Valuing Learning Effects as a Real Option

Application to PEM Fuel Cells in the Indian Telco Market

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EXECUTIVE SUMMARY

The key purpose of this thesis is to value, purely from an economic perspective, the choice of backup power generation source presented to operators of telecommunication towers. Conventional backup power from diesel generators (DG) are compared to and challenged by one specific alternative, the proton exchange membrane (PEM) fuel cell technology. The thesis is conducted within a specific setting, the Indian telecommunication market, which is found to be an appropriate case due to three main reasons; (*i*) Intelligent Energy, a British-listed fuel cell manufacturer, recently announced a billion-dollar deal with the Indian telco tower operator GLT Limited to supply electricity to more than 27,000 telco sites in the coming years. Secondly (*ii*), telco towers in India are subject to lengthy periods of outages due to an unreliable grid-network, thus implying an extensive demand for backup power solutions, and thirdly (*iii*), the market is one of the biggest of its kind yet projected to grow in the coming years. Having established the Indian case, the PEM fuel cell system is compared to a conventional diesel generator through the levelized cost of energy (LCOE) model in order to determine its present cost competitiveness. The model reveals that PEM fuel cell are still far more expensive from a total cost of ownership perspective. To investigate whether the fuel cell may become a viable choice in the future, learning effects attached to repetitive production are estimated in order to evaluate potential cost reductions in the manufacturing process. Based on the historical figures on cost development and installed cumulative capacity, the learning rate for PEM fuel cells is estimated to be 23.15% for each doubling in cumulative production. Lastly, findings from both the LCOE model regarding the cost structure of the systems and the learning rate approximations are applied in a real option valuation to estimate the true cost of backup power with higher degrees of precision. Specifically, the ROV shows that the flexibility of choice between either backup power systems carries a value of 462 USD per telco site thus lowering the actual costs of backup power compared to conclusions derived through the conventional LCOE model.

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1. INTRODUCTION

For many decades, fuel cells and the hydrogen economy have been considered potential solutions to help solve some of the world's energy problems. However, fuel cells have yet to reach a mass-market stage at which they are fully commercialized, and potential buyers might have become disillusioned with them, Richard Asplund (2008) argues. While the viability for certain applications can be questioned, fuel cells are competing on an everyday basis in the power backup market though. In particular, Intelligent Energy (2015), a global fuel cell company, recently disclosed that it will "supply energy-management services across more than 27,400 telecom towers in India." Now, while such deal does seem to provide backup power to a large number of telecommunication towers, there are approximately 400,000 towers yet relying on diesel generators as backup source. From the Indian tower operator's perspective, it should therefore be of interest to evaluate whether or not it makes sense economically and financially to replace diesel generators with fuel cells. The technology is initially expensive to purchase and inexpensive to operate, but if the historical production costs exhibit a decreasing trend and the technology is simultaneously becoming increasingly efficient, there is expected to be value in waiting to choose fuel cells as an option for backup power. This is particularly relevant given uncertainty about tomorrow's fuel prices for the conventionally deployed diesel generators.

In this way, the aim of the thesis becomes two-fold. Firstly, estimating technology learning for fuel cells through an assessment of past and potential cost reductions is the objective. William Grove discovered the principle of fuel cells in 1839 already, but major developments did not take off until the 1960s when NASA employed the technology for space crafts, and fuel cells have recently been employed in widely different applications. Likewise, research on cost developments is substantially growing (see e.g. Schoots et al., 2010). This thesis will specifically contribute to such studies by estimating learning effects for the proton exchange membrane fuel cell (PEMFC), which is one of the most widely used fuel cell across stationary, mobile, and portable applications. Secondly, the estimated learning effects are used as input to a real options setting in which the value of waiting can be estimated given uncertainty in diesel prices for the conventional backup solution. Consequently, the study contributes to understanding how learning effects (or lack of) and diesel fuel volatility can help to explain the value of deploying fuel cells as backup systems while simultaneously yielding an indication as to why or why not fuel cells are commercially applied in an Indian telecommunications setting.

1.1. Problem Statement and Research Question

This thesis will attempt to bridge the increasing demand for stable, reliable energy sources with the commercialization and development of such technologies. Along with economic progress, emerging countries face the perpetually challenging task of establishing the required infrastructure to facilitate such economic growth. For some emerging economies this task is further complicated by geo- and demographic circumstances including extreme weather conditions and vast distances between urbanized areas, which are among the factors contributing to lengthy grid outages. In periods of grid unreliability, conventional backup power generation systems provide costly electricity based on expensive diesel consumption. Consequently, demand for alternative energy solutions is on the rise, and while such solutions have been around for centuries, it is the technological development and potential commercialization that make the research particularly worthy. This thesis will focus specifically on the PEMFC technology as it carries certain features that make it suitable for backup solutions. Arguably, the Indian telecommunications (hereinafter, also referred to as "telco") market experiences one of the largest accumulated grid outages in the world, for which reason it is particularly interesting to investigate here whether conventional backup solutions can be economically and financially challenged by fuel cells as an alternative solution to the 2.5 kW backup choice.

The empirical context in which the thesis is conducted relies on theoretical frameworks from the sphere of economics and finance, where models from both fields are applied to the fuel cell technology in order to investigate the main research question:

> **How can established energy comparison models, and the learning effects from PEMFC production, be applied in a real options setting to analyze the choice of replacing conventional backup power systems in India?**

The main research question focuses on the economic choice of replacing current diesel generators with PEM fuel cells as grid backup power systems in order to supply electricity whenever outages occur in the Indian telecommunications market. Naturally, the choice of replacement is a function of the economic costs and benefits relating to the fuel cell system as a backup source compared to the conventional diesel generators. Importantly, one has to acknowledge the different identities carried by new, still-developing technologies and stable, well-known diesel generators. One of the main features of a yet fully commercialized technology is the learning effects of further production. Consequently, while a present cost comparison of fuel cells and diesel generators should be the foundation of an economic choice through traditional discounting techniques, learning effects and the potential value of delaying the replacement choice could be included in the analysis to establish a thorough understanding of the case for fuel cells.

To structure the thesis and to complement the main research question, four separate sub questions have been developed. These sub questions serve the dual purpose of breaking up the main research question into smaller parts that naturally follow each other, and to carry the reader through these different sections to maintain the focus on the main research question.

1.2. Sub Questions

(1) *What are the features of fuel cells as an energy source, and which characteristics make the Indian telecommunications and tower markets particularly relevant as a case?*

The first sub question is designed to establish the case of fuel cells as backup power systems to the grid in the delivery of electricity to telecommunication towers. Specific characteristics of the technology and the present state of the technological diffusion will be presented. Additionally, the reasons for focusing on the Indian telecommunications market and its dynamics will be outlined as well as its recent development.

(2) *What is the cost structure of PEM fuel cell production and how does it compare to a conventional backup system?*

The second sub question calls for a detailed analysis of cost components in a PEMFC system deployed as a 2.5 kW backup system in India. The cost structure analysis encompasses both capital expenditures (CAPEX) and operational expenditures (OPEX) related to the lifetime of a fuel cell system, as opposed to the conventional diesel generator. Lastly, a levelized cost comparison of the PEM fuel cells and current diesel generators is carried out to evaluate and identify cost drivers of the present scenario. Through a levelized cost model, one is able establish how large the cost gap is between the two technologies while simultaneously understand how traditional discounting techniques calculate and evaluate net present values (NPV) of installing the systems.

(3) *How can learning effects from PEM fuel cell manufacturing be quantified?*

The third sub question aims to estimate learning effects in the manufacturing of PEM fuel cells. Inspiration is drawn from historical development of other technologies and their current commercialization stages to better understand how their learning effects are quantified, while simultaneously analyzing historic data on both PEM and other types of fuel cell production. An assessment of past manufacturing costs is one input into the estimation, while cumulative installed capacity is another. Data collected for an almost twenty-year long period is used to calculate progress rates, implied learning rates, and the uncertainty of such, in order to project potential of cost development in the future. Answering this sub question enables the thesis to help assess potential commercialization of the technology not only today but also in the coming years, and ultimately help define one of the parameters of the real options model.

(4) *How can technology improvements in PEMFC production and volatility in fuel prices for the diesel generator be applied in a real option setting to analyze the choice of replacing conventional power backup systems with fuel cells?*

Lastly, the forth sub question will draw on findings from the cost structure analysis as well as the quantified learning effects, in order to fully evaluate the replacement choice. In addition, fuel price volatility is estimated through econometric analysis to capture the uncertainty in having diesel generators running as backup sources in the future. On the other hand, the inherent uncertainty in PEMFC learning effects is also applied to a real options model, yet they are used only as scenario generations for changes in the technology's production costs. In this way, the real options framework incorporates the value that fuel cell buyers may attain from both cost changes and fuel price volatility by delaying the decision of replacing current diesel generators with fuel cell system.

1.3. Methodology

This thesis is divided into seven chapters as illustrated by the figure below.

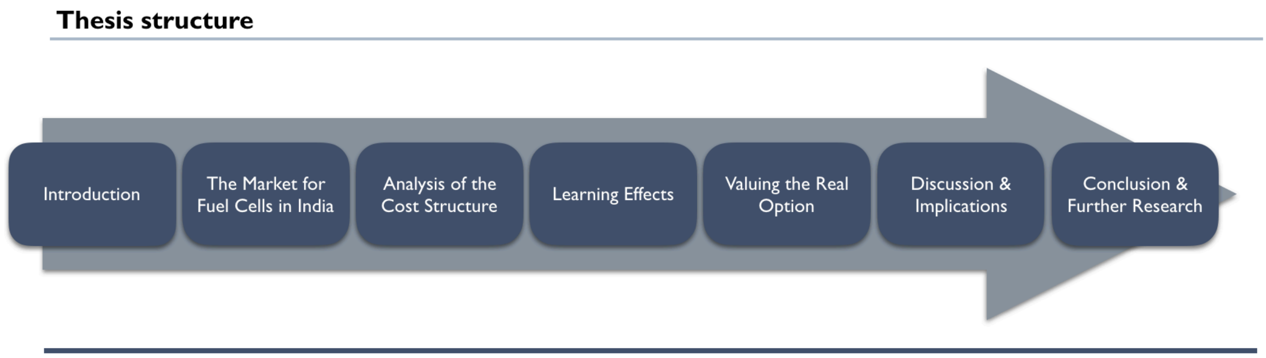

Figure 1.1: Thesis structure. Source: own work.

The introductory chapter aims to motivate the thesis as well as presenting the research questions and structure. To establish the necessary foundation for subsequent analysis, chapter 2 will provide a presentation of the current fuel cell market and discuss different technologies and its applications. The reader's takeaway will include an understanding of the fuel cell technology, its advantages and disadvantages and the motive behind focusing on PEM fuel cells specifically. Complementarily, the Indian telecommunications market and the related challenges with regards to constant energy supply will be presented. Together, this background chapter will set the scene and carefully supply the reader with the necessary knowledge to comprehend the following analytical chapters as well as answering the first sub question.

The next three chapters embody the main analytical parts. For each chapter, relevant empirics and theories will be discussed. In turn, this means that the reader will be introduced to the relevant theory preceding to its application in each chapter, rather than in a collective theoretical section prior to the analytical chapters. This approach has been taken to ensure a constant red thread throughout the thesis.

Chapter 3 will answer the second sub question by first analyzing the cost structure of a PEM fuel cell and thereafter conducting a levelized cost of energy comparison with a conventional diesel generator. Financial theories related to the LCOE-model, including the discounted cash flow (DCF) model and weighted average cost of capital (WACC), will be discussed. The third sub question is addressed in chapter 4. Here, the learning effects of PEM fuel cell production will be quantified based on the historical cost development and the cumulative capacity installed during the specified period. In order to perform this quantification, the theoretical framework for learning effects is introduced and reviewed for comparable technologies before using simple regression tools to estimate learning and progress rates and then calculate their associated uncertainty. In the next section, chapter 5 will bridge takeaways from the analysis of PEMFC cost components, the LCOE comparison to DGs, and the estimated learning effects. Together, these findings will be synthesized into the formulation of a real option. Prior to the formulation and calculation of the real option, the theoretical background on the backbone of real options, namely financial options theory will be discussed. Next, a brief literature review is presented on real options analysis of renewable and alternative energy technologies, and its applicability for policy evaluation, power generation, R&D and commercialization investments. Subsequently, the real options framework for the replacement decision can be established through the model's parameter definitions. Importantly, econometric methods are applied to estimate price volatility for diesel fuel in order to quantify the uncertainty of relying on diesel generators as the backup solution in the future. Having specified that and the other parameters too, the real options model is set up and results in a theoretical value of keeping the option alive to replace. To understand the impact of the more important inputs into the model, sensitivity analyses are performed and evaluated.

Altogether, the chapters each add arguments to answer why conventional discounting methods might not be the only solution to valuing investment choices in energy. However, having estimated a real options value—whether suggesting sound replacement opportunities or not—an implications chapter is added to introduce perspectives on the potential of PEMFC technology in the Indian telco market. Indeed, as the real options model is contingent on future development (and uncertainty), it is by no means certain that cumulative capacity will double the estimated way and production costs will fall simultaneously. In other words, a "chicken and egg" problem arises. Before concluding on the thesis and its research questions, a brief discussion on those perspectives is thus useful to understand strategic implications of the estimations.

Finally, it should be mentioned that all necessary data used in the different chapters and associated analyses are introduced separately rather than obsequiously listing e.g. market reports, data sources, or cost analyses here. Overall, the thesis relies on publicly available information except for certain reports on cost and capacity developments used in the learning effects estimations. Although these are listed correctly in the references index, the authors are grateful for Dr. Koen Schoots, scientific researcher for the Policy Studies of the Energy Research Center of the Netherlands (ECN), who has supplied relevant reports. It is specified explicitly which sources are supplied by Dr. Schoots in chapter 4. On another note, Danish Power Systems ApS (hereinafter, also referred to as "DPS") has supplied publicly available reports to be used in the LCOE analysis. The input of the company is thus not specifically for data, rather DPS has helped to scale and interpret validity and application of inputs in the analyses. Here, it also stated explicitly in which applications it has been necessary to use inputs and assumptions evaluated by the authors and the company for whom the thesis is written. As this thesis aims not to provide a market analysis confidential to and contingent on DPS' organization, it shall not be treated as confidential. Rather, the paper aims to provide better understanding about and to which extent economic analyses of fuel cell production and financial real options modeling can help to evaluate investment decisions in fuel cell technology through a case in Indian markets for towers and telecommunications.

1.4. Scope and Delimitations

In order to address the subject of the thesis adequately, it is necessary to limit its scope and understand that the estimation of learning effects is undertaken for only one specific type of fuel cell, the PEM.

1.4.1. Scope

The choice between replacing diesel generators with fuel cells or not is one facing primarily the owner or operator of a telco tower. In this way, the thesis results are directly aimed at any such decision maker. On the other hand, however, the research is conducted *for* DPS, which is a R&D-intensive manufacturing company producing an input into a PEM fuel cell. DPS acknowledges that fuel cells (and other new energy technologies) are initially expensive and is constantly working on developing more cost effective fuel cells with increasingly superior performance. This is in line with the learning curve analogy, which means that the scope of the project does not merely belong to the Indian telco operator, but is applicable to players manufacturing, commercializing, and potentially purchasing PEM fuel cells in the industry.

1.4.2. Delimitations

Having disclosed the scope of the project, it should be mentioned (again) that the calculation of learning effects and the real options are applicable only to PEMFCs. Therefore, important delimitations are necessary and particularly needed with regards to environmental externalities, political arguments, technological specifications, and factors regarding the telco market.

1.4.2.1. Externalities

Generally, renewable energy technologies produce less pollution than their fossil fuel counterparts, and this is an often praised feature of fuel cells too. Although electricity generated by fuel cells are not strictly renewable, hydrogen is very abundant in availability and associated (lack of) emissions are similar to that of renewables. Therefore, this thesis will often associate fuel cell technology with renewables and use the term interchangeably. Fossil fuel negatives, such as pollution and carbon dioxide emissions, have been and are major catalysts for the clean energy industry, yet this thesis will not attempt to quantify any such effect into the estimation of learning effects nor include it in the real options calculation. The thesis will touch upon fuel cells' technological advantages and disadvantages, however, environmental issues are not dealt with any further.

1.4.2.2. Politics

Choosing between fuel cells and diesel generators will necessarily include arguments of non-economic character. Politics has both succeeded and failed to limit emissions quotas, facilitated special investment infrastructures for renewable energy technologies, and generally been an important catalyst for the clean energy industry. The investment environment in which the real option is valued carries many features, which can be politically discussed, yet these arguments are too large to be covered here and deserves the attention of students in other fields.

1.4.2.3. The Technology

This thesis will focus solely on the PEMFC as its subject. There are different types of fuel cells, which will be introduced, yet only learning effects for the PEMFC are estimated. In addition, learning effects and real options applications from other renewable energy technologies are included as reference to add perspective to this project's findings.

1.4.2.4. Telecommunication Factors

Standards in telco markets are constantly changing, and the world is becoming increasingly interconnected. This has had major implications historically for the Indian market too for which reason it is difficult to say how it might change in the future. Therefore, the real options calculation will assume an environment in which telco towers' power specifications and grid unreliability are constant and disregard any potentially technological disruptions. In the section on the Indian tower and telco markets, a market report by Deloitte (2015) does predict some of the future trends, yet this thesis will be isolated around the decision to deploy and potentially replace backup power systems at the towers.

1.4.2.5. Revenue vs. Cost

This thesis is strictly focused on cost-comparison of technologies rather than relying on revenue generation. As it becomes apparent in the analyses, the models do not necessarily change. One should instead interpret the results carefully and understand that the decision maker is utility maximizing through cost minimization. In addition, the analyses are carried out ignoring any subsidy grants distorting the real of cost of energy generation.

2. TECHNOLOGY DESCRIPTION AND THE MARKET FOR FUEL CELLS

Initiating this chapter, the fuel cell system is described to help the reader understand how electricity is actually produced within the system. Subsequently, technological variations for a range of fuel cell systems as well as various applications are introduced followed by an outline of the current state of the industry. While it should be noted that the technological engineering of fuel cells is outside the scope of this paper, the description serves as a primer on power generation by fuel cells, while the next part of the chapter introduces its application in the market of Indian telecommunication towers. Subsequently, motivated by Intelligent Energy's recent contract in India, it is assessed to which extent (lack of) reliability in the electricity grid is a challenge to telecommunication tower operators before characterizing the size of the industry, its main players, and why it is in their interest to evaluate the choice of backup power systems today and in the future.

2.1. The Fuel Cell Technology

Practically, a fuel cell converts chemical energy into electric energy through a chemical reaction. The basic fuel cell system is made up of two flow plates, two electrodes (one anode and one cathode) and an electrolyte in between. As pictured below, fuel in the form of pure hydrogen or hydrogen-carrying fuel such as methanol is applied on the left-hand side. At the anode, hydrogen atoms react with a catalyst layer containing platinum, which creates positively charged ions and a negatively charged electrons. The proton continues through the membrane while the electron passes across a circuit where the electricity is created.

On the right-hand side, at the cathode, the ions and electrons react with supplied oxygen and turn into water and heat – the only by-products of a basic fuel cell. The electrolyte plays an important role in the system by allowing only the proper ions to travel from the anode to the cathode. Outside substances would disrupt the chemical reaction and disturb the electricity generation.

In this way, the fuel cell can provide continuous energy as long as hydrogen and oxygen are supplied to the system. Isolated, a single fuel cell system can roughly generate enough electricity to keep a light bulb on, but once multiple systems are stacked together, the total power output can reach levels with much higher applicability than illuminating a simple light bulb, Fuel Cells 2000 explains (2016).

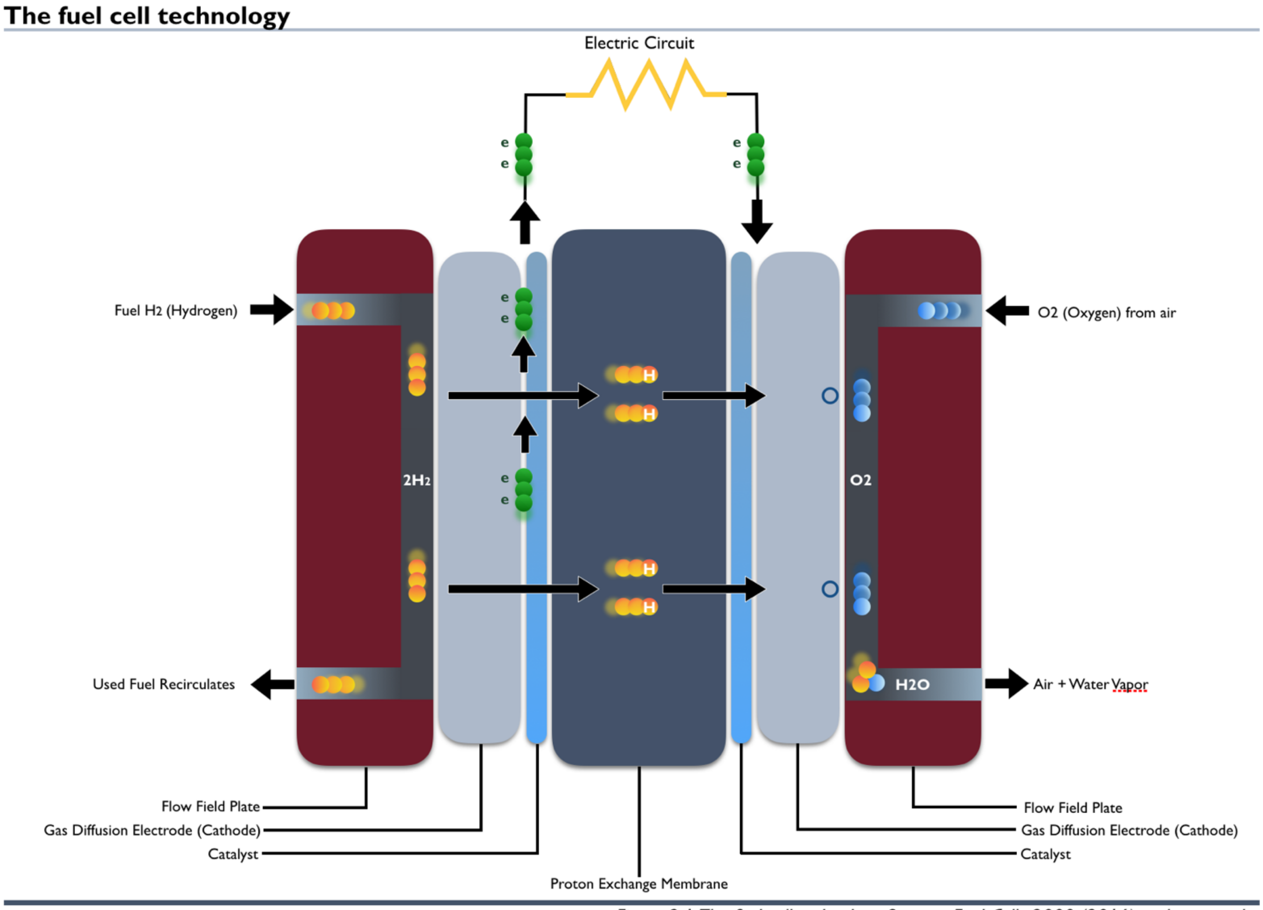

Figure 2.1:The fuel cell technology. Sources: Fuel Cells 2000 (2016) and own work.

2.1.1. Different Types of Fuel Cells

The technical workings of a fuel cell system showed above only apply to a certain type of fuel cell systems, namely the PEM fuel cell system. In reality, the "fuel cell system" is a label for various technologies that relate to energy generation based on hydrogen and oxygen. The aim of this section is not to go in depth with technical definitions of multiple technologies, rather, the purpose is to provide the reader with a brief comprehension of key differences between technologies to understand the differences in applicability of fuel cell systems. The main differences relate to the electrolyte material, operating temperature, and output efficiency. It should be noted that this section by no means is exhaustive in terms of the number of fuel cell technologies being described but limited to technologies, which been found relevant to fulfil the purpose of the section.

2.1.1.1. Alkaline (AFC)

The alkaline fuel cell is one of the early fuel cell technologies and was used during Apollo space missions to supply electricity and drinking water on board. The system requires compressed hydrogen and oxygen at high levels of purity. The purity is required to avoid "poisoned" air containing CO_2 to interfere the chemical reaction, which is one reason why AFCs have been used in space where carbon dioxide is absent. The electrolyte is made up of potassium hydroxide in water and the system thus contains liquid meaning that the alkaline system is subject to leaks, potentially limiting reliability and lifetime. The efficiency of alkaline fuel cells is around 50-70 percent and while the first AFCs operated at around 150-200 degrees Celsius, present operating temperatures are around 70 degrees (FuelCellToday 2016).

2.1.1.2. Molten Carbonate (MCFC)

MCFCs are built around an electrolyte consisting of a porous ceramic matrix using molten carbonate salt. The principle is the same; ions travel through the electrolyte between the two electrodes while the electrons flow through the electrical circuit. The MCFCs operate at a temperature around 650 degrees Celsius which possess a number of advantages compared to other technologies. The high temperature means noble metals in catalysts are not needed to speed up the chemical reaction. It also makes the system less vulnerable to "poisoning", which means that the system can run of a range of non-hydrogen pure fuels such as methane or natural gas since the separation of hydrogen is conducted internally at high temperatures. On the contrary, high operating temperatures make MCFCs subject to accelerated breakdowns and corrosion of components, decreasing system lifetime. MCFCs are mainly used in large megawatt scale stationary power plants and in combined heat and power solutions.

2.1.1.3. Solid Oxide (SOFC)

Operating at the highest temperatures (around 800-1,000 degrees Celsius) of all fuel cell systems, the SOFC reaches overall efficiencies of more than 80% when heat exploitation is included. High temperatures remove the need of noble metal catalysts as well as the need for external reformation of fuel into pure hydrogen. One of the main disadvantages of extreme operating temperatures is longer start up times and need for very heat-resistant materials in the construction of the system. While SOFCs and MCFCs are quite similar, there is one major difference; the SOFC has a solid ceramic electrolyte of zirconium oxide stabilized with yttrium oxide as opposed to the liquid electrolyte within a MCFC. In recent years, the SOFC technology has proven its applicability and many of the world's most renowned companies are currently powering buildings, data centers, and factories by these fuel cells. One of the most prominent producers of SOFC is American-based Bloom Energy whose customers operate in many industries ranging from technology and banking, to retailing and logistics, and include e.g. Apple, JP Morgan, IKEA and FedEx (Bloom Energy 2016).

2.1.1.4. Proton Exchange Membrane (PEM)

The PEMFC's electrolyte is referred to as the proton exchange membrane or polymer electron membrane interchangeably in the literature. The PEM is small and light and functions at low temperatures with fast start up times. In practice, the term PEMFC covers both low temperature (LTPEM) systems operating at around 80 degrees Celsius and high temperature (HTPEM) systems operating at around 200 degrees Celsius. The main difference of the two lies in the degree of fuel purity needed for the system to function with latter requiring the lowest purity levels.

2.1.2. Fuel Cell Applications

As outlined, "fuel cells" are by no means a homogenous designation but instead a term covering a range of technological variations originating from the same base of electricity generation based on hydrogen and oxygen through chemical reactions. The range of applications in which fuel cells are deployed is equally diverse and manifold. Fuel cell applications are generally divided into three main categories: portable, stationary, and transportation.

2.1.2.1. Portable

Portable fuel cells are small and easy-to-carry systems with output power ranging from 5-500 W. These systems are highly suitable for basically any personal electronic device such as laptops, smartphones, and cameras. Due to very low operating noise levels, portable fuel cells are particularly applicable to military operations powering various portable equipment. Other applications include camping, surveillance, and emergency rescue operations in need of power supply to equipment during longer periods than regular batteries can handle (Sharaf & Orhan 2014). The hydrogen is typically compressed in small lightweight cartridges which can easily be carried along with the portable fuel cell.

2.1.2.2. Transportation

Arguably, fuel cells deployed in transportation vehicles, which includes buses, forklifts, and personal cars are the ones gaining the most attention from the media. They represent a direct competitor to electric vehicles and regular internal combustion engine vehicles as they carry certain advantages such as close-to-zero emissions, fast refueling, low service requirements, and long range. In recent years, car manufacturers have spent millions of dollars on R&D trying to develop fuel cell-vehicles running on PEMFCs and the results are starting to show up. Back in 2008, Honda released its FCX Clarity and last year, Toyota released the "Mirai", which has been highly awaited. Despite the vast amount of attention, these fuel cell cars are yet to become economically viable and estimations show that Toyota is losing as much as USD 100,000 on every sold Mirai (Clean Technica 2014). One of the main challenges for fuel cell cars is the required hydrogen infrastructure of refueling stations, which is currently very limited. As an example, while constituting one of the densest hydrogen infrastructures in the world, Denmark currently has only 8 hydrogen refueling stations compared to roughly 2000 gas stations (Hydrogen Link Denmark 2016, Danish Oil Industry Association 2016).

2.1.2.3. Stationary

Stationary fuel cells are utilized in various primary and secondary power mixtures and output ranges from anywhere between 1 kW to large scale MW deployments. They are used both as stand-alone power generation sources (off-grid) and as an integrated backup power solution in e.g. telecommunication towers. They can be used in conjunction with heating systems, so-called combined heat and power (CHP) systems that utilize the heat produced internally in fuel cells, which are particularly suitable for residential buildings, offices, hospitals, etc., and can be scaled from a few kW to large MW depending on the end-user power needs. Furthermore, stationary fuel cells are deployed as RAPS (Remote Area Power Supply) in desserts, forests, and islands for similar reasons; low or zero grid-dependence, strong consistency, and ability to function in harsh environments. Still, challenges with regards to transporting fuel to remote locations remain one of the key issues of the RAPS application (Sarah & Orhan 2014). Other applications include emergency systems such as the SINE (Safety Network) operated by the Danish Centre of Emergency Communication, which is backed up by fuel cells ensuring continuous operation in case of power outages in the regular grid network in situations of critical emergencies locally as well as nationally (Ballard 2014).

2.1.3. The Fuel Cell Industry in Numbers

To conclude the section on the fuel cell technology and its applications, a few notes on recent figures from the industry will be presented in order to further motivate the choice within this thesis to focus on the PEMFC technology in the stationary application space and specifically within the telecommunication industry. The figures are reported in the report "The Fuel Cell and Hydrogen Annual Review" published by Adamson (2015). As shown in figure 2.2, the global fuel cell industry as a whole has experienced exponential growth during recent years with respect to shipped units, reaching a compound annual growth rate of almost 50% in the period 2009-2014.

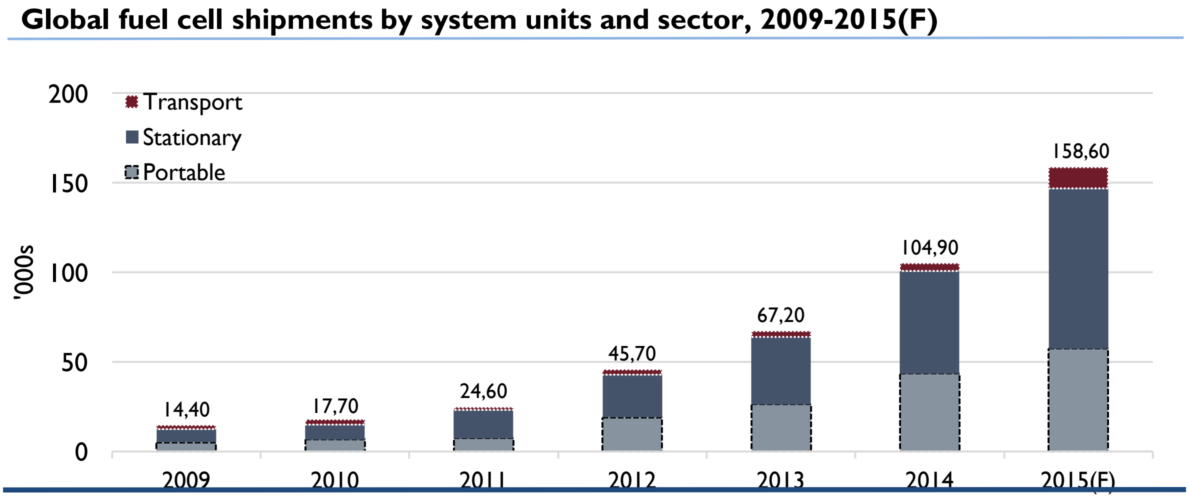

Figure 2.2: Global fuel cell shipments by system units and sector, 2009-2015(F). Sources: Adamson (2015) and own work.

Albeit impressive, one should note the low base of less than 15,000 units shipped in 2009 Evidently, stationary fuel cells account for the biggest share of this growth and the picture becomes even clearer when looking at the shipped MW split of 2014 (figure 2.3), in which stationary fuel cell accounted for 81%.

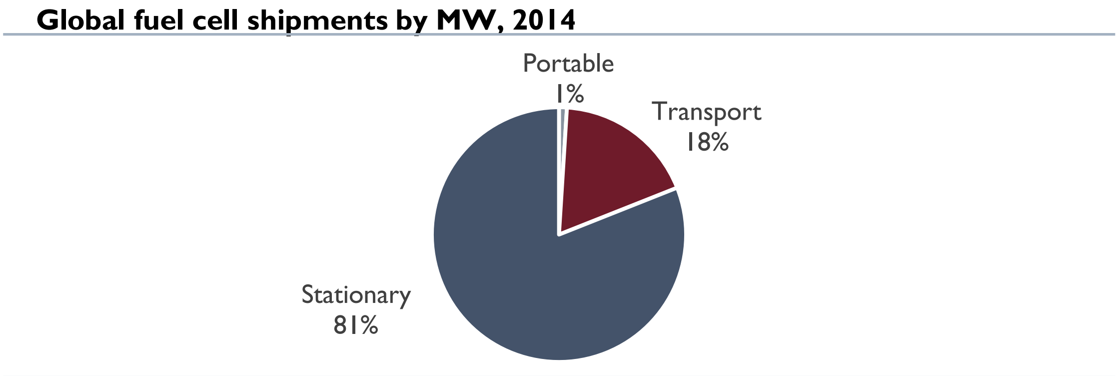

Figure 2.3: Global fuel cell shipments by MW, 2014. Sources: Adamson (2015) and own work.

Furthermore, reviewing the split of shipped MWs for different the fuel cell technologies (electrolytes) it becomes apparent that PEMFCs are the most widespread with the largest share of any single technology and, importantly, the technology with the biggest forecasted growth (see figure 2.4). Estimates by

Adamson (2015) show that the PEMFCs could be on the verge of taking off and potentially reach more than 400 MW total shipments by the end of 2015.

Global fuel cell shipments by electrolyte and MW, 2009-2015(F)

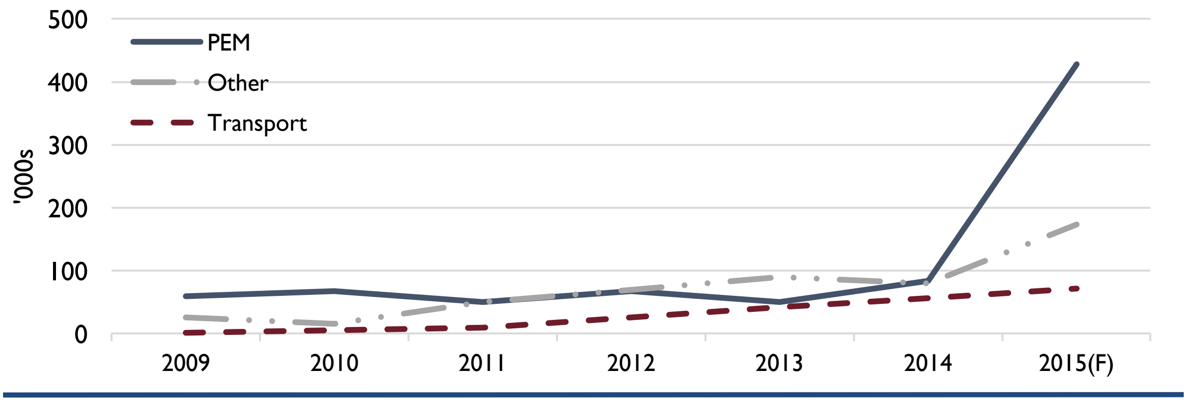

Figure 2.4: Global fuel cell shipments by electrolyte and mW, 2009-2015(F). Sources: Adamson (2015) and own work.

Nonetheless, and particularly interesting for the purpose of this thesis, the telecommunication industry accounts for a very small fraction of overall unit shipments in recent years. Figure 2.5 below shows the fuel cell shipments broken out by subsectors and shows that residential CHPs are the main driver of fuel cell shipments as of today. This represents an interesting paradox considering the vast amount of recent attention and deals in the telecommunication space, exemplified by Intelligent Energy's billion-dollar deal, which will be touched upon in the next section.

