The Environmental and Cost Impacts of Vehicle Electrification in the Azores

by

Maximilian Parness

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Author . . . .
Technology and Policy Program, Engineering Systems Division
May 6, 2011

Certified by . . . .
Stephen Connors
Director, Analysis Group for Regional Energy Alternatives
Thesis Supervisor

Certified by . . . .
Ignacio J. Pérez-Arriaga
Visiting Professor, Engineering Systems Division
Professor of Electrical Engineering, Universidad Pontificia Comillas,
Madrid, Spain
Thesis Supervisor

Accepted by . . . .
Dava J. Newman
Professor of Aeronautics and Astronautics and Engineering Systems
Director, Technology and Policy Program

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Abstract

Electric vehicles (EVs) have the potential to reduce transportation sector CO_2 emissions in São Miguel, an island in the Azores, while simultaneously reducing mobility operating costs. This thesis attempts to quantify the cost and environmental impacts of using EVs on São Miguel, using an economic dispatch and unit commitment model. The number of EVs and the ways that they charge are varied. The composition of São Miguel's electric power generation portfolio is varied from its current composition to one that incorporates higher levels of renewable generation.

Emissions reductions stemming from EVs vary according to how the vehicles are charged and when renewable generation, which is less expensive and less CO_2-intensive than thermal generation, is available. Charging "optimally" can save hundreds of thousands of Euros in system mobility costs per week and, in some cases, halve transportation CO_2 emissions. Optimal charging results also show that, in certain cases, charging during periods of high electric demand is acceptable. This result is contrary to previous literature on vehicle charging, and is due primarily to the limited number of generators on São Miguel.

CO_2 abatement costs stemming from the use of EVs vary from 26 to 160 Euros per tonne of CO_2. Portugal's tax on gasoline and subsidization of EVs make calculating the exact cost of EVs in São Miguel difficult, but a simple discounted cash flow shows that, for a 950 electric vehicle fleet, the internal rate of return over a ten year period is 8.24%. Other costs associated with EVs, including the installation of new grid infrastructure and charging stations, are also considered.

Thesis Supervisor: Stephen Connors
Title: Director, Analysis Group for Regional Energy Alternatives

Thesis Supervisor: Ignacio J. Pérez-Arriaga
Title: Visiting Professor, Engineering Systems Division
Professor of Electrical Engineering, Universidad Pontificia Comillas, Madrid, Spain

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Chapter 1

The Promise and Prospects of Electric Vehicles

Transportation accounts for about $1/5^{\text{th}}$ of global energy use and $1/4^{\text{th}}$ of world-wide CO_2 emissions. In 2006, about half of this energy use was accounted for solely by light duty vehicle (LDVs). Overall emissions from this sector are expected to increase; in 2006, there were 800 million LDVs, but by year 2050, it is expected that there will be over two billion LDVs on the road [19]. There are many ways to reduce transportation sector emissions, including technological improvement of LDVs, such as more efficient drivetrains [46], or increasing use of public transportation.

An increasingly common method is through the deployment of Electric Vehicles (EVs) [10]. EVs retain the high level of independent mobility associated with traditional personal transportation. During the late 1800s in the US, the use of EVs was not uncommon. They were recognized as being easier and more reliable to start than other vehicles at the time [46]. However, over time, the internal combustion engine (ICE) came to be the predominant mode of vehicle power train. Conventional ICE vehicles use fuel as the sole source of energy for propulsion, whereas EVs use a motor that is powered by an on-board battery.

Vehicle electrification is not an all-or-nothing matter: EVs can be thought of as having a degree of electrification, ranging from nothing (containing only an ICE) to fully electrified (containing only a motor, and no engine). A graphic of this can be

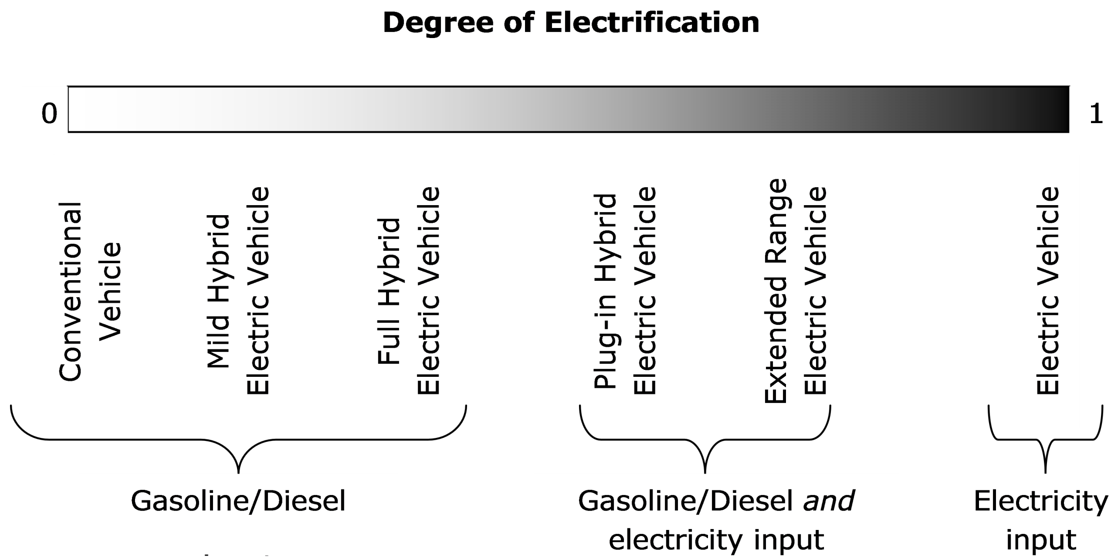


Figure 1-1: Degree of Electrification of EVs. Adapted from [9].

seen in Figure 1-1. The more "electrified" a vehicle is, the more it relies upon a battery and motor to provide vehicle propulsion. "Pure" EVs are often referred to as Battery EVs (BEVs), and appear on the far right of Figure 1-1. The Nissan LEAF, which was released in December, 2010, is an example of a BEV. Its only source of power for propulsion is the energy stored in its battery, which is recharged by plugging into a power outlet.

Vehicles that exist in the middle of this range are referred to as "hybrids," or hybrid electric vehicles (HEVs). An example of an HEV is the Toyota Prius, which uses a small battery pack to recover energy from braking and to power a motor for low speed stop-and-go driving. However, all input energy to the vehicle comes from gasoline or diesel. Further to the right on Figure 1-1 exist the Plug-in Hybrid Electric Vehicle (PHEV) and Extended Range Electric Vehicles (EREV). These vehicles contain both an ICE and and motor/battery propulsion system, and can both refuel with gasoline/diesel or recharge from a power outlet. An example of this configuration is the Chevrolet Volt, which has a battery that can provide about 40 miles of pure electric propulsion, after which the ICE turns on to recharge the battery. Alternate drive-train configurations also exist, under which the ICE is used to power the drive-train directly, instead of acting solely as a generator to supply power to the motor.

PHEVs are a compromise between pure electric and traditional ICE vehicles. This compromise was brought about by consumer "range anxiety," which is a result of the limited driving range of EVs. For example, the Nissan LEAF, which is equipped with a 24 kWh battery, can only drive up to 100 miles before it needs to be recharged. This charging process can take anywhere from seven to 20 hours, depending on the voltage and amperage available at the charging station [35].[1] And although the average US car owner only drives around 33 miles per day [28], many rely on having the ability to drive longer distances when necessary. Thus, EREVs, such as the Volt, serve as a compromise between a purely electric and a purely ICE powertrain, providing customers with the guarantee that, when the battery is depleted, they can rely on an ICE to continue their travel. From this point on in this paper, the term "EV" will refer to any form of vehicle from a PHEV to a pure BEV; that is, any vehicle that can charge directly from an electric outlet to supply all or part of its power for propulsion.

EVs are poised to shift transportation emissions from individual vehicle tailpipes to the electric power sector. The key question here is: *From an environmental perspective, is this an improvement?* This thesis aims to address the potential of EVs in the Azores to reduce CO_2 emissions, stemming from fuel combustion, and costs associated with mobility. It does so by modeling the power system in São Miguel island, as explained in the following two chapters. The model treats EVs as new load on the power system, which charge according to on-peak, off-peak, and "optimal" charging schemes. The percent of EVs as a substitute for gasoline light-duty vehicles on São Miguel is varied from 5% to 100%. The composition of the power generation sector is also varied from its current composition, which is described in Chapter 2, to formulations that have an increasing amount of renewable-based generation.

[1] The Nissan website states that an 80% charge can be accomplished in around 30 minutes, but most EVs owners will likely not have access to this kind of charging equipment. Instead, they will have to charge at a lower rate, which will require more time to complete.

1.1 Discussion of Previous Research Results in the Literature

There is a growing body of literature which attempts to determine the extent to which EVs can reduce GHG emissions. From a life-cycle perspective, the primary source of EV emissions result from the vehicles' energy needs for mobility, and not from its production, as shown in Figure 1-2.

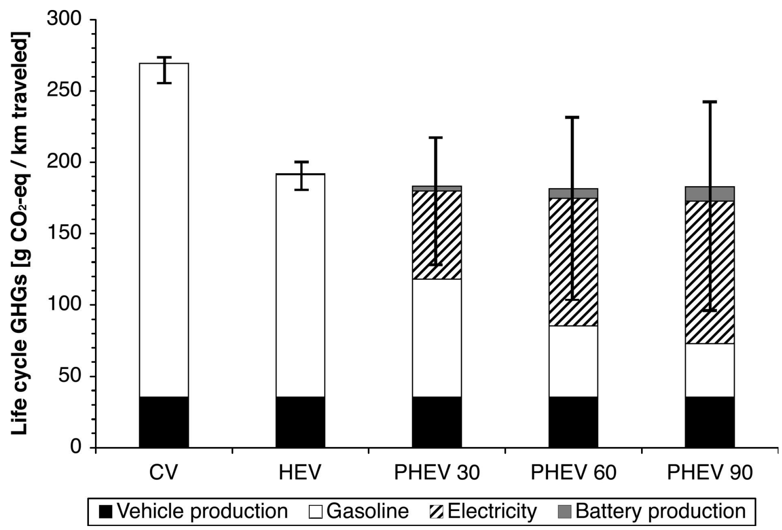


Figure 1-2: Life cycle GHG emissions from a conventional vehicle (CV), a HEV, and PHEVs that drive an initial 30, 60, or 90 km using only electric power. Taken from [45].

In general, the literature looks at two kinds of emissions associated with EV charging: Average and marginal [21]. In the former, emissions associated with the charging of an EV are calculated based on the average carbon intensity of a power sector, and is more appropriate for macro-level studies, such as in [3, 7, 28, 45, 51]. This works well in situations where many gigawatts of generation capacity are being analyzed, making an in-depth model of the power system too complicated or too tedious to perform.

In the case of marginal emissions, EVs are added onto the power system 'on top' of the existing load. Frequently, doing this may require that another generator be turned on, in order to meet the higher demand for power. Whether or not an additional generator must be turned depends on the time at which EVs begin to charge, the current status of the generators, and the kind of charging scheme employed by the EVs. Some studies, such as [37, 44, 49, 50], model each generator in the power system, and thus have a fine level of detail. These models are referred to as "economic dispatch" or "unit commitment" models. Other papers, such as [34], use a more sectoral approach, treating each generator that uses a certain type of technology (nuclear, coal, etc.) as similar.

One of the more frequently citied studies was a join study between the Natural Resources Defense Council and the Electric Power Research Insitute [34], in which the authors use a generalized power system model to calculate the marginal emissions associated with 20%–80% market penetration of a PHEV with a 20 mile all-electric range.[2] This report shows that the average emissions from EVs greatly depend upon the composition of the power sector. For instance, Figure 1-3, taken from this report, shows that PHEVs charged using electricity produced by coal power plants have higher emissions than a regular hybrid vehicle. However, PHEVs charged using renewable or other low-carbon forms of electric power generation result in a vehicle with a very low over all emissions profile. In some cases, HEVs even have a lower emissions footprint than EVs.

This important result – that EV emissions depend upon the electricity used to charge them – has been demonstrated in several other studies. [11] uses a life cycle analysis tool developed by Argonne National Laboratory to quantify marginal emissions associated with PHEV-20s deployed throughout the US, showing again that cleaner power sectors produced lower-emission driving. [28] also uses the same tool to quantify emissions impacts of PHEVs on the US electrical grid, finding that it could support the full electrification of up to 73% of the US light duty vehicle (LDV) fleet, using existing generation capacity.

In general, studies show that the electrification of LDVs results in a decrease in overall GHG emissions, while NO_x tends to vary according to how much coal is used in a region and whether or not it is ozone season [49]. Of course, this all depends upon

[2]Sometimes called a PHEV-20.

