING BY DOING PARAMETERS - HYDROGEN TECHNOLOGIES

                inlch    cph0     lrnh
electrolysis     5.0       1      -.2009
coal-h2-CCS     23.81      1      -.0893
gas-h2-CCS      07.99      1      -.0740;
```

- Main file

In the main file, the formulation of the cost of energy is modified. The terms related to energy production are updated in the cost of energy equation. For technologies without learning, the sets of technologies are updated to keep only the needed technologies. In the following code, only the modified lines are included.

```
costnrg(rg,tp,sw)$(pp(tp) and st(tp,sw))..
EC(rg,tp,sw) =g= .001 * (

*   Electric production cost (without learning)
sum((NLBDE_nonvre,ts),PE(NLBDE_nonvre,tp,ts,rg,sw)*ecst(NLBDE_nonvre,tp,rg)*
cstred(tp))
                    + …

* Hydrogen production cost (without learning)
 + sum(nht, PH(nht,tp,rg,sw)*hcst(nht,tp,rg)* cstred(tp))

* Non-electric production cost (without learning)
 + sum(NLBDN, PN(nlbdn,tp,rg,sw)*ncst(nlbdn,rg)* cstred(tp))

*   Electric lbde learning costs
+   sum((LBDET,ts),LBDETP(LBDET,'inlce')*PE(LBDET,tp,ts,rg,sw)*(CPE(tp,sw,lbdet)/
LBDETP(LBDET,'cpe0'))**LBDETP(LBDET,'lrne'))

*   Nonelectric lbdn learning costs
+           sum(LBDNT,LBDNTP(LBDNT,'inlcn')*PN(LBDNT,tp,rg,sw)*(CPN(tp,sw,lbdnt)/
LBDNTP(LBDNT,'cpn0'))**LBDNTP(LBDNT,'lrnn'))

*   Hydrogen lbd learning costs
+           sum(LBDHT,LBDHTP(LBDHT,'inlch')*PH(LBDHT,tp,rg,sw)*(CPH(tp,sw,lbdht)/
LBDHTP(LBDHT,'cph0'))**LBDHTP(LBDHT,'lrnh'))
```

```
                    + … );
```

- Execution

To run the model using the Manne-Barreto approach, the files containing the updated LBD formulation must be used. This new formulation enables the use of multiple electric and non-electric learning technologies. To implement additional technologies, the corresponding technology characteristics need to be added to the data file. The solving process of this approach is the same as that of AD-MERGE 2.0 without LBD.

The user has to make sure that `$setglobal lbd = yes` in the input scenario. However, if using `lbd = no`, the code might not run smoothly. In this case, it is preferable to use a version of AD-MERGE 2.0 without the new LBD equations.

5.2 MERGE-ETL approach

The MERGE-ETL approach, similar to the Manne-Barreto approach, involves using a data file and a main file. However, because the solving loop of the MERGE-ETL approach is implemented in three steps that are modelled separately, it uses one data file and three main files, one for each submodule.

- Data file

In the data file, the following technology characteristics are incorporated. Similarly to the Manne-Barreto approach, sets of technologies with learning are defined.

```
SETS
    etl(et)       ELECTRICITY TECHNOLOGIES WITH LEARNING
                  /igcc/

    ntl(nt)       NON ELECTRIC TECHNOLOGIES WITH LEARNING
                  /rnew/

    htl(ht)       HYDROGEN TECHNOLOGIES WITH LEARNING
                  /electrolysis, coal-h2-ccs, gas-h2-ccs/;
```

Note: Similarly to the Manne-Barreto approach, hydrogen technologies with learning are neither electric nor nonelectric. They belong to a separate category, "HTL." Again, the data related to *igcc* and *rnew* have not been updated since their initial implementation as learning technologies.

The following sets are the technologies without learning.

```
SET
NETL(ET)  index of ET technologies without learning;
NETL(ET)=ET(ET)-ETL(ET) ;

SET
NETL_nonvre(et) interserction of nonvre(et) and NETL(et);
NETL_nonvre(et) = NETL(et) * nonvre(et);

SET
NNTL(NT)  index of NT technologies without learning;
NNTL(NT)=NT(NT)-NTL(NT) ;

SET
NHT(ht) hydrogen technologies without learning
/coal-h2,gas-h2/;
```

The following parameters and equations are related to learning-by-doing and learning-by-searching.

```
PARAMETER
pr(etl)  progress ratio for learning-by-doing
/igcc          0.94/

prn(ntl)  progress ratio for learning-by-doing
/rnew       0.90/

prh(htl)  progress ratio for learning-by-doing
/electrolysis       0.87
coal-h2-ccs        0.94
gas-h2-ccs         0.95/

prrd(etl)  progress ratio related to R&D
/igcc          0.96/

prrdn(ntl)  progress ratio related to R&D
/RNEW       0.95/
```

```
prrdh(htl)  progress ratio related to R&D
/electrolysis   0.99
coal-h2-ccs    0.94
gas-h2-ccs     0.99/

cap0(etl)  initial capacity in GW
/igcc          0.48/

cap0n(ntl)  initial capacity in EJ per year
/rnew        1./

cap0h(htl)  initial capacity in EJ
/electrolysis       0.006
coal-h2-ccs        0.024
gas-h2-ccs         0.080/

cf(etl)  capacity (load) factor
/igcc          0.7/

cfn(ntl)  capacity (load) factor
/rnew       1/

cfh(htl)  capacity (load) factor
/electrolysis   0.55
coal-h2-ccs    0.9
gas-h2-ccs     0.9/

spcost1(etl) specific investment cost in 2000 (in USD per kW)
/igcc 2019.59/

spcostfl(etl) floor investment cost (in USD per kW)
/igcc 562.08/

spcost1n(ntl) specific investment cost in 2015 (in USD per GJ)
/rnew 6/

spcostfln(ntl) floor investment cost (in USD per GJ)
/rnew    2.25/

spcost1h(htl) specific investment cost in 2015 (in USD per GJ)
/electrolysis    5
coal-h2-ccs     23.81
gas-h2-ccs      7.99/

spcostflh(htl) floor investment cost (in USD per GJ)
```

```
/electrolysis    1.25
coal-h2-ccs     11.91
gas-h2-ccs      4.00/

life(etl)  life time in years
/igcc            30/

lifen(ntl)  life time in years
/rnew       30/

lifeh(htl)  life time in years
/electrolysis    25
coal-h2-ccs     40
gas-h2-ccs      40/

crd0(etl)  initial cumulative R&D spending in 1989 (billion USD90)
/igcc         7.05/

crd0n(ntl)  initial cumulative R&D spending in 1989 (billion USD90)
/RNEW        1.0/

crd0h(htl)  initial cumulative R&D spending in 2015 (billion USD2015)
/electrolysis    0.46
coal-h2-ccs     2.10
gas-h2-ccs      3.57/;

TABLE ard_exo(ETL,tp)  annual R&D expenditures in billion USD90
              2020    2030    2040    2050    2060    2070    2080    2090
2100    2110    2120    2130    2140    2150    2160
igcc          1.16    1.59    2.16    2.72    3.36      4      4.2    4.7      5
5.5     5.7     5.8     5.9     6       6.1;

TABLE ardn_exo(ntl,tp)  annual R&D expenditures in billion (USD90)
                2015    2020    2030    2040    2050    2060    2070    2080
2090    2100    2110    2120    2130    2140    2150    2160
RNEW                    0.20    0.26    0.33    0.41    0.51    0.8     0.9
1       1.1     1.2     1.1     1.1     1.0     1       1;

TABLE ardh_exo(htl,tp)  annual R&D expenditures in billion (USD2015)
                2015    2020    2030    2040    2050    2060    2070    2080
2090    2100    2110    2120    2130    2140    2150    2160
electrolysis    0.19    0.66    10      11      12      13      14      15
15.5    15      15      14.5    14      14      14      13.5
coal-h2-ccs     2.10    2.11    7.8      8      9       10      10.5    11
11.5    12      12.5    12      12      12      12      11.5
```

```
gas-h2-ccs      3.57     3.58     13.26     14      15       16       16       16
16.5     16       16       15.5     15       15       15       14.5;
```

The following parameters and equations are related to the formulation of the learning curve.

```
PARAMETERS
aanew(etl)    specific cost at unit cum. cap. and R&D expenditures
aannew(ntl)   specific cost at unit cum. cap. and R&D expenditures
aahnew(htl)   specific cost at unit cum. cap. and R&D expenditures

bb(etl)       learning by doing index
bbn(ntl)      learning by doing index
bbh(htl)      learning by doing index

ccf(etl)      learning by searching index
ccfn(ntl)     learning by searching index
ccfh(htl)     learning by searching index

crd(tp,etl)   cumulative R&D expenditures (exogenous)
crdn(tp,ntl)  cumulative R&D expenditures (exogenous)
crdh(tp,htl)  cumulative R&D expenditures (exogenous)

spcost(etl)   SC0: specific investment cost in $ per kW
spcostn(ntl)  SC0: specific investment cost in $ per GJ
spcosth(htl)  SC0: specific investment cost in $ per GJ;

bb(ETL)    = -log(pr(ETL))/log(2);
bbn(NTL)   = -log(prn(NTL))/log(2);
bbh(HTL)   = -log(prh(HTL))/log(2);

ccf(ETL)   = -log(prrd(ETL))/log(2);
ccfn(NTL)  = -log(prrdn(NTL))/log(2);
ccfh(HTL)  = -log(prrdh(HTL))/log(2);

crd(TP,ETL)=crd0(ETL)+sum(TPP$(ord(TPP)LE ord(TP)),nyper(TPP)*ard_exo(ETL,TPP));
crdn(TP,NTL)=crd0n(NTL)+sum(TPP$(ord(TPP)LEord(TP)),nyper(TPP)*ardn_exo(NTL,TPP)
);
crdh(TP,HTL)=crd0h(HTL)+sum(TPP$(ord(TPP)LEord(TP)),nyper(TPP)*ardh_exo(HTL,TPP)
);

spcost(ETL) = sum(rg,1000*param(ETL)*cstfr(ETL)*ecst(ETL,"2015",rg)/crfac(ETL));
spcostn(NTL)= sum(rg,paramn(NTL)*cstfrn(NTL)*ncst(NTL,rg)/crfacn(NTL));
spcosth(HTL)= sum(rg,paramh(HTL)*cstfrh(HTL)*hcst(HTL,"2015",rg)/crfach(HTL));

aanew(ETL) = spcost(ETL) * (cap0(ETL)**bb(ETL)) * (crd0(ETL)**ccf(ETL));
```

```
aannew(NTL) = spcostn(NTL) * (cap0n(NTL)**bbn(NTL)) * (crd0n(NTL)**ccfn(NTL));
aahnew(HTL) = spcosth(HTL) * (cap0h(HTL)**bbh(HTL)) * (crd0h(HTL)**ccfh(HTL));
```

- Main file (MIP formulation)

In the main file of the MIP formulation, only the ETA-ETL module is solved. This is where the piecewise linear approximation of the cost function is included. The following equations assign the initial and maximum cumulative cost for each learning technology.