Global fuel cell shipments by sub-sector, 2013-2015(F)

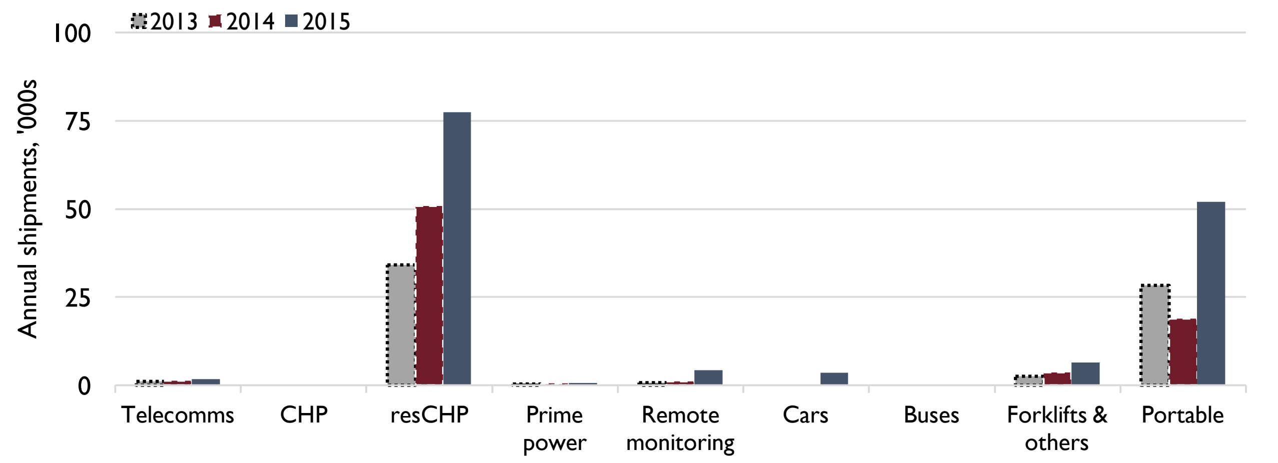

Figure 2.5: Global fuel cell shipments by sub-sector, 2013-2015(F). Sources: Adamson (2015) and own work.

2.2. India's Telco Industry

Before analyzing the actual cost structures of and potential investments in fuel cell technology, it is important to understand in which setting it is applied. Below, it will be argued that the Indian telco market makes an interesting case for small stationary application of fuel cells. Through empirical observations, a primer on the size and potential of Indian telco and tower sites, and projections for the future, it is argued that the telco market provides a useful case for the research question in this thesis. Particularly, because regular grid power is highly unreliable or in some cases even non-existing in remote areas, there are reasons to investigate the case for fuel cells. In periods of grid power outages, diesel generators (DGs) provide backup power, which represents costly power generation due to high operation costs in terms of diesel fuel. In the Indian case, it has been estimated that 70% of all telco towers experience above 8 hours per day of grid power outages and are thus vastly dependent on backup power by DGs (Intelligent Energy 2012). Indian authorities have estimated that 1.035 billion telephone subscribers are active as of November 2015 (Telecom Regulatory Authority of India 2016), making India's telco market one of the largest in the world (IBEF 2016). In Sahu, Schultz, and Beig's (2014) article, it is discussed how India has emerged as one of the fastest growing telco markets in the world, creating a big challenge in developing India with regards to the increasing energy demand. As diesel is the primary source of backup power, there are significant costs (both financially and as externalities) associated with outages in the electricity grid.

To understand why the Indian telco industry might be an important market for fuel cell commercialization, there are particularly three major catalysts to be addressed. Firstly, Intelligent Energy (2015) recently announced a large deal to supply 27,000 towers with fuel cells. Secondly, the high amount of power outages and lack of grid reliability deserve a closer look. Finally, if Sahu and colleagues' (2014) findings are true, the growing telco market will necessarily also demand new sites for towers to be deployed, again raising the question about choice of backup power. While this thesis explores only the choice of *replacing* conventional and already installed diesel generators, setting up new telco towers should add power to the argument that an apparent grid unreliability will require reliable backup solutions in the future. A case for fuel cells could perhaps be made then. Altogether, the following sections will thus lay the foundation for India's telco market as a business case after which attention will be turned towards breaking down the cost structures of PEMFCs.

2.2.1. Intelligent Energy's India Contract

On October 1, 2015, British technology company, Intelligent Energy, announced that it had agreed to provide services to about 27,000 Indian telco towers in a proclaimed USD 1.8 billion deal (Greentech Media 2015). In an interview about India's potential as a fuel cell market, CEO of Intelligent Energy, Henri Winand, comments that their presence is highly important for the long-term commercialization potential of fuel cells (Quartz 2015). Indeed, as the energy deal contracts Winand's company over a ten-year period, the argument is that they will benefit from visibility through market presence and, consequently, be able to scale up production and achieve learning effects. While perhaps not wrong, such line of thinking is not useful. Instead, what we might question is whether India's GTL Limited, the telco operator, is making the economically right choice to replace diesel generators today. If the Intelligent Energy CEO is correct, learning effects will make any capital expenditure more inexpensive in the future and simultaneously create more efficient backup solutions, for which reasons telco operators should wait to replace the conventional DGs. Now, in this case, there are yet many towers operating with DGs as backup sources. Greentech Media (2015) reports approximately 425,000 cell towers in India, constituting more than 90% of the cases with DGs to be replaced. Assuming no market presence by companies other than Intelligent Energy, there are thus good reasons to question why telco operators do not use fuel cells as the standard backup power system on a wide-scale basis. Whilst studies conducted by the company itself reveal that diesel generators are highly costly to operate (Intelligent Energy 2012) and it might then seem as an easy decision to choose the backup solution for the long term setting up new telco towers, there are not found thorough research on the option to replace diesel generators for the *existing* towers in the future. Therefore, using Intelligent Energy's business deal purely as a motivator, the thesis' research question will also shed light onto why—and why not—it might be more economically sound to implement fuel cells in the future.

2.2.2. Grid Reliability and Electricity Outages

Being the second largest telco market in the world and adding new active connections every day, telco towers need to operate efficiently in order to connect their users. One major concern, however, is India's challenges in electrifying these towers through the grid. In a 2010 report by GSMA, it is estimated that 82.2% of approximately 390,000 towers are connected to the grid (the rest being off-site/grid) and among these, as many as 46.3% experience unreliable access to electricity with frequent power outages. Indeed, in the same survey, Indian tower companies experience outages for at least 4 to 6 hours per day at 95% of the towers in rural sites. This necessitates the need of employing a backup solution to the grid, such as the conventional diesel generator. Particularly, grid-connected towers experience power outages for different durations as segmented below.

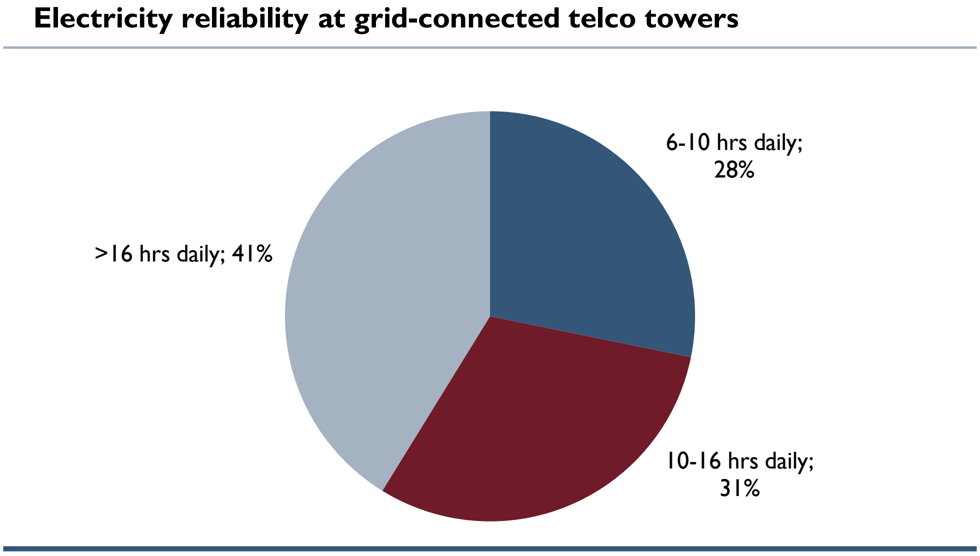

Figure 2.6: Electricity reliability at grid-connected telco towers. Source: GSMA (2010).

Whereas GSMA relies on direct feedback from tower companies, it is a challenge that there is limited centralized data repository on power cuts and outages in India (Lakshane 2012). To track the country's power outages on the individual level, one crowdsourced database has been particularly successful, for example. The project, "Power Cuts in India", has logged user reports on power outages throughout the entire Indian market from May 2011 through May 2014. From the publicly available data it becomes clear that the electricity grid fails to be reliable (Power Cuts in India 2011). Likewise, in a conference paper on insights into home energy consumption in India, Batra et al. (2013) acknowledge that it is difficult to find reliable data sources on power outages. Therefore, by deploying an experiment themselves during May-July 2013, they report a total of 107 power outages in a 61-day period, each averaging approximately an hour. In this way, the user reports highlight that the Indian electricity grid is generally unreliable, however, they do not disclose anything about telco towers' need to employ backup utilities, nor does such field study represent India as a whole. Particularly relevant for the Indian telco operators, Greenpeace discloses statistics from the Central Electricity Authority in a 2011 report in which it becomes apparent that major telco circles face challenges with outages in the electricity grid as graphed below.

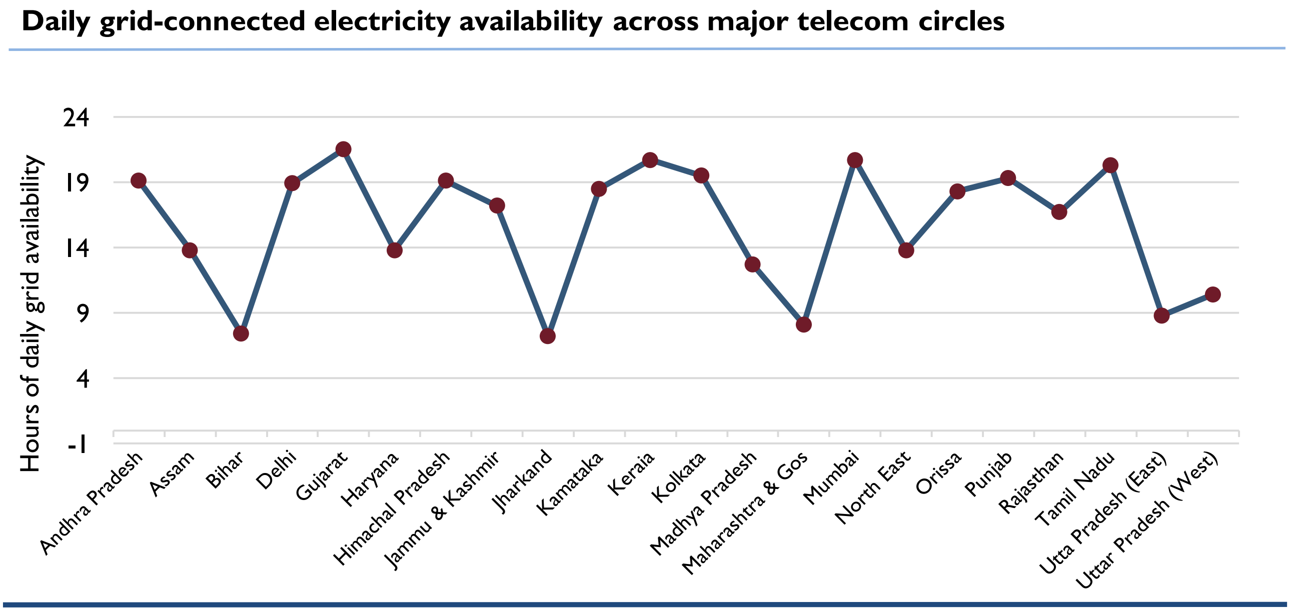

Figure 2.7: Daily grid-connected electricity availability across major telecom circles.. Sources: Greenpeace (2011) and own work.

Clearly, these telco circles face electrification issues to which diesel generators are the current solution. Although published by the Ministry of Power and thus the Government of India, there are not further evidence, which can be used to statistically distribute the magnitude of the electrification problem. Therefore, information on grid reliability is not fully transparent, one might argue. However, the data, which is publicly disclosed, supports the need for backup power systems. In a book published by the World Bank and the International Bank for Reconstruction and Development (Tenenbaum et al. 2014: 41), "it has been estimated that about 150,000 of India's 400,000 mobile-telephone towers are located in off-grid areas or areas with an unreliable electricity supply from the grid." In their analysis, they find that as much as 40 percent of operating expenses for a typical telco tower origin in fuel and power costs whereas as European telco towers compare with approximately 12 percent. Such a cost difference could be attributable to the failure of the electricity grid and hence the employment of diesel generators as backup. The cost analysis will look into how fuel cell systems differ to the conventional diesel generator in the Indian telco market. Before embarking that analysis, it might therefore be helpful to understand for whom these costs are incurred.

2.2.3. The Indian Tower Industry

The Indian telco market is often praised as being one of the largest in the world, yet little attention is paid towards the tower industry, which, admittedly, has been a key enabler in connecting people in India. Through the establishment as well as market offering of adequate infrastructure and the ability to contract tower facilities to mobile operators (e.g. through leasing), tower companies are gaining bar-gaining power in the telco industry. The significant development in subscribers and data usage coupled with growth forecasted to continue are challenging Indian telco operators to offer better solutions in an increasingly competitive landscape. Particularly, as it is reported by GTL in their annual report from 2014, "competitive telecom tariff alone is not a strategic advantage to telecom operators. Pricing along with better network quality will be a key driver for operators to retain and acquire new subscribers. The quality of customer experience becomes all the more important with the growth of data services" (GTL 2015: 4). In other words, tower companies are offering important solutions for telco operators to improve electricity reliability and thus reduce costs considerably. Thus, hypothesizing fuel cells are better alternatives to backup power than diesel generators is important to test so that reliability can be increased. As competition is fierce already, cost reductions will enable operators to allocate significantly more resources towards core marketing activities aimed directly at existing and potential customers.

Whereas Greentech Media counts about 425,000 towers in October 2015, Deloitte reports approximately 400,000 towers in India as of May 2015. This supports an increasingly growing industry in which Deloitte (2015) has analyzed the market share composition. The telco towers are shared by various industry players, including GTL from the Intelligent Energy deal. In fact, there are many larger players than GTL in terms of current tower infrastructure assets.

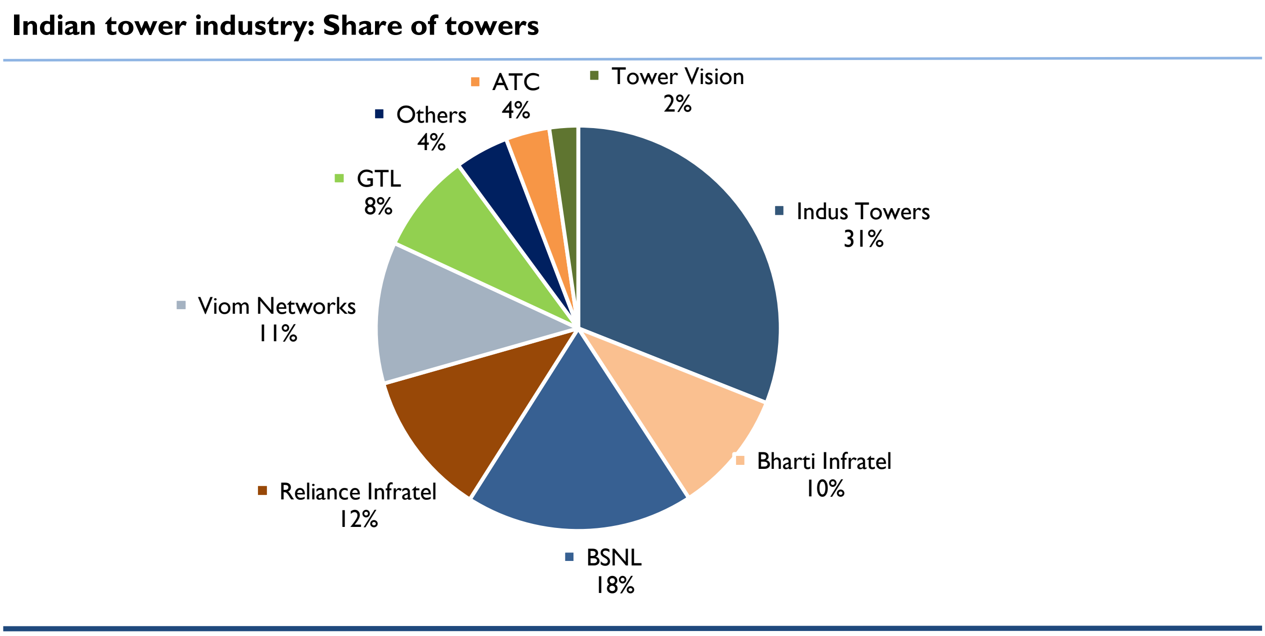

Figure 2.8: Indian tower industry: Share of towers as of May 2015. Source: Deloitte (2015) and own work.

Whereas figure 2.8 shows a conventional market share split by assets (or towers), figure 2.9 illustrates the share of tenancies split below. Bharti Infratel has 42% equity interest in Indus Towers and is thus the second largest tower infrastructure provider in India with ~85,000 towers deployed. It can be approximated that, together, these account for ~49% of tenancies in the market.

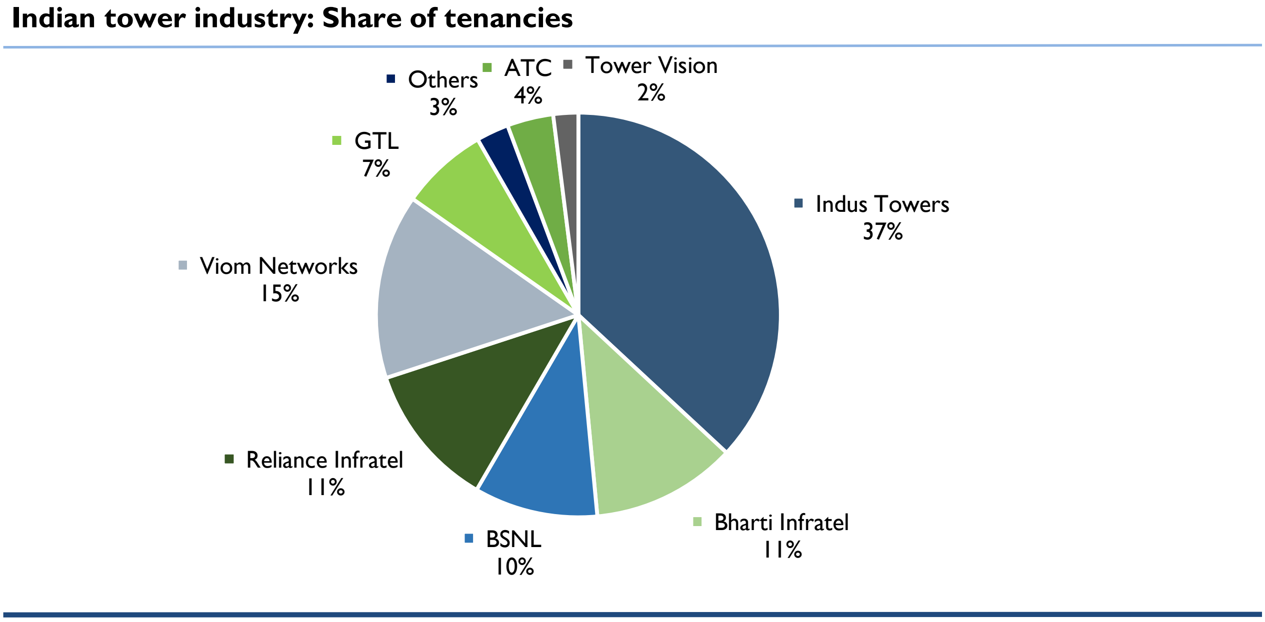

Figure 2.9: Share of tenancies as of May 2015. Source: Deloitte (2015) and own work.

However, their share of towers is also above 40% of total assets in India. In one case study by the World Bank and the International Bank for Reconstruction and Development (Tenenbaum et al. 2014), it is explained how Bharti Infratel signs a time-constrained contract with an energy provider, such as Intelligent Energy, who in turn supplies electricity to the specified towers for the period negotiated. As it is commented in the case study (2014: 41), "operation of [backup] units is a headache for most operators because producing electricity at thousands of locations is not their core business." In this way, the contracted electricity supplier is essentially seizing the task of operation, and the tower company (or mobile-phone company) can focus on its core competencies. This setup creates an important decision for the contracted electricity operator and supplier. Among other considerations, the established grid unreliability calls for a backup system installed, and because contracts usually are of longer term (e.g. Omnigrid Micropower Company's 10-year-contract from 2012 as explained in the case study or Intelligent Energy's equally lasting contract from 2015), it is important to consider, on the one hand, which system to employ, and on the other hand, the value of being able to replace a diesel generator by e.g. a fuel cell in the future, should fuel prices increase, costs of fuel cell systems decrease, or any other quantified uncertainty impact such value. Companies, such as Omnigrid Micropower Company and Intelligent Energy, contracted over a longer term, will inevitably face uncertainty in capital budgeting, yet it is equivocal whether or not the decision to replace conventionally installed systems by fuel cells in the future is evaluated. In practice, applying Deloitte's market share estimates and Greentech Media's count of existing telco towers, contracted electricity suppliers face a potential customer group demanding substantial power generation to be delivered. Assuming the 425,000 towers less Intelligent Energy's share rely on 2.5 kW backup systems, the major Indian telco tower players could contract suppliers for the following amount of megawatt hours.

Market size for electricity suppliers

Company	Share	Towers	Supply (MW)
Indus Towers	31.0%	123,380	308.5
Bharti Infratel	9.8%	39,004	97.5
BSNL	18.2%	72,436	181.1
Reliance	11.6%	46,168	115.4
Viom Networks	11.3%	44,974	112.4
GTL	8.0%	31,840	79.6
Others	4.3%	17,114	42.8
ATC	3.5%	13,930	34.8
Tower Vision	2.3%	9,154	22.9
Total	**100%**	**398,000**	**995**

Table 2.1: Market size of electricity suppliers. Sources: Deloitte (2015), Greentech Media (2015) and own work.

Assuming the approximations from Deloitte and Greentech Media are correct, a market potential of up to 1 TW exists today. Looking forward, Deloitte (2015) projects total number of towers (i.e. both telco towers and data towers) to grow at a 3% compound annual growth rate including 2020, which, if realized, will demand electricity supply to grow as well. In the scenario where this happens, and backup systems can continue to be powered by 2.5 kW specifications, the following trend is forecasted.

Projection of tower sites and power supply

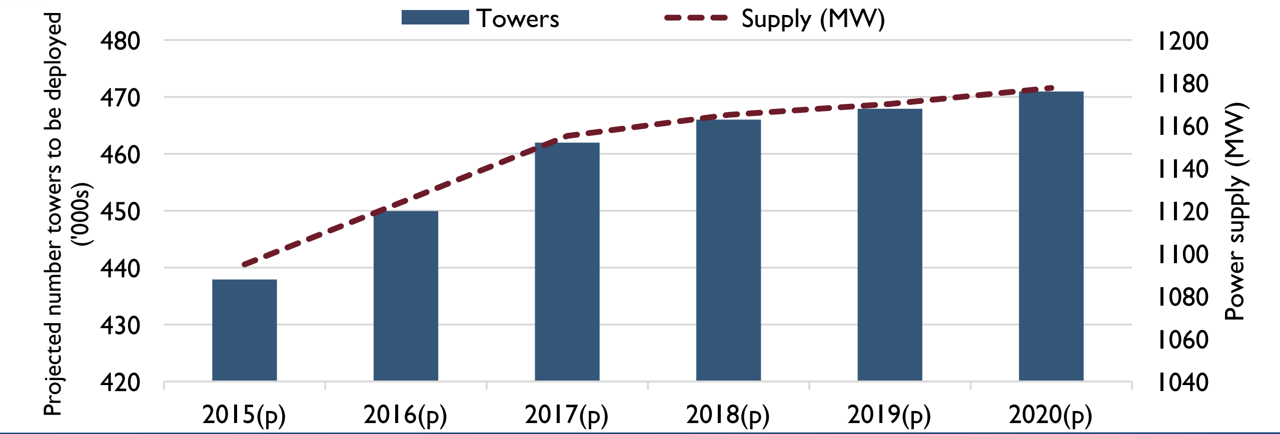

Figure 2.10: Projection of tower sites and power supply. Sources: Deloitte (2015), Greentech Media (2015) and own work.

Thus, Indian telco towers will demand close to 1.2 TW by the backup systems on aggregate, and if one includes data towers in the calculation as well, projected at 511,000 by 2020, such demand is well above that threshold.

Considering Intelligent Energy's recent contract and the general expectations of growth in the Indian telco market coupled with an unreliable electricity grid, it is no surprise that Deloitte (2015: 2) lists "operational optimization" as the number one key trend in the current and future tower industry. For these tower companies, there is no flexibility in the decision about electricity. They need it. Thus, whether they contract other service providers or resort to alternative solutions, backup systems need to be deployed. In this matter, fuel cells might help to optimize operational performance. In the next chapter, before continuing with the backup system decision in a more financially motivated framework of real option application, an analysis of the backup systems' cost structures are performed. Key cost drivers are identified and help to understand where value is derived or can be created.

3. ANALYSIS OF THE COST STRUCTURE

Installing diesel generators as backup sources for the electricity grid hold many advantages for operators in India: they are convincingly reliable, predictable, and the cost of purchasing and installing the systems has been historically inexpensive. Why bother with an investigation of alternatives to the conventional diesel generator, critics will perhaps ask. When comparing diesel generators with fuel cell systems, one will immediately see a significant difference in capital expenditures, yet such comparison fails to capture the full picture. It is the general consensus that renewable energy associates costs as its most significant problem (see e.g. Lloyd and Forest 2010; Trainer 1995, 2010), yet this is heavily contingent on how the *cost* is measured (Carson 2013). Therefore, this chapter will examine how measuring renewable energy's value through a levelized cost analysis will help to explain the price differences in fuel cells and diesel generators. Having established the levelized cost of energy, and what components constitute such cost, we will then discuss how (or if) an alternative approach or methodology can help to evaluate the decision to deploy fuel cells as backup sources in India.

3.1. Calculating Levelized Costs

In this chapter, we will present the levelized cost of energy model and subsequently calculate the dollar cost per megawatt of electricity generated by the two systems of comparison; a PEM fuel cell and a conventional diesel generator. Before such presentation and calculation, a few words on the theoretical foundation of the model will be addressed.

3.1.1. Discounted Cash Flows and WACC

The discounted cash flow model is one of the most, if not the most, widespread financial valuation tool used to value future cash flows. On the backbone of the DCF model lies the time value of money concept, which states that "a dollar today and a dollar in one year are not equivalent" (Berk & DeMarzo 2014: 98). Evidently, a dollar inflow today is worth more than a dollar inflow one year from now, based on the one-year interest one can earn on the dollar in hand today. Similarly, and more importantly for the purpose of this thesis, the time value of money implies that a one-dollar cash *outflow* today is costlier than a one-dollar cash outflow one year from now for the same reason; one could invest the dollar today and earn interest. To compare cash flows today and cash flows in the future, the DCF model corrects the value of future cash flows through discounting, which effectively subtracts a given portion of the nominal value of the future cash flow. The DCF formula is given by:

$$PV = \sum_{i=0}^{N} \frac{C_n}{(1+r)^n} \qquad \textbf{EQ 3.1}$$

where *PV* is the present value, *C* is the cost in a given year *n,* and *r* is the appropriate rate that discounts value from the future cash flow. The summation of future cash flows is the NPV. In this way, the DCF model allows for fair comparison of different projects and investments with large possible variations in the timing of cash flows. From a revenue perspective, a typical investment case would postulate negative cash outflows at initial stages and subsequent positive cash inflows later on. This implies that the earlier the investment can start to generate positive cash flows, the bigger the positive impact on the net present value of the investment will be. Conversely, from a cost perspective, the NPV will, through the effects of discounting, benefit if costs can be postponed to later dates. Albeit rather obvious, these considerations have important implications for the LCOE analysis, which is undertaken purely from the cost perspective, and will undeniably impact the final dollar per megawatt comparison.

Besides the immediate and projected future costs, the key input to equation 3.1 to determine the present value is the discount factor denoted by *r*. In practice, the discount factor, or the cost of capital, is more commonly referred to as the weighted average cost of capital. The WACC is defined as the average cost of capital that a corporation must pay to both types of its investors, equity holders and debt holders, weighted by share of the capital structure that each of the two investor types takes up (Berk & DeMarzo 2014):

$$r_{WACC} = \frac{E}{E+D} r_E + \frac{D}{E+D} r_D (1-\tau_C) \qquad \textbf{EQ 3.2}$$

where r_{WACC} is the weighted average cost of capital, *E* and *D* is the value of equity and debt respectively, r_E and r_D is the appropriate equity and debt cost of capital, and t_C is the corporate tax rate making the WACC the effective after-tax cost of capital to the firm. The WACC hereby allows for comparison of projects with similar risk, capital structure, and corporate tax rate.

How can one determine the appropriate discount factor for a given project or investment, and more specifically, how can one estimate the discount factor (WACC) for backup power energy generation for telecommunication tower operators in India? This question is not an easy task to answer and the thesis could have been devoted entirely hereto. While constituting an interesting investigation of the risk and return profile of backup power in the case of India, it is outside the scope of this project to undertake such analysis. Instead, we rely on existing literature on the matter to gain insights on the appropriate risk and return measures in our rather specific Indian telecommunication case. In the broad sense of energy finance and economics, Carson (2013: 136) notes that "in many studies of levelized cost, the WACC is, alas, frequently obscured". He further proclaims that "even in those that do make clear this important input, some state the WACC in real values and others in nominal terms, with the WACC ranging from 5 to 15 percent". The spectrum between a WACC of 5 to 15 percent is quite substantial, and will impact the LCOE to a great extend depending on which end of the spectrum one chooses to adopt. To narrow down the applicable WACC in the case of telecommunication backup power, we turn to Aswarth Damodaran's online public database at NYU Stern, which includes financial valuation industry average multiples and estimates of equity risk premiums as well as costs of capital (Damodaran 2016). Through the database, we have been able to identify key metrics for the industry labelled "Telecommunication Equipment in India" which will serve as the base for the WACC adopted in our LCOE analysis. The database includes 20 companies within the industry and estimates the average capital structure to be 75.73% equity and 24.63% debt and with a beta of 1.15 and marginal tax rate of 35%. The cost of equity amounts to 18.58%, based on an equity risk premium of 9.28%, while the reported cost of debt is 12.12%. Applying equation 3.2, the WACC is estimated:

$$r_{WACC} = \frac{0.7573}{1} 18.58\% + \frac{0.2463}{1} 12.12\%(1\text{-}35\%) = 15.96\% \qquad \text{EQ 3.3}$$

Being an approximation, the WACC of 15.96% cannot be concluded as an unambiguous figure. Nonetheless, based on the findings from the relevant literature it has been found applicable for use in the LCOE analysis. An important assumption, which has been taken here, is that the two energy generation sources, fuel cell and diesel generator, have similar financial characteristics as outlined above. Additionally, and as long as these assumptions are upheld, the WACC is merely an (important) input to the overall LCOE analysis that allows for a fair comparison of the two energy generation sources in question. Furthermore, sensitivity analyses of the WACC impact on the LCOEs will be carried out to shed additional light on its effects.

3.1.2 Real vs. Nominal LCOE

As mentioned in section 3.1.1., *real* versus *nominal* WACC have led to some confusion. This applies to the entire LCOE calculation as well, which can be expressed in real or nominal values, or, put differently, in current or constant dollar terms (Carson 2013). The distinction, however, is very important as the nominal (constant dollar) LCOE measured in dollar per megawatt will always be higher than the real (current dollar) LCOE due to corrections for inflation in the latter. Therefore, when comparing costs between different power generation sources, discrepancies in the consistent use of *either* constant or current dollars can lead to wrongful conclusions.

Following Carson's (2013: 131) example of a supercritical coal plant, in which both the current and constant levelized costs are reported, the impact of applying either one or the other is offered. While the current dollar levelized cost is a non-changing value, the nominal constant dollar levelized cost must rise to correct for inflation. The result is two, different, incomparable levelized costs at time zero i.e. today. Another way to understand the difference, suggested by Black & Veatch (2011) is to compare the levelized cost with a power purchasing agreement of electricity that rises each year with inflation (constant dollar amount), and a fixed, unchanging electricity price throughout the lifetime of the project (current dollar amount). Consequently, in year 0, the fixed price will start at a higher point than the rising current dollar price and thus the reason for the differences in the two levelized cost measures. Importantly, both the current and the constant dollar levelized costs methods are equivalently sound and both methods find widespread use (Carson 2013). For simplicity and to keep focus on the real objective of this thesis, we have chosen to follow the constant dollar levelized cost approach which will, of course, be applied to calculations of LCOE for both the fuel cell system and the diesel generator system.

3.1.3. Applicable Exchange Rate

In line with the discussion above concerning the use of nominal and real values, some brief considerations on the applicable exchange rate to non-US dollar denominated data will be presented here. As noted, one must carefully evaluate the inputs to the LCOE calculation and its possible impact on the bottom line cost comparison. We showed how inconsistencies among real and nominal LCOE calculations disrupts the comparative foundation between technologies. Likewise, cost data denominated in different currencies are exposed to noise from exchange rate movements, which may fluctuate to a large extend in a short period of time. While collected data on the PEM fuel cell system and its related costs are mainly denominated in US dollar (USD), diesel generator inputs are almost entirely denominated in Indian Rupee (INR). In line with methodology of Schoots et al. (2010), we apply a 3-year average INR/USD exchange of 0.01615 between March 2014 and March 2016 (Investing 2016). With regards to averaging exchange rates over time, the term *average* has, in some instances, wrongfully covered two mathematically distinct averages; arithmetic and geometric (Brodsky 1982). For geometric averaged exchange rates, proportionally equivalent fluctuations, appreciative or depreciative, have the same effect on the overall average whereas the arithmetic average is subject to an upward bias. For the purpose of this thesis, when referring to average exchange rates, we specifically refer to the *geometric* average exchange rate, which is also the common practice (Schmitz et al. 2012).

3.1.4. Modeling the LCOE

The levelized cost of energy is one of the foremost methods of calculating electricity costs and compare these across different energy generation sources. For any given electricity source (e.g. plant or backup source), the LCOE framework calculates the present value of the total cost of building or setting up the system and its operational costs over its lifetime and presents a flat price during this period.

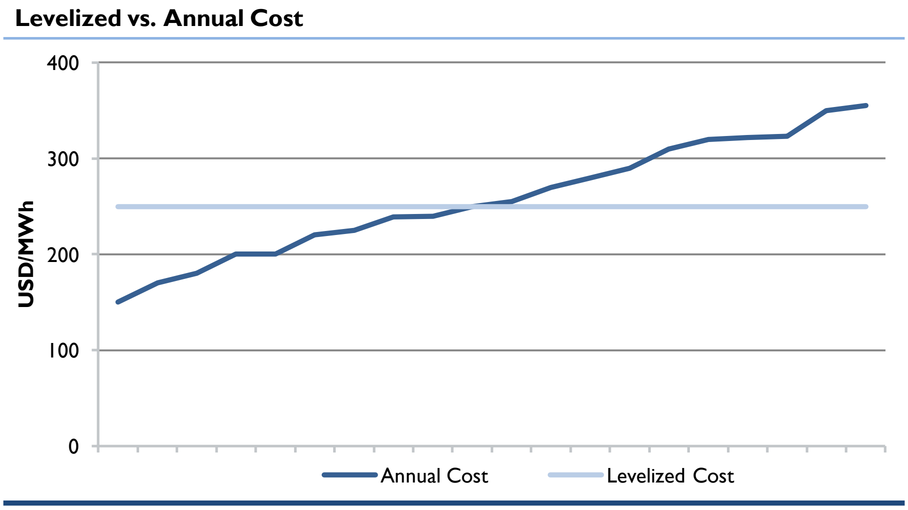

Figure 3.1: Levelized vs. annual cost. Source: CEC (2009) and own work.

To illustrate, figure 3.2 shows a (fictional) relationship between annual and levelized costs, which states that the levelized cost is equal to the present value of current and future annual costs (CEC 2009). While annual costs for different generation sources may vary substantially and thereby difficult to compare, the LCOE method allows for a simple, easily digestible comparison across generation sources. As Borenstein (2012: 70) comments, one way to think about the LCOE is as the "price for power that would equate the net present value of revenue from the plant's output with the net present value of the cost of production" or, as Rothwell (2010: 16) notes, it is "the equivalent to (long run) average costs in microeconomics". Following the works of Carson (2013), which is similar to the line of thought presented by Borenstein (2012: 70), the LCOE can be written as:

$$TLR_{PV} = TLKC_{PV} + TLOMC_{PV} + TLFC_{PV} \qquad \text{EQ 3.4}$$

Where TLR_{PV} is the present value of total lifetime revenue generated by the generation source, $TLKC_{PV}$ is the present value of total lifetime capital costs, $TLOMC_{PV}$ is the present value of total lifetime operating and maintenance costs, and finally, $TLFC_{PV}$ is the present value of total lifetime fuel costs.

The estimated LCOE for one technology will thus be in similar units to that of another technology, making it convenient to compare electricity prices of different sources. In the literature (see e.g. Borenstein 2012; Carson 2013; CEC 2009; Lazard 2015), the technological specifications and inputs to the LCOE framework are relatively easy to establish with reasonable prediction. For the most part, researchers agree on which inputs to use and what outputs will result. However, it can be a challenge to compare levelized costs in economically different environments. Therefore, as Borenstein's (2012) analysis explains, economic variables are usually the factors behind large discrepancies among levelized cost estimates, for which reason any renewable energy researcher needs to carefully address such differences when examining the technology's cost. In the case for fuel cells as backup systems, it is therefore crucial to understand that such LCOE will yield different results in India than in East Asia, Europe, or the United States (where many LCOE studies have been undertaken already). This applies for other energy sources too. As systems and "plants are heterogeneous in location, architecture, and other factors, even plants with similar technology will not have the same levelized cost of energy" (Borenstein 2012: 70). In order to arrive at a reliable LCOE for fuel cell systems deployed as backup power for Indian telco towers, this chapter will therefore both examine the underlying technological inputs to the framework and use these in the economic setting of Indian telecommunications and towers.