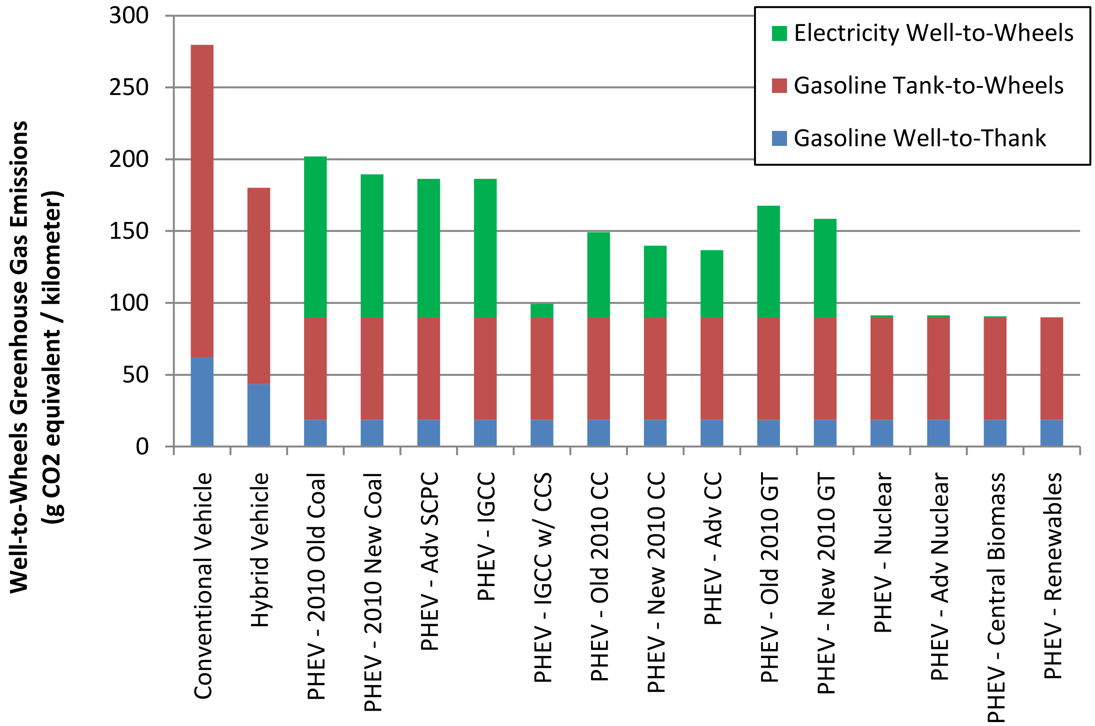


Figure 1-3: Year 2010 comparison of PHEV-20 GHG emissions when charged entirely with electricity from specific power plant technologies (12,000 miles driven per year). Adapted from [34].

the make-up of the power generation sector. If PHEVs were charged from all wind or solar energy, there would be no increase in GHGs, SO_2, or NO_x. Studies of this nature typically use different assumptions regarding the number of EVs in existence, battery size, and how/when when the EVs charge. This makes a direct comparison across studies somewhat difficult, as discussed in [36], although it highlights a clear trend that EVs have the capability to reduce mobility-related emissions, as compared with conventional vehicles.

Clearly, the degree to which an EV affects environmental metrics (GHG, SO_2, NO_x, etc.) depends upon the power sector. But the literature, especially studies that use a 'marginal' approach to studying emissions impacts, also show that the time of day at which the EVs charge is also a very important factor. During periods of already high demand for electric power, such as in early evening, the marginal emissions associated with charging an EV could be quite large. The power system will have to use some of its least-efficient generating units, typically called 'peaker plants' (because they exist only to meet these periods of peak load), in order to meet this demand.

1.1.1 Charging Schemes

Studies typically refer to a variety of charging schemes, which are summarized in Table 1.1.

Charging Scheme	**Characteristics**
On-peak/"Unconstrained"	EVs charge during peak times, typically evening.
Off-peak	EVs charge when the demand for power is low, typically late at night.
Indirect	Price or environmental signals are sent to EVs, which then choose to charge itself based on stated preferences by the individual EV owner.
Direct/Smart	Grid operator or charging aggregator tells EVs when to charge, typically for an "optimal" charging scheme.
Continuous/"Opportunistic"	EVs charge throughout the day, whenever they have the opportunity to do so, i.e. mid-day at the workplace.

Table 1.1: Charging schemes that frequently appear in the literature.

A large cause of concern in the literature is on-peak charging, in which EV owners, returning home from work at around the same time, plug in their vehicles to begin recharging immediately. With a significant number of EVs on the road, this would contribute to the system peak, potentially requiring the investment in and dispatch of additional power plants. Currently, EVs such as the Nissan LEAF have a built in electronic timer that allows them to start charging at a pre-determined time. The owner can also tell the EV to start charging remotely, using a smartphone application [35]. However, neither of these options rule out the possibility that EV owners will charge their vehicles as soon as they return home. The Independent System Operator/Regional Transmission Organization (ISO/RTO) Council, an organization made up of the groups that manage the electric grid, commissioned a study in 2010 that showed that on-peak charging by one million EVs in New York City could lead to electricity market price increases as high as 10%, due to the sudden addition of several hundred MWs of load [20]. The ISO/RTO Council concludes by saying:

> The greatest estimated impact occurs where high concentrations of vehicles charge over a short period of time on a peak day ... Exposing customers to some mechanism, whether it be dynamic pricing, special tariffs, or managed charging, could help self-regulate the potential problem of price impacts from PEV charging [20].

But it is unclear which mechanism would be the best way to go about preventing impacts from EV charging. In the literature, there is no "standard" form of charging, nor is there any standard way for studies to approach charging schemes. [1, 4, 14, 15, 21, 23, 29, 37, 38, 54] all use on-peak charging to establish a baseline for comparing other forms of charging. [5] and [28] additionally use a form of valley-filling charging, in which EVs charge when there is the greatest availability of spare generation capacity. Some, such as [17, 41] propose the use of "aggregators," to synchronize the charging of large numbers of EVs, which could be considered a form of direct charging. Because these vehicles would be told individually when to start and stop charging, based on the current status of the power network, the effects of charging on the power system could be minimized. In cases where there is time-of-use pricing for electricity, the use of these aggregators may also directly reduce costs to EV owning participants.

Many papers, including [2, 16, 48], use off-peak charging as a comparison. The time at which off-peak charging starts and stops depends on the power system, but it is typically after 10 PM and before 7 AM. A few papers, such as [21] use direct charging, while others, such as [31], use price or environmental signals to govern when charging starts and stops. In all cases, any form of off-peak or directed charging is superior to on-peak charging, as measured by system costs and emissions. The extent to which these forms are superior very much depends upon the number of EVs being charged, the rate (kW) at which they charge, and what kind of power (i.e. renewables, coal etc.) they use to charge.

1.1.2 Vehicle-to-Grid Charging

A final variation on EV charging schemes is known is "Vehicle-to-Grid" (V2G), and was initially proposed by Kempton in [30] and then expanded upon in [25, 26]. V2G allows for bi-directional power flow between an EV and the grid; that is, the EV can both charge from and discharge to the grid. In effect, V2G turns EVs into mobile battery storage/generators. This would allow an EV to provide power to the grid, serving as a provider of ancillary services, such as frequency regulation, or to act as an electricity source during periods of high demand, helping to "shave" the peak. [25] states that profits for individual EV owners could be as high as $2,500 per year, all derived from ISO-operated markets. [27] extends the V2G model to fleets of EVs, reporting similar potentials for profit. V2G is increasingly mentioned in academic literature on EVs, as well in the general conversation about ways of storing electrical energy.

V2G services may also play an environmental role. [53] attempts to predict the impact of V2G on GHG emissions up until 2100, finding that V2G could be an important mechanism for reducing emissions by storing energy from intermittent generation resources (such as wind), and then using that energy to off-set what would normally have been produced by a thermal generator. [49] uses an economic dispatch model to find that V2G also has some potential in reducing emissions in Texas, primarily by shifting spinning reserve away from partially loaded plants and onto vehicle batteries.

[55] provides a more in-depth study of V2G, which investigates the possible profits from participating in NYISO's regulation and energy markets. Driving distance, battery life, and charging rate are all considered as factors in the paper's analyses. Predicted annual profits vary widely, with an absolute minimum of -$291, and a maximum of $4,478, after accounting for wear on the battery and the cost of retrofitting the vehicle to make it V2G-enabled. Higher profits were seen with higher charging rates, longer battery lifespans and shorter average daily driving (as this left more energy in the battery).

[40] makes use of battery degradation data resulting from actual urban drive cycles provided in [39]. The authors calculate that, after factoring in the additional battery degradation caused by using the battery as a form of storage, EV owners could only expect to make as much $120 per year. The large disparity between this and the previous figures is accounted for by Peterson et al's skepticism about the possibility of EVs receiving capacity payments, in which which the market operator pays the EV owner simply for their availability to provide services, in addition to paying for the actual power delivered.

In [55] and [25], the authors derive much of their profit from these capacity payments. The authors state that the use of aggregators would enable the "bundling" of separate EV batteries together to provide the MW-h[3] increments necessary for capacity market payments[4]. Peterson et al point out that there are "transaction costs and grid costs" involved in participating in the ancillary services market, and seems to imply that these costs may be significant. In order to get a clear view of the value of using an EV as a form of battery storage, Peterson et al choose to examine only energy arbitrage, in which the EV charges when the price of power is low and then provides power to a home when the price of power is high.

Peterson et al are skeptical of V2G for frequency regulation applications, saying:

> Ancillary services such as frequency regulation are not discussed here because only a small number of vehicles will saturate those markets (for California, less than 200,000 vehicles for regulation and a comparable number for spinning reserve) . . . The number of vehicles that can benefit is typically less than 1% of the total [40].

White et al are also concerned about the effect of high levels of EV penetration on the V2G profitability. They expect that increased participation in any V2G scheme (ancillary services or simply energy) would result in reduced profits for two reasons: First, there would be an increase in the availability of power during peak demand,

[3]Here this means a megawatt of available generation capacity for one hour, and not a MWh of energy.

[4]The payment scheme varies from market to market.

which would drive down market prices during those periods. Second, there would be an increase in the demand for power during off-peak, driving up the price of power. Still, V2G might be very useful in the provision of secondary reserves, assuming that it would be cost-competitive with other technology.

There are still many open questions in the V2G literature, including:

- What is the real cost of retrofitting a vehicle to make it V2G ready? [25] estimates $400 for the power electronics; [27] (and [55], citing [27]) use a figure of $90/year over a period of ten years. But these estimates are based two citations, one of which is "unpublished data" and the other of which is a "personal communication." It would be useful to see a further and more detailed breakdown of these costs.

- What are the costs of operating and maintaining an aggregation service? There is virtually no discussion of this in the literature, although there have been several papers on algorithms that would be used by these aggregators.

- Are ISOs and RTOs really interested in purchasing services provided V2G on any meaningful scale? PJM ISO is currently working with Kempton, as part of the Mid-Atlantic Grid Interactive Cars Consortium to provide V2G services using several EVs, but this is currently a limited pilot project. Informal conversations with a few members of the utility industry have indicated that utilities are interested in V2G, but they do not anticipate it in any serious volume in the near term.

- Are automotive manufacturers interested in selling vehicles that are also stationary battery storage? This is an important issue; if V2G is to happen at any significant scale, vehicles would need to be brought to market V2G ready, as opposed to first purchasing and then retrofitting an EV.

- Would automotive battery manufacturers approve the use of their batteries for V2G applications? It is conceivable that they might object, or change the warranty for batteries used in V2G applications.

Further research in these areas will help settle doubts about V2G's viability, particularly with regards to its ability to be competitive in a market for ancillary services, as per White et al's comments, and the additional costs associated in retrofitting and aggregating EVs in order to provide this service in any meaningful quantity. In the future, if and when all of these questions have been resolved, V2G may prove to be a promising form of energy storage. However, because of these substantial questions, this thesis will not attempt to address the potential impact of V2G on EV charging in São Miguel. Instead, it will focus solely on the environmental and economic impact of EV charging, under increasing EV market penetration and use of renewable electric power generation. CO_2 is the main GHG on the island, and stems primarily from the combustion of liquid fuels in ICE vehicles and electric power generators.

Chapter 2

Mobility and Electricity in the Azores

The nine islands of the Azores form an archipelago 1,400 kilometers west of the Portuguese mainland, with a total land area of 2,346 km^2. The islands are shown in Figure 2-1.

Figure 2-1: Map of the Azores [32].

The research in this thesis is part of the MIT-Portugal Program's Green Islands Project, which focuses on the islands of the Azores. Project collaborators include PhD and master's students in both MIT and several Portuguese Universities, as well as staff and faculty from the same schools. The local electric utility, Electricidade dos Açores (EDA), as well as several local businesses, are also participating.

The Green Islands project strives to fundamentally change energy use in the Azores, in order to address climate change, energy security, and economic and social development. The regional government's target is to produce 75% of all electricity via renewable sources by 2018, up from a current average of 28%. Additionally, the government seeks to increase the rate of electricity in total primary energy from its current 40% to 50%. EV deployment can play an important role in both of these goals: In the former, increased levels of renewable energy can be used to provide mobility, and in the latter, EVs will reduce the amount of primary energy supplied by gasoline and diesel while simultaneously increasing the amount provided by electricity. Table 2.1 summarizes population, transportation, and energy use indicators for all islands.

Island Name	Population	Land Area (km^2)	Primary Energy (TJ)	Electricity Production (GWh)	Number of Vehicles
São Miguel	133,281	745	9,118	429	49,525
Terceira	55,844	400	3,102	208	27,736
Faial	15,527	173	1,065	53	8,491
Pico	14,840	445	701	43	7,416
São Jorge	9,492	244	596	27	5,099
Santa Maria	5,565	97	453	20	2,989
Graciosa	4,879	61	234	13	2,231
Flores	4,099	141	271	11	2,527
Corvo	479	17	214	1	93
Total	**244,006**	**2,322**	**15,563**	**805**	**113,102**

Table 2.1: Population, transportation and energy statistics for the Azores, 2007 [32].

2.1 Vehicle Fleet Characteristics

Before further discussing the impacts of vehicle electrification in the Azores, it is important to first understand the composition of the current vehicle fleet. São Miguel, being the largest of the islands, accounts for almost half of all vehicles in the Azores. In 2007, Azoreans bought 27.3 new vehicles per thousand inhabitants, slightly higher than the Portuguese national average of 24.3. As shown in Figure 2-2, most of the vehicles on São Miguel are light duty vehicles (LDVs), which are the vehicles most commonly suggested for electrification, due to their small size.