```
* Assignment of initial cumulative cost
ccost0(ETL)= aanew(ETL) / (1-bb(ETL)) * (cap0(ETL)**(1-bb(ETL)));
ccost0n(NTL) = aannew(NTL) / (1-bbn(NTL)) * (cap0n(NTL)**(1-bbn(NTL)));
ccost0h(HTL) = aannew(HTL) / (1-bbh(HTL)) * (cap0n(HTL)**(1-bbh(HTL)));

* Assignment of the maximum cumulative cost
ccostm(ETL)= aanew(ETL) / (1-bb(ETL)) * (ccapm(ETL)**(1-bb(ETL)));
ccostmn(NTL) = aannew(NTL) / (1-bbn(NTL)) * (ccapmn(NTL)**(1-bbn(NTL)));
ccostmh(HTL) = aannew(HTL) / (1-bbh(HTL)) * (ccapmn(HTL)**(1-bbh(HTL)));
```

The following loops compute the weighting of the segment lengths.

```
weig('0',ETL)=0;
scount=1;
LOOP(KP$(ORD(KP) GE 2),
  weig(KP,ETL)$(ORD(KP) LE SEG(ETL) + 1) =
  (2**(-SEG(ETL)+scount-1))/(sum(RP$(ORD(RP) LE SEG(ETL)),2**(-SEG(ETL)+ORD(RP)-
1)));
  scount=scount+1;
  );

weign('0',NTL)=0;
scount=1;
LOOP(KP$(ORD(KP) GE 2),
  weign(KP,NTL)$(ORD(KP) LE SEGn(NTL)+1) =
  (2**(-SEGn(NTL)+scount-1))/(sum(RP$(ORD(RP) LE SEGn(NTL)),2**(-
SEGn(NTL)+ORD(RP)-1)));
  scount=scount+1;
  );

weigh('0',HTL)=0;
scount=1;
LOOP(KP $(ORD(KP) GE 2),
  weigh(KP,HTL)$(ORD(KP) LE SEGn(HTL)+1) =
```

```
  (2**(-SEGn(HTL)+scount-1))/(sum(RP$(ORD(RP) LE SEGn(HTL)),2**(-
SEGn(HTL)+ORD(RP)-1)));
  scount=scount+1;
 );
```

The following equations compute the cumulative cost at each kink point.

```
ccostk('0',ETL)=ccost0(ETL);
scount=1;
LOOP(KP $(ORD(KP) GE 2),
  ccostk(KP,ETL) $(ORD(KP) LE SEG(ETL)+1)=
    ccostk(KP-1,ETL)+((ccostm(ETL)-ccost0(ETL))*weig(KP,ETL));
  scount=scount+1;
  );

ccostkn('0',ntl)=ccost0n(ntl);
scount=1;
LOOP(KP $(ORD(KP) GE 2),
  ccostkn(KP,ntl) $(ORD(KP) LE SEGn(ntl)+1)=
  ccostkn(KP-1,ntl) + ( (ccostmn(ntl)-ccost0n(ntl))*weign(KP, ntl));
  scount=scount+1;
  );

ccostkh('0',htl)=ccost0h(htl);
scount=1;
LOOP(KP $(ORD(KP) GE 2),
  ccostkh(KP,htl) $(ORD(KP) LE SEGn(htl)+1)=
  ccostkh(KP-1,htl) + ( (ccostmh(htl)-ccost0h(htl))*weigh(KP, htl));
  scount=scount+1;
  );
```

The following equations compute the cumulative capacity at each kink point.

```
ccapk(KP,ETL)$(ORD(KP) LE SEG(ETL)+1) =
((1-bb(ETL))*ccostk(KP,ETL)/aanew(ETL))**(1/(1-bb(ETL)));

ccapkn(KP,NTL)$(ORD(KP) LE SEGn(NTL)+1) =
((1-bbn(NTL))*ccostkn(KP,NTL)/aannew(NTL) )**(1/(1-bbn(NTL)));

ccapkh(KP,HTL)$(ORD(KP) LE SEGn(HTL)+1) =
((1-bbh(HTL))*ccostkh(KP,HTL)/aannew(HTL))**(1/(1-bbh(HTL)));
```

The following equations are related to the interpolation of the cumulative cost.

```
* Assignment of beta coeff. for interpolation of cumulative cost
```

```
beta(KP,ETL) $(ORD(KP) LE SEG(ETL)+1)=
  (ccostk(KP,ETL)-ccostk(KP-1,ETL))/(ccapk(KP,ETL)-ccapk(KP-1,ETL));

betan(KP,NTL) $(ORD(KP) LE SEGn(NTL)+1)=
  (ccostkn(KP,NTL)-ccostkn(KP-1,NTL))/(ccapkn(KP,NTL)-ccapkn(KP-1,NTL));

betah(KP,HTL) $(ORD(KP) LE SEGn(HTL)+1)=
  (ccostkh(KP,HTL)-ccostkh(KP-1,HTL))/(ccapkh(KP,HTL)-ccapkh(KP-1,HTL));

* Assignment of alpha coeff. for interpolation of cumulative cost
alph(KP,ETL) $(ORD(KP) LE SEG(ETL)+1)=
  ccostk(KP-1,ETL) - beta(KP,ETL)*ccapk(KP-1,ETL);

alphn(KP,NTL) $(ORD(KP) LE SEGn(NTL)+1)=
  ccostkn(KP-1,NTL) - betan(KP,NTL)*ccapkn(KP-1, NTL);

alphh(KP,HTL) $(ORD(KP) LE SEGn(HTL)+1)=
  ccostkh(KP-1,HTL) - betah(KP,HTL)*ccapkh(KP-1, HTL);
```

The next equations define the cumulative capacity for learning technologies.

```
CAPE(RG, ETL,TP,ts) $(ORD(TP) GT 2) ..
  sum(sw,PE(ETL,TP,ts,RG,sw))/(CF(ETL)*UNITS(ETL)) =E= SUM(TT$((ORD(TT) LE
ORD(TP)) AND (ORD(TT) GT ORD(TP)-LIFE(ETL)/NYPER(TP))),
 EINV(RG,ETL,TT)*nyper(TT)) +
sum(sw,PE(ETL,"2015",ts,RG,sw))/(CF(ETL)*UNITS(ETL))*resid(TP);

CAPNE(RG, NTL,TP) $(ORD(TP) GT 2) ..
  sum(sw,PN(NTL,TP,RG,sw))/CFN(NTL) =E= SUM(TT$((ORD(TT) LE ORD(TP)) AND
(ORD(TT) GT ORD(TP)-LIFEN(NTL)/NYPER(TP))),
  NINV(RG,NTL,TT)*nyper(TT)) + sum(sw,PN(NTL,"2015",RG,sw))/CFN(NTL)*resid(tp);

CAPH(RG, HTL,TP) $(ORD(TP) GT 2) ..
  sum(sw,PH(HTL,TP,RG,sw))/CFN(HTL) =E= SUM(TT$((ORD(TT) LE ORD(TP)) AND
(ORD(TT) GT ORD(TP)-LIFEN(HTL)/NYPER(TP))),
  HINV(RG,HTL,TT)*nyper(TT)) + sum(sw,PH(HTL,"2015",RG,sw))/CFN(HTL)*resid(tp);

GROWTH(ETL,TP) $(ORD(TP) GT 2) ..
  GCAP(ETL,TP) =E=  SUM(TT $ ((ORD(TT) LE ORD(TP)) AND (ORD(TT) GT 2)),
                        SUM (RG, EINV(RG,ETL,TT)*nyper(TT))/CAP0(ETL)) +1.0;

GROWTHN(NTL,TP)$(ORD(TP) GT 1) ..
   GCAPN(NTL,TP) =E= SUM(TT $ (ORD(TT) LE ORD(TP)), SUM(RG, SUM(SW,
PN(NTL,TT,RG,SW)*nyper(TT)))/CAP0N(NTL)) + 1.0;
```

```
GROWTHH(HTL,TP)$(ORD(TP) GT 1) ..
   GCAPH(HTL,TP) =E= SUM(TT $ (ORD(TT) LE ORD(TP)), SUM(RG, SUM(SW,
PH(HTL,TT,RG,SW)*nyper(TT)))/CAP0N(HTL)) + 1.0;

GROWTHI(ETL,TP) $(ORD(TP) LE 2) ..  GCAP(ETL,TP) =E= 1.0;
GROWTHNI(NTL,TP)$(ORD(TP) LE 1) ..   GCAPN(NTL,TP) =E= 1.0;
GROWTHHI(HTL,TP)$(ORD(TP) LE 1) ..   GCAPH(HTL,TP) =E= 1.0;
```

The following equations define the cumulative capacity interpolation and the cumulative cost interpolation.

```
EQCCAP(TP,ETL)..  GCAP(ETL,TP) * CAP0(ETL) =E=
  SUM(KP$((ORD(KP) GE 2)$(ORD(KP) LE SEG(ETL)+1)), LAMBD(TP, ETL, KP ));

EQCCAPN(TP,NTL )..  GCAPN(NTL,TP ) * CAP0N(NTL) =E=
  SUM(KP$((ORD(KP) GE 2)$(ORD(KP) LE SEGN(NTL)+1)), LAMBDN(TP,NTL,KP));

EQCCAPH(TP,HTL )..  GCAPH(HTL,TP ) * CAP0N(HTL) =E=
  SUM(KP$((ORD(KP) GE 2)$(ORD(KP) LE SEGN(HTL)+1)), LAMBDH(TP,HTL,KP));

* Force sum of binary variables delta to 1
EQDEL(TP, ETL )..
  SUM(KP$((ORD(KP) GE 2)$(ORD(KP) LE SEG(ETL)+1)), DELTA(TP,ETL,KP)) =E= 1;

EQDELN(TP,NTL)..
  SUM(KP$((ORD(KP) GE 2)$(ORD(KP) LE SEGN(NTL)+1)), DELTAN(TP,NTL,KP)) =E= 1;

EQDELH(TP,HTL)..
  SUM(KP$((ORD(KP) GE 2)$(ORD(KP) LE SEGN(HTL)+1)), DELTAH(TP,HTL,KP)) =E= 1;

* Cumulative Cost Interpolation
EQCCOS(TP,ETL )..
  CCOST(TP,ETL) =E=
  SUM(KP$((ORD(KP) GE 2)$(ORD(KP) LE SEG(ETL)+1)),
      LAMBD(TP,ETL,KP)*BETA(KP,ETL)+DELTA(TP,ETL,KP)*ALPH(KP,ETL));

EQCCOSN(TP,NTL)..
  CCOSTN(TP,NTL) =E=
  SUM(KP$((ORD(KP) GE 2)$(ORD(KP) LE SEGN(NTL)+1)),
  LAMBDN(TP,NTL,KP)*BETAN(KP,NTL)+DELTAN(TP,NTL,KP)*ALPHN(KP,NTL));