If a system lasts T periods and produces q_n in period t, then discounting future cash flows (costs) at the real cost of capital r, the levelized cost of energy is defined by:

$$\sum_{t=1}^{T} q_t \frac{LCOE}{(1+r)^t} = \sum_{t=1}^{T} \frac{C_t(q_1,\ldots,q_t)}{(1+r)^t} \Leftrightarrow LCOE = \frac{\sum_{t=1}^{T} \frac{C_t(q_1,\ldots,q_t)}{(1+r)^t}}{\sum_{t=1}^{T} \frac{q_t}{(1+r)^t}} \qquad \text{EQ 3.5}$$

where $C_t(q_1, \ldots, q_T)$ is the real (in period 0 dollars) expenditures in period t to produce the steam of output $(q_1, \ldots, q_T)$. Therefore, as suggested by the formula, the LCOE includes capital costs borne before any production of electricity can take place. In other words, the cost at which the system or plant is purchased and installed is also captured by the LCOE calculation. The presentation of levelized cost is most commonly denoted as dollars per MWh or cents per kWh.

3.2. Assumptions and Inputs for Backup Power

Before commencing the actual levelized costs calculations of the fuel cell system and the conventional diesel generator system, this section will outline the overall assumptions that both systems share.

3.2.1. Run Time

This thesis will analyze the case of backup power to cell towers in periods of grid power outages. Specifically, this study will apply to cell towers operating at an average of 2.5 kWh power demand (nameplate capacity), enough to supply three Base Transceiver Stations (BTS). On average, 70% of the towers in India experience outages of more than 8 hours each day (Intelligent Energy 2012). Telco towers exhibit a range of different power configurations in which the electrical grid, batteries, and backup power systems are incorporated. For our specific analysis it has been chosen to assume that the backup power system will run 6 hours a day or 2,190 a year (assuming 8,760 hours a year). This means that the capacity factor, the period of operation as a percentage of total possible operation, of the systems will be 25% i.e. 2910/8,760 = 25%. In accordance with DPS, systems have an assumed expected operating lifetime of 30,000 hours and thus 30,000/2,190 = 13.7 years (rounded to 15 years for simplicity).

Next, both systems cannot be expected to run during the entire period of planned operation. Although planned maintenance and replacement of certain components can be undertaken within non-operating periods, unforeseen outages must be taken into account. Albeit difficult to estimate, these unforeseen outages are captured by the "outage multiplier" set to 98% in line with DPS estimates. Together, average power demand or nameplate capacity, along with the capacity factor and outage multiplier, yield yearly *nominal* and *yearly* delivered kWh of 5,475 and 5,366 respectively. Table 3.1 presents these assumptions and inputs.

Common assumptions and inputs	
Hours per year	8,760
Run time per day (hours)	6
Run time per year (hours)	2,190
Capacity factor	25%
Nameplate capacity (kW)	2.5
Outage multiplier	98%

Table 3.1: Common assumptions and inputs. Source: Own work.

3.2.2. Efficiency and Heat Rate

One of the key distinctions of power generation sources is the rate at which the system converts energy carried in a given fuel type to actual, useful electricity. This rate is known as the *efficiency*. Energy can be measured in e.g. Joule and Watt but in this case the "British Thermal Unit" (BTU) is convenient as it allows for the efficiency to be calculated. By definition, one kWh holds 3,414 BTUs (EIA 2015) and similarly, different fuel types hold different amounts of energy measured in BTU. As a result, the amount of fuel (energy) consumed in order to produce one kWh is the actual efficiency. One must note the difference between electrical efficiency and total efficiency as the latter is frequently reported in the literature. Total efficiency relates to total energy produced by a given generation source including heat energy and electrical energy. For the purpose of this thesis, heat energy is not applicate and hence the term efficiency refers to electrical efficiency. *Heat rate* is a related concept, which is simply the amount of BTUs a given generation source consumes in order to produce one kWh. As an example, large new natural gas combined-cycle power plants have heat rates around 7,100 BTU (Greentech Media 2013), which corresponds to an efficiency of 3,413/7,100 = 48%. Heat rates and thus efficiency is used to calculated fuel consumption during the operational lifetime of each system. One key assumption for both systems is that the heat rate will increase (efficiency decrease) during the course of operation. DPS has estimated that the heat rate will increase 20% after 10 years of operations, which translates to a compound annual growth rate of 1.84%.

3.2.3. Timing of Costs

Another important assumption for the levelized cost of energy calculations relates to the timing of incurred costs. As the fundamental objective of this thesis is to evaluate the choice of *replacing* the conventional diesel generator with a fuel cell, it is assumed that the diesel generator has already been bought. Specifically, it is assumed that the diesel generator is bought "yesterday", which we label *year 0*, while the first operating expenses will not occur before year 1. Additionally, operating expenses are assumed to be incurred at the end of each period, meaning that all expenses during year 1 will be discounted back to today i.e. the first day of year 1. For capital expenditures, we assume that they will incur on the first day of a time-period, which implies that any capital expenditures taking place in year 1 shall not be discounted like operating expenses during the same year. This will be of particular importance in chapter 5 in which the real option value to replace the diesel generator will be examined.

3.3. Cost of Energy Generation Model: PEM Fuel Cell

Similar to California Energy Commission's (CEC) comparative costs of central station electricity generation, this study will use a "Cost of Generation Model" (CEC 2009: 11) through which dozens of economic, financial, and system-specific assumptions are captured. In summary, the levelized costs for fuel cells and diesel generators will be calculated on basis of the following information.

Summary of levelized cost components

CAPEX	**Section**
Capital — Total cost of construction, installation, and sales markups	3.3.1
OPEX	
Fixed O&M — Staffing and other costs independent of operating hours	3.3.2
Fuel Costs — Cost of fuel used	3.3.3
Variable O&M — Operation and maintenance costs that are a function of operating hours	3.3.4

Table 3.2: Summary of levelized cost components. Source: Own work.

Generally, levelized cost components will be made up by the above listed posts as well as other fixed costs such as insurance, ad valorem (e.g. property taxes), and corporate taxes. In the case of backup power to Indian telco towers, however, it assumed that such costs will be similar for a fuel cell system and a diesel generator. It is therefore not listed and consequently disregarded by this LCOE calculation. If one intends to compare the results of this paper to research or estimations conducted outside this project, one should thus carefully address how such costs would change the levelized costs before any comparison would be legitimate. Nevertheless, within the scope of this paper, the levelized costs are equally comparable.

3.3.1. Capital Costs

The capital cost is the total price paid for the system, including the cost of installing it. Therefore, capital expenditure will capture the cost of manufacturing the system plus the manufacturer's margin. In other words, the cost is incurred from the purchaser's point of view. In this subsection, the total cost of construction is broken down to each component in order to understand their significance. Ultimately, this will also help the research to show where the largest learning effects occur (or fail to happen). To get an overview, the manufacturing costs of the fuel cell system are captured by the items below.

Manufacturing costs	**Section**
Polybenzimidazol (PBI) Membrane	3.3.1.2
Gas Diffusion Electrode (GDE)	3.3.1.3
Membrane Electrode Assembly (MEA) Frame	3.3.1.4
Separator Plates – Half Plates (HAPs)	3.3.1.5
Stack Assembly	3.3.1.6
Balance of Plants (BOP)	3.3.1.7
Fuel Processor	3.3.1.8

Table 3.3: Manufacturing costs. Source: Wei et al. (2014), Danish Power Systems (2016), and own work.

Within the recent years and particularly since the turn of the millennium, there have been an extensive amount of research on fuel cells and their cost structures. One should be careful in evaluating the extent to which each of such studies will add value to the particular problem in one's research. As Short, Packey, and Holt (1995) write, much depends on the purpose of the analysis. This paper will use an Ernest Orlando Lawrence Berkeley National Laboratory study as the primary input to the cost components, referred to as Wei et al. (2014). In their total cost of ownership model for high temperature PEM fuel cells in combined heat and power applications, a group of fuel cell manufacturers have provided company-level data, including Danish Power Systems. Although Wei and colleagues report costs for CHP fuel cells, it has been verified by DPS that they—with the right scaling—are applicable for 2.5 kW PEM fuel cells deployed at tower sites. In this way, Wei et al. (2014) provide adequately precise data on capital costs. Through a stepwise analysis of each component of the manufacturing costs, this study will reveal where the main cost drivers of fuel cell production lie.

3.3.1.1. Scaling Manufacturing Costs

Using data from Wei et al. (2014) on systems of 10 kW and 100 kW stacks, the results are scaled for 1 kW and 2.5 kW outputs linearly below. For example, to accurately estimate the square meter price for PBI membranes, the cost increase from 100 kW to 10 kW is linearly growing for the 1 kW system, so that the relationship can be described as $y = ax + b$, where y is the output in kW, x is the cost in USD, a is the slope (calculated as $\Delta y/\Delta x$), and b is the intercept when cost is zero. Describing output as a function of cost (or vice versa) will thus has its constraints. For example, cost cannot be negative (other than sub-components within total costs, e.g. scrap/waste), and output is limited to the 100 kW maximum by Wei et al. (2014). Given this scaling, proper cost estimates are calculated for 1 and 2.5 kW systems. As there are no functional specifications available for a system at 2.5 kW exactly in the analysis by Wei et al. (2014), DPS comments that the 1 kW specifications can be up-scaled by a factor of 2.5. Such extrapolation is used in calculating plate areas, cells per stack, and stacks per system, which in turn is used to arrive at USD per system and USD per kW costs at each manufacturing component. Wei et al. (2014) report the following specifications.

Functional specification

	Units	**1 kW**	**10 kW**	**100 kW**
Total Plate Area	cm^2	725	725	725
GDL Coated Area	cm^2	468	468	464
Cells per Stack		21	105	136
Stacks per System		1	2	15

Table 3.4: Functional specification. Source: Wei et al. (2014) and own work

3.3.1.2. PBI Membrane

The polybenzimidazol (PBI) membrane is an important feature of the high temperature PEMFC in order to be able to resist certain fuel impurities, hold fast electrode kinetics, and a simplified water and thermal management due to high operational temperature (see e.g. Seel et al. 2009). Wei and colleagues (2014) analyze both first and second generation polymeric materials, however, the second generation has been chosen as the input for this project in collaboration with DPS. As the materials used in the PBI-based membrane are assumed to be largely commodity-type materials, the analysis does not incorporate any discounts in the cost of materials as a function of volume.

PBI Membrane		Wei et al. (2014)		Scaling		%
	kW	**10**	**100**	**1**	**2.5**	**2.5**
	USD/m²	**55.11**	**17.00**	**58.92**	**58.29**	**100.00 %**
Scrap/Waste		9.46	2.19	10.11	10.01	17.17%
Building		2.96	0.30	3.16	3.13	5.37%
Operational	USD	4.53	1.08	4.84	4.79	8.22%
Capital		22.88	2.36	24.46	24.20	41.52%
Direct Labor		6.64	2.43	7.10	7.02	12.05%
Direct Materials		8.64	8.64	9.24	9.14	15.68%
	m²/system	15.23	147.90	1.52	3.81	3.81
	USD/system	839.05	2,514.30	89.71	221.85	221.85
	USD/kW	**83.90**	**25.14**	**89.71**	**88.74**	**88.74**

Table 3.5: PBI Membrane. Source: DPS (2016), Wei et al. (2014), and own work

For the PBI membrane it becomes apparent that costs are largely capital-intensive for the 2.5 kW system as opposed to a 100 kW configuration in which direct materials are the primary cost driver. One argument for such trend is an apparent under-utilization of resources and high scrap percentages at the smaller systems.

3.3.1.3. GDE

In the fuel cell literature, one will often read the terms "gas diffusion layer "(GDL) and "gas diffusion electrode" (GDE) with little chance to distinguish between the two. In the high temperature PEM fuel cell, the catalyst is commonly deposited on the GDL and therefore called GDE (Wei et al. 2014). Fabrication of GDEs is made through the use of ink slurry, containing a substantial amount of platinum. As reported, approximately 80% of the slurry origins from platinum.

Pt-Chr-Cob alloy used in making ink slurry for GDE

Alloying Element	Composition	Loading (mg/cm^2)
Platinum	79.82%	0.700
Cobalt	11.29%	0.099
Chromium	8.89%	0.078

Table 3.6: Pt-Chr-Cob alloy used in making ink slurry for GDE. Source: Wei et al. (2014) and own work

Having established which elements constitute direct materials in the GDE fabrication, it thus becomes clear that platinum is by far the most significant contributor to that cost.

GDE (≈ GDL)		Wei et al. (2014)		Scaling		%
	kW	**10**	**100**	**1**	**2.5**	**2.5**
	USD/m^2	**340.80**	**271.46**	**347.73**	**346.58**	**100.00 %**
Scrap/Waste	USD	-3.50	-9.57	-3.57	-3.56	-1.03%
Building	USD	2.37	0.25	2.42	2.41	0.70%
Operational	USD	1.37	0.24	1.40	1.39	0.40%
Capital	USD	10.70	1.11	10.92	10.88	3.14%
Direct Labor	USD	0.34	0.34	0.35	0.35	0.10%
Direct Materials	USD	329.52	279.09	336.22	335.11	96.69%
	m^2/system	9.83	94.66	0.98	2.46	2.46
	USD/system	3,349.38	25,695.32	341.75	851.54	851.54
	USD/kW	**334.94**	**256.95**	**341.75**	**340.62**	**340.62**

Table 3.7: GDE (≈ GDL). Source: DPS (2016), Wei et al. (2014), and own work

Altogether, direct materials contribute to approximately 340 USD per kW of which 263 USD per kW is from the use of platinum. In other words, it appears as if platinum is quite a significant part of the process, for which reason it makes sense that DPS is interested in continually improving the efficiency of such. At this stage, however, attention will remain on the cost analysis for the purpose of this chapter's LCOE modeling. Also, another interesting observation is the fact that the scrap (or waste) item is incurred as a negative cost. Because scrap material is not discarded, but instead shipped to a platinum recovery firm, the manufacturer can actually gain from its waste.

3.3.1.4. MEA Frame

Although direct materials constitute a large part of the manufacturing costs, the MEA frame is the most insignificant contributor to the total production costs. Among the major cost drivers in high temperature MEA frames are the use of polyimide and Viton. Interestingly, as opposed to the waste value of e.g. platinum, scrap costs are largely due to the fact that a defective framed MEA will imply a loss in all upstream work hitherto.

MEA Frame		Wei et al. (2014)		Scaling		%
	kW	**10**	**100**	**1**	**2.5**	**2.5**
	USD/part	**4.65**	**3.51**	**4.76**	**4.75**	**100.00 %**
Scrap/Waste	USD	2.09	1.65	2.14	2.13	44.95%
Building	USD	0.02	0.01	0.02	0.02	0.43%
Operational	USD	0.10	0.07	0.10	0.10	2.15%
Capital	USD	0.66	0.31	0.68	0.67	14.19%
Direct Labor	USD	0.47	0.16	0.48	0.48	10.11%
Direct Materials	USD	1.31	1.31	1.34	1.34	28.17%
	parts/system	210.00	2,040.00	21.00	52.50	52.50
	USD/system	976.50	7,160.40	100.04	249.11	249.11
	USD/kW	**97.65**	**71.60**	**100.04**	**99.65**	**99.65**

Table 3.8: MEA Frame. Source: DPS (2016), Wei et al. (2014), and own work

Whereas the cost per part is scaled by the method introduced above, the number of parts per 1 kW system is given by Wei et al. (2014). This number is then scaled by a factor of 2.5 to match the backup system, verified by DPS.

3.3.1.5. HAP

Half plates (HAPs) are used to supply reactants to each individual cell while also providing cooling channels. Verified by DPS, there is a need for two HAPs each cell in the system as well as one on top of the stack. This implies e.g. 43 HAPs in the 1 kW system, arbitrarily converted to 107.50 in the fuel cell deployed at a telco site. In this scenario, much of the costs are operational, capital, and direct labor, accounting for more than 92% together. In other words, it is hard at this stage already to expect significant learning effects here.

HAP		Wei et al. (2014)		Scaling		%
	kW	**10**	**100**	**1**	**2.5**	**2.5**
	USD/HAP	**11.32**	**7.65**	**11.69**	**11.63**	**100.00 %**
Scrap/Waste	USD	0.10	0.02	0.10	0.10	0.88%
Building		0.19	0.06	0.20	0.20	1.68%
Operational		2.63	2.58	2.72	2.70	23.23%
Capital		4.84	4.04	5.00	4.97	42.76%
Direct Labor		3.03	0.43	3.13	3.11	26.77%
Direct Materials		0.53	0.52	0.55	0.54	4.68%
	HAPs/system	421.00	4,081.00	43.00	107.50	107.50
	USD/system	4,765.72	31,219.65	502.54	1,249.78	1,249.78
	USD/kW	**476.57**	**312.20**	**502.54**	**499.91**	**499.91**

Table 3.9: HAP. Source: DPS (2016), Wei et al. (2014), and own work

3.3.1.6. Stack Assembly

While the actual semi-automatic assembly line is understood better elsewhere (see Wei et al. 2004: 41-42), we see that direct materials are the largest cost contributor, yet building and capital processes account for a similar amount when aggregated. As Wei et al. (2014) comment, there are significant economies of scale in the assembly line, continually increasing direct materials' importance as production volume increases. In our 1,000 systems per year case, direct materials are important, yet still at the stage where building and capital processes as well as direct labor constitute are serious cost drivers.

Stack Assembly		Wei et al. (2014)		Scaling		%
	kW	**10**	**100**	**1**	**2.5**	**2.5**
	USD/kW	**41.86**	**5.63**	**45.48**	**44.88**	**100.00 %**
Building	USD	8.74	1.22	9.50	9.37	20.89%
Operational		0.74	0.13	0.81	0.80	1.78%
Capital		9.49	1.56	10.31	10.17	22.67%
Direct Labor		4.47	0.06	4.85	4.79	10.67%
Direct Materials		18.42	2.66	20.01	19.75	44.00%
	USD/system	418.60	562.50	45.48	112.20	112.20
	USD/kW	**41.86**	**5.63**	**45.48**	**44.88**	**44.88**

Table 3.10: Stack Assembly. Source: DPS (2016), Wei et al. (2014), and own work

3.3.1.7. BOP

As there is no state-of-the-art balance of plants components in a fuel cell system, Wei et al. (2014) build upon previous analyses with system modifications and simplifications appropriate for the HT PEM technology. As in the previous cost components Wei et al. (2014) report only for 10 kW and 100 kW systems in the BOP analysis, however, in their source for BOP, one is able to find data on a 1 kW HT PEM fuel cell. Rather than down-scaling here, the project relies on Wei et al.'s reference, James (2014), from whom a more precise estimate can be given. Also, as discussed with DPS, it should be mentioned that different subsystems might be necessary in the future.

BOP

	kW	1	2.5
	USD/system	**3,788.96**	**9,472.40**
Fuel Processor Subsystem	USD	2,556.82	6,392.05
Fuel Cell Subsystem		1,232.14	3,080.36
	USD/kW	**3,788.96**	**3,788.96**

Table 3.11: BOP. Source: DPS (2016), Wei et al. (2014), James (2014), and own work

These costs are the heaviest part of manufacturing costs, however, inevitable for the producer (and the consumer). In order for the fuel system to function, proper balance is needed. In other words, the BOP helps to maintain high reliability and functionality in the system. Major cost drivers are here identified as the fuel processor (67%).

3.3.1.8. Total System Costs

Accumulating manufacturing costs reveal the total cost of the fuel cell system deployed as a backup power station. At the stated assumptions, producing a 2.5 kW system will cost more than 12,000 USD.

System Cost

		Wei et al. (2014)		Scaling	
	kW	**10**	**100**	**1**	**2.5**
	USD	26,910.26	140,505.17	4,868.49	12,156.89
	USD/kW	**2,691.03**	**1,405.05**	**4,868.49**	**4,862.75**

Table 3.12: System Cost. Source: DPS (2016), Wei et al. (2014), and own work

Table 3.13. presents the summarized component costs and their respective percentage of the total 2.5 kW system cost. Evidently, BOP is the main cost driver constituting approximately 78 percent while no other single component accounts for more than 10 percent. As a reference point, the BOP accounts for around 76 percent and 60 percent in the 1 kW and 10 kW production costs respectively (Wei et al.

2014). Whether extensive learning effects can be achieved within the BOP component is left for coming chapters; for now, it is merely noted that HT PEM fuel cell system production costs are primarily driven by this particular component.

Component cost summary

Component	USD	%
PBI Membrane	221.85	2%
GDE (≈ GDL)	851.54	7%
MEA Frame	249.11	2%
HAP	1,249.78	10%
Stack Assembly	112.20	1%
BOP	9,472.40	78%
System Cost	**12,156.89**	**100%**

Table 3.13: Component cost summary. Source: DPS (2016), Wei et al. (2014), and own work

3.3.1.9. Sales Markup

In order to understand fully what the Indian telco tower company will pay for the system, one needs to know which corporate mark-up the seller (system manufacturer) operates with. Following James (2014), vertical integration can to a large extend the impact of "layers" of markups before the final system price can be derived. While high degrees of vertical integration can reduce the number of links in the value chain and thus the number of markups, low production volumes are typically associated with low levels of vertical integration due to low machinery utilization and lack of expertise within a certain manufacturing process. Standard practice necessitates markups to be applied to account for e.g. general and administrative expenses, R&D, and company profit are presented as a percentage value. Due to large differences in the manufacturing process setup, it can be difficult to determine concise margin, and it ranges between as much as 10-100%. During talks with DPS it has been found appropriate to apply 28% sales margin to the distinct case of this project. Assuming an installation cost of 2,500 USD as reported by Lipman et. al (2004), total installed cost of the 2.5 kW system becomes approximately 18,000.

3.3.2. Fixed O&M

Fixed operating and maintenance (O&M) costs include staffing, overhead, and equipment among other miscellaneous direct costs (CEC 2009). In accordance with DPS, an estimated yearly fixed cost equal to half of BOP purchases distributed over its lifetime is appropriate. Therefore, fixed O&M of 315.75 USD is assumed to occur annually.

3.3.3. Fuel Costs

Having stated how Short, Packey, and Holt (1995) emphasize using data fit only for one's own analysis, information on fuel (and delivery) costs has been disclosed by DPS' Indian sales agent, Vispadh Group, and is thus found highly relevant in this project's economic environment. In this way, one kilogram of methanol sells at 0.34 USD using the 3-year average exchange rate from INR as reported above. Based upon Vispadh Group's advisory, fuel price growth is estimated to 2.43% derived as the compound annual growth rate from March 2002 through March 2016 based on yearly prices—methodology similar to the diesel case. While methanol pricing has indeed been highly variable and cyclical (see e.g. MMSA 2015), Vispadh Group's data is evaluated as the most reliable source in this setup.

Fuel consumption is contingent on the system's efficiency. As reported by Wei et al. (2014), the electrical efficiency is 29% at which a fuel cell heat rate approximates 11,769. Now, as the methanol to water ratio is 68%, and there are 56,800 methanol BTUs per gallon, fuel consumption is 38,624 BTUs per kg. At 0.34 USD per kg, the *real* fuel price is then approximately 8.78 USD per MMBTU.

3.3.4. Variable O&M

Whereas fixed O&M is an estimate on the lifetime of BOP components and their substitution costs, variable O&M is calculated as follows.

$$O_t = G \cdot \gamma \, [1+\mu(t-1)] \qquad \textbf{EQ 3.6}$$

where G is measured as yearly delivered kWh, γ is annual variable O&M costs per delivered kWh, μ is the annual variable O&M escalation factor in percent at time t. Thus, contingent on the year of operation, variable O&M costs are determined by G (see table 3.14), γ equal to 0.04 per kWh defined by Lazard's recent LCOE report (2015), and μ is reported to be 2% by DPS.

3.3.5. Results

The LCOE calculations are summarized in table 3.13. The levelized cost for the fuel cell system during the operational lifetime of 15 years amounts to 311 USD per delivered MWh. A more detailed analysis of the results and a comparison of these to calculations of the diesel generator LCOE is conducted in section 3.5. For now, it is worth noting that the results confirm the general perception that fuel cells are associated with very large initial costs captured by total installed costs in the present calculation. Similarly, the calculations verify the second general assumption that fuel cells have relatively low operational and maintenance costs; the resulting LCOE excluding CAPEX amounts to no more than 89 USD per delivered MWh.

LCOE Model for Fuel Cell System

Results	
PV of Costs	25,025
Annual Levelized Cost	1,668
Average Delivered kWh	5,366
LCOE excluding CAPEX	87
LCOE (USD/kWh)	**311**

For Reference	
PV Fuel Costs	3,861
PV Fixed & Variable O&M	3,103

PEM Fuel Cell Characteristics	
Absolute Yearly Heat-Rate Increase	216.54
Absolute Yearly Capacity Degradation	0.00
Annual Fixed O&M (USD)	315.75
Annual Variable O&M/kWh (USD)	0.04
Losses Multiplier	1.00
Outage Multiplier	0.98
Instant Installation Cost (USD)	2,500
Production Cost (USD)	12,157
Sales Margin	0.28
Total Installed Cost (USD)	18,061
WACC	15.96%

Assumptions	
Nameplate Capacity (kW)	2.50
Capacity Factor	0.25
Run Time per Year (Hours)	2,190
Variable O&M Escalation Factor	0.02
Electrical Efficiency	29.00%
Heat-Rate	11,769
Methanol/H20 Ratio	0.68
Methanol BTU/Gal	56,800
Methanol Fuel Price (USD/kg)	0.34
Methanol Fuel Price (USD/MMBTU)	8.78
Growth Rate for Methanol Prices	2.43%

System Figures	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Capacity		2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5
Yearly Nominal kWh		5,475	5,475	5,475	5,475	5,475	5,475	5,475	5,475	5,475	5,475	5,475	5,475	5,475	5,475	5,475
Yearly Delivered kWh		5,366	5,366	5,366	5,366	5,366	5,366	5,366	5,366	5,366	5,366	5,366	5,366	5,366	5,366	5,366
Heat-Rate after Degradation		11,769	11,986	12,202	12,419	12,635	12,852	13,068	13,285	13,501	13,718	13,934	14,151	14,367	14,584	14,801
Fuel Consumption, MMBTU		63	64	65	67	68	69	70	71	72	74	75	76	77	78	79
OPEX																
Fuel Costs		568	593	618	644	671	700	729	759	790	822	855	890	925	962	1,000
Fixed O&M Costs		316	316	316	316	316	316	316	316	316	316	316	316	316	316	316
Variable O&M Costs		219	223	228	232	237	242	247	251	256	262	267	272	278	283	289
Fixed & Variable O&M Costs		535	539	544	548	553	557	562	567	572	577	583	588	593	599	605
Net Cost Streams	**18,061**	**1,103**	**1,132**	**1,162**	**1,192**	**1,224**	**1,257**	**1,291**	**1,326**	**1,362**	**1,399**	**1,438**	**1,478**	**1,519**	**1,561**	**1,605**
Present Values																
Discount Factors	1.00	0.86	0.74	0.64	0.55	0.48	0.41	0.35	0.31	0.26	0.23	0.20	0.17	0.15	0.13	0.11
PV of Cost Streams	**18,061**	**951**	**842**	**745**	**659**	**584**	**517**	**458**	**406**	**359**	**318**	**282**	**250**	**222**	**196**	**174**

Table 3.14: LCOE Model for Fuel Cell System. Sources: Own work.

3.4. Cost of Energy Generation Model: Diesel Generator

Having analyzed the cost structure of the PEM fuel cell system, its high associated CAPEX and relatively low OPEX, we now turn to a similar analysis of the conventional backup power source, namely diesel generators. As noted, one of the main motivating factors for this thesis is the recent billion-dollar contract between Intelligent Energy and GTL Limited, in which Intelligent Energy has committed to provide around 27,000 fuel cell systems in the coming 10-year period. But what about the existing 90% of the total approximate 425,000 cell towers at which diesel generators are currently deployed? What are the current costs of backup power today?

To evaluate whether fuel cells are, or at some point in the future will be, an economically sound choice, the present costs of conventional backup electricity supply must be understood. To do this, we apply the same cost of energy generation model as for fuel cells with the necessary assumptions taken into account. It is the utmost purpose to perform the cost analysis on the highest level of comparability in order for our findings to be as relevant as possible for actual decision making. Having said that, we, and the reader, must acknowledge that the calculations can, by no means, be better and more precise than the inputs and available data allow for.

While the cost of energy generation model for fuel cells rests on inputs from the Ernest Orlando Lawrence Berkeley National Laboratory study, in which data is collected from a wide array of fuel cell manufacturers, data on the diesel generator cost of generation model will (mainly) be based on an Indian case study performed by Intelligent Energy (2012) (see appendix 1). Albeit data on expenditures for diesel generators originate from a fuel cell producer and thus calls for careful evaluation, the case study is indeed based on surveys from actual Indian cell tower cites and dealers of products providing electricity to these towers, which makes the study highly relevant in the rather specific setting of this thesis. The study is presented by Grupe Spécial Mobile Association (GSMA), a worldwide organization representing the interests of mobile operators, handset and device makers, software companies, equipment providers and internet companies as well as organizations in adjacent industries (GSMA 2016), manifesting the credibility of the study. Additionally, data on e.g. fuel consumption and costs of acquiring such a generator has been crosschecked with multiple sources (see e.g. AbleSales 2014 and Clickindia 2016) to further validate the data quality of the study.

3.4.1. Assumptions

Before proceeding with the actual calculations, a few notes on some of the assumptions will be set forth. The first important issue to note is that cost figures, quoted in INR, from the 2012 study has been inflated with Indian inflation (Statista 2016) for the period 2012-2014 and exchanged at the 3-year average exchange rate. This has been done in order ensure that data on both electricity generation sources remain comparable and rely on the same base year i.e. 2014. Secondly, a number of assumptions on e.g. fuel price (and its growth rate) rely on inputs from sources outside the study. Lastly, a set of assumptions have been replicated across the two systems due to either lack of generation source specific data or for simplicity (see section 3.2.).

3.4.2. CAPEX and OPEX

As opposed to the analysis of the production costs of the fuel cell system, we will not go into detail with the components and its costs of the diesel generator system. First of all, the diesel generator merely serves as cost comparison reference to the price of conventional backup power to the cell sites. Secondly, as the aim of the thesis is to analyze the decision to *replace* the conventional generators, one should compare the fuel cell LCOE to the LCOE of diesel generators *excluding* the landed costs of buying and setting up the system. Nonetheless, and for reference, the landed cost of the diesel generator is presented in the calculations. OPEX is decomposed by (1) fixed O&M which includes preventive maintenance as well as minor and major overhauls, (2) variable O&M constitutes unscheduled maintenance and (3) fuel costs. Based on talks to DPS, variable O&M costs for fuel cells are estimated to growth 2% a year, which likewise has been assumed for diesel generators.

3.4.3. Fuel and Efficiency

Data on the Indian diesel fuel price is calculated as an average of March 16, 2016 quoted prices across Delhi, Kolkata, Mumbai, and Chennai (IndianOil 2016) and exchanged to USD at the 3-year average exchange rate. The resulting figure used for calculations is 0.84 USD per liter of diesel. The price includes the cost of fuel delivery, which based on the Indian study is estimated to be 0.04 USD per liter. Fuel price growth rate is derived as the compound annual growth rate from the period 2002-2015 based on yearly prices as quoted by IndianOil (2016) and amounts to 6.99%. While concerns on whether the CAGR for the chosen time frame is a representative measure of future price increases is deliberate, it is chosen to remain consistent with data on price development for methanol, which has been gathered for the same 12-year period.

The study from 2012 reports that fuel consumption is estimated to 1.8 liters per hour in order to supply the cell tower at 2.5 kW. This implies a diesel generator efficiency of just below 14%, which is much lower than regular reported efficiencies for diesel generators. Normally, efficiencies and size of the system is positively correlated, with variations in efficiencies being much lower for bigger systems. For up to 62.5 kVA (50 kW) systems, efficiencies vary between 20-60% due to differences in engine type and technology (Shakti 2014). Nonetheless, the efficiency of 13.98% applied to the present calculations is based on the fuel consumption input from the study and the physical energy in diesel in line with the following argument: the physical energy of diesel is 129,500 BTU per gallon, or 34,168 per liter (Gable 2014). By definition 1 kWh amounts to 3,413 BTU, which implies that providing 2.5 kWh must equal a total energy use ≈ 8,600. BTU. As the diesel generator consumes 1.8 liters of diesel (61,503 BTU) per hour, the implied efficiency is 8,600/65,541= 13.98%.

3.4.4. Results

Below, the levelized cost calculations are presented. The data and calculations resemble a 10 kVA diesel generator used to supply one cell tower with 3 Base Transceiver Stations requiring an energy output of 2.5 kWh.

LCOE Model for Diesel Generator

Results		**Diesel Generator Characteristics**		**Assumptions**	
PV of Costs	16,750	Absolute Yearly Heat-Rate Increase	449.06	Nameplate Capacity (kW)	2.50
Annual Levelized Cost	1,117	Absolute Yearly Capacity Degradation	0.00	Capacity Factor	0.25
Average Delivered kWh	5,366	Annual Fixed O&M (USD)	556.45	Run Time per Year (Hours)	2,190
LCOE excluding CAPEX	**161**	Annual Variable O&M/kWh (USD)	301.14	Variable O&M Escalation Factor	0.02
LCOE (USD/kWh)	208	Losses Multiplier	1.00	Electrical Efficiency	13.98%
		Outage Multiplier	0.98	Heat-Rate	24,406
		Instant Installation Cost (USD)	0.00	Diesel/H20 Ratio	1.00
		Production Cost (USD)	3,764	Diesel BTU/Gal	129,500
For Reference		Sales Margin	0.00	Diesel Fuel Price (USD/kg)	0.86
PV Fuel Costs	3,861	Total Installed Cost (USD)	3,764	Diesel Fuel Price (USD/MMBTU)	6.63
PV Fixed & Variable O&M	3,103	WACC	15.96%	Growth Rate for Diesel Prices	6.99%

System Figures	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Capacity		2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5
Yearly Nominal kWh		5,475	5,475	5,475	5,475	5,475	5,475	5,475	5,475	5,475	5,475	5,475	5,475	5,475	5,475	5,475
Yearly Delivered kWh		5,366	5,366	5,366	5,366	5,366	5,366	5,366	5,366	5,366	5,366	5,366	5,366	5,366	5,366	5,366
Heat-Rate after Degradation		24,406	24,855	25,304	25,754	26,203	26,652	27,101	27,550	27,999	28,448	28,897	29,346	29,795	30,244	30,693
Fuel Consumption, MMBTU		131	133	136	138	141	143	145	148	150	153	155	157	160	162	165
OPEX																
Fuel Costs		929	1,012	1,102	1,200	1,306	1,422	1,547	1,682	1,829	1,988	2,161	2,348	2,550	2,769	3,007
Fixed O&M Costs		556	556	556	556	556	556	556	556	556	556	556	556	556	556	556
Variable O&M Costs		307	313	320	326	332	339	346	353	360	367	374	382	390	397	405
Fixed & Variable O&M Costs		864	870	876	882	889	896	902	909	916	924	931	938	946	954	962
Net Cost Streams	**3,764**	**1,792**	**1,882**	**1,978**	**2,082**	**2,195**	**2,317**	**2,449**	**2,591**	**2,745**	**2,912**	**3,092**	**3,286**	**3,496**	**3,723**	**3,969**
Present Values																
Discount Factors	1.00	0.86	0.74	0.64	0.55	0.48	0.41	0.35	0.31	0.26	0.23	0.20	0.17	0.15	0.13	0.11
PV of Cost Streams	**3,764**	**1,546**	**1,399**	**1,269**	**1,152**	**1,047**	**953**	**869**	**793**	**724**	**662**	**607**	**556**	**510**	**469**	**431**

Table 3.15: LCOE Model for Diesel Generator. Sources: Own work.

The LCOE calculations results in a price of 208 USD/MWh for the 10 kVA diesel generator. This is the levelized cost of energy each year during the lifetime of operation. Not surprisingly, the difference in the USD/MWh price between calculations with and without the landed cost is not significant and amounts to 208-161 = 47 USD. This finding confirms the general perception that diesel generators are inexpensive to acquire but very costly to operate. Further analysis of the LCOE findings will be presented and compared to the fuel cell LCOE calculations in the next section.

3.5. Cost of Energy Generation Model Comparison

Having carried out descriptions of the cost of energy generation model, its assumptions, and calculations for the HT PEM fuel cell and diesel generator system respectively, this section is devoted to an analytical comparison of the results. In practice, the two separate systems should act as perfect substitutes with regards to energy generation for telco towers in time of grid outages. Motivated by the recent billion-dollar deal between Intelligent Energy and GTL Limited, it has been of particular interest to analyze, purely from an economic perspective, if and to which extend the fuel cell system is cost competitive compared to the diesel generator. Notably, we analyze the situation in which the diesel generator is already in place as the case is for the vast majority of tower cites today. The resulting fact is that the costs of buying and installing the system, total installed cost, is disregarded for the diesel generator.

The overall conclusion of our LCOE calculations is, not surprisingly, that the fuel cell system is comparably more expensive to buy, install, and operate than the diesel generator currently in place. At 311 USD per delivered MWh, the fuel cell system cost is far beyond that of the installed diesel generator operating at a levelized cost of 208 USD per delivered MWh. While other LCOE studies of fuel cells report costs as low as 106-167 USD per MWh for a 2.4 MW system (Lazard 2015), one should acknowledge the vast impact of system size and application on final levelized cost. Therefore, it can be difficult to compare LCOE findings of the particular study to circumstances outside the Indian telco tower case.

