THE IMPACT OF BATTERY ELECTRIC VEHICLES ON THE LEAST-COST ELECTRICITY PORTFOLIO FOR SOUTH AFRICA

by

Joanne Rita Calitz

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SUMMARY

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Joanne Rita Calitz

Supervisor:	Prof. R.C. Bansal
Department:	Electrical, Electronic and Computer Engineering
University:	University of Pretoria
Degree:	Master of Engineering (Electrical Engineering)

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This study has quantified the impact of future battery electric vehicle (BEV) charging on the least-cost electricity generation portfolio in South Africa (SA). This was done by performing a capacity expansion optimization of the generation portion of the SA power system for the year 2040 in the software package PLEXOS. This study assumed that there would be 2.8 million BEV's in SA by 2040 which was informed by global adoption estimates.

All existing power stations expected to be operational in the year 2040 were modelled according to their technical performance characteristics and running costs. Additionally, a suite of new technology options were configured in the model according to their expected investment and running costs. These supply options included coal, nuclear and gas-fired capacity as well as renewable energy. The 2040 electricity demand was obtained from the national Integrated Resource Plan 2016. The optimization formulation in the power system model was set to minimize total generation cost which is the sum of all new investment build decisions and their associated running costs, as well as the running cost of existing

power stations while adhering to a set of constraints. Boundary condition constraints included an annual CO_2 emissions limit. The installed capacity and electricity supply (energy shares) for each technology type were optimized and presented for each scenario. The resulting total generation costs as well as environmental emissions were also presented per scenario.

The study looked at four main scenarios, as well as sensitivity analysis on the adoption of BEV's. First a reference scenario, the Base Case (BC), was developed in which the model was set up without incorporating BEV's in South Africa's power system. The least-cost new build capacity included 34.6 GW of solar photovoltaic (PV), 38.1 GW of wind, 0.3 GW of landfill gas, 8.8 GW of combined cycle gas turbines (CCGT) and 23.2 GW of open cycle gas turbines (OCGT) in 2040 for the given input assumptions.

A second scenario was then developed, the Fixed Charging (FC) scenario, with the same input assumptions as the BC scenario but with the inclusion of a 2.8 million BEV fleet (informed by global adoption estimates) in a Grid-to-Vehicle (G2V) configuration, assuming a fixed aggregated charging profile from previous literature. The BEV charging demand increased the annual electricity demand by 9 TWh (~2.5%). The least-cost optimal supply portfolio from this scenario increased the total generation cost by R9 billion compared to the BC and supplied most of the charging demand with new wind generation.

A sensitivity analysis was conducted on the FC scenario whereby the adoption of BEV's was increased to 100% of all passenger vehicles. This resulted in a BEV fleet of 8.4 million vehicles, which increased the system demand by 28 TWh and the peak demand by 5.9 GW. This additional charging demand increased the mean hourly upwards and downwards system demand gradients (ramping requirements) and thus the demand for flexible generation. The optimal supply portfolio in terms of technology type did not change for this higher BEV adoption assumption, indicating robustness in the technology choice going forward. As expected, more capacity was required in this scenario than the Base Case which resulted in an increase in the total system cost of R28 billion compared to the Base Case.

A third scenario, the Optimized Charging (OC) scenario, was developed in order to test the impact of a system optimized charging profile. The model was configured to allow flexible charging which for a least-cost optimization means that the batteries are charged during periods of lowest cost supply to the power system. As expected, the optimized charging profile showed that it is least-cost to the power system to charge during off peak periods of the day. This profile also resulted in a reduction of total generation cost of R3 billion compared to the FC scenario. This equates to a savings of about R1 000 per BEV per annum. This system saving is based on the optimized charging of the whole electric vehicle fleet and thus presents the maximum possible savings to the power system.

A last scenario, the V2G scenario, was developed in order to determine the impact on the least-cost supply portfolio if the BEV fleet is able to discharge back into the grid in the V2G configuration. The results from this scenario showed that further generation cost reductions could be achieved compared to the FC and OC scenarios. Both the OC and V2G scenarios built more new solar PV capacity and less wind capacity than the FC scenario, demonstrating the advantage of cheap solar PV generation during the middle of the day. For all scenarios including BEV's, the energy share from existing coal and nuclear was reduced. This indicates a higher need for flexibility in the power system in the presence of electric vehicles. The V2G scenario represented the lowest energy share from gas-fired power which is indicative of the additional flexibility gained from the electric vehicles in the V2G configuration. It was also found that less mid-merit gas and more peaking gas was built in the OC scenarios.

In conclusion, in all scenarios additional capacity was built to meet the additional charging demand in 2040. This indicates that the exclusion of BEV's in the capacity expansion will lead to a sub optimal energy mix. Additionally, for all scenarios, the least-cost capacity investment technologies chosen by the optimization model were solar PV, wind, landfill gas, mid-merit and peaking gas-fired capacity. This finding is significant as it indicates that although the quantity and energy share of these new supply options vary per scenario, the least-cost technology choice is the same with and without the presence of BEV's. The least-cost technology choice is therefore robust against the change in the demand profile caused by the addition of electric vehicle charging demand. The OC and V2G configurations led to lower system costs and a slightly higher energy share from solar PV relative to the FC scenario.

LIST OF ABBREVIATIONS

BEV	Battery Electric Vehicles
BNEF	Bloomberg New Energy Finance
CO_2	Carbon Dioxide
DoE	Department of Energy
DoT	Department of Transport
G2V	Grid-to-Vehicle
GW	Gigawatt
ICE	Internal Combustion Engine
IEA	International Energy Agency
IPPP	Independent Power Producer Programme
IRP	Integrated Resource Plan
LDC	Load Duration Curve
LCOE	Levelized Cost of Electricity
MIP	Mixed Integer Programming
PHEV	Plug-in Hybrid Electric Vehicle
PV	Photovoltaic
REIPPP	Renewable Energy Independent Power Producer Programme
SA	South Africa
TWh	Terawatt-hour
V2G	Vehicle-to-Grid

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CHAPTER 1 INTRODUCTION

1.1 PROBLEM STATEMENT

1.1.1 Context and background

Electric vehicles are broadly categorized into two types, namely Plug-in Hybrid Electric vehicles (PHEV) and Battery Electric Vehicles (BEV). BEVs have no conventional internal combustion engine (ICE) and are powered from a rechargeable battery. Literature on global electric vehicle forecasts indicate that electric vehicles are expected to play an increasing role in the transport sector going forward with some forecasts estimating that electric vehicles will account for 35-54% of global passenger vehicle sales by 2040 [1]. In South Africa (RSA), the National Department of Transport's (DoT) Green Transport Strategy [2] is promoting the uptake of electric vehicles by committing to a 5% reduction of emissions in the transport sector by 2050. Additionally, as part of the Paris climate agreement, RSA estimated that the country will have more than 2.9 million electric vehicles by 2050.

RSA's electricity demand is currently supplied mostly by coal-fired power stations which are primarily owned and operated by the national power utility, Eskom. The existing coal-fired power stations have 50 year design lifespans with the majority of the coal fleet capacity planned to be decommissioned over the next 30 years. In addition to this, according to national plans the electricity demand is expected to increase in the long term horizon [3]. Although some new capacity additions are currently being commissioned (Medupi and Kusile coal-fired power stations) and utility-scale renewable energy is being deployed via the Renewable Energy Independent Power Producer Programme (REIPPP), the expected increasing demand and overall net reduction in supply capacity going forward creates a need for additional supply capacity from as early as 2021 according to the Department of Energy's (DoE) latest (November 2016) Integrated Resource Plan (IRP) [4].

The IRP is currently the national energy planning document for RSA and was conducted using a least-cost optimization of the RSA power system (generation only) within certain constraint assumptions. The least-cost optimal electricity portfolio is dependent on the existing supply capacity, the electricity supply options available, their relative costs and technical characteristics, defined constraints and boundary conditions, as well as the expected future electricity demand.

A large adoption of electric vehicles could have a substantial impact on both the magnitude and profile (chronological pattern) of the future electricity demand. The IRP did not consider the uptake of electric vehicles in any of the published scenarios and thus disregarded the potential change in the electricity demand profile and resulting optimal/least-cost electricity supply portfolio and system cost impacts. This analysis aims to address this gap by conducting a least-cost capacity expansion optimization of the RSA power system with an assumed BEV uptake and associated charging demand requirements. This was tested for two charging configurations, namely grid-to-vehicle (G2V) and vehicle-to-grid (V2G). In the G2V configuration BEV's can only draw power from the grid whereas V2G also allows discharging of the batteries back into the grid. Including BEV's in the least-cost capacity expansion plan allows for the quantification of the impact of BEV's on the least-cost supply portfolio as well as ensuring that enough capacity is built to meet the additional BEV charging demand.

In addition to the impact on the electricity portfolio, this analysis also addresses the potential value of system optimized BEV charging versus typical charging behaviour. System optimized charging (smart charging) provides an indication of when it is least-cost to the power system to meet BEV charging demand. Quantifying this value can give an indication of whether it is worth incentivizing customer charging behaviour in future, through payback schemes or differential time of use tariffs.

1.1.2 Research gap

A literature review indicates that to the best of the authors' knowledge, there has not been a published study quantifying the impact of BEV's on the least-cost electricity portfolio in RSA. Additionally no publication of a study quantifying the value to the power system of system optimized battery charging or the system value of BEV's in the vehicle-to-grid configuration in RSA could be found. This research aims to address this gap in electricity planning which would contribute to the energy planning knowledge base and could guide policy and decision making within the energy sector.

1.2 RESEARCH OBJECTIVE AND QUESTIONS

1.2.1 Research objectives

The specific research objectives are as follows:

- Quantifying the potential impact on SA's electricity demand profile resulting from the adoption of BEV's which use the electricity grid for charging in the G2V configuration using typical passenger vehicle charging profiles in future;
- Quantifying the impact on the least-cost electricity supply portfolio in SA in future resulting from the adoption of BEV's in the G2V configuration, considering expected customer charging profiles, including the impact on electricity system costs and related environmental emissions (electricity sector only);
- Analysing whether there could be a monetary benefit to the power system of system optimized charging profiles;
- Quantifying the impact on the least-cost electricity supply portfolio in RSA in future resulting from BEV's configured to be able to discharge into the power grid in the V2G configuration, including the impact on electricity system costs and related station emissions.

1.2.2 Research questions

The associated research questions are as follows:

- What is the expected uptake of BEV's in RSA in the future?
- What is the impact on the hourly electricity demand profile resulting from the adoption of BEV's which use the electricity grid for charging in the G2V configuration using a typical charging profile from existing literature?
- What is the impact on the least-cost electricity supply portfolio in RSA resulting from the adoption of BEV's in the G2V configuration, using a typical charging profile from existing literature, including the impact on electricity system costs and related station emissions?
- What is the value to the power system of system optimized charging profiles?
- What is the impact on the least-cost electricity supply portfolio in RSA in the future resulting from the adoption of BEV's in the V2G configuration, including the impact on electricity system costs and related station emissions?

1.3 APPROACH

The research approach consisted of a comprehensive literature review, followed by the development of a capacity expansion model of the RSA power system. Publically available data as well as data derived from experiential knowledge was used as input into the power system model for a future year. The year 2040 was chosen in order to represent a large enough BEV fleet in the future.

The power system model was configured as a least-cost optimization model of the RSA power system (generation only), with existing power supply capacity decommissioning schedules, new supply options, system reliability requirements and a forecasted electricity demand based on the 2016 Integrated Resource Plan. To quantify the impact of BEV's on the RSA power system the modelling and analysis steps listed below were followed:

(i) Base Case (BC): A least-cost capacity expansion model of the RSA generation system was developed without the presence of BEV's for the year 2040. The resulting expansion build formed the base results from which the other scenarios were compared.

(ii) Fixed Charging Profile (FC): The model was configured to run a least-cost capacity expansion optimization of the RSA generation system with the presence of BEV's for the year 2040, assuming BEV's will be charged as per a typical aggregated charging profile from previous literature

(iii) The impact on the least-cost electricity supply portfolio and system cost was quantified by comparing the BC scenario with the FC scenario.

(iv) System Optimized Charging (OC): The model was configured to run the least-cost capacity expansion optimization with BEV's charging as per power system needs (i.e. system optimized charging with least-cost as the objective function).

(v) Calculation of the system monetary value of optimized charging in RSA by comparing the OC scenario with the BC scenario.

(vi) V2G: The model was configured to run the least-cost capacity expansion optimization of the RSA generation system with BEV's in the V2G configuration.

(vii) Compare the BC, FC and V2G scenarios to quantify the impact on the least-cost electricity supply portfolio and system cost due to BEV's in the V2G configuration.

1.4 RESEARCH GOALS

The goal of this research is to contribute towards the electricity planning knowledge base by applying a systems approach to find the least-cost optimal generation capacity portfolio of the RSA power system considering a moderate uptake of BEV's.

1.5 RESEARCH CONTRIBUTION

This research looked at the impact of BEV’s on the least-cost electricity supply portfolio in RSA which is important for energy planning purposes as it affects policy and financial decisions on what type of supply capacity to procure in the future as well as an understanding of the utilization and dispatch regime of the generation fleet. Generation costs typically constitute around 70% of the total power system cost, with transmission, distribution and other system services making up the remaining costs. It is thus important to aim for a least-cost generation portfolio in order to provide affordable electricity to customers.

This research further determined the value of system optimized charging in order to aid in determining whether the system operator/electricity wholesaler should consider the implementation of incentives to drive customer charging behaviour to match system needs.

Lastly, the research considered the impact of electric vehicles in the vehicle-to-grid configuration on the optimal generation portfolio. This provides useful planning information as the generation portfolio is expected to change due to the vehicles essentially playing a vital role in providing flexibility to the power system. The potential system value (system cost impact) of vehicles in this configuration was also quantified.

1.6 DISSERTATION/THESIS OVERVIEW

In Chapter 2 a literature study was performed.
In Chapter 3 the main research method and input assumptions are discussed.
In Chapter 4 the results obtained, are provided.
In Chapter 5 the results are discussed and main observations provided.
In Chapter 6 some concluding remarks are made.

CHAPTER 2 LITERATURE REVIEW

2.1 CHAPTER OVERVIEW

In Section 2.2 an overview of capacity expansion planning is given and how this is currently conducted in RSA. In Section 2.3 an overview of battery electric vehicles is discussed in the context of forecasted adoption rates and battery charging behaviour. In Section 2.4 the potential impacts of battery electric vehicles on the electricity system are discussed.

2.2 GENERATION CAPACITY EXPANSION PLANNING IN SOUTH AFRICA

2.2.1 Generation capacity expansion planning overview

Generation capacity expansion planning for electricity is a long-term planning approach, most often with the objective of optimizing the generation mix to meet a forecasted electricity demand at the least-cost possible. This is usually achieved while adhering to set reliability, environmental and policy constraints as well as remaining within the technical operating limits of existing and new power generation technologies. In RSA, the Department of Energy (DoE) in collaboration with the National Energy Regulator of South Africa (NERSA) and the System Operator (Eskom), are mandated to carry out capacity expansion planning which is published in the form of an Integrated Resource Plan (IRP).

The outputs from a capacity expansion plan include the capacity and timing of new power generation as well as how these generators are expected to operate (energy output). Figure 2.1 illustrates the least-cost capacity expansion planning optimisation problem. The least-cost plan falls at the investment level which minimises the sum of the investment cost and the production cost. Investment costs include new capital investment costs while production costs include all costs associated with operating existing and new generation capacity investments.

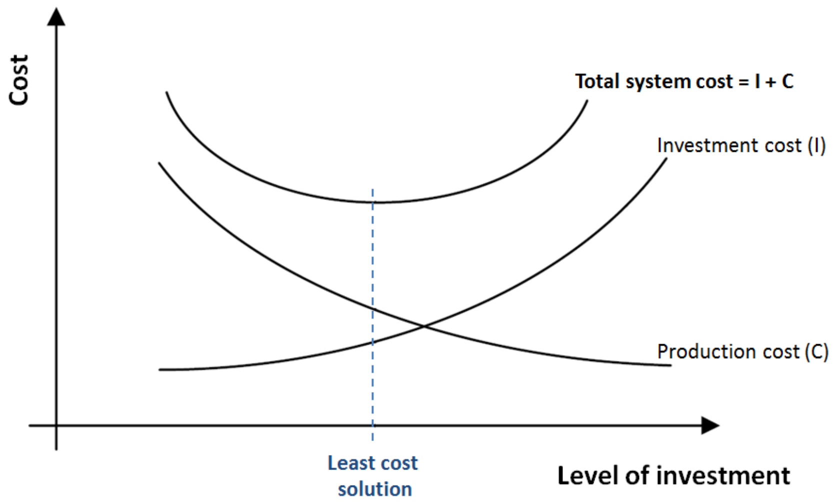


Figure 2.1. Illustration of the capacity expansion planning optimization [5]

Over the last decade, there has been a global shift towards cleaner generation technologies with a drive to lower CO_2 emissions in the electricity sector. This has led to the rapid uptake of variable renewable energy technologies in recent years, contributing to considerable cost reductions of these technologies. In 2017, 52.5 GW of new onshore wind and 74 GW of solar PV was installed globally, with approximately half of this capacity being installed in China [6], [7]. The greatest cost reductions have occurred for wind and solar PV, to the extent that they are already cost competitive with conventional generation technologies in a number of countries today. Due to the variability of wind and solar PV, traditional generation expansion planning methods have been forced to adopt new ways of capturing system flexibility requirements for large uptakes of renewable energy [8]–[11].

An important aspect in catering for system flexibility requirements brought on by wind and solar PV in power systems is solving the capacity expansion planning problem with a sufficient level of chronological temporal resolution. Since both the timing and magnitude of available wind and solar PV generation influence the complimentary generation mix, these two aspects must be sufficiently captured in the modelling process. The magnitude of available wind and solar PV at any moment in time is highly dependent on the spatial location of these plants. A major disadvantage of trying to capture a high level of temporal and spatial detail in capacity expansion modelling is the significant additional computational complexity and time required to solve the optimization. In addition to this, incorporating detailed technical constraints for conventional generators such as ramping capability, start up profiles and the reserve provision capability further adds to the computational burden. Poncelet *et al.* [12] found that improving the temporal resolution in long-term capacity expansion planning with high shares of renewables gives superior results to those obtained by incorporating detailed techno-economic constraints.

Various techniques have been studied which aim at reducing computational complexity such as the use of representative days [13] which retains some level of chronology and the load duration curve (LDC) approach. Nweke *et al.* [14] compared the outcomes from using a chronological approach versus the traditional LDC approach and found that the latter approach resulted in a higher share of renewable energy technologies and higher production costs than the chronological approach. Frew *et al.* [15] found that there is roughly a <6% accuracy loss when simplifying model complexity by making use of a representative subset of hours from a full year.

The application of various mathematical models to solve capacity expansion problems have been widely applied in [16]–[21]. Connolly *et al.* [22] compared 37 computer tools that can be used to analyse the integration of renewable energy. Mixed Integer Programming models are generally well suited to handle constraints and reduce computational time [23], [24] and has been used in multiple power system modelling software packages. Some popular existing commercial and open-source energy modelling software packages available today include OSeMOSYS [25], MARKAL-TIMES [26], PLEXOS [27], WASP (Wien Automatic System Planning Package), European Electricity Market Model (EMMA) [28], and Python for power system analysis (PyPSA) [29].

2.2.2 Electricity demand in South Africa

According to Eskom's 2017 Integrated Report [30], the total electricity demand in the 2016/17 financial year supplied by a combination of Eskom-owned generators, electricity imports and energy produced by IPP's was 237 TWh. This electricity demand makes up around 97% of RSA's total electricity demand with the remaining demand met by embedded generation (residential and commercial) and energy produced by municipalities and industry for self-consumption. Figure 2.2 shows the total country electricity demand over the last 30 years as published by Statistics South Africa [31]. It can be seen that the electricity demand has remained relatively constant since 2007.

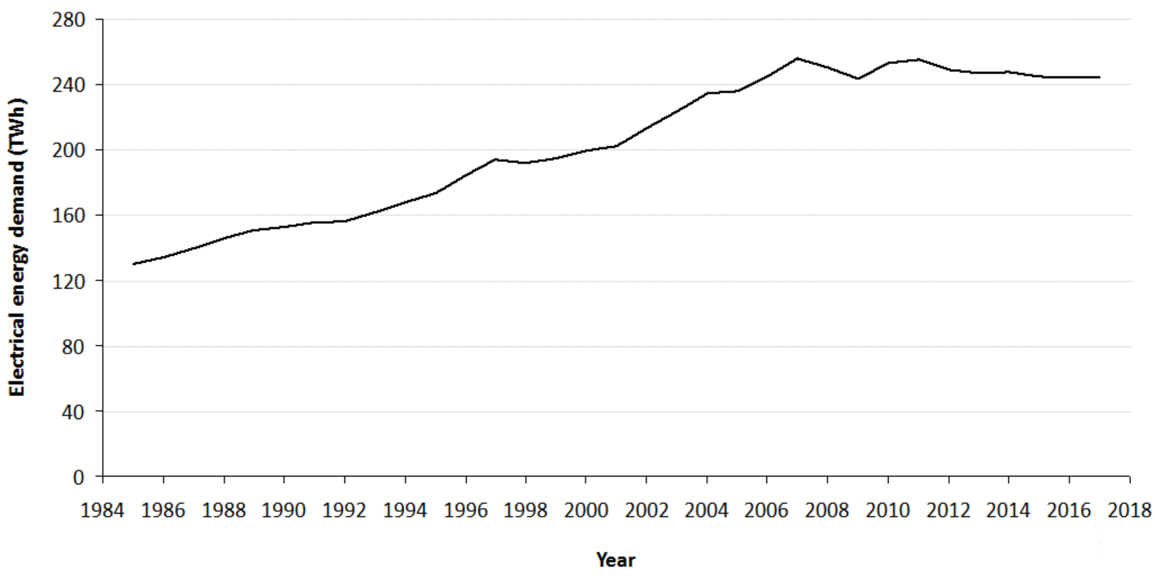


Figure 2.2. Historical electricity demand in South Africa [31]

RSA's average day hourly electricity demand profile in summer and winter in 2017 [32] is shown in Figure 2.3. It can be seen that there is a peak in electricity demand during the morning and evening which is more prominent in winter. The overall demand level is higher during the winter season.

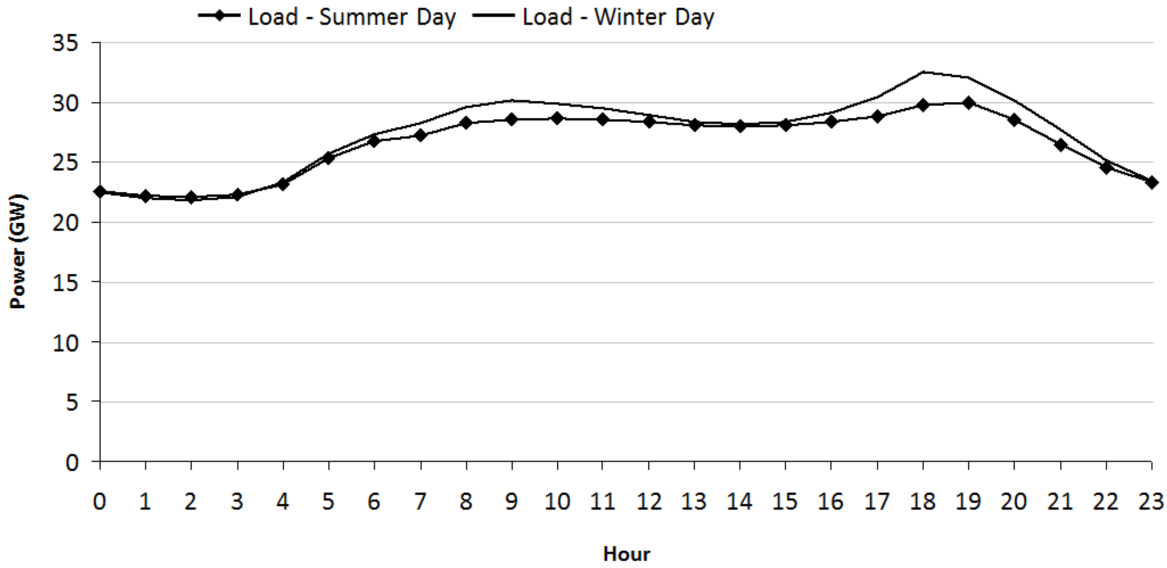


Figure 2.3. Average day hourly electricity demand in RSA in summer and winter (2017) [32]

2.2.3 Overview of the generation portfolio in South Africa

RSA's electricity demand is currently supplied mostly by coal-fired power stations (>80%) which are primarily owned and operated by Eskom, the national power utility. Eskom supplies over 95% of the country's total electricity demand, with the remaining demand being met by municipalities, imports and independent power producers (IPPs). Figure 2.4 shows the actual monthly average diurnal courses of the total power supply in SA for the months from Jan-Dec 2014 [33]. It can be seen that the majority of demand is met by coal, with renewable energy only playing a minimal role. This was a particularly energy supply constrained year which is evident by the high usage of the diesel generation fleet.

The existing operational coal-fired power stations have an expected 50 year life span. As shown in Figure 2.5 [4], the majority of the coal fleet capacity (Eskom-owned) is planned to be decommissioned over the next 30 years. In addition to this, according to national plans the electricity demand is expected to increase in the long term [3]. The expected increasing demand and overall reduction in supply capacity going forward creates a need for additional supply capacity from as early as 2021 according to the Department of Energy's (DoE) 2016 Draft Integrated Resource Plan (IRP) [4].