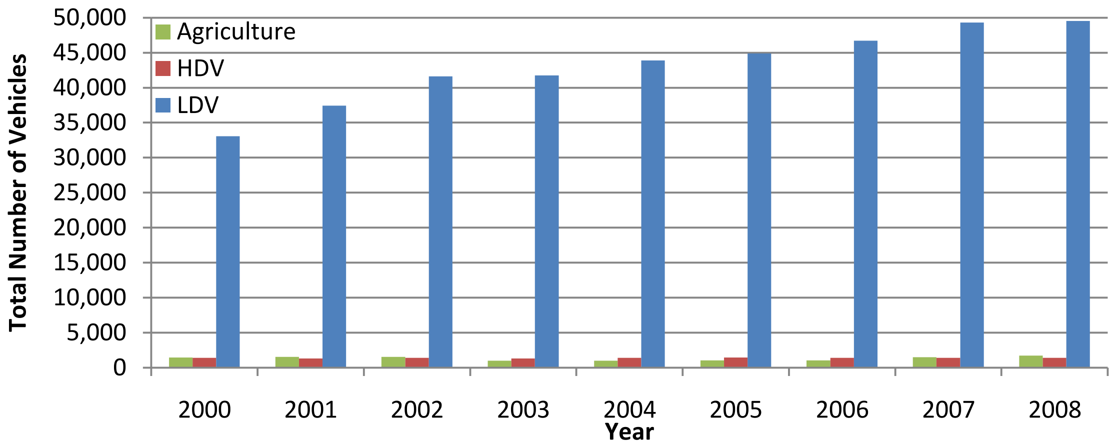


Figure 2-2: Number and types of vehicles on São Miguel. Heavy Duty Vehicles (HDVs) include trucks and buses [6].

Approximately 45% of all vehicles in the Azores are five to ten years old, and an additional 32% are more than ten years old [33]. New vehicles are typically driven the most, as shown in Figure 2-3.

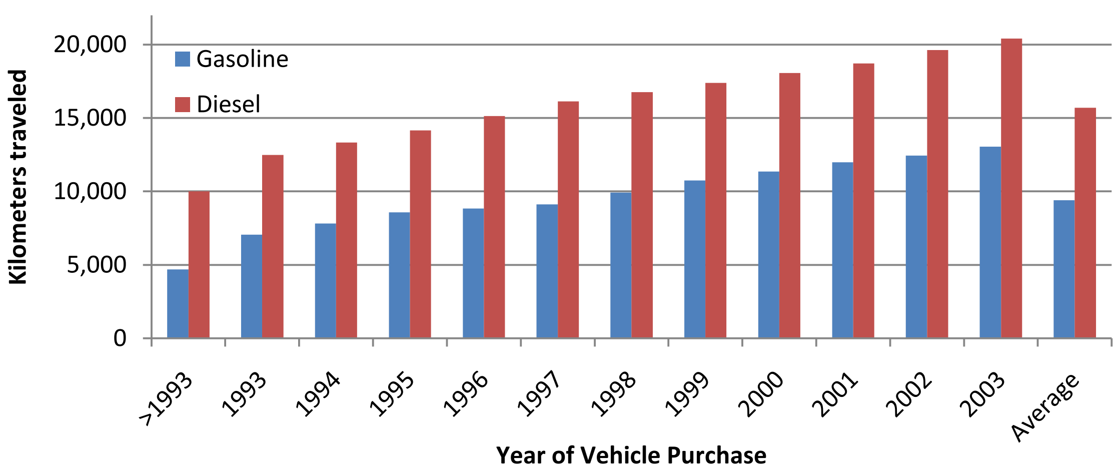


Figure 2-3: Average annual mobility of Azorean LDVs in 2003, by vehicle fuel type.

The average time spent commuting in the Azores is 15 minutes, as compared to an average of 22 minutes for all of Portugal [43]. The shorter commute time in the

Azores is due to the small size of the islands. More than 50% of respondents to a study on mobility in the Azores said that their commute was less than 5 km, with a mean commute distance of 9.7 km [42].

But despite the limited number of places to drive to, the number of passengers using public transportation on São Miguel in 2009 was only around 1,000, down from the previous year. Only 8% of São Miguel residents use public transit to commute to work. Low use of public transit is explained by the poor coverage of routes [42]. Based on the increase in car purchases, and the decrease in public transit use, it seems clear that personal vehicle ownership will continue to grow in São Miguel in the coming years.

Unlike in the US, where almost all LDVs use only gasoline, 53% of the LDVs in the Azores use diesel, with the remaining 47% relying upon gasoline. Figure 2-4 shows gasoline and diesel use for all vehicles on São Miguel. The high values for diesel fuel use in this figure also include fuel for HDVs.

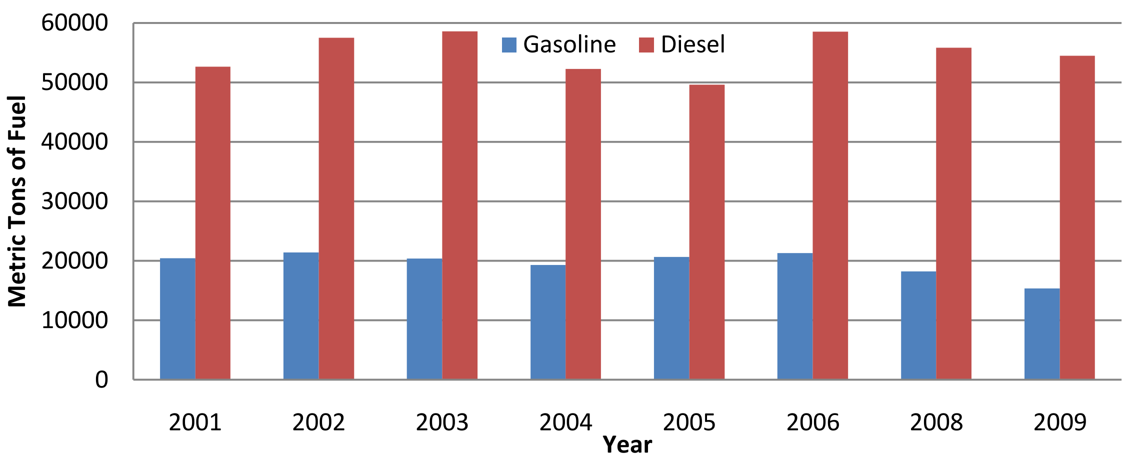


Figure 2-4: Yearly fuel used for transportation on São Miguel in metric tons of fuel. Data for 2007 is not available [6].

The 19,000 gasoline LDVs on São Miguel have a mean daily travel distance of 26 km (≈26 miles), compared with the diesel LDV distance of 44 km. Given that electric vehicles tend to be used to travel shorter distances, the model in this thesis will be used to evaluate the impact of electrifying only the gasoline LDV fleet. Currently, the gasoline LDV fleet has an average of about 9.4 Liters/100 km (≈25 MPG). Some basic properties of the gasoline used in the Azores are given in Table 2.2.

Gasoline Property	Value
Energy content	42.5 Mega-Joules/kg fuel
GHG content	3.44 kg CO_2/kg fuel
Density	31,875 MJ/m^3

Table 2.2: Basic properties of gasoline used by the LDV fleet in the Azores.

All fuels must be shipped onto the islands, at further expense. Many commodities on the Azores, including gasoline and diesel, are subsidized by the Portuguese government to be the same general price as on the mainland. This subsidization of fuel prices on the islands is an additional "hidden" cost of traditional mobility, from a societal perspective.

2.2 Electric Power Generation Characteristics

The power system in the Azores varies from island to island. Each island must generate its own electricity as there are no transmission lines connecting islands to each other or the mainland. São Miguel has no electric storage capacity. The island uses a combination of renewable and diesel (fuel oil) generation to meet the needs of its 130,000 residents. Table 2.3 lists all the major sources of generation on the island. Some small sources, such as a biodiesel and hydropower plant, have been left out of the analysis due to capacity factors of less than 5%, meaning that these plants were virtually never used during the year. All hydropower plants are run of the river, meaning that their power output depends upon the quantity and velocity of water available at any given time.

Hydropower and geothermal plants are listed as having a maximum power, but no minimum. The maximum and minimum power output of the hydropower plants depends upon the time of the year; during the rainy season, the hydropower power plants can produce their maximum output, but could also produce less. There is no "minimum" power output per se, except whatever the minimum power produced by the river is. The geothermal plants operate in a similar fashion.

Generator Name	Generator Type	Fuel Type	Entered Service	Minimum Power (MW)	Maximum Power (MW)
Siemens 8M601 1	Diesel	Fuel oil	1987	3.848	7.2
Siemens 8M601 2	Diesel	Fuel oil	1987	3.848	7.2
Siemens 8M601 3	Diesel	Fuel oil	1990	3.848	7.2
Siemens 8M601 4	Diesel	Fuel oil	1993	3.848	7.2
Wärtsillä 18V46 1	Diesel	Fuel oil	2002	8.41	16.82
Wärtsillä 18V46 2	Diesel	Fuel oil	2002	8.41	16.82
Wärtsillä 18V46 3	Diesel	Fuel oil	2004	8.41	16.82
Wärtsillä 18V46 4	Diesel	Fuel oil	2004	8.41	16.82
				Total Thermal:	96.08 MW
Pico Vermelho	Geothermal	-	2007	-	13
Ribeira Grande	Geothermal	-	1994	-	14.8
Túneis	Hydro	ROR	2000	-	1.658
Canário	Hydro	ROR	1990	-	0.4
Foz da Ribeira	Hydro	ROR	1990	-	0.8
Ribeira da Praia	Hydro	ROR	1991	-	0.8
Salto do Cabrito	Hydro	ROR	1997	-	0.67
				Total Renewable:	32.13 MW
				Total Generation:	128.21 MW

Table 2.3: São Miguel Generation Capacity as of 2008. “8M601” and “18V46” refer to two kinds of generators, produced by Siemens and Wärtsillä, respectively. There are four 8M601 generators and four 18V46 generators. “ROR” stands for run-of-river.

Hydropower and geothermal plants tend to serve as baseload units, meaning that they provide a roughly unvarying source of power. One of the larger fuel oil units is always running, and serves both demand and as frequency regulation. Other units are turned on and off as necessary, with the smaller fuel oil units typically serving as "peakers," running when demand is particularly high.

The price of fuel oil for generators has gone up over the past several years, as shown in Table 2.4. Basic properties of the fuel oil used on the island are given in Table 2.5.

Year	2004	2005	2006	2007	2008
Price (Euro/kg)	0.22	0.27	0.35	0.33	0.45
Euro Cents/Mega-Joule	0.53	0.65	0.83	0.80	1.09

Table 2.4: Fuel oil prices for the Azores, 2004-2008. Fuel oil is used for thermal power plants on São Miguel.

Fuel Oil Property	Value
Energy content (Mega-Joules/kg fuel)	41.5
Energy content (Thermies/kg fuel)	9.912
GHG content (kg CO_2/kg fuel)	3.4
Density (MJ/m^3)	39,557.8

Table 2.5: Basic properties of fuel oil used by thermal generators in the Azores.

If this price trend continues upward, then the cost for electric power on the island will also increase. However, given that the cost for fuel oil and gasoline are closely related, the cost of providing mobility for ICE vehicles will also likely increase. This already high cost is partially due to Portugal's tax on gasoline, which results in prices equivalent to approximately \$8/gallon.[1]

Because ICE vehicles are fully reliant upon diesel and gasoline for transport, while EVs rely on any form of electric power, it seems likely that EVs and ICE vehicles would experience different economic impacts. If the Azores is to deploy electric vehicles, there should be no expectation that electric miles driven will necessarily cost less than

[1] As of March 30th, 2011.

conventional ICE miles driven. This is due to the higher average cost of electricity from renewable sources, as compared with conventional generation sources.

In examining a power system, it is often useful to see how often power generation exceeds a certain threshold, in order to characterize high and low demand. An annual load duration curve for São Miguel, generated using 2009 hourly data, provides this data in Figure 2-5. A few other statistical indicators are provided in Table 2.6.

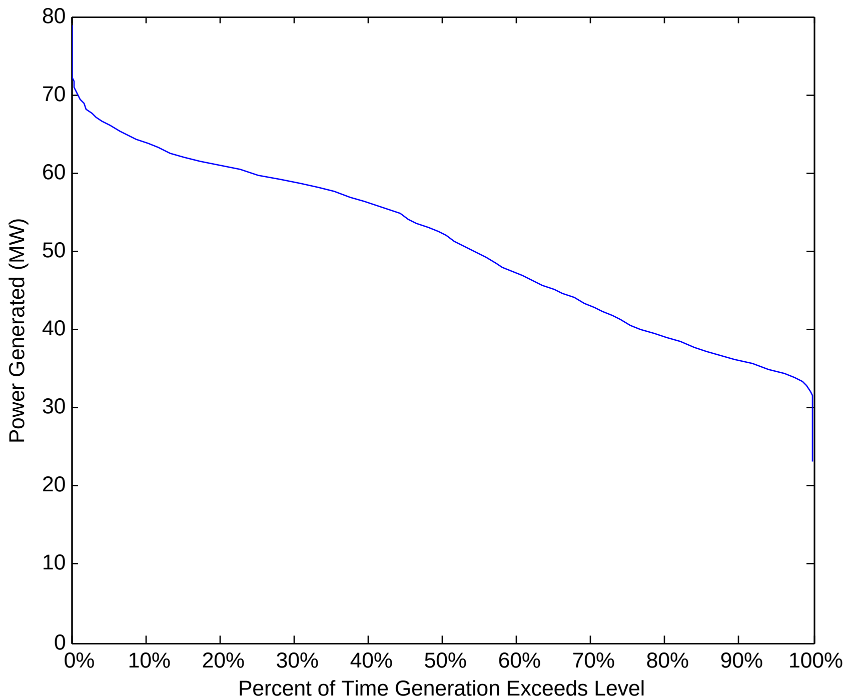


Figure 2-5: Load duration curve for 2009, derived from hourly data.