As mentioned earlier, the WACC should be expected to impact the results to a large extend. Evidently, this is indeed the case for the LCOE calculations presented here. The LCOE of both systems are highly sensitive to the applied WACC and span from 345-296 for the HT PEM fuel cell, which corresponds to a 14 percent decrease in the LCOE due to a 10 percentage point WACC increase. For the diesel generator, the percentage gap is even wider; the LCOE decreases 36 percent as a consequence of a similar 10 percentage point WACC increase. The reason for these differences will be addressed below.

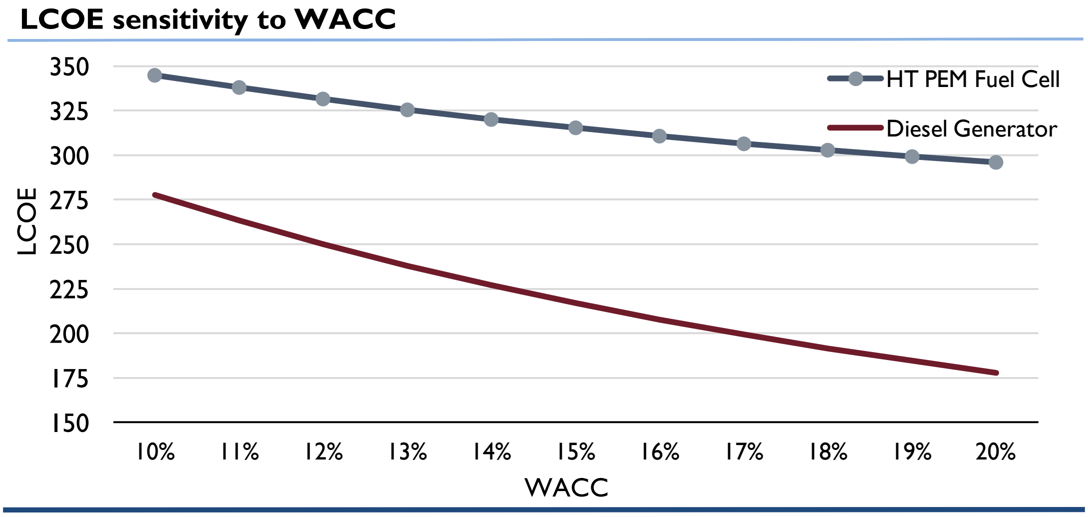

Figure 3.2: LCOE sensitivity to WACC. Source: own work.

The obvious price difference between the fuel cell and the diesel generator explains why diesel generators have been the primary backup power source, and wisely so. On the contrary, the immediate price tells nothing about the underlying cost drivers of each system. Albeit CAPEX is disregarded from the replacement decision, figure 3.6. presents the LCOE of each generation source as a percentage split between three categories: CAPEX, fixed and variable O&M, and fuel costs, to achieve a more detailed picture of the total LCOE. Evidently, CAPEX is by far the largest contributor accounting for 72 percent of the overall LCOE of the fuel cell. On the contrary, fuel costs and O&M costs amounts to just 16 and 12 percent respectively. For the diesel generator, if one were to buy and install the system today, the CAPEX would only represent 22 percent of the lifetime LCOE whereas fuel costs and O&M costs corresponds to 48 percent and 30 percent.

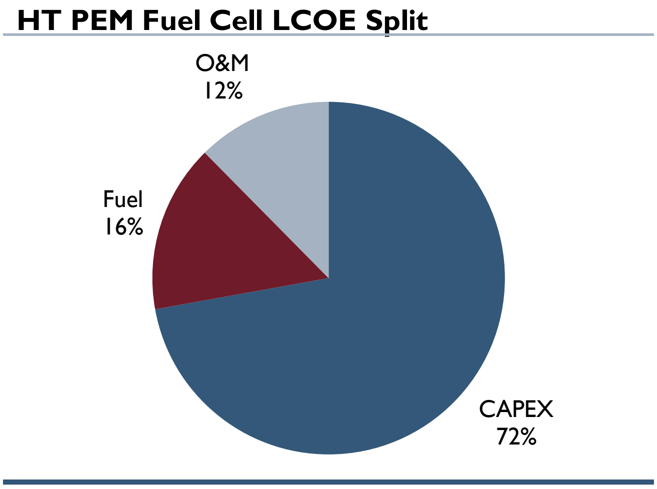

Figure 3.3(a): HT PEM Fuel Cell LCOE split. Source: Own work.

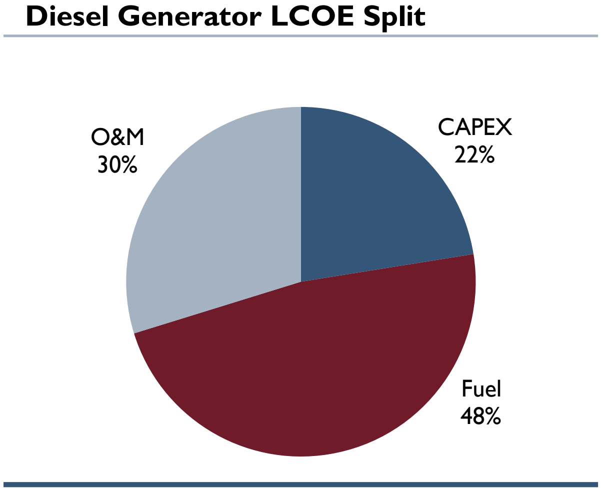

Figure 3.3(b): Diesel generator LCOE split. Source: Own work.

The actual dollar comparison is shown in figure 3.4, presenting the total LCOE as well as LCOE excluding CAPEX for both systems.

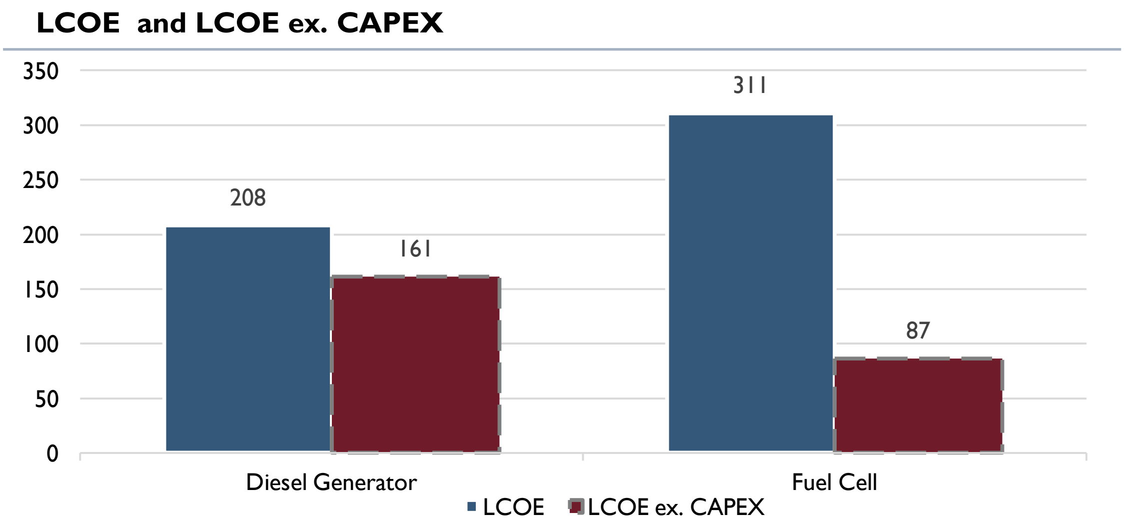

Figure 3.4: LCOE and LCOE ex. CAPEX. Source: Own work.

The main conclusion to be drawn is similar to above; the costs of replacing the diesel generator with the fuel cell system today by far outweighs those of keeping the diesel generator. However, the figure also visualizes the comparative LCOE of operating each system, and these costs are evidently much lower for fuel cells at 87 USD per MWh compared to 161 for the diesel generator. This finding underlines the fact that the high costs associated with the production of fuel cells are indeed the main challenge to the commercialization of the system and thus the reason for a lower impact of WACC as CAPEX expenditures are incurred immediately. The motivation for further understanding of the production of fuel cells and particularly learning effects, which could potentially lead to decrease of these should hereby be clear.

3.6. Extensions to the LCOE Calculations

Currently, the levelized costs are based on assumptions unique to our project, yet it is not difficult to extent the calculations with even more inputs. As Carson (2013) discusses, policy makers might impose environmental taxes for certain technologies or subsidize renewable energy projects in a given time period. Such modification will clearly change the costs (and revenue) of generating electricity. While it is straightforward to include such subsidies, this project intends to evaluate whether or not it makes no sense to replace diesel generator with fuel cells *without* any external factors causing one or the other to have a special economic cost advantage. Also, despite the Indian Ministry of New and Renewable Energy's (2016) strong focus on fuel cell technology in the Chemical Sources of Energy Programme, there is no evidence supporting economic incentives or preferential tax treatments to tower companies replacing diesel generators with fuel cells.

Shimon Awerbuch (1993, 1995, 1996) argues that the use of a firm's WACC in evaluating energy projects can lead to distorted results and hence sub-optimal decisions. In Awerbuch's words (1996: 127), the traditionally employed WACC is based on assumptions "… held in previous technological eras when technologies were expense intensive and technological progress was low. The attributes of renewables, however, do not lend themselves to traditional cash-flow based valuation." According to the reasoning, there is a significant difference in discounting cost streams and net cash flows of the firm. Using the firm's WACC actually tends to over-estimate the *real* discount rate for which reason a different approach is suggested. Because the WACC does not take into account whether costs are e.g. cyclical, counter-cyclical, or fixed, it is suggested that project costs should have separate discount rates. Transferring such intuition to this project's levelized costs could then be built on four different cost categories: (*i*) fuel costs, (*ii*) other risk-free costs, (*iii*) debt equivalent costs, and (*iv*) cyclical costs.

On the first category, (*i*) fuel costs might be zero for certain renewable energy technologies (e.g. solar photovoltaics or wind power), but they are an important expense for both the fuel cell and diesel generators. It could therefore be interesting to see how discounting by a more reasonable rate changes its weight in the final LCOE split. As Bolinger, Wiser, and Golove (2006) demonstrate, gas has a negative or close to zero value of beta, which makes the price of such counter-cyclical. In other words, positive economic growth is associated with downward pressure on gas prices, according to their estimates. Or as Awerbuch (1995: 60) puts it, "… higher fuel prices have historically caused the economy, and hence the returns on other assets, to decline." Whether that is true, and to which extent the same could be said about the beta of methanol, could be investigated in order to discount fuel costs by a market-rate different from the conventional WACC. Secondly, (*ii*) risk-free costs, such as e.g. depreciation tax shelters and other tax benefits, will accrue over time for which reason they can be discounted at the after-tax risk-free rate. Thirdly, (*iii*) debt equivalent costs cover fixed maintenance and fixed contractual obligations, which also are incurred in both setups. As the outlays of such is made given a sufficient amount of electricity generation (and hence revenue to cover that), debt-equivalent costs should be discounted at a rate close to the firm's cost of debt. Finally, (*iv*) cyclical costs include variable O&M, which, ceteris paribus, changes with output and levels of economic activity. According to Awerbuch, a more correct estimate is thus based upon a beta estimate against the market, or one could approximate by using a post-tax WACC.

Altogether, such extensions will levelize the costs for both backup systems differently. One scholar from Copenhagen Business School employs such a method in his LCOE on gas turbines and solar photovoltaics, in which project Nicolet (2010) yields significantly different results. In the market-modified LCOE framework, present value of fuel costs contributes most notably to an overall high increase in cost of energy generation. Considering the effect of Nicolet's model, it could be interesting to investigate to which extent discounting fuel costs for gas and methanol differently would change their overall contribution to each technology's levelized costs. All else equal, fuel costs are currently a larger part of the costs for the diesel generator than methanol is for fuel cell. So, following the analogy from Nicolet's findings, extending the LCOE calculations with the inputs of Awerbuch as well as Bollinger and colleagues could close the cost gap between the technologies remarkably. Therefore, if LCOE modeling in the telco market for Indian backup power is the core aim of other researchers, these findings motivate a closer look into these suggestions, yet for the purpose of this project, the results are found robust and plausible to use and approach the replacement decision in a learning effect and real options environment in the following chapters.

3.7. Shortcomings of Levelized Costs: A Motivation for Options Approaches?

Throughout the modeling of LCOEs on fuel cells and diesel generators it has become clear that levelized costs are notoriously sensitive to inputs. In other words, this paper's assumptions depend heavily on the authors' own assessments and DPS' inputs, and replicating the calculations in one year's time from now would most likely change the cost of energy notably. Capital costs can change rapidly, fuel prices are constantly evolving, potential subsidies and tax credits might distort the picture, and other factors are likely different from today. In addition, all else equal, the employed discount rate is crucial to the calculation as well. Applying similar assumptions outside the setting of this project would not yield a reliable result. More weaknesses of the framework could continue to be listed, yet the overall message is explicit. As Carson (2013: 139) writes: "… the costs of complexity can become quite high", or one could state instead that replacing diesel generators with fuel cells at Indian telco tower sites involves a (high) degree of uncertainty.

3.7.1. Applying Real Options to Electricity Generation Projects

Without presenting the theoretical framework of real options thoroughly, the cost gap between the two technologies calls for different investment criteria than an LCOE methodology to justify replacement. One interesting aspect of fuel cells is assessing whether the technology is fully commercialized, or if there are cost reductions to be expected. If there is value in delaying the replacement decision to a point in time at which the benefits of deploying fuel cells outweigh the costs of operating diesel generators, then a real options framework could help to evaluate when such decision should or could be made. On such reasoning Carson (2013: 140) comments that "the options revolution in finance has spread to the valuation of real assets, including those involved in energy production." Some of the uncertainties associated with fuel cells could therefore be included (and contained) by a real option.

In Dixit and Pindyck's (1994) book on "Investment under Uncertainty" particularly four conditions are suggested to be honored before real options techniques are deemed appropriate. Firstly, (*i*) uncertainty about investment outcome, which can be partially met or limited by (*ii*) managerial flexibility and the possibility to abandon or delay a project. This extends to the third criteria and (*iii*) the investment being totally or partially irreversible, with (*iv*) asymmetric payoffs. To the conditions, Bräutigam et al. (2003) emphasize the importance of criteria (*i*) and (*ii*) to signal the presence of options most notably. In the fuel cell case there are many uncertainties associated and indeed an opportunity for the decision maker to be flexible about timing and scale, as opposed to DCF and LCOE valuation. In such case, "… real options theory offers a useful approach for the appreciation of uncertainty over time" (Kumbaroglu et al. 2008: 1883).

With the real options framework conceptualizing a "value of waiting," it becomes particularly interesting to establish which learning (curve) fuel cells exhibit, among other technologies. In the next two chapters, the thesis will therefore investigate the extent to which learning effects occur for fuel cells and how these can be implemented into real options modeling. Then, one will be able to understand the diffusion possibilities of fuel cells in the Indian telco market more clearly.

4. LEARNING EFFECTS

In the previous chapter, levelized costs are estimated to compare the two technologies if the decision to choose backup power had to be taken today. Nonetheless, the LCOE model does not capture any assessment of past cost reductions, nor considerations about how such might influence the future. To address historical costs and development in installed cumulative capacity of fuel cells, this chapter introduces the concepts of learning effects and progress rates. Firstly, the theoretical background of learning is established after which literature on comparable technologies is reviewed. In this way, estimates on other progress rates can be compared to the one obtained from PEMFC production. Secondly, empirical data is gathered and used to estimate fuel cell learning. In this process, corrections for inflation, economies-of-scale, and platinum prices are undertaken to finally model the learning curve. Consequently, a progress rate, a learning rate, and the uncertainty of such are yielded. Finally, before embarking on the real options framework, limitations of the learning curve are briefly evaluated.

4.1. Definition of Learning Effects

Within the field of human psychological, the acquisition of knowledge is in its simplest form labelled as *learning*, or put differently, learning is the product of experience. It is a process of learning-by-doing and the repeated efforts to solve a particular problem; learning only takes place during activity (Arrow 1962). As a related concept, the *learning curve* originates from the observation that productivity increases as more units of a given product are produced. The concept dates back to year 1936 in which Wright in his paper "Factors Affecting the Cost of Airplanes" report that unit labor costs in air-frame manufacturing decrease considerably with accumulated experience measured as cumulative production.

Since then, the effects of learning, learning-by-doing, the learning curve, the process of learning, and the experience curve has been investigated widely. In practice this broad range of labels covers the same intuition that productivity increases with experience gained during repetitive and cumulative production. Nevertheless, there are some distinctions in the actual definitions among these labels. Baptized by Wright (1936), the learning curve originally covered solely the changes in productivity of direct labor due to experience gained in cumulative production within a manufacturing plant. Later on, the concept of learning curve was broadened as an *experience curve*, first labelled in 1966 by the founder of Boston Consulting Group, Bruce D. Henderson, in which not only labor but all manufacturing costs were incorporated (BCG 1974). The experience curve covered the view that accumulated experience at early technological stages can act as a strategic tool to maximize profitability of firms and market share. Some distinguish the learning curve and the experience curve through the dependent variable(s); labor cost per unit (learning curve) and direct cost per unit including production, labor, distribution, etc. (experience curve) (Policonomics 2016).

Recently, Bahk & Gort (1993) decomposed learning by doing into "organizational learning", "capital learning", and "manual task learning" in efforts to reach a more nuanced picture of the drivers of decrease in manufacturing costs. Regardless of the scope of definition of the effects of learning, the notion that unit costs decrease by a constant factor as a result of accumulated production remains the same. In this project, we adopt the view that learning and thus decreases in cost can originate from increases in labor productivity, production methods, capital inputs, distribution and so on.

4.1.1. Mathematical Definition

To be more concrete, the learning curve is quantified through an operationalization of experience (learning) as the explanatory variable using cumulative production as a proxy. While it may be argued that learning takes place over time, it is important here to note that *time* is not a direct cause of learning; it is the repetitive activity and accumulated experience that translates into increased productivity. Analogously, "unlike a fine wine, a technology design that is left on the shelf does not become better the longer it sits unused" (McDonald & Schrattenholzer 2001: 255). The effects of learning and technological improvement act as the dependent variable measured as changes in production costs due to cumulative production. The model is described by:

$$C_t = C_0 \left(\frac{q_t}{q_0}\right)^{-b} \qquad \text{EQ 4.1}$$

in which C is unit cost at time t, q is cumulative production and b is the learning coefficient which can be determined through regression tools. The learning coefficient implies the following two relationships:

$$pr = 2^{-b} \qquad \text{EQ 4.2}$$

$$lr = (1 - pr) \qquad \text{EQ 4.3}$$

where the progress rate, pr, is the unit cost in relative terms expressed as a percentage left after cumulative production has doubled, so that the learning rate, lr, (also in percentage) is the relative cost reduction after a doubling in cumulative production (Nemet 2006). It is important for the reader to grasp that production costs decrease at a faster pace with *lower* progress rates while the opposite is true for learning rates.

The learning curve implicitly hypothesizes that production costs decrease at a constant rate every time cumulative production doubles. The relationship between learning and cost reductions is a power function, figure 4.1(a), and therefore a linear, downward-sloping curve on a double-logarithmic scale, figure 4.1(b):

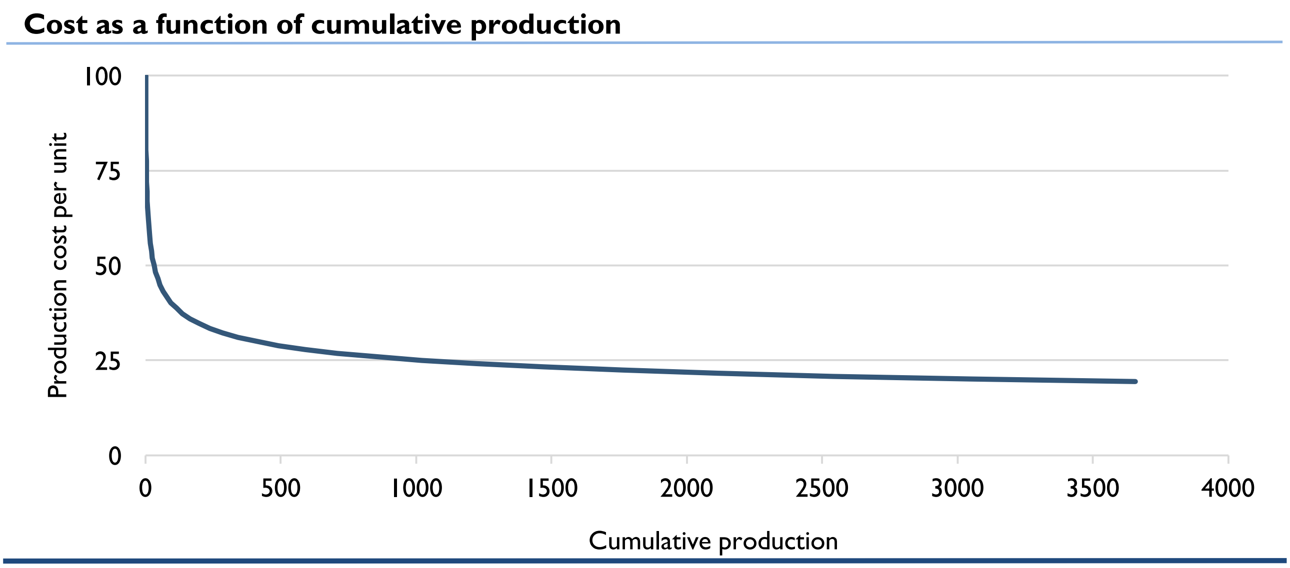

Figure 4.1(a): Cost as a function of cumulative production. Source: Own work.

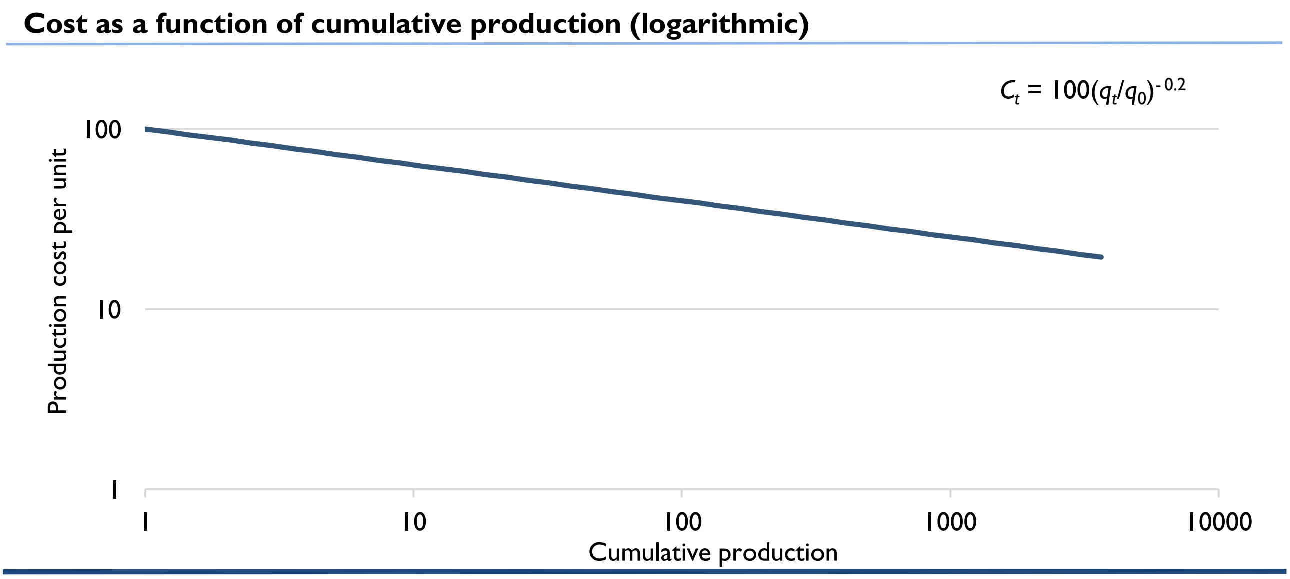

Figure 4.1(b): Cost as a function of cumulative production (logarithmic). Source: Own work.

Hypothetically exemplified in figure 4.1., initial production costs of the first unit may amount to 100 with a learning coefficient *b* of -0.2, which corresponds to the (negative) downward slope of the power function. Using equation 4.2 the progress rate equals 87.1% meaning that production costs decrease by just below 13% (1-0.871) each time cumulative output has doubled.

4.1.2. Learning Effects Measure: Production Costs

While the following may seem obvious to some, it must be stated explicitly that, for the present learning effects analysis, unit *production cost* will serve as the measure of learning and dependent variable.

Due to potential challenges with regards to reliable data collection as such data are typically kept in discretion by firms, one may be tempted towards the use of unit price. Prices however, can be a very imperfect and misleading measure of costs due to a number of reasons. One example is the case of Brazilian ethanol price developments between 1979-1995 analyzed by Goldemberg and colleagues (2004). Despite overall price reductions during the period (progress rate of 70% between 1980-1992 and 90% in the years afterwards), a closer look at the data suggest that price movements, both up- and downwards can largely be attributed to changes in international oil prices, as opposed to effects of learning (McDonald & Schrattenholzer 2001). While cumulative production of ethanol did increase significantly during the investigated time frame, prices may very well have been a result of factors outside the variables in the model.

Another example of outside factors interrupting the learning rate estimations is the worldwide study on gas turbine combined cycle (GTCC) power plants between 1981-1991 by Ulrika Claeson in 1999. Although the authors of this thesis have not had access to her study, McDonald & Schrattenholzer (2001) report that instead of investment costs, she investigates the concrete investment price related to the construction of such plants and actually concludes on a -11% learning rate for the period. As noted, one possible explanation to the increase in investment prices of GTCC power plants is not technological deterioration; it is the oligopolistic pricing behavior imbedded in the industry during the period.

In general, market-oriented factors can impact pricing to a much larger extend than technological improvements and thereby production costs, which in turn can make the effects of learning appear much different than they actually are. Only in the idealized case, where competitive and stable markets and constant margin are present, it can be expected that the shape of the price curve and cost curve move in tandem (Colpier & Cornland 2012). To depict the more common case, consider figure 4.2., which portrays a general relationship between production costs and pricing, with the same independent variable on the horizontal as for the learning curve i.e. cumulative production.

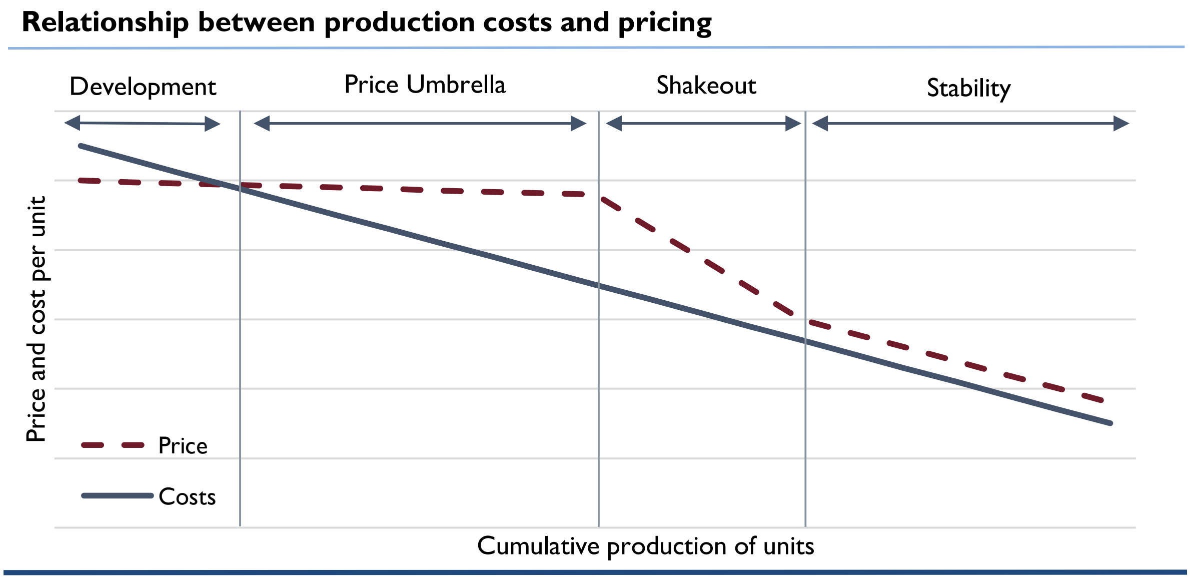

Figure 4.2: Relationship between production costs and pricing. Sources: Colpier & Cornland (2012) and own work.

Note how price in some instances are set below production costs for low levels of production (development phase), which can be a tool for manufacturers to establish a market for a new product in the anticipation of lower production costs later on. Subsequently, prices can remain at considerably higher levels than costs due to benefits of low competition as a consequence of first-mover advantages and the effects of learning accumulated in the production. In mature stages (stability phase), as competition become fierce with more players in the market, prices tend to move towards production costs and finally reach *perfect competition* at which price equal marginal cost according to classic microeconomic theory.

In short, the examples above underline the obvious but important point that the dependent variable in the estimates of learning effects must be production costs rather than price since a wide array of forces can impact pricing and disturb the true effects of learning.

4.1.3. Learning Effects and Technological Development Stages

As shown above, the stage of development for a particular technology can impact its price and distract the estimations of true effects of learning if these are based on the relationship between cumulative production and price. On the other hand, technological development stages can contain valuable information for the learning effects estimations, even when estimations are based correctly on production cost data.

Stylized stages of technological development

Stage	Mechanisms	Cost	Learning rate
Invention	Seeking and stumbling upon new ideas; breakthroughs; basic research	High, but difficult to attribute to a particular idea or product	Unable to express in conventional learning curve
Innovation	Applied research, development and demonstration (RD&D) projects	High, increasingly focused on particular promising ideas and products	Unable to express in conventional learning curve; high (perhaps >50%) in learning curves modified to include RD&D
Niche market commercialization	Identification of special niche applications; investments in field projects; "learning by doing"; close relationships between suppliers and users	High, but declining with standardization of production	20-40%
Pervasive diffusion	Standardization and mass production; economies of scale; building of network effects	Rapidly declining	10-30%
Saturation	Exhaustion of improvement potentials and scale economies; arrival of more efficient competitors into market; redefinition of performance requirements	Low, sometimes declining	Close to 0%
Senescence	Domination by superior competitors; inability to compete because of exhausted improvement potentials	Low, sometimes declining	Close to 0%

Table 4.1: Stylized stages of technological development. Source: Grübler et al. (1999) and own work

Attempts to distinguish different stages of technological development have, among others, been carried out by Grübler et al. (1999), who outline six distinct phases; invention, innovation, niche market commercialization, pervasive diffusion, saturation, and senescence (table 4.1.). In connection to learning effects, the interesting argument here is that learning rates are substantially higher for technologies at early development stages (20-40% for niche market technologies and potentially above 50% at earlier stages). Naturally, this makes sense as technologies at these stages are not well understood quite yet and plentiful room for improvement exists. On the flipside, infant technologies with high potential learning rates are associated with high levels of uncertainty and as Grübler et al. postulate, both potential for improvement and whether the technology will reach widespread commercialization are associated with high levels of uncertainty. Nonetheless, and of particular interest for the case of fuel cells, they further note that "Learning rates in manufacturing, including production of energy-related technologies, mainly vary from 10 to 30%. In some cases, typically at the early stages of commercialization of a technology, learning rates approaching 50% have been observed" (Grübler et al. 1999: 253). While the task to determine the exact development stage of fuel cells at present may be a difficult and arbitrary task, it is fairly safe to assume that the technology situates somewhere between "innovation" and "pervasive diffusion".

4.2. Learnings Effects of Other Technologies

At this stage, we have briefly touched upon concrete examples of estimated learning curves for distinct technologies. It has been shown how factors outside the cost of production have influenced the learning effect estimates of ethanol prices in Brazil, in which international oil price volatility were the main cause (Goldemberg 1996), and of GTCC power plants where an oligopolistic market structure seems to have been the main driver of investment prices as opposed to the true costs of such investment. Furthermore, we have recognized how stages of technological development may influence the learning rate and how early-phase technologies may be subject to steeper learning curves albeit higher degrees of uncertainty regarding whether such costs reductions may be realized and achievement of wide-spread commercialization.

We now turn to a deeper analysis of learning curves previously estimated for other technologies to reach conclusions on whether such estimates can provide helpful insights for the subsequent learning effects estimates for the HT PEM fuel cell technology.

In the literature of learning effects, the Dutton & Thomas (1984) article is one of the most widely cited studies, in which they collect data on more than 100 studies of progress ratios across manufacturing industries such as electronics, machine tools, automobiles and system components (see figure 4.3.). Each of the studies are estimates of the progress rate based on unit (or average) cost of production as a function of cumulative production and thus fulfill the condition proposed earlier; learning effects must be measured based on production costs rather than unit prices.

Distribution of progress ratios

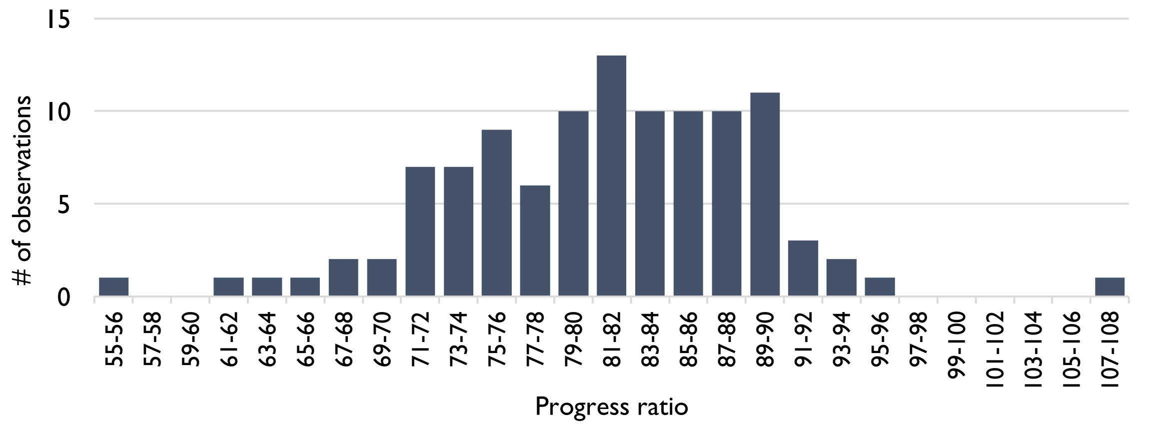

Figure 4.3: Distribution of progress ratios. Sources: Dutton & Thomas (1984) and own work.

Evidently there are large variations in the estimated progress rates. To recap, the progress rate is the percentage cost of production left each time cumulative production doubles. Albeit widely dispersed, the distribution of progress rates is somewhat bell-shaped with the majority of observations in the range 71-90%.

The sources of learning can be manifold meaning that it can be a difficult task to determine exactly how and why costs of production decrease. In principle, repetitive production could take place without the occurrence of learning but this contrasts the general perception that human effectivity has increased since the early days of our existence. Some plausible causes of learning are presented in the adjacent table.

Sources of learning effects

Autonomous Learning	Induced Learning
Exogenous origins	
General growth in scientific and technical knowledge that flows freely into the firm. Continuously improving productivity gathered when a firm periodically replaces its equipment.	Learning of capital goods' suppliers induced by the users' experience with the equipment. Investment in improved capital good in order to hasten the rate of progress. Copying and adapting the technological innovation of a successful competitor
Endogenous origins	
Direct-labor learning due to the "practice-makes-perfect" principle or wage-incentive-plan. Routine production planning.	Increased tooling. Manufacturing process changes. Model or product design changes to effect efficiencies.

Table 4.2: Sources of learning effects. Sources: Dutton & Thomas (1984) and own work.

The sources differ in whether they originate from within the firm (exogenous) or from outside constituencies (endogenous) and in whether they arise autonomously or due to inducement by others. While investigating the exact causes of learning is an attractive endeavor (see Dutton & Thomas and their reviewed literature for a detailed presentation of each of the sources of leaning effects), it is outside the scope of this project; learning will be treated as an overall concept independent from the concrete origin and cause.

4.2.1. Learning Effects of Energy Technologies

While Dutton & Thomas (provide a highly acknowledged proof that learning rates do exist among a wide array of manufacturing industries, one may question its explanatory power in relation to estimating learning effects for electricity-generating technologies. To accommodate such concern, it may provide superior insights to turn to studies on learning rates of technologies specifically within the energy industry. McDonald & Schrattenholzer (2001) carry out an analysis of learning rates of 26 energy technologies and reach results highly comparable to those of Dutton & Thomas' (1984) non-industry specific study. The median learning rate, i.e. 1-*pr*, in the former study lies in the interval 16-17% while the median value for the latter lies within 19-20%. As they note, the results suggest that learning rates and their variations are a general phenomenon not restricted to particular industries and sectors. On the other hand, they also conclude that some of the estimates within the study is flawed by outside factors such as price swings (see Goldemberg 1996) and marketing strategies which is to be considered both random and inconsequential for long-term energy modelers.

In a more recent study, the economics of the combined cycle gas turbine (or GTCC) and its experience curve has been analyzed (Colpier & Cornland 2002). The results (a progress rate of >100% between 1981-1991 and around 75% until 1997) are in itself not of particular interest; the estimates are based on investment prices of the GTCC plants, which, as touched upon earlier, possibly leading to flawed results mainly reflecting market developments. The interesting aspect of the study, in relation to the learning effects estimations for fuel cells, is the concluding remarks. The authors conclude that the GTCC technology under investigation is subject to limited gains in experience since variations in fuel prices and improvements in thermal efficiency can be expected to have higher influence on the costs of generating electricity than variations in the progress ratio. The generalization of this conclusion implies that energy technologies, for which capital costs are not one of the major cost drivers, cannot expect to have a large potential for future cost decreases in the foreseeable future. On the other hand, technologies for which production costs *are* the biggest component of the overall price of delivering electricity, one can assume that the effects of learning of cumulative production may be significant in the future. To recall the findings of the LCOE calculations presented in chapter 3, the overall levelized cost of energy for the HT PEM fuel cell system is mainly driven by CAPEX and amounted to a total of 72% of the overall LCOE of 311 USD per delivered MWh.