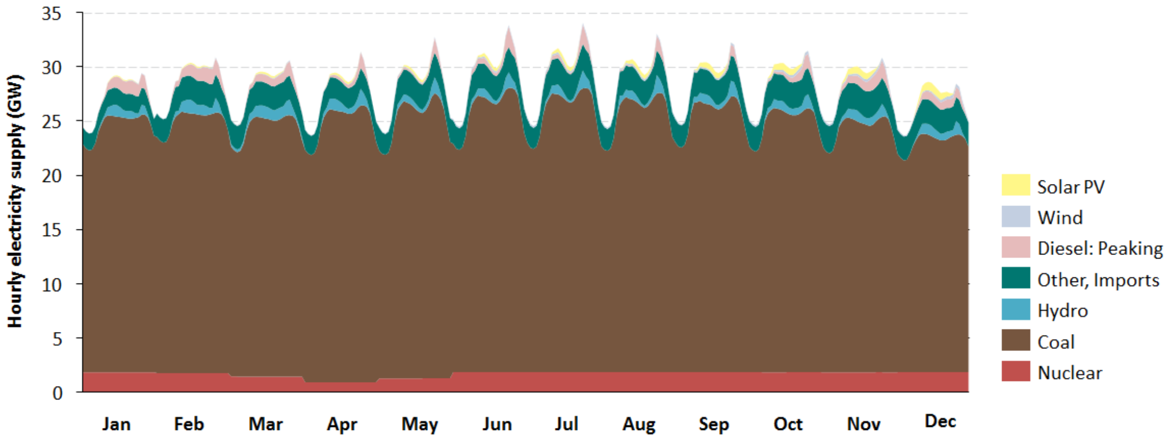


Figure 2.4. Actual monthly average diurnal courses of the total power supply in SA for the months from Jan-Dec 2014

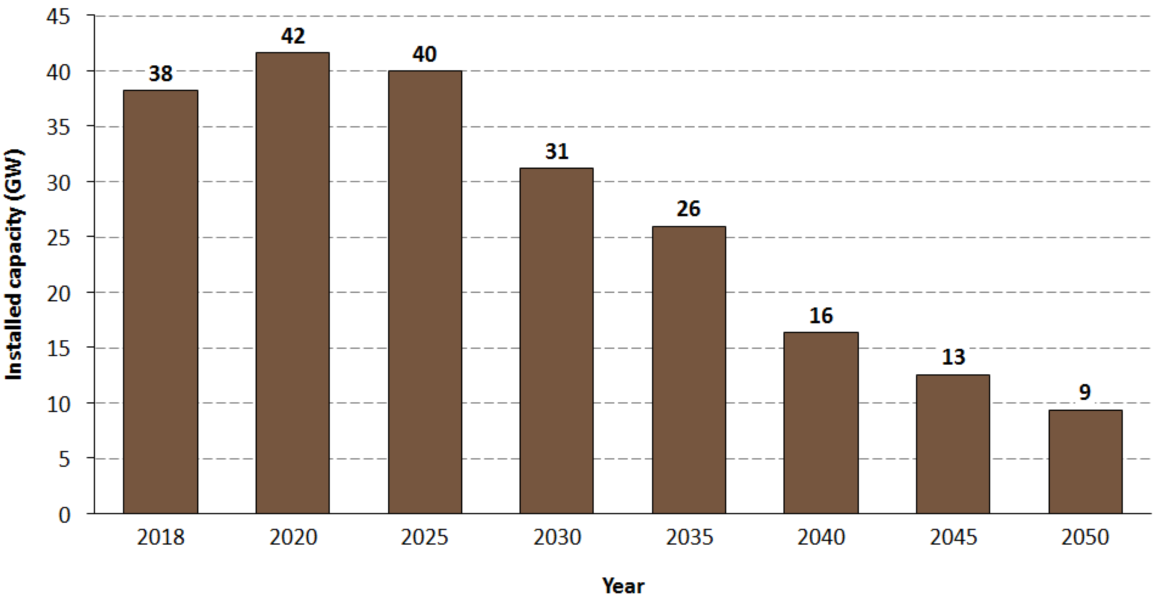


Figure 2.5. Decommissioning schedule of the coal-fired power stations in South Africa

The IRP is currently the national energy planning document for RSA and is a capacity expansion plan which was conducted using a least-cost optimization model of the RSA power system (generation only). The installed capacity and energy shares of the Draft IRP 2016 Base Case are shown in Figure 2.6 [34]. The IRP 2016 Base Case represents the least-cost expansion plan within the boundary constraint of an annual new build limit of wind and solar photovoltaic (PV) capacity as well as an environmental CO_2 emissions constraint. The least-cost optimal electricity portfolio is dependent on the existing supply capacity, the electricity supply options available, their relative costs and technical characteristics, defined constraints and boundary conditions, as well as the expected future electricity demand.

In 2017, the Council for Scientific and Industrial Research (CSIR) published a least-cost electricity scenario for RSA [35] based on a number of updated technology assumptions from the Draft IRP 2016 Base Case. The CSIR demonstrated that the IRP 2016 Base Case changes dramatically with the removal of the annual new build limit constraints on wind and solar PV. This finding demonstrates the impact which constraints and boundary conditions have on the least-cost generation portfolio. In both studies the share of renewable energy in RSA's power system is expected to increase, while coal-fired power decommissions over time.

Total Installed Capacity (GW) per Technology

	Year			
	2016	**2030**	**2040**	**2050**
Solar PV	1.5	7.5	12.4	15.8
CSP	0.2	1.1	1.1	-
Wind	1.3	11.1	21.3	30.4
Other	0.3	0.7	0.7	0.5
Peaking	3.4	8.9	12.8	13.8
Gas	0.4	7.3	16.8	22.0
Hydro*	4.1	6.1	7.6	7.6
Nuclear	1.9	1.9	4.6	20.4
Coal	36.8	37.9	31.4	25.2
Total	**49.9**	**82.5**	**108.7**	**135.7**

*Hydro installed capacity and electricity supplied includes pumped storage;
CSP = Concentrated Solar Power

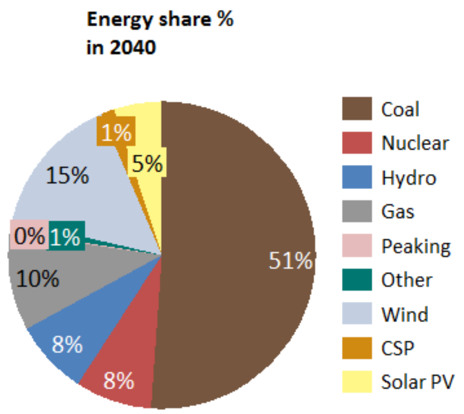


Figure 2.6. Draft IRP 2016 installed capacity from 2016-2050 and energy share in 2040 adapted from [34]

2.3 OVERVIEW OF BATTERY ELECTRIC VEHICLES

2.3.1 Battery electric vehicle adoption

Some countries have already established policies and transportation sector targets to encourage the adoption of electric vehicles in order to meet their climate change commitments. One such initiative is the Paris Declaration on Electro-Mobility and Climate Change presented at COP21 in 2015 [36], which aims to increase the global share of electric vehicle sales to 35% by 2030. According to a 2017 study released by Bloomberg New Energy Finance (BNEF) [37], by 2040 35% of passenger vehicle sales globally are expected to be from passenger electric vehicles. BNEF subsequently stated that their team has since revised this prediction to 54%.

In RSA, the National Department of Transport's (DoT) Green Transport Strategy [2] is promoting the uptake of electric vehicles by committing to reducing transport sector emissions by 5% by 2050. This forms part of RSA's Intended Nationally Determined Contribution (INDC), which aims to limit the country's CO_2 emissions. Additionally, as part of the Paris climate agreement, RSA estimated that the country will have more than 2.9 million electric vehicles by 2050.

Besides policy and infrastructure support, a significant driver for BEV uptake is expected to be the declining cost of BEV's compared to conventional internal combustion engines, resulting from battery cost reductions. BNEF predict that electric vehicles will cost less than internal combustion engines in most countries by 2030 [1]. Battery costs have decreased significantly over the past decade and are expected to continue to do so in future. Figure 2.7, shows the historical battery cost developments and forecasted capital costs from the IRP 2016 [4], BNEF [37] and Nykvist *et al.* [38].

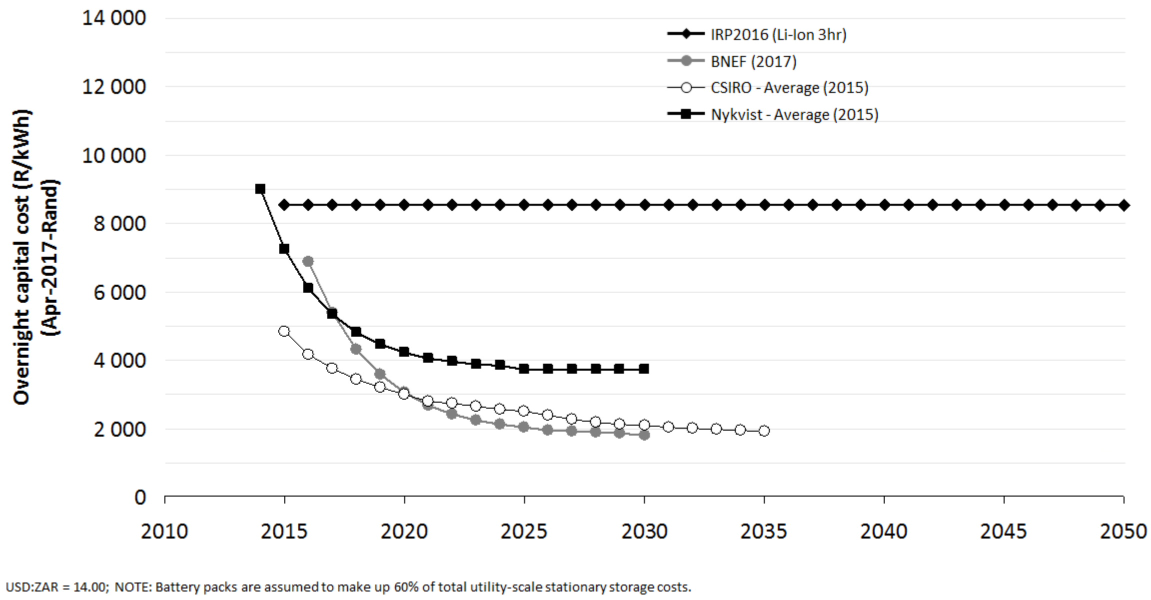


Figure 2.7. Historical trend of battery storage costs adapted from [4], [37] and [38]

As shown in the literature, the combination of initiatives, policies and continuing cost reductions of electric vehicles have increased historical BEV sales and will likely continue to do so in the future. Neither the promulgated IRP 2010 nor the most recent Draft IRP 2016 considers the impact of BEV's on the power system. A large adoption of electric vehicles could have a substantial impact on both the magnitude and profile of the future electricity demand. It is thus important to investigate the impact electric vehicles can have on the country's electricity system.

2.3.2 Battery electric vehicle charging profiles

A number of international studies have attempted to generate typical daily charging profiles of BEVs [39]–[44]. In one study, Markel *et al.* [45] established that for 90% of the time, BEVs are parked, while spending 60% of the time connected to the grid. For most BEV's available today, alternative current (AC) charging times range from 6 to 12 hours for a full battery charge [46], while direct current (DC) fast chargers can reduce the charging times to less than 3 hours.

In a study conducted in the United States (US) under the US Department of Energy's Smart Grid Investment Grant (SGIG) program [42], it was found that the vast majority of BEV owners charged their vehicles overnight during off-peak periods. Figure 2.8 shows three weekday aggregated electric vehicle charging profiles adapted from the California Energy Commission [40], the U.S Department of Energy [42] and EPRI [47].

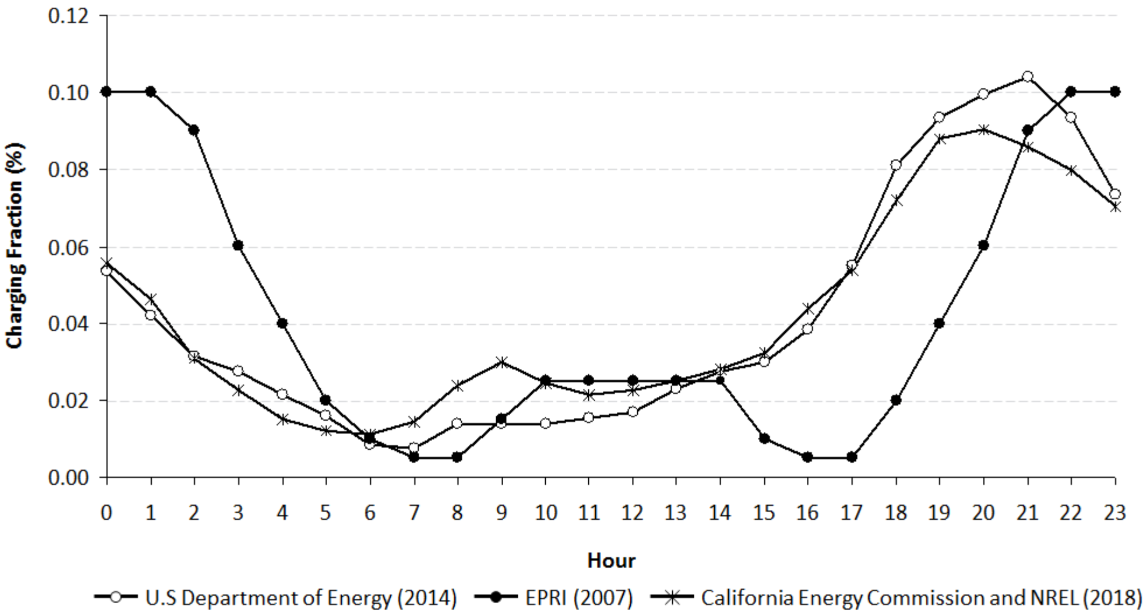


Figure 2.8. Aggregated weekday hourly electric vehicle charging profiles

It can be seen that there is some commonality amongst the charging profiles with a sharp increase in charging demand during the early evening and through the night with some charging also taking place during the middle of the day. Since this charging behaviour is primarily driven by the fact that most people follow similar daily schedules, using charging profiles from international studies should be appropriate to represent the expected charging profiles in RSA.

2.4 THE IMPACT OF BATTERY ELECTRIC VEHICLES ON THE ELECTRICITY SYSTEM

2.4.1 Grid-to-Vehicle (G2V) charging configuration

In the G2V configuration, BEV’s can consume electricity from the grid for charging but cannot discharge energy back into the grid. If the majority of BEV charging occurs during off-peak periods where the power system is running the lowest marginal cost generators, BEV charging may not significantly increase the total system cost or constrain the power system (at a generation system level). If the timing however largely coincides with peak periods of demand, system constraints could be experienced along with a more significant increase in the total generation cost. Since the charging demand from individual electric vehicles is relatively low, it is reasonable to assume that the proportion of total BEV’s in the transport fleet would play a significant role in determining whether additional generation capacity would be required to meet the increase in demand resulting from aggregated BEV charging.

A number of studies have tried to quantify the impact of electric vehicle charging on electricity demand, primary energy use, transmission and distribution grids as well as environmental emissions [48]–[51]. Roe *et al.* [52] found that a 20% electric vehicle penetration resulted in less than 1% increase in peak demand. This observation is largely dependent on the electricity demand profile of the country and may be vastly different for the RSA case.

The timing of electric vehicle charging will influence the country’s overall demand profile. If this charging could be optimized to occur during times of the day where the short-run marginal cost of electricity is low, it is reasonable to hypothesise that there would be a positive reduction in the wholesale electricity cost. Some studies have shown that optimized charging could be based on minimizing environmental emissions [53], [50], however this study will focus on the cost benefits of optimized charging.

The impact of BEV's on the power grid, more specifically at the distribution level, may be significant at high penetrations of BEV's but these impacts have not been considered in this study.

2.4.2 V2G charging configuration

Configuring electric vehicles to discharge back into the national power grid (V2G) further enhances the power systems' flexibility and storage capacity. Although there have been a number of pilot studies over the last few years, V2G is not yet commercially applied. A relatively new study called V2GB (Vehicle to Grid Britain) is currently being undertaken by MOIXA [54] whereby the "National Grid and Western Power Distribution are looking into the ways electric vehicles can support the grid and earn revenue". They are currently paying UK customers to provide battery capacity in support of the grid, rewarding customers a minimum of £50 a year.

Through the use of Mixed Integer Linear Programming (MILP) to perform unit commitment dispatch modelling, Pavić *et al.* [55] found that BEVs in the V2G configuration can reduce CO_2 emissions as well as reduce wind curtailment and system operation costs. Similar findings based on the Netherland's power system were summarized in [56] where the authors found that BEV's were used to reduce the system peak load and provided flexibility to the power system. Additional opportunities for V2G were identified in [57], which included the provision of reactive power. Zhou *et al.* [58] conducted a review on the impact of V2G on power system stability and found that detailed work on stability analysis with V2G adoption is limited.

Since the future RSA power system is expected to consist of a large share of renewable energy technologies, additional flexibility resources could provide major economic benefit to the power system. It is thus useful to consider the impact of V2G in capacity expansion planning for RSA to quantify the potential economic cost benefits.

2.5 CHAPTER SUMMARY

In this chapter an overview of capacity expansion planning was provided as well as how the uptake of battery electric vehicles could influence such planning.

In Section 2.2 literature on capacity expansion planning and the RSA electricity system was given. It was summarized that capacity expansion planning is a long-term planning approach with the objective of meeting the forecasted electricity demand at the least-cost possible while adhering to set reliably, environmental and policy constraints as well as the technical operating limits of existing and new power generation technologies. Context was also provided on the current RSA power system and electricity demand.

In Section 2.3 the forecasted adoption of battery electric vehicles globally was summarized as well as different charging demand profiles from previous literature.

In Section 2.4 literature on the impact of battery electric vehicles on the electricity system was summarized. The literature showed that there are various impacts to the energy portfolio of a power system with the introduction of battery electric vehicles depending on their adoption rates, charging profiles and system configuration. This study aims to build on these findings by conducting least-cost capacity expansion modelling on the RSA power system with and without the presence of BEV's.

CHAPTER 3 POWER SYSTEM MODEL AND INPUT ASSUMPTIONS

3.1 STUDY SCENARIOS

This study looked at four scenarios in order to quantify the impact of BEV's with varying charging regimes on RSA's least-cost electricity portfolio. An additional sensitivity was conducted whereby the BEV adoption was set as 100% of the passenger vehicle fleet. The scenarios are summarized in Table 3.1.

Table 3.1. Summary of study scenarios

Scenario	Description
Base Case (BC)	Least-cost capacity expansion assuming no BEV's in 2040
Fixed Charging (FC)	Least-cost capacity expansion assuming 33% and 100% share of BEV's in 2040, assuming BEV's will be charged as per a fixed charging profile from previous literature.
Optimized Charging (OC)	Least-cost capacity expansion assuming 33% share of BEV's in 2040, with BEV's charging as per power system needs (optimized)
Vehicle-to-Grid (V2G)	Least-cost capacity expansion assuming 33% share of BEV's in 2040 with BEV's in the V2G configuration.

The Base Case (BC) scenario represents the least-cost capacity expansion plan when BEV's are excluded from the planning data. The purpose of the BC is to form a comparative reference year against which scenarios including BEV's can be compared on the basis of total system cost and differences in supply portfolios. The impact of BEV's on the power system is then quantified for the Fixed Charging profile discussed in Section 3.3.7 relative to the BC. The Optimized Charging (OC) scenario was then modelled where the BEV fleet charging was done during periods of lowest cost supply to the power system (system optimized). A final scenario was then considered where the BEV's could discharge back into the grid in a V2G configuration.

3.2 POWER SYSTEM MODEL

For this research, the RSA electricity system was modelled in the PLEXOS® Integrated Energy Model software tool [27], using publically available data where possible for the year 2040. Only the generation component of the power system was modelled and as such, transmission and distribution level optimization was not considered in this research analysis. This approach is widely used in energy planning as the total cost of generation typically constitutes around 70% of the total power system cost, with transmission, distribution and other system services making up the rest. Furthermore, incorporating the transmission system into a capacity expansion optimization model adds substantial computational complexity.

PLEXOS is essentially a mathematical model which was used to co-optimise long-term investment and operational dispatch decisions over the specified planning horizon. Since the majority of existing power stations in RSA will be decommissioned over the next 30 years, there will essentially be an opportunity to rebuild the entire generation fleet. Since investment in new power generation assets is generally substantial and long-lived, a long term, least-cost capacity expansion model is a useful and often critical tool in energy planning. The capacity expansion problem is formulated in PLEXOS as a Mixed-Integer Linear Programming (MILP) problem with the objective function set to minimize the net present value of total fixed (including capital cost of new generators) and variable generation costs for all new and existing generators, subject to a set of specified constraints. The core MILP equation for the PLEXOS capacity expansion model is shown below.

Variables:

$\boldsymbol{UnitBuild_{g,y}}$	Number of generating units built in year y for generator g
$\boldsymbol{UnitCost_g}$	Overnight build cost of generator g
$\boldsymbol{FOMCost_g}$	Fixed operations and maintenance cost of generator g
$\boldsymbol{VOMCost_g}$	Variable operations and maintenance cost of generator g
$\boldsymbol{FuelCost_g}$	Fuel cost of generator g
$\boldsymbol{HR_g}$	Heat rate of generator g
$\boldsymbol{ExistUnit_g}$	Existing number of units of generator g
$\boldsymbol{GenLevel_{g,t}}$	Generation level of generator g in period t
$\boldsymbol{DR_y}$	Discount Rate in year y
$\boldsymbol{DR_t}$	Discount Rate in period t
$\boldsymbol{Demand_t}$	Electricity demand in period t
$\boldsymbol{ED_t}$	Aggregated electric vehicle charging demand in period t
$\boldsymbol{Dispatch_{g,t}}$	Dispatch level of generating unit g in period t
$\boldsymbol{MaxCap_g}$	Maximum capacity of generator g
$\boldsymbol{UE_t}$	Unserved energy in dispatch period t
$\boldsymbol{COUE}$	Cost of unserved energy

Objective Function:

$$
\begin{aligned}
Minimize{:}\, C \;=\; & \sum_{y}\sum_{g} DR_y + \left(UnitBuild_{g,y} \times \; UnitCost_g\right) \\
& + \sum_{y} DR_y \;\; (FOMCost_g \\
& \times \; MaxCap_g \; (ExistUnit_g \; + \sum_{i \le y} UnitBuild_{g,i})) \\
& + \sum_{t} DR_{t \in y} \; \times \; Demand_t \; (COUE \; \times \; UE_t \\
& + \sum_{g} [\, GenLevel_{g,t} \; (VOMCost_g + \; (HR_g \\
& \times \; FuelCost_g) \;)]
\end{aligned}
\tag{3.1}
$$

Subject to:

Energy Balance

$$\sum_{g} GenLevel_{g,t} + UE_t = Demand_t + ED_t \qquad \forall t \tag{3.2}$$

Feasible Energy Dispatch

$$GenLevel_{g,t} \leq MaxCap_g \left(ExistUnit_g + \textstyle\sum_{i \leq y} UnitBuild_{g,i}\right) \tag{3.3}$$

Integrality

$$UnitBuild_{g,y} \in Z \tag{3.4}$$

Equation (3.1) depicts the least-cost optimization formulation where C is the total system cost, while (3.2) to (3.4) set the boundary conditions. Equation (3.2) states that the electricity supply must equal electricity demand, with any demand not met being equal to unserved energy. Since unserved energy is costed in the objective function, the optimal solution will aim to minimize unserved energy. The objective function ensures the overall supply mix leads to the lowest R/kWh system cost.

Power system demand was aggregated for the entire country and as such was represented as a single nodal model. The geospatial impact of onshore wind and solar PV was however included in the model through the use of aggregating individual wind and solar PV time series production data over 27 areas in the country (explained further in Section 3.3.3). The model was configured using hourly temporal resolution and maintains chronological consistency across the one year horizon. As discussed in Section 2.2.1, temporal resolution as well as chronology is important when representing large shares of renewable energy generation.

Within the power system model, BEV charging demand was included as a purchaser of energy from the system i.e. adding to the total electricity demand. Total BEV charging demand EV_t is expressed as:

$$EV_t = \textstyle\sum_t N_t \ (EC_t \times D_t) \qquad \forall t \tag{3.5}$$

where N_t is the number of electric vehicles in period t, EC_t is the average energy consumption per electric vehicle and D_t is the average distance travelled per electric vehicle in time period t. EC_t is expressed as:

$$EC_t = \frac{BC_t}{R} \qquad \forall t \tag{3.6}$$

where, BC_t is the battery capacity and R is the average battery range in kilometers (km). For each period, the EV_t was then multiplied by the unitized charging profile f_t obtained from previous literature in order to calculate the total aggregated charging demand per time period ED_t as shown in (3.7).

$$ED_t \ = \ EV_t \times f_t \qquad \forall t \tag{3.7}$$

For the Optimized Charging profile, the model was configured such that the intra-day charging demand is flexible and scheduled as per the least-cost system needs within the daily boundary constraint:

$$OC_d = \ EV_d \qquad \forall t \tag{3.8}$$

where OC_d is the total optimized charging demand in a day and EV_d is the total aggregated fixed charging demand in a day which is expressed as:

$$EV_d = \ \sum_{t=1}^{24} EV_t \qquad \forall t \tag{3.9}$$

In addition to the above equations, the model also included constraints on the dispatch capabilities of all power generators. The technical characteristics of the other power generators that were represented in the model are listed below and summarized in Addendum A:

- Power station rated capacities (including decommissioning dates)
- Maximum ramp-up and down rates
- Minimum stable levels
- Minimum up and down times (start-up constraints or profiles)

- Heat rates/ power station efficiencies
- System operational reserve provision requirements
- Water consumption and CO_2 emissions rates
- Renewable energy generation profiles
- Pumped storage efficiencies and dam level constraints
- Planned and unplanned outage rates with mean times to repair estimates

The primary input costs that were incorporated in the model include:

- Capital costs of new power plants
- Fixed operations and maintenance costs of new and existing power generators
- Variable operations and maintenance costs of new and existing power generators
- Fuel costs
- Start-up costs

Figure 3.1 shows a high level summary of the PLEXOS model set up.

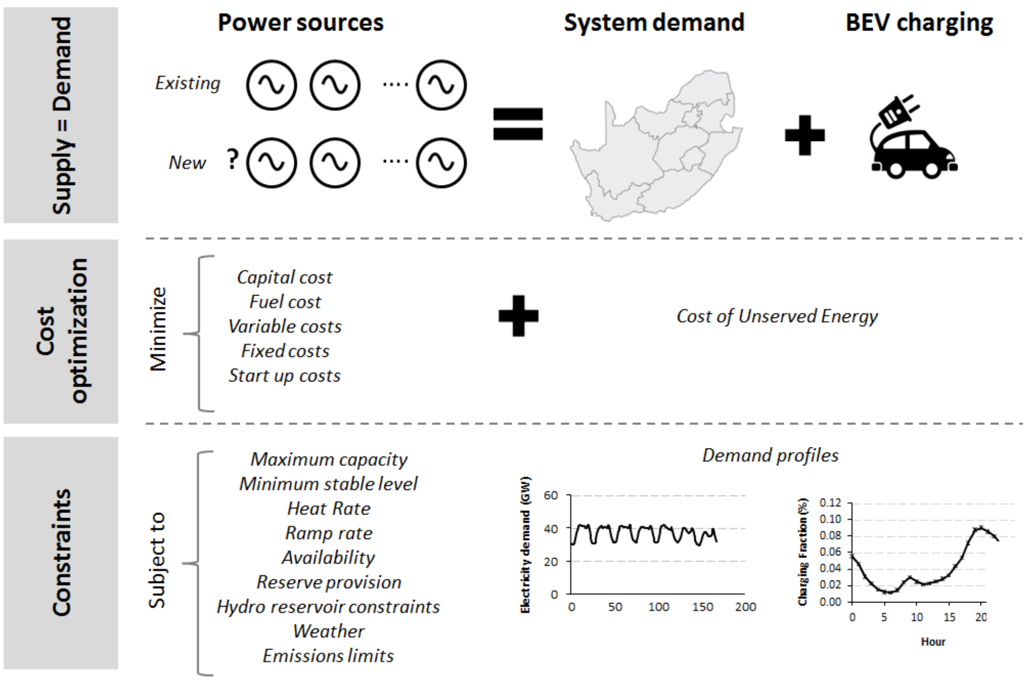


Figure 3.1. Illustration of the power system model dimensions

3.3 INPUT ASSUMPTIONS

Where possible, all input assumptions were obtained from publically available sources which are most relevant to the RSA power system and existing energy planning studies.

3.3.1 Demand forecast

The electricity demand forecast that was used in this analysis is the IRP2016 Low forecast which was developed by the CSIR [3] and is shown in Figure 3.2. For the purpose of this study, the starting point of the forecast was aligned to the 2017 historical actual electricity demand and then continues to grow as per the annual growth rate assumption in [3]. This forecast projects that the electricity demand will be approximately 337 TWh in 2040, a 38% growth in demand from 2017. The peak demand is expected to be about 53 GW. This demand forecast does not include any charging demand for electric vehicles and was based on an average annual Gross Domestic Demand (GDP) growth forecast of 2%.