EQCCOSH(TP,HTL)..
  CCOSTH(TP,HTL) =E=
  SUM(KP$((ORD(KP) GE 2)$(ORD(KP) LE SEGN(HTL)+1)),
  LAMBDH(TP,HTL,KP)*BETAH(KP,HTL)+DELTAH(TP,HTL,KP)*ALPHH(KP,HTL));
```

```
* Constraints on lambda
EQLOG1(TP,ETL,KP)$((ORD(KP) GE 2)$(ORD(KP) LE SEG(ETL)+1))..
  LAMBD(TP,ETL,KP) =G= CCAPK(KP-1,ETL)*DELTA(TP,ETL,KP);

EQLOG1N(TP,NTL,KP)$((ORD(KP) GE 2)$(ORD(KP) LE SEGN(NTL)+1))..
  LAMBDN(TP,NTL,KP) =G= CCAPKN(KP-1,NTL)*DELTAN(TP,NTL,KP);

EQLOG1H(TP,HTL,KP)$((ORD(KP) GE 2)$(ORD(KP) LE SEGN(HTL)+1))..
  LAMBDH(TP,HTL,KP) =G= CCAPKH(KP-1,HTL)*DELTAH(TP,HTL,KP);

EQLOG2(TP,ETL,KP)$((ORD(KP) GE 2)$(ORD(KP) LE SEG(ETL)+1))..
  LAMBD(TP,ETL,KP) =L= CCAPK(KP,ETL)*DELTA(TP,ETL,KP);

EQLOG2N(TP,NTL,KP)$((ORD(KP) GE 2)$(ORD(KP) LE SEGN(NTL)+1))..
  LAMBDN(TP,NTL,KP )=L= CCAPKN(KP,NTL)*DELTAN(TP,NTL,KP);

EQLOG2H(TP,HTL,KP)$((ORD(KP) GE 2)$(ORD(KP) LE SEGN(HTL)+1))..
  LAMBDH(TP,HTL,KP )=L= CCAPKH(KP,HTL)*DELTAH(TP,HTL,KP);

* Investments to be discounted 1st period
EQIC1(RB,ETL)..
  ICOST(RB,ETL) =E= CCOST(RB,ETL) * (crd(RB,ETL)**(-ccf(ETL))) - ccost0(ETL) *
(crd0(ETL)**(-ccf(ETL)));

EQIC1N(RB,NTL)..
  ICOSTN(RB,NTL) =E= CCOSTN(RB,NTL) * (crdn(RB,NTL)**(-ccfn(NTL))) -
ccost0n(NTL) * (crd0n(NTL)**(-ccfn(NTL)));

EQIC1H(RB,HTL)..
  ICOSTH(RB,HTL) =E= CCOSTH(RB,HTL) * (crdh(RB,HTL)**(-ccfh(HTL))) -
ccost0n(HTL) * (crd0n(HTL)**(-ccfh(HTL)));

* Investments to be discounted , other periods
EQIC2(TP+1,ETL)..
  ICOST(TP+1,ETL) =E= CCOST(TP+1,ETL) * (crd(TP+1,ETL)**(-ccf(ETL))) -
CCOST(TP,ETL) * (crd(TP,ETL)**(-ccf(ETL)));

EQIC2N(TP+1,NTL)..
  ICOSTN(TP+1,NTL) =E= CCOSTN(TP+1,NTL) * (crdn(TP+1,NTL)**(-ccfn(NTL))) -
CCOSTN(TP,NTL) * (crdn(TP,NTL)**(-ccfn(NTL)));

EQIC2H(TP+1,HTL)..
  ICOSTH(TP+1,HTL) =E= CCOSTH(TP+1,HTL) * (crdh(TP+1,HTL)**(-ccfh(HTL))) -
CCOSTH(TP,HTL) * (crdh(TP,HTL)**(-ccfh(HTL)));
```

The following equation corresponds to the updated formulation of the cost of energy with a two-factor learning curve. In the MIP formulation, this is the objective function. Only the modified lines are included.

```
OBJETAMIP..
    COSTMIP =g= .001 * (
* Electric costs, discounted
SUM((TP,ETL,rg), 0.001 *ICOST(TP,ETL) *(1-SALV_INV(ETL,TP)) *
       (1+depr(rg))**(-nyper(tp)*time(TP)))
* Non-Electric learning costs, discounted
+ SUM((TP,NTL,rg), ICOSTN(TP,NTL) *(1-SALV_INVN(NTL,TP)) *
       (1+depr(rg))**(-nyper(tp)*time(TP)))
* Hydrogen learning costs, discounted
+ SUM((TP,HTL,rg), ICOSTH(TP,HTL)*(1-SALV_INVH(HTL,TP))*
       (1+depr(rg))**(-nyper(tp)*time(TP)))
* Discounted non-learning part of generation cost of tech with learning
+ SUM((TP,RG), (1+depr(rg))**(-nyper(tp)*time(TP)) * DISCPP(tp) * (
         SUM((sw,ETL,ts), (1.-cstfr(ETL))*PE(ETL,TP,ts,RG,sw) *ECST(ETL,tp,RG))
+ SUM((sw,NTL), (1.-cstfrn(NTL))*PN(NTL,TP,RG,sw)*NCST(NTL,RG))
+ SUM((sw,HTL), (1.-cstfrh(HTL))*PH(HTL,TP,RG,sw)*HCST(HTL,tp,RG))))
*   Costs for electric technologies without learning
+ sum((NETL_nonvre,ts,tp,rg,sw),
PE(NETL_nonvre,tp,ts,rg,sw)*ecst(NETL_nonvre,tp,rg)* cstred(tp))

                    + …

*   Costs for hydrogen technologies without learning
+ sum(nht, PH(nht,tp,rg,sw)*hcst(nht,tp,rg)* cstred(tp))

*   Costs for non-electric technologies without learning
+ sum(nntl, PN(nntl,tp,rg,sw)*ncst(nntl,rg)* cstred(tp))

                    + … ));
```

- Main file (NLP formulation)

In the main file of the NLP formulation, the whole AD-MERGE model with ETL equations is solved. The data file contains the same information as the MIP formulation. The following equations compute the cumulative capacity for each learning technology, but without linearization.

```
CAPE(RG, ETL,TP) $(ORD(TP) GT 2) ..
  sum((ts,sw),PE(ETL,TP,ts,RG,sw)/(CF(ETL)*UNITS(ETL))) =E=  sum((ts,sw),SUM(TT$
((ORD(TT) LE ORD(TP)) AND (ORD(TT) GT ORD(TP)-LIFE(ETL)/NYPER(TP))),
```

```
       EINV(RG,ETL,TT)*nyper(TT)) +
PE(ETL,"2015",ts,RG,sw)/(CF(ETL)*UNITS(ETL))*RESID(TP));

GROWTH(ETL,TP) $(ORD(TP) GT 2) ..
  GCAP(ETL,TP) =E=  SUM(TT $ ((ORD(TT) LE ORD(TP)) AND (ORD(TT) GT 2)),
                      SUM (RG, EINV(RG,ETL,TT)*nyper(TT) )/CAP0(ETL)) +1.0 ;

GROWTHI(ETL,TP) $(ORD(TP) LE 2) ..  GCAP(ETL,TP) =E= 1.0;

CAPNE(RG, NTL,TP) $(ORD(TP) GT 2) ..
  sum(sw,PN(NTL,TP,RG,sw)/CFN(NTL)) =E=  sum(sw,SUM(TT $ ((ORD(TT) LE ORD(TP))
AND (ORD(TT) GT ORD(TP)-LIFEN(NTL)/NYPER(TP))),
       NINV(RG,NTL,TT)*nyper(TT)) + PN(NTL,"2015",RG,sw)/CFN(NTL)*resid(tp));


GROWTHN(NTL,TP)$(ORD(TP) GT 1) ..
   GCAPN(NTL,TP) =E= SUM(TT $ (ORD(TT) LE ORD(TP) ), SUM ((RG,sw),
PN(NTL,TT,RG,sw)*nyper(TT))/(CAP0N(NTL)*CFN(NTL)*LIFEN(NTL))) +1.0 ;

GROWTHNI(NTL,TP)$(ORD(TP) LE 1) ..   GCAPN(NTL,TP) =E= 1.0;

CAPH(RG, HTL,TP) $(ORD(TP) GT 2) ..
  sum(sw,PH(HTL,TP,RG,sw)/CFH(HTL)) =E=  sum(sw,SUM(TT $ ((ORD(TT) LE ORD(TP))
AND (ORD(TT) GT ORD(TP)-LIFEH(HTL)/NYPER(TP))),
       HINV(RG,HTL,TT)*nyper(TT)) + PH(HTL,"2015",RG,sw)/CFH(HTL)*resid(tp));

GROWTHH(HTL,TP)$(ORD(TP) GT 1) ..
   GCAPH(HTL,TP) =E= SUM(TT $ (ORD(TT) LE ORD(TP) ), SUM ((RG,sw),
PH(HTL,TT,RG,sw)*nyper(TT) )/(CAP0H(HTL)*CFH(HTL)*LIFEH(HTL))) +1.0 ;

GROWTHHI(HTL,TP)$(ORD(TP) LE 1) ..   GCAPH(HTL,TP) =E= 1.0;
```

The following equation is the updated formulation of the cost of energy with a two-factor learning curve for the NLP formulation. Only the modified lines are included.

```
costnrg(rg,tp,sw)$(pp(tp) and st(tp,sw))..    EC(rg,tp,sw) =g= .001 * (
*   Learning costs electric
sum((ETL,ts), (((gcap(ETL,TP)**(1-bb(ETL)))*(crd(TP,ETL)**(-ccf(ETL))) -
                    (gcap(ETL,TP-1)**(1-bb(ETL)))*(crd(TP-1,ETL)**(-ccf(ETL))))
/ (1-bb(ETL))* cap0(ETL)*spcost(ETL) * (crd0(ETL)**ccf(ETL)) * (1-
salv_inv(ETL,TP-1)))$(ord(TP) GT 2))
+ sum(etl,( ((gcap(ETL,"2015")**(1-bb(ETL)))*(crd("2015",ETL)**(-ccf(ETL))) -
1*(crd0(ETL)**(-ccf(ETL)))) / (1-bb(ETL))
```

```
                    *cap0(ETL) *spcost(ETL) * (crd0(ETL)**ccf(ETL)) * (1-
salv_inv(ETL,"2015")))$(ord(TP) EQ 1))

* Learning costs non-electric
+ sum(NTL, (((gcapn(NTL,TP)**(1-bbn(NTL)))*(crdn(TP,NTL)**(-ccfn(NTL))) -
                    (gcapn(NTL,TP-1)**(1-bbn(NTL)))*(crdn(TP-1,NTL)**(-
ccfn(NTL)))) / (1-bbn(NTL))* cap0n(NTL)*spcostn(NTL) * (crd0n(NTL)**ccfn(NTL)) *
(1-salv_invn(NTL,TP-1)))$(ord(TP) GT 2))
                    + sum(ntl,( ((gcapn(NTL,"2015")**(1-
bbn(NTL)))*(crdn("2015",NTL)**(-ccfn(NTL))) - 1*(crd0n(NTL)**(-ccfn(NTL)))) /
(1-bbn(NTL))
                    *cap0n(NTL) *spcostn(NTL) * (crd0n(NTL)**ccfn(NTL)) * (1-
salv_invn(NTL,"2015")))$(ord(TP) EQ 1))