4.2.2. Learning Effects of Comparable Technologies

Takeaways from the analyses of earlier learning effects studies show that the most valuable knowledge, with regards to estimating learning effects of the fuel cell technology, may lie within technologies of similar purpose and similar cost-structure. It has just been shown that technologies for which CAPEX constitutes the largest cost component has the biggest potential for future cost reductions. Albeit the learning curve empirically is phenomenon recognized for a wide array of technologies across many industries, it is assumed that electricity generation technologies must be considered as the greatest contributor to the understanding of the learning effects of fuel cells as well.

Photovoltaic (PV) solar modules and wind power, although representing very distinct technologies, share some of the same attributes as fuel cells; clean energy source and high initial capital costs. Moreover, both technologies have gone through a much longer-lived cost reduction process and as a consequence they are able to produce electricity at substantially lower costs compared to what fuel cells are able to as of today (Lazard 2015).

Interestingly, some evidence exists that the potential for future fuel cells are indeed competitive to both wind and solar energy (Adamson 2015). Consider figure 4.3. below, which shows the USD per kW for a range of technologies at different stages of cumulative MW shipments. In 2014, the cumulative shipments of PEM fuel cells surpassed 100 MW, at which point the costs of the technology compared very well with the costs of wind and solar at the same cumulative shipment level. Note that the figure says nothing about the timing of the 100 MW cumulative shipments for solar and wind; the figure shows that the PEM fuel cell system was cost competitive at a *similar* shipment level as for the two technologies of comparison.

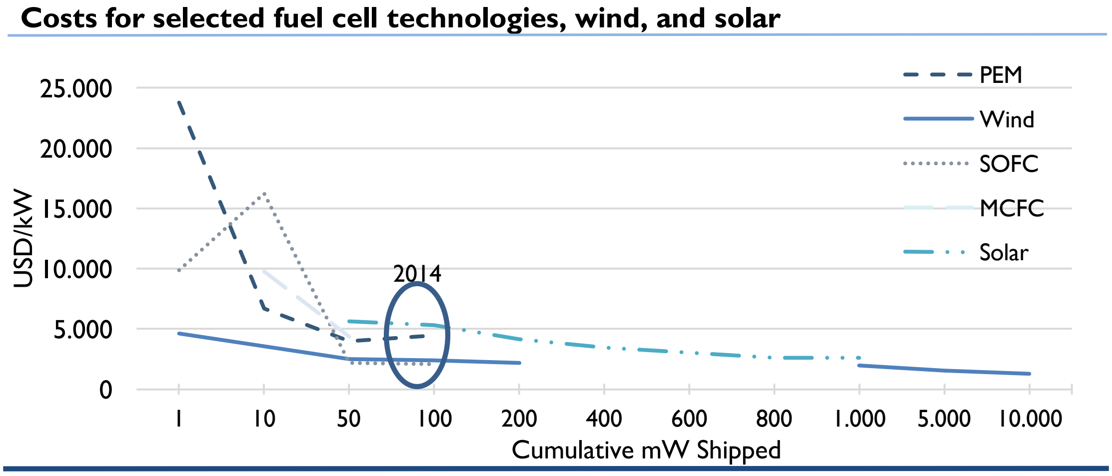

Figure 4.4: Costs for selected fuel cell technologies, wind, and solar. Sources: Adamson (2005) and own work.

To understand the effects of learning on PV solar modules, Nemet (2006) analyses two comprehensive world surveys of PV prices in which learning rates of 26% and 17% are constructed respectively. The causes of the discrepancy in the estimates are not covered here, their studies are mainly presented to give the reader an understanding of the impact that such a difference in the estimates, which may seem small, may have in the longer term. Nemet (2006) shows that the two learning rates result in a 28-year difference in reaching a crossover point defined as a 0.30 USD per W threshold at which the costs will be competitive with conventional alternatives. In the former, the threshold will be reached in 2039 while the same is true as late as in 2067. Whether 26% or 17% learning rate (or somewhere in between) is in fact the true rate is not to be concluded upon here, we merely note the vast impact on future cost conclusions that the learning rate estimates may have.

In a more recent paper, the learning rate of PV solar modules and potential future levelized costs of electricity are bridged by La Tour et al. (2013). They model future prices of modules based on silicon prices, which constitutes one of the major cost component, and on a learning rate of 20.1% during the period between 1990-2011. In the average scenario case, they find that module prices will fall from 1.52 USD/kWp in 2011 to 0.5 USD/kWp in 2020 of which increases in cumulative capacity (and thus learning effects) account for 75% while projected decreases in silicon prices account for 25%. With these projections in hand, they move on to estimate the LCOE of PV solar modules in 2020. To highlight the usefulness of their study in relation to the present PEM fuel cell project, consider the cost structure of the PV solar system as noted by the authors (2013: 346); "Module price accounts for 40% of the total price of an average system in 2011 […] 95% of the cost of a PV system over its lifetime is capital expenditure". In chapter 3 we showed that for the Indian PEM fuel cell case, CAPEX accounts for 72% of the lifetime costs.

One of the key limitations of the LCOE model is that our findings are applicable only in a very specific setting i.e. the Indian telecommunications tower industry. La Tour et al. (2013: 347) also states that "the differences in the results illustrate the importance of the geographic location". Their projected LCOE calculations for the year 2020 ranges from 75-150 USD/MWh depending on different ASI levels (2000 and 1000 respectively, where ASI is defined as Annual Solar Irradiation which is a measure of sunlight availability.

To round off this section on learning effects of comparable technologies, we briefly report the results from the conceptual review and meta-analysis of studies of learning rates for wind power undertaken by Lindman & Söderholm (2012). Their econometric analysis builds on 113 distinct estimates of learning rates presented in a total of 35 studies and thus implies a wide and general perspective on the effects of learning for the wind power technology. Specifically, the mean learning rate across the observations is 10.1% with a standard deviation as large as 6.83 and a minimum and maximum learning rate of -3 and 33% respectively. The authors then move on to the task of identifying the underlying drivers of learning rate estimates with a sub-division of independent variables as opposed to single-factor models in which all learning effects are captured in increases in cumulative production. From the range of independent variables, which among other include *scale effect*, *time trend*, and *public R&D*, the variable *geographical scope* has the greatest statistical significance and is the one of highest interest in relation to our project. The geographical scope (GS) is defined as the average fraction of cumulative capacity in a given country of total global capacity. They show that learning rate estimates, for which GS equals one i.e. where global cumulative capacity is considered, are statistically significantly higher than estimates based on country-specific cumulative capacity. As argued, one of the reasons for the difference is that individual countries have much lower cumulative capacities, which implies that a doubling of capacity can take place at a faster rate, and thus result in lower estimates due to the way learning rates are calculated.

The key takeaway for the study is, yet again, to show how different inputs to the learning rate estimates can impact the results to a great extent. Whether global or country-specific inputs on cumulative capacity are the best reflection of reality, derives from the question of whether knowledge-spillovers within the technology can be assumed to take place on a local or global basis. We will return to this question in more detail in coming sections.

4.2.3. Learning Rates of the Fuel Cell Technology

While extensive research on the effects of learning for the fuel cell technology is yet to be done, some studies do exist and show that well documented learning rates found in many other industries also apply to fuel cells. Rivera-Tinoco et al. (2012) studied the learning curve for SOFCs which share many of the same characteristics with the PEM fuel cells (see chapter 2). Comparable to the present PEM analysis for which BOP stands for 78% of production costs (see chapter 3), the authors estimated BOP to account for 64% of the manufacturing costs for a 5 kW SOFC system. They found learning rates of 19% and 17% for 1 kW and 250 kW systems respectively. The interesting question is whether experience within one of the system sizes creates spillovers onto the other and vice versa.

For the PEM fuel cell system specifically, and despite the fact that the study is carried out more than a decade ago, Tsuchiya & Kobayashi (2004) provides a noteworthy example of an attempt to estimate the learning effects for the particular technology. One should note that their study was aimed at PEMFCs for automobiles with a power output of 50 kW.

The authors decompose the learning rate of manufacturing costs into a subset of component-specific learning rates; one for (1) power density, one for (2) membrane, electrodes, and bipolar plates combined, and one for (3) platinum loadings (platinum prices assumed constant). They further establish three scenarios for future costs decreases corresponding to rapid, moderate, and slow where the moderate case implies learning rates of 4%, 18%, and 8% for (1), (2), and (3) respectively (the authors report progress rates, which for clarity reasons has been converted to learning rates here). From an initial starting point of a USD/kW cost of 1,833 in the year 2000, they estimate a future cost of 38 USD/kW in 2020.

These estimates may seem rather optimistic to the reader. To shed light on estimates, one may consider the underlying assumption, which suggests that a deployed base of 40 fuel cell automobiles in Japan in the year 2000 would increase to 5 million in 2020. As a reference, two of the most prominent fuel cell automobile producers, Honda and Toyota expect to sell 200 and 2,000 total fuel cell-powered vehicles in 2016 (Edelstein 2015). Despite highly ambitious and perhaps a tint unrealistic, the study exemplifies the potential development for the technology if deployment on a wide-scale basis is in the realm of takeoff.

4.2.4. Summary of Studies on Learning Effects

In the previous paragraphs, studies of learning effects have been examined for a range of industries and technologies. Together, these studies assist the understanding of how the effects of learning have been estimated, but more importantly, they help to build a framework of how the learning attached to repetitive production can impact the forecasts of future costs of a respective technology. The studies are summarized in table 4.3.

Overview of learning effect studies

Authors	Scope	Period	Focus area	Learning rate
Dutton & Thomas (1984)	Mfg.	1920-1980	Mfg. (108 obs.)	16-17% median
McDonald & Schrattenholzer (2001)	Energy	1909-1997	Energy tech (26 obs.)	19-20% median
Goldemberg et al. (2004)	Energy	1979-1995	Ethanol prices in Brazil	30% & 10%
Claeson (1999)*	Energy	1981-1991	GTCC	-11%
Colpier & Cornland (2012)	Energy	1981-1997	CCGT	<0% & ≈25%
Nemet (2006)	RET	1975-2001	PV Solar Panels	17% & 26%
La Tour et al. (2013)	RET	1990-2011	PV Solar Panels	20.1%
Lindman & Söderholm (2012)	RET	1971-2008	Wind power (113 obs.)	10.1% mean
Rivera-Tinoco et al. (2012)	Fuel Cells	Undisclosed	SOFC	17% & 19%
Tsuchiya & Kobayashi (2004)	Fuel Cells	2000-2020(F)	PEMFC	4%, 18%, & 9%

Table 4.3: Overview of learning effect studies. Source: Own work
** Consult McDonald & Schrattenholzer (2001) for a discussion and reference of this paper*

4.3. Estimating Learning Effects in PEM Fuel Cell Manufacturing

At this point we have discussed a substantial number of studies on learning effects from comparable technologies. Based on preliminary motives, there are reasons to investigate the potential of technology learning for fuel cells, it seems. Before embarking on to the actual estimation of learning effects for fuel cells, it is important to distinguish between two types of analyses. First, a study might look at specified manufacturers' learning curves, or, second, one might investigate learning effects a level above, that is, on a global scale. In their study on both, Schoots and colleagues (2010) report the following results.

Summary of fuel cell learning curve analysis

Fuel Cell Type	Development Start	Period Investigated	Progress Rate	R^2
Manufacturer				
AFC	1952	1964 – 1970	82 ± 9%	0.84
PAFC	1965	1993 – 2000	75 ± 3%	0.75
PEMFC	1959	2002 – 2005	70 ± 9%	0.83
Global				
PEMFC	1959	1995 – 2006	79 ± 4%	0.73

Table 4.4: Summary of fuel cell learning curve analysis. Sources: Schoots et al. (2010) and own work.

In this project, we will use these results to investigate the global learning for PEMFCs until 2014 rather than 2006. Indeed, as it has been shown, it is no trivial task to determine a global learning curve. This project will therefore rely primarily on the framework proposed by Schoots and colleagues as well as on the input of DPS. Whereas the latter manufactures fuel cell inputs with different applicability, one should be careful in comparing data for each. Using cost inputs from both stationary, transportation, and portable use of PEMFCs could cause inappropriate scattering of data points, possibly biasing or leading to an unreliable learning rate. To limit the magnitude of such challenges in the analysis, the estimation of learning effects will rely on manufacturing cost of PEMFCs used to power road vehicles. Now, as these will share widely different system characteristics than the small fuel cell deployed at an Indian tower site, one is surely expected to question the validity or transferability of the results. In the rather technological description of the fuel cell and particularly the PEM, it has been acknowledged that PEMFC systems are used for essentially all purposes. Based upon the 2006 market for example, PEMFCs are almost as present in the small stationary segments as within transportation.

PEMFC use and corresponding characteristic capacity

Application	PEMFC Share in 2006 (%)	Characteristic capacity (kW)
Large stationary	18	180 – 540
Small stationary	96	2 – 4
Buses	100	200 – 250
Cars	100	50 – 80
Portable	46	0.05 – 0.10

Table 4.5: PEMFC use and corresponding characteristic capacity. Source: Schoots et al. (2010)

Based upon general consensus in the literature and discussions with DPS, we will therefore assume transferability in learning effects from PEMFC in transportation to (small) stationary application. In this way, the estimation will be based upon (*i*) the cumulative capacity of PEMFCs overall and (*ii*) the development in manufacturing cost of PEMFCs to power road vehicles. Firstly, while many studies and reports provide data on number of installed units, it would not be appropriate to simply count the number of installations as the variances in power output would distort the aggregate capacity and ultimately yield a sample too heterogeneous. This issue is therefore addressed by using overall cumulative capacity. Secondly, while it has been established that PEMFCs dominate applicability within transportation, data availability is also significantly more transparent within this sector. Altogether, this approach yields meaningful results, yet it is also associated with (at least) two apparent disadvantages. First, as we have seen in the LCOE modeling, different cost components yield different cost-scaling behavior. For example, whereas we have assumed linearity in e.g. the balance of plates, the MEA or GDE are both contingent on sensitive areas of direct material, with which pre-specifications exist for both 1, 10, and 100 kW systems. Such differences or scaling effects are addressed and minimized by analyzing only one application. Second, albeit a narrow range of fuel cells is analyzed, differences in cell capacity might even then exist. The capacity difference depends on the specific design, and we expect, if existing, the effect to be insignificant.

With the incentives established for investigating the global learning of PEMFCs, the analysis continues by presenting the growth in cumulative capacity and reporting historic cost developments. In the latter, a three-step modification model is also presented to correct costs for (*i*) inflation, (*ii*) scale economies, and (*iii*) volatility in platinum prices, after which the global learning for 1995 through 2014 can be estimated adequately.

4.3.1. Cumulative PEMFC Capacity

In order to report the cumulative PEMFC capacity overall, a number of sources have been consulted. Firstly, for the period from 1995 through 2008, categorized capacity according to the table 4.5 above is available from Adamson (2004, 2006, 2007, 2009), Adamson and Crawley (2006), Butler (2009), Callaghan Jerram (2008, 2009), and Crawley (2006). As mentioned in the methodology section of the thesis, these sources are listed appropriately in the references index, yet they are not easily found in the public sphere today. Dr. Koen Schoots, whose work this paper draws great inspiration from, has provided the papers through personal communication. As they each contribute to the specification of cumulative number of fuel cell units installed, development in capacity can then be calculated. From the table provided by Schoots et al. (2010), a market share based on 2006 levels is utilized to calculate the PEMFC capacity for each category. Subsequently, it should then be acknowledged that the learning effects (or lack of) assume roughly the same share in the application of PEMFCs. Next, Adamson reports overall installed capacity for the 2009-2014 period. Adamson (2015) does project a significant increase in 2015, yet we choose to exclude this forecast as it is not well explained how such increase is justified. From these numbers one is then able to aggregate the 1995-2008 and 2009-2014 periods to report overall cumulative PEMFC capacity from 1995 through 2014. The results are reported below.

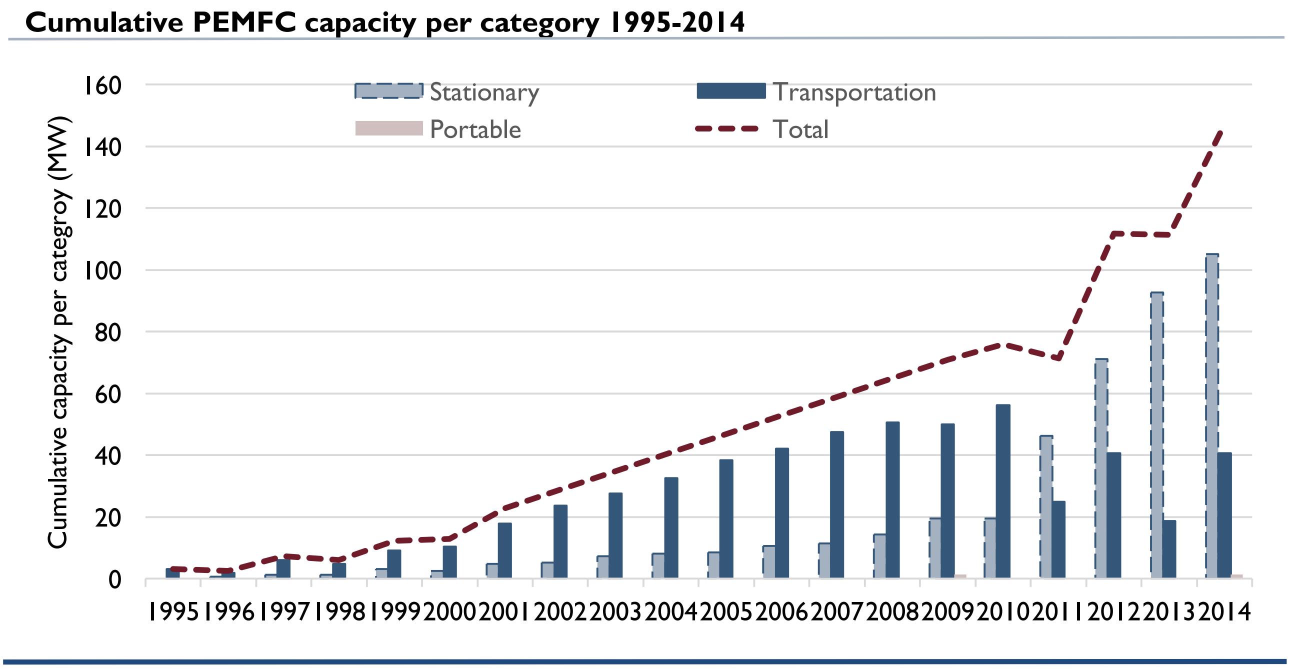

Figure 4.5: Cumulative PEMFC capacity per category.
Sources: Adamson (2004, 2006, 2007, 2009, 2015), Adamson and Crawley (2006), Butler (2009), Callaghan Jerram (2008), Crawley

4.3.2. Global PEMFC Cost Development

In order to investigate global cost developments from 1995 through 2014, it is necessary to collect data from a number of sources. One criterion is that costs are reported in nominal terms and, as discussed, they need to apply for our application within transportation. Whereas the United States Department of Energy (2015) provide easily accessible data since 2006, costs are not as transparent for the remaining years. In 1998, Rogner reports 4,500 USD/kW to be a reasonable cost during year 1995. As the production scale is not mentioned, we assume a conservative number to be around 40 units similar to Tsuchiya & Kobayashi's observations 2004, also applicable for 50 kW systems. Their analysis decreases the cost to 1,833 USD/kW in year 2000. Next, Schoots et al. (2010) report costs from TIAX to be around 1,500 EUR/kW in 2002, yet this point is excluded from our analysis. From the source TIAX (2002), it is not clear whether published data is for SOFC or PEMFC applicability, and it is not a trivial task to extrapolate the work of Schoots and colleagues with satisfactory accuracy. Similarly, is the 2004 observation from Lipman et al. (2004) excluded. In 2005, Carlson et al. (2005) report cost to be 108 USD/kW, but now at mass production of 500,000 units of 80 kW systems. Altogether, these constitute the nominal costs over the 1995-2014 period as plotted below.

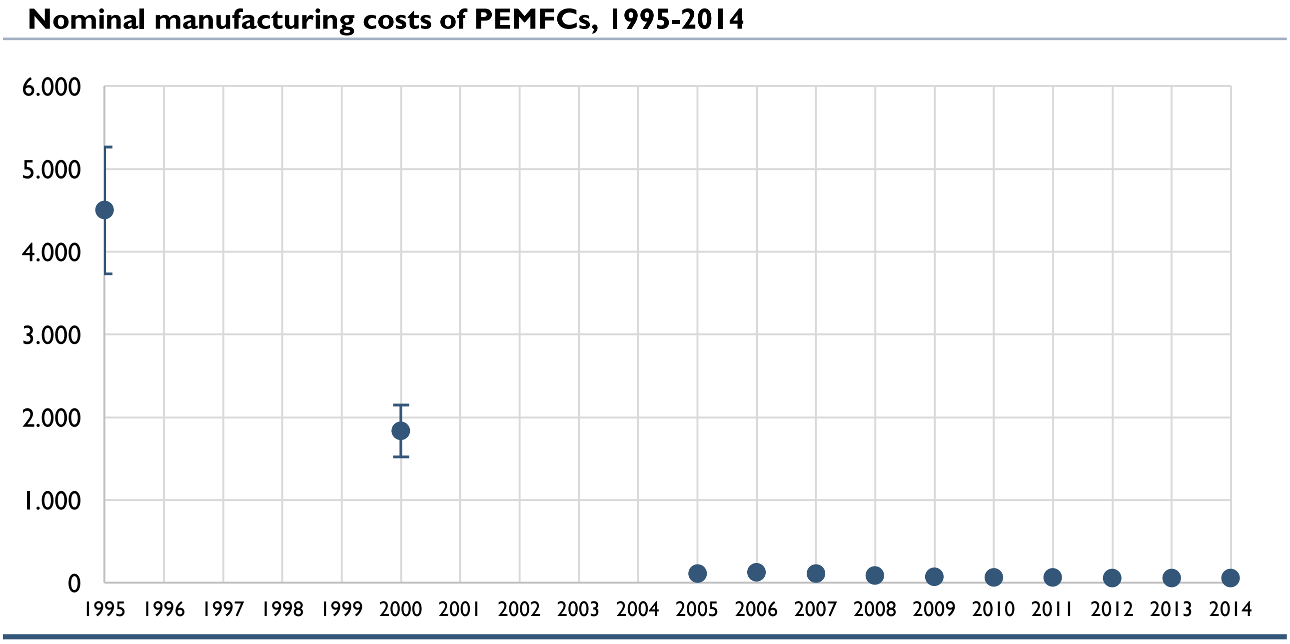

Figure 4.6: Nominal manufacturing costs of PEMFCs, 1995-2014.
Sources: Rogner (1998), Tsuchiya & Kobayashi (2004), Carlson et al. (2005), Department of Energy (2015), and own work.

Because of the differences in fuel cell capacity in the systems from 1995-2000 and 2005-onwards, an error margin is employed. Based on the estimations of Schoots et al. (2010), approximately 17% of manufacturing costs is allowed to account for capacity differences, as shown by the vertical error bars on each cost point. Having established the nominal costs for each year, we will proceed by correcting the estimates for (*i*) inflation, (*ii*) scale economies, and (*iii*) platinum volatility. It can then be assessed to which extent such corrections help to estimate global learning effects more adequately.

4.3.2.1. Correcting for Inflation

First, is the inflation correction. Costs are reported for an almost twenty-year long period for which reason the nominal US dollar terms might be hard to compare. Using the US producers price index for hardware manufacturing (US BLS 2016), monthly inflation is averaged for each year during 1995-2014 and indexed with regards to year 2014 as base year. Such correction changes the costs per kW to develop as follows.

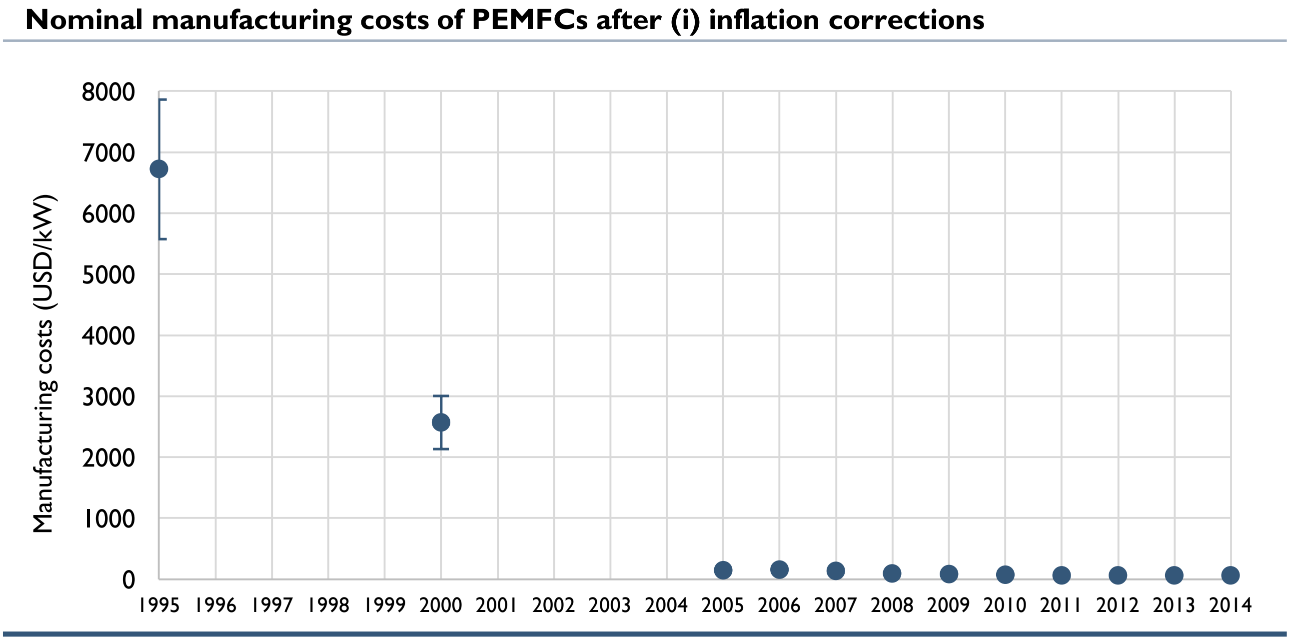

Figure 4.7: Nominal manufacturing costs of PEMFCs after (i) inflation corrections. Sources: US BLS (2015) and own work.

Due to the rather long period of observations, the effect seems large for the 1995 and 2000 estimates while relatively little is corrected within the last 10 years.

4.3.2.2. Correcting for Economies of Scale

One notable difference between early manufacturing in 1995-2000 and 2005-2014 is the scale at which fuel cells are produced. Whereas Rogner (1998) as well as Tsuchiya & Kobayashi (2004) assume only 40 units to be manufactured, Carlson et al. (2005) and the Department of Energy (2015) are reporting costs at mass production of 500,000 units in all cases. Therefore, it might prove useful to correct for economies of scale. As supported by the LCOE model in chapter 3, manufacturing costs are expected to vary notably for different production scales. Thus, in order to make costs mutually comparable, costs are converted to an annual production of 500 fuel cells as in the analysis of Schoots et al. (2010). The correction is performed so that the following relationship is honored.

$$C_{500} = C_{lit}\left(\frac{S_{lit}}{500}\right)^{1-\lambda} \qquad \text{EQ 4.4}$$

Where C_{500} are the converted manufacturing costs at fuel cell production of 500 units, C_{lit} are the costs reported in the literature, and S_{lit} is production scale assumed in that specific literature. Finally, λ is the factor used to correct for economies of scale adequately. Here, we will use the work of McLean and colleagues (2002) to justify a scaling factor, λ, of 69%. Such normalization is thus highly contingent on the choice of scaling factor. The real manufacturing costs of PEMFCs between 1995 and 2014 can now be graphed before (a) and after (b) the economies-of-scale correction below.

Costs after (*ii*) the economies-of-scale corrections

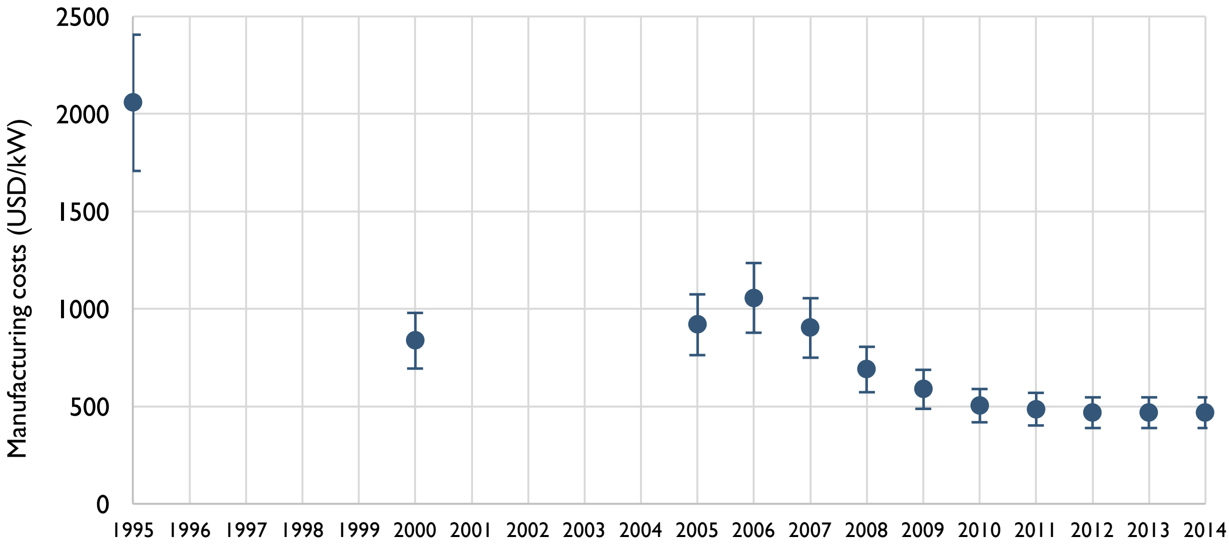

Figure 4.8: Nominal manufacturing costs of PEMFCs, 1995-2014 after (ii) economies-of-scale corrections.
Sources: Rogner (1998), McLean et al. (2002), Tsuchiya & Kobayashi (2004), Carlson et al. (2005), Schoots et al. (2010), Department

As it can be seen, these corrections change the costs remarkably. Whereas the early productions of few units are normalized to a lower cost, the recent mass production costs are normalized the other way around. One important argument for the observed effect is put forward by Schoots et al. (2010: 2893) stating that "technology learning is implicitly time-dependent while economies-of-scale are not. Therefore, filtering out economies-of-scale is what […] should be done in order to determine learning-by-doing proper." For this reason, our estimation of learning effects distances itself from that of other studies by correcting for scale economies, which are admittedly present in the fuel cell industry (as well as in other renewables) according to the cited sources.

4.3.2.3. Correcting for Platinum Volatility

Finally, while platinum (whose scientific symbol is denoted as "Pt") proves to be just above 5% of total manufacturing costs for a stationary 2.5 kW system, it is yet an important and expensive part of the CAPEX. However, as the spot price of platinum is essentially subject to supply and demand in the market rather than technological learning, correcting for its volatility could help to minimize the spread in the observed data both prior to and after the (*i*) inflation and (*ii*) economies-of-scale adjustments.

Efficiency has generally increased during the observed period, literature and reports reveal. Indeed, while this might constitute a learning effect itself, the amount of platinum required to produce one kW is widely different in 2014 than in 1995. The literature used for manufacturing costs are not consistently reporting platinum usage (or efficiency) for which reason a linear relationship is assumed for the development from 1988 (reported by Ticianelli et al. 1988) through 2005 (reported by Carlson et al. 2005). Then, the Department of Energy (2015) has published platinum efficiency from 2007 through 2014 and a conservative target by 2020. Using the linear relationship between two data points from 2005 and 2007, an appropriate prediction for 2006 is achieved. Altogether, the resulting platinum load (gPt/kW) enables us to estimate amount used for each of the fuel cell systems in the period. In turn, we are then able to calculate platinum cost at time t, $c[\text{Pt}]_t$, by multiplying its market price, $p[\text{Pt}]_t$, obtained from Khan (2016) with the corresponding amount used per kW, $a[\text{Pt}]_t$:

$$c_t^{\text{Pt}} = p_t^{\text{Pt}} \, a_t^{\text{Pt}} \qquad \text{EQ 4.5}$$

We can then determine platinum costs with respect to base year 2014, $c[\text{Pt}]_{t,\text{Pt2014}}$:

$$c_{t,\text{Pt2014}}^{\text{Pt}} = p_{2014}^{\text{Pt}} \, a_t^{\text{Pt}} \qquad \text{EQ 4.6}$$

With this established, the fuel cell manufacturing costs at time t can then be compensated for volatility in platinum prices during the period:

$$c_{t,\text{Pt2014}}^{\text{FC}} = c_t^{\text{FC}} - c_t^{\text{Pt}} + c_{t,\text{Pt2014}}^{\text{Pt}} \qquad \text{EQ 4.7}$$

The resulting manufacturing costs after corrections are graphed below. Indeed, correcting for platinum volatility yields only a small effect. In this way, the final estimates are coherent with the findings from the LCOE modeling, that is, platinum constitutes a smaller fraction of total manufacturing cost than initially expected. In light of the economies-of-scale correction, it proves to be rather negligible. These findings are consistent with those of Schoots et al. (2010). Platinum's effect (or lack of) is plotted in the following graph from which it is hard observe notable differences as compared to the (*ii*) economies-of-scale corrections.

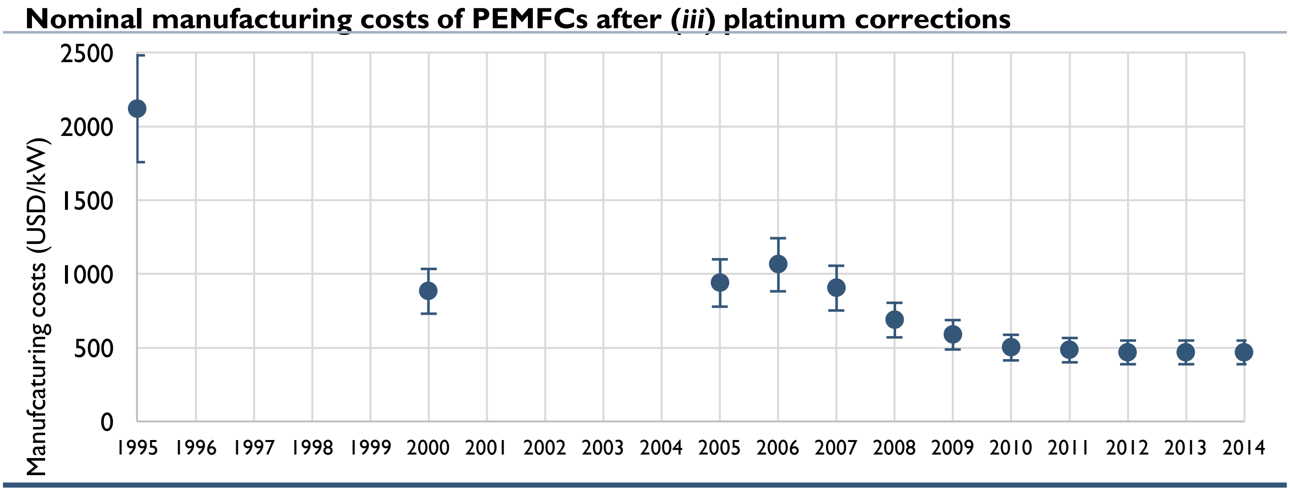

Figure 4.9: Nominal manufacturing costs of PEMFCs after (iii) platinum corrections.
Sources: Ticianelli et al. (1988), Carlson et al. (2015), Department of Energy (2015), Khan (2016) and own work.

4.3.3. Modeling the Learning Curve

Having corrected the cost estimates for *(i)* inflation, (*ii*) economies-of-scale, and (*iii*) differences in the usage and price of platinum, the learning curve can finally be estimated. We combine the cumulative capacity of PEMFC (from section 4.3.1.) and the corrected cost figures (from section 4.3.2.) to plot the relationship on a double-logarithmic scale below.