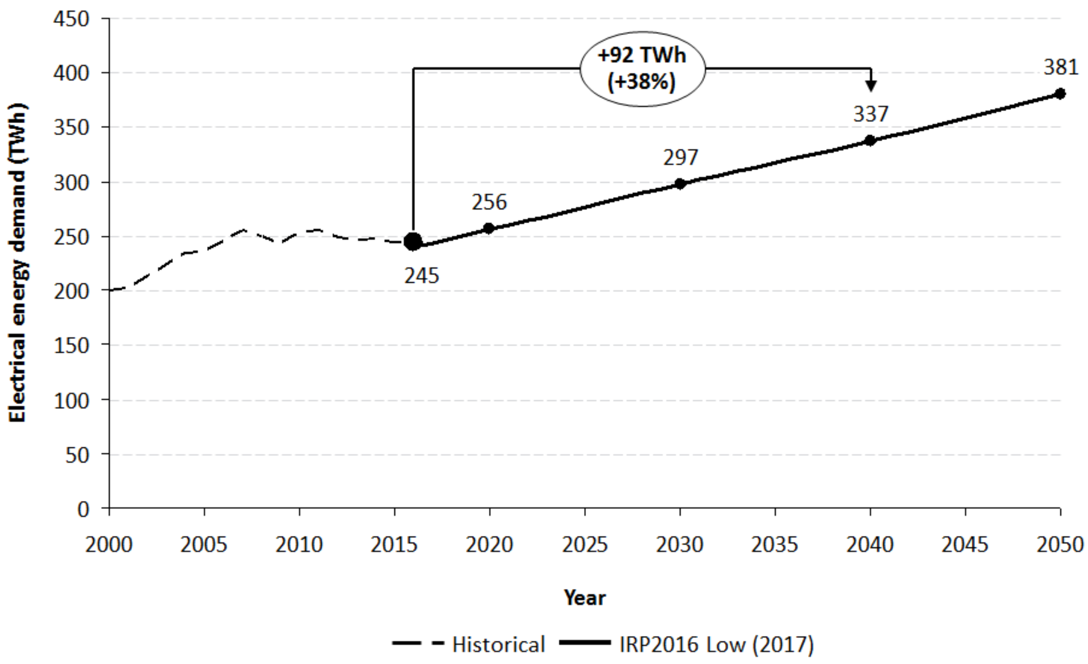


Figure 3.2. Annual electricity demand forecast

3.3.2 Existing and planned power stations

All existing utility-scale power stations in RSA are modelled individually in the power system model. Installed capacities, fuel costs, fixed and variable costs, decommissioning dates and technical operating characteristics such as ramping rates and reserve provision capability were obtained from Eskom's website, experiential knowledge and [4]. The total installed capacity per technology type in RSA in 2016 is shown in Table 3.2.

Table 3.2. Existing power stations in South Africa in 2016

Technology	**Installed capacity (GW)**	**Energy produced[1] (TWh/annum)**	**Energy share (%)**
Coal	36.8	200.0	81.3
Nuclear	1.9	14.7	6.0
Diesel Turbines	3.4	2.0	0.8
Gas	0.4	0.8	0.3
Hydro[2]	2.2	15.8	6.4
Pumped Hydro	2.9	3.0	1.2
Other	0.3	1.6	0.7
Wind	2.8	4.5	1.8
Solar Photovoltaic (PV)	1.6	2.6	1.1
Concentrated Solar Power (CSP)	0.6	0.9	0.4
Total	52.9	245.9	100.0

The operational characteristics of the Eskom power stations were sourced from the Eskom website while the planned availability of the fleet was assumed as to be the same as the

[1] Calculated based on typical capacity factors per technology type

[2] Includes hydro energy imported from Mozambique (Cahora Bassa)

Draft IRP 2016 Base Case. Generic technical parameters were used for the existing non-Eskom capacity, with the decommissioning dates as per [4].

The planned completion of the two coal fired power stations currently under construction (Medupi and Kusile) were assumed to be operational in 2040 as per the Draft IRP2016. Additionally, all capacity from the Renewable Energy Independent Power Producer Procurement Programme (REIPPPP) Bid Window (BW) 1, 2, 3, 3.5 and 4 were assumed to be committed and included in the power system model, with only part of this capacity still being operational in 2040. In December 2017, a total of 2 078 MW of wind and 1 474 MW of solar PV capacity from the REIPPPP were operational [32]. Figure 3.3 shows the actual daily average diurnal wind and solar PV generation in 2017 from this operational capacity.

The proposed new-build coal IPPs, Thabametsi (560 MW) and Khanyisa (306 MW), were not considered committed in this analysis and were thus excluded in the model.

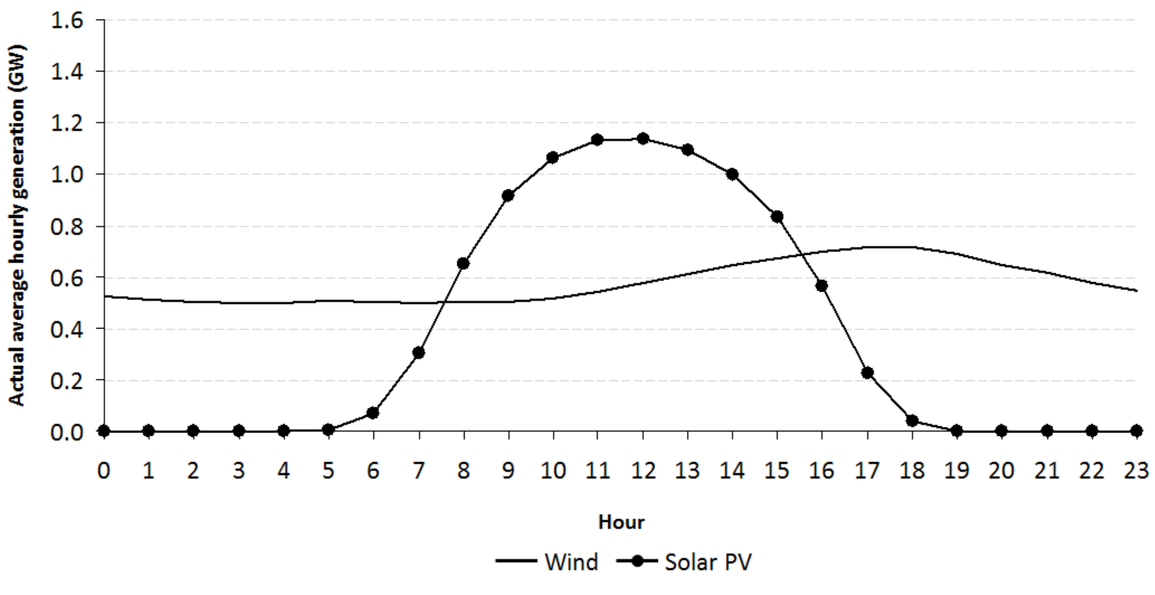


Figure 3.3. Actual daily average diurnal wind and solar PV generation in South Africa 2017

3.3.3 Future supply options

The future supply options and their corresponding costs and technical characteristics that were modelled in this study were obtained from [34], [59]. The only adjustments that were made from these assumptions were the cost assumptions for solar PV and onshore wind, which were obtained from the 2017 CSIR study [60] and are shown in Figure 3.4 below. The expected cost reductions for wind and solar PV in the long term vary across the literature [61]–[63] with the BNEF 2018 [64] study suggesting that their costs will decline by 58% and 71% by 2050 respectively. The future cost reduction assumption for both wind and solar PV in this study is thus conservative.

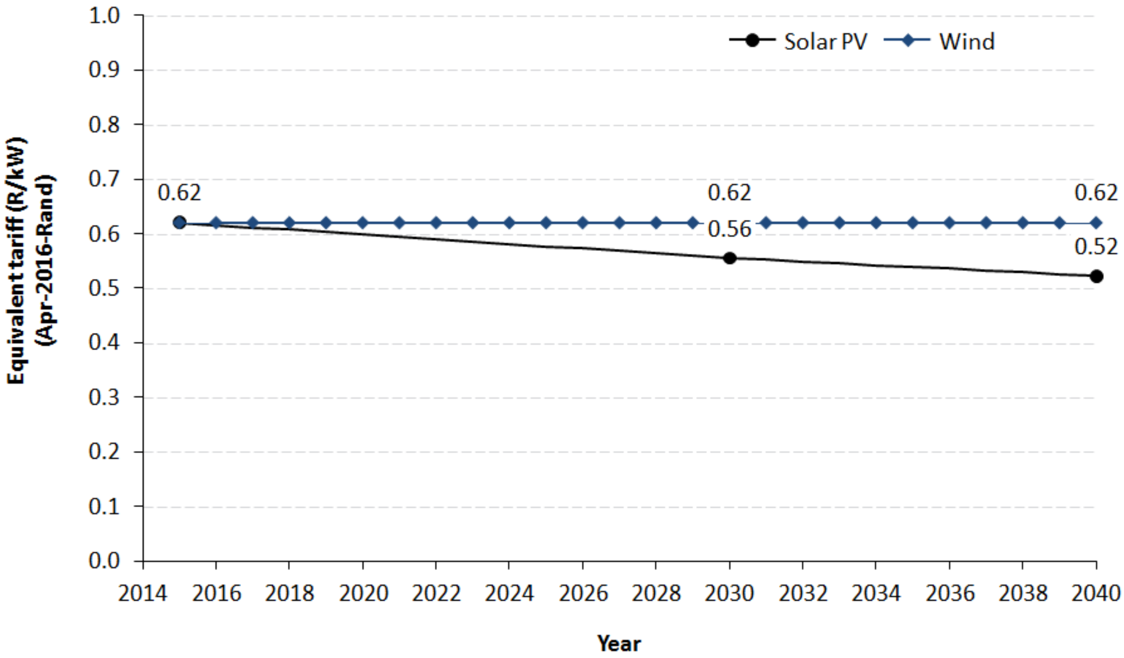


Figure 3.4. Future wind and solar PV cost assumptions [60]

A summary of the other supply technology options and their assumed capital costs are shown in Table 3.3.

The Levelized Cost of Electricity (LCOE) values are based on assumed capacity factors for illustration purposes. The mathematical optimization solves for the least-cost economic dispatch of each power station which together with the cost of the power station translates into an equivalent LCOE. The individual cost structures for each technology were thus explicitly included in the mathematic model (CAPEX, fuel cost, variable and fixed operations and maintenance costs, start/shutdown costs etc.).

The LCOE can at a high level be used to compare alternative technologies which vary in cost, lifespan and operation. The LCOE for a particular generation type is calculated as the net present value of the total life cycle costs incurred divided by the total energy produced over the lifespan of the technology. It is expressed mathematically as:

$$\mathrm{LCOE} = \frac{\sum_{t=1}^{n} \frac{I_t + O_t + F_t}{(1+r)^t}}{\sum_{t=1}^{n} \frac{E_t}{(1+r)^t}} \tag{3.2}$$

where,

I_t = Investment costs in year t (including financing)

O_t = Operations and maintenance costs in year t

F_t = Fuel costs in year t

r = Discount Rate

n = Lifespan of generator

E_t = Total electricity produced in year t

The mathematical optimization model was configured to first solve the capacity expansion problem in order to solve the investment decision for new capacity. This plan was then run in a more detailed production cost model in order to get the hourly dispatch profiles of each generation technology.

For this study OCGT capacity is referred to as “Gas: peaking” due to OCGT’s typically providing peaking energy with an annual capacity factor <10%, while CCGT capacity is referred to as “Gas: Mid-merit” with an annual capacity factor between 20 – 50 %.

Table 3.3. New generation supply options included in this study

Generation technology	CAPEX[1] (R/kW)	FOM[2] (R/kW/a)	Fuel[3] (R/kWh)	Capacity factor (%)	LCOE (R/kWh)
Coal (Pulverised Fuel)	35 463	924	0.4	82	1.0
Coal (Fluidized Bed Combustion)	42 806	621	0.3	82	1.3
Nuclear	60 447	968	0.1	90	1.1
Combined Cycle Gas Turbine (CCGT)[4]	8 975	165	1.1	36	1.5
Open Cycle Gas Turbine (OCGT)	8 173	161	1.7	6	3.6
Biomass (forestry)	74 450	1 655	0.5	85	1.3
Bagasse	17 821	172	2.2	50	2.6
Biogas	77 287	422	1.4	20	2.3
Landfill-gas	31 048	2 373	0.1	85	0.8
Pumped Storage	22 326	201	0	33	-
CSP (9h storage)	93 260	1 009	0	60	2.0

The daily variability of wind and solar PV were captured in the model through the use of hourly generation profiles obtained from a 2016 wind and solar PV resource aggregation study [65] for RSA. These profiles were generated based on actual 15 minute wind and solar irradiation measurements over a 5 year period and converted into normalized power time-series profiles. Time-series profiles for wind and solar PV were generated for a spatial resolution of 5 km by 5 km across the entire country. These profiles were then aggregated

[1] All costs are in April 2016 RSA Rands

[2] FOM = Fixed operations and maintenance costs

[3] Fuel cost includes variable operations and maintenance costs

[4] Assuming liquefied natural gas at 150 R/GJ

across 27 Eskom supply areas based on the RSA transmission grid as shown geographically in Figure 3.5. Figure 3.6 and Figure 3.7 show the 15 minute normalized power output for wind and solar PV across the 27 supply areas over 1 day. The aggregation effect (smoothed profile) can be seen by looking at the average power output across the supply areas.

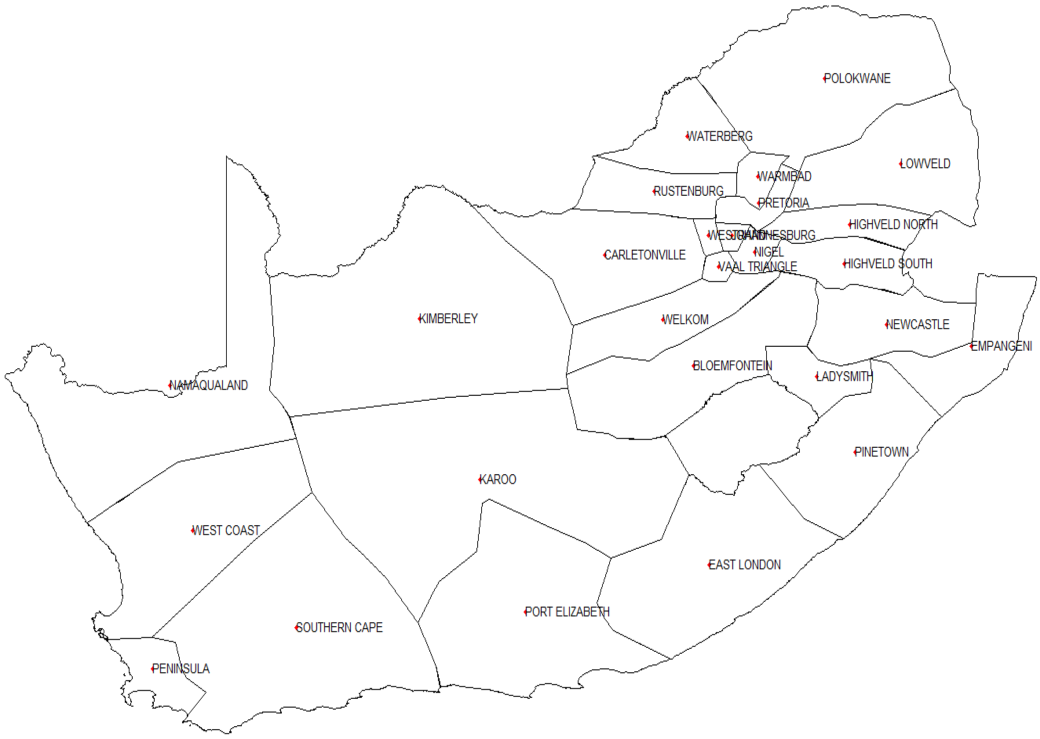


Figure 3.5. The 27 supply areas of South Africa

This study found that the potential for solar PV and wind deployment in RSA is technically unlimited at a national level where up to 22 000 GW of solar PV capacity and 5 400 GW of wind capacity could be built. The average national annual capacity factor for solar PV and wind in 2012 assuming a uniform spatial distribution across RSA was found to be 20.8% and 36.5% respectively.

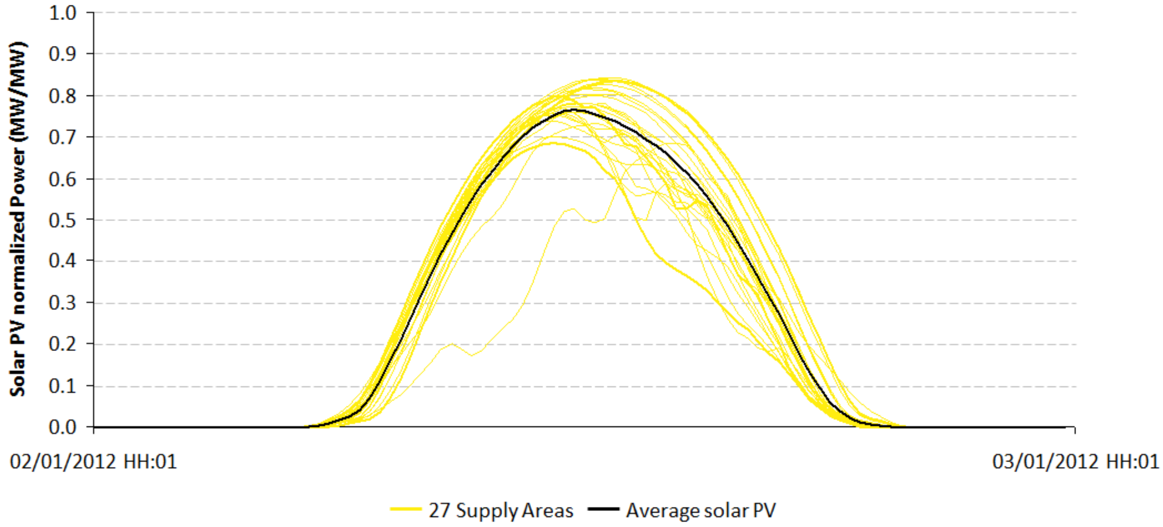


Figure 3.6. 15 minute normalized solar PV power across 27 Eskom supply areas for 1 day in 2012

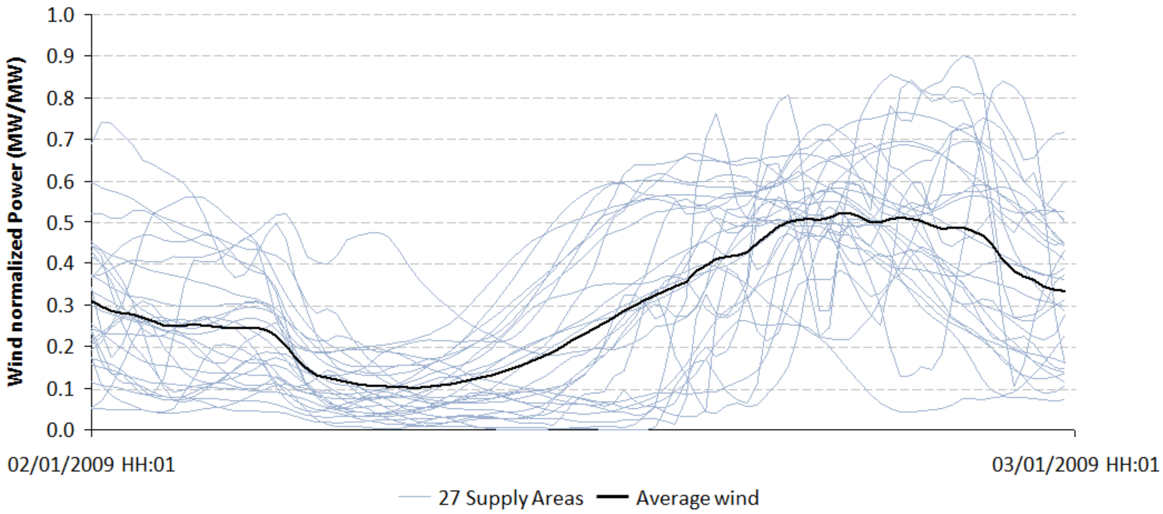


Figure 3.7. 15 minute normalized wind power across 27 Eskom supply areas for 1 day in 2009

3.3.4 Economic parameters

The economic input parameters used in this analysis were based on [4] and are as follows:

- Real Discount Rate of 8.2% (post-tax)
- Cost of Unserved Energy (COUE) equivalent to 77.30 R/kWh

As described in Section 3.2, the objective function of the model is to minimize the Net Present Value (NPV) of all future costs. The Discount Rate is used to translate costs incurred in future years to a present day value. Combined with additional explicit reserve requirements (see Section 3.3.6), the inclusion of the COUE ensures that a minimum level of acceptable system adequacy is achieved.

3.3.5 Environmental constraints

The water consumption and CO_2 emission rates for each generator was included in the modelling analysis and was based on [4]. No CO_2 tax was included in this study. A boundary condition annual CO_2 emissions limit from the power sector was applied as per the IRP 2016 Moderate Decline CO_2 trajectory as shown in Figure 3.8.

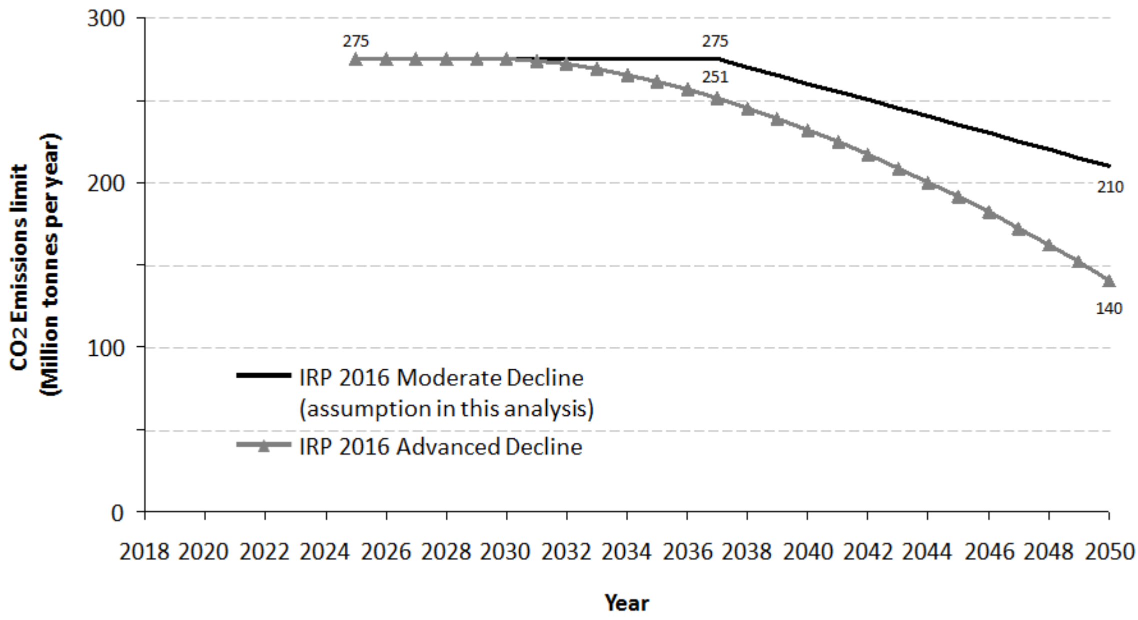


Figure 3.8. CO_2 electricity sector emissions trajectories for South Africa.

3.3.6 Power system reliability

System reliability is an important requirement in the modelling set up. As discussed earlier, by including a high cost of unserved energy in the objective function, the optimal solution will aim to minimize unserved energy which ensures a certain level of system reliability. The inclusion of operational reserve requirements in the model was also used to ensure an acceptable level of system adequacy across all scenarios. A simplified approach was taken where the system operational reserve requirements were modelled as per Eskom's ancillary reserves document [66] up to 2022 and were extrapolated thereafter to 2050 assuming that system reserves would scale with electricity demand.

3.3.7 Battery electric vehicles

In the modelling approach, it was assumed that the regulations, policies and infrastructure required to support the uptake of BEVs would be in place by 2040. BEV's were modelled based on the Tesla Model S60, assuming an average battery size of 60 kWh with a range of 338 km. The average annual km travelled by electric vehicles in 2040 was assumed to be constant at 18 500 km/year based on the average for passenger vehicles from [67]. An aggregated unitized vehicle charging profile was used in this analysis which was adapted from the California Energy Commission study with NREL [40] as shown previously in Figure 2.8. This profile consists of a weekday and a weekend charging profile and was scaled according to the number of electric vehicles, battery size and average annual distance travelled assumptions for this study, resulting in an annual charging demand of 9 TWh for a BEV fleet of 2.8 million passenger vehicles. A summary of the BEV input assumptions are shown in Table 3.4.

Two electric vehicle penetrations by the year 2040 were considered. A "moderate" adoption of electric vehicles was assumed for all study scenarios which was based on BNEF's 2017 Electric Vehicle Outlook [37], which assumes that 33% of vehicles will be electric. An additional sensitivity was tested where 100% of passenger vehicles are assumed to be electric by 2040. The projected total number of passenger vehicles in RSA in 2040 was based on [35], resulting in a total of 8.4 million passenger vehicles in 2040 as shown in Figure 3.9.

Table 3.4. Input assumptions for electric vehicles

Electric Vehicle Specifications	
Battery capacity (kWh)	60
Average range (km)	338
Average energy consumption (kWh/km)	0.178
Average annual distance travelled (km)	18 500
Number of electric vehicles (millions)	2.8
Average aggregated daily charging demand (kWh)	9

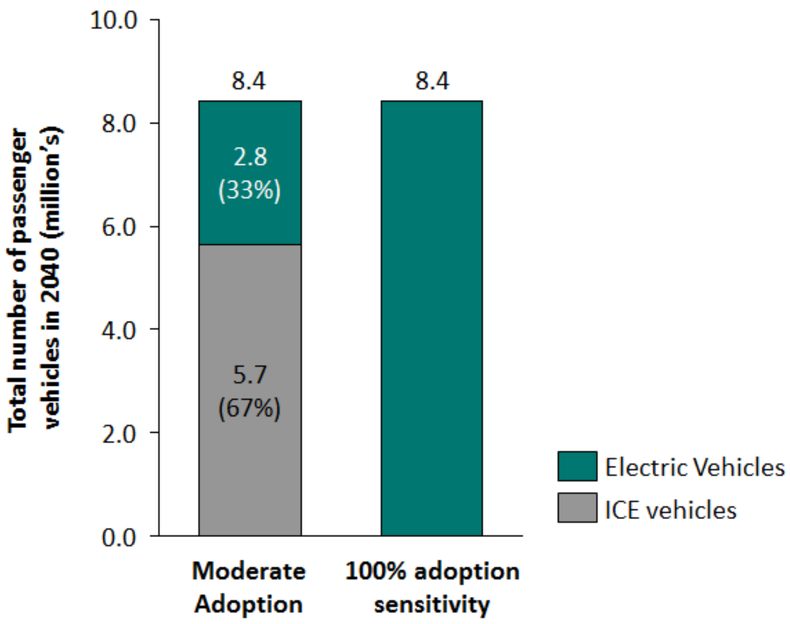


Figure 3.9. Proportion of electric and ICE vehicles in 2040 assumed in this study

Figure 3.10 shows the PLEXOS visualization of the supply generators linked to the system and electric vehicle charging demand.