* Learning costs hydrogen
+ sum(HTL, (((gcaph(HTL,TP)**(1-bbh(HTL)))*(crdh(TP,HTL)**(-ccfh(HTL))) -
                    (gcaph(HTL,TP-1)**(1-bbh(HTL)))*(crdh(TP-1,HTL)**(-
ccfh(HTL)))) / (1-bbh(HTL))* cap0h(HTL)*spcosth(HTL) * (crd0h(HTL)**ccfh(HTL)) *
(1-salv_invh(HTL,TP-1)))$(ord(TP) GT 2))
                    + sum(htl,( ((gcaph(HTL,"2015")**(1-
bbh(HTL)))*(crdh("2015",HTL)**(-ccfh(HTL))) - 1*(crd0h(HTL)**(-ccfh(HTL)))) /
(1-bbh(HTL))
                    *cap0h(HTL) *spcosth(HTL) * (crd0h(HTL)**ccfh(HTL)) * (1-
salv_invh(HTL,"2015")))$(ord(TP) EQ 1))

*   Costs for energy supplies that are not learning
+ sum((ETL,ts), (1.-cstfr(ETL)) * PE(etl,tp,ts,rg,sw) * ecst(etl,tp,RG))
+ sum((NTL,ts), (1.-cstfrn(NTL)) * PN(ntl,tp,rg,sw) * ncst(ntl,rg))
+ sum((HTL,ts), (1.-cstfrh(HTL)) * PH(htl,tp,rg,sw) * hcst(htl,tp,RG))

*   Costs for electric and nonelectric energy supplies (without learning)
+ sum((NETL_nonvre,ts), PE(NETL_nonvre,tp,ts,rg,sw)*ecst(NETL_nonvre,tp,rg)*
cstred(tp))

+ …

* Hydrogen production cost (without learning)
+ sum(nht, PH(nht,tp,rg,sw)*hcst(nht,tp,rg)* cstred(tp))

* Non-electric production cost (without learning)
+ sum(nntl, PN(nntl,tp,rg,sw)*ncst(nntl,rg)* cstred(tp))

+ … );
```

Additionally, the following equation is updated to account for R&D expenditures.