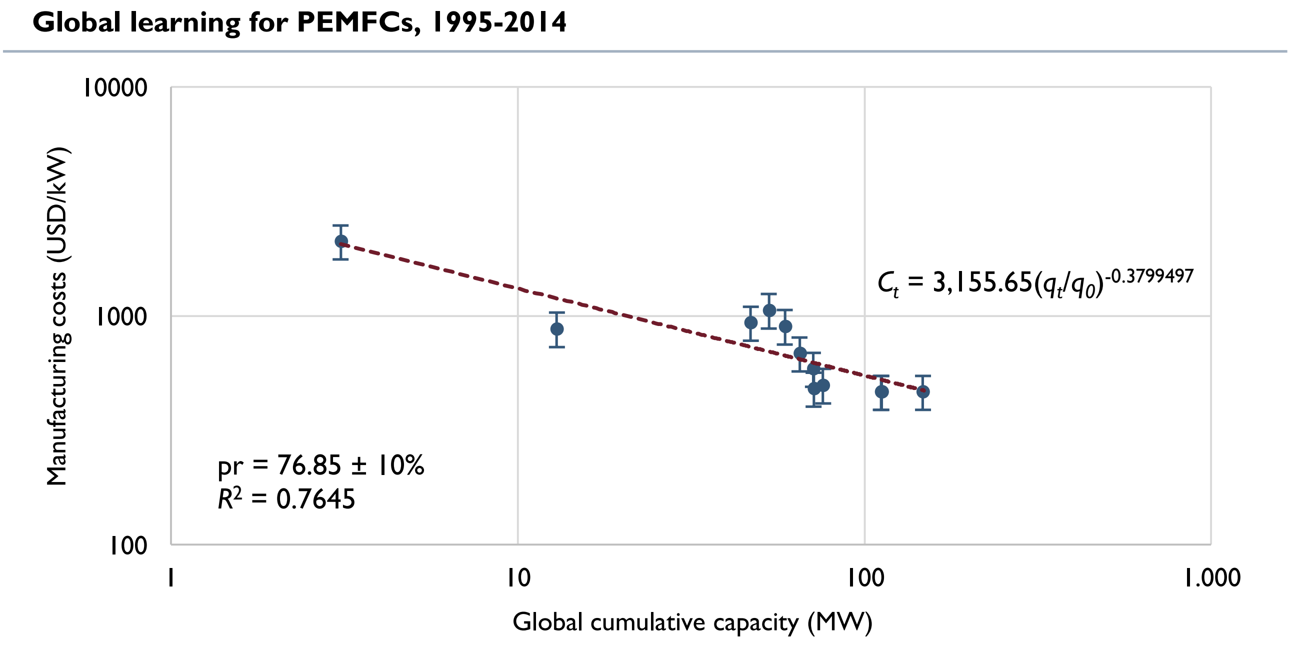

Figure 4.10: Global learning for PEMFCs, 1995-2014. Source: Own work.

The most widely applied method for estimating a relationship between an independent and a dependent variable (e.g. denoted by y and x) is usually referred to as an ordinary least squares (OLS) procedure. The OLS chooses the regression coefficients so that the estimated regression line is as close as possible to the observed data, where closeness is measured by the sum of the squared mistakes made in predicting y given x (Stock & Watson 2012). The sum of the squared mistakes is given by the following expression:

$$\sum_{i=1}^{n}\left(y_i - b_0 - b_1 x_{1i} - \ldots - b_k x_{ki}\right)^2 \qquad \text{EQ 4.8}$$

where b_0 and $b_1, \ldots, b_k$, are some estimators of the intercept, β_0, and the coefficients, respectively β_0 and $\beta_1, \ldots, \beta_k$. Thus, the OLS predicted values, $\hat{y}_i$, and residuals, $\hat{u}_i$, are given by the following expressions:

$$\hat{y}_i = \hat{\beta}_0 + \hat{\beta}_1 x_{1i} + \ldots + \hat{\beta}_k x_{ki} \qquad \text{EQ 4.9}$$

$$\hat{u}_i = \bar{y}_0 - \hat{y}_0 \qquad \text{EQ 4.10}$$

In measuring the fit of regression, we report the R^2 and the standard error of regression. While the latter estimates the standard deviation of the error term, i.e. the spread of the distribution of the dependent variable (y) around the regression line, the regression R^2 is the fraction of the sample variance of y_i predicted by the regressor(s). In applying the OLS method to data on cumulative capacity and manufacturing costs, it is important to note that OLS assumes that large outliers are unlikely. In this way, the method is coherent with our exclusion of outliers from TIAX (2002) and Lipman et al. (2004). Finally, it should be mentioned that the applied OLS fitting is performed *after* a log-transformation of the variables. Then, using the least-squares fitting procedure in Stata to plot the straight line, we determine the model to be explained by the following relationship (as in EQ 4.1):

$$C_t = C_0\left(\frac{q_t}{q_0}\right)^{-b} \Rightarrow C_t = 3{,}155.65\left(\frac{q_t}{q_0}\right)^{-0.3799497} \qquad \text{EQ 4.11}$$

where C is the unit cost at time t, q is the cumulative capacity, and b is the (learning) coefficient used to define progress and learning rates. The estimated model does indeed reveal presence of data scattering, however, we observe that the correlation coefficient R^2 is 0.7645, suggesting that the model explains 76.45% of the variance in the dependent variable. In the 1995-2006 model estimated by Schoots et al. (2010: 2894), an R^2 of approximately 74% is associated, which is deemed "[…] imperfect, but acceptable for [their] purposes." Likewise, considering also our model predicts almost twice the period, we find the correlation coefficient to be sufficiently high for our purposes. In this way, we utilize the learning coefficient and the relationships explained in EQs 4.2 and 4.3 below:

$$pr = 2^{-b} \Rightarrow pr = 2^{-0.3799497} = 0.7685 \qquad \text{EQ 4.12}$$

where *pr* is the unit cost in relative terms expressed as a percentage left after cumulative capacity has doubled. Next, we calculate the learning rate*, lr*:

$$lr = (1\text{-}pr) \Rightarrow lr = (1\text{-}0.7685) = 0.2315 \qquad \text{EQ 4.13}$$

where *lr* can then be interpreted as the relative cost reduction after a doubling in cumulative capacity. Intuitively, the model predicts a 23.15% cost reduction in PEMFC manufacturing for each doubling of cumulative capacity. These rates are close to the findings of Schoots et al. (2010) who find a progress rate of 79% and a learning rate of 19%. In their paper, they also report an error margin rate for the progress rate of (±) 4%. Similarly, we can calculate an uncertainty range for our results. Using the power rule to the Gauss error propagation law as stated in Bronshtein et al. (2007), if variables x_j occur as:

$$z = f(x_1, x_2, \ldots, x_k) = a x_1^{b_1} x_2^{b_2} \ldots x_k^{b_k} \qquad \text{EQ 4.14}$$

which, by logarithmic differentiation, yields a relative error of:

$$\frac{df}{f} = b_1 \frac{dx_1}{x_1} + b_2 \frac{dx_2}{x_2} + \ldots + b_k \frac{dx_k}{x_k} \qquad \text{EQ 4.15}$$

from which we get the mean relative error (by the error propagation law):

$$\frac{\tilde{\sigma}_f}{f} = \sqrt{\sum_{j=1}^{k} \left(b_j \frac{\tilde{\sigma}_{\bar{x}_j}}{\bar{x}_j} \right)^2} \qquad \text{EQ 4.16}$$

Finally, with the input from the Stata regression, we calculate the relative (±) error margin:

$$\delta z = \frac{\tilde{\sigma}_f}{f} = \sqrt{\left(0.3799497 \frac{1.068539}{3.919984}\right)^2} = 0.3799497 \frac{1.068539}{3.919984} = 0.10356959 \qquad \text{EQ 4.17}$$

The calculated progress rate is thus associated with an uncertainty of (±) 10.36%.

Finally, it should again be commented that our learning curve models the evolution in PEMFC cost figures from transportation (and not all applications) against cumulative capacity overall (from all applications). As in Schoots et al. (2010), we expect that all applications of PEMFCs have contributed to the observed cost reductions. In other words, we also expect the observed learning effects to apply for non-transportation use, and we are therefore confident that, all else equal, small stationary (like the 2.5 kW backup system) experiences similar technology learning. We can therefore use the estimations to model the choice of whether or not to replace diesel generators with fuel cells as the backup system in the Indian telco market confidently.

4.4. Limitations of the Learning Curve

While the results from the analysis are generally coherent with that of the reviewed literature (e.g. Dutton & Thomas 1984), one should always carefully understand the assumptions behind the estimated learning curve. Indeed, because learning effects will differ from company to company, and also from industry to industry, one should acknowledge that their transferability might not be easy. In our model, we assume that the technological development in transportation application of PEMFCs is transferable to the application of the very same technology within small stationary and the backup system. DPS understands the importance of this assumption and comments that cost decreases of PEMFC transportation usage will help to decrease cost of manufacturing for small stationary similarly. Therefore, based on these acknowledgments, we can move forward with the estimated results in a real options context. In addition, whilst these results could be an important tool for a manager in the PEMFC industry, one must also be aware that learning curves are in constant change. In order to make as well-evaluated a decision as possible, one must apply the latest accurate inputs for the model to be applicable *today*. In other words, it is highly appropriate to reevaluate the results as new or current information becomes available.

5. VALUING THE REAL OPTION

At this point the LCOE model has yielded results confirming that the weights of each cost component is widely different for the fuel cell system compared with that of a diesel generator. Indeed, calculations show that CAPEX captures as much as 72% of levelized costs for the fuel cell while only 22% for the diesel generator. Vice versa, for the fuel cell, fixed and variable O&M and fuel costs amount to 16% and 12% respectively. For the diesel generator, the same figures were estimated to 48% and 30%. Therefore, with the knowledge of past developments in PEMFC production costs, learning effects might have a significant impact on the cost of energy generation for the fuel cell in the future, given an estimated doubling in the technology's cumulative capacity. All else equal, the results motivate a way to model more carefully how future costs might change. In this chapter, it is thus reviewed how financial options theory values uncertainty and is bridged into a real options framework. Through an introduction to the real options framework, more general valuation models are established and literature with application to both conventional and renewable energy projects is reviewed. Altogether, a framework is developed to capture the uncertainty of keeping diesel generators installed. In this way, diesel fuel volatility serves as one of the options parameters while the estimated learning effects motivate a decreasing strike price of a replacement option, the fuel cell, as another parameter. Conclusively, the model generates results highly contingent on the specified assumptions. Therefore, the chapter includes a section in which sensitivity analyses are performed before discussing the results in the following implications chapter.

5.1. Financial Option Definition

A financial option is a contract among two parties, a buyer and a writer, to trade an underlying asset which can be all sorts of financial assets such as stocks, commodities, and currencies. Since the introduction of publicly traded options on the Chicago Board Options Exchange (CBOE) in 1973, options have become one of the most actively traded assets and tools for investors as well as for corporate managers (Berk & DeMarzo 2014). Options can be bought for purely speculative reasons but can also be very useful as a hedging instrument to corporations as an alternative to classic forward and futures contracts on e.g. currencies.

More specifically, two distinct types of option contracts exist; *call* options and *put* options. The former gives the owner the right to *buy* the asset while the latter gives the owner the right to *sell* the asset. From the writer's perspective, a call option implies that the writer has the obligation to sell the asset and the put option implies an obligation to buy the asset. Consequently, option trading always consists of these two parties where the buyer is said to be in a *long* position and the seller in a *short* position. The holder of the option can choose to enforce the contract, i.e. buy or sell the underlying asset at a predefined *strike* (or exercise) *price*. For the call option, he or she will only choose to do so if the underlying asset price is higher than the strike price which implies that the option is *in the money*. When the underlying asset price is below the strike price, he or she simply walks away implying that the option is *out of the money*. To depict the payoff scheme of a simple call option on a stock, consider figure 5.1(a).

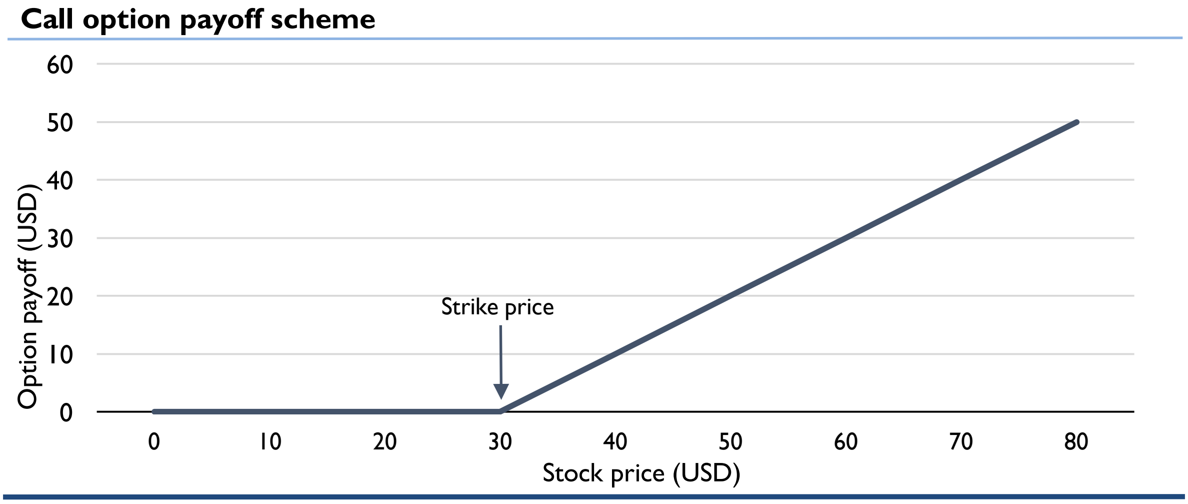

Figure 5.1(a): Call option payoff scheme. Source: own work.

A holder of this option will never enforce the contract as long as the price of the underlying stock stays below USD 30. However, as soon as the stock price rallies above the strike price, the option is in the money and carries value to the holder; at a price of USD 50, the holder of the option can buy the stock at USD 30 and immediately sell the stock in the market for USD 50 for a gain of USD 20 i.e. the value of the option. Generally, the payoff scheme for a call option can be described by:

$$C = \max(S - K, 0) \quad \text{EQ 5.1}$$

where C is defined as the call option value, S as the stock price at expiration and K being the strike price. The same analogy applies to the put option with opposite signs; as long as the stock price stays above the strike price, the holder walks away while he or she starts to make money when the stock price falls below the strike price as seen in figure 5.1(b):

$$P = \max(K - S, 0) \quad \text{EQ 5.2}$$

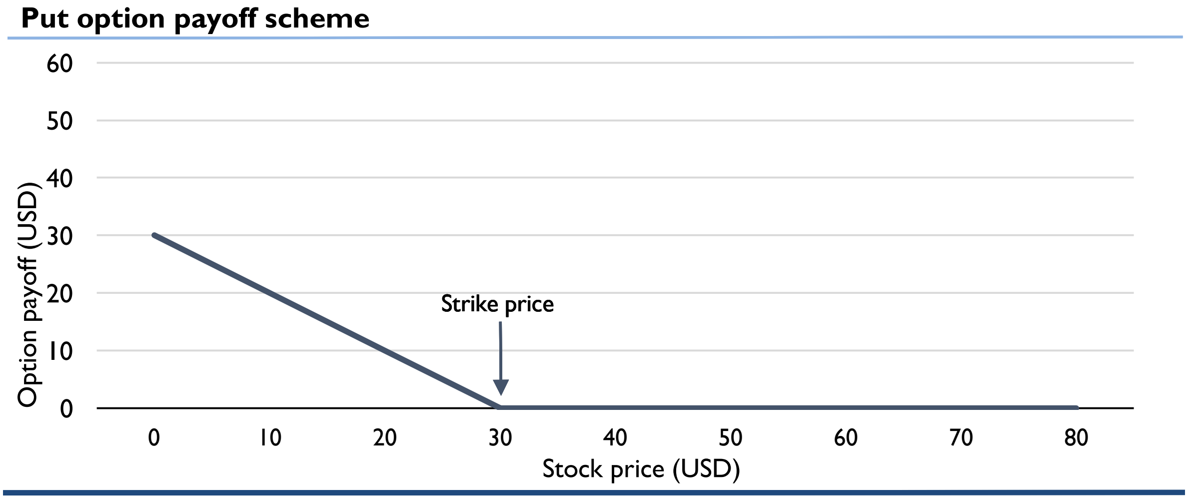

Figure 5.1(b): Put option payoff scheme. Source: own work.

An interesting feature of options is that more risk is rewarding; uncertainty regarding price movements of the underlying asset adds value to the option. To understand this, remember that the holder of a call option is shielded from downward price movements in the underlying asset (the holder can simply choose not to exercise the option, while he or she is rewarding from upwards price movements. Consequently, the higher the uncertainty, defined as *volatility*, the higher the chances for large upwards movements in the asset price and thereby increasing the value of the option. We will, at later stages, turn to the estimation of volatility but for now we simply note that the volatility in the underlying asset is assumed constant during the lifetime of the option.

Despite any geographical restriction or reference, option contracts can either be American or European. The only difference between the two types is that the American option can be exercised at any time prior to or at the expiration date, while the European option can only be exercised at the predetermined expiration date.

Financial options, long and short or calls and puts, can be combined in endless ways to construct specific payoff profiles, these will not be covered in this paper. While certain combinations can be very useful to bet on (against) e.g. volatility such as a long (short) straddle or for hedging, they serve little purpose in the real option setting that we intend to apply later on. Instead, we direct the attention towards financial option pricing, which is highly relevant in light of the subsequent real option application.

5.1.1. Option Valuation (Black-Scholes)

For the purpose of this thesis, we will use the *binomial lattice option valuation model* due to its flexibility and ease of presentation (see subsequent sections). Nevertheless, any project incorporating option theory should present the (perhaps) most widely used option valuation tool, namely the famous Black-Scholes model, which is defined by the following (Kodukula & Papudesu 2006: 67):

$$C = N(d_1)S_0 - N(d_2)Xe^{-rT} \qquad \textbf{EQ 5.3}$$

where C is the value of the call option, S_0 is the current value of the underlying asset, X is the strike price, r is the risk-rate rate of return, and T is the time to expiration. $N(d_1)$ and $N(d_2)$ are the cumulative normal distribution functions, which can be obtained from a Microsoft Excel spreadsheet (see Kodukula & Papudesu 2006: 67 for definitions of d_1 and d_2). With the inputs in hand, one can easily determine the option price through the formula above. For the purpose of real options however, the model has some weaknesses. The most important weakness, and the reason why we disregard the Black-Scholes model in our calculations, is that the strike price is deemed fixed. As we will show, our calculations on the value of the option to replace a diesel generator with a fuel cell incorporate changing strike prices over the course of the option, which is possible using the binomial lattice model.

5.1.2. Option Valuation (Binomial Lattice)

As opposed to the Black-Scholes method, which constitutes a continuous modeling, the binomial lattice model uses discrete time steps (Kodukula & Papudesu, 2006: 70). At any discrete time step, t, in which the asset price is S, the price of the asset in the following time step, $t+1$, can only take one of two values; "up-value" or "down-value". In this way, price of the underlying asset moves through a "tree" of ups and downs until it reaches a final price at expiration as shown in figure 5.2, which also depicts the option value, C, at each node.

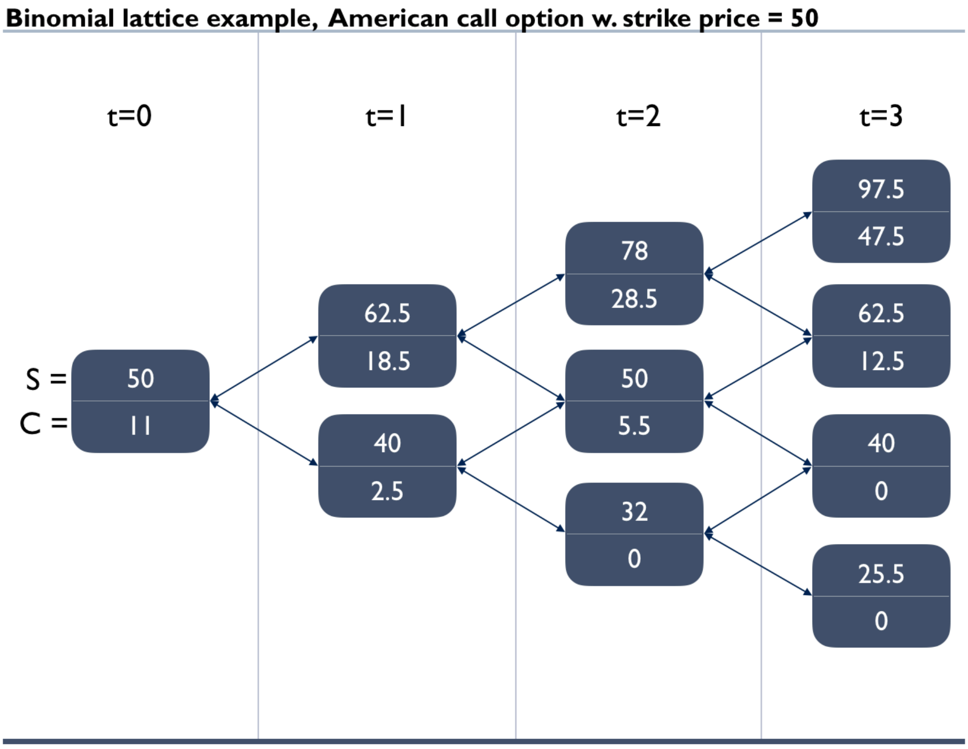

Figure 5.2: Binomial lattice example, American call option w. strike price = 50. Source: own work.

For each movement, up (*u*) or down (*d*), the resulting asset price increases to *Su* or falls to *Sd*, where *u* and *d* factors are calculated based on the volatility of the asset through the following formulas:

$$u = e^{\sigma\sqrt{\delta\tau}}, \quad d = e^{-\sigma\sqrt{\delta\tau}} \qquad \text{EQ 5.4}$$

where δt is the number of steps in the tree as a fraction of one period of volatility. Put differently, if the volatility is yearly and each step in the binomial lattice is half a year, δt is equal to 0.5. Next, to determine the likelihood of up and down price movements, one estimates the so-called risk-neutral probability of either movement through the following equation:

$$p_u = \frac{e^{r\delta t} - d}{u - d}, \quad p_u = (p_u\text{-}1) \qquad \text{EQ 5.5}$$

with *r* being the risk-free rate of return. The implicit assumption is that investors are indifferent toward risk allowing one to discount future expected income with the risk-free rate.

Before the actual option valuation is carried out, the underlying asset values are calculated for each node as seen in the figure above. At the end of the tree, the difference between the asset price and the strike is exactly equal to the option value; if one has the option to buy the stock at 50, while the market price at expiration is 97.5, the difference, 47.5 is equal to the value of the option. One can to derive this value (zero if underlying asset is below strike price) for all nodes at the end of the tree, defined as max$(S_t - X_t; 0)$, with the probability of "ending" in each of the nodes is determined by the binomial probability distribution function, in which the probability of k up-movements in T periods is defined by (Jorion 2007: 143):

$$f(k) = \binom{T}{k} p^k (1\text{-}p)^{T\text{-}k} \qquad \text{EQ 5.6}$$

With the underlying asset prices, and the option values in the end (right-hand side) of the tree in hand, one can calculate the option values in each of the nodes thus solving the tree backwards and ending with the option value in time 0. In each node, one is subject to a maximization problem in which one has choice to exercise the option and get $S_t - X$ or hold on to the option, where the decision depends on which of the two that has the highest value. To find the value of each node, one solves the tree backwards through a weighted discounting of the two possible outcomes one step ahead using the following equation:

$$\max\left[\left(pC_{t+1,u} + (1\text{-}p)C_{t+1,d}\right)e^{-r\Delta t}; S_t\text{-}X_t\right] \qquad \text{EQ 5.7}$$

Where $C_{t+1,u}$ is the value of the option in the up case and $C_{t+1,d}$ the value in the down case. The fact that the option can be exercised in every step, meaning that equation 5.6 is maximized at each node implies the construction of an American call option, opposing the European version that can only be exercised at expiration.

5.2. Real Options Valuation: Basic Principles and Literature Review

In order to understand real options valuation properly, traditional options theory from finance is presupposed. Therefore, having outlined the major characteristics above, the findings are bridged here. Subsequent to a general description of the framework and an introduction to (some of) its different valuation models, a literature review on the application within energy markets and technologies are carried out. Thus, this subsection serves a primer on real options theory and the background for the practical modeling of a replacement decision at Indian telco towers.

5.2.1. The Bridge from Financial Options Theory

Whereas the financial option is traded in competitive markets, a real option is typically not. Nevertheless, real options share many of the underlying principles of the financial option (as established in section 5.1.) for which reason they are more easily understood using a similar framework. Following the descriptions above, and according to Black and Scholes (1973: 637), "an option is a security giving the right to buy or sell an asset, subject to certain conditions, within a specified period of time." In this way, options are rights to the decision maker, and the yield of an option will therefore always be above zero as the rights would not be exercised, should the yield be negative. The real options framework draws both on the rights to buy (call) or sell (put) assets at pre-specified price or time respectively. Likewise, a real option can thus also be *in the money* when its exercise price is less (higher) than the price of its underlying asset for a call (sell) option. If not, it is then *out of the money*. In this project, we will assume an American options framework in which the rights can be exercised at any time up to the option's maturity date, and not only on that data as in the European option.

5.2.2. Defining Real Options

Having bridged some of the main ideas from the financial options, it is appropriate to define exactly what constitutes a real option. In the words of Copeland & Antikarov (2001: 5), a real option is "the right, but not the obligation to take an action (e.g., deferring, expanding, contracting or abandoning) at a predetermined cost called the exercise price, for a predetermined period of time—the life of the option." Another explanation follows from Kogut & Kulatilaka (2001: 746) who write that "a real option is technically defined by an investment decision that is characterized by uncertainty, the provision of future managerial discretion to exercise at the appropriate time, and irreversibility." With both of these definitions, it can be established that the opportunity to make an investment is similar to an American call option, and the decision-maker would then only choose such investment as long as it would generate a net payoff at the time of the decision. Using the bridge from financial options theory to the framework of a real option, as conceptualized in Fernandes et al. (2011), they share the following analogies.

Analogy of the call option and the project characteristics

Project characteristics	Call option
PV of expected cash flows	Stock price
PV of investment outlays	Exercise price
Length of deferral time	Time to maturity
Time value of money	Risk-free rate
Volatility of project's return	Variance of stock returns

Table 5.1. Analogy of the call option and the project characteristics. Sources: Fernandes et al. (2011)

Admittedly, whilst such comparison helps to compare the over-arching framework, it fails to tell much about the differences. In particular, the valuation of financial and real options is (or can be) based on widely different assumptions. One important feature of financial markets is the availability of information. Without extensively dwelling into the discussion of an efficient market hypothesis (Berk & DeMarzo 2014), information is comparably less transparent and easily accessible for more advanced real options applications. In addition, Haahtela (2012) argues that lengths of investment periods are usually non-equal for financial options and real options, for which reason the estimation of uncertainty (and volatility) can thus become a more significant challenge. The estimation of volatility in the paper will arguably add power to such proposition. Having some of the more major differences in the table above, real options types are specified next.

5.2.3. Types of Real Options

Although there are several more types of real options in practice, Berk & DeMarzo (2014) concentrate on three kinds most frequently used, namely (*i*) the option to delay an investment opportunity, (*ii*) to option to grow, and (*iii*) the option to abandon an investment opportunity. Instead of obsequiously explaining each of these, (*i*) to option to delay an investment opportunity is deemed most important for the purpose of this paper. Theoretically, the defer option gives the holder the opportunity to delay and thus collect more information and possibly reduce the uncertainty associated with the decision. This is highly relevant for management in the capital budgeting decision. Introduced by Myers (1977) in his paper on corporate borrowing, real option modeling affects capital budgeting in the sense that without the investment option, the decision is simply an NPV choice in which it is optimal as long as the value is above zero. However, with the option, it will usually only be optimal if the NPV is substantially greater than zero. To understand this result, we can think of two mutually exclusive projects, namely (1) with investment today and (2) with the ability to wait. Whenever faced with two mutually exclusive projects, the NPV rule states that we should choose the project generating the higher NPV (Berk & DeMarzo 2014). In other words, investment should only be done (1) today if the associated NPV exceeds that of (2) waiting to invest. Then, if we are able to always walk away from the project, (2) the deferring option will have a positive NPV, and (1) the investment today must thus generate a significantly higher NPV to justify this choice rather than waiting.

In addition to the NPV of the investment, there are other important factors influencing the value of an investment and the decision to exercise an option. Particularly, as it is the case for financial options too, both the volatility of a project's return and 'dividends' are significant contributors to the decision. Whereas the higher the volatility is the more valuable the real option (and the ability to wait) holds, dividends from the financial terminology correspond to any value given up in order to wait before exercising the option. In other words, there is an associated opportunity cost with the real option. That is, the greater the cost of waiting is, the less attractive the real option becomes.

5.2.4. Valuing Real Options

With the inputs to the Black-Scholes pricing model outlined above, Amram & Kulatilaka (1999) propose one approach to understand how real options can be valued. Indeed, one must (*i*) first understand in which environment the real option is applied. (*ii*) Secondly, the holder must identify the inputs and assumptions of the valuation model. (*iii*) Thirdly, in order to interpret the results correctly, appropriate benchmarks shall be established. (*iv*) Fourthly and finally, steps (*i*) through (*iii*) shall be implemented, reviewed, and redesigned if necessary. In other words, the final step is an evaluation of the results and their applicability.

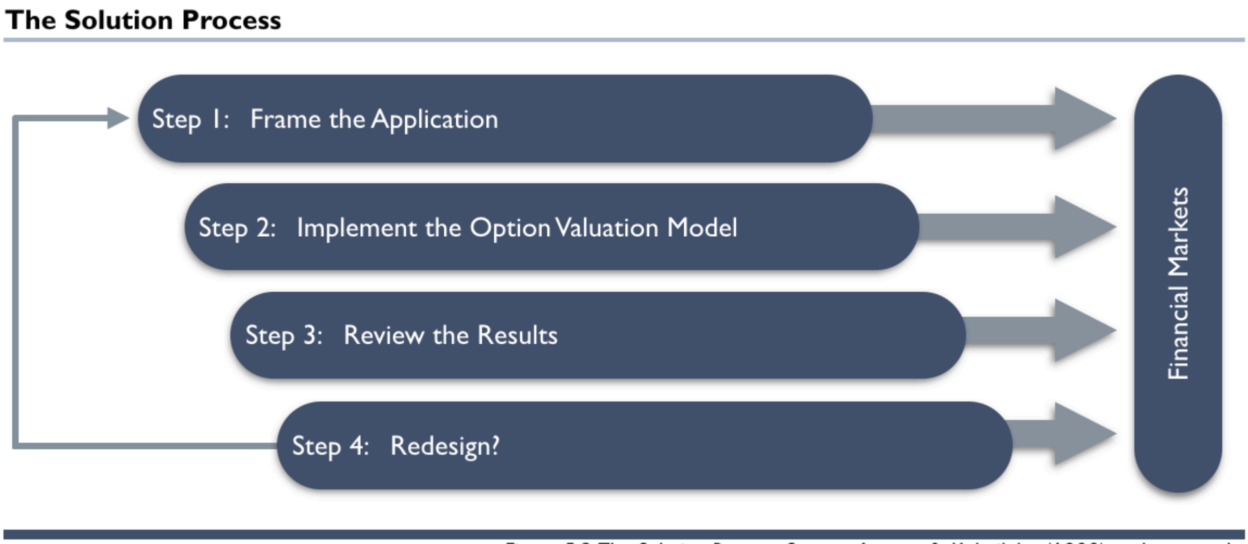

Figure 5.3:The Solution Process. Source: Amram & Kulatilaka (1999) and own work.

Following this four-step process, the option holder must thus first understand the application framing, what does the decision entail, when is it possible to exercise, and how is it carried out in practice. Through this step, it is also proposed that sources of uncertainty are identified and discussed how they evolve throughout the decision period.

The second step is then based upon the application framing of the first. There will thus be no single approach for all real options in practice. As the authors of the process highlight, guided by the contributions of Black-Scholes (1973) and Myers (1977), there are several valuation models that can be carried out. In their review on real options approaches in energy sector investments by Fernandes and colleagues (2011), particular attention is drawn towards three groups of solutions: partial differential equation (PDE), dynamic programming, and simulation. Literature exists for each of these methods' application in the energy industry (see table 5.2 below), yet brief introductions help to motivate the choice of approach undertaken in this project. Firstly, the PDE approach is carried out through mathematically expressing the value of an option by a partial differential equation contingent on specified boundaries. Such expression(s) can then be solved by analytical solutions or approximations e.g. to specify when an investment makes sense financially to undertake. Secondly, the dynamic programming technique is an approach to optimize the decision one point in time influencing future payoffs. In this way, dynamic programming can utilize decision trees, a graphical representation of alternative decisions and potential outcomes in an uncertain project. Such method can thus depart from the binomial option valuation model. Thirdly, simulation approaches can stem from numerous models, yet Monte Carlo simulation seems to among the most frequently used (Fernandes et al. 2011). With this method, an almost infinite amount of possible future states can be simulated and then evaluate the probability of each. The option holder is then able to base the decision on NPVs computed upon the simulations, which have incorporated the use of real options.

Returning to Amram & Kulatilaka (1999), the third step is then to interpret the results from the valuation model specified above and benchmark them against other techniques, e.g. against traditional discounted cash flows. After such comparison and evaluation, perhaps the fourth step necessitates a reconfiguration of the model in which case the flaws should be assessed and corrected. If not, the results yield an outcome for the option holder to make a decision.

Altogether, the use of real options enables investment decisions to be evaluated differently than by traditional NPV tools. As a way of thinking, real options can contribute significantly to strategic decision-making through e.g. value-adding uncertainty (or volatility) and the option to wait. Yet, real options are not widely used in practice. In a survey on business managers' familiarity with the term 'real options', Simkins & Kemper (2013) were surprised by the lack of knowledge about its technique and concept in practice. Whereas it might be the case that real options modeling holds a degree of complexity to carry out and that there are perhaps too few corporate incentives to undertake investments supported by real options analysis, there are yet benefits to the application. In fact, the gradual liberalization of the energy sector since the 1970s has challenged conventional DCF methods to evaluate energy projects. With increasingly more competitive markets and associated uncertainty, real options approaches have been adapted by (some) practitioners and academics. Therefore, to understand why real options are useful in energy markets and how it is applicable to the case of fuel cells in India, a literature review on the more important contributions is carried out in order to model our choice optimally.

5.2.5. Application of Real Options in Energy Projects and RETs

Whereas real options approaches can be dated back to the late 1970s for the general energy sector (see e.g. Tourinho 1979), renewable energy technologies (RETs) have exhibited less use of the framework. Nevertheless, Fernandes et al. (2011) identify real options use in particularly three major areas of RETs, namely power generation, policy evaluation, and R&D investments and programs. The following studies exemplify real options use within those applications.

Historical perspective on the use of real options on RETs

Authors	Year	Resource type	Area of application	Solution method
Venetsanos et al.	2002	Wind energy	Power generation	PDE
Davis & Owens	2003	RETs	R&D program	PDE
Kjærland	2007	Hydropower	Policy evaluation	PDE
Siddiqui et al.	2007	RETs	R&D program	PDE
Kumbaroğlu et al.	2008	RETs	Policy evaluation	DP
Muñoz et al.	2009	Wind energy	Power generation	DP
Knutsen & Holand	2010	Hydropower	Policy evaluation	PDE; DP; CC
Nicolet	2010	Solar PV	Power generation	PDE; DP
Martínez-Ceseña et al.	2011	Hydropower	Power generation	DP; MC simulation

Table 5.2. Historical perspective on the use of real options on RETs. Sources: Fernandes et al. (2011) and own work.

This list of literature is not intended to be exhaustive, rather it aims to provide some examples of works in which real options analysis has helped to evaluate investments, power generation, and policy issues in a renewable energy context. Although fuel cell systems are not interpreted as renewables like e.g. wind or solar PV (as they can be fueled by non-renewable resources as methanol), the use of real options in such contexts might help to motivate similar application for a technology exhibiting comparable characteristics in its commercialization stages (see e.g. section 4.1.3).

In one of the earlier real options papers within renewables, Venetsanos et al. (2002) evaluate uncertainties of fossil fuel prices, environmental regulations, development in energy demand, supply, capital costs, and changing market structure following the then introduced deregulation. Using a framework inspired by Black-Scholes thinking, they find positive option value for a wind project for power generation, whilst traditional NPV analysis yields negative value. In another application, Kjærland (2007) as well as Copenhagen Business School alumni, Knutsen & Holand (2010), utilize the framework developed by Dixit & Pindyck (1994) to evaluate investment opportunities in the Norwegian hydropower industry. For example, solving through PDE and DP techniques, the latter finds an optimal trigger price for an investment and an associated investment value. In an extensive review of real options theory applied to electricity generation projects (EGP) also, Martínez Ceseña and colleagues (2011: 578) conclude that real options "theory can be used to enhance the financial value of projects under uncertainty such as EGP and REP [renewable energy projects]" and highlight that "existing [real options] literature addressing EGP is scarce and, as a result, new research in the area would be valuable." In addition, there are studies (e.g. Davis & Owens 2003, Nicolet 2010, or Siddiqui et al. 2007) in which the value of R&D investments and programs can be quantified into a real options context to evaluate R&D and policy decisions. For example, Nicolet (2010) addresses the option value of avoided fossil fuel costs by installing infrastructure for solar PV in a Californian setting with federal grants and finds considerable benefits to real options analysis as opposed to traditional discounted cash flows models such as the NPV technique.

Altogether, as exemplified by a brief introductory literature review above, real options theory seems to have become increasingly popular in energy applications and particularly those of renewable characteristics. On the other hand, however, the literature above also highlights how it is limited to certain technologies and is by no means exhausting. As Fernandes and colleagues (2011: 4496) state, "these projects have high initial costs, high financial risk and uncertainties" and real options theory can perhaps help to provide more useful information about investment, policy, and R&D decisions, which "[…] traditional project evaluation techniques alone [are] insufficient to properly deal with". Having written those words, it seems only appropriate to see to which extent valuing backup power solutions in an Indian telco setting can be carried out and possibly benefit from real options thinking.

5.3. Setting up the Real Option

The third section of the real option chapter concerns itself with linking earlier analysis of LCOE and the effects of learnings to the options framework that has been elaborated upon in sections 5.1 and 5.2, in order to set up the real option model based on inputs from the analyses. Prior to a detailed designation of each option parameter, section 5.3.2. will bridge previous work with the coming real-option calculation. But at first, in 5.3.1., the value of the option will be described on a more theoretical level i.e. what is actually meant when referring to the option *value*?