In general, demand for electricity rarely exceeds 70 MW, and typically does not fall below 35 MW.

Mean	Median	Minimum	Maximum
51.1	52.46	22.9	79.2

Table 2.6: General statistical indicators for 2009 power generation in São Miguel. All values in MW.

Electric power demand follows a fairly regular schedule, with lower demands on the weekends, a predictable peak during the weekday, and then another lower peak as people return home from work. Figures 2-6 and 2-7 show typical weekly schedules for low and high electricity production levels, respectively. All figures start on Saturday at midnight.

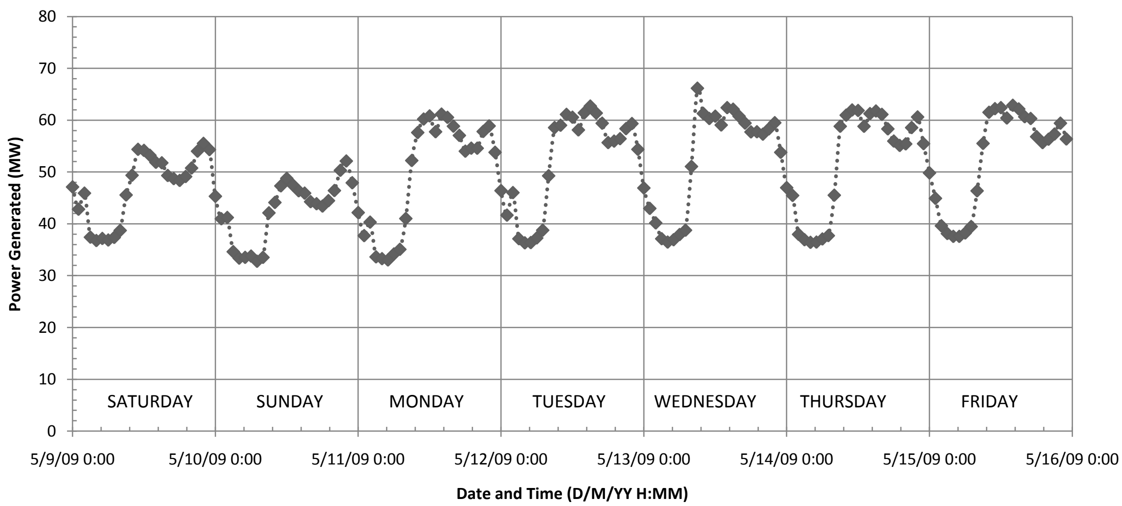


Figure 2-6: Typical 2009 weekly electricity production, low.

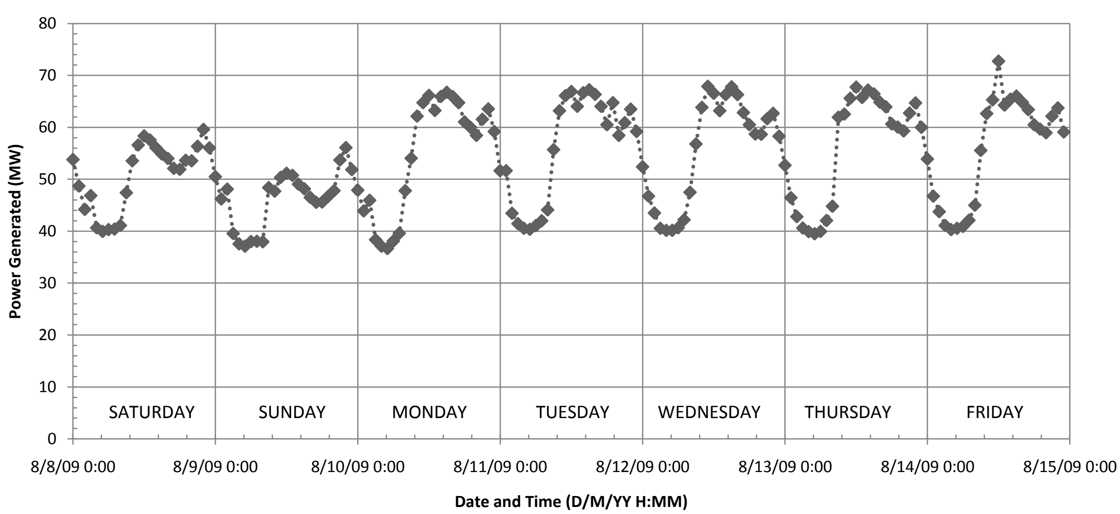


Figure 2-7: Typical 2009 weekly electricity production, high.

Because the Azores is a popular tourist destination, many people visit the islands during holidays for vacation, especially during the summer. However, towards the end of the year, around Christmas and New Years, the daily peaks tend to exceed 70 MW, as shown in Figure 2-8. Note that the summer profile has an evening peak demand of an additional 5 MW. This could potentially interfere with some of the previously described EV charging schemes.

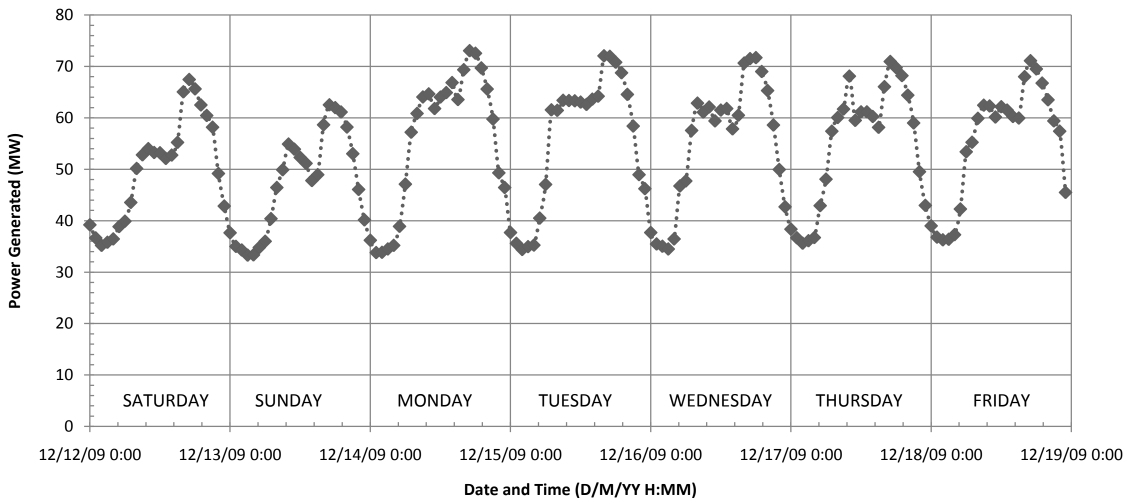


Figure 2-8: Typical 2009 weekly electricity production, winter.

Given this information on the mobility and electric power characteristics of São Miguel, it is possible to make some simplifying assumptions to assist in the creation of a model. The vehicles to be "electrified" on the island include only the 19,000 gasoline LDVs, as these have the shortest travel distance. The energy needed to charge their batteries for mobility will be produced by the generators on the island, plus some additional hypothetical generators, as discussed in Chapter 4. These EVs will be benchmarked against the conventional gasoline LDVs already on the island.

Chapter 3

Model Design, Assumptions, Parameters, and Validation

In order to accurately assess the impact of EVs on the power generation sector in São Miguel, an economic dispatch and unit commitment model is used. In the parlance of utilities, to "dispatch" a plant is to turn it on in economic merit order (least expensive first) to meet demand for electric power. This kind of model allows for the characterization of each generator in a power system, according to a variety of physical and economic (cost) parameters. The overall goal of an economic dispatch model is to minimize the cost of providing electricity, subject to a variety of constraints.

"Unit commitment" ensures that the model turns generators on and off in a realistic fashion. Combining the unit commitment and economic dispatch constraints forms a mixed-integer linear program that is run using the Generalized Algebraic Modeling System (GAMS), a language and software environment that is meant for optimizing complex algebraic models. Further detail on optimization and its application the power sector can be found in [56]. The mathematical formulation of the model is discussed further in the following section. Section 3.2 provides numerical values and derivations for data used in the model. Unit commitment and spinning reserve requirements can be considered to be sub-components of the larger economic dispatch model, and act to ensure that a "real-world" dispatch is produced.

This model treats the entire grid as a single node, meaning that there is no consideration of the spatial aspects of generation and consumption. MW values produced by the model are at the bus-bar level, meaning before transmission and distribution (T&D). There is no T&D system in this model, meaning that transmission losses are not considered. It is possible that the addition of EVs to the electric power grid in São Miguel could result in power line congestion or lower power quality; answering these questions is beyond the scope of this thesis.

This model is formulated in a deterministic fashion, meaning that the model knows exactly what electricity demand will be in each hour of the week, with 100% certainty. In reality, no utility operators knows with exact certainty what will happen in the future – perhaps a generator will malfunction, or wind output will be different from what was predicted, or the demand for power will peak earlier than average. For this reason, utilities or system operators ensure that their network has surplus generation.

In a large, interconnected system, such as in the Northeastern US or mainland Portugal, ensuring the adequate provision of reserves is complicated by the complexity and size of the grid. These concerns are much less germane for the 745 km^2 island of São Miguel, which has no interconnections to other islands or larger electric grids. Table 2.3 shows thats the island has spare generation capacity, such that if a generator were to malfunction, sufficient back up would be available. Additionally, the island's thermal generators are fast, meaning that one can brought online quickly in the case that another generator malfunctions.

3.1 Model Design

This model is adapted from one developed at the ICAI School of Engineering at Universidad Pontificia Comillas, Madrid. It has been modified to incorporate the presence of EVs on São Miguel. The purpose of this section is to describe the constraints and objective function that formulate the mathematical model. Much of the explanation given here follows directly from that presented in [13]. The actual values used in the model are described in Section 3.2.

The first step in the design of the model is to define p, the numbered set of time periods in the model. The model uses an hourly time step over the course of a week, for a total of 168 hours. $p1$ is the first hour, $p2$ is the second and so on. The next step is to define EV, the set of all EVs on the island, as well as g, the set of all generators on the island.

3.1.1 Generation Constraints

The generation constraints are those which govern how generators behave. They include physical limitations of the generators, such as unit commitment and ramping rates. In modeling the physical elements of generators, it is important to consider their minimum and maximum output values, $\underline{q}_g$ and $\overline{q}_g$, respectively, both in MW. These values are provided in Table 2.3. $q_{g,p}$ is simply the net power dispatched by generator g at any time p. The term $q'_{g,p}$ refers to the amount of power produced over the minimum stable load, $\underline{q}_{g,p}$. Additionally, k_g is a term known as the "auxiliary load factor," which converts gross power generated by g to the net power that is seen after deducting the generators internal load. k_g is always a value greater than zero and less than one.

Minimum and maximum power output constraints are introduced into this model via a binary variable, $u_{g,p}$. When generator g is online during period p, $u_{g,p}$ is set to one; otherwise, it is set to zero. Equation 3.1 uses u to set power output to be above the minimum value for generator g, while Equation 3.2 use u to set a maximum output.

$$q_{g,p} = u_{g,p} \times k_g \times \underline{q}_g + q'_{g,p},\ \forall g, p \tag{3.1}$$

$$q'_{g,p} \leq u_{g,p} \times k_g \times (\underline{q}_g - \overline{q}_g),\ \forall g, p \tag{3.2}$$

In effect, Equation 3.1 gives the current output of generator g at time p to be equal to its minimum net stable load plus however much is being produced over this minimum stable load. Equation 3.2 complements this equation, preventing $q'_{g,p}$ from exceeding the generator's maximum output. The use of the $u_{g,p}$ in both of these equations prevents the generator from dispatching any power, from either $\underline{q}_g$ or $q'_{g,p}$, when generator g is turned off at time p.

Generators are additionally characterized by an upward and downward ramping rate, given in MW/unit time. This describes the rate of change in electric power production that a generator is capable of producing. Upward ramping rates are referred to as ru_g, while downward ramping rates are rd_g. The algebraic constraints for upward and downward ramping are given in Equations 3.3 and 3.4, respectively.

$$q'_{g,p} - q'_{g,p-1} \leq ru_g,\ \forall g, p \tag{3.3}$$

$$q'_{g,p-1} - q'_{g,p} \leq rd_g,\ \forall g, p \tag{3.4}$$

In the case of Equation 3.3, the power produced over minimum in the current period cannot exceed the power produced over minimum in the prior period. Equation 3.4 operates in a similar fashion.

These equations use q', instead of just q, because ramping only affects moving from one level of power production above the minimum to another, instead of from off to on. Constraints for modeling generators ramp rate from off to on are known as cold-start and warm-start constraints. The former refers to situations where the generator has been off for several hours, while the latter refers to situations where the generator has only recently been shut down. These constraints are important in generators that have a large boiler, which takes time to heat up, and are typically seen in coal or nuclear power plants. The cold-start and warm-start constraints on the 8M601 and 18V46 generators on São Miguel are minimal, and thus are not considered in this model.

In order to model unit commitment, an additional binary variable, $y_{g,p}$, is introduced. When its value is set to one, this indicates that generator g will start up during period p. An additional variable, $z_{g,p}$ is used similarly, except for shutdown decisions.

$$u_{g,p} = y_{g,p} - z_{g,p} + \begin{cases} u_{g,p-1} & \text{if } p > 1,\ \forall g, p \\ u_{g,p1}^{\text{initial}} & \text{if } p = 1,\ \forall g, p \end{cases} \tag{3.5}$$

This constraint allows u is to be changed from zero to one, one to zero, or stay fixed, according to the state of generator g during period p. For instance, if generator g is already running during period period p, then $y_{g,p}$ and $z_{g,p}$ are both zero (as there is no scheduled startup or shutdown for that period), and $u_{g,p-1}$ is one. Thus, $u_{g,p}$ is equal to one.