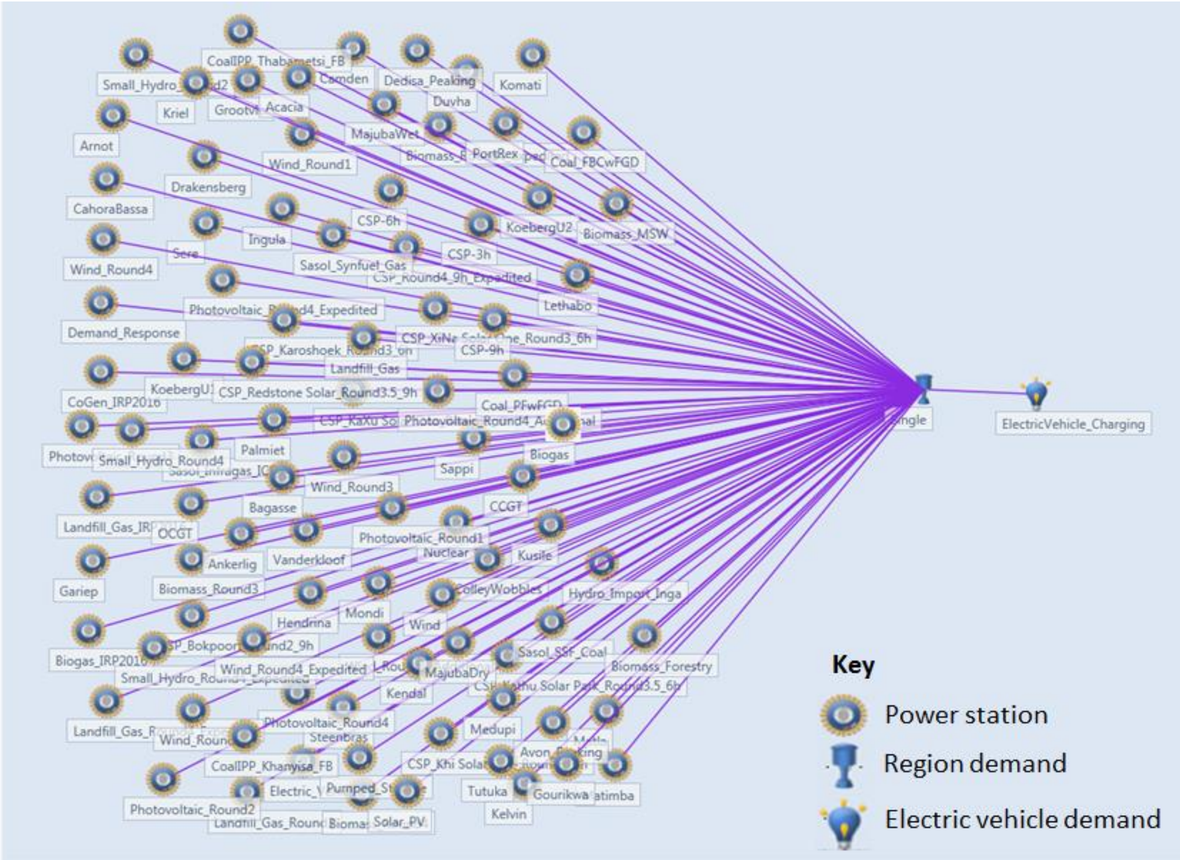


Figure 3.10. PLEXOS visualization of the supply generators and system demand

3.4 CHAPTER SUMMARY

In this chapter an overview of the input assumptions and power system model configuration was provided. The analysis and modelling results are shown in the next chapter.

CHAPTER 4 RESULTS

4.1 CHAPTER OVERVIEW

This chapter summarizes the modelling results obtained for the four study scenarios for both BEV adoption assumptions. The primary outputs that are reported on for each scenario in the year 2040 include:

- The generation capacity per technology type
- The expected energy output of the generation portfolio (energy mix)
- The electricity sector CO_2 emissions and water consumption
- The resulting total annual power system cost (generation cost only)

4.2 BASE CASE

The Base Case (BC) scenario represents the least-cost capacity expansion plan when BEV’s are excluded from the planning data. The purpose of the BC is to form a comparative reference year against which scenarios including BEV’s can be compared on the basis of total system cost and differences in supply portfolios. The impact of BEV’s on the power system can then be quantified relative to the BC.

The modelling results of the BC scenario are shown in Figure 4.1 and include the total installed capacity and energy expected from the existing and new generation capacity per technology type. Figure 4.2 shows only the new build capacity which was chosen through the least-cost optimization of the power system. The results are also tabled in the Addendum.

The analysis shows that it is least-cost to build 34.6 GW of new solar PV, 38.1 GW of new wind, 0.3 GW of landfill gas, 8.8 GW of CCGT's (Gas: mid-merit) and 23.2 GW of OCGTs (Gas: Peaking) in 2040 for the given input assumptions. The largest energy contribution comes from wind at 33%, followed by 30% from coal-fired power, 18% from solar PV, 8% from gas-fired power, 1% from landfill gas and the rest from existing CSP (1%), hydro (5%) and nuclear (4%) power. The energy mix in 2040 is significantly different to that of today's energy mix in South Africa, where renewable energy contributes less than 10% (including hydro) and coal 80% to the total electricity demand [68]. The transformation of the power system from coal-based to renewables-based occurs simply due to wind and solar PV being the cheapest new-build generation options in South Africa today.

The total annual curtailed wind and solar PV energy is approximately 3.5 TWh. This represents a curtailment factor of 2.0%, which is the proportion of available wind and solar PV curtailed. The curtailment factor is an outcome of the optimization. Curtailed energy effectively reduces the amount of useful energy provided by wind or solar PV which effectively increases their levelized cost to the power system which is captured in the objective function. The inclusion of a monetary value for curtailed energy (assuming it could be sold for other purposes) was not included in this study.

This least-cost energy mix results in a total system cost of R269 billion and is also shown in Figure 4.1. The total system cost is the sum of all generation investment costs, fuel costs and fixed and variable operating costs for existing and new power generators. As discussed previously, generation costs constitute approximately 70% of total electricity costs.

The total CO_2 emissions and water usage from this generation portfolio equates to 115.6 million tonnes and 36.0 million tonnes respectively.

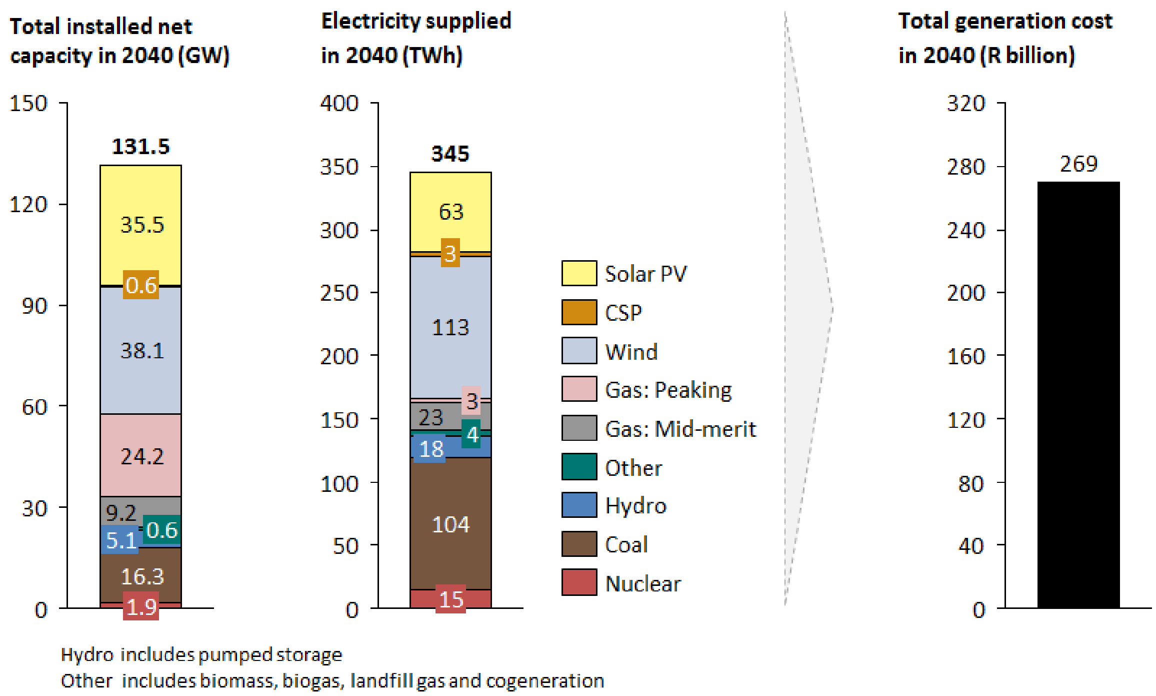


Figure 4.1. Least-cost electricity portfolio and total cost for the BC

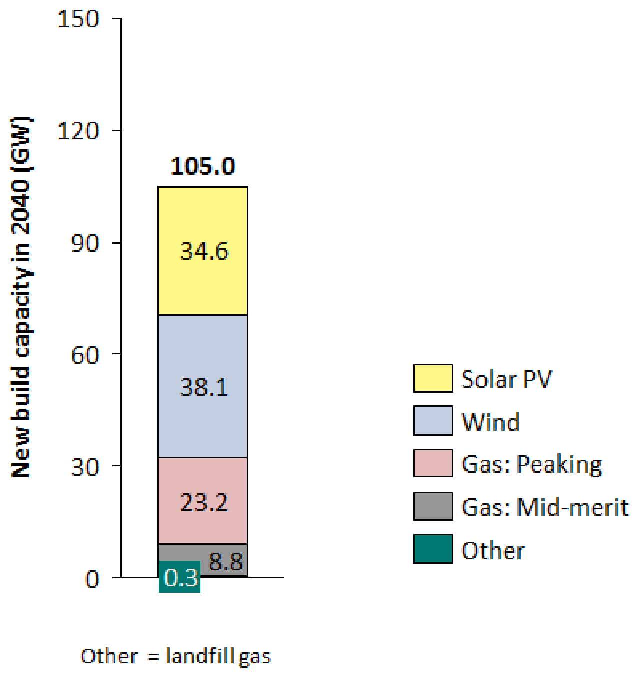


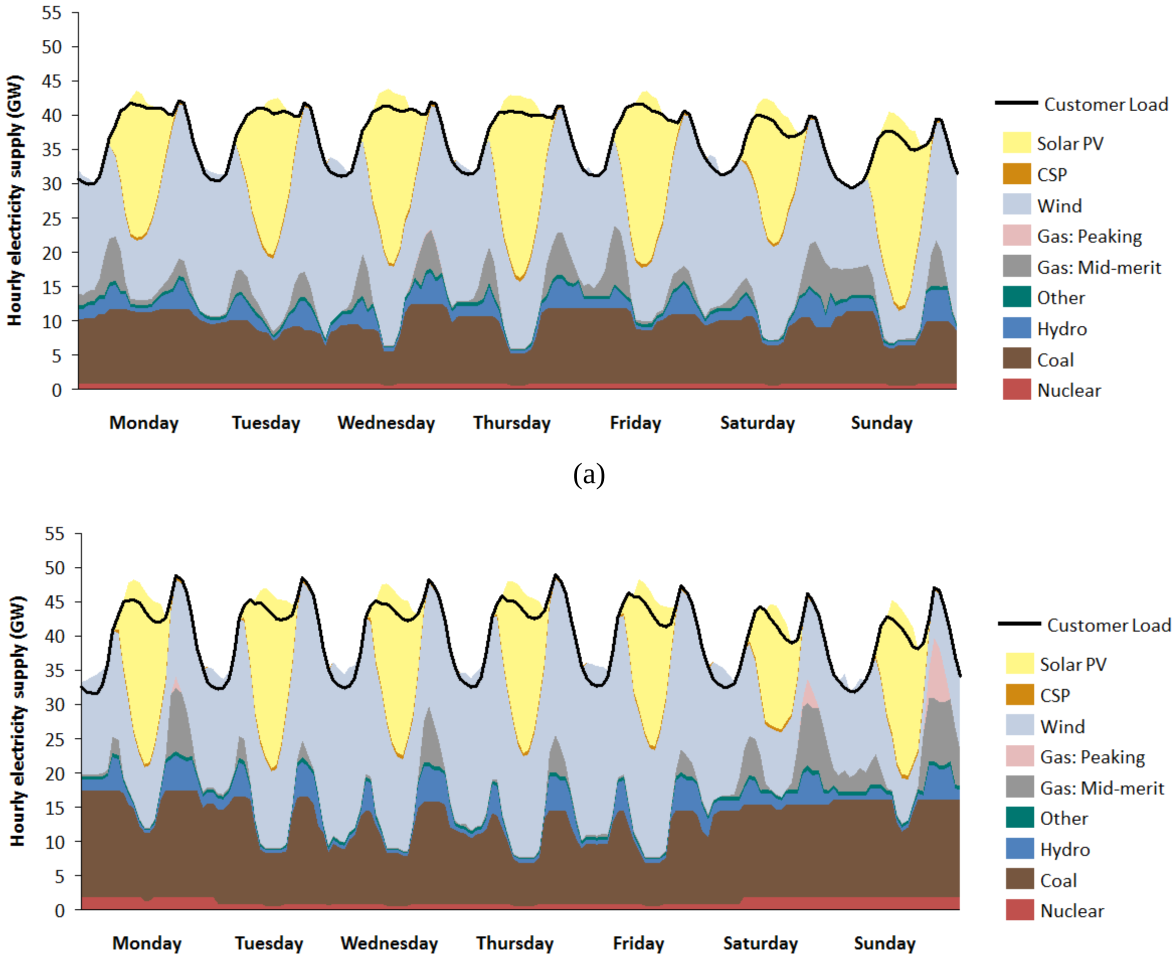
Figure 4.2. New build capacity in 2040 for the BC

Figure 4.3 shows the simulated total hourly generation from existing and new build capacity for an exemplary summer and winter week in 2040. It is evident from the hourly generation profiles that wind and solar PV are fully utilized when available and coal, gas and hydro power provide flexibility and supply the residual load. Customer load equates to the system total electricity demand, excluding the additional load from pumped storage in pumping mode. Electricity supply above the customer load level represents the pumping load for the hydro pumped storage generators which generally occurs during the middle of the day when solar PV supply peaks as well as in the middle of the night when the system demand is the lowest. Gas and hydro power provide peaking capacity during the morning and evening peak periods, while nuclear and coal are dispatched as much as possible during all hours of the day.

It is important to note that the weekly generation profiles are an outcome of a detailed hourly unit commitment and dispatch simulation which considers the technical limitations of the different power generators as well as system adequacy requirements. This includes aspects such as the ramping rates of the dispatchable power generators, reservoir levels of the pumped hydro generators as well as system reserve requirements (primary, secondary and tertiary reserves). The power generators are dispatched according to the least-cost order of dispatch.

There is curtailment of wind and/or solar PV (not shown) on some days during the middle of the day when solar PV generation peaks and is coincident with relatively high wind production on those days. Curtailment is also more prevalent on weekends and public holidays where system demand is lower.

The load duration curve showing the system load and residual load for the BC scenario is shown in Figure 4.4. The load duration curve shows the hourly demand for the year 2040 sorted in order of highest magnitude to lowest magnitude.



(a)

(b)

Figure 4.3. Hourly electricity supply for a summer and winter week in 2040 for the BC

(a) Summer week, (b) Winter week.

The load duration curve shows that the combination of wind and solar PV present in the BC considerably increases the requirement for peaking capacity (from 8 to 20 GW) to meet the residual load, assuming peaking capacity typically supplies demand for less than 1 000 hours per year. Similarly the large share of renewable energy greatly reduces the requirement for "base load" capacity which typically supplies demand for more than 6 000 hours of the year.

The residual load (RL) is calculated as follows:

$$RL = SL - G_w - G_s \tag{4.1}$$

Where SL represents the System Load, G_w represents the total wind generation and G_s represents the total solar PV generation.

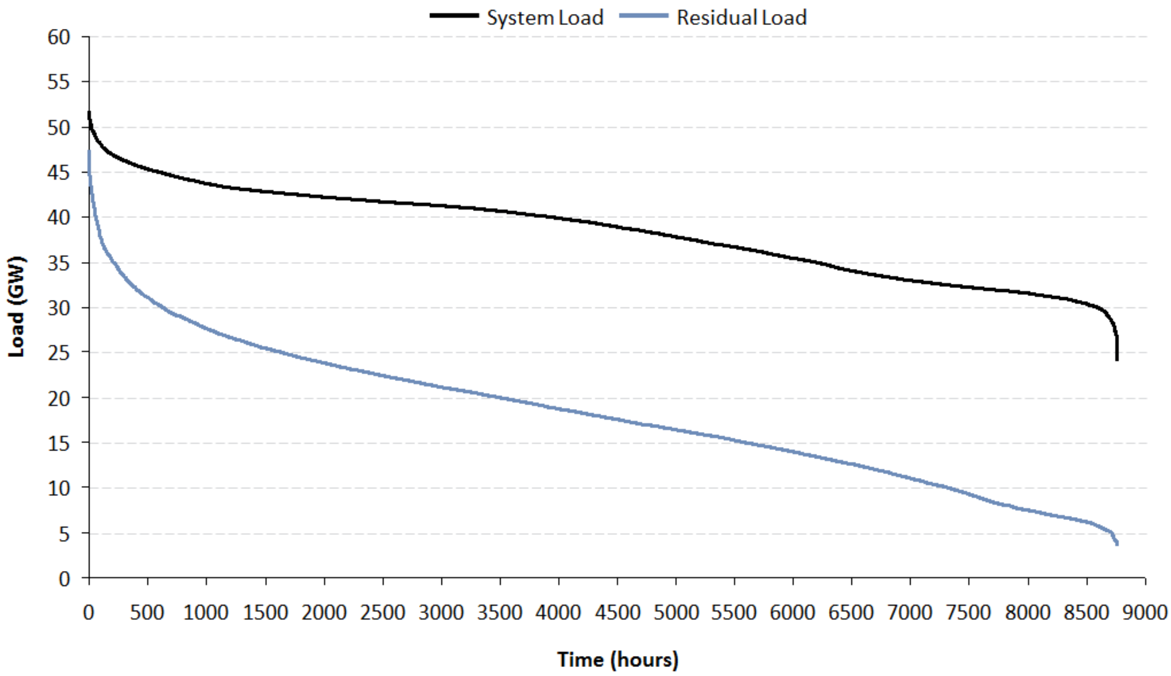


Figure 4.4. Load duration curve for the BC

Figure 4.5 shows the cumulative frequency of the hourly ramping requirements for both the system demand and the residual demand. It can be seen that the presence of wind and solar PV increase both the upwards and downwards hourly ramping requirements of the power system. For 90% of the hours in the year, the upwards system ramping demand is below 2.6 GW, which increases to 4.5 GW for the residual load.

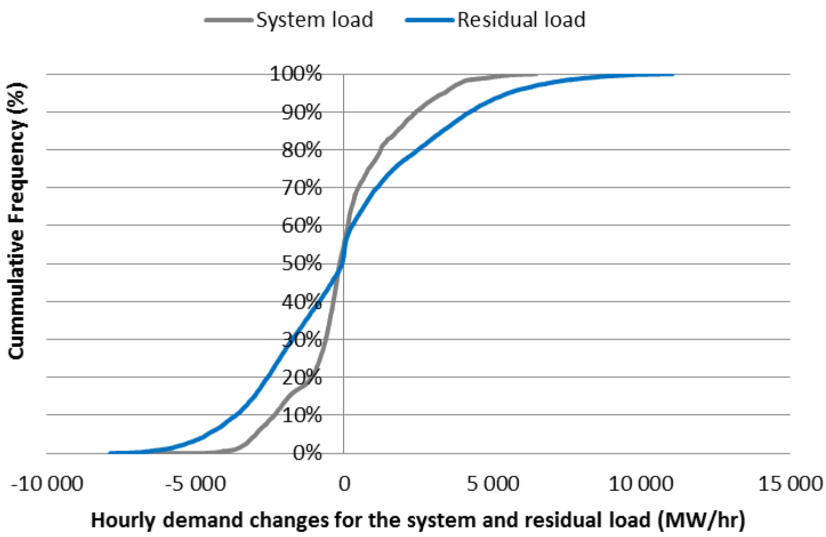


Figure 4.5. Hourly ramping requirements of system and residual load for the BC

4.3 FIXED CHARGING PROFILE

The Fixed Charging Profile (FC) scenario was modelled with the same input assumptions as the BC scenario but with the inclusion of a 2.8 million BEV fleet (33% of all passenger vehicles) in a G2V configuration, assuming a fixed aggregated charging profile from previous literature as summarized in Section 3.3.7. The BEV charging demand increased the annual electricity demand by 9.2 TWh and the annual peak demand by 1.8 GW. The increase in hourly electricity demand is shown in Figure 4.6 relative to the BC scenario for a summer week in 2040. It can be seen that BEV charging increases the evening peak demand as well as mid-day and night time periods.

Table 4.1 shows the hourly system demand gradient for the BC and the FC scenario. It can be seen that the mean upward hourly system gradient increases by 110 MW, while the mean downward gradient increases by 55 MW.

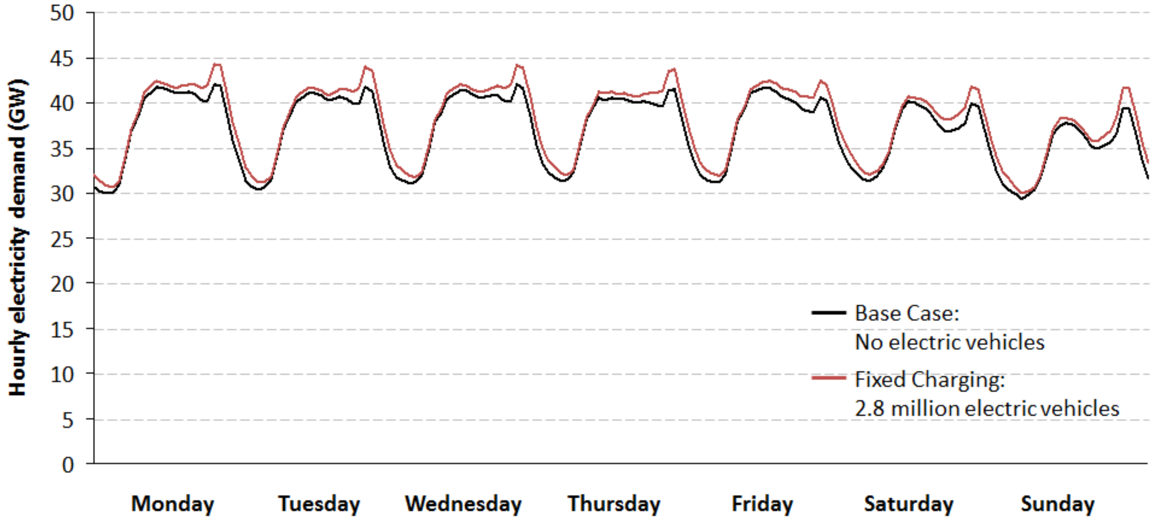


Figure 4.6. Hourly electricity demand with and without electric vehicles for a summer week

Table 4.1. Hourly system demand gradient statistics: FC with 2.8 million BEVs

Hourly system gradients	Base Case (MW)	Fixed Charging (MW)
Mean Upwards Ramp	1 429	1 539
Mean Downwards Ramp	1 165	1 220
Maximum Upwards Ramp	6 461	6 442
Maximum Downwards Ramp	6 263	6 635

The modelling results of the FC scenario are shown in Figure 4.7 and include the total installed capacity and energy expected from the existing and new generation capacity per technology type. The results are also tabled in the Addendum.

The analysis shows that it is least-cost to build 35.0 GW of new solar PV, 40.3 GW of new wind, 0.3 GW of landfill gas, 9.5 GW of CCGT’s and 24.4 GW of OCGT’s in 2040 for the given input assumptions. The largest energy contribution comes from wind at 34%, followed by 29% from coal-fired power, 18% from solar PV, 8% from gas-fired power and the rest from existing CSP, hydro and nuclear power. This represents an increase in both the capacity and energy contribution from wind and gas-fired power due to the addition of

BEV's in the power system. The total annual curtailed wind and solar PV energy in the FC scenario is approximately 3.9 TWh. This represents a curtailment factor of 2.1% which is marginally higher than the curtailment observed in the BC.

The 2.8 million BEV's thus impacted the optimal capacity and energy mix of the least-cost capacity expansion power system in 2040. Additionally, the FC least-cost energy mix results in a total system cost of R278 billion, an increase of R9 billion (3% increase) compared to the BC. An increase in system cost from the BC is expected as the demand increased by roughly 3%.

The total CO_2 emissions and water usage for the FC scenario equates to 116.4 million tonnes and 36.3 million tonnes respectively, which is marginally more than the BC. This indicates that the majority of additional charging demand is met by CO_2^- and water-neutral technologies.

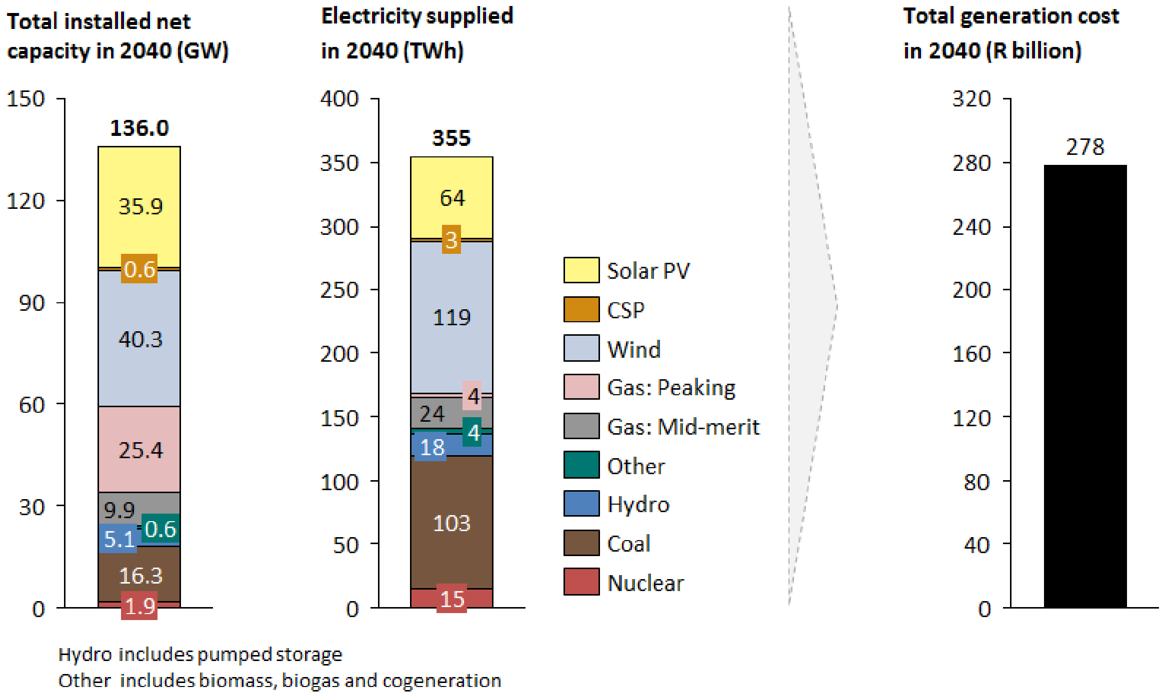


Figure 4.7. Least-cost electricity portfolio and total cost for the FC scenario (2.8 million BEVs)

Figure 4.8 shows only the new build capacity from the FC scenario and compares this to the capacity built in the BC. Figure 4.9 shows the total energy difference from the BC which includes 0.1 TWh of additional pumping load and 9.1 TWh of charging demand. The majority of the charging demand was supplied by wind and gas-fired capacity, with the energy contribution from the existing fleet only changing marginally from the BC.