5.3.1 Definition of the Option Value

To begin with, real option valuation is a financial tool to estimate the true value of investments more precise than traditional valuation tools such as the NPV-method. ROV analysis should thus provide decision maker with a more nuanced picture of what lies ahead, which in theory should lead to better decision-making.

Back in chapter 3, it was concluded that the diesel generator as of present is the backup power source that represents the most economical choice to telco tower operators. The levelized cost of energy generated by the diesel generator is 208 USD per delivered MWh, corresponding to a total cost of ownership of 16,750 USD in present values, while the LCOE of the HT PEM fuel cell is 311 USD per MWh, or 25,025 USD total cost of ownership. But with an assumed lifetime of 15 years, and in times of great technological leaps and uncertain energy prices, how certain can the telco tower operator be that these calculations will last accordingly? The real option framework shall assist the tower operator addressing the uncertainty inherently embedded in the LCOE calculations with explicit assumptions about a range of costs that stretch far into in the future. Specifically,

> *the real option value quantifies the flexibility of choice that the telco tower operator has between the two backup power generation sources.*

Therefore, the true cost of providing back power to telco towers during the next 15 years is the initial total cost of ownership of the diesel generator, that was establish in chapter 3, less any option value, which will limit the costs to the telco tower operator should the economic environment turn to the disadvantage of diesel generators since the value of being able to replace the diesel generator is also taken into account. The definition of option value depicted here is very similar to the one presented by Herbelot (1992) in his dissertation on environmental investments in the electric power industry. He examines the costs that a high-sulfur coal plant utility sustains in order to comply with the 1990 introduction of Clean Air Act Amendments imposing that utilities must bring down emissions to a certain level or continue emit above this level through the purchase of "emission allowances". A utility that continues operations as usual and purchases allowances in order to comply with the Amendment is defined as the maximum compliance costs. Herbelot then investigates possible ways to decrease emissions either by shifting to low-sulfur coal or installing "scrubbers". Each of the possibilities represents alternative solutions for which the value of flexibility is quantified and depends on the development in allowance market prices and premium paid for low-sulfur coal. The true cost of compliance is thus decreased from V_{tot} to $V_{tot} - V_{swi}$ - V_{scr}. In similar fashion, the true cost of providing backup power for the telco tower operator is the total cost of operating the diesel generator less the value of the choice to replace it with a fuel cell for the remainder of the lifetime of the generator.

5.3.2. From the LCOE Model and the Learning Curve to the Options Framework

In chapter 3, the cost comparison between operating a diesel generator and a fuel cell for backup power to telco towers in India was analyzed. To no surprise, it was concluded that the total cost of ownership of the fuel cell system during its lifetime surpassed the costs of the diesel generator by a fair margin. Consequently, if the telco tower operator were to choose between the fuel cell and the diesel generator today, the choice would be straightforward in favor of the conventional generator. Some of the interesting findings from chapter 3 were related to the cost drivers of each of the two systems. We showed how the OPEX of the fuel cell system undercut those of the diesel generator OPEX, of which fuel costs constitutes as much as 62 percent, while the substantial CAPEX of the fuel cell system drove much of its total lifetime cost of ownership (72 percent) in the LCOE.

Then, in chapter 4, we dug into the effects of learning, a widely studied phenomenon for new technologies, which have received particular interest in the field of new energy generation technologies. Through a combination of takeaways from previous studies and our own estimations, we established a learning rate of 23.15% for the PEM fuel cell technology, meaning that for each doubling in the installed cumulative capacity, the costs of production fall by 23.15%.

In this section, we aim to show how the analysis and its takeaways from both chapters can be modelled in a real option context in order to better evaluate the choice of replacing diesel generators with fuel cells, purely from an economic perspective. Previously, we have established the analogy between real options and an American call option (see table 5.1); in the coming paragraphs each of these parameters for the real option will be outlined and applied to our Indian telecommunication tower case.

5.3.3. Defining Options Parameters

The parameter inputs that will be designated in the following are (1) the underlying asset, (2) the strike price, (3) the time to maturity, (4) the risk-free rate of return, and (5), the volatility of the underlying asset. Recall the assumptions regarding timing of costs back in section 3.2.3. Here it is established that CAPEX is assumed to be incurred on the first day of each period while OPEX is incurred on the last day of each period. Moreover, year 0 corresponds to "yesterday" where the diesel generator is assumed to have been bought. Therefore, in our model, the decision to replace the diesel generator can be made for the first time on the first day of year one while the decision can be made no later than the first day of year 15. As a consequence, the real option model will be modelled in a 14-step binomial lattice.

5.3.3.1. Underlying Asset

In the financial option context, the underlying asset is the stock that a holder of the option has the right to buy at some predetermined strike price. For the general real option, the underlying asset is the present value of the cash flows that one expects to receive from investing in a project once the investment has been undertaken. In the present case, the choice to replace the diesel generator with a fuel cell implies, if the decision is made, that the operating expenditures of the diesel generator is saved. Savings can be viewed as a negative cost, which has the same impact on present values as positive cash flows. Therefore,

> *the forgone expenditures of operating the diesel generator (OPEX), for the remainder of its lifetime, will serve as the underlying asset for the real option calculations.*

Recall that one of the assumptions presented earlier in the LCOE calculations is that the diesel generator is already in place, meaning that any costs relating to the acquisition and installation of the diesel generator are sunk and cannot be rendered. Furthermore, no scrap value of a replaced diesel generator is included in the underlying asset since (1) the initial CAPEX of the diesel generator is rather low, and (2) any costs relating to the transportation from the telco tower to a potential buyer is assumed to outweigh any remaining value of the generator.

As explained in chapter 3, the OPEX of the diesel generator consists of fuel consumption, fixed O&M, and variable O&M, of which the former by far constitutes the biggest cost component. While for the LCOE calculations, both fuel and variable O&M components were assumed to grow at a constant rate throughout the lifetime, this assumption will only remain in the real option calculation for the latter. Conversely, diesel fuel costs will be calculated based on the volatility in diesel prices (see section 5.3.3.5) implying that each node in the binomial lattice will contain a diesel price based on up- and down movements. The underlying asset value will thus depend, to a large extend, on fluctuations in the diesel prices since fuel costs constitute a substantial part of the total lifetime OPEX of the diesel generator.

Specifically, the underlying asset value, S, in each of the nodes in the binomial lattice is most easily explained by starting in the utmost "up" scenario at the end of the tree, $S_{u14,d0}$ i.e. 14 up-movements in the diesel price (see appendix 3 for the binomial lattice for diesel fuel prices). In this specific node, the asset value amounts to the remaining OPEX, which is fuel consumption, fixed and variable O&M solely for year 15. As the diesel generator has an assumed economic lifetime of 15 years, the telecommunication tower operator must make a new decision on the first day of year 16 to buy either a generator or a fuel cell—a decision which should be based on LCOE calculations similar to those carried out in chapter 3. The decision to be made in year 16 is thus the start of a new "economic lifetime period", which will not be covered in this thesis. Returning to the objective of calculating the underlying asset value in the last year of operation, year 15, recall from chapter 3 that operating expenses are incurred at the end of each year, variable O&M are multiplied by its yearly escalation factor of 2%, while fuel costs are multiplied by the yearly growth rate of 6.99% (both figures can be found in the LCOE tables). The underlying asset value in year 15 is thus calculated as:

$$S_{u14,d0} = PV\left(OPEX_{u14,d0}\right) = \frac{DP_{u14,d0} DC_{15}\left(1+g_{DP}\right)^{1} + FC_{OM} + VC_{OM}\left(1+g_{v}\right)^{15}}{(1+WACC)^{15}} \qquad \text{EQ 5.8.}$$

where DP is the diesel price in the utmost up-scenario at the end of the tree, DC is the consumed diesel in year 15, FC_{OM} is fixed O&M costs, VC_{OM} is variable O&M costs, and g_{DP} and g_V is growth rate and escalation rate of fuel prices and variable costs respectively, while $WACC$ is the weighted average cost of capital that were applied in chapter 3 as well. Similarly, the remaining lifetime OPEX in the node corresponding to 13 up-movements are:

$$S_{u13,d0} = PV\left(OPEX_{u13,d0}\right) = \frac{DP_{u13,d0} DC_{14}\left(1+g_{DP}\right)^{1} + FC_{OM} + VC_{OM}\left(1+g_{v}\right)^{14}}{(1+WACC)^{14}} + \frac{DP_{u13,d0} DC_{15}\left(1+g_{DP}\right)^{2} + FC_{OM} + VC_{OM}\left(1+g_{v}\right)^{15}}{(1+WACC)^{15}} \qquad \text{EQ 5.9.}$$

The assumption for the underlying asset value is thus that, if the telco tower operator replaces the diesel generator in year 14, the diesel generator OPEX savings are the sum of remaining operating expenditures, for which the diesel price will grow at the constant rate g_{DP} until the end of the economic lifetime from the price observed at node in the binomial lattice at which the decision to replace was taken. To generalize, the underlying asset value at each node, $S_{t,u,d}$, will be calculated as:

$$S_{t,u,d} = PV\left(OPEX_{t,u,d}\right) = \sum_{\substack{t=1 \\ u=0 \\ d=0}}^{T} DP_{t,u,d} \left[\frac{DC_t\left(1+g_{DP}\right)^{1} + FC_{OM} + VC_{OM}\left(1+g_{v}\right)^{t}}{(1+WACC)^{t}} + \cdots + \frac{DC_t\left(1+g_{DP}\right)^{T-t+1} + FC_{OM} + VC_{OM}\left(1+g_{v}\right)^{T}}{(1+WACC)^{T}}\right] \qquad \text{EQ 5.10.}$$

where $u = 1, 2, \ldots, T$ and $d = 1, 2, \ldots, T$ so that $u+d = t-1$.

5.3.3.2. Strike Price

In the section on real option definition, the strike price known from financial options was analogized as the present value of investment outlays needed to "reach", or gain the underlying asset. This analogy is straightforwardly applied to the present case through following argumentation. To save the present value of operating the diesel generator for the remainder of its lifetime, naturally, one has to stop the operation while continuously providing electricity to the telecommunication. This is exactly what the fuel cell can fulfill at the cost of buying, installing, and operating the fuel cell. Therefore,

> *the strike price is defined as the lifetime cost, CAPEX, and OPEX, during the period for which the diesel generator would have been running otherwise.*

This definition implies that the model does not include expenses incurred after year 15, which is the final year of operation for the diesel generator. This assumption seems valid; in order for the fuel cell to make an economic sensible acquisition, the total cost of ownership should be lower for the given period, compared to keeping the diesel generator already in place.

As the option approaches its expiration in year 15, the present value of the strike price will decrease, not only due to the time value of money (and fewer years left of incurred operating expenses), but also due to the decreasing production costs which is a direct a result of the learning effects that we estimated in chapter 4. While the strike price for financial options are usually constant, varying strike prices are not uncommon for real options. In a real put option setting, Kodukula & Papudesu (2006: 108-110), depict an example in which the strike price is defined as the salvage value of radio frequency identification hardware, for which the value decreases as the option is kept alive. Conveniently, the binomial lattice model is can easily be adjusted to accommodate the falling strike price, which we will calculate through the following:

$$X_t=PV(CAPEX+OPEX)=\frac{Prod(1\text{-}lr)^{t\text{-}1}(1+M)+Inst+\sum_{t=1}^{T} VC_{OM}\left(1+g_{VC}\right)^{T\text{-}t+1}+FC_{OM}+FP\left(1+g_{FP}\right)^{t}}{(1+WACC)^{t}} \quad \text{EQ 5.11.}$$

where *Prod* is the initial production costs estimated in chapter 3, *LR* is the yearly learning rate of approximately 6.5%, *M* is the markup of 28%, *Inst* is the installation costs amounting to USD 2,500, VC_{OM} is variable O&M costs cell (which will not start to escalate until the option is exercised), FC_{OM}

is fixed O&M, *FP* is the fuel costs, and g_{VC} and g_{FP} are growth rates for variable O&M costs and fuel costs respectively.

As it has been explained in estimation of learning effects, the learning rate accounts for the percentage cost decreases at each doubling in cumulative capacity. Now, just as it is difficult to forecast fuel prices, it is probably harder to predict installed (cumulative) capacity in the future. Nevertheless, the options framework looks 15 years forward for which reason an estimate is necessary for how the learning rate helps to decrease costs of the fuel cell system. Performing an exponential regression on the 1995-2014 period of cumulative capacity, a growth rate of 19.42% is achieved (with intercept 3.91 MW and R^2 of 91%). While this is a crude, but easy way to analyze the trend, it helps to estimate the historic doubling time of capacity, a predictor for the future 15 years in this model. Using Klein's (2001) mathematical methods for economics, we find that the growth rate, δ, and doubling time, τ, such that

$$e^{\delta\tau} = 2 \Leftrightarrow \tau = \frac{\ln(2)}{\delta} \qquad \text{EQ 5.12.}$$

Solving for doubling time, τ, yields 3.569, which in turn is used to annualize the learning rate. As a final note on the strike price, one should acknowledge that the learning rate does not impact the total CAPEX of the fuel cell system per se. As we showed in chapter 3 the total CAPEX of the fuel cell amounts to just above 18,000 USD—a cost figure that includes markup of 28% and installation costs of 2,500. Logically, there are no learning effects associated with markups and while it may be the case for installation costs it is assumed to be zero in our model. Consequently, the learning rate will only cause a decrease in the true costs of production, which we in chapter 3 estimated to be 12,157 USD.

5.3.3.3. Time to Expiration

For the real option, the expiration date is, theoretically, how long the holder of the option is able to push the decision to excise or abandon the option, depending on whether or not the option carries any value. For the telco tower operator, this will be the last year of operation for the diesel generator i.e. year 15. As explained, the generator is assumed to have an economic lifetime of 15 years, which implies that in the following year, year 16, the telco tower operator faces a new decision to buy either a new generator or a fuel cell. This decision is not covered in this thesis, and therefore, the expiration date of the option is the first day of year 15 where capital expenditures are assumed to be incurred.

5.3.3.4. Risk Free Rate of Return

Following Kodukula & Papudesu (2006), the risk-free annual interest rate should be determined on the basis of the U.S Treasury spot rate of return with the maturity equivalent to the time to expiration for the real option. For the calculations in this thesis, we will use the Indian Government 15-year bond rate of 7.93% as observed at the time of writing, May 7, 2016 (Trading Economics 2016), which was also used for the WACC in the LCOE calculations in chapter 3.

5.3.3.5. Volatility

From the discussion of financial theory and real options it should be clear that managers need not fear uncertainty, but rather welcome it as opportunity. In the LCOE model, a constant growth rate of diesel prices is assumed based upon historical costs in India. Now, looking fifteen years ahead and valuing the option to replace the diesel, one major parameter is the volatility. Whereas the LCOE framework models one scenario in which fuel prices grow at a constant rate, options theory enables uncertainty to be used to calculate multiple outcomes based on probabilities. In other words, the base case LCOE predicts diesel prices to grow constantly. Applicable to both diesel prices and commodity markets in general, prices are not easy to forecast in practice and do not unanimously follow simple growth rates. For example, Wiser and colleagues (2004: 343) comment that "fuel price risk is among the most significant risks in the electricity industry". Because the backup power generators burn diesel to empower the telco towers, the operators are exposed to uncertainty in diesel prices. As it has been established in the LCOE model, the cost of a diesel generator is heavily dependent its fuel expenditure in the base case scenario. Therefore, fuel volatility is an important parameter to consider.

In Tsay's (2010: 111) book on financial time series, he mentions that "although volatility is not directly observable, it has some characteristics that are commonly seen." Particularly, volatility clusters so that returns may be high in some periods and low in other periods. Secondly, volatility evolves continuously over time, which generally will prevent unreasonable spikes and jumps. Thirdly, volatility is usually described by a stationary process. Fourthly, volatility usually reacts differently to large increases or decreases in the underlying asset. The final characteristic is sometimes referred to as the leverage effect. In the literature, many different models are presented to estimate volatility on financial instruments and commodities, yet it is outside the scope of this thesis to evaluate how *all* the models differ. While the literature is ambiguous on the optimal, two popular models of volatility clustering are the autoregressive conditional heteroscedasticity (ARCH) and generalized ARCH (GARCH) models (Stock &

Watson 2012). The next two sections will firstly present the theoretical framework of those and secondly apply them in order to estimate a volatility.

5.3.3.5.1. Frameworks for Volatility Estimation

Robert Engle's ARCH framework from 1982 provides a systematic model for volatility prediction. Whilst theory of econometric time series forecasting cannot be explained in one short subsection, the basic idea is that (a) the shock a_t of an asset or commodity return is serially uncorrelated, but dependent, and (b) the dependence of a_t can be described by its past squared values. Specifically, an ARCH model of order *p*, denoted ARCH(*p*), assumes that (Tsay 2010, Stock & Watson 2012):

$$a_t = \sigma_t \varepsilon_t \, , \; \sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \alpha_2 a_{t-2}^2 + \ldots + \alpha_p a_{t-p}^2 \qquad \text{EQ 5.12}$$

where α_0, α_1, …, α_p are unknown coefficients, and $\{\varepsilon_t\}$ is a sequent of independent and identically distributed (i.i.d.) random variables, that is, normally distributed with mean zero and variance 1. It follows that large squared shocks will necessitate a large conditional variance σ_t^2 on α_p. From Tsay's characteristics above, volatility clustering can essentially occur because of this, that is, one (large) shock tend to be followed by another. Such feature might be argued as a weakness of ARCH models. Because positive and negative returns are squared, they have the same effects on volatility, which is not necessarily the case for stocks or commodities in practice. Another weakness is the fact that an ARCH model is only a mechanical way of analyzing the conditional variance and its behavior, failing to explain the reason for such behavior. In addition, Tsay also argues that ARCH models can overestimate volatility when large shocks occur in the return series.

While ARCH models provide a somewhat straightforward framework to predict volatility (particularly with the help of modern statistical software packages), a useful generalization of Engle's mechanics is the GARCH model developed by Bollerslev in 1986. In addition to the dependence of σ_t^2 on its squared errors, Bollerslev lets the variance depend on its own lags too. Thus, the GARCH(*p*,*q*) model can be written as:

$$\sigma_t^2 = \boldsymbol{\omega}_0 + \alpha_1 a_{t-1}^2 + \ldots + \alpha_p a_{t-p}^2 \; + \; \boldsymbol{\phi}_1 \boldsymbol{\sigma}_{t-1}^2 + \ldots + \boldsymbol{\phi}_p \boldsymbol{\sigma}_{t-p}^2 \qquad \text{EQ 5.13}$$

where ω_0, α_1, …, α_p, Φ_1, …, Φ_q are unknown coefficients. By incorporating dependence of the variance on its past squared lags, Stock & Watson (2012) argue that a GARCH model can capture slowly changing variances more efficiently than Engle's ARCH model, that is, essentially with fewer parameters. While equation 5.13 specifies the traditional GARCH model, its family is large and includes many different functional specifications (e.g. exponential GARCH or threshold GARCH). This thesis will only use the basic model.

Most importantly, ARCH and GARCH allow for application in returns time series in which time-varying volatility can be observed and estimated. As in financial markets for stocks, empirical data is available for commodities to be applied. Wang & Wu (2012) investigate the use of GARCH and show substantial use of its various specifications in energy markets. For example, Sadorsky (2006) finds evidence for fitting a GARCH(1,1) model on crude and unleaded gasoline volatilities, while others (see e.g. Kuen & Hoong 1992 or Walsh & Tsou 1998) recommend other models. In other words, empirical evidence from the literature supports the idea that it is no trivial and effortless task to predict volatility accurately. As in any model, the result is only as good as its underlying assumptions. In the following subsection, an ARCH and a GARCH model is set up to help estimating a volatility for diesel fuel. With rather preliminary theory established on the regressions, the section will elaborate on constraints and explanatory power of the models in practice, ultimately yielding the input for the real options model.

5.3.3.5.2. Estimation of USLD Volatility

Having investigated the econometric specifications of ARCH and GARCH models briefly, it also becomes clear that other approaches exist. Indeed, forecasting uncertainty is a risky endeavor. In the LCOE model, the backup generator runs on diesel, which is the input for estimation here. As there is only limited data available for diesel as a commodity in an Indian setting, the analysis is based on historical spot prices of the New York Harbor Ultra-Low-Sulfur No. 2 Diesel Fuel. The United States Energy Information Administration (EIA) provides daily, weekly, and annual data since 2006, which is not optimal, yet sufficient to be analyzed. Also, it is reasonable well aligned with data used in the LCOE model. Here, a constant growth of approximately 7% (IndianOil 2016) is employed over the diesel generator's lifetime; an assumption which will be significantly challenged by the estimation of volatility here.

First, a general understanding of the uncertainty is derived below. Returns are calculated as a continuously compounding series from differences in daily natural logarithms.

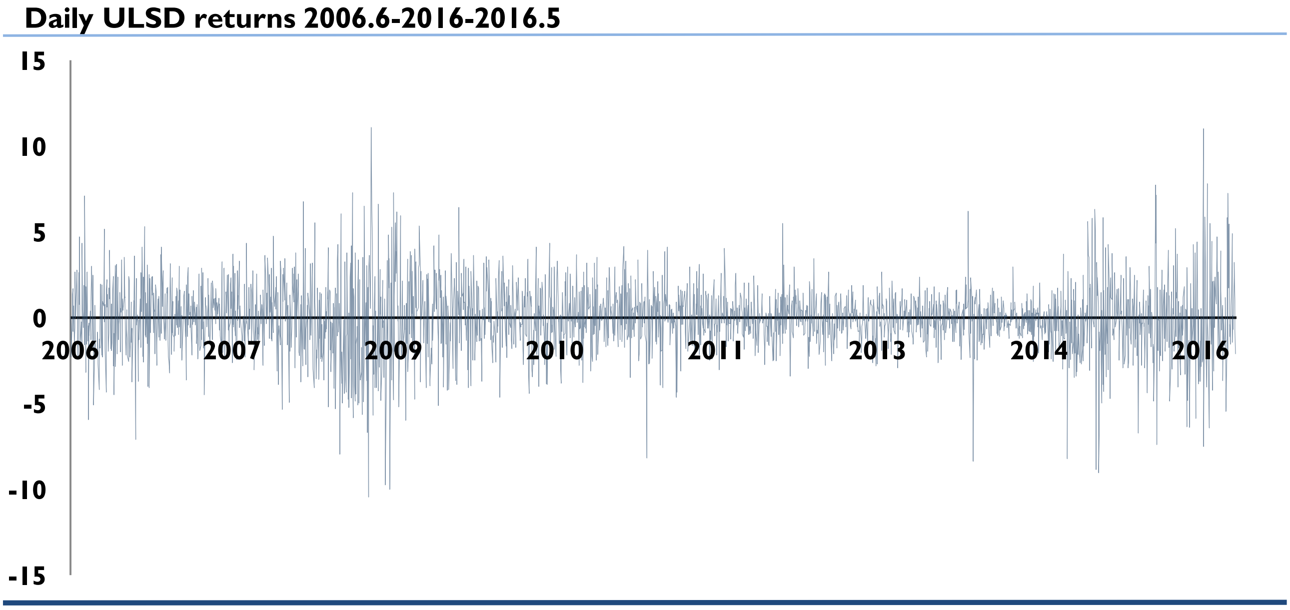

Figure 5.4. Daily ULSD returns 2006.6-2016.5. Sources: EIA (2016) and own work.

The time series seems to be characterized by somewhat random, rapid changes in the returns and is described as volatile (or exhibiting white noise). In addition, it seems that the data shows some degree of time-varying volatility. Nevertheless, the initial graph does not reveal much about its statistical significance, if any. Using Stata to generate the series' empirical distribution of returns, a histogram shows signs of leptokurtosis. In other words, the data exhibits many returns around the mean and also a relatively large number of observations far from the center of the histogram.

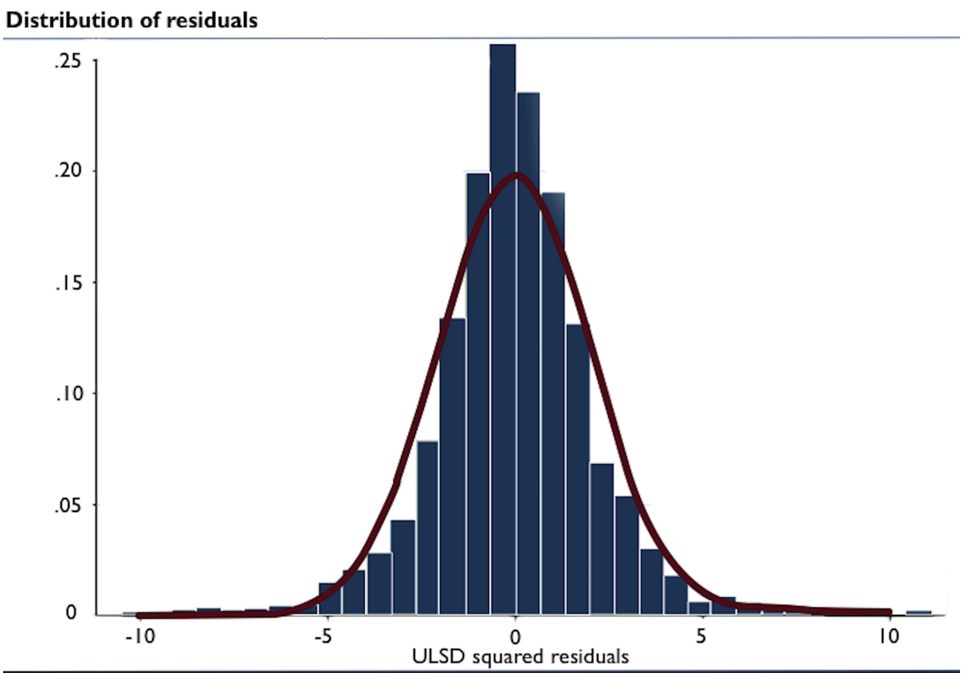

Figure 5.5: Distribution of residuals. Source: Own work.

Utilizing a Lagrange Multiplier (LM) test, it is then hypothesized that no ARCH effects exist. Having stated the mean equation in Stata and subsequently squared the estimated return residuals, the test statistic indicates that we fail to reject the alternative hypothesis, that is, ARCH effects are present.

ARCH-LM test

Test	**Lags**	**Null Hypothesis**	**Statistics**	***p*-Value**
ARCH-LM	0	No ARCH Effects	χ^2 = 80.048	0.0000

Table 5.3: ARCH-LM test. Source: Own work.

Next, we run ARCH(1) and GARCH(1,1) models in Stata and generate the following output:

ARCH and GARCH Results

Parameter	ARCH(1)	GARCH(1,1)
Omega, ω	N/A	0.017535*
Alpha, α_1	0.251157*	0.051252*
Phi, Φ_1	N/A	0.945852*
Annualized Volatility	**31.8788%**	**30.5167%**

*Table 5.4: ARCH and GARCH Results. *Coefficients statistically significant at a 1% level. Source: Own work.*

We observe that both models report highly, statistically significant coefficients at a 1% level. As daily data is used, the (daily) mean fits for ARCH(1) and GARCH(1,1) are annualized by factor √Δt = √(252), as there are 252 points of spot prices annually. In terms of validity, Engle (2001) comments that the sum of coefficients α_1 and Φ_1 (= 0.997) must be less than one in the GARCH model. In addition, from Engle's calculation of the long-run average variance, $[\omega - (1–\alpha–\Phi)]^{½}$, is estimated at 2.46%, or approximately 39% annualized. Altogether, both models exhibit signs of time-varying volatility, as it can be seen in the plots on variances below.

ARCH (1)

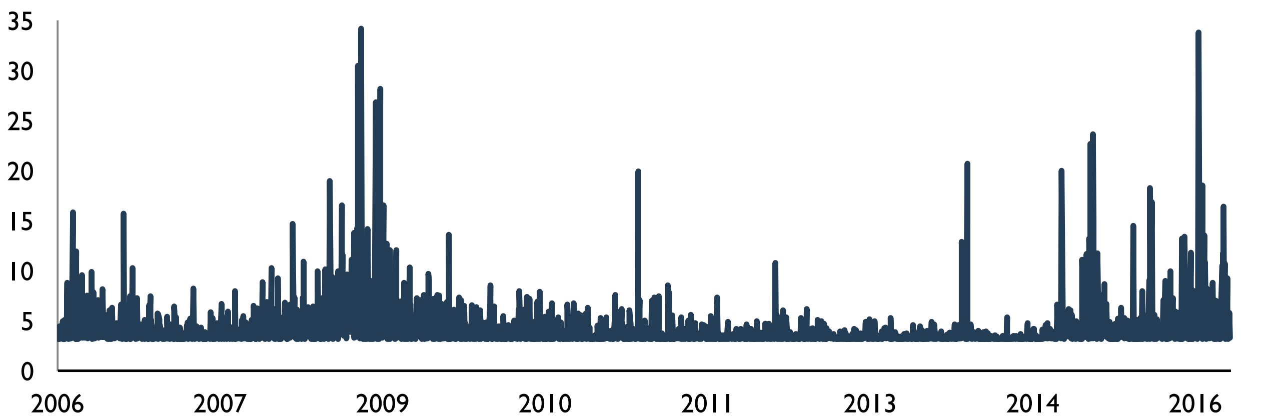

Figure 5.6: ARCH (1). Sources: EIA (2016) and own work.

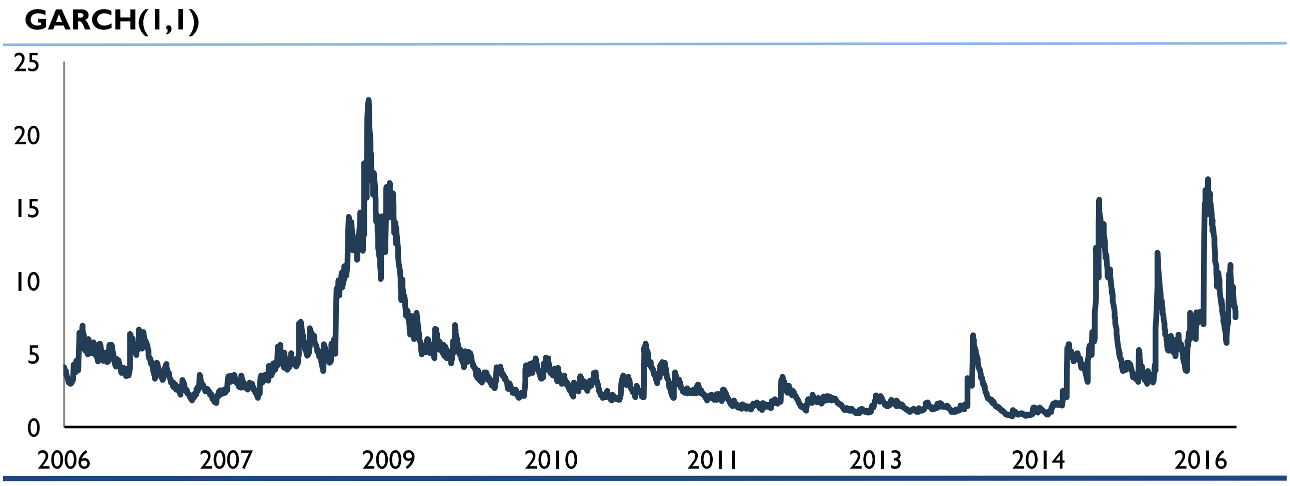

Figure 5.7: GARCH(1,1). Sources: EIA (2016) and own work.

It is possible that certain commodities might exhibit signs of seasonality in their return volatility, yet the approach here relies on the basic GARCH(1,1) model for the option input (and not e.g. a p-GARCH specification). From the analyzed data, returns on ULSD exhibit clear volatility, and the specification here finds an estimate of 30.50% to be implemented in the real options. As this is a rather significant input into the real options model, sensitivity analysis on this estimate will also be carried out.

5.4. Calculating the Real Option Value

Table 5.5 presents the calculations of the real option value to replace the diesel generator with a fuel cell, a choice of flexibility which is readily available to the Indian telco tower operator. The calculations have been carried out using the binomial lattice valuation model and are computed in Microsoft Excel. The upper figure shows the evolution in the strike price, that is, the total present value cost of ownership of the fuel cell from time 0 to the remainder of the economic time frame i.e. year 15. Naturally, the present value is decreasing from period to period due to discounting, but also a result of the effects of learning on production that we have explained previously.

The option is valued in a 14-step lattice with 1-year increments as shown in the table. In practice it means that the telco tower operator evaluates the choice to replace the diesel generator on the first day of each year starting on the first day of year 1. Recall that, in our model, year 0 is "yesterday" in which the diesel generator is assumed to have been bought, thus not presenting the telco tower operator with any choice. One assumption, which albeit rather unrealistic impacts the calculations to a small extend, is that the fuel cell can be bought and start to operate immediately. In reality one would expect some lead time from the point in time in which the decision to replace the diesel generator until the fuel cell is up and running; this lead time has been disregarded for simplicity (supported by DPS who argue that lead time can be as little as a few hours).

The table below presents the binomial grid. Note the difference between figure 5.5. that shows a regular of a binomial lattice where up and down movements are depicted by "north east" movements and "south east" movements respectively. Our model, presented in table 5.5, shall be interpreted slightly differently; a horizontal move towards east represents one *up*-movement, while a diagonal (south east) move represents a *down* movement.

Each of the cells contain two figures; the underlying asset value (upper figure) and the value of the option (lower figure). The binomial lattice is constructed by calculating the value of the underlying in each node using Equation 5.10. which is in turn based on the path of the diesel price through the grid depending on *up* and *down* movements as shown in appendix 3.

5.4.1 Results of the Real Option Model

The value of the flexibility choice presented to the telco tower operator as of the first day of operation i.e. the first day of year one is found in the left-most cell in the binomial lattice. Evidently, the underlying asset value (upper figure) is lower than the strike price which resembles to the findings of chapter 3; at present, the diesel generator, with today's best forecast of future fuel prices, is less expensive to operate during its lifetime compared to the fuel cell. The value, 12,986 USD is the total lifetime cost of operating the diesel generator a figure which is substantially lower than the total lifetime cost of buying and operating the fuel cell (25,505 USD).

The lower figure in the left-most cell in the lattice is reported as 641,73 USD in present values. This is the value of the flexibility that the telco tower operator has in choosing either to continue operation of the diesel generator or to replace it with the fuel cell. To put the option value into perspective, 642 USD corresponds to a decrease of 5 percent in the true cost of operating the diesel generator since now the value of the flexibility is taken into account as well.

Notably, as one moves through the lattice, in some instances the strike price actually falls below the value of the underlying asset meaning that the cost of operating the diesel generator for the remainder of its lifetime now becomes more expensive than buying and operating the fuel cell, focusing solely on the remainder of the economic lifetime of the generator. This is primarily due to high levels of diesel prices and secondarily a result of the learning effects of producing the fuel cell that translates to a lower strike price.

To be more specific, in year 4, after three consecutive *up*-movements in the diesel price, the value of the underlying asset lies above the strike price implying that it will make economic sense to install the fuel cell system. Nonetheless, at this particular node, the value of keeping the option alive is greater and is it thus not exercised. However, in the rather unlikely case of five consecutive *up*-movements which corresponds to year 6 in the lattice, the value of the underlying asset less the strike price becomes greater than the value of keeping the option alive. To the operator, this means that the generator should in fact be replaced in year 6 by the fuel cell. The exact diesel prices at the end of the period and its associated probabilities are shown at the right-most column of the table and indicate the low probabilities of diesel prices reaching extreme levels. For reference, probability distributions throughout the option's time to expiration are shown in appendix 4.

One should also acknowledge that for a large part of the binomial tree the option stops to carry any value, which happens for the first time in the case of four consecutive *down*-movements in the diesel price. The implication of the option no longer carrying any value is that the operator can simply disregard the fuel cell choice for the remainder of the operating diesel generator lifetime. The complete set of optimal decisions is presented in table 5.6.

PEMFC life-time costs	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	
Strike price		25,025	20,695	17,112	14,143	11,677	9,627	7,919	6,494	5,302	4,304	3,467	2,763	2,170	1,670	1,247	
ROV	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	P[Outcome] and diesel price
Underlying asset value		12,986.19	14,008.91	14,686.48	15,556.59	16,590.08	17,745.71	18,964.68	20,163.52	21,224.70	21,984.45	22,426.94	21,612.91	19,753.93	16,076.18	9,825.77	0.02%
Option value		**641.73**	**1,078.30**	**1,802.04**	**2,994.41**	**4,946.09**	**8,118.90**	**11,045.84**	**13,669.98**	**15,922.72**	**17,680.42**	**18,960.27**	**18,850.13**	**17,583.97**	**14,406.43**	**8,578.85**	508.40
			9,547.66	9,620.19	9,836.13	10,174.52	10,608.52	11,102.33	11,607.27	12,056.59	12,358.82	12,599.17	11,977.58	10,895.30	8,834.60	5,384.73	0.19%
			211.56	**367.88**	**636.37**	**1,094.75**	**1,872.45**	**3,183.50**	**5,113.73**	**6,754.61**	**8,054.79**	**9,132.49**	**9,214.80**	**8,725.35**	**7,164.84**	**4,137.81**	276.15
				6,868.33	6,728.95	6,689.79	6,731.82	6,831.75	6,959.78	7,076.75	7,130.48	7,261.03	6,743.96	6,083.57	4,901.19	2,972.50	1.03%
				54.14	**98.33**	**177.73**	**319.44**	**570.44**	**1,010.85**	**1,774.77**	**2,826.45**	**3,794.35**	**3,981.19**	**3,913.61**	**3,231.44**	**1,725.58**	149.99
					5,041.23	4,797.00	4,626.12	4,512.10	4,435.40	4,371.86	4,290.60	4,361.51	3,901.23	3,469.98	2,764.69	1,662.25	3.55%
					8.59	**16.68**	**32.39**	**62.90**	**122.16**	**237.25**	**460.76**	**894.83**	**1,138.45**	**1,300.03**	**1,094.94**	**415.33**	81.47
						3,768.89	3,482.37	3,252.14	3,064.24	2,902.65	2,748.07	2,786.59	2,357.14	2,050.37	1,604.21	950.57	8.45%
						0.00	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	44.25
							2,861.12	2,567.77	2,319.47	2,104.62	1,910.21	1,931.14	1,518.44	1,279.27	973.87	564.00	14.77%
							0.00	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	24.04
								2,196.04	1,914.93	1,671.15	1,455.12	1,466.48	1,062.89	860.44	631.49	354.03	19.54%
								0.00	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	13.06
									1,695.20	1,435.71	1,207.92	1,214.10	815.44	632.94	445.52	239.98	19.95%
									0.00	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	7.09
										1,307.82	1,073.65	1,077.01	681.04	509.37	344.51	178.03	15.84%
										0.00	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	3.85
											1,000.72	1,002.55	608.04	442.26	289.64	144.38	9.79%
											0.00	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	2.09
												962.10	568.38	405.80	259.84	126.11	4.66%
												0.00	**0.00**	**0.00**	**0.00**	**0.00**	1.14
													546.84	386.00	243.65	116.18	1.68%
													0.00	**0.00**	**0.00**	**0.00**	0.62
														375.24	234.86	110.79	0.45%
														0.00	**0.00**	**0.00**	0.34
															230.08	107.86	0.08%
															0.00	**0.00**	0.18
																106.27	0.01%
																0.00	0.10

Binomial lattice parameters	
Volatility	30.52%
Diesel price t=0	6.63
Time step (years)	1
Expiration (T)	15
Up-movement (u)	1.357
Down-movement (d)	0.737
Risk neutral prob. (p)	0.557
Risk-free rate (r)	7.93%

Table 5.5: Real Options Valuation. Source: Own work.