$u_{g,p1}^{\text{initial}}$ refers to the original setting for generator g at time $p1$. This value is manually set by the modeler. For example, in this model, all the baseload hydropower and geothermal units are initially set to run. Other thermal units are left off, and are turned on when the model needs to do so.

Although the current generation system on São Miguel does not currently contain any wind turbines, there are plans to install ten turbines within the next one to two years. Unlike geothermal, hydropower, or thermal plants, wind power output varies a great deal during the year. For this reason, wind power is added into the model as the cost of generating a MWh of wind power times the amount of wind power. Use of wind power is opportunistic, in that the model cannot generate more of it on demand (as it would with ramping up a thermal generator), although the model is able to curtail its use. For these reasons, power produced by wind is not accounted for in a $q_{g,p}$ variable, but instead in its own variable, wg_p.

The cost of operating generator g is a combination of several factors, which are summarized in Table 3.1.

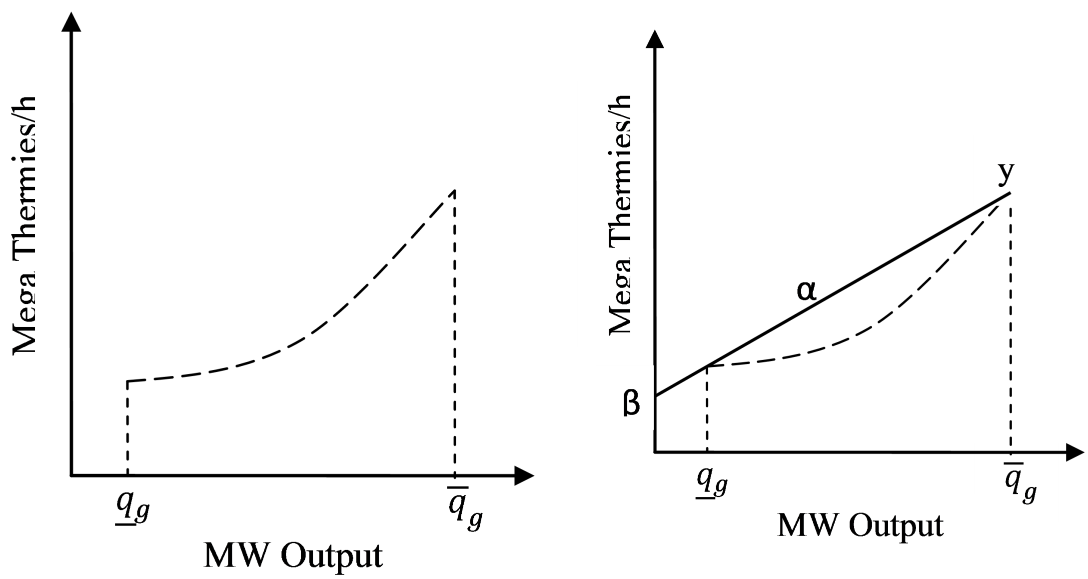
γ varies from generator to generator. In large generators, fuel is expended bringing the boiler up to its proper temperature, but none of this fuel actually produces electricity. γ may also internalize costs associated with wear and tear on the generator due to thermal expansion during start-up. Similarly, θ reflects fuel wasted when the generator is shut down, as well as wear and tear from that process.

α and β are best described as the slope and y-intercept, respectively, of a linear fit to a generator's input-output curve. This curve, an illustration of which is given

Name	Description
γ_g	Start-up costs (Euro/start up)
θ_g	Shut-down costs (Euro/shut down)
α_g	Incremental fuel consumption rate (kTh/MWh)
β_g	Fixed fuel consumption rate (kTh/hour)
o_g	Operation and maintenance (O&M) costs (Euro/MWh)
wc	Cost of wind power (Euro/MWh)

Table 3.1: Factors Affecting Generator Costs. kTh (Kilo-thermies) are a unit of energy. 1 Th = 4.1868 MJ = 3968.3 BTU

in Figure 3-1(a), shows the required energy input (derived from fuel oil) per hour, in order to get a certain gross electric power output. The linear fit of line 'y' can be seen in Figure 3-1(b). The fuel required per hour to produce power output q_g MW of output is equal to $\alpha \times q_g + \beta$.



(a) Sample Generator Input-Output Curve (b) Linearized Input-Output Curve

Figure 3-1: Visual Derivation of α and β

Note that the input-output curve is not a linear function; the line between $\underline{q}_g$ and $\overline{q}_g$ is bowed outward (the effect of which has been greatly exaggerated in this figure), and the y-intercept is not equal to zero. Incorporating the convexity of the real input-output curve into the model would likely have little effect on its results given that the input-output curves for the 18V46 and 8M601 generators, as shown in Figures 3-3 and 3-4, are almost straight lines. As a result, this convexity is not included in the model.

The effect of β, however, is included in the model. As a result of this non-linearity, generators produce the most power output per fuel consumed when operating at $\overline{q}_g$. For this reason, this model generally attempts to run generators at full load. The higher β is, the more pronounced this effect is.

o_g are costs associated with operating and maintaining generator g, per MWh of output. This could include costs such as personnel, additional costs associated with environmental controls installed on the generator and so on. Unlike all other previously mentioned factors affecting generator cost, o_g does not depend on the price of fuel.

Summing all these factors together, the cost function for generators operated in time p is given in Equation 3.6, the unit of which is Euros:

$$\text{Cost of Fuel} \times \left(\overbrace{\gamma_{g,p} \times y_{g,p} + \theta_{g,p} \times z_{g,p} + \alpha_{g,p} \times \frac{q_{g,p}}{k_g} + \beta \times u_{g,p}}^{\text{Function of Cost of Fuel}} \right) + \overbrace{o_g \times \frac{q_{g,p}}{k_g} + wc \times wg_p}^{\text{Fixed per MWh}} \tag{3.6}$$

3.1.2 Complexity Constraints

Unlike generator constraints, which concern the dynamics of individual generators, complexity constraints tie the operation of all the generators and load together. A few new factors are introduced in Table 3.2.

d_p is an exogeneous parameter, based on previous or predicted demand for electric power. usp_p is a variable that represents unserved power, which refers to any demand for electric power that is not met. It is included as part of the objective function as a penalty. Whenever usp is greater than zero for time p, a brown-out is occurring. usp_p could be greater than zero because there is not enough generation capacity to meet demand, or because the model decides that it is less expensive to pay a penalty for not meeting demand than to generate the required power. However, in the case

Name	Description
d_p	Bus-bar demand for electric power, not including EVs (MW)
$cs_{EV,p}$	Charging schedule for each EV (kW)
usp_p	Unserved power (MW)
res_p	Spinning reserve requirement (% of current demand)
η	Efficiency of EV charging hardware
$sto_{EV,p}$	The power stored in each EV's battery (kWh)
$\psi_{EV,p}$	The power required to drive a distance (kWh)
wg_p	Wind power generation

Table 3.2: Factors Affecting the Entire Generation System

that demand exceeds supply, usp allows the model to solve what would otherwise be an infeasible problem.

$cs_{EV,p}$ is a variable that indicates that vehicle EV is charging during period p. Charging can happen at a fixed or variable rate, measured in kW. $sto_{EV,p}$ reflects the total amount of energy in vehicle EV at any period p, and is used by the model in deciding when, and if, to charge that vehicle, according to its demands for energy. sto increases or decreases according to Equation 3.7.

$$sto_{EV,p} = \eta \times cs_{EV,p} - \psi_{EV,p} + \begin{cases} sto_{EV,p-1} & \text{if } p > 1,\ \forall EV, p \\ sto^{\text{initial}}_{EV,p1} & \text{if } p = 1,\ \forall EV, p \end{cases} \tag{3.7}$$

Where, as in Equation 3.5, there are two separate cases: In the case of $p > 1$, the amount of charge in vehicle EV depends on how much was in it previously. In the initial case where $p = 1$, the modeler has the option to set the battery to be "pre-charged" with some kWh value. The battery in vehicle EV discharges during period p according to the power demands of a driving schedule, ψ, that is determined by the modeler.

In certain charging schemes, such as the on-peak and off-peak charging schemes described in Table 1.1, it may be desirable to produce a charging pattern that decreases monotonically over time during a fixed period of time. By doing so, the modeler ensures that the charging pattern resembles that of a vehicle simply plugging in at a certain time and then charging until the desired charging level is met.

This behavior is enforced using Equation 3.8.

$$cs_{EV,p} \geq cs_{EV,p+1}, \ \forall p \text{ that are during on-peak or off-peak periods} \tag{3.8}$$

Given that the supply of power (including power not served) must always equal demand, the balance constraint is given in Equation 3.9.

$$\sum_{g} q_{g,p} + usp_p + wg_p = d_p + \sum_{EV} cs_{EV,p}, \ \forall p \tag{3.9}$$

Equation 3.9 simply states that the sum of all power output at anytime, including wind, plus any unserved power, must be equal to the previously determined demand for electric power, plus the additional demand generated by electric vehicles.

res_p refers to the additional amount of power that could be produced by the set of generators already running during period p, referred to as operating reserves. The inequality constraint for these operating reserves is given in Equation 3.10.

$$\sum_{g} \left(u_{g,p} \times \overline{q}_g \times k_g - q_{g,p} \right) \geq res_p, \ \forall p \tag{3.10}$$

Thus, the sum of all the available generation capacity at any time p must not only be used to meet the load (which is dispatched at $q_{g,p}$), but must also have some remaining amount that is greater than or equal to the required operating reserves. Note that wind power does not count as part of reserve capacity, because it cannot be reliably controlled.

In the context of this model, this refers to a safety margin of additional power that could be generated very quickly, in the case that another generator were to unexpectedly go offline or become otherwise disabled. Clearly, generators within a computer model do not suddenly break; instead, res_p is used to represent the fact that utilities always have a small margin of extra generation capacity available in case of an emergency.

The final objective function is shown in Equation 3.11.

$$
\min \sum_p \Bigg[wc \times wg_p + \text{Cost of Unserved Power } \times usp_p + \\
\sum_g \Bigg(\text{Cost of Fuel} \times \Big(\gamma_{g,p} \times y_{g,p} + \theta_{g,p} \times z_{g,p} + \alpha_{g,p} \times \frac{q_{g,p}}{k_g} + \beta \times u_{g,p} \Big) + o_g \times \frac{q_{g,p}}{k_g} \Bigg) \Bigg] \tag{3.11}
$$

And is subject to the constraints listed in Equations 3.1, 3.2, 3.3, 3.4, 3.5, 3.7, 3.8, and 3.9. Running GAMS on this model produces an hourly dispatch schedule that states what generators are on and off and their output at any time p, in addition to a total system cost for that dispatch, over the course of an entire week.

3.2 Model Parameters

Whereas the previous section described the general model formulation, this section provides the actual values that are used in the model and, as necessary, describes their derivations.

Ramping rates for thermal generators are given in Table 3.3. Within the model, these rates are converted into MW/hour. The geothermal and hydropower plants also have ramping rates, but no official EDA data was available on these values. Based on an analysis of generator data provided by EDA, these values could be as high as approximately 5 MW/hour. For all practical purposes, however, the ramping rates of these generators hardly matters at all, since they serve as baseload and are typically fully dispatched.

Ramping Rate (MW/minute)	8M601	18V46
Upward	2	3
Downward	-2	-3

Table 3.3: Thermal generator ramping rates, as provided by EDA and implemented in the model.

EDA does not used a fixed level of reserves. Instead, system operators vary them according to renewable production, time of day, and even the experience of the system operators themselves. An analysis of 2009 EDA dispatch data for São Miguel shows that there is a wide variation in operating reserves from hour to hour. Figure 3-2 shows hourly operating reserves for 2009, with a one day moving average. The average level of operating reserves is is 24.21%. Using such a high level of reserves in the model produces an output that does not resemble EDA's actual dispatch. Instead, an operating reserve of 1% is selected, as this value produces a dispatch that most closely resembles EDA's dispatch.

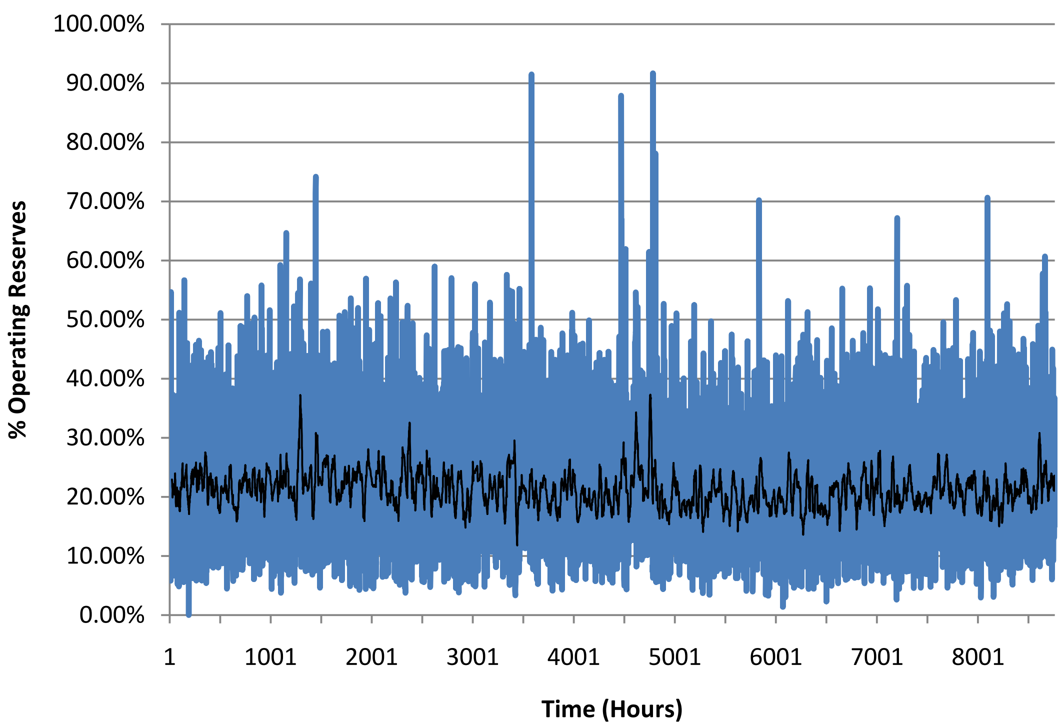


Figure 3-2: EDA Hourly Operating Reserves, 2009, as a percent of total dispatched power. The blue line is interpolated from hourly data points (1 – 8760). The black line is a 24 period (one day) moving average.