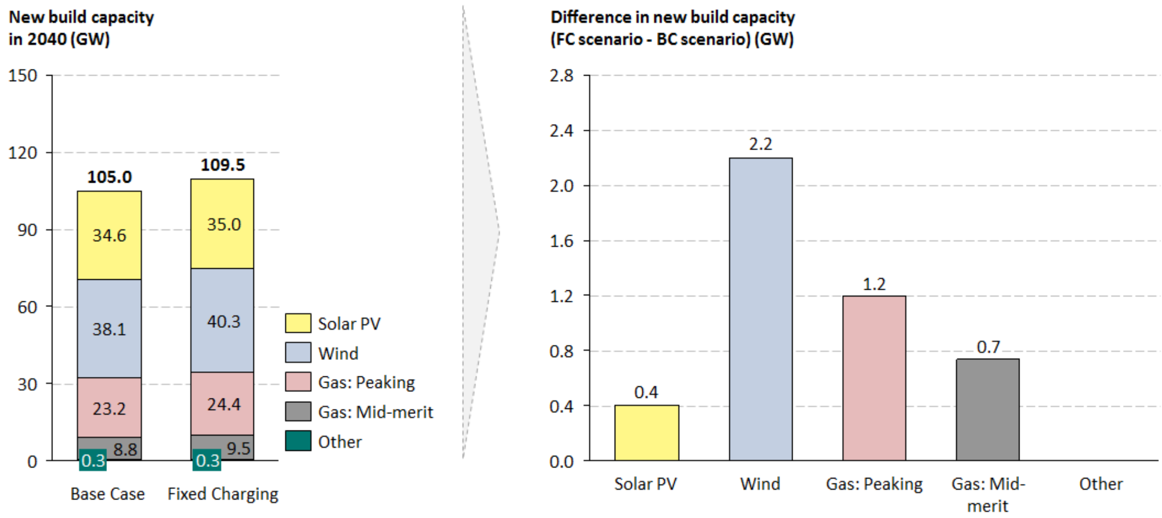


Figure 4.8. Difference in new capacity built in the FC scenario versus the BC

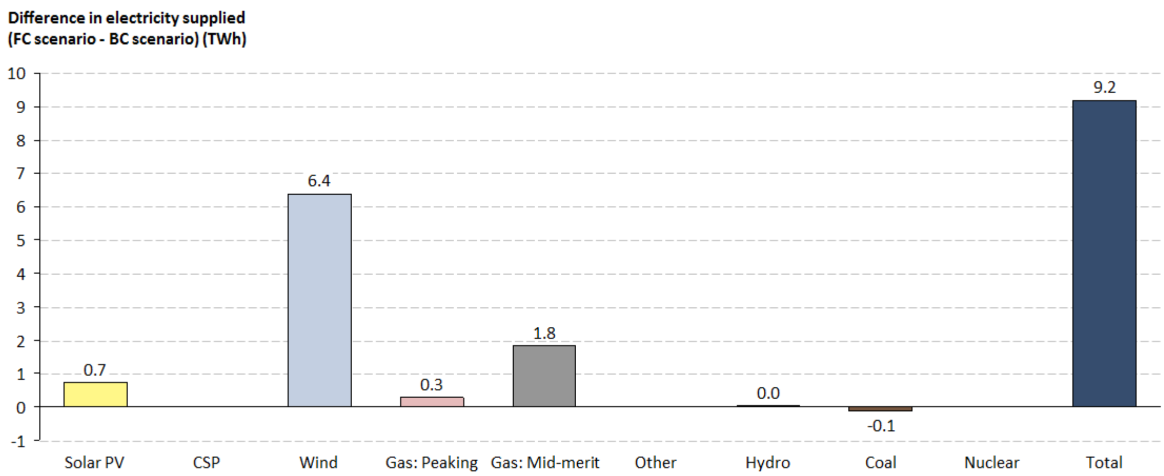
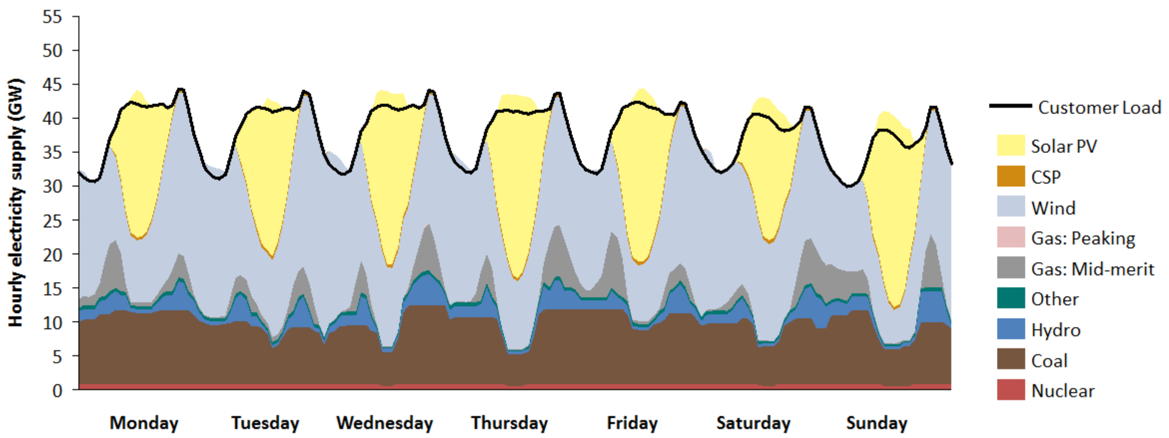
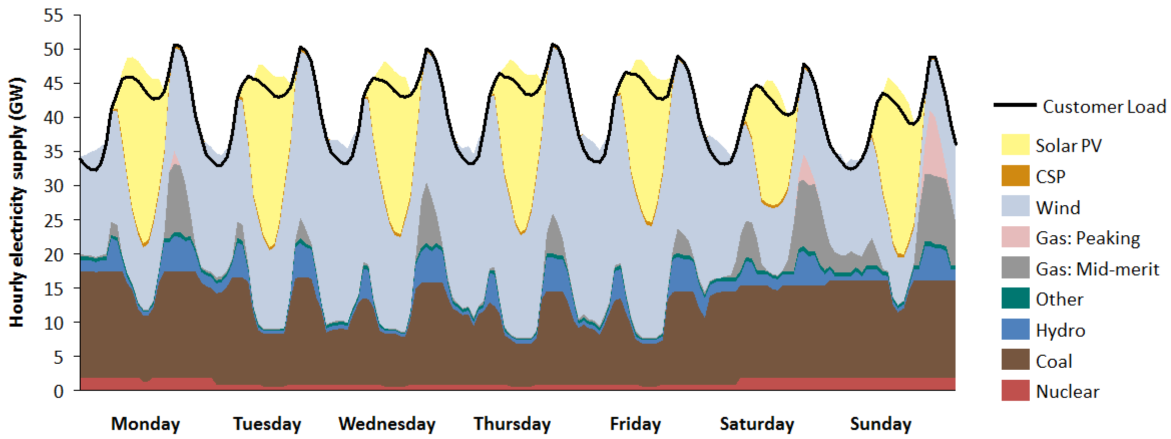


Figure 4.9. Difference in total electricity supplied for the FC scenario versus the BC

Figure 4.10 shows the simulated total hourly generation from existing and new build capacity for the same summer and winter week shown previously for the BC. As observed in the BC results, the FC scenario shows a similar supply dispatch profile, with wind and solar PV fully utilized when available and coal, gas and hydro power provide flexibility and supply the residual load. In the FC scenario, the total wind energy production is 1% higher than the wind production in the BC scenario.



(a)



(b)

Figure 4.10. Hourly electricity supply for a summer and winter week in 2040 for FC scenario

(a) Summer week, (b) Winter week.

Figure 4.11 shows the load duration curves for the BC and FC scenario. It can be seen that the presence of BEV charging demand increases the requirement for peaking capacity (from 7.8 to 8.3 GW), assuming peaking capacity typically supplies demand for less than 1 000 hours per year. It is also evident that the peak demand is increased with the presence of BEV's.

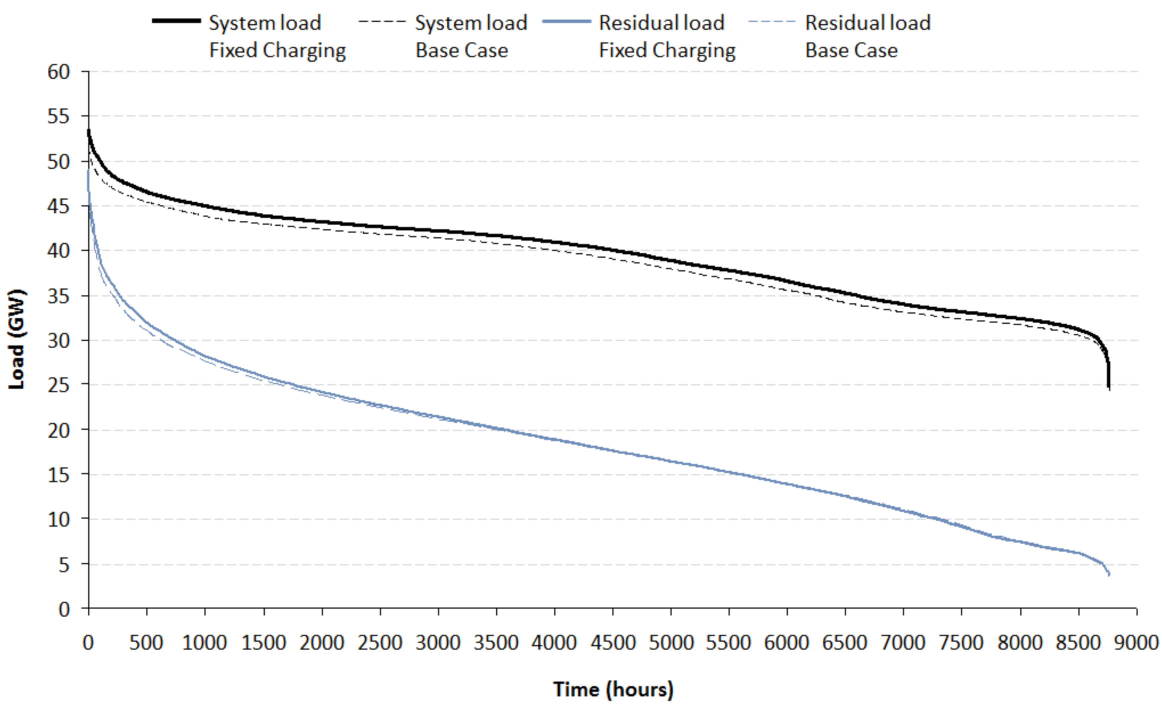


Figure 4.11. Load duration curve for the FC scenario vs. the BC

Figure 4.12 shows the cumulative frequency of the hourly ramping requirements for both the system demand and the residual demand of the FC scenario. It can be seen that the presence of wind and solar PV increase both the upwards and downwards hourly ramping requirements of the power system. For 90% of the hours in the year, the upwards hourly system ramping demand is below 2.7 GW (0.1 GW higher than the BC), which increases to 4.7 GW (0.2 GW higher than the BC) for the residual load.

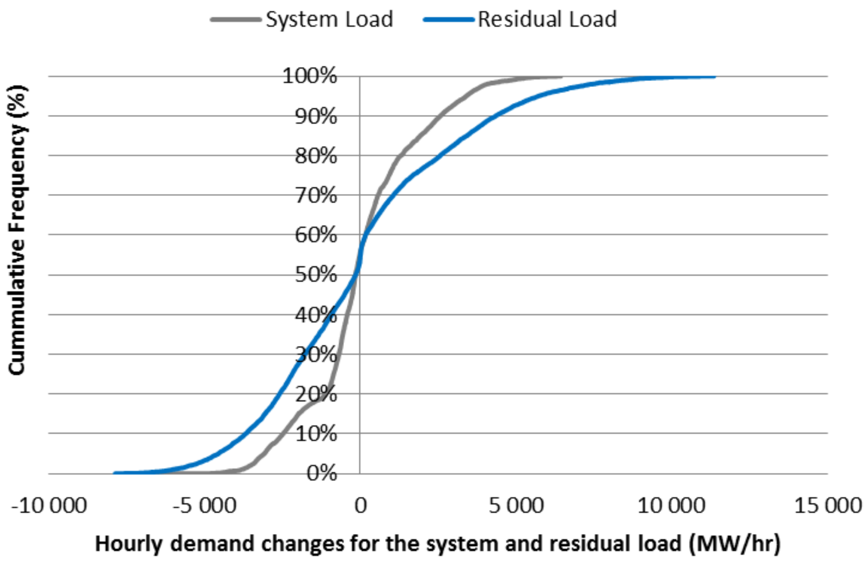


Figure 4.12. System and residual load hourly ramping requirements for the FC scenario

4.4 SENSITIVITY: FC WITH 8.4 MILLION ELECTRIC VEHICLES

The Fixed Charging Profile (FC) scenario was repeated assuming 8.4 million BEV fleet (100% of all passenger vehicles) in a G2V configuration, assuming the same fixed aggregated charging profile as before. The BEV charging demand increased the annual electricity demand by 28 TWh and the annual peak demand by 5.9 GW. This sensitivity represents an extreme scenario in order to test whether there are any significant deviations in the results as compared to the FC scenario with 2.4 million BEV's. The increase in hourly electricity demand is shown in Figure 4.13 relative to the BC scenario for a summer week in 2040. It can be seen that BEV charging increases the evening peak demand as well as mid-day and night time periods. Table 4.2 shows the hourly system demand gradient for the BC and the FC scenario. It can be seen that the mean upward hourly system gradient increases by 253 MW, while the mean downward gradient increases by 287 MW.

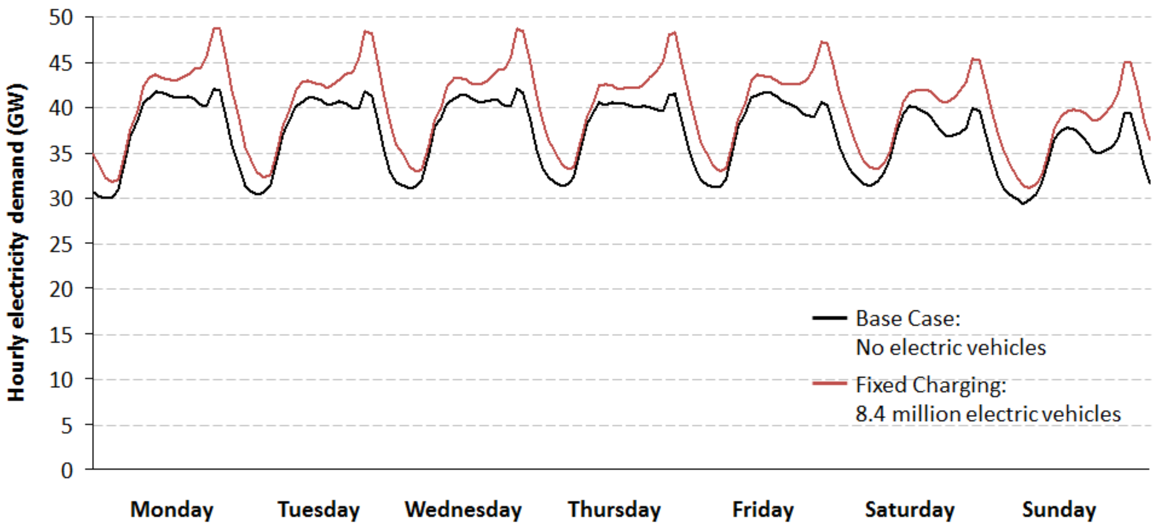


Figure 4.13. Hourly electricity demand with and without 8.4 million BEVs for a summer week

Table 4.2. Hourly system demand gradient statistics: FC with 8.4 million BEVs

Hourly system gradients	Base Case (MW)	Fixed Charging (MW)
Mean Upwards Ramp	1 429	1 682
Mean Downwards Ramp	1 165	1 452
Maximum Upwards Ramp	6 461	6 404
Maximum Downwards Ramp	6 263	6 872

The modelling results of the FC scenario with 8.4 million BEV's are shown in Figure 4.14 and include the total installed capacity and energy expected from the existing and new generation capacity per technology type.

The analysis shows that it is least-cost to build 35.7 GW of new solar PV, 44.7 GW of new wind, 0.3 GW of landfill gas, 11.0 GW of CCGT's and 26.7 GW of OCGT's in 2040 for the given input assumptions. The largest energy contribution comes from wind at 35%, followed by 28% from coal-fired power, 18% from solar PV, 9% from gas-fired power and the rest from existing CSP, hydro and nuclear power. This represents an increase in both the capacity and energy contribution from wind and gas-fired power due to the addition of

BEV's in the power system. The total annual curtailed wind and solar PV energy in the FC scenario is approximately 4.6 TWh. This represents a curtailment factor of 2.3%.

The 8.4 million BEV's thus impacted the optimal capacity and energy mix of the least-cost capacity expansion power system in 2040. Additionally, the FC least-cost energy mix results in a total system cost of R297 billion, an increase of R27 billion (10% increase) compared to the BC. An increase in system cost from the BC is expected as the demand is increased by roughly 8%.

The total CO_2 emissions and water usage for the FC scenario equates to 118.0 million tonnes and 34.3 million tonnes respectively. This represents a slight drop in water consumption with the addition of BEV's and marginally higher CO_2 production. This indicates that the majority of additional charging demand is met by CO_2 neutral technologies while the drop in water consumption comes mainly from a drop in coal-fired generation.

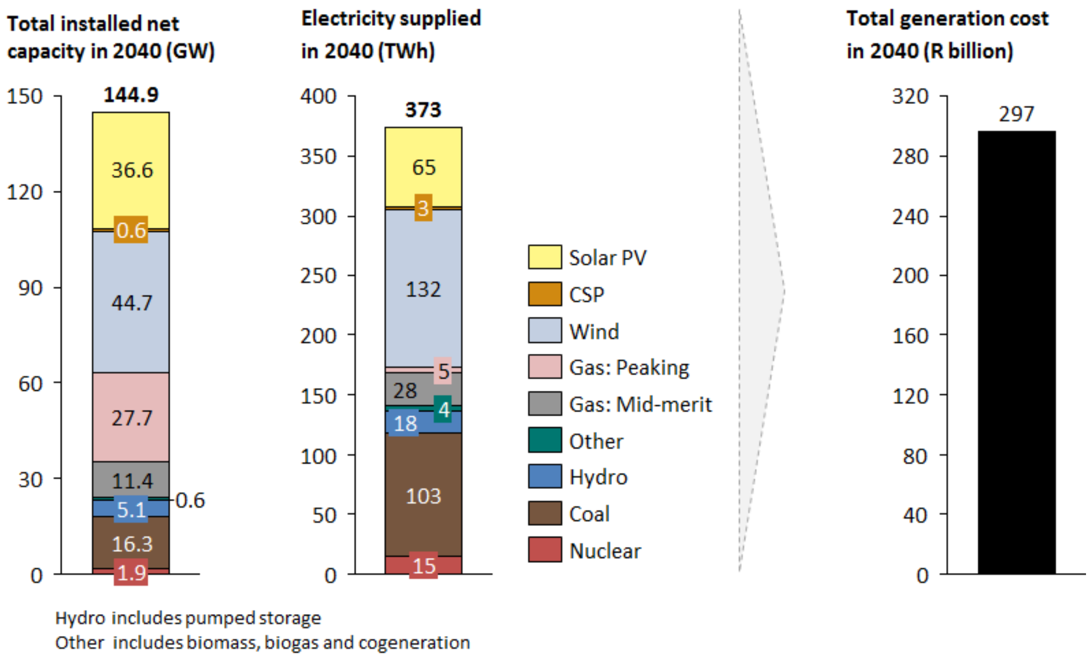


Figure 4.14. Least-cost electricity portfolio and total cost for the FC sensitivity

Figure 4.15 shows only the new build capacity from the FC scenario and compares this to the capacity built in the BC. Figure 4.16 shows the total energy difference from the BC which includes 0.2 TWh of additional pumping load and 27.7 TWh of charging demand.

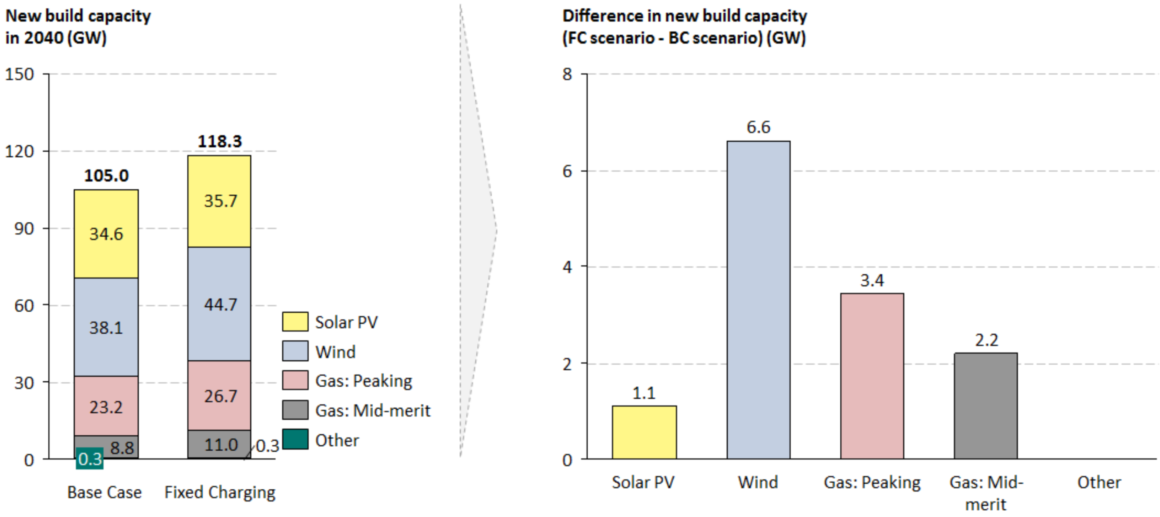


Figure 4.15. Difference in new capacity built in the FC sensitivity versus the BC

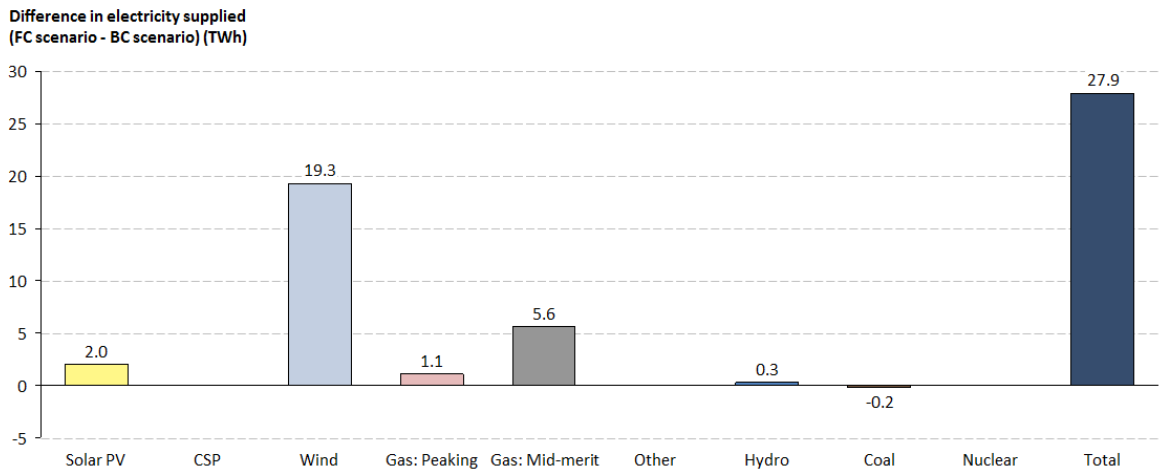


Figure 4.16. Difference in total electricity supplied for the FC sensitivity versus the BC

Figure 4.17 shows the energy share per supply source that is supplying the charging demand for the FC scenario with 2.8 and 8.4 million BEV's. The energy share from peaking capacity is marginally higher for higher BEV adoption case but overall there is not a significant difference between the two supply portfolios.

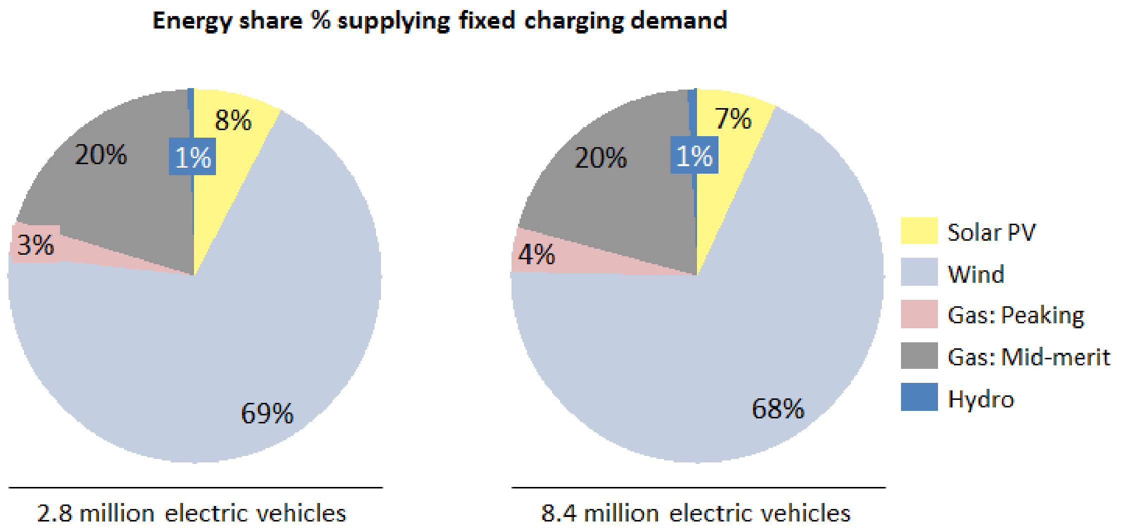


Figure 4.17. Share of energy supply sources supplying the charging demand for 2.8 and 8.4 million electric vehicles

Figure 4.18 shows the simulated total hourly generation from existing and new build capacity for the same summer and winter week shown in Figure 4.3. As observed in the BC results, the FC scenario shows a similar supply dispatch profile, with wind and solar PV fully utilized when available and coal, gas and hydro power provide flexibility and supply the residual load.

Figure 4.19 shows the load duration curves for the BC and FC sensitivity scenario. It can be seen that the high adoption of BEV's significantly increases the requirement for peaking capacity (from 7.8 to 9.7 GW), assuming peaking capacity typically supplies demand for less than 1 000 hours per year. Additionally, the BEV charging demand reduces the energy requirements from conventional generation sources (i.e. coal and nuclear) which was also evident in the energy mix.