```
cc(rg,pp,sw)$st(pp,sw)..     Y(rg,pp,sw) =e=
C(rg,pp,sw) + I(rg,pp,sw) + EC(rg,pp,sw) + MD(rg,pp,sw) + NTX("nmr",pp,rg,sw)
+ 0.001*SUM(ETL, ard_exo(ETL,PP))
+ 0.001*SUM(NTL, ardN_exo(NTL,PP))
+ 0.001*SUM(HTL, ardh_exo(HTL,PP));
```

- Execution

To run the model using the MERGE-ETL approach, the files containing the ETL equations need to be executed in the correct order. The solving loop is implemented in three different models but can eventually be automated for more iterations. However, having three separate models is more manageable for debugging. Each model file has its own data and report files.

1. The first file to run is AD-MERGE 2.0 without ETL. After solving the model, a GDX file containing the demands E and N is generated.
2. The second file to run is the MIP formulation. It takes the demands stored in the previous GDX file (generated from AD-MERGE) as input. This file contains only the ETA equations and the ETL equations. This file contains the piecewise linear approximation of the cost function. After solving the model, the new demands E and N are stored in a new GDX file.
3. The third file to run is the NLP formulation. Again, it takes the demands stored in the GDX file (generated from the MIP model) as input. This file contains the complete AD-MERGE and ETL equations (without linearization). After solving the model, the new demands E and N are stored in a new GDX file.
4. If needed, the MIP and NLP formulation are solved again until the demands E and N stop changing. The user has to make sure to input the correct GDX file when running the MIP formulation more than once. The first time the MIP model is solved, it takes the GDX from AD-MERGE as input, but for subsequent solves, it takes the GDX from the NLP model as input.

The user has to make sure that `$setglobal lbd = no` in the input scenario because the two-factor learning curve is used instead of the LBD formulation.

Chapter 6
Learning data for hydrogen technologies

Reliable data is crucial to produce accurate results in any analysis. However, obtaining good ETL data can be a challenge since the data varies from country to country. Furthermore, when merging countries into regions, the accuracy of the data is further compromised. When using global learning rates, technologies are assumed to be learning identically in different parts of the world without distinction between countries. This approach can be problematic since other countries have different technological capabilities and adopt new technologies at a different pace. Analyzing new technologies can also be difficult since no historical data is usually available. In such cases, learning parameters can be derived from similar conventional technologies with similar learning patterns.

6.1 Technology characteristics

When adding new learning technologies to the model, many parameters must be added as well. Depending on the type of learning curve implemented, installed capacities, cumulative production, R&D data, learning-by-doing rate, and learning-by-searching rate must be input into the model. An additional difficulty is finding data that match the base year used in the model. For instance, AD-MERGE 2.0 uses 2015 as a base year, whereas AD-MERGE 1.0 uses 2000 as a base year. All data must be updated and actualized in terms of the base year. Some promising technologies in the early 2000s might be mature today and therefore irrelevant to study as learning technologies. Learning technologies must be selected carefully to be relevant and insightful. Two technologies have been kept since the MERGE-ETL approach: integrated gasification combined cycle (IGCC) and renewables (RNEW), which come from biomass. These technologies were the first to be implemented as learning technologies in AD-MERGE 2.0 as they served as testers for solving the model. These technologies were modelled in the 2002 version of MERGE-ETL and were still used in AD-MERGE 1.0 as non-learning technologies. Since they were already in the model, adding their learning parameters from already available data was simpler. It is important to note that the learning parameters of IGCC and RNEW have not been updated because the choice of electric and non-electric learning technologies is likely to change in further versions of AD-MERGE 2.0.

Because the integration of hydrogen into the model constitutes a big part of the current research works on AD-MERGE 2.0, the current study of learning effects is focused mainly on hydrogen technologies.

The first hydrogen technology incorporated as a learning technology is electrolysis, which uses electricity to split water into hydrogen and oxygen (U.S. Department of Energy, 2020). The device in which this process occurs is known as an electrolyser. The latter comes in different sizes and can produce hydrogen on a small to large scale. Several forms of electrolysis exist: polymer electrolyte membrane or proton exchange membrane (PEM), alkaline, solid oxide electrolyser cell (SOEC) and anion exchange membrane (AEM). SOEC and AEM are maturing, while PEM and alkaline are commercially available (IEA, 2023c). Since the type of electrolysis currently being implemented in AD-MERGE 2.0 is PEM, learning effects are only specific to PEM electrolysers. Currently, hydrogen production from electrolysis accounts for less than 5% of total hydrogen production (IEA, 2023c).

Hydrogen production from coal gasification with carbon capture and storage (CCS) is the second hydrogen technology incorporated as a learning technology. This technology is known as "coal-h2-CCS" in the model. This process involves mixing coal with an oxidant like steam, air, or oxygen to create a synthetic gas consisting of hydrogen, carbon dioxide and other gases and particles. After cleaning, cooling, and shifting, the synthetic gas mainly comprises hydrogen and carbon dioxide (Megía, Vizcaíno, Calles & Carrero, 2021). The hydrogen can be used after purification while the carbon dioxide is captured and sequestered (Midilli, Kucuk, Topal, Akbulut & Dincer, 2021). Currently, hydrogen production from coal without CCS accounts for approximately 20% of total hydrogen production (IEA, 2023c). Coal gasification (without CCS) is a mature technology and is expected to be augmented with other renewable technologies, as well as the incorporation of the CCS process over the long term (National Energy Technology Laboratory [NETL], n.d.).

The final hydrogen technology implemented as a learning technology is steam-methane reforming (SMR) of natural gas with CCS defined as "gas-h2-CCS" in the model. During steam-methane reforming, methane reacts with steam to produce hydrogen and carbon monoxide (U.S. Department of Energy, 2020). The remaining carbon monoxide can then be captured and stored (with CCS) or not (without CCS). Natural gas reforming (without CCS) is a mature and advanced technology, but its counterpart with CCS is emerging (Lewis et al., 2022). Most hydrogen production comes from natural gas (without CCS), representing approximately 60% of the total production, while hydrogen production from fossil fuels with CCS, including coal gasification, accounts for 0.6% (Global CCS Institute, 2021; IEA, 2023c).

The following three tables summarize the techno-economic characteristics of hydrogen technologies in the model. The data source is provided for each parameter.

***Table 6.1**: Learning characteristics for electrolysis*

Technology	Parameter	Value	Source
electrolysis	Learning-by-doing rate	13%	Hydrogen Council, 2020
	Learning-by-searching rate	1%	Estimation using IRENA, 2020
	Capacity factor	55%	IEA, 2023c
	Initial capacity (EJ)	0.006	IEA, 2023c
	Global maximum capacity (EJ)	23.915	IEA, 2021b
	Initial cumulative R&D spending (billion USD 2015)	0.46	IEA, 2021a
	Lifetime (years)	25	IEA, 2023c
	Floor cost (USD/GJ)	1.25	NREL, 2022

***Table 6.2**: Learning characteristics for coal-H2 with CCS*

Technology	Parameter	Value	Source
coal-h2-CCS	Learning-by-doing rate	6%	Rubin et al., 2015
	Learning-by-searching rate	6%	Estimation using IEA, 2023d
	Capacity factor	90%	NREL, 2022
	Initial capacity (EJ)	0.024	IEA, 2023e
	Global maximum capacity (EJ)	2.000	IEA, 2023e
	Initial cumulative R&D spending (billion USD 2015)	2.10	IEA, 2023d
	Lifetime (years)	40	NREL, 2022
	Floor cost (USD/GJ)	11.91	NREL, 2022

***Table 6.3**: Learning characteristics for gas-H2 with CCS*

Technology	Parameter	Value	Source
gas-h2-CCS	Learning-by-doing rate	5%	Rubin et al., 2015
	Learning-by-searching rate	1%	Estimation using IEA, 2023d
	Capacity factor	90%	NREL, 2022
	Initial capacity (EJ)	0.080	IEA, 2023e
	Global maximum capacity (EJ)	6.696	IEA, 2023e
	Initial cumulative R&D spending (billion USD 2015)	3.57	IEA, 2023d
	Lifetime (years)	40	NREL, 2022
	Floor cost (USD/GJ)	4.00	NREL, 2022

Several transformations and assumptions are made to ensure the data meets the model's criteria. When a range of values is provided, the middle value is used. Capacities in exajoules have been converted from MV or GW. Monetary values that were not available in USD 2015 have been converted using an inflation multiplicator. When a value is unavailable, such as learning-by-searching rates, it is estimated using available data and assumptions. Estimations follow the methodology of Glenk, Holler and Reichelstein in their analysis of the cost and conversion efficiency of hydrogen technologies (Glenk, Holler, & Reichelstein, 2023). Initial values are for the base year (2015). In this table, the floor cost is the levelized cost in the year 2050, and the global maximum capacities are projected in the year 2050. The chosen learning rates are conservative and vary significantly in the literature. Choosing higher learning rates will usually imply an earlier implementation of the technology.

6.2 R&D investments

In the MERGE-ETL approach, R&D budget data is updated using the International Energy Agency database (IEA, 2023a). This dataset contains detailed public budgets for energy Research, Development and Demonstration (RD&D) for countries that are part of the IEA. The annual data by country is expressed in 2022 prices and exchange rates. Data is converted in the model to USD 2015 and aggregated into corresponding regions. Some countries that are not part of IEA do not have an available R&D budget in this database. Their values are estimated and based on other data sources.

Chapter 7
Results

The following table compares the solutions of each version of AD-MERGE 2.0. The first version is the original AD-MERGE 2.0 model without endogenous technological learning, with learning-by-doing switched off. The second version is the same but with learning-by-doing switched on (only LBDE and LBDN). These two first versions are the baseline versions for comparison purposes. The third version is an updated version of learning-by-doing with more technologies (*igcc, rnew, electrolysis, coal-h2-CCS, gas-h2-CCS*). Lastly, the fourth version includes the two-factor learning curve with the linearization process and the same learning technologies as in version 3.

Table 7.1*: Comparison of solving methods for ETL in AD-MERGE 2.0*

<table>
<tr><th>Model version</th><th>Solver</th><th>Optimum</th><th>Solving time[1]</th></tr>
<tr><td>1. Original AD-MERGE 2.0, lbd = no</td><td>CONOPT4</td><td>Global</td><td>1</td></tr>
<tr><td>2. Original AD-MERGE 2.0, lbd = yes</td><td>CONOPT4</td><td>Local</td><td>0.55</td></tr>
<tr><td rowspan="3">3. Manne-Barreto approach (with more technologies)</td><td>CONOPT4</td><td>Local</td><td>1.14</td></tr>
<tr><td>BARON</td><td>Local</td><td>3.50 (without maxiter)