Input output curves for the 18V46 and 8M601 generators can be seen in Figures 3-3 and 3-4, respectively. Both show an interpolated blue line connecting data points, and a black line, which is a linear fit to the data points. In both cases, the linear fit is very close, with R^2 values exceeding 0.99. The coefficient for x is the value used for α, and the y-intercept is the value used for β.

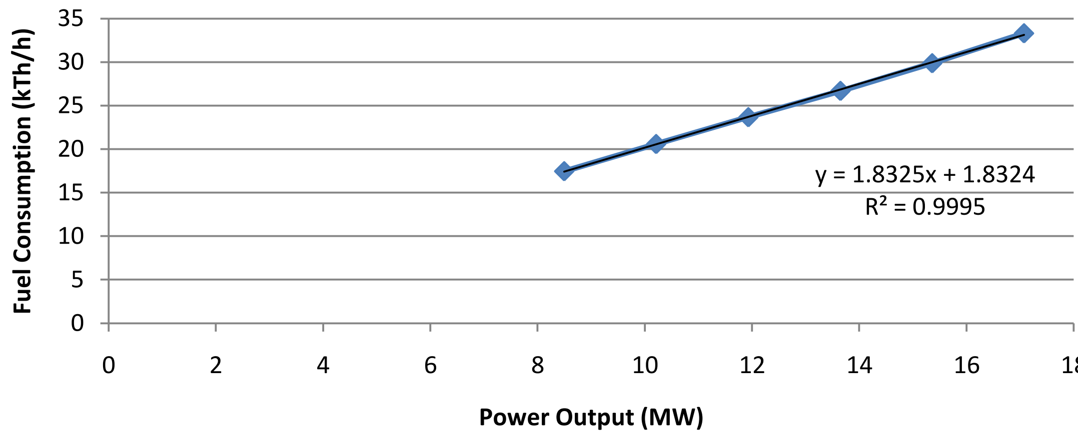


Figure 3-3: 18V46 Input-Output Curve. Produced using data from Wärtsillä.

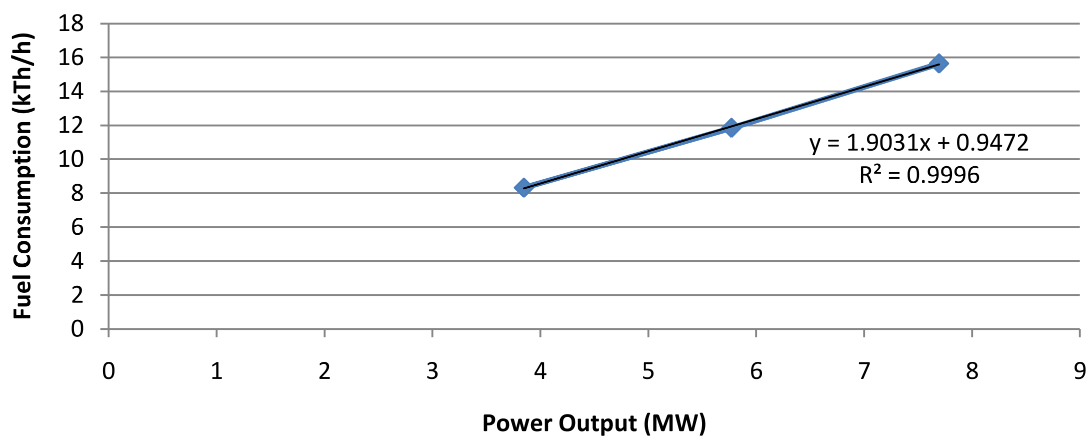


Figure 3-4: 8M601 Input-Output Curve. Produced using data from EDA.

Numerical values for factors that affect generation cost, as initially described in Table 3.1, are provided in Table 3.4.

	Generator Type				
Parameter	18V46	8M301	Geothermal	Hydropower	Wind
γ_g	910	455	0.001	0.001	-
θ_g	910	455	0.001	0.001	-
α_g	1.8325	1.9031	0.001	0.001	-
β_g	1.8324	0.9472	0.001	0.001	-
o_g	10.9	10.9	84	84	84
k	0.94	0.94	1	1	-
Cost of Fuel	45.461	45.461	0.001	0.001	-

Table 3.4: Numerical Values for Generation Costs. Units are the same as in Table 3.1. Values derived from EDA data.

Note that geothermal and hydropower are included in this table. In many cases, the power output from these plants is treated as being completely free, meaning that these generators would not even be included as part of the dispatch. The argument for doing so is that these plants only have initial capital costs, and that the marginal cost of generating a MWh of power is zero because the water or steam used to turn the turbines is costless. The data provided by EDA indicates that, unlike the thermal generators, EDA does not operate the hydropower and geothermal generators. Instead, it contracts their operation out to a subsidiary. The only data available on the costs of these plants was an aggregate cost per MWh generated. To implement this in the model, these costs were all treated as operation and maintenance costs, since that parameter is also in the unit of Euros/MWh.

It may not be the case that the cost of operating the geothermal and hydropower plants scales linearly with their electric power output. For instance, personnel costs are likely fixed. However, this is the best data available, and the fact that EDA chose to identify their costs in a per MWh fashion indicates that there is a link between electric power production and cost. Perhaps this is due to the billing arrangement that EDA has with its third party operator. Furthermore, the model always fully utilizes these plants, resulting in a dispatch that resembles that of EDA. Therefore, the functionality of the dispatch is likely correct, but the cost of the dispatch may be suspect. However, as shown in Section 3.3 of the model, the model's system costs are close to EDA's actual system costs.

Wind power plants, as with geothermal and hydropower, are operated by a third party. They bill EDA 84 Euros/MWh of power produced by the turbines. Thus, wc is set to 84. wg is the sum of wind power production by ten 900 Enercon E-44 turbines to be installed on São Miguel within the next one to two years. The process of preparing this wind dispatch data is further described in the appendix, but, in brief, it uses historical data to construct an available upper bound of power production for each hour p during the simulation. This is a deterministic wind dispatch that the model can choose to curtail, and should be viewed as a "best case" dispatch.

The output of the hydropower and geothermal plants vary somewhat. Figure 3-5 shows their output over the course of 2009. Note that the hydropower plant's output does not vary according to season. Sudden decreases in output to zero MW are due either to a temporary failure in data acquisition or the plant being brought offline.

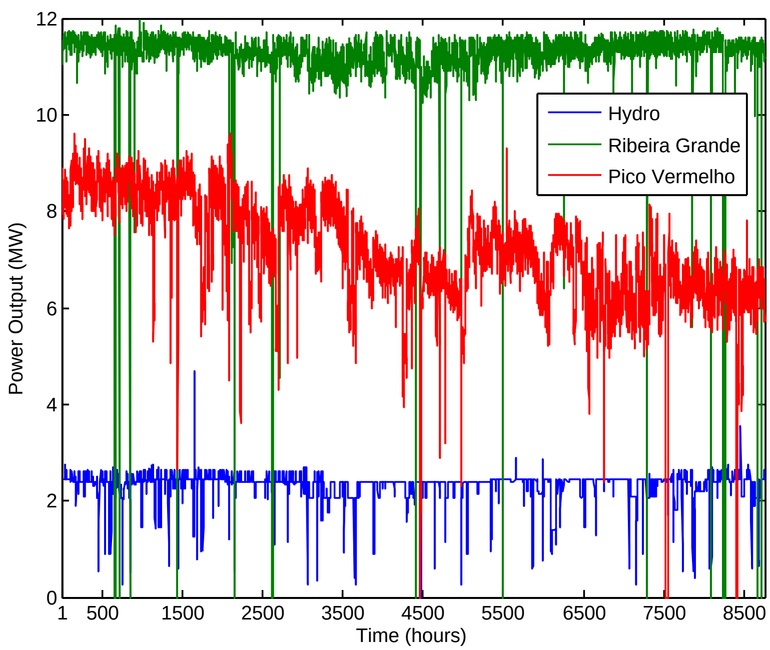


Figure 3-5: Hourly Power Output of Renewables Plants, 2009. Ribeira Grande and Pico Vermelho are both geothermal plants.

Other values in Table 3.4 for hydropower and geothermal are set to 0.001. This low value is used because GAMS will not allow a value of zero. The cost of unserved power is 1,800 Euros per MWh, which results in the model always fully meeting the required load.

3.2.1 Electric Vehicle Parameters

Table 3.5 shows numerical values for EV parameters that affect system costs. Because this thesis is part of the MIT-Portugal Program, values that have been used in related studies, such as [8], are used here. This includes driving power requirements, charging rate, and η. The charging rate is variable, meaning that its per-vehicle value can vary anywhere between zero and its upper value. EVs start the week's simulation with 4 kWh of energy already in their batteries. This is done to in order to avoid the model having to charge all of the vehicles on Saturday morning. The EVs also end the week with 4 kWh in their batteries, meaning that that all of the electric power provided for them throughout the week is utilized only for mobility, and that none is carried via battery storage into or out of the time frame of the simulation. This is done in order to allow for a direct comparison between electric power mobility emissions and ICE mobility emissions.

Parameter	Value
η EV charging efficiency	0.9
Battery Size	9 kWh (≈56 km)
Charging Rate	Maximum of 3 kW
Driving Energy Requirement	0.16 kWh/km
res_p	1%

Table 3.5: Numerical Values for Vehicle System Costs. All values except for battery size and res_p are taken from [8].

$\psi_{EV,p}$ is the driving energy requirement × the daily drive schedule, given in kilometers traveled in each period p. Studies such as [47] and [39] leverage empirical driving cycle data derived from dynamometer driving schedules, which provide average information on the distance, speed, and time of when vehicles travel. Unfortunately, the Azores does not have drive schedule data at such a high level of detail. Figure 3-6, which shows that many vehicles arrive home in the early evening, clearly represents a weekday schedule; it is unclear when people arrive home on the weekends, since no data on this is available.

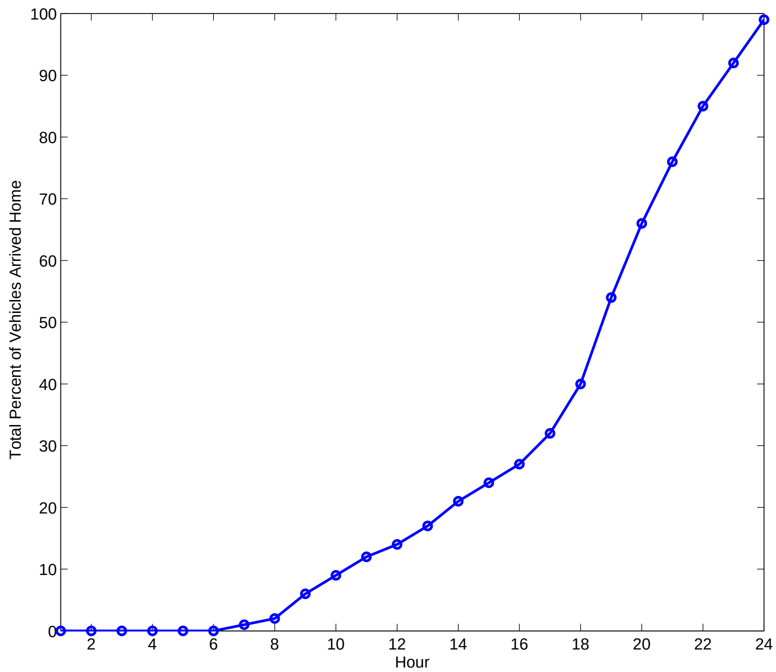


Figure 3-6: Cumulative time of arrival at home for LDVs in the Azores. Data taken from [18].

More detailed driving data exists for mainland Portugal, but it is not likely that this data would be relevant for Azorean drivers. Because of the small size of the islands, commuting patterns are very likely different from what would be seen in a city in Portugal. For this reason, a drive schedule had to be created. It can be seen in Table 3.6. It reflects the return home time seen in Figure 3-6 and provides a daily average travel distance of 26 km, which is the mean daily distance traveled by gasoline powered LDVs in the Azores.

Day	Time	Distance Traveled (km)	Reason
Saturday	Noon – 3PM	18	Scenic Drive
Sunday	6 – 7 PM	5	Visiting friend
Monday – Friday	8 AM	9.7	Commute
Monday – Friday	2 PM	12	Errands
Monday – Friday	5 PM	9.7	Commute

Table 3.6: Vehicle Drive Schedule

While this approach is not ideal, it still captures the expected net average energy use that would be required by EVs on São Miguel. Furthermore, in the context of vehicle charging, an important factor is period of time when the EV is available to charge. As previously discussed, many papers indicate that charging should be done at night, when demand is low. Reference cases using on-peak charging are also frequently implemented, which this travel schedule also permits. The travel schedule presented in Table 3.6 would such charging schedules to be implemented, in addition to other types of charging presented in Table 1.1.