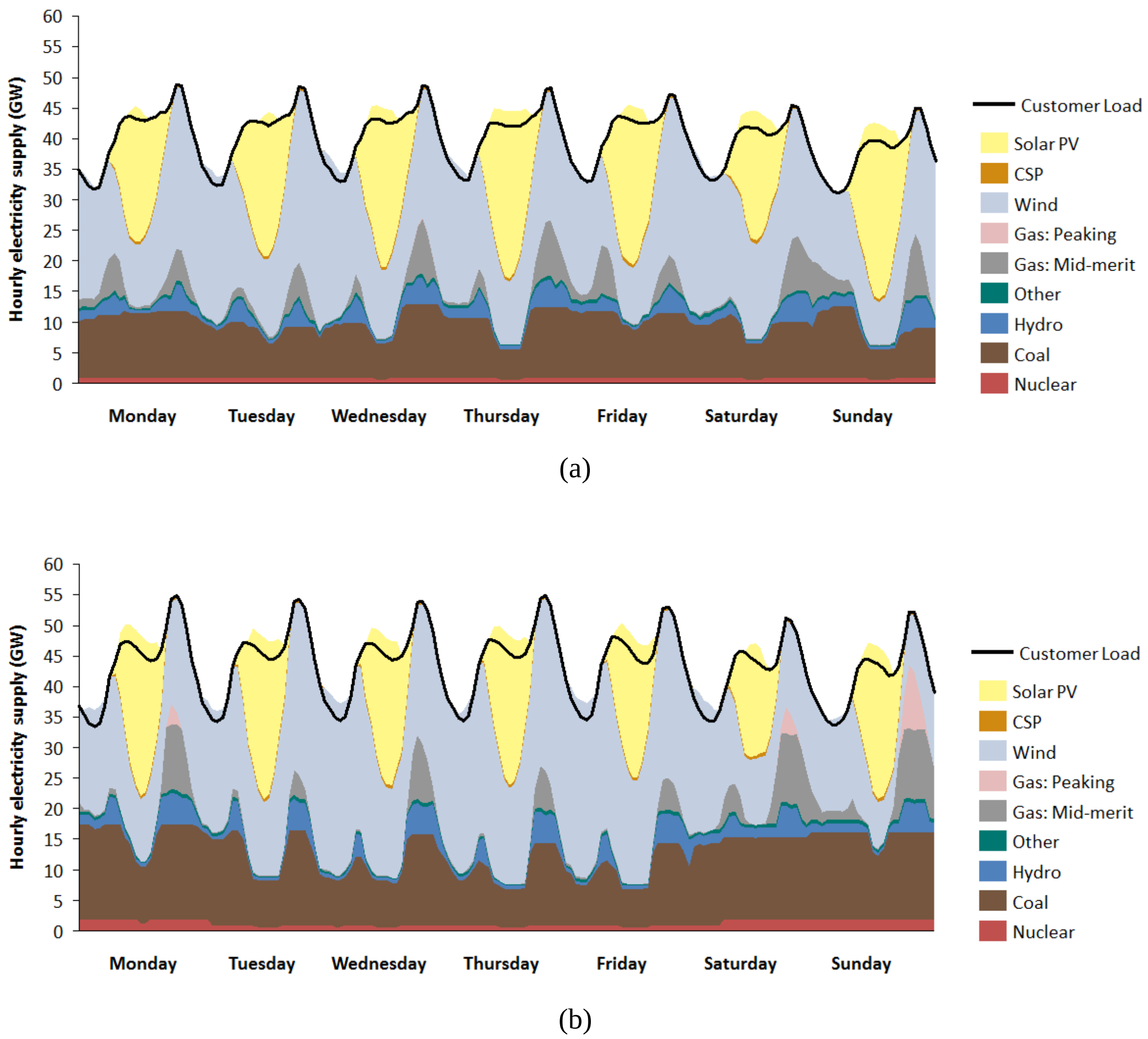


Figure 4.18. Hourly electricity supply for a summer and winter week in 2040 for FC sensitivity (a) Summer week, (b) Winter week.

Figure 4.20 shows the cumulative frequency of the hourly ramping requirements for both the system demand and the residual demand of the FC sensitivity scenario. It can be seen that the presence of wind and solar PV increase both the upwards and downwards hourly ramping requirements of the power system. For 90% of the hours in the year, the upwards system ramping demand is below 3 GW (0.4 GW higher than the BC), which increases to 5 GW (0.5 GW higher than the BC) for the residual load.

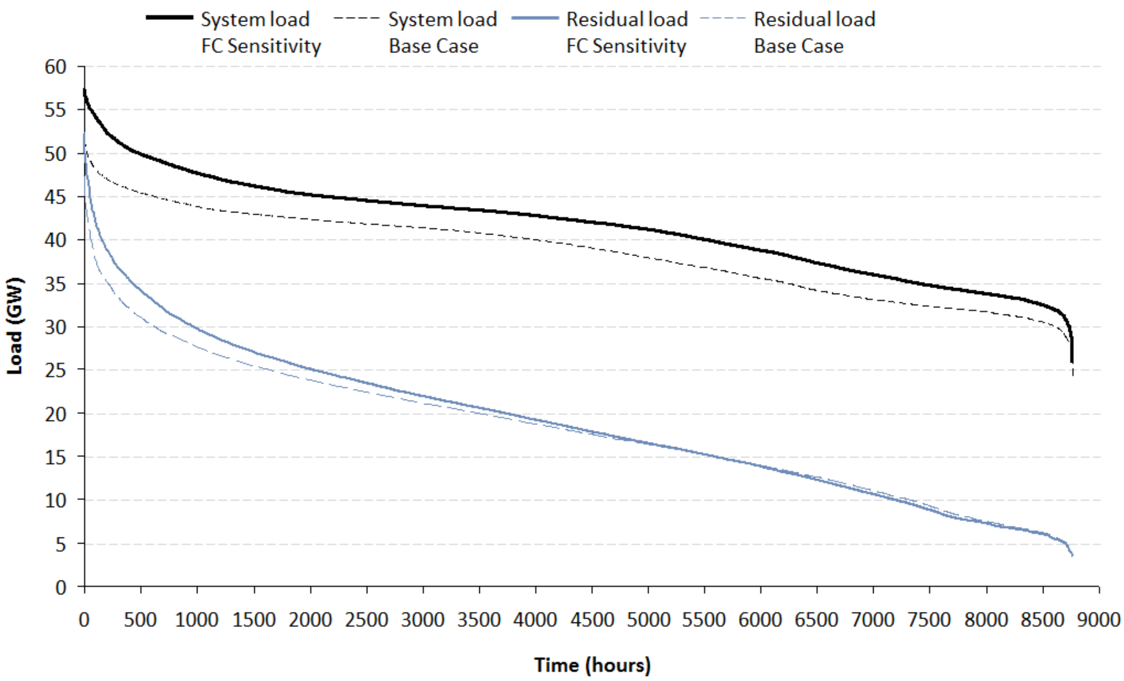


Figure 4.19. Load duration curve for the FC sensitivity

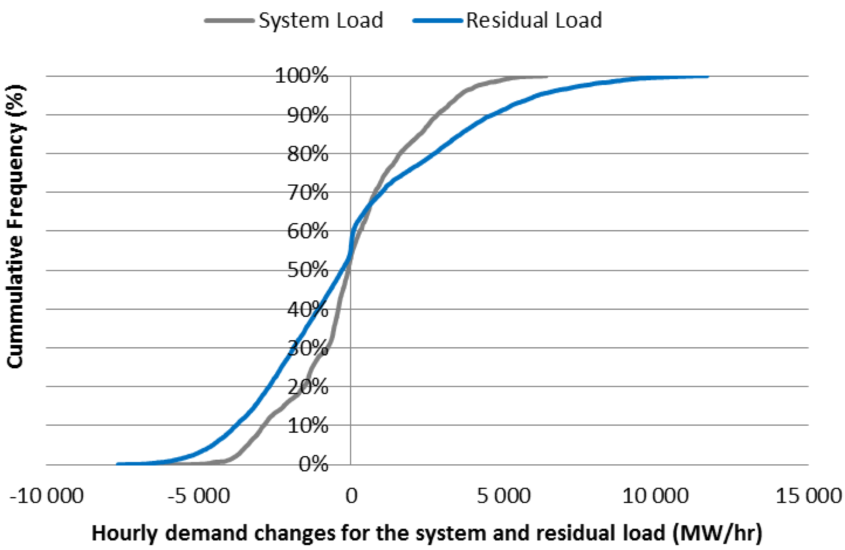


Figure 4.20. Hourly ramping requirements of system and residual load for the FC sensitivity

4.5 SYSTEM OPTIMIZED CHARGING

The Optimized Charging (OC) scenario was modelled with the same input assumptions as the BC scenario but with the inclusion of a 2.8 million BEV fleet in a G2V configuration assuming that the batteries are charged during periods of lowest cost supply to the power system (system optimized).

The BEV's were configured in the PLEXOS model such that they can be charged during any hour of the day, as long as the daily charging demand is met. The optimized charging profile is thus an output of the modelling optimization in PLEXOS and is included in the optimization formulation. The BEV charging demand of 9 TWh is thus met at the least-cost to the power system instead of adhering to a fixed charging demand profile.

Table 4.3 shows the hourly system demand gradient for the BC, FC and OC scenarios. It can be seen that the mean upward/downward hourly system gradient increases slightly in the OC scenario, while the maximum ramping requirements are reduced.

Table 4.3. Hourly system demand gradient statistics: OC with 2.8 million BEVs

Hourly system gradients	Base Case (MW)	Fixed Charging (MW)	Optimized Charging (MW)
Mean Upwards Ramp	1 429	1 539	1 594
Mean Downwards Ramp	1 165	1 220	1 232
Maximum Upwards Ramp	6 461	6 442	6 342
Maximum Downwards Ramp	6 263	6 635	5 440

The modelling results of the OC scenario are shown in Figure 4.21 and include the total installed capacity and energy expected from the existing and new generation capacity per technology type. The results are also tabled in the Addendum.

The analysis shows that it is least-cost to build 38.0 GW of new solar PV, 39.2 GW of new wind, 0.3 GW of landfill gas, 8.1 GW of CCGT's and 26.3 GW of OCGT's in 2040 for the given input assumptions. The largest energy contribution comes from wind at 33%, followed by 29% from coal-fired power, 20% from solar PV, 7% from gas-fired power, 1% from landfill gas and the rest from existing CSP, hydro and nuclear power. This represents a slight decrease in wind and gas-fired power compared to the FC scenario but an increase in solar PV capacity. Additionally, the OC least-cost energy mix results in a total system cost of R275 billion, a cost reduction of R3 billion (<2% decrease) compared to the FC scenario with the same BEV adoption rate.

The total annual curtailed wind and solar PV energy in the OC scenario is approximately 3.8 TWh. This represents a curtailment factor of 2.0%, similar to the FC scenario. The total CO_2 emissions and water usage for the OC scenario equates to 115.5 million tonnes and 34.0 million tonnes respectively, which is marginally less than the FC scenario.

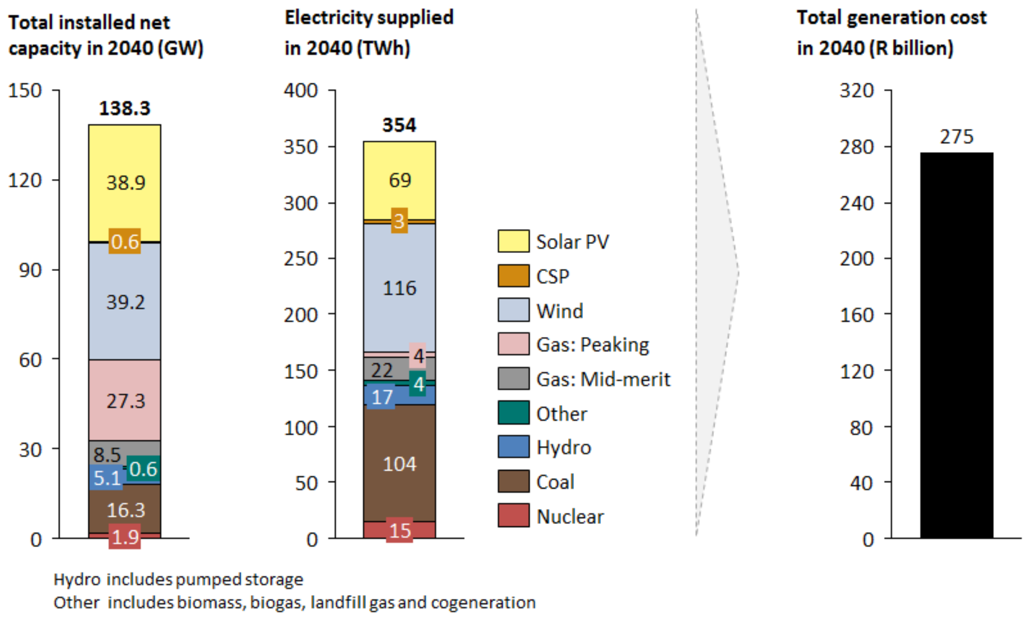


Figure 4.21. Least-cost electricity portfolio and total cost for the OC scenario

Figure 4.22 and Figure 4.23 show the difference in the additional capacity built in the OC scenario versus the FC and BC scenarios. In comparison to the FC scenario, it can be seen that an additional 3 GW of solar PV and 1 GW less wind was built was in the OC scenario in order to make the most use of solar PV for battery charging in the middle of the day. There is also less mid-merit gas and more peaking gas built in the OC scenario as less charging demand needs to be met by gas.

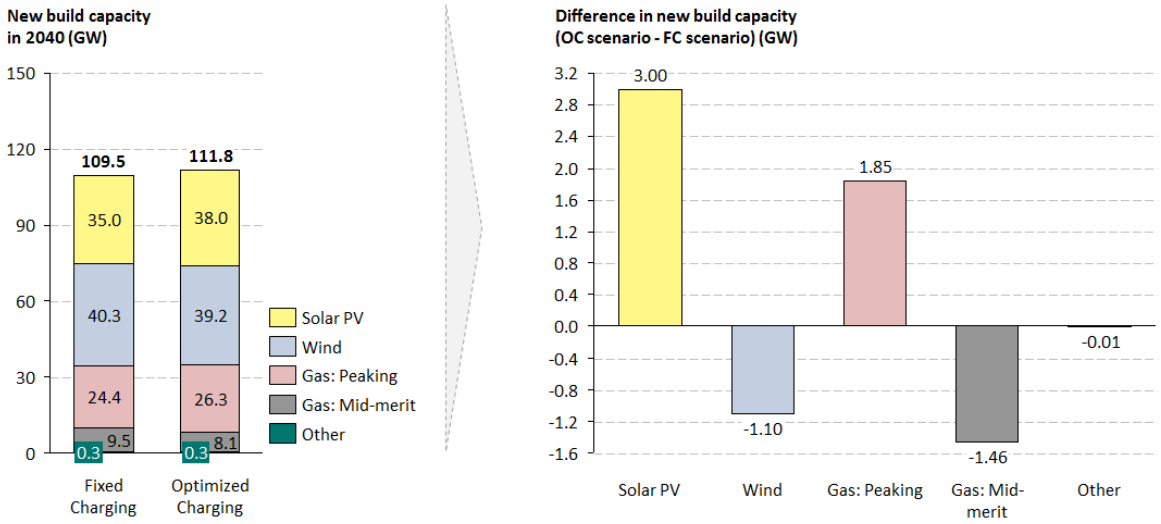


Figure 4.22. Difference in new capacity built in the OC scenario versus the FC scenario

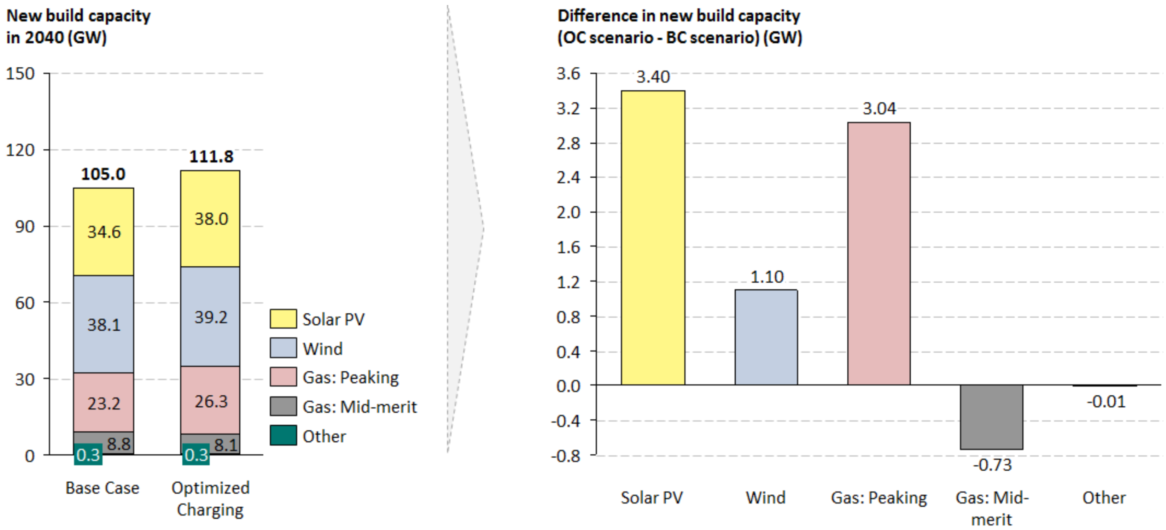


Figure 4.23. Difference in new capacity built in the OC scenario versus the BC

Figure 4.24 and Figure 4.25 show the total energy difference between the BC, FC and the OC scenarios. The total vehicle charging demand is the same between the FC and OC scenarios but there is 0.7 TWh less pumping load in the OC scenario. The OC solution resulted in more BEV charging demand being met by solar PV as opposed to wind in the FC scenario.

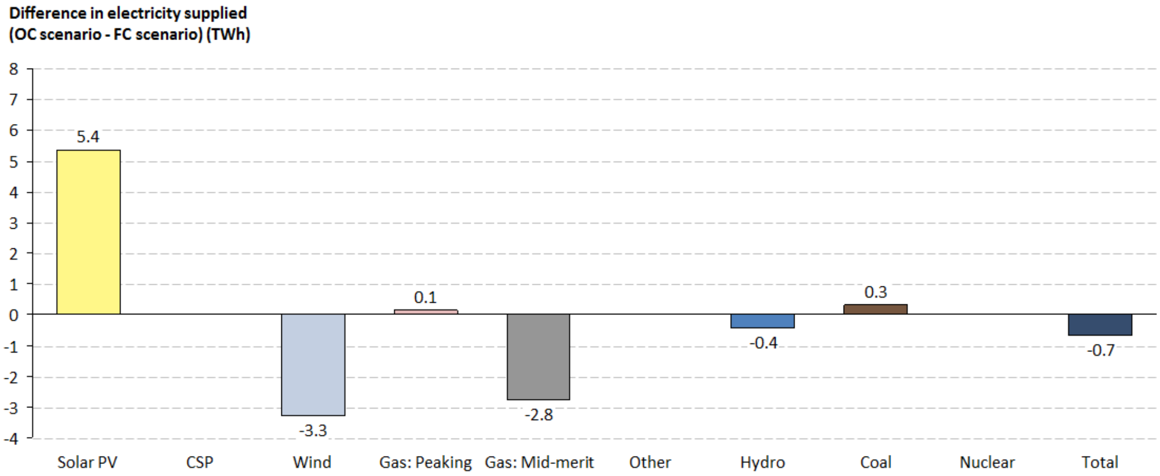


Figure 4.24. Difference in total electricity supplied for the OC scenario versus the FC scenario

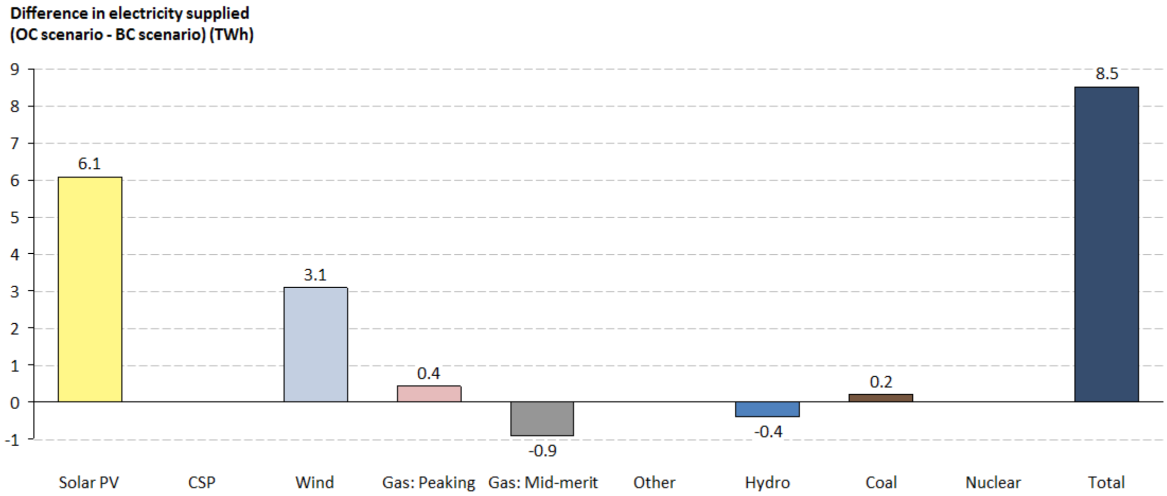
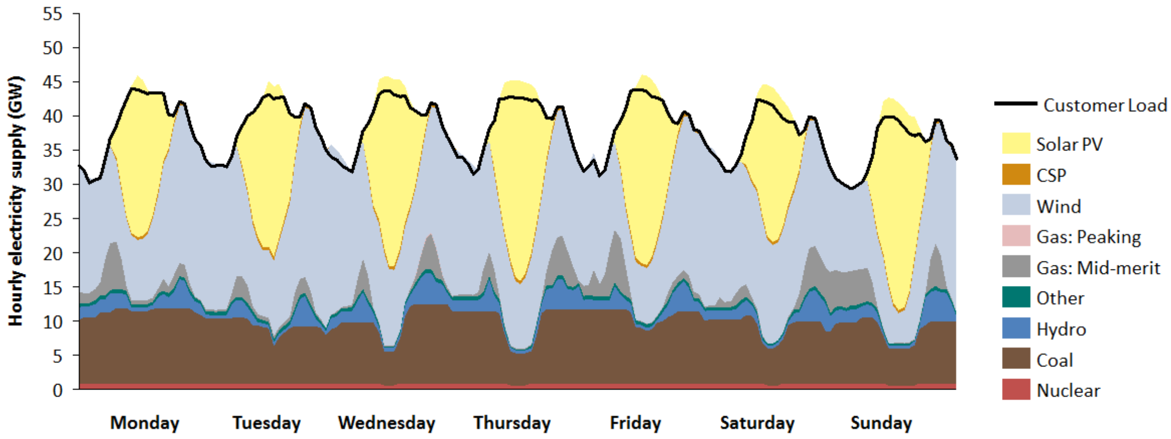


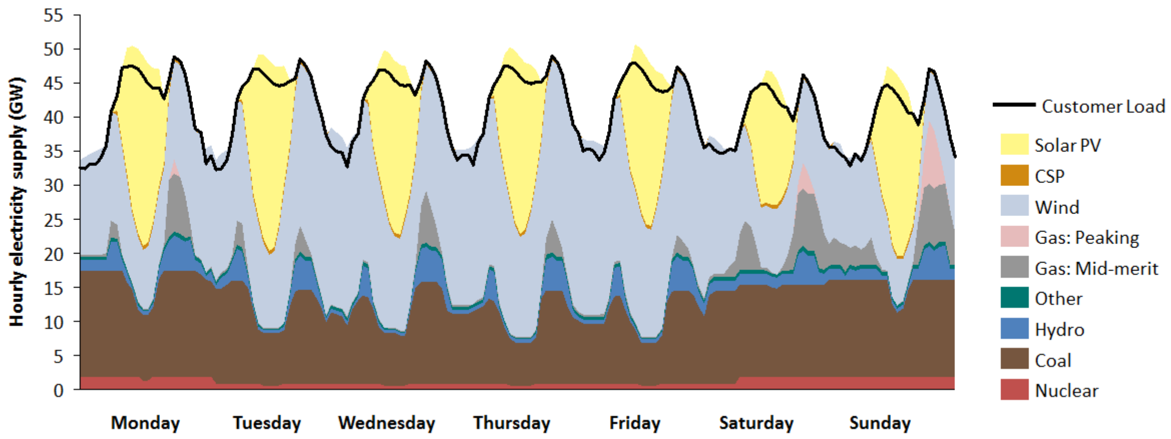
Figure 4.25. Difference in total electricity supplied for the OC scenario versus the BC

Figure 4.26 shows the simulated total hourly generation from existing and new build capacity for the same summer and winter week shown in the previous two scenarios. The

OC scenario shows a similar supply dispatch profile as the previous scenarios, however the customer load profile has been altered according to the system optimized charging demand requirements. The fixed charging demand profile from the FC scenario is overlaid with the optimized charging profile (modelling output) for a weekday in summer and winter in Figure 4.27. As expected, it can be seen that it is least-cost to the system to charge the BEV's during off-peak periods of the day.



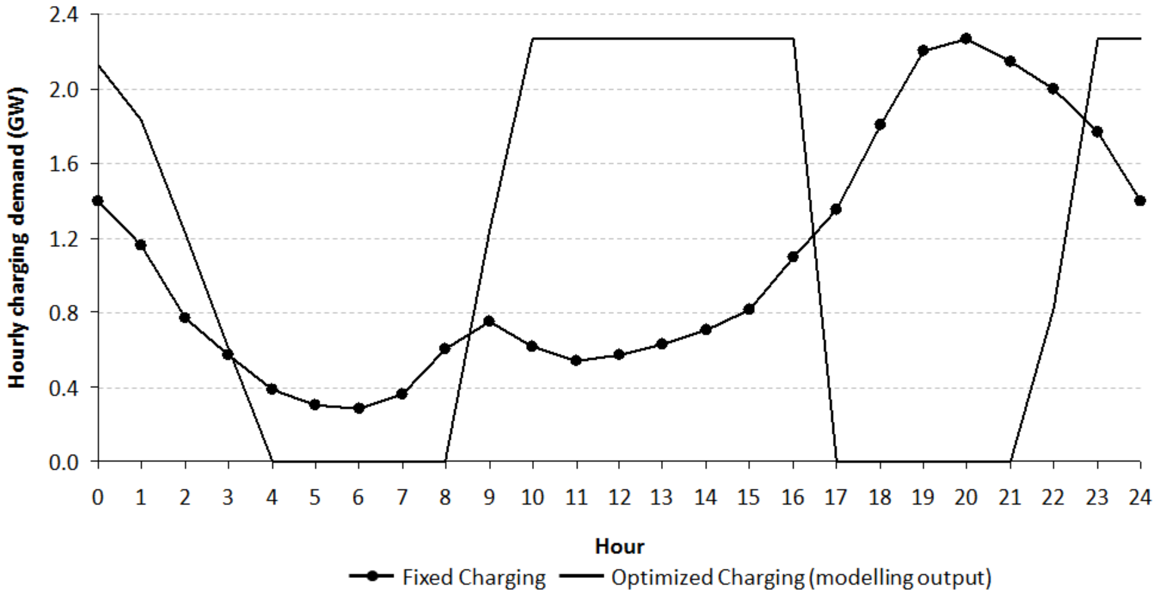
(a)



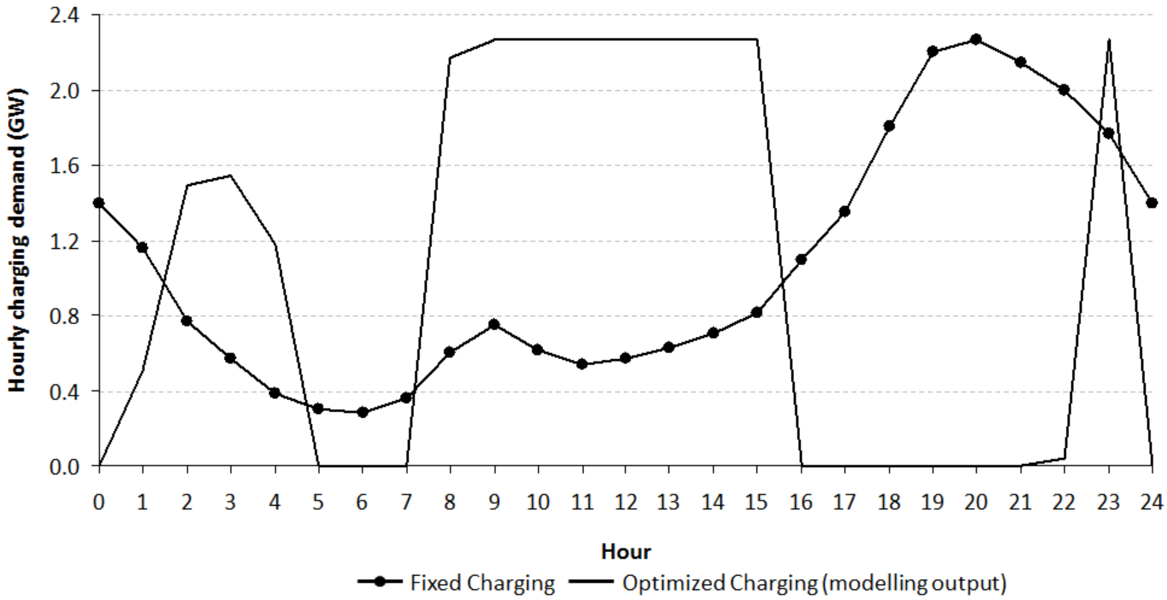
(b)

Figure 4.26. OC: Hourly electricity supply for a summer and winter week in 2040

(a) Summer week, (b) Winter week.