0.14 (with maxiter)</td></tr>
<tr><td>Knitro</td><td>Local</td><td>6.96</td></tr>
<tr><td>4. MERGE-ETL approach</td><td>CONOPT4, MIP</td><td>Global[2]</td><td>2.13</td></tr>
</table>

[1] For comparison purposes, the solving time of AD-MERGE 2.0 without ETL and without LBD is set to 1 and is used as a baseline. Because solving time depends on the computer processing power, each solving time is expressed in terms of the solving time of AD-MERGE 2.0. For reference, the solving time of model 1 is 00:48:19.

[2] The linear approximation is solved until global optimality, which gives a reasonable approximation of the global optimum in the final model. Therefore, the optimum of the MERGE-ETL approach is assumed to be global.

As previously mentioned, the first model is the baseline. If endogenous technological learning is not required in the analysis, this version can be used instead. Because model 1 does not include ETL equations, the formulation is convex; therefore, the local optimum is also a global optimum. Model 2 with LBDE and LBDN can also be used for a vague estimation of the learning-by-doing effects on electric and non-electric technologies without being specific to technologies. The computation time of model 2 is reduced because of the formulation of learning-by-doing equations. When activating the LBD parameter, technologies like solar and wind are removed from the model as they are integrated into the technology "LBDE", and similarly for non-electric technologies. It is also important to note that the initial formulation of LBD in model 2 has not been updated since its implementation in 2004. Therefore, the data and technologies might be different from current trends. Lastly, with the inclusion of learning-by-doing into model 2, the optimum is no longer global.

Model 3 includes five learning technologies subject to learning-by-doing. This version allows the exploration of the gradual implementation of new technologies with returns on adoption without the complexity of a two-factor learning curve. When solved with CONOPT4, the solution is improved with a slightly longer computation time. However, this solution is not guaranteed to be a global optimum. When solved without the *maxiter* option, BARON fails to provide a global optimum, and the computation time is tripled compared to the baseline. In this case, the solution is local, and the impact on the objective value is negative. When solved with unlimited branch-and-reduce iterations, BARON provides a local solution that is slightly better than without the *maxiter* option but is still not as good as the CONOPT solution. However, when unlimited iterations are specified, the computation time is reduced, representing as little as 0.14 of the baseline's solving time. Overall, when solved with BARON, the objective value found is significantly reduced compared to the CONOPT one.

When solved with Knitro without multi-start, the solution is the same as the one found with CONOPT, which is an improvement compared to the baseline. However, the solving time is considerably higher than with other methods. When solved with multi-start, Knitro is not able to provide a solution within the allocated time. By fixing a time limit on each starting point and reducing the number of multi-start points, Knitro can provide feasible solutions but no optima. In these instances, neither BARON nor Knitro are able to provide a global solution or provide a better solution than CONOPT. One of the reasons BARON and Knitro perform poorly could be linked to the presence of infinite bounds on some variables that limit the algorithm's ability to infer appropriate bounds (GAMS, 2024a).

Overall, solving version 3 with CONOPT is preferable, as it provides the best solution in less time. Compared to the baseline, this version generates a better objective value, and the quantity of hydrogen produced is greater, particularly for electrolysis.

Model 4 includes the same five learning technologies but uses a two-factor learning curve. Because the solving loop has three steps, three submodules must be executed to solve the whole model. First, the model is solved without ETL; this is equivalent to running the baseline. Then, the ETA module with a linearized cost curve is solved, and finally, the complete non-linear model with ETL equations is solved. This results in a higher computational time and increased complexity as many equations and submodules are implemented. The iterative process between the MIP solution and the subsequent NLP solution ensures the final solution is global.

Overall, model 4 provides a better objective value and hydrogen production than model 1 and model 2, which means incorporating ETL equations benefits the model. The solving time is higher, as expected, because the solving is executed in three steps. The complexity is also much higher. Compared to model 3, model 4 has a slightly higher objective value and hydrogen production is higher throughout the time horizon. For the same learning-by-doing rate, hydrogen production from electrolysis is higher in model 4, as it also includes cost reductions from R&D expenditures. As for the choice of technologies, the final energy mix is similar in both models 3 and 4. In addition, model 4 generates an optimum that is assumed to be global, but the complexity and solving time are higher.

The following figures on the next page show the production of hydrogen after solving models 1, 2, and 3.

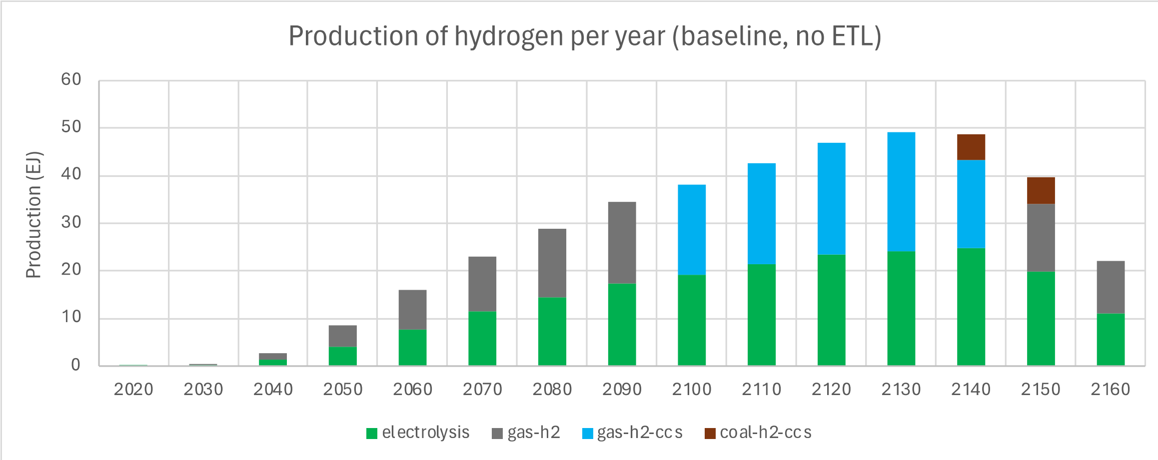

Figure 7.1: *Production of hydrogen per year in model 1. This is the output of the original AD-MERGE 2.0 without ETL, solved by CONOPT4.*

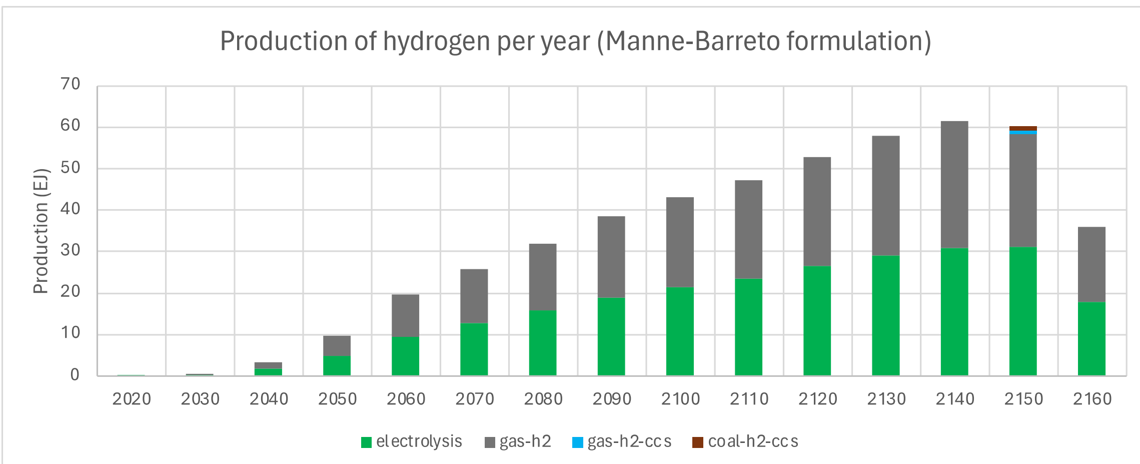

Figure 7.2: *Production of hydrogen per year in model 3. This is the output of the Manne-Barreto formulation using the one-factor learning curve solved by CONOPT4.*

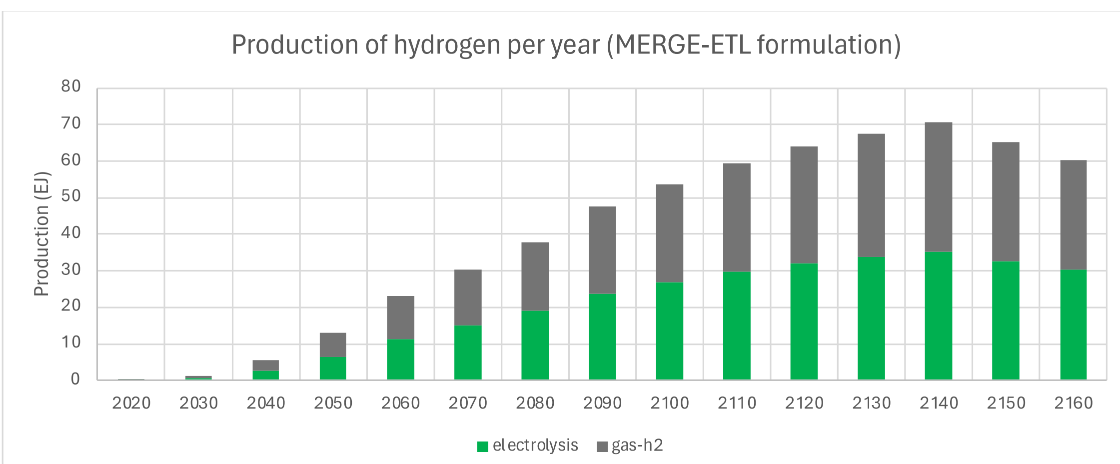

Figure 7.3: *Production of hydrogen per year in model 4. This is the output of the MERGE-ETL formulation using the two-factor learning curve, solved with the iterative heuristic.*

In **Figure 7.1**, an issue arises with the production of *gas-h2* and *gas-h2-ccs*. Because cost reductions are specified exogenously, the model starts producing hydrogen from natural gas with CCS in 2100 because it becomes more cost-competitive than without CCS. The “low-cost” natural gas reforming with CCS temporarily replaces the production of natural gas reforming without CCS. In this case, the cost reductions are time-dependent and do not account for acquired experience and investments. In reality, CCS technologies should be incorporated gradually as they accumulate experience, and their cost should decrease over time based on this accumulation of experience.

In both **Figure 7.2** and **Figure 7.3**, the issue concerning the exogenous cost reductions is rectified as the two formulations imply endogenous cost reductions. Because natural gas reforming is a mature technology with a low initial cost, it is preferred over its counterpart with CCS.

With the Manne-Barreto approach, the two technologies with CCS are barely incorporated into the energy mix as their chosen learning rates are conservative. They are incorporated only at the end of the time horizon, as the model wants to respect the lower bound imposed on these technologies. With the MERGE-ETL formulation, hydrogen production primarily comes from electrolysis and natural gas without CCS. Similarly to the Manne-Barreto approach, even with endogenous cost assumptions, mature fossil-fuel-based hydrogen technologies are prioritized over new ones as they have lower costs than emerging technologies. However, in both ETL models, increasing learning rates of CCS technologies will incorporate them sooner.

For an additional comparison, **Figure 7.4** and **Figure 7.5** on the next page show the production of electric and non-electric energy in 2015, 2030, 2050 and 2100 for the baseline, the MERGE-ETL approach and the Manne-Barreto approach. The two graphs show that the baseline model has a higher overall energy production. This is because it doesn't account for endogenous technological advancements, which mainly come from hydrogen production. As the baseline model produces less hydrogen compared to other models, other energy sources are used to compensate for the gap. For the Manne-Barreto approach, the production of the two learning technologies IGCC and RNEW is higher and incorporated earlier than the other models, which could be attributed to the learning effects.

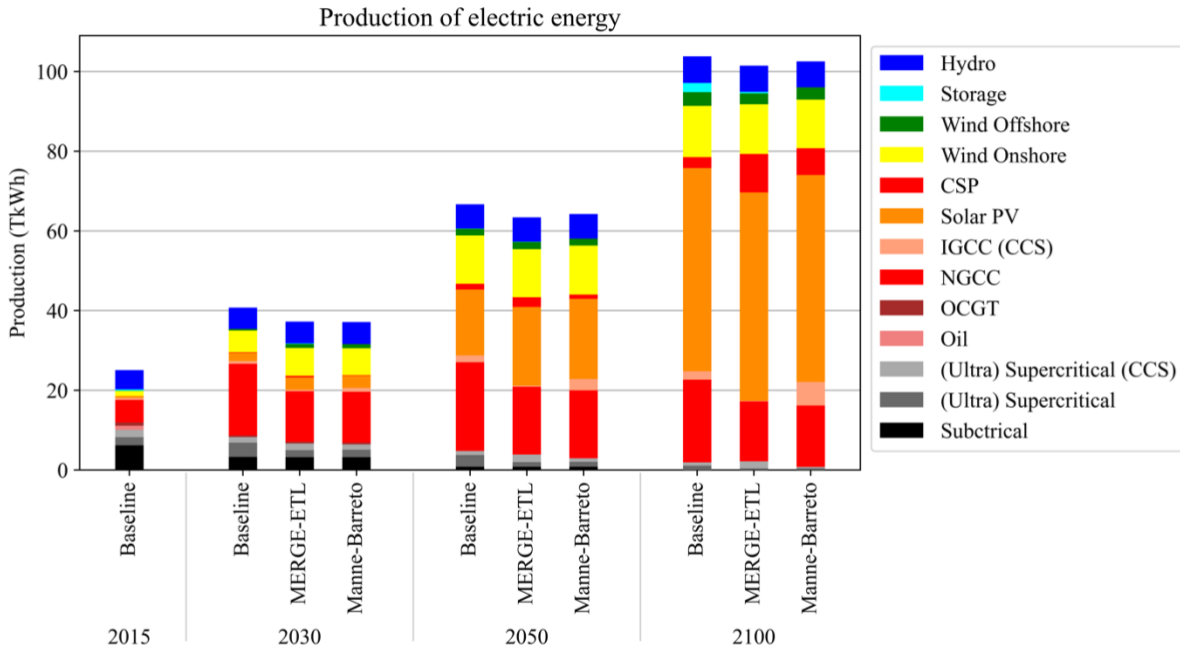

Figure 7.4: *Production of electric energy per year for the baseline (model 1) solved with CONOPT4, the Manne-Barreto approach (model 3) solved with CONOPT4 and the MERGE-ETL approach (model 4) solved with the heuristic loop.*

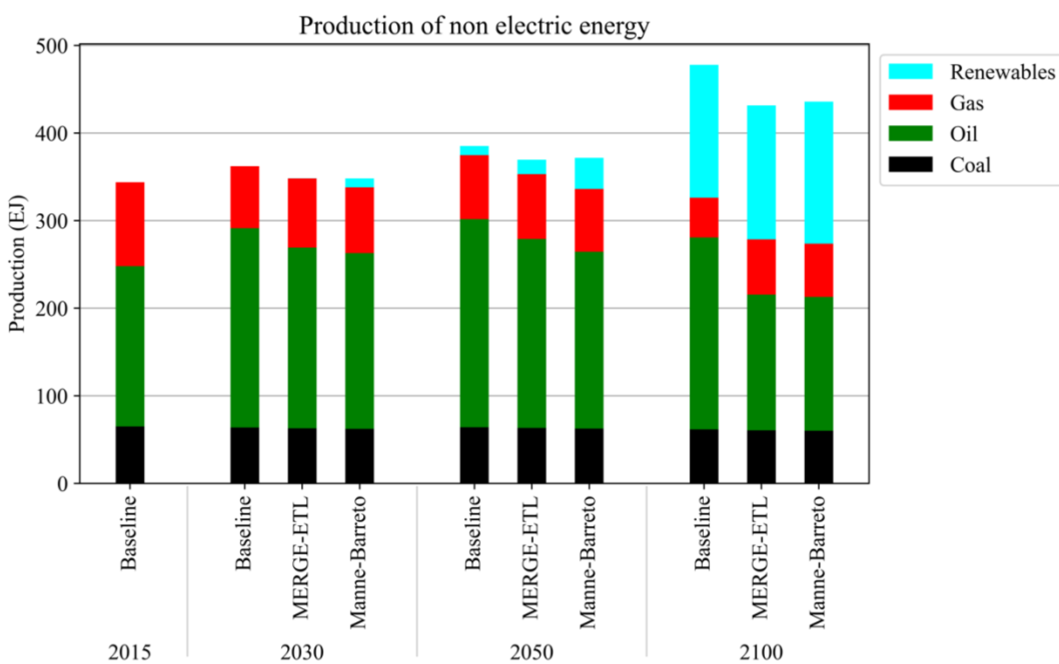

Figure 7.5: *Production of non-electric energy per year for the baseline (model 1) solved with CONOPT4, the Manne-Barreto approach (model 3) solved with CONOPT4 and the MERGE-ETL approach (model 4) solved with the heuristic loop. This graph does not include the production hydrogen.*

Chapter 8
Conclusion

This study aimed to implement endogenous technological learning in AD-MERGE 2.0 in two distinct ways: the Manne-Barreto approach, which was initially implemented in MERGE in 2004 through a one-factor learning curve, and the MERGE-ETL approach, which was initially implemented in 2002 through a two-factor learning curve.

When compared, each approach was found to have its own advantages and disadvantages. Ultimately, the model user must weigh these factors to determine which approach is best suited for their needs.

Both the Manne-Barreto approach and the MERGE-ETL approach provided a better solution than the baseline without endogenous technological learning. The Manne-Barreto approach has a simpler implementation, and the solving time is comparable to the baseline’s solving time. On the other hand, the MERGE-ETL approach performs better than the Manne-Barreto approach but the computational complexity and solving time are higher.

The two implementations allow the user to choose the preferred approach depending on the nature of the analysis. They produce valid outputs but to a different degree of precision. One should opt for the MERGE-ETL approach to analyze the impact of different learning effects in different scenarios. The two-factor learning curve allows more flexibility to adjust learning from the accumulation of experience or the R&D expenditures. On the other hand, if one wants to account for learning without making it the centre of the analysis and without increasing the complexity of the model, then the Manne-Barreto approach is sufficient.

Because of the additional parameters linked with the R&D expenditures, gathering all regional and technological data related to the second factor in the learning curve can be difficult. Learning-by-doing has been extensively researched in the past decades, allowing for an extensive range of available data. If data collection is an issue, it can be easier to work with learning-by-doing only, using the Manne approach, as more data is available in the literature.