The model is able to handle any number of vehicles, each with different driving patterns. However, in order to reduce the complexity of the model, the number of discrete vehicles included has been reduced to 50. The electric power demand of these 50 vehicles vehicles is multiplied by a scaling factor, so that each represents an aggregated number of vehicles. By permitting the model to change individual vehicle charging start/stop times and rates, a more optimal (and possibly realistic) solution is produced than by models which combine all vehicles into a single representational vehicle, such as [14]. This measure also reduces the model's run time. The number 50 was selected as it produced a good trade-off between time required to run the model and the optimality of the solution that it produced, as measured by reductions in the objective function (cost).

3.3 Model Validation

In order to demonstrate that the results produced by the GAMS model are reasonable and capture the general characteristics of EDA's dispatch (both system costs and timing/duration of generator dispatches), two sample outputs are shown. Each compares the GAMS model dispatch to real EDA dispatch data from 2009. Each sample output represents a different week: One is a week with an average demand for power, and the other is a week with higher than average demand for power. Dispatches are shown as stacked area plots; each color corresponds to a separate generator on São Miguel, as described in Table 2.3. All of the hydro plants are combined into a single plant, named ‘HYDROROR’ (hydro run-of-river). Pico Vermelho and Ribeira Grande are shortened to ‘PVERMELHO’ and ‘RGRANDE,’ respectively. As there are four of each of the 18V46 and 8M601 generators, a subscript is used to distinguish between them.

The x-axis is time, given in hours, *starting at 5 AM on Saturday.* This starting time is used because it is when the demand for power is at its lowest. By starting with the lowest demand for power, the GAMS model is initially provided with a steadily increasing demand for power, which produces a smooth dispatch. Starting at midnight, when the demand for power falls off, and then rises again starting at around 7 AM, would result in the model turning generators on and then back off in an unnecessary fashion that is just a symptom of the boundaries of the data.

The y-axis is total power dispatched, in MW. A legend at the bottom of each figure maps colors to specific generators. In general, the ‘coolest’ colors (blues) correspond to renewable generators, while ‘hotter’ colors (yellows, oranges, and reds) correspond to thermal generators. The dispatch in the top half of the figure is recreated from data provided by EDA in half-hourly increments. Because the GAMS model runs in hourly increments, the EDA data was averaged hourly, to allow for a more direct comparison. The bottom dispatch is what was produced by running the GAMS model using the same demand for electric power that EDA had to meet. No EVs are included in this dispatch.

In Figure 3-7, which represents a week with average demand for power, the GAMS and EDA baseloaded renewable dispatches match closely. This is largely because the hydropower and geothermal plants are typically fully dispatched, due to their low cost. Since these costs are directly copied into GAMS, the model similarly also fully dispatches these units. One noticeable difference between the EDA and GAMS dispatches is that the EDA dispatch for these units has a small amount of variation in it, which is not captured in the GAMS dispatch. This variation is likely due to small perturbations in the stream supplying the hydropower plant or the steam supplying the geothermal plants.

In the GAMS dispatch, at approximately hours 72, 96, 120, and 144, there are

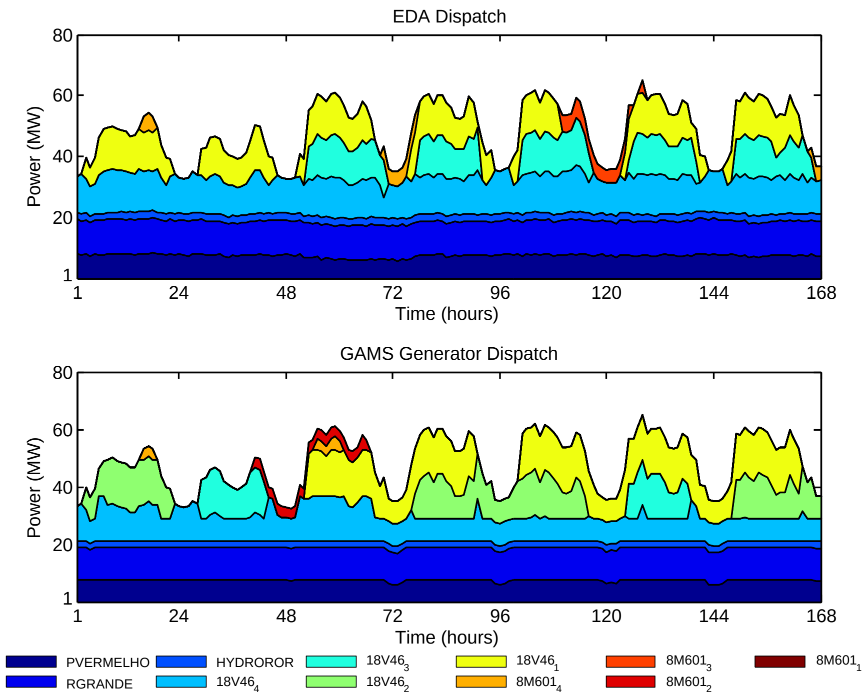


Figure 3-7: Comparison of EDA and GAMS Dispatches, for an average level of demand. 5 AM Saturday April 11th – 4 AM Friday April 18th (Hours 2405 – 2572). Weekly system cost: 801.8 kEuros.

small temporary decreases in power output by the renewable units. This is due to the decrease in overall demand for power. Because thermal unit $18V46_2$ is already on, has a startup and shutdown cost and cannot produce less than its minimum power output, the least expensive way to meet demand is by decreasing power output from the hydro and geothermal generators.

Producing simulated thermal generator behavior that exactly matches EDA's dispatch is somewhat more challenging. EDA typically leaves $18V46_4$ on full-time, both to serve load and perform frequency regulation. Generators $18V46_1$ and $18V46_3$ run on a daily cycle, helping to meet demand for all but a few hours each day. The GAMS dispatch also leaves $18V46_4$ on full-time, but uses $18V46_2$ to meet load on Saturday and $18V46_3$ to meet load on Sunday, in a fashion similar to what the EDA dispatch does using only $18V46_1$. In both cases, $8M601_4$ is used on Saturday at peak time to help meet demand. On Sunday night, the GAMS dispatch uses $8M601_2$ and $8M601_4$ to meet load overnight, and then peak load on Monday. The EDA dispatch meets this load by using $18V46_3$ on Monday.

Monday – Friday, EDA uses $18V46_1$ and $18V46_3$ in a daily cycle to meet demand. The GAMS dispatch uses $18V46_1$, $18V46_2$, and, on Thursday, $18V46_3$ to meet load. The former two generators are left on for two days at a time. This is because there is a cost associated with turning the generators on and off; thus, GAMS prefers to meet load by using generators that are already running. It would be possible to decrease the shutdown cost to encourage the shutdown of generators overnight. Similarly, it would also be possible to place a constraint on $y_{18V46_1,p}$ to force it to turn off at a specified time p, or to state that it must turn off once per day, at the time that the model determines to be the least expensive.

However, the purpose of this model is not to exactly reproduce EDA's dispatch. Instead, the goal is to produce a reasonable dispatch, in support of determining the impact of EVs. From midday on Wednesday to the morning of Thursday, EDA dispatches generator $8M601_3$. Why this generator is used instead of $18V46_1$ is unclear; it may be the case that $18V46_1$ had to be taken offline unexpectedly. The same could be said for $18V46_1$ and $8M601_4$ on Monday night. Again, the model could be modified to reproduce this behavior – but the model's purpose is not to reproduce EDA's dispatch, but instead to produce a reasonable dispatch that contains some of the major characteristics of EDA's dispatch.

Figure 3-8 compares a GAMS and EDA dispatch for a week with higher than normal demand for electric power.

As in Figure 3-7, the power output of the renewable plants slightly declines during hours of low demand when an already-active thermal plant is at its minimum capacity, for the previously explained reasons. On Saturday both the GAMS and EDA dispatches make use of two 8M601 plants to meet peak load. The GAMS dispatch keeps these generators on overnight on Sunday, because it will use them on to meet peak on Sunday and Monday, and does not want to incur a startup and shutdown cost.

And again, as in Figure 3-7, $18V46_4$ is active throughout the week. To help meet the high level of demand, $18V46_3$ is also left running throughout the week. The EDA

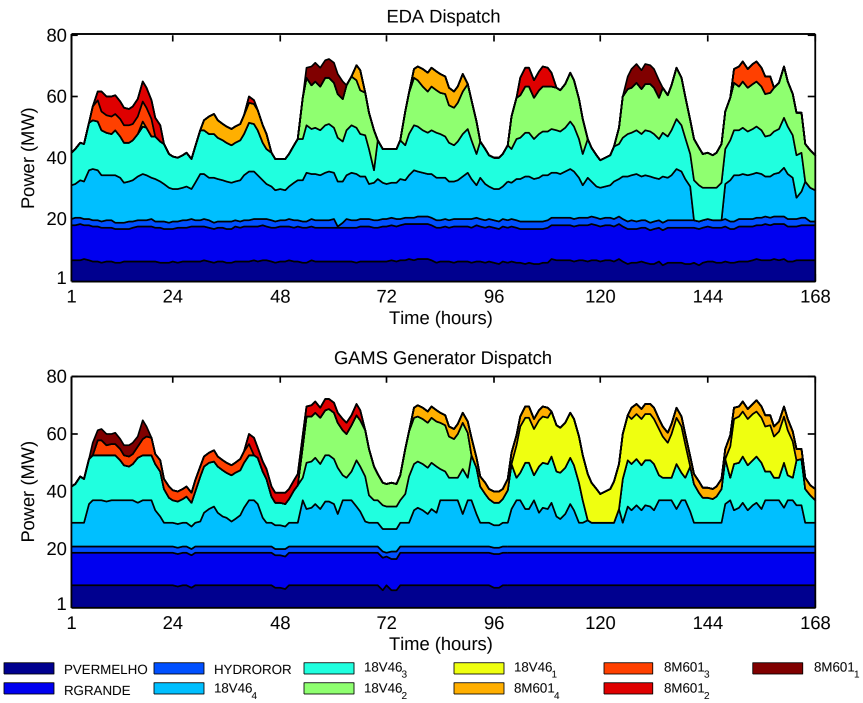


Figure 3-8: Comparison of EDA and GAMS Dispatches, for a high level of demand. 5 AM Saturday September 5th – 4 AM Friday September 12th (Hours 5933 – 6100). Weekly system cost: 946.1 kEuros.

dispatch shuts this generator down over Thursday night; the GAMS dispatch turns $18V46_4$ off over Wednesday night. It is difficult to determine why EDA turns $18V46_4$ off over Thursday night, a night that has a level of demand equivalent to Wednesday night, when $18V46_4$ was left running. It may be the case that the generator was unexpectedly forced offline, or that EDA was predicting that the demand would stay lower on Friday during the day. The GAMS dispatch turns $18V46_4$ off over Wednesday night because there is a large period of time when demand can be met using just $18V46_1$. Thus, despite the similar visual appearance, it seems unlikely that the overnight shutdown of these generators by EDA and by GAMS are related.

During the day, both EDA and GAMS dispatch an 8M601 generator to meet peak demand. GAMS leaves these generators on for 24+ hours at a time, in order to avoid startup and shutdown costs, and because it knows that it will need to meet peak demand again the next day.

The weekly system costs for the average demand week and high demand week are

801.8 kEuros and 946.1 kEuros, respectively. EDA's average annual weekly system cost for São Miguel in 2009 was 918.05 kEuros. Unfortunately, data on weekly EDA system costs are unavailable, so no direct comparison can be made. That the GAMS dispatch has an average lower weekly cost than the EDA dispatch is no surprise. The GAMS dispatch knows exactly what load it will have to meet at what time, faces no uncertainty, and never suffers from unexpected generator outages. Therefore, its dispatch is much more efficient (and less costly) than the EDA dispatch.

In conclusion, the differences between the GAMS and EDA dispatches raise a few important points:

- Looking at an EDA dispatch ex-post provides the viewer with only a general idea of how EDA operates its plants. It is impossible to look only at a dispatch and discern with total certainty why a plant was taken offline. Perhaps it was for scheduled maintenance, or perhaps the plant had to be suddenly shutdown. This is one reason why EDA and GAMS dispatches may not directly resemble one another.

- EDA's dispatch is affected by uncertainty; perhaps demand was higher than expected (as at the peak at around hour 130 in Figure 3-7) or suddenly dropped. Meeting unexpected demand may result in a seemingly wasteful dispatch, with multiple lower efficiency plants being turned on when, as seen ex-post, a single larger plant should have been dispatched.

  Unlike EDA, the GAMS model never faces any uncertainty. It knows the exact level of demand it will have to meet for each hour of the simulation. For that reason, comparing the EDA and GAMS dispatches to one another is an unfair and not particularly useful comparison. The GAMS model can be relied upon to provide a "reasonable" dispatch, with general characteristics similar to those of EDA, but it will never produce a dispatch that is exactly the same as EDA's. Weekly system costs produced by the GAMS model should be viewed in a similar light.

- In order to approximate the general trends of the EDA dispatch as closely as possible, it is important to tune the GAMS model. This means selecting an appropriate hour in which to start the simulation. It may also mean adjusting power output from the Pico Vermelho plant, which Figure 3-5 shows to vary widely throughout the year.

- The goal of the GAMS model is not to produce an exact replica of the EDA dispatch. Instead, the model's goal is to produce a "reasonable" dispatch with the same general characteristics and approximate costs as EDA's dispatch, in support of assessing the impact of adding additional demand for electric power due to EVs. Of course, it would be possible to force the GAMS dispatch to closely resemble EDA's. However, doing so would require the imposition of many additional constraints or changes in system costs. These would greatly complicate the model, but would not necessarily produce more informative or accurate results after EVs had been added to the system. In fact, these additional costs and constraints might make assessing the impact of EVs even more difficult.