(a)



(b)

Figure 4.27. Hourly BEV charging demand for fixed and optimized charging profiles for a summer and winter day

(a) Summer day. (b) Winter day.

Figure 4.28 shows the load duration curves for the BC and OC scenario. It can be seen that the optimized charging demand is distributed such that the system load and peak load remains relatively similar to that of the BC.

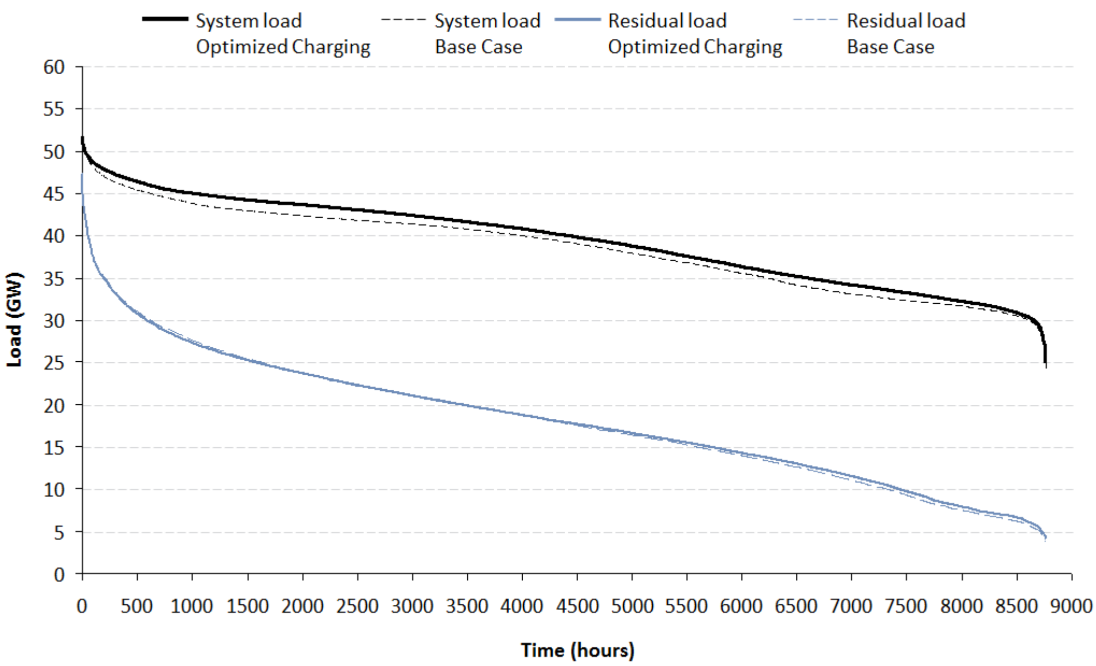


Figure 4.28. Load duration curve for the OC scenario

Figure 4.29 shows the cumulative frequency of the hourly ramping requirements for both the system demand and the residual demand of the OC scenario. For 90% of the hours in the year, the upwards system ramping demand is below 2.7 GW (0.1 GW higher than the BC), which increases to 4.3 GW (0.2 GW lower than the BC) for the residual load. The optimization of the timing of the charging demand thus lowered the hourly residual ramping requirements of the power system relative to the BC.

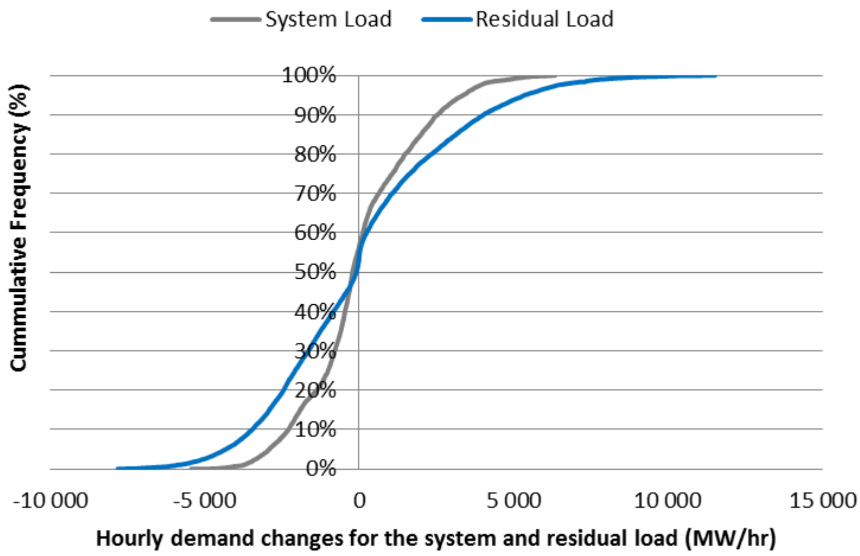


Figure 4.29. Hourly ramping requirements of system and residual load for the OC scenario

4.6 V2G SCENARIO

The V2G scenario was modelled with the same input assumptions as the BC scenario but with the inclusion of a 2.8 million BEV fleet in a V2G configuration, meaning that the BEV's are allowed to discharge energy back into the grid if required by the power system. The BEV charging demand of 9 TWh must still be met on an annual basis (system optimized) but the BEV's were modelled such that a portion of their capacity can be charged or discharged as needed by the system in any hour. However the charging and discharging capacity provided for V2G must balance on a daily timescale. This effectively means that the BEV's do not provide or consume additional energy to the system due to V2G but they can shift demand to periods of least-cost.

The energy that the vehicles can provide through charging and discharging on a daily basis were adapted from [35] which inherently includes an assumption on the proportion of the BEV fleet that is connected simultaneously during any given time and are summarized in Table 4.4.

Table 4.4. V2G input parameters

Property		Value
Number of BEV's	(Millions)	2.8
Annual BEV charging demand	(TWh)	9.2
Daily BEV charging demand	(GWh)	25.0
BEV capacity to increase demand	(MW)	26 790
BEV capacity to decrease demand	(MW)	1 043

The modelling results of the V2G scenario are shown in Figure 4.30 and include the total installed capacity and energy expected from the existing and new generation capacity per technology type. Figure 4.31 shows only the new build capacity which was chosen through the least-cost optimization of the power system and is compared to the OC scenario. The results are also tabled in the Addendum.

The analysis shows that it is least-cost to build 39.2 GW of new solar PV, 39.1 GW of new wind, 0.3 GW of landfill gas, 7.3 GW of CCGT's and 26.7 GW of OCGT's in 2040 for the given input assumptions. The largest energy contribution comes from wind at 33%, followed by 29% from coal-fired power, 20% from solar PV, 7% from gas-fired power, 1% from landfill gas and the rest from existing CSP (1%), hydro (5%) and nuclear (4%) power. The total energy share per technology type is only marginally different to the energy share of the OC scenario as depicted in Figure 4.32.

The V2G least-cost energy mix results in a total system cost of R273 billion, R4 billion more than the BC scenario. The V2G scenario is R5 billion less than the FC scenario and R2 billion less than the OC scenario. The total CO_2 emissions and water usage for the V2G scenario equates to 115.1 million tonnes and 35.7 million tonnes respectively.

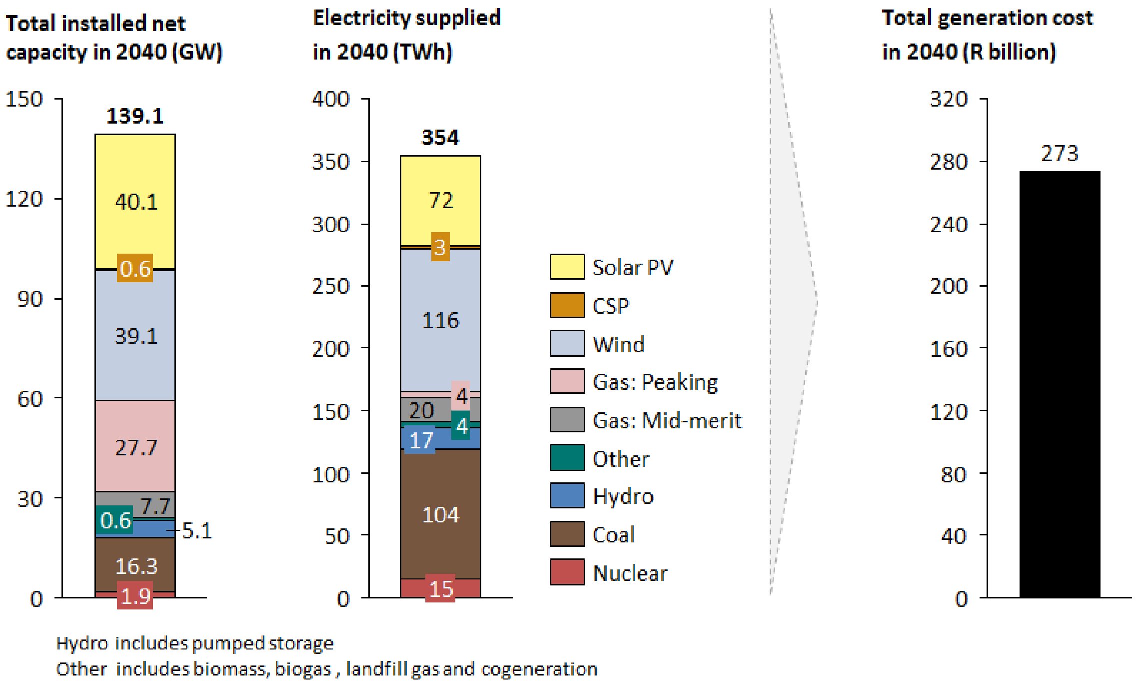


Figure 4.30. Least-cost electricity portfolio and total cost for the V2G scenario

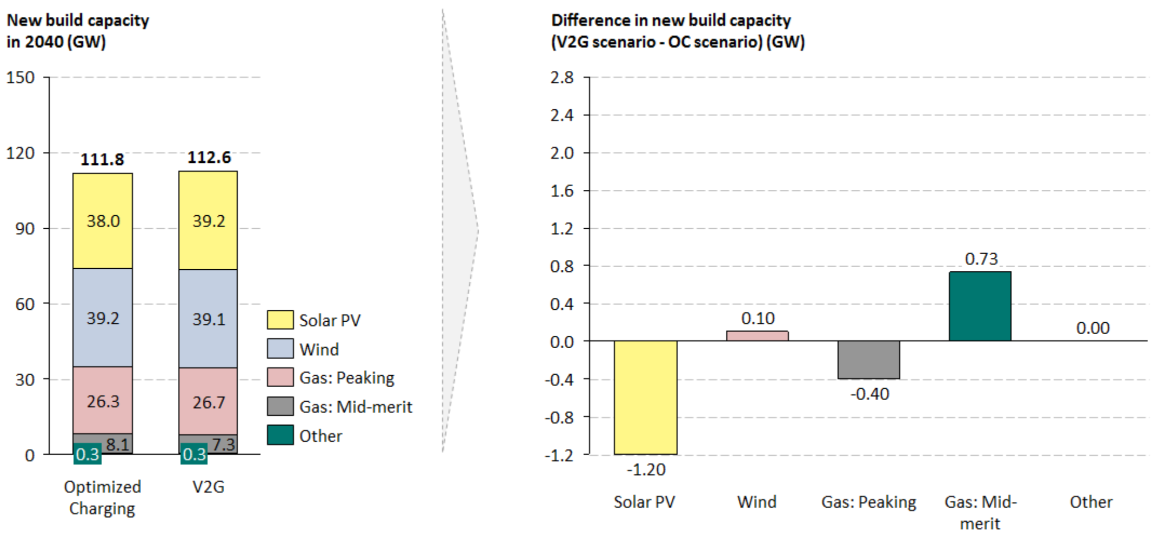


Figure 4.31. Difference in new capacity built in the V2G versus the OC scenario

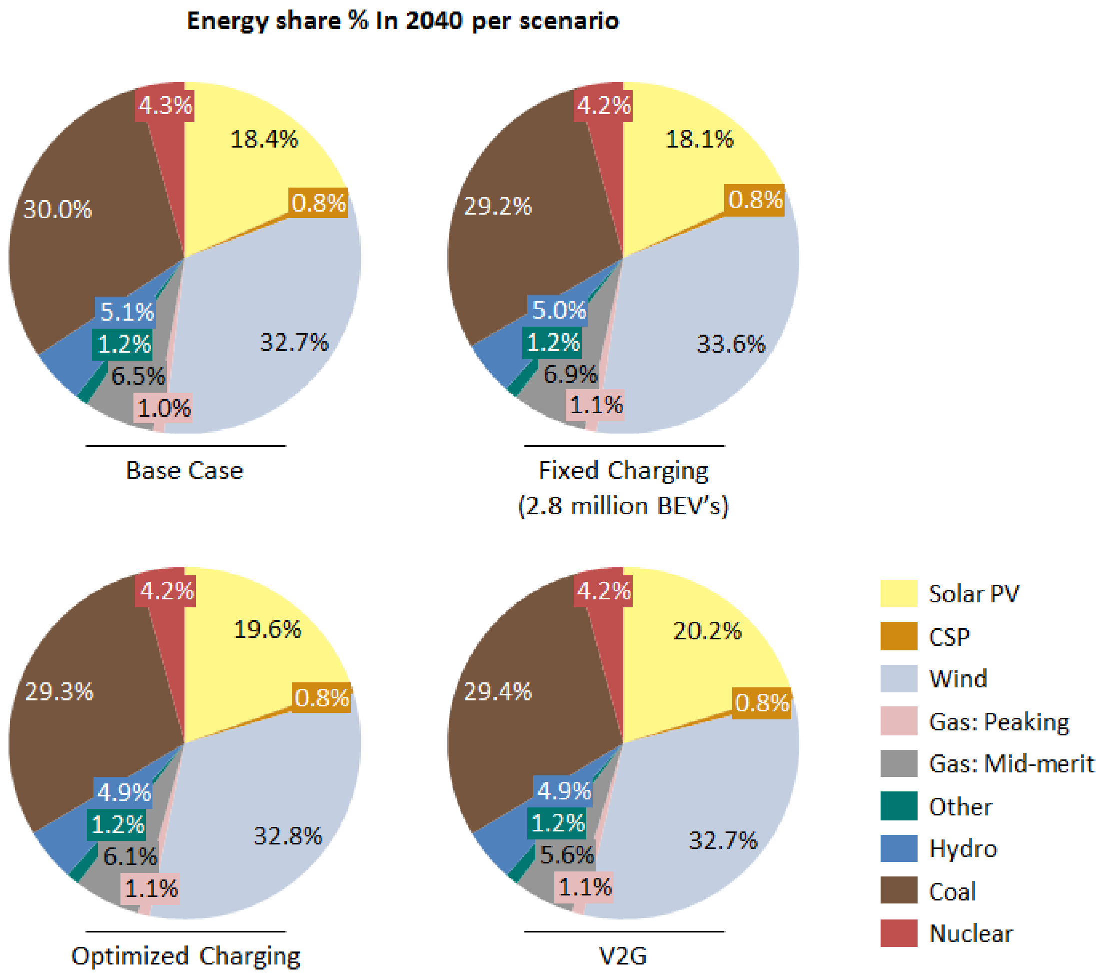
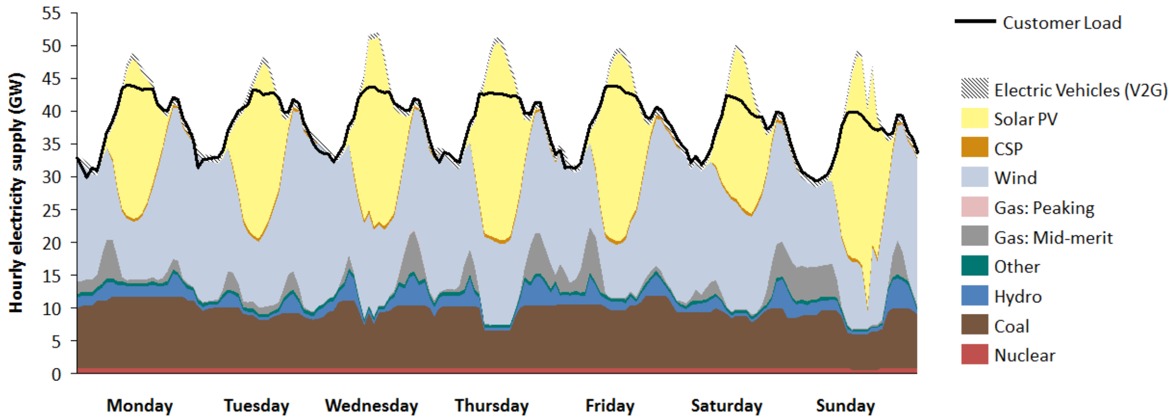
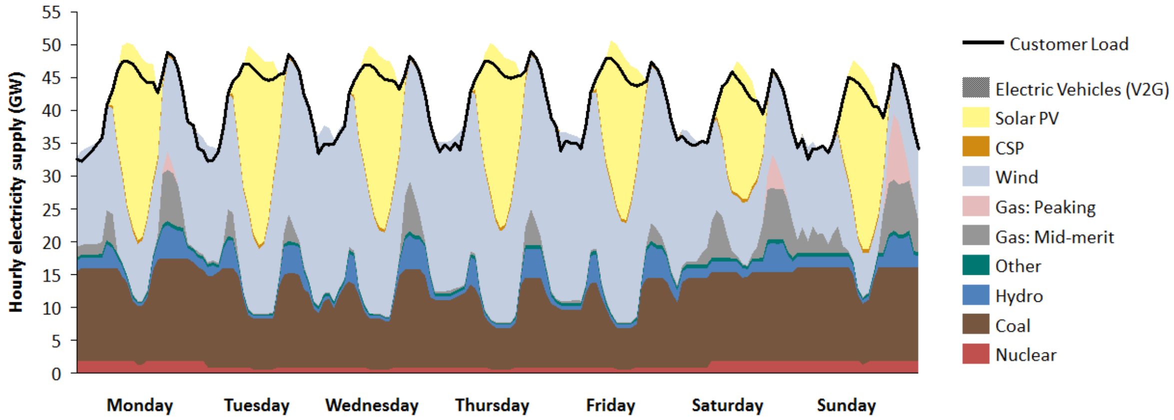


Figure 4.32. Total energy share per technology type per scenario

Figure 4.33 shows the simulated total hourly generation from existing and new build capacity for the same summer and winter week shown in the previous scenarios. As observed in the other scenarios, the V2G scenario shows a similar supply dispatch profile, with wind and solar PV fully utilized when available and coal, gas and hydro power providing flexibility and supplying the residual load. However, the customer load profile has been altered according to the charging and discharging of the electric vehicles. The battery discharging is shown explicitly in Figure 4.33, while the charging demand is inherent in the total supply stack. The use of solar PV during the day for battery charging is apparent in the summer week. During this particular winter week, energy from the electric vehicles was not utilized.



(a)



(b)

Figure 4.33. V2G: Hourly electricity supply for a summer and winter week in 2040

(a) Summer week, (b) Winter week.

Figure 4.34 shows the load duration curves for the BC and V2G scenario. It can be seen that the charging demand is distributed such that the system load and peak load remains relatively similar to that of the BC. The negative residual load duration curve represents 2 hours of excess supply (surplus energy).

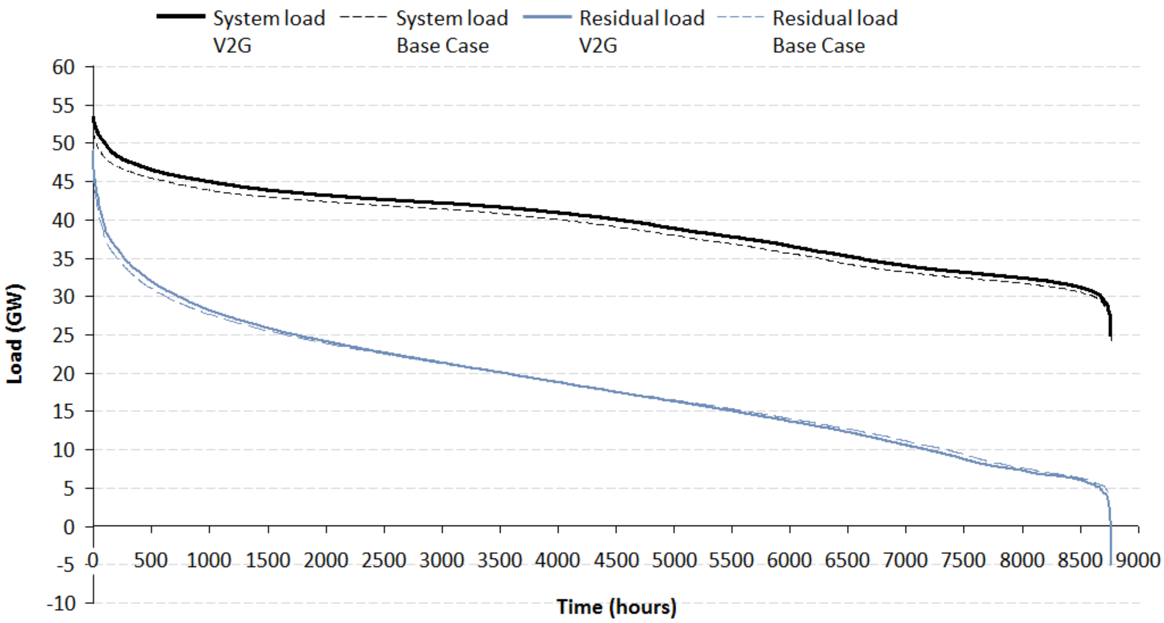


Figure 4.34. Load duration curve for the V2G scenario

Figure 4.35 shows the cumulative frequency of the hourly ramping requirements for both the system demand and the residual demand of the V2G scenario. For 90% of the hours in the year, the upwards system ramping demand is below 2.8 GW (0.3 GW higher than the BC), which increases to 4.8 GW (0.3 GW higher than the BC) for the residual load.

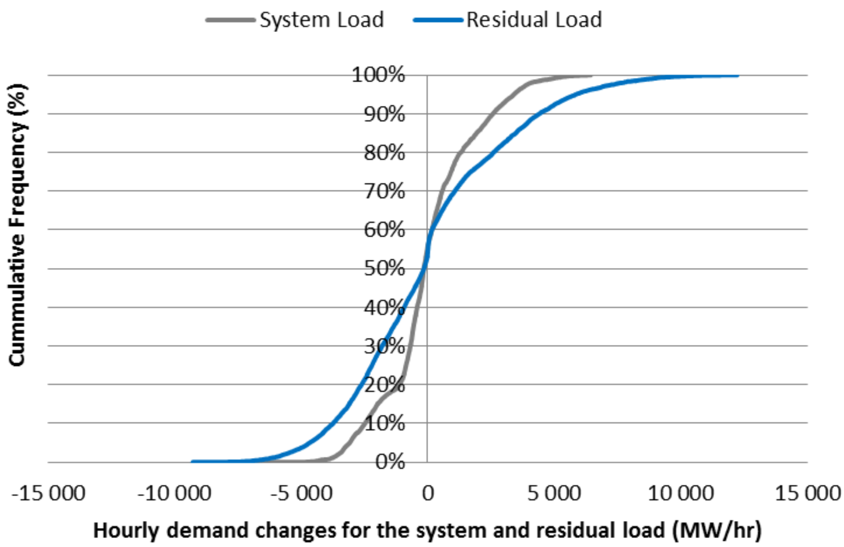


Figure 4.35. Hourly ramping requirements of system and residual load for the V2G scenario

4.7 POWER SYSTEM MODEL COMPLEXITY

The problem formulation size and solve time is shown in Table 4.5 for each scenario. It can be seen that the problem size did not increase significantly with the addition of optimized charging or V2G for this particular model configuration.

Table 4.5. PLEXOS problem size per scenario

Scenario	**Problem size (number of non-zeros)**	**Peak memory usage (GB)**
BC	7 843 293	6.2
FC	7 843 293	6.2
FC sensitivity	7 843 293	6.2
OC	7 869 963	6.4
V2G	8 141 307	6.4

4.8 DISCUSSION AND SUMMARY OF FINDINGS

4.8.1 Summary results

In this chapter an overview of the power system modelling results were given for 5 different scenarios. The results were presented in the form of the impact to the least-cost supply portfolio and power system cost for each scenario. The total installed capacity and energy from the four scenarios assuming a BEV adoption rate of 33% by 2040 (2.8 million electric vehicles) are summarized in Figure 4.36 and Figure **4.37**. In all scenarios additional capacity was built to meet the charging demand in 2040. This indicates that the exclusion of BEV's in the capacity expansion will lead to a sub-optimal energy mix.