Regardless of the chosen approach, it is essential to have reliable data. The choice of accurate learning parameters is essential to a precise analysis. The more complex the approach is, the more data is needed, and the more the accuracy is reduced if data is not accurate. There are various layers to explore when analyzing data related to technological learning. For instance, learning rates usually differ from one technology to another, but learning rates can vary from region to region and throughout time. In addition, learning rates are not always constant along the learning curve, depending on the maturity stage of the technology. Dealing with several countries in a single region can add more uncertainty; each country has its own infrastructure and technological advancement. This study assumed a constant learning rate per technology without regional distinctions. Adding regional and temporal dimensions to the learning rates could add depth to the analysis in future works. The model also assumed perfect spillover between regions, using global learning rates instead of regional ones. This means that as soon as a technology is available in a region, it is also available globally. A possible extension could be to model technological learning with spillovers by using regional learning rates and by analyzing the effect of a larger or smaller spillover coefficient.

Additionally, a sensitivity analysis of learning rates could extend this study. There is considerable uncertainty associated with the learning rates of learning technologies. When updating the characteristics of learning technologies in Chapter 3, some learning rates have been estimated by calculation and assumptions or by choosing a value from a range of learning rates. The conservative learning rates chosen in this study did not significantly change the final energy mix. However, higher learning rates could have led to an earlier implementation of emerging technologies. Conservative learning rates have been used in this study because they follow the trends of a middle-of-the-road pathway, as in the SSP2 scenario. By comparing several versions of the model using different learning rates in a one—or two-factor learning curve, decision-makers can observe the impact of the learning effect on the output. This sensitivity analysis can provide them with various scenarios to understand the implications of learning rates on technology costs, globally or regionally.

Another possible extension of this study could be to study the impact of segmentation of the piecewise linear approximation to optimize the generated solution. Adding more segments to the linear approximation will usually provide a more accurate approximation, but the computation time will increase. The decision-maker must balance the trade-off between precision and computation time. Again, this could be performed using a sensitivity analysis to determine the optimal number of segments to use in the linear approximation and its effect on the computation time and the quality of the solution.

Additionally, different algorithms can be used. In this study, the direct non-linear solvers CONOPT, BARON and Knitro were tested in addition to using an iterative heuristic approach. BARON and Knitro performed poorly in solving the Manne-Barreto approach, but further analyses can be explored. For instance, solution times and the search for optimal solutions can be improved by using the different solver options. For BARON and Knitro, only a few solver options have been used, but many more can be used. Incorporating different solvers into the heuristic approach could also be interesting to see if the output changes. Using a global solver like BARON for the MERGE-ETL formulation could be a great way to confirm that the optimal solution is indeed a global optimum.

Moreover, only PEM electrolysis is included in the model. However, PEM electrolysers account for 30% of electrolysis capacity, while alkaline electrolysers account for 60%, and the remaining 10% is attributed to SOEC and AEM electrolysers (IEA, 2023c). The proportion of hydrogen production from electrolysis is expected to increase considerably in the following years, and including all types of electrolysers in AD-MERGE could be beneficial. In addition, because SOEC and AEM electrolysers are still maturing, studying their learning effects will give valuable insights to decision-makers.

As mentioned previously, decision-makers have different behaviours based on their priorities. While some may be more climate-oriented and optimistic about the energy transition, they might value more technological development, resulting in an earlier incorporation of clean energy into the energy mix. Some other decision-makers might prioritize economic development and continue investing in fossil-fueled energies that are already commercially viable and accessible. The results of AD-MERGE 2.0 based on SSP2 showed that fossil-fueled-based energies were still an essential part of the energy mix. A possible extension of this study could be to explore the impact of endogenous technological learning through different SSP-based scenarios to have different perspectives on the world's outcome. For example, SSP1 emphasizes sustainable development with lower energy consumption. It could be informative to examine how technological developments might change if sustainability became an even higher priority. However, this exploration could be tedious, as it would imply recalibrating the whole model to a new scenario.

Finally, it is essential to note that the AD-MERGE 2.0 model is still changing and is not final. Other industries and sectors in the model are still evolving and will be finalized in the following months. In addition, data should also be continuously updated periodically in the following years for the model predictions to remain accurate.

The model must align with the energy trends of the next few years. Although Canada's potential for hydrogen is still in its early stages, significant developments are expected in the next 25 years. Like many other nations, Canada has committed to achieving net-zero GHG emissions by 2050. However, Canada has a history of missing its GHG reduction targets and must now work harder to achieve the 2050 goal. The energy sources that have the potential to contribute significantly to the net-zero target are limited, but the most important ones are electricity, hydrogen, and biofuels (Layzell, 2023). In addition to low-cost energies with a high potential for decarbonization, Canada requires a resilient energy system that can withstand disruptions to ensure that the transition to sustainable energy is reliable and long-lasting.

The number of hydrogen projects that are announced every year is considerably increasing and needs to be tracked and deployed to achieve net zero emissions targets (IEA, 2023b). While it is still early for emerging technologies, there is an increasing potential to explore CCS technologies for mature technologies. For these technologies, such as steam-methane reforming and coal gasification, production costs can be reduced because existing facilities and knowledge can be used. However, the learning effects are smaller, and the floor cost will be achieved quickly. For now, even though coal gasification plants with CCS are in operation, their carbon footprint is too high (IEA, 2023c) to compete with green hydrogen.

Overall, this study aimed to explore the impact of endogenous technological learning in an energy model. Whether technological learning is incorporated exogenously or endogenously via a one— or two-factor learning curve, it still impacts the output in different ways. Understanding the impact of ETL can help diversify the energy mix, adjust the energy transition timeline, and reduce technology costs. Modelling learning effects into a global model provides a reasonable picture of today's economy, which can then be used as a tool for real-life decision-making.

Bibliography

Aboumahboub, T., Auer, C., Bauer, N., Baumstark, L., Bertram, C., Bi, S., Dietrich, J., Dirnaichner, A., Giannousakis, A., Haller, M., Hilaire, J., Klein, D., Koch, J., Körner, A., Kriegler, E., Leimbach, M., Levesque, A., Lorenz, A., Luderer, G., … Ueckerdt, F. (2020). *REMIND - REgional Model of INvestments and Development - Version 2.1.0*. https://www.pik-potsdam.de/research/transformation-pathways/models/remind

Anandarajah, G., McDowall, W., & Ekins, P. (2013). Decarbonising road transport with hydrogen and electricity: Long term global technology learning scenarios. *International Journal of Hydrogen Energy*, *38*(8), 3419–3432. 10.1016/j.ijhydene.2012.12.110

Argote, L., & Epple, D. (1990). Learning curves in manufacturing. *Science*, *247*(4945), 920–924. https://doi.org/10.1126/science.247.4945.920

Artelys. (2023). *Knitro Documentation*. https://www.artelys.com/app/docs/knitro/index.html

Asher, H. (1956). *Cost-quantity relationships in the airframe industry*. (Report No. 291). RAND Corporation. https://www.rand.org/pubs/reports/R291.html

Bahn, O., de Bruin, K., & Fertel, C. (2019). Will Adaptation Delay the Transition to Clean Energy Systems? An Analysis with AD-MERGE. *The Energy Journal*, *40*(4), 207–234. https://doi.org/10.5547/01956574.40.4.obah

Bahn, O., Haurie, A., & Zachary, D. S. (2004). Mathematical modeling and simulation methods in energy systems. *Les Cahiers du GERAD*, *G-2004*(41), 1–18.

Bahn, O., & Kypreos, S. (2002). *MERGE-ETL: An Optimisation Equilibrium Model with Two Different Endogenous Technological Learning Formulations*, (Report No. 02-16), Paul Scherrer Institute. https://www.psi.ch/sites/default/files/import/eem/PublicationsTabelle/2002_Bahn_MERGE.pdf

Bahn, O., & Kypreos, S. (2003). Incorporating different endogenous learning formulations in MERGE, *International Journal of Global Energy Issues*, *19*(4), 333–358. 10.1504/IJGEI.2003.003199

Bosetti, V., Massetti, E., & Tavoni, M. (2007). The WITCH Model: Structure, Baseline, Solutions. *Fondazione Eni Enrico Mattei*, *2007*(10). http://dx.doi.org/10.2139/ssrn.960746

Castelnuovo, E., Galeotti, M., Gambarelli, G., & Vergalli, S. (2005). Learning-by-doing vs learning-by-searching in a model of climate change policy analysis. *Ecological Economics 54*(2), 261–276. 10.1016/j.ecolecon.2004.12.036

GAMS Development Corporation. (2024a). *BARON*. https://www.gams.com/latest/docs/S_BARON.html

GAMS Development Corporation. (2024b). *CONOPT4*. https://www.gams.com/latest/docs/S_CONOPT4.html

GAMS Development Corporation. (2024c). *KNITRO*. https://www.gams.com/latest/docs/S_KNITRO.html

Glenk, G., Holler, P., & Reichelstein, S. (2023). Advances in Power-to-Gas Technologies: Cost and Conversion Efficiency. *MIT Center for Energy and Environmental Policy Research*, CEEPR WP 2023-09.

Global CCS Institute. (2021). *Blue Hydrogen.* https://www.globalccsinstitute.com/wp-content/uploads/2021/04/CCE-Blue-Hydrogen.pdf

Goldstein, G.A., Kanudia, A., Lehtilä, A., Remme, U., & Wright, E.L. (2016). *Documentation for the TIMES Model PART III* [Technical documentation]. Energy Technology Systems Analysis Programme. https://iea-etsap.org/docs/Documentation_for_the_TIMES_Model-Part-III_July-2016.pdf

Hausfather, Z. (2018). *Explainer: How 'Shared Socioeconomic Pathways' explore future climate change.* Carbon Brief. https://www.carbonbrief.org/explainer-how-shared-socioeconomic-pathways-explore-future-climate-change/.

Hydrogen Council. (2020). *Path to Hydrogen Competitiveness* [Technical report]. Hydrogen Council. https://hydrogencouncil.com/wp-content/uploads/2020/01/Path-to-Hydrogen-Competitiveness_Full-Study-1.pdf.

IEA. (2021a). *Global Hydrogen Review 2021* [Technical report]. IEA. https://www.iea.org/reports/global-hydrogen-review-2021

IEA. (2021b). *Global installed electrolysis capacity by technology, 2015-2020* [Chart]. IEA. https://www.iea.org/data-and-statistics/charts/global-installed-electrolysis-capacity-by-technology-2015-2020.