Chapter 4

Presentation and Discussion of Modeling Results

The previously described GAMS model is used to find the system costs and CO_2 emissions for several scenarios. There are three power sector configurations, which are described in Table 4.1. Each power sector configuration describes the generation assets on São Miguel for that scenario. The exact configuration of each power sector is described in detail in each of their respective sections. These power sector configurations are based on EDA plans to expand their generation capacity with renewables. Because they take place in the future, when demand for electric power will have also grown, a projected weekly power demand in GWh is also provided.

There are also three charging schemes and three rates of EV market penetration into the São Miguel gasoline LDV fleet, described in Tables 4.2 and 4.3, respectively. The EV market penetration rates are not the result of a market study based on demand for EVs. Instead, they are meant to illustrate the impact of EVs on the electric power sector as the number of EVs on São Miguel increases. Similarly, the charging schemes presented here are not based on proposed charging standards in Portugal, but on some of the general schemes outlined in Table 1.1.

Optimal charging is meant to viewed as a "best case" (lowest-cost) scenario: It allows charging at any time during the day, and charges using a smart-charging scheme. In all schemes, EVs are not allowed to charge while traveling. Travel times are listed

Power Sector Configuration	Weekly Demand for Power (MWh)	New Generation Additions
Current	8.1	None
Short-term Future	9.68	+9 MW Wind
Long-Term Future	10.38	+10 MW Geothermal expansion

Table 4.1: Power Sector Configurations Used in the Model

Charging Scheme	Hours Active
On-peak	7 - 11 PM
Off-peak	11 PM - 6 AM
Optimal	Anytime except when traveling

Table 4.2: Charging Schemes Used in the Model

in Table 3.6.

EV penetration refers to the number of EVs used in the model. The low, medium, and high cases are 5%, 50%, and 100% of the 19,000 gasoline LDVs on São Miguel, respectively.

Each scenario category (Charging Scheme, EV Penetration, Power Sector) refers to a different model configuration that is simulated using GAMS. For instance, there is a scenario with on-peak charging, low EV penetration, using the current power sector. There is another scenario with on-peak charging, low EV penetration, using the short-term future power sector, and so on. There are a total of $3 \times 3 \times 3 = 27$ scenarios. Each scenario results in a dispatch, similar to the figures shown in Section 3.3. However, for the purpose of brevity, only the dispatches that illustrate important points are shown here; the rest appear in the appendix.

EV Market Penetration of Gasoline LDV Fleet	Equivalent Number of Electric Vehicles
Low - 5%	950
Medium - 50%	9,500
High - 100%	19,000

Table 4.3: EV Market Penetration Rates Used in the Model

The demand for EVs is added on top of the normal demand for electric power. The day used is the same one as in Figure 3-7, which represents an average level of demand for the power system. Its weekly cost was 801.86 kEuros, and emitted 3507.5 metric tonnes of CO_2. As in previous sector, the only GHG emissions are from the CO_2 associated with the thermal generation units. This is the baseline emissions level and system cost. In all cases, CO_2 emissions from the power sector are calculated using data from Table 2.5.

On São Miguel, the demand for electric power has been increasingly steadily year-over-year. A very simple method is used to project future demand: A linear fit is applied to monthly total demand for electric power from January 2001 to December 2008. This linear fit is then used to project several years into the future for the near and long-term future scenarios. Hourly values are simply multiplied by the percent increase that is found by using the linear fit.

There are two problems with using this form of projection. First, it assumes a stationary process; i.e., nothing fundamentally changes São Miguel's change in demand for electric power and at what times during the day it consumes that power. But there are many things that might bring about these kinds of change, such as the rise of a new industry (potentially electricity-intensive) on the island, a population boom, and so on. Second, using a linear fit does not account for elasticities of demand. It is possible that, as demand grows, some of it will shift to night time[1], meaning that simply multiplying all hours of consumption by the same scaling factor is certainly incorrect. Although this form of projection is almost certainly inaccurate, it nonetheless provides a rough sense of expected increase in demand for electric power, and does so in a transparent and easy to understand fashion. The R^2 value for this linear fit is 0.96.

Fuel oil prices are kept the same across all three power sector configurations. It is quite possible that fuel prices might rise or fall during the near and long-term scenarios. Incorporating changes of fuel oil price into the GAMS model is quite

[1]Shifting demand would require some kind of price signal from EDA or governmental regulation of a particular process. This itself would fundamentally change consumption patterns.

straight forward, but forecasting these changes is quite difficult. Furthermore, there are already quite two influential variables that change from scenario to scenario: power sector configuration and exogenous demand for electric power. Changing a third variable across all scenarios might further obscure the economic and environmental impact of EVs on electric power generation.

EV emissions change most drastically when the composition of the power sector changes, i.e. more renewable generation capacity is added. ICE emissions and costs, however, stay the same regardless of the power sector, and are shown in Table 4.4.

EV Market Penetration	Equivalent Number of Vehicles	Equivalent Taipipe ICE CO_2 Emissions (metric tonnes)	Fuel Costs (kEuros)
5%	950	41.47	24.59
50%	9500	414.71	245.93
100%	19000	829.42	491.86

Table 4.4: Internal Combustion Engine Vehicle Emissions for LDVs per Week

4.1 Current Power Sector Scenario

One fear of system operators is the impact of on-peak charging on their systems. On-peak charging, which occurs when drivers returning home from work immediately plug-in their EVs to recharge, is regarded to be the worst possible form of EV charging. It adds more demand for electric power when demand is already at its peak. But São Miguel's dispatch is hardly affected by a low number of EV charging on peak, as shown in Figure 4-1. The top graph shows exogenous system load in blue and new demand, due solely to EV charging, in red. The bottom graph shows the GAMS generator dispatch.

Note that the GAMS dispatch is virtually the same as in Figure 3-7. There is enough reserve generation capacity already in operation to simply meet the new demand from EVs on-peak, without needing to turn on any additional generators.

It is true that on-peak charging could present an issue if it were used with 100% EV penetration. However, given that the average age of a vehicle on São Miguel is

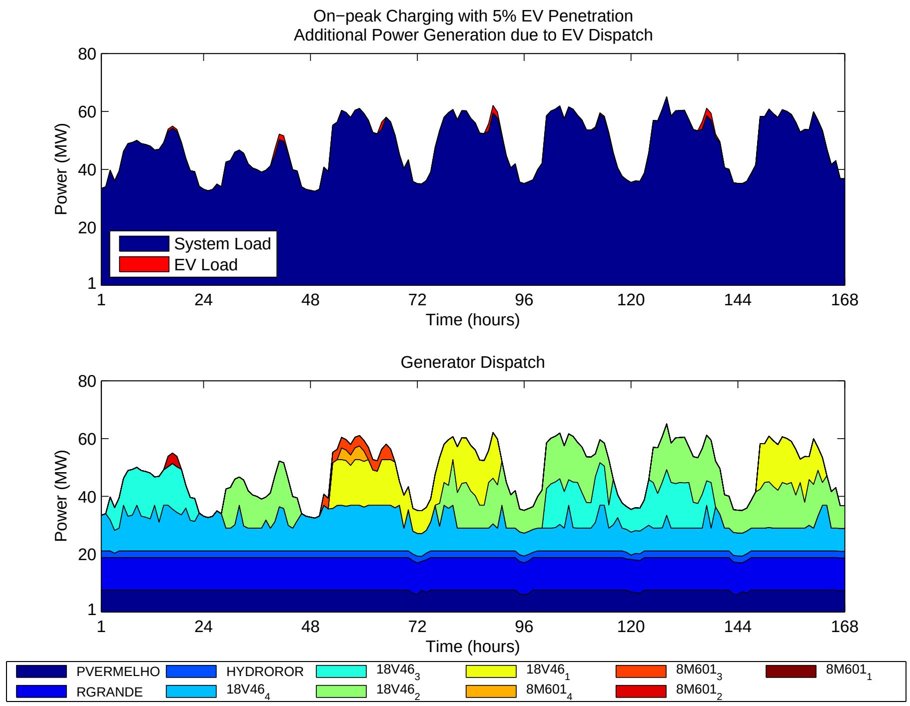


Figure 4-1: Dispatch for Current Power Sector, 5% EV Market Penetration, On-peak Charging. System costs were 804.391 kEuros, emissions were 3521.6 metric tonnes.

approximately ten years, it seems very unlikely that market forces would result in an entirely new electric fleet being adopted within the current year.

It seems plausible that, as EV penetration increases, off-peak charging would become the norm. Moving to this form of charging would be rather simple; it would only require that a timer be installed in the EV to delay the start of charging until a specified time. The Nissan LEAF already has this capability, as does the Chevrolet Volt. 50% market penetration off-peak EV charging is shown in Figure 4-2. By the time EV market penetration on São Miguel reached 50%, it seems likely that all EVs would have a similar feature.

There is a spike in demand for power when all the cars initially begin charging, but which decreases over time as their batteries begin to fill up. This effect is approximated using the constraint shown in Equation 3.8. Because the charge rate is a continuous variable between zero and 3 kW, the model is given a wide range of rates at which to charge. This would not be the case in practice, where vehicles would likely charge at a fixed rate until the battery reaches a 90% charge level, at which point

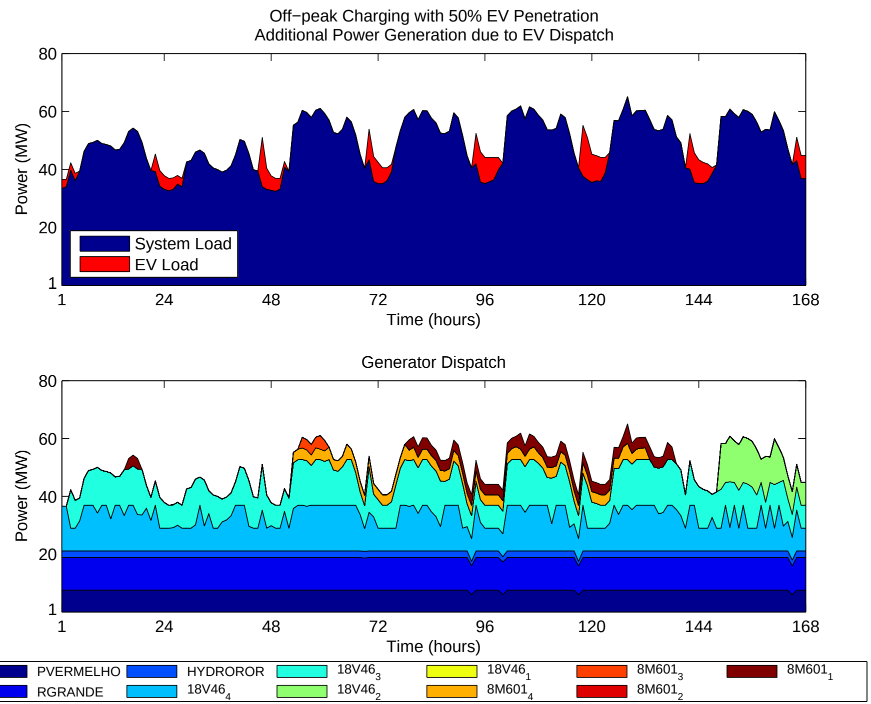


Figure 4-2: Dispatch for Current Power Sector, 50% EV Market Penetration, Off-peak Charging. System costs were 827.77 kEuros, emissions were 3699 metric tonnes.

the battery "trickle charges" at a slower rate, due to limitations related to battery chemistry.

Many studies that address EV charging, including [2, 15, 24, 28], state that EVs should ideally always charge during the night, using a "valley filling" scheme. In this approach, EVs charge at a time of relatively low demand for electric power, using spare thermal generation capacity. An illustration of this is shown in Figure 4-3.

The results produced by the GAMS model tell a different story. Figure 4-4 shows that charging takes place on-peak on Sunday and Monday – Friday. The charging on Friday is more power-intensive than other days because the simulation must end with 4 kWh of energy in each vehicle's battery. In all cases, this charging is done using spare generation capacity; no new generators are started up to support this charging. Overnight, charging is done at a level such that the 18V46 generators all operate above their $\underline{q}$. Thus, the model shows that although valley filling can be part of a charging scheme, it is sometimes appropriate to charge while on-peak, depending upon available capacity. This is because running a generator at its maximum capacity

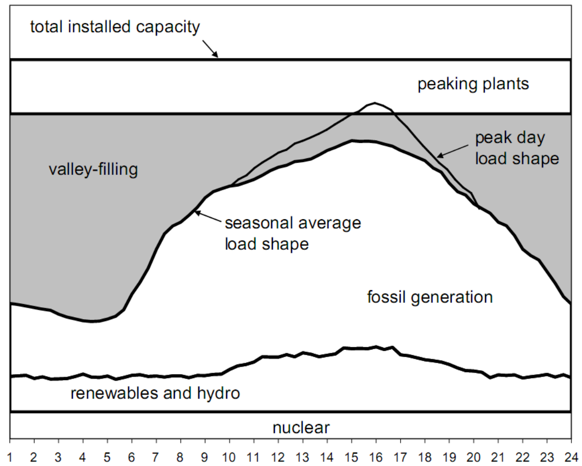


Figure 4-3: Typical Valley-Filling Charging Scheme. Illustration taken from [28].

produces the least expensive marginal kWh of power, as shown in the input-output curves in Figures 3-3 and 3-4, and because it is less expensive to charge using an already active generator than having to newly activate one.

Charging overnight allows all of the 18V46 generators to run continuously from