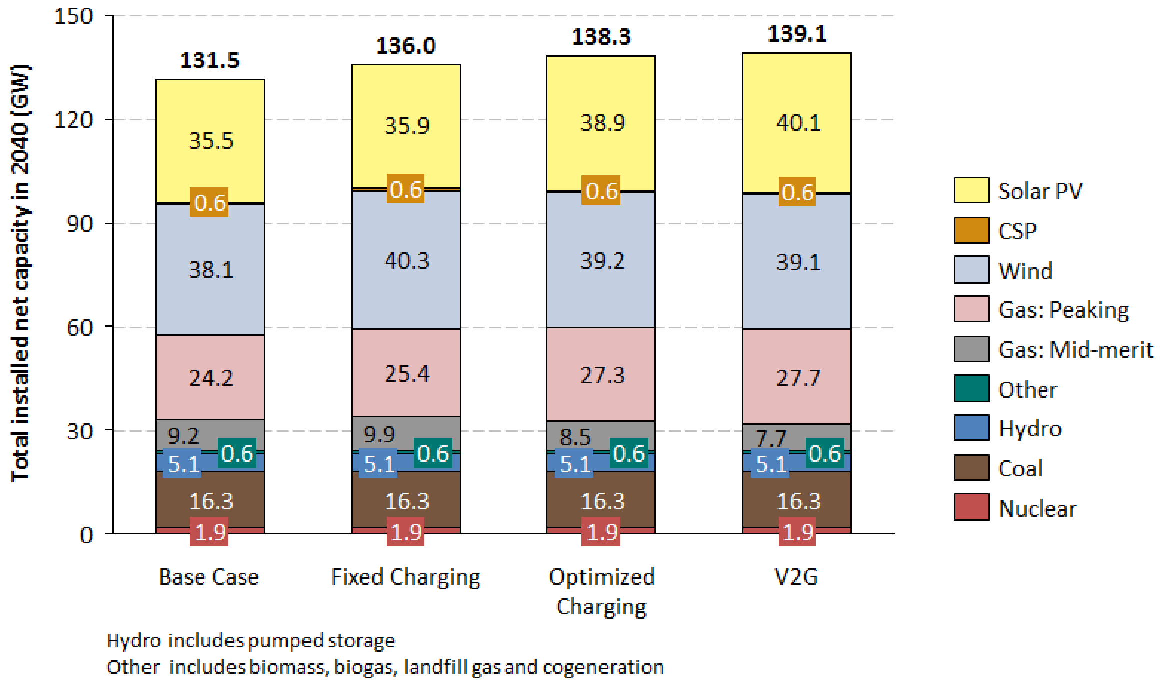


Figure 4.36. Least-cost total installed capacity per scenario

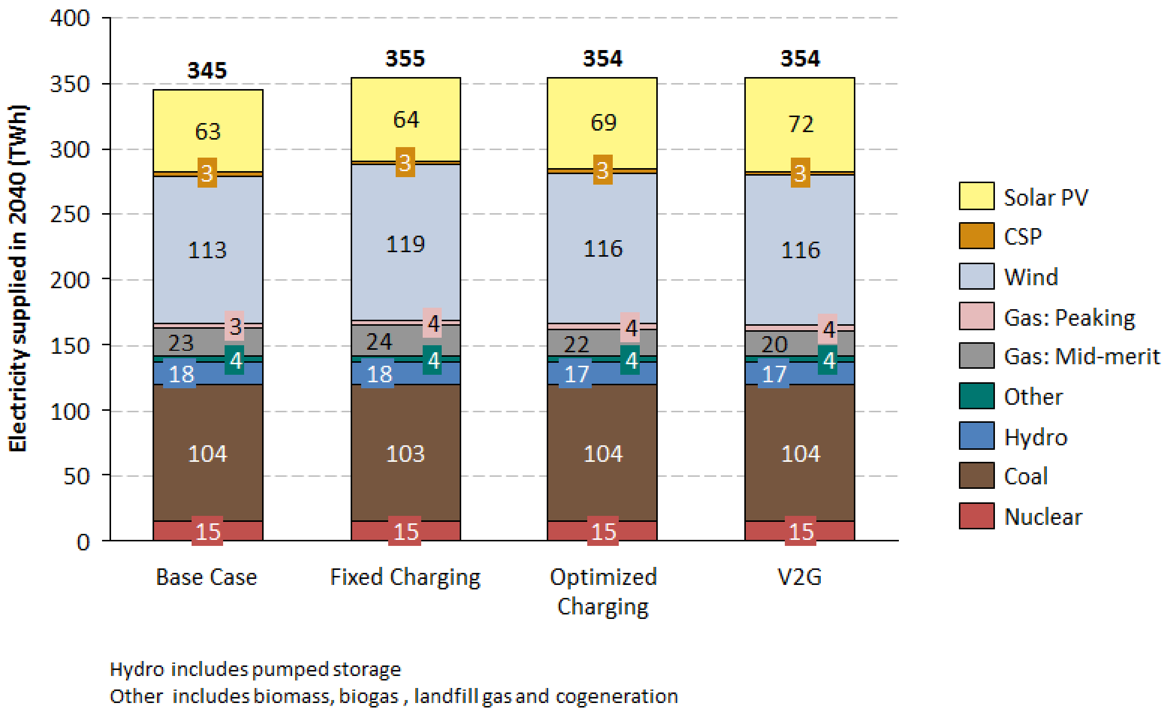


Figure 4.37. Total energy supplied per technology type per scenario

The charging demand of 2.8 million electric vehicles increases the annual electricity demand of the BC scenario by roughly 9 TWh and the annual peak demand by 2 GW. The capacity expansion for the OC and V2G scenarios led to a slightly lower annual demand than the FC scenario due to better utilization of the hydro pumped storage fleet.

The new capacity built per scenario is summarized in Figure 4.38. For all scenarios, the least-cost capacity investment technologies chosen by the optimization model were solar PV, wind, landfill gas, CCGT's and OCGT's. This finding is significant as it indicates that although the quantity and energy share of these new supply options vary per scenario, the least-cost technology choice is the same with and without the presence of BEV's. The least-cost technology choice is therefore robust against the change in the demand profile caused by the addition of electric vehicle charging demand. The choice of technology types is also not surprising given the low cost combination of wind, solar PV and gas-fired generation in RSA compared to new coal or nuclear capacity.

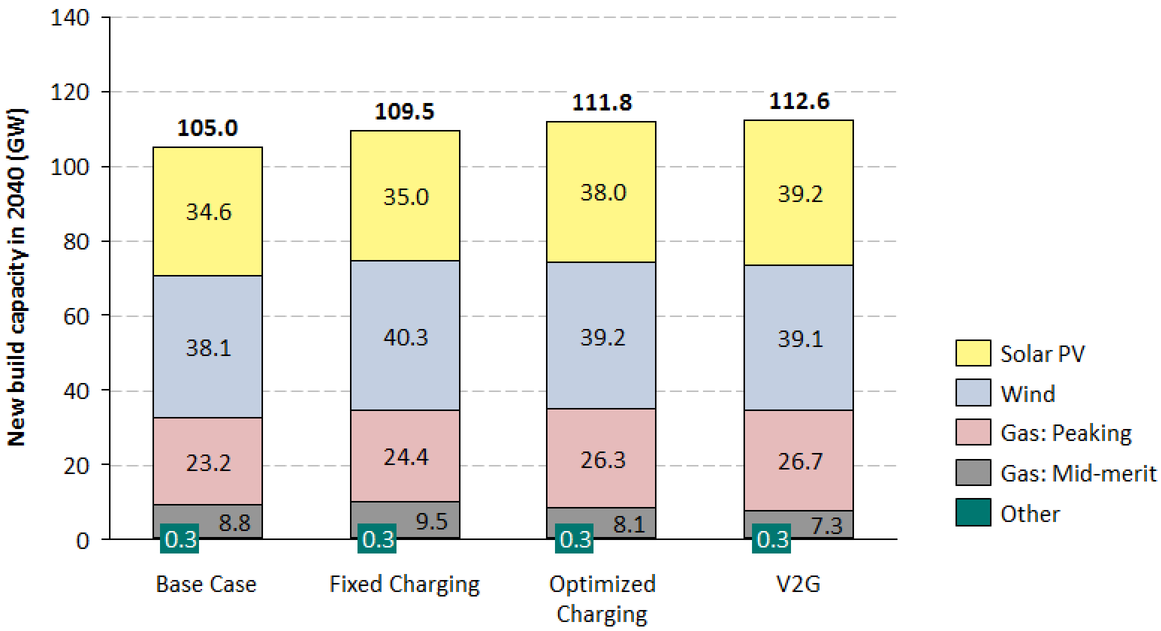


Figure 4.38. Summary of new build capacity per scenario

Figure 4.39 summarizes the total energy shares per supply technology per scenario. For all scenarios including BEV's, the energy share from existing coal and nuclear was reduced. This indicates a higher need for flexibility in the power system with the presence of electric vehicles. The V2G scenario represented the lowest energy share from gas-fired power which is indicative of the additional flexibility gained from the electric vehicles in the V2G configuration.

The majority of the battery charging demand was met by wind in all scenarios. For the OC scenario, the analysis showed a slight decrease in wind and gas-fired power supply compared to the FC scenario with an increase in solar PV capacity. This indicates that the OC profile influenced the new supply portfolio by preferring to build more solar PV capacity to meet the charging demand than the FC scenario.

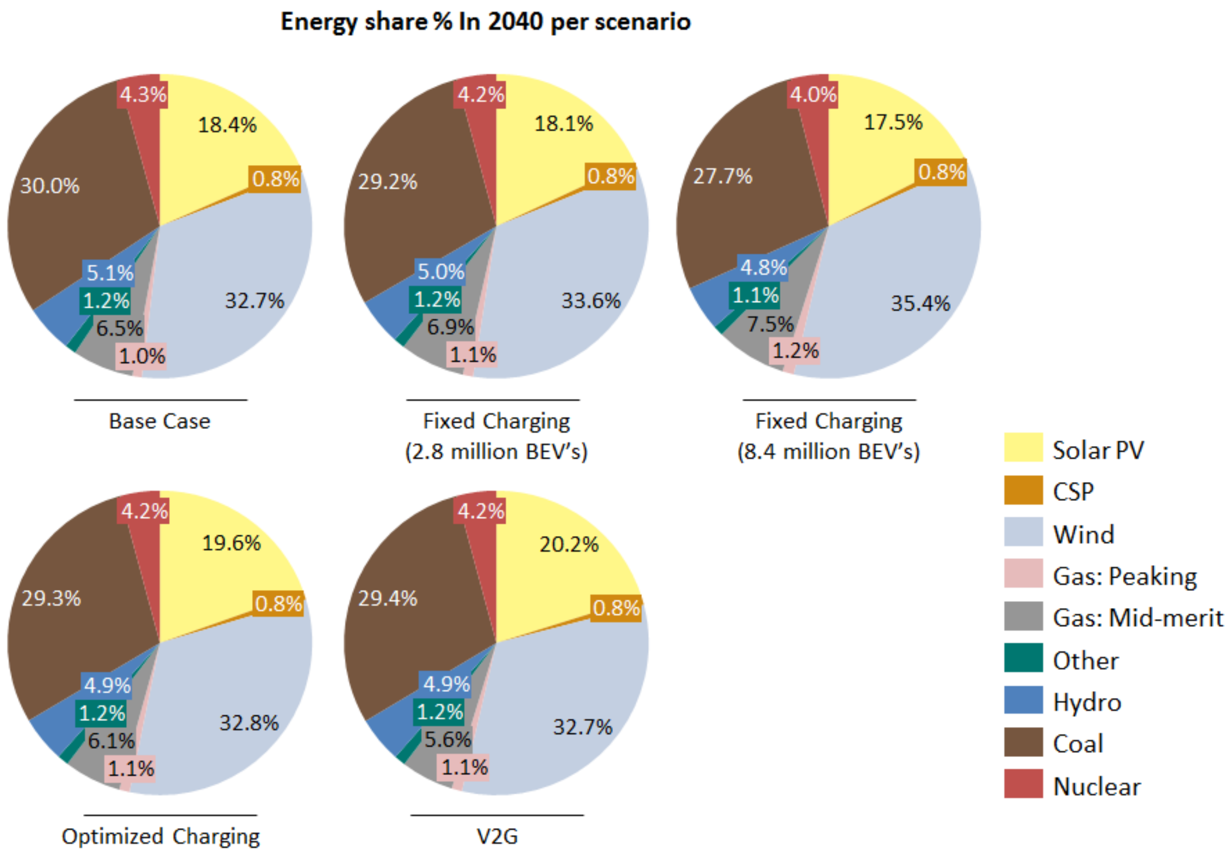


Figure 4.39. Summary of total energy share per technology type per scenario

The total generation cost per scenario is summarized in Figure 4.40. The presence of 2.8 and 8.4 million BEV's assuming a fixed charging profile increases the total generation cost by R9 billion (3%) and R28 billion (10%) respectively. The OC and V2G scenarios also resulted in a higher total generation cost but are relatively less costly than the FC scenario, showing that there is a system cost benefit to optimized charging and using electric vehicles for system flexibility.

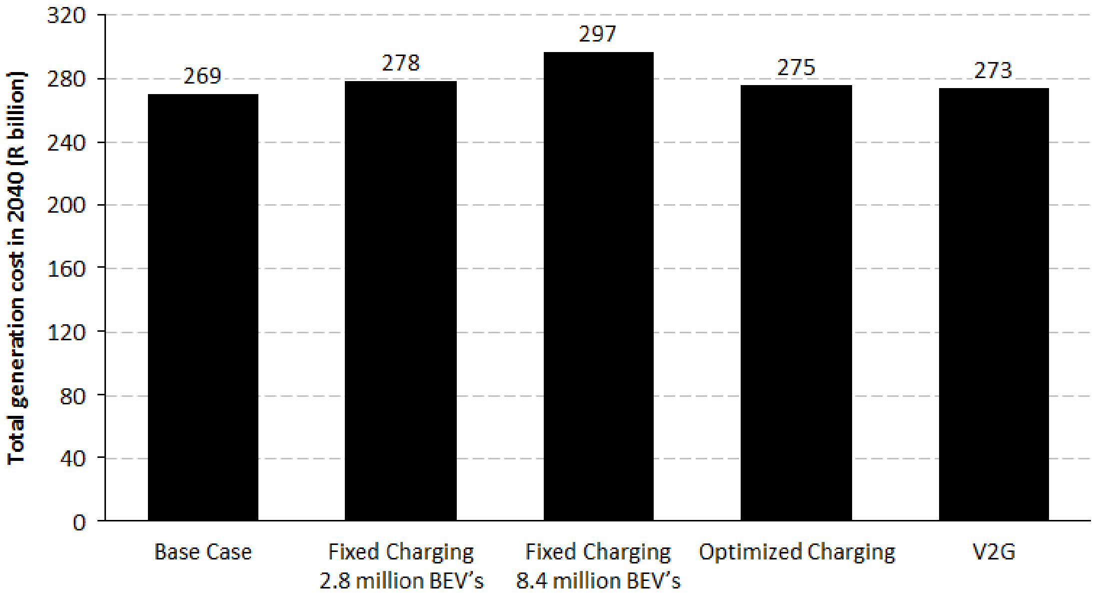


Figure 4.40. Summary of total generation cost per scenario

CHAPTER 5 CONCLUSION AND SCOPE FOR FURTHER WORK

5.1 SUMMARY OF FINDINGS

A literature review indicated that to the best of the authors' knowledge, there has not been a published study quantifying the impact of BEV's on the least-cost electricity portfolio in RSA. Additionally no publication of a study quantifying the value to the power system of system optimized battery charging or the system value of BEV's in the vehicle-to-grid configuration in RSA could be found. This research addressed this gap in electricity planning by studying the impact of incorporating BEV's in a power system capacity expansion model for RSA.

This capacity expansion plan was developed in the power system modelling software package PLEXOS and was configured for the year 2040 and simulated in hourly temporal resolution. All existing power stations expected to still be online in the year 2040 were modelled as per their technical performance characteristics, operating constraints and running costs. A suite of new technology options were configured in the model according to their expected capital costs, start/shutdown costs, fuel costs and variable and fixed operations and maintenance costs. Hourly solar PV and wind generation profiles for RSA were used to ensure that the variability of renewable energy is fully captured in the model.

The optimization formulation in the power system model was set to minimize total generation cost which is the sum of all existing power station costs and new investment build decisions and their associated running costs, while adhering to an annual CO_2

emissions constraint as well as the configured technical capabilities of each power station. The optimization was solved using Mixed Integer Linear Programming and all scenarios were configured to meet system demand with the same level of system adequacy. The installed capacity and electricity supply (energy shares) for each technology type were presented for each scenario. The resulting total generation cost as well as CO_2 emissions and water consumption were also presented for each scenario. Total generation cost includes the capital and running costs of new build investment as well as the fixed and variable operating costs of the existing supply capacity.
The study looked at four main scenarios, as well as sensitivity analysis on the adoption of BEV's. First a reference scenario, termed the Base Case (BC), was developed in which the model was set up without incorporating BEV's in the RSA's power system. The least-cost expansion plan resulted in 34.6 GW of new solar PV, 38.1 GW of new wind, 0.3 GW of landfill gas, 8.8 GW of CCGT's (Gas: mid-merit) and 23.2 GW of OCGT's (Gas: Peaking) in 2040 for the given input assumptions. The largest energy contribution came from wind at 33%, followed by 30% from coal-fired power, 18% from solar PV, 8% from gas-fired power, 1% from landfill gas and the rest from existing CSP, hydro and nuclear power.

A second scenario was then developed, termed the Fixed Charging (FC) scenario, with the same input assumptions as the BC scenario but with the inclusion of a 2.8 million BEV fleet (33% of all passenger vehicles) in a G2V configuration, assuming a fixed aggregated charging profile from previous literature. The BEV charging demand increased the annual electricity demand by about 9 TWh (~2.5% increase) and the annual peak demand by 2 GW. The least-cost optimal supply portfolio from this scenario resulted in a system cost increase of R9 billion compared to the BC. The majority of the additional charging demand was supplied by wind generation. There were marginal differences in CO_2 emissions and water consumption between the FC scenario and BC.

A sensitivity analysis was conducted on the FC scenario whereby the adoption of BEV's was increased to 100% of all passenger vehicles. This resulted in a BEV fleet of 8.4 million vehicles which increased the system demand by 28 TWh and the peak demand by 5.9 GW. This additional charging demand increased the mean hourly upwards and downwards system demand gradients (ramping requirements) and thus the demand for flexible generation. The optimal supply portfolio in terms of technology type did not change for this higher BEV adoption assumption, indicating robustness in the technology choice going forward. As expected, more capacity was required for this scenario and it resulted in an increase in the total system cost of R28 billion compared to the BC.

A third scenario, termed the Optimized Charging (OC) scenario, was developed in order to test the impact of changing the fixed charging demand profile in the second scenario to a system optimized charging profile. The model was configured to allow flexible charging which for a least-cost optimization meant that the batteries were charged during periods of lowest cost supply to the power system. As expected, the OC profile generated from the power system model solution showed that it is least-cost to the power system to charge batteries during off peak periods of the day. This profile also resulted in a reduction of total generation cost of R3 billion compared to fixed charging profiles. This equates to a system savings of approximately R1 000 per annum per electric vehicle. This system saving is based on the optimized charging of the whole electric vehicle fleet and thus presents the maximum possible savings to the power system.

A last scenario was developed in order to determine the impact on the least-cost supply portfolio if the BEV fleet is able to discharge back into the grid in the V2G configuration. The results from this scenario showed that further generation cost reductions could be achieved compared to the FC and OC scenarios. Both the OC and V2G scenarios built more new solar PV capacity and less wind capacity that the FC scenario, demonstrating the advantage of cheap solar PV generation during the middle of the day. For all scenarios including BEV’s, the energy share from existing coal and nuclear was reduced. This indicates a higher need for flexibility in the power system with the presence of electric vehicles. The V2G scenario represents the lowest energy share from gas-fired power which is indicative of the additional flexibility gained from the electric vehicles in the V2G configuration. It was also found that less mid-merit gas and more peaking gas was built in the OC scenarios.

5.2 SCOPE FOR FURTHER WORK

The analysis in this study was undertaken for the year 2040 which is useful in giving an indication of a future state of the power system. However it would also be valuable to repeat the analysis for the entire study horizon from today to 2040 and beyond in order to gain a better understanding of the rate of deployment of new generation capacity as well as the rate of electric vehicle adoption over time.

The analysis presented in this report can also be reproduced for varying input assumptions in order to capture a wider set of possible futures. A sensitivity analysis is valuable in dealing with uncertainty in long term planning. The demand forecast plays a crucial role in energy planning and would be a good starting point for sensitivity analysis.

Follow up work should also look at the introduction of utility-scale stationary battery storage in the modelling analysis which would essentially compete with electric vehicles in the V2G configuration as well as provide additional system flexibility for charging electric vehicles in the conventional G2V configuration. Some studies have indicated that electric vehicle batteries still have significant capacity remaining for alternative uses such as energy storage for power systems once they reach end of life (around 8 years) [46], which also calls for further investigation.

There is also scope for additional research in terms of the viability of V2G. Depending on the power system requirements, electric vehicle batteries operating in the V2G configuration may experience excessive battery cycling which would increase the stress on the batteries and potentially shorten battery lifespan.

Further investigation into the impact of electric vehicles at the transmission and distribution level in RSA would also provide useful information to the energy planners.

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ADDENDUM A MATERIAL CONSTANTS AND OTHER PARAMETERS

A.1 DETAILED INPUT ASSUMPTIONS

A.1.1 Existing generation fleet capacities in MW

Table A.1. Existing generation fleet capacities in MW

Name	Technology	Capacity 2018	Capacity 2040
Arnot	Coal	2 220	-
Camden	Coal	1 520	-
Duvha	Coal	2 900	-
Grootvlei	Coal	1 080	-
Hendrina	Coal	1 900	-
Kendal	Coal	3 840	3 200
Komati	Coal	900	-
Kriel	Coal	2 880	-
Kusile	Coal	723	4 338
Lethabo	Coal	3 540	-
Majuba	Coal	3 840	3 840
Matimba	Coal	3 720	620
Matla	Coal	3 480	-
Medupi	Coal	2 166	4 332

Name	**Technology**	**Capacity 2018**	**Capacity 2040**
Tutuka	Coal	3 480	-
Sere	Wind	100	-
Koeberg	Nuclear	1 860	1 860
Drakensberg	Pumped Storage	1 000	1 000
Ingula	Pumped Storage	1 332	1 332
Palmiet	Pumped Storage	400	400
Gariep	Hydro	360	360
Vanderkloof	Hydro	240	240
Acacia	Peaking	171	-
Ankerlig	Peaking	1 332	-
Gourikwa	Peaking	740	-
PortRex	Peaking	171	-
Biomass IPPP	Biomass	17	42
CSP IPPP	CSP	600	600
Landfill Gas IPPP	Biogas	13	13
Solar PV IPPP	Solar PV	1 894	850
Small Hydro IPPP	Hydro	19	19
Wind IPPP	Wind	2 662	-
Municipal Coal	Coal	160	-
Other Coal	Coal	600	-
Avon Peaking	Peaking	670	670
Dedisa Peaking	Peaking	335	335
Other Engines	Gas	175	175
Other OCGT	Gas	250	250
Cahora Bassa	Hydro	1 500	1 500
Colley Wobbles	Hydro	65	65
Mondi	Biomass	120	120
Sappi	Biomass	144	144
Steenbras	Pumped storage	180	180

A.1.2 Existing generation fleet assumed technical characteristics

Table A.2. Existing generation fleet assumed technical characteristics

Generator	**Property**	**Value**	**Units**
Coal	Minimum Stable Factor	65	%
Coal	Design efficiency	35	%
Coal	Run Up Rate	1.3	MW/min
Coal	Minimum Up Time	8	h
Coal	Minimum Down Time	8	h
Coal	Maximum Ramp Up	2	MW/min
Coal	Maximum Ramp Down	2	MW/min
Wind	Rating	Hourly profile	MW
Nuclear	Maximum capacity per unit	1860	MW
Nuclear	Minimum Stable Factor	70	%
Nuclear	Heat Rate	11.111	GJ/MWh
Nuclear	Re-fueling	1	Event/year
Pumped Hydro	Minimum Stable Factor	33	%
Pumped Hydro	Pump Efficiency	73-78	%
Hydro	Minimum Stable Factor	33	%
OCGT	Minimum Stable Factor	40	%
OCGT	Heat Rate	11.519	GJ/MWh
OCGT	Run Up Rate	12	MW/min
OCGT	Run Down Rate	12	MW/min
OCGT	Minimum Up Time	0.5	h
OCGT	Minimum Down Time	1	h
OCGT	Maximum Ramp Up	3.4	MW/min
OCGT	Maximum Ramp Down	3.4	MW/min
Biomass R 3	Maximum capacity per unit	17	MW
Biomass R 3	Minimum Stable Factor	40	%

Generator	**Property**	**Value**	**Units**
Biomass	Minimum Capacity Factor Month	80	%
Biomass	Maximum capacity per unit	25	MW
Biomass	Minimum Stable Factor	40	%
Biomass	Minimum Capacity Factor Month	80	%
CSP	Rating	Hourly profile	MW
Landfill Gas	Minimum Stable Factor	40	%
Landfill Gas	Minimum Capacity Factor Month	80	%
Photovoltaic	Rating	Hourly profile	MW
Small Hydro	Minimum Stable Factor	33	%
Small Hydro	Maximum Capacity Factor Month	70	%
Small Hydro	Minimum Capacity Factor Month	50	%
Wind	Rating	Hourly profile	MW
Cahora Bassa	Minimum Stable Factor	33	%
Cahora Bassa	Maximum Capacity Factor Month	85	%

A.1 TABLES OF RESULTS

A.1.1 Base Case: Total capacity and generation in 2040

Table A.3. Base Case: Total capacity and generation in 2040

Technology	Total Capacity [MW]	Total Generation [GWh]
Solar PV	35 450	63 383
CSP	600	2 822
Wind	38 100	112 866
Gas: Peaking	24 237	3 462
Gas: Mid-merit	9 209	22 529
Other	645	4 130
Hydro	5 096	17 726
Coal	16 330	103 560
Nuclear	1 860	14 868
Total	**131 527**	**345 346**

A.1.2 Base Case: Total CO_2 emissions and water consumption in 2040

Table A.4. Base Case: Total CO_2 emissions and water consumption in 2040

Units	CO_2 Emissions	Water Consumption
Million Tonnes	115.6	34.1

A.1.3 FC Scenario: Total capacity and generation in 2040

Table A.5. FC Scenario: Total capacity and generation in 2040

Technology	Total Capacity [MW]	Total Generation [GWh]
Solar PV	35 850	64 098
CSP	600	2 822
Wind	40 300	119 259
Gas: Peaking	25 425	3 742
Gas: Mid-merit	9 941	24 370
Other	645	4 130
Hydro	5 096	17 771
Coal	16 330	103 453
Nuclear	1 860	14 868
Total	**136 047**	**354 514**

A.1.4 FC Scenario: Total CO_2 emissions and water consumption in 2040

Table A.6. FC Scenario: Total CO_2 emissions and water consumption in 2040

Units	CO_2 Emissions	Water Consumption
Million Tonnes	116.3	34.1

A.1.5 OC scenario: Total capacity and generation in 2040

Table A.7. OC scenario: Total capacity and generation in 2040

Technology	Total Capacity [MW]	Total Generation [GWh]
Solar PV	35 850	64 098
CSP	600	2 822
Wind	40 300	119 259
Gas: Peaking	25 425	3 742
Gas: Mid-merit	9 941	24 370
Other	645	4 130
Hydro	5 096	17 771
Coal	16 330	103 453
Nuclear	1 860	14 868
Total	**136 047**	**354 514**

A.1.6 OC scenario: Total CO_2 emissions and water consumption in 2040

Table A.8. OC scenario: Total CO2 emissions and water consumption in 2040

Units	CO_2 Emissions	Water Consumption
Million Tonnes	116.3	34.1

A.1.7 Vehicle-to-grid scenario: Total capacity and generation in 2040

Table A.9. V2G scenario: Total capacity and generation in 2040

Technology	Total Capacity [MW]	Total Generation [GWh]
Solar PV	35 850	64 098
CSP	600	2 822
Wind	40 300	119 259
Gas: Peaking	25 425	3 742
Gas: Mid-merit	9 941	24 370
Other	645	4 130
Hydro	5 096	17 771
Coal	16 330	103 453
Nuclear	1 860	14 868
Total	**136 047**	**354 514**

A.1.8 Vehicle-to-grid scenario: Total CO_2 emissions and water consumption in 2040

Table A.10. V2G scenario: Total CO_2 emissions and water consumption in 2040

Units	CO_2 Emissions	Water Consumption
Million Tonnes	116.3	34.1