Decision tree

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
"Yesterday"	WAIT	WAIT	WAIT	WAIT	WAIT	REPLACE	REPLACE	REPLACE	REPLACE	REPLACE	REPLACE	REPLACE	REPLACE	REPLACE	REPLACE
		WAIT	WAIT	WAIT	WAIT	WAIT	REPLACE	REPLACE	REPLACE	REPLACE	REPLACE	REPLACE	REPLACE	REPLACE	REPLACE
			WAIT	WAIT	WAIT	WAIT	WAIT	WAIT	REPLACE	REPLACE	REPLACE	REPLACE	REPLACE	REPLACE	REPLACE
				WAIT	WAIT	WAIT	WAIT	WAIT	WAIT	WAIT	REPLACE	REPLACE	REPLACE	REPLACE	REPLACE
					NO VALUE	NO VALUE	NO VALUE	NO VALUE	NO VALUE	NO VALUE	NO VALUE	NO VALUE	NO VALUE	NO VALUE	NO VALUE
						NO VALUE	NO VALUE	NO VALUE	NO VALUE	NO VALUE	NO VALUE	NO VALUE	NO VALUE	NO VALUE	NO VALUE
							NO VALUE	NO VALUE	NO VALUE	NO VALUE	NO VALUE	NO VALUE	NO VALUE	NO VALUE	NO VALUE
								NO VALUE	NO VALUE	NO VALUE	NO VALUE	NO VALUE	NO VALUE	NO VALUE	NO VALUE
									NO VALUE	NO VALUE	NO VALUE	NO VALUE	NO VALUE	NO VALUE	NO VALUE
										NO VALUE	NO VALUE	NO VALUE	NO VALUE	NO VALUE	NO VALUE
											NO VALUE	NO VALUE	NO VALUE	NO VALUE	NO VALUE
												NO VALUE	NO VALUE	NO VALUE	NO VALUE
													NO VALUE	NO VALUE	NO VALUE
														NO VALUE	NO VALUE
															NO VALUE

Table 5.6: Decision tree. Source: Own work.

5.4.2 Real Option Sensitivity Analysis

Having established the main results of the base case real option valuation, we now turn to a sensitivity analysis of the impact on the option value of (some) the most important inputs. While endless scenarios could be analyzed, it has been found most relevant to focus on the three main inputs to the calculations; (1) the effects of learning, (2) the volatility of diesel prices, and (3) the weighted average cost of capital.

5.4.2.1. Effects of Learning

Defining, reviewing, and estimating the effects of learning have constituted a big role in this thesis. Being a technology in an infant stage of commercialization, it has been of great interest to analyze the impact on potential diffusion of the fuel cell system and specifically its impact on the decision to replace diesel generators with fuel cells in the Indian telecommunication tower case presented here. The effects of learning play its part through decreasing the strike price in the real option model as costs of production decreases along with increases in the cumulative capacity of installed HT PEM fuel cell systems. In figure 5.8 below we graph the real option value at the commencement of operation in year 1 as a function of yearly learning rate keeping every other assumption constant from the base case.

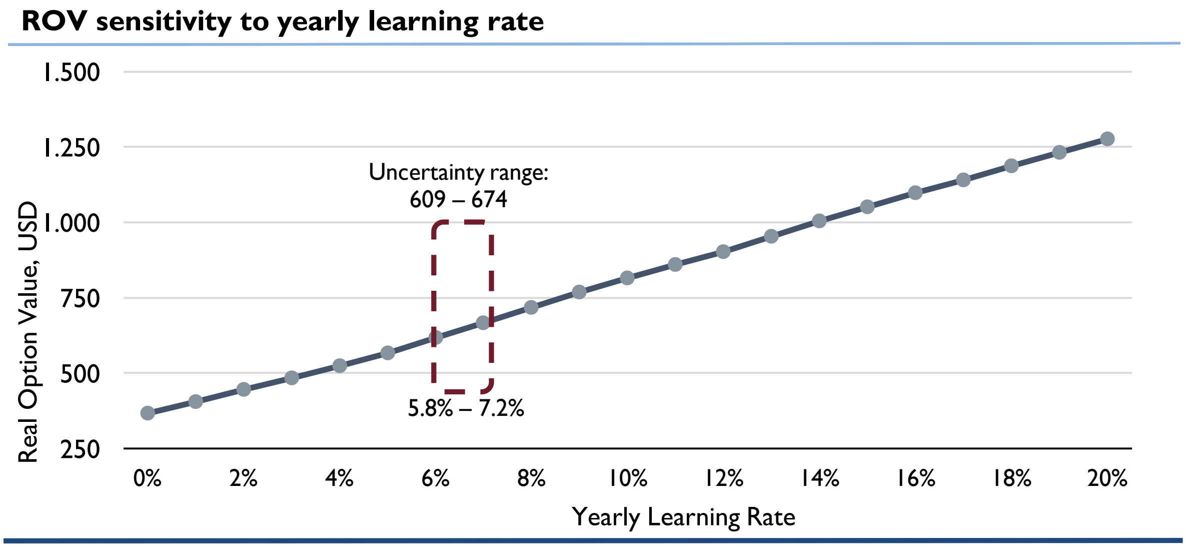

Figure 5.8: ROV sensitivity to yearly learning rate. Source: own work.

As an additional feature, the uncertainty of the learning rate estimations in chapter 4 is included in the table. The yearly learning rate uncertainty range between 5.8 – 7.2 percent implies a real option value of 609 (lower bound) to 674 (upper bound). The yearly learning rate is of course a function on how fast the cumulative capacity of HT PEM fuel cells doubles, which can be very hard to forecast. As seen in the figure, extreme levels of learning rates approaching 20% a year would impact the real option value significantly but must be concluded as rather unrealistic.

5.4.2.2. Diesel Price Volatility

The biggest single cost component of operating the diesel generator was found to be the diesel fuel. Accordingly, the value of the underlying asset has been assumed to move in tandem with volatility in diesel prices since the other cost components of operation, fixed and variable O&M costs, are more straightforward to forecast. Consequently, it is of particular interest to analyze the impact on the option value of changes in the estimated diesel price volatility. As the figure below shows, the option value is quite sensitive to the volatility input which should be to no surprise. The higher the volatility in fuel prices, the higher the uncertainty, and hence a higher value of the real option. As it has been discussed in the theory of financial and real options, uncertainty about future outcomes will necessarily generate option value to defer a decision. Associating higher volatility with diesel fuel prices makes knowledge about tomorrow and the rest of the lifetime less certain. Hence, it becomes increasingly more valuable to have the opportunity to replace the conventional backup system with a fuel cell, as volatility in ULSD fuel becomes larger. In another paper, Wang, Wu, and Yang (2016) estimates an annualized volatility for WTI oil just above 50%. At NYU Stern's Volatility Institute (2016), there are similarly historic data for volatility levels at 70% in February 2016 or below 20% during the summer in 2014. Altogether, considering Wong's (2016) correlation between crude oil and ULSD to be as much as 98%, there are support for the fact that different methods yield different results. As in any other real option, the volatility input should thus be evaluated carefully. In the above stated literature, it should also be mentioned that both Wang et al. (2016) and NYU Stern's Volatility Institute (2016) also provide estimates between 30-35%. Although this is in line with the econometric GARCH(1,1) specification in this paper, it should still be challenged. The graph illustrates how the increases in diesel volatility generates notably different values for the option holder and supports the hypothesis that risk (i.e. uncertainty) is rewarding.

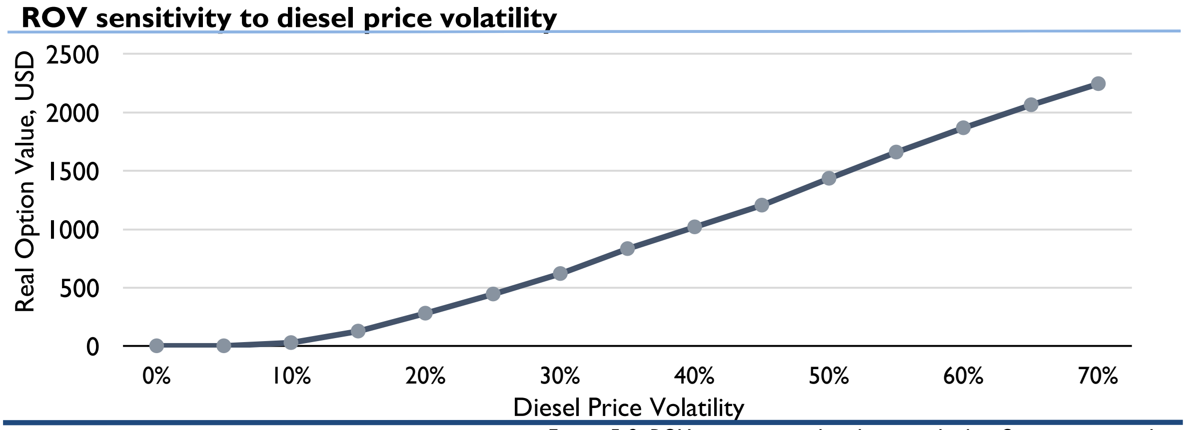

Figure 5.9: ROV sensitivity to diesel price volatility. Source: own work.

5.4.2.3. WACC

Analogous to analysis of the LCOE's sensitivity to the WACC, which was undertaken in chapter 3, we attach a few words to the impact of the cost of capital on the real option value. Increasing the WACC input from 10 to 20 percent implies that the option value drops to one tenth of its value, from 2,284 to a mere 232 USD. As in the LCOE model, such calculation underlines how important an input it is and shows that also the option value is notoriously sensitive to the cost of capital. For this reason, the sensitivity analysis calls for a highly accurate estimation of WACC in projects for Indian telco and tower companies. As it has been outlined in the LCOE framework, this estimate relies on empirical observations and calculations from Damodaran (2016). The applied WACC is based upon companies involved in general telecommunications equipment, which is appropriate for this project, yet the reader should also be aware that such estimate might change continuously and quite possibly be different at the time of reading. Thus, the sensitivity to WACC calls for careful evaluation in order to capture the true option value.

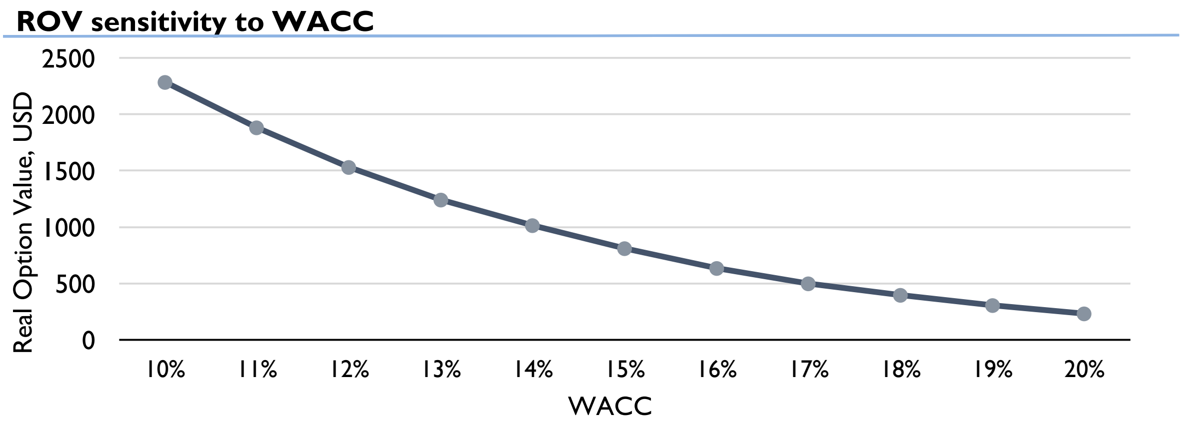

Figure 5.10: ROV sensitivity to WACC. Source: own work.

6. DISCUSSION

Having performed the real option valuation, it is important to consider which implications the results might have, and to which extent the underlying inputs to the framework are true. Therefore, several assumptions will be discussed below. Firstly, the growth rates of diesel and methanol fuel are evaluated. Next, it is questioned whether potential correlation between diesel prices and learning effects might exist, and how one can address the impact of such in the setting within this thesis. Thirdly, an inevitable question arises with regards to a classic chicken and egg problem. Who buys systems first and who waits because expectations are that prices fall, and what are the implications for future levels of effects of learning? Finally, after looking into the extrapolation potential of the results, the real options framework is reviewed to answer whether or not the results are understandable and reasonable.

6.1. Assumptions on Growth in Diesel and Methanol Prices

In our estimation of volatility in diesel fuel, it becomes clear that historical prices follow a path dependent on its past returns, yet the analysis also shows high uncertainty in predicting the future path. In other words, while such estimation can be used to generate value in a real options framework, the calculations in this thesis assume a constant growth rate of fuel prices for the diesel generator's remaining lifetime. In the base case scenario, an annual growth rate of almost 7% is applied. If one had applied a growth equal to the inflation rate instead, which Statista (2016) estimates to average at 8.4% over the recent five years, it would appear that the base case is potentially under-estimating the option value as it is currently calculated—with the effect increasing as remaining lifetime decreases. The chosen growth rate in diesel fuel is based on historical prices—like its volatility too—yet that does not guarantee a predictive outcome of the future. When it all comes to one, it should therefore be explicitly stated here that our option value is contingent on such assumption.

Likewise, the fuel cell needs supply of methanol paid at a market-offered price as for diesel. In the LCOE, historical costs support a calculation of 2.4% as growth rate for Indian methanol prices. This is an important assumption, yet fuel (and hence OPEX) is less significant in the total cost of ownership of the fuel cell system as opposed to that of the diesel generator. In addition, the options framework applied in this thesis is not based upon uncertainty on the operational side of the fuel cell system. Thus, it should be mentioned here that fuel for fuel cells also assumes a growth rate, whose estimate can be challenged, but it is not as crucial for the outcome of the option value as opposed to that of diesel.

6.2. Correlation between Diesel Prices and Learning Effects

How does lower or higher diesel prices affect learning effects? While this thesis does not attempt to estimate the historical relationship between the two, one could be encouraged to think that higher diesel prices lead to more financial viability in installing fuel cells, all else equal. In turn, installing more fuel cells increases the cumulative capacity, which leads to an increase in the learning rate, as production costs are expected to decrease as more systems are manufactured. These spillover effects or linkages are not addressed in the calculation of the replacement option. Rather, disregarding how any change of diesel price might influence cumulative capacity and potentially manufacturing costs, the base case assumes a constantly decreasing strike price based on calculations of historical learning effects. Therefore, the real option might fail to capture the true value in scenarios in which the diesel price increases and thus makes generators comparably less attractive to keep, all else equal. While the authors have not found literature revealing empirical evidence on correlation, or even causality, between learning effects and fuel prices, the discussion reveals that it is an issue, which needs to be addressed. Here, the authors choose to disregard potential correlation, realizing that such assumption might not capture the true relationship. From this discussion, another question arises: a chicken and egg problem.

6.3. Fuel Cells in the Indian Backup Market: A Chicken and Egg Problem?

Learning effects are based and estimated on historical development, and as it is today, Intelligent Energy seems to be among the few to deploy fuel cells at Indian tower sites. The question this section raises addresses whether buyers of fuel cells need to purchase systems for learning to occur or if they wait for learning to happen and then exercise their opportunity to purchase. If potential buyers are in fact waiting for costs to decrease, which the present state might indicate, the question is, will costs fall without fuel cell commercialization happening specifically in the Indian telecommunications and tower markets? To address this chicken and egg problem in this thesis, focus has been on global learning for the PEMFC rather than local learning for manufacturers offering small stationary products to be used in backup power setting. As it is argued in both the technology description and the chapter on learning effects, global progress in PEMFC technology is expected to be applicable for all of its applications despite both transportation and (large) stationary being the primary drivers of cumulative capacity installments. Recall that the physical PEMFC technology (or product) is essentially small cells of membranes stacked to produce and generate the required electricity supply. Thus, the chicken and egg problem is deemed important to address for a holistic view on fuel cell commercialization, yet this thesis draws on global learning to be transferable to local learning for backup systems—an assumption supported by DPS. It could understandably be argued that developing the actual systems intended for backup deployment generates comparably more learning than systems for other purposes. However, among other of their advantages, the technological specification of fuel cell systems and their scalability suggest otherwise.

6.4. Extrapolation of Results

In the real options model, the value of flexibility is calculated only for a single telco tower. An extrapolation can be applied to a larger pool of towers, e.g. so that the option value is quantified for the players in the Indian tower market as a whole. However, such extrapolation should only be interpreted as approximations. While power generation needed for a backup system is defined clearly, i.e. 2.5 kW, it would be unrealistic to assume that levelized costs will be equal for all competitors in the market. Among the thousands of towers, vast differences exist between the amount of base transceiver stations and thus power demand. Therefore, a power demand of 2.5 kW will not apply to all cites but serves as a valuable base case. Nonetheless, if we disregard different power demands and keep the 2.5 kW assumption, the option value can be approximated for each of the major players, as shown below.

Extrapolated option values

Company	Share	Towers	Option Value in mUSD
Indus Towers	31.0%	123,380	79.177
Bharti Infratel	9.8%	39,004	25.030
BSNL	18.2%	72,436	46.484
Reliance	11.6%	46,168	29.627
Viom Networks	11.3%	44,974	28.861
GTL	8.0%	31,840	20.433
Others	4.3%	17,114	10.983
ATC	3.5%	13,930	8.939
Tower Vision	2.3%	9,154	5.874
Total	**100%**	**398,000**	**255**

Table 6.1: Extrapolated option values. Source: Own work.

If every tower in the market applies to the framework developed in this thesis, today's option value for the entire industry is approximated to 255 million USD. On the contrary, as it has just been discussed, if everyone exercised such option simultaneously, increases in cumulative capacity call for decreases in manufacturing costs—also despite each system's relatively small size. In a more realistic scenario, the option value is particularly relevant for a company like GTL who has entered into contract with Intelligent Energy.

6.5. Real Options and the Solution Process: A Call for Redesign?

In Amram & Kulatilaka's (1999: 90) book, one real options academic and practitioner comments that "the more realistic the model, the more time-consuming it is to compute and estimate, and to understand and use intelligently […] If the model becomes too complex, you lose a lot of the intuition", while the authors themselves add that poorly framed applications are often the biggest source of error. The question is then whether real options application in this thesis yields realistic results and an understandable model. Clearly, the latter is perhaps distorted somewhat by the numerous assumptions taken. Nevertheless, the application is framed so that managers in the fuel cell industry as well as in tower or telco can understand it. It is the intention, of course, to implement the option valuation model so that the managers of DPS understand the replacement value of fuel cells in Indian backup power, but the application should also be understandable elsewhere. Amram & Kulatilaka (1999: 98) also refer to the pareto principle and state that "as with most models, the 80/20 rule applies: 80% of the required realism can be obtained by incorporating 20% of the possible real-world features." The authors of this project will not attempt to quantify the realism of assumptions but, as objective outsiders of the industry, inputs are not tailored individually to match a self-fulfilling prophecy in which fuel cells solve India's challenges in backup power. If anything, the objective is to depict the scenario as realistic as possible. With the results of the model, it also becomes clear that uncertainty does generate an embedded options value. In fact, if one sets volatility equal to zero, there are no contingent decisions, and the options value seizes to exist, that is, the value of the running diesel generators is as predicted by the LCOE discounting method. In order to generate *better* results, one can always question the set of investment alternatives. There are potentially other technologies providing better solutions than fuel cells, for example long-lasting batteries. While this is surely possible, this thesis has been shaped by constraints from the collaboration company too and they are, of course, focused on fuel cells primarily. Altogether, the applied options model does not call for redesign within the delimitations proposed in this thesis. On the other hand, however, the authors have chosen to disregard alternative opportunities and methods to be implemented, some of which are discussed in the suggestions for further research subsequent to the conclusion.

7. Conclusion

This concludes the main analysis. The principal focus of this thesis has been to understand how the diffusion of a commercially infant technology may take place. To analyze this rather broad area, we have investigated a particular technology, the HT PEM fuel cell, in the particular setting of the Indian telecommunication tower backup power case. The aim has been to better evaluate the economic choice between the conventional power generation source and the fuel cell technology. Now, having carried out the analysis, the main research question, along with the supportive sub questions, will be concluded upon.

7.1. Sub Question 1: Understanding the Technology and the Telco Market

The first sub question was addressed in chapter 2 and aided the understanding the fuel cell technology and its different applications. It was outlined how a relatively simple chemical reaction between hydrogen and oxygen sparks the energy that the fuel cell converts to readily available electricity. The technology is appropriate in a wide range of applications ranging from large-scale plants powering e.g. entire data-centers and hospitals to powering tiny devices such as smartphones and laptops. Despite numerous applications, it was concluded that the fuel cell technology is yet to experience widespread commercialization while the coming years do seem promising.

Chapter 2 also established the Indian telecommunication market as a particularly relevant case to investigate. The relevance of the Indian case was supported by three main factors. Firstly, the recent multi-billion-dollar deal between Intelligent Energy and the telco tower operator GLT Limited indicates that some degree of economic rationale behind installing fuel cells as a backup power solution must exist. Secondly, it was shown that while India is one of the biggest telecommunication markets with more than 1 billion active subscriptions, 70% of all telco towers that should support the telecommunication infrastructure experience power outages of more than eight hours per day. Lastly, despite being one of the biggest markets, the Indian telecommunication market is expected to experience continuing growth in the coming years thus creating an increasing demand for power generation sources.

7.2. Sub Question 2: LCOE Estimates for PEMFC and DG

The second sub question addressed the important question on how the fuel cell system is stacking up against the conventional power generation source i.e. a standard diesel generator in terms of the associated costs. The first and foremost barrier to widespread adoption of the fuel cell technology has been the costs of producing the system due to expensive materials and processes. In chapter 3, it was concluded that PEM fuel cells are, albeit relatively inexpensive to operate, much more expensive to produce than diesel generators and thus much more expensive to buy as an end-user (telco tower operator). The analysis was based on the levelized cost of energy model, a well-known framework of comparing different energy sources through which the cost of each delivered mega-watt-hour can be compared. The comparison concluded that the LCOE of the fuel cell system during its 15-year economic lifetime is 311 USD per MWh corresponding to a total present value cost of ownership of 25,025 USD. As the thesis analyzes the choice to *replace* the diesel generator, these figures were compared to the OPEX of the generator that amounts to 161 USD per MWh, or 12,986 USD in present values.

7.3. Sub Question 3: PEMFC Learning Effects

Inherent in all types of manufacturing, and especially relevant in the case of infant technologies, learning from repetitive production should result in more efficient and cost effective production. This assumption, defined as the effects of learning, was investigated in chapter 4 in order to answer the third sub question; how can learning effects from PEM fuel cell production be quantified? In answering this question, it was firstly studied how previous works on the estimations of learning rates for other energy technologies could provide insights into the learning effects of fuel cells. Then, secondly, we estimated the learning rate for PEM fuel cells specifically based on the global cumulative installed capacity and historical cost figures obtained in the literature. The estimations resulted in a learning rate of 23.15% for each doubling in cumulative capacity.

7.4. Sub Question 4: Real Options Modeling with Diesel Volatility

The last sub question was addressed in chapter 5, which modelled the real option based on inputs from both the LCOE model in chapter 3 and the estimated learning rate in chapter 4. Originating from the sphere of financial options valuation, the real options setting was found to present decision makers with a more nuanced picture of future decisions and to estimate costs with a higher level of precision. Specifically, the possible OPEX savings related to replacing the diesel generator with a fuel cell system was defined as the underlying asset with total cost of ownership of the fuel cell system acting as the strike price. The learning rate of fuel cell production implied a decreasing strike price and with substantial volatility in diesel prices, the value of the underlying asset could rise to remarkable levels. In concluding, the real option model showed that the flexibility of backup power generation source does add value to the operator through a decrease in the true cost of powering the telecommunication towers.

7.5. Main RQ Conclusion: LCOE and Learning Effects Applied into an ROV Model

Finally, we will conclude on the main research question. The first finding of this thesis is that the Indian telecommunication market postulates an interesting case for fuel cells as a backup power source to telco tower due to both long periods of grid outages and future growth potential. The second finding confirms the well-established perception of the current state of the PEMFCs that they are very expensive to produce but relatively inexpensive to operate. Currently, from an economic point of view, the conventional diesel generator should be the choice of backup power solution as it, still, provides the cheapest total lifetime cost of ownership. Thirdly, it is concluded that the PEM fuel cell technology has exhibited a learning rate of 23.15% during the past few years and continuing decrease in the costs of production will be one of the important catalysts for wide-spread commercialization.

The main object of the thesis, to apply the conclusions above in a real option context resulted in an option value of 642 USD thus quantifying the flexibility of choice of backup power. As of today, the PEM fuel cell technology remains unable to compete with the conventional source of backup power but, as the preceding analysis shows, the PEMFCs may be subject to technological diffusion in years to come, should diesel prices and learning rate reach levels favorable to the high temperature proton exchange membrane fuel cell.

7.6. Suggestions for Further Research

In this thesis, research is carried out to show how theories of economics and finance can help managers of Danish Power Systems to understand the value of fuel cells in the Indian telecommunications and tower markets. Building on three major frameworks of (*i*) LCOE modeling, (*ii*) learning estimation, and (*iii*) real options valuation, the thesis shows that delimitation has been necessary too. Therefore, certain extensions and opportunities are not captured here but rather suggested for future work.

(*i*) Within the LCOE framework, possible extensions include a market-modifying model in which the traditional WACC is challenged. As it is discussed in section 3.6., levelized costs could benefit from discounting fuel costs, other risk-free costs, debt equivalent costs, and cyclical costs separately. Indeed, the LCOE is notoriously sensitive to discounting for which reason the findings support a closer look to the value of such benefits.

(*ii*) Secondly, the estimated learning effects are based on the transportation sector in this thesis. While it might be a challenge to collect sufficient data on the global cost development and cumulative capacity within small stationary application of PEMFCs, it is also possible to carry out the model at the manufacturer's level and yield comparable results. As DPS provides inputs for the actual fuel cell manufacturer, it could be valuable to assess the learning effects of such a company.

(*iii*) In the real options model, important delimitations are made too. From the reviewed literature, a general idea of other methods is presented. Whereas the solution builds on a binomial lattice in this model, future research might include other computational methods and arrive at different conclusions. Perhaps more applicable to this thesis, Herbolet (1992) presents an options valuation in which two uncertainties are included. Instead of assuming a certain decrease in the strike price of the fuel cell system, as it is done in this project, it could be interesting to quantify the underlying uncertainty in learning effects differently. On another suggestion, it could similarly be valuable to estimate not only uncertainty in diesel prices but also quantify volatility in methanol prices. In this way, a more realistic estimate of cost savings from operating a fuel cell as compared to a diesel generator could be quantified.

Altogether, these topics call for further investigation before hypotheses can be tested, but it could be in the interest of DPS to evaluate the ideas. Fuel cell commercialization is not a topic exclusive to the tower and telecommunications markets of India either. If carried out properly, the models applied here should be transferable to different settings. It could be interesting to evaluate similar flexible investment or replacement decisions in other markets exhibiting grid unreliability, for example.

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APPENDIX 1

Assumptions for Diesel Generator Costs

	Unit	**10 kVA Diesel Generator**
Landed Cost (CAPEX)	USD	3,764
OPEX		
Fixed O&M		
Preventive maintenance	USD per visit	14.12
Freq. of visit	hours	300
Minor overhaul	USD per overhaul	564.54
Frequency of minor overhaul	hours	5,000
Major overhaul	USD per overhaul	941.07
Freqyence of major overhaul	hours	10,000
Variable O&M		
Unscheduled maintenance	USD	301.14
Fuel delivery costs	per liter	0.038
Fuel price	USD	0.84
Fuel consumption	liter per hour	1.8
Fuel price growth rate	CAGR	6.99%

Appendix 1: Assumptions for Diesel Generator Costs. Sources: Intelligent Energy (2012) and own work.

APPENDIX 2

The following code is applied in Stata (v12.0) to yield results for ARCH(p) and GARCH(p,q) analyses:

```
* Stata Code for ARCH(1) and GARCH(1,1) Models
* ----------------------------------------------
* Create dates and declare time series
* ----------------------------------------------
rename var1 r
gen date = m(2006m6) + _n - 1
format date %td
tsset date
* ----------------------------------------------
* Time series plots and histograms
* ----------------------------------------------
tsline r, name(g1, replace)
qui histogram r, normal name(h1, replace)
* ----------------------------------------------
* LM test for ARCH(1)
* ----------------------------------------------
regress r
predict ehat, residual
gen ehat2 = ehat * ehat
qui reg ehat2 L.ehat2
scalar TR2 = e(N)*e(r2)
scalar pvalue = chi2tail(1,TR2)
scalar crit = invchi2tail(1,.05)
scalar list TR2 pvalue crit
* ----------------------------------------------
* Built-in LM Test for ARCH(1)
* ----------------------------------------------
regress r
estat archlm, lags(1)
* ----------------------------------------------
* ARCH(1)
* ----------------------------------------------
arch r, arch(1)
predict htarch, variance
tsline htarch, name(g2, replace)
* ----------------------------------------------
* GARCH(1,1)
* ----------------------------------------------
arch r, arch(1) garch(1)
predict htgarch, variance
tsline htgarch, name(g3, replace)
```

APPENDIX 3

Diesel Prices	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
	6.63	7.09	9.62	13.06	17.72	24.04	32.61	44.25	60.05	81.47	110.55	149.99	203.52	276.15	374.69	508.40
			5.23	7.09	9.62	13.06	17.72	24.04	32.61	44.25	60.05	81.47	110.55	149.99	203.52	276.15
				3.85	5.23	7.09	9.62	13.06	17.72	24.04	32.61	44.25	60.05	81.47	110.55	149.99
					2.84	3.85	5.23	7.09	9.62	13.06	17.72	24.04	32.61	44.25	60.05	81.47
						2.09	2.84	3.85	5.23	7.09	9.62	13.06	17.72	24.04	32.61	44.25
							1.54	2.09	2.84	3.85	5.23	7.09	9.62	13.06	17.72	24.04
								1.14	1.54	2.09	2.84	3.85	5.23	7.09	9.62	13.06
									0.84	1.14	1.54	2.09	2.84	3.85	5.23	7.09
										0.62	0.84	1.14	1.54	2.09	2.84	3.85
											0.45	0.62	0.84	1.14	1.54	2.09
												0.34	0.45	0.62	0.84	1.14
													0.25	0.34	0.45	0.62
														0.18	0.25	0.34
															0.13	0.18
																0.10

Binomial lattice parameters	
Volatility	30.52%
Diesel price t=0	6.63
Time step (years)	1
Expiration (T)	15
Up-movement (u)	1.357
Down-movement (d)	0.737
Risk-neutral prob. (p)	0.557
Risk-free rate (r)	7.93%

Appendix 3: Diesel Prices. Source: Own work.

APPENDIX 4

Probabilities	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
	"Yesterday"	100%	55.74%	31.07%	17.32%	9.65%	5.38%	3.00%	1.67%	0.93%	0.52%	0.29%	0.16%	0.09%	0.05%	0.03%
			44.26%	49.34%	41.25%	30.66%	21.36%	14.29%	9.29%	5.92%	3.71%	2.30%	1.41%	0.86%	0.52%	0.31%
				19.59%	32.76%	36.52%	33.92%	28.36%	22.13%	16.45%	11.79%	8.21%	5.60%	3.74%	2.47%	1.60%
					8.67%	19.33%	26.94%	30.03%	29.29%	26.12%	21.84%	17.39%	13.33%	9.91%	7.18%	5.09%
						3.84%	10.70%	17.89%	23.26%	25.93%	26.02%	24.17%	21.17%	17.70%	14.25%	11.12%
							1.70%	5.68%	11.08%	16.47%	20.66%	23.03%	23.53%	22.49%	20.37%	17.66%
								0.75%	2.93%	6.54%	10.94%	15.24%	18.69%	20.83%	21.57%	21.04%
									0.33%	1.48%	3.72%	6.92%	10.60%	14.18%	17.13%	19.09%
										0.15%	0.74%	2.06%	4.21%	7.04%	10.20%	13.26%
											0.07%	0.36%	1.11%	2.48%	4.50%	7.02%
												0.03%	0.18%	0.59%	1.43%	2.79%
													0.01%	0.09%	0.31%	0.81%
														0.01%	0.04%	0.16%
															0.00%	0.02%
																0.00%
Probability of Waiting		100.0%	100.0%	100.0%	100.0%	96.2%	82.2%	58.4%	51.4%	26.1%	21.8%	0.0%	0.0%	0.0%	0.0%	0.0%
Probability of Replacement		0.0%	0.0%	0.0%	0.0%	0.0%	5.4%	17.3%	11.0%	23.3%	16.0%	28.2%	20.5%	14.6%	10.2%	7.0%
Probability of No Option Value		0.0%	0.0%	0.0%	0.0%	3.8%	12.4%	24.3%	37.6%	50.6%	62.1%	71.8%	79.5%	85.4%	89.8%	93.0%

Appendix 4: Probabilities. Source: Own work.

ABBREVIATIONS

AFC – Alkaline Fuel Cell
ARCH – Autoregressive Conditional Heteroscedasticity
ASI – Annual Solar Irradiation
BCG – Boston Consulting Group
BOP – Balance of Plants
BTS – Base Transceiver Stations
BTU – British Thermal Unit
CAGR – Compound Annual Growth Rate
CAPEX – Capital Expenditures
CBOE – Chicago Board Options Exchange
CCGT – Combined Cycle Gas Turbine
CEC – California Energy Commission
CEO – Chief Executive Officer
CHP – Combined Heat and Power
Chr – Chromium
cm^2 – Square Centimeter
CO_2 – Carbon Dioxide
Cob – Cobalt
DCF – Discounted Cash Flow
DG – Diesel Generator
DP – Dynamic Programming
DPS – Danish Power Systems ApS
ECN – Energy Research Center of the Netherlands
EIA – United States Energy Information Administration
EPG – Electricity Generation Projects
FC – Fuel Cell
GARCH – Generalized Autoregressive Conditional Heteroscedasticity
GDE – Gas Diffusion Electrode
GDL – Gas Diffusion Layer
GS – Geographical Scope
GSMA – Groupe Spécial Mobile Association
GTCC – Gas Turbine Combined Cycle
H_2O – Dihydrogen Monoxide
HAP – Half Plate
HTPEM – High Temperature Proton Exchange Membrane
i.i.d. – Independent and identically distributed
INR – Indian Rupee
kg – Kilogram
kVA – Kilovolt Ampere
kW – Kilowatt
kWh – Kilowatt hour
kWp – Kilowatt Peak
LCOE – Levelized Cost of Energy
LM – Lagrange Multiplier
lr – Learning Rate
LTPEM – Low Temperature Proton Exchange Membrane
MC – Monte Carlo
MCFC – Molten Carbonate Fuel Cell
MEA – Membrane Electrode Assembly
Mfg – Manufacturing
mg – Milligram
MMBTU – Million British Thermal Units
MW – Megawatt
NPV – Net Present Value
O – Oxygen
O&M – Operating & Maintenance
OLS – Ordinary Least Squares
OPEX – Operational Expenditures
PBI – Polybenzinmidazol
PDE – Partial Differential Equation
PEM – Proton Exchange Membrane
PEMFC – Proton Exchange Membrane Fuel Cell
pr – Progress Rate
Pt – Platinum
PV – Present Value
R&D – Research and Development
R^2 – Correlation Coefficient
RAPS – Remote Area Power Supply
RET – Renewable Energy Technologies
ROV – Real Option Valuation
SINE – Safety Network
SOFC – Solid Oxide Fuel Cell
solar PV – Solar Photovoltaic
Telco – Telecommunication
TW – Terawatt
ULSD – Ultra-Low-Sulfur No. 2 Diesel Fuel
USD – United States Dollar
WACC – Weighted Average Cost of Capital

FIGURES

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TABLES

EQUATIONS