IEA. (2023a). *Energy Technology RD&D Budgets Data Explorer* [Dataset]. IEA. https://www.iea.org/data-and-statistics/data-tools/energy-technology-rdd-budgets-data-explorer.

IEA. (2023b). *ETP Clean Energy Technology Guide* [Technical documentation]. IEA. https://www.iea.org/data-and-statistics/data-tools/etp-clean-energy-technology-guide.

IEA. (2023c). *Global Hydrogen Review 2023* [Technical report]. IEA. https://www.iea.org/reports/global-hydrogen-review-2023

IEA. (2023d). *World Energy Investment 2023* [Technical report]. IEA. https://www.iea.org/reports/world-energy-investment-2023.

IEA. (2023e). *World Energy Outlook 2023* [Technical report]. IEA. https://iea.blob.core.windows.net/assets/86ede39e-4436-42d7-ba2a-edf61467e070/WorldEnergyOutlook2023.pdf.

IPCC. (2022). *Climate Change 2022: Impacts, Adaptation, and Vulnerability* (Report No. 6). IPCC. https://www.ipcc.ch/report/sixth-assessment-report-working-group-ii/

IRENA. (2020). *Green Hydrogen Cost Reduction: Scaling up Electrolysers to Meet the 1.5ºC Climate Goal* [Technical report], International Renewable Energy Agency. https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2020/Dec/IRENA_Green_hydrogen_cost_2020.pdf

Jamasb, T. (2006). Technical Change Theory and Learning Curves: Patterns of Progress in Energy Technologies. *The Energy Journal*, *28*(3-4), 1–24. 10.5547/ISSN0195-6574-EJ-Vol28-No3-4.

Junginger, M., van Sark, W., & Faaij, A. (2010). *Technological Learning in the Energy Sector: Lessons for Policy, Industry and Science* (1st ed.). https://doi.org/10.4337/9781849806848

Kim, S., Koo, J., Lee, C. J., &Yoon, E. S. (2012). Optimization of Korean energy planning for sustainability considering uncertainties in learning rates and external factors. *Energy*, *44*(1), 126–134. 10.1016/j.energy.2012.02.062

Kypreos, S. (2005). Modeling experience curves in MERGE (Model for Evaluating Regional and Global Effects). *Energy, 30*(14), 2721–2737. https://doi.org/10.1016/j.energy.2004.07.006

Layzell, D. B. (2023). *Hydrogen 101: Challenges and opportunities of hydrogen as a zero-emission energy carrier* [Webinar]. Edmonton Region Hydrogen Hub. https://erh2.ca/hydrogen-101-challenges-and-opportunities-of-hydrogen-as-a-zero-emission-energy-carrier/

Layzell, D. B., Young, C., Lof, J., Leary, J., & Sit, S. (2020). *Towards Net-Zero Energy Systems in Canada: A Key Role for Hydrogen* (Report No. 2.3). Transition Accelerator Reports.

https://transitionaccelerator.ca/reports/towards-net-zero-energy-systems-in-canada-a-key-role-for-hydrogen/

Lee, H., Kim, H., Choi, D.G., & Koo, Y. (2022). The impact of technology learning and spillovers between emission-intensive industries on climate policy performance based on an industrial energy system model. *Energy Strategy Reviews*, 43, 100898. https://doi.org/10.1016/j.esr.2022.100898

Leibowicz, B. D. (2015). Growth and competition in renewable energy industries: Insights from an integrated assessment model with strategic firms. *Energy Economics*, 52, 13–25. 10.1016/j.eneco.2015.09.010

Lewis, E., McNaul, S., Jamieson, M., Henriksen, M. S., Matthews, H. S., White, J., Walsh, L., Grove, J., Shultz, T., Skone, T. J., & Stevens, R. (2022). *Comparison of commercial, state-of-the-art, fossil-based hydrogen production technologies* [Technical report]. National Energy Technology Laboratory. https://netl.doe.gov/projects/files/ComparisonofCommercialStateofArtFossilBasedHydrogenProductionTechnologies_041222.pdf.

Loulou, R., Lehtilä, A., Kanudia, A., Remme, U., & Goldstein, G.A. (2016). *Documentation for the TIMES Model PART II* [Technical documentation]. Energy Technology Systems Analysis Programme. https://iea-etsap.org/docs/Documentation_for_the_TIMES_Model-Part-II_July-2016.pdf

Luderer, G., Leimbach, M., Bauer, N., Kriegler, E., Baumstark, L., Bertram, C., Giannousakis, A., Hilaire, J., Klein, D., Levesque, A., Mouratiadou, I., Pehl, M., Pietzcker, R., Piontek, F, Roming, N., Schultes, A., Schwanitz, V. J., & Strefler, J. (2015). *Description of the REMIND Model (Version 1.6)* [Technical documentation]. Potsdam Institute for Climate Impact Research. https://www.pik-potsdam.de/en/institute/departments/transformation-pathways/research/energy-systems/remind16_description_2015_11_30_final

Magne, B., Kypreos, S., & Turton, H. (2010). Technology Options for Low Stabilization Pathways with MERGE. *The Energy Journal*. *31*(1). https://doi.org/10.5547/ISSN0195-6574-EJ-Vol31-NoSI-4

Manne, A. S., & Barreto, L. (2004). Learn-by-doing and carbon dioxide abatement. *Energy Economics, 26*(4), 621–633. https://doi.org/10.1016/j.eneco.2004.04.023

Manne, A. S., Mendelsohn, R., & Richels, R.G. (1995). MERGE: a model for evaluating regional and global effects of GHG reduction policies. *Energy Policy*, 23(1), 17–34.

Marcucci, B. A. (2012). *Realizing a sustainable energy system in Switzerland in a global context* [Doctoral dissertation, ETH Zurich]. ETH Zurich Research Collection. https://doi.org/10.3929/ethz-a-007566975.

Mattsson, N. (1997). *Internalizing Technological Development in Energy Systems Models* [Doctoral dissertation, Chalmers University of Technology]. Research Chalmers. https://research.chalmers.se/publication/182391/file/182391_Fulltext.pdf

Mattsson, N., & Wene, C. O. (1997). Assessing new energy technologies using an energy system model with endogenized experience curves. *International Journal of Energy Research*, *21*(4), 385–393. https://doi.org/10.1002/(SICI)1099-114X(19970325)21:4<385::AID-ER275>3.0.CO;2-1

Mattsson, N. (2019). *Learning by modeling energy systems* [Doctoral dissertation, Chalmers University of Technology]. Research Chalmers. https://research.chalmers.se/publication/514513/file/514513_Fulltext.pdf

Megía, P. J., Vizcaíno, A. J., Calles, J. A., & Carrero, A. (2021). Hydrogen Production Technologies: From Fossil Fuels toward Renewable Sources. *Energy Fuels, 35*(20), 16403–16415. https://doi.org/10.1021/acs.energyfuels.1c02501

Midilli, A., Kucuk, H., Topal, M. E., Akbulut, U., & Dincer, I. (2021). A comprehensive review on hydrogen production from coal gasification: Challenges and Opportunities. *International Journal of Hydrogen Energy*, *46*(50), 25385–25412. 10.1016/j.ijhydene.2021.05.088

Messner, S. (1997). Endogenized technological learning in an energy systems model. *Journal of Evolutionary Economics*, *7*, 291–313. https://doi.org/10.1007/s001910050045

National Energy Technology Laboratory. (n.d.). *Technologies for Hydrogen Production* [Datasheet]. https://netl.doe.gov/research/carbon-management/energy-systems/gasification/gasifipedia/technologies-hydrogen

National Renewable Energy Laboratory. (2022). *H2A Production Models* [Datasets]. https://www.nrel.gov/hydrogen/h2a-production-models.html

Natural Resources Canada. (2020). *Hydrogen Strategy for Canada: Seizing the Opportunities for Hydrogen. A Call to Action* [Technical report]. Government of Canada. https://publications.gc.ca/collections/collection_2021/rncan-nrcan/M134-65-2020-eng.pdf

Newell, A., & Rosenbloom, P. (1980). *Mechanisms of skill acquisition and the law of practice* [Technical report]. University of Southern California. https://www.researchgate.net/profile/Paul-Rosenbloom/publication/243783833_Mechanisms_of_skill_acquisition_and_the_law_of_practice/links/5461086e0cf2c1a63bff7b62/Mechanisms-of-skill-acquisition-and-the-law-of-practice.pdf

Ouassou, J.A., Straus, J., Fodstad, M., Reigstad, G., & Wolfgang, O. (2021). Applying Endogenous Learning Models in Energy System Optimization. *Energies*, *14*(16), 4819. https://doi.org/10.3390/en14164819

Riahi, K., van Vuuren, D. P., Kriegler, E., Edmonds, J., O'Neill, B. C., Fujimori, S., Bauer, N., Calvin, K., Dellink, R., Fricko, O., Lutz, W., Popp, A., Cuaresma, J. C., KC, S., Leimbach, M., Jiang, L., Kram, T., Rao, S., ... Tavoni, M. (2017). The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview. *Global Environmental Change*, *42*, 153–168. https://doi.org/10.1016/j.gloenvcha.2016.05.009

Ritter, F. E., & Schooler, L. J. (2001). The learning curve. *International encyclopedia of the social and behavioral sciences* (1st ed.). 8602–8605. https://doi.org/10.1016/B0-08-043076-7/01480-7

Rout, U. K., Blesl, M., Fahl, U., Remme, U., & Voß, A. (2009). Uncertainty in the learning rates of energy technologies: An experiment in a global multi-regional energy system model. *Energy Policy*, *37*(11), 4927–4942. https://doi.org/10.1016/j.enpol.2009.06.056

Rubin, E. S., Azevedo, I. M. L., Jaramillo, P., & Yeh, S. (2015). A review of learning rates for electricity supply technologies. *Energy Policy*, 86, 198–218. https://doi.org/10.1016/j.enpol.2015.06.011

Sagar, A. D., & Van der Zwaan, B. (2006). Technological innovation in the energy sector: R&D, deployment, and learning-by-doing. *Energy policy*, *34*(17), 2601–2608. https://doi.org/10.1016/j.enpol.2005.04.012

Sahinidis, N. (2023). *BARON user manual v. 2023.6.23* [Technical documentation]. The Optimization Firm, LLC. https://minlp.com/baron-solver

Seebregts, A.J., Kram, T., Schaeffer, G.J., Stoffer, A., Kypreos, S., Barreto, L., Messner, S., & Schrattenholzer, L. (1998). *Endogenous Technological Change in Energy Systems Models:*

Synthesis of Experience with ERIS, MARKAL, and MESSAGE [Research report]. Paul Scherrer Institute. https://www.researchgate.net/publication/246064301_Endogenous_Technological_Change_in_Energy_System_Models

Thomassen, G., Van Passel, S., & Dewulf, J. (2020). A review on learning effects in prospective technology assessment. *Renewable and Sustainable Energy Reviews*, *130*, 109937. https://doi.org/10.1016/j.rser.2020.109937

Thompson, P. (2010). Learning by doing. In Hall, B. H., & Rosenberg, N., *Handbook of the Economics of Innovation* (1st ed., *1*, 429–476). Elsevier. https://doi.org/10.1016/S0169-7218(10)01010-5

United Nations Framework Convention on Climate Change. (n.d.). *Integrated Assessment Models (IAM) and Energy-Environment-Economy (E3) Models*. https://unfccc.int/topics/mitigation/workstreams/response-measures/modelling-tools-to-assess-the-impact-of-the-implementation-of-response-measures/integrated-assessment-models-iams-and-energy-environment-economy-e3-models

U.S. Department of Energy. (n.d.). *Hydrogen Production and Distribution.* https://afdc.energy.gov/fuels/hydrogen_production.html

U.S. Department of Energy. (2020). *Hydrogen Strategy Enabling a low-carbon economy* [Technical report]. Office of fossil energy. https://www.energy.gov/sites/prod/files/2020/07/f76/USDOE_FE_Hydrogen_Strategy_July2020.pdf

Weyant, J. (2018). Some Contributions of Integrated Assessment Models of Global Climate Change. *Review of Environmental Economics and Policy*, *11*(1), 115–137. 10.1093/reep/rew018

Wright, T.P. (1936). Factors Affecting the Cost of Airplanes. *Journal of the Aeronautical Sciences*, *3*, 122–128. https://doi.org/10.2514/8.155

Yelle, L. (1979). The Learning Curve: Historical Review and Comprehensive Survey. *Decision Sciences*, *10*(2), 302–308. https://doi.org/10.1111/j.1540-5915.1979.tb00026.x

Zeyen, E., Victoria, M., & Brown, T. (2023). Endogenous learning for green hydrogen in a sector-coupled energy model for Europe. *Nature Communications*, *14*(1), 3743. 10.1038/s41467-023-39397-2

Zhang, S., Bauer, N., Yin, G., & Xie, X. (2020). Technology learning and diffusion at the global and local scales: A modeling exercise in the REMIND model. *Technological Forecasting and Social Change*, *151*, 119765. 10.1016/j.techfore.2019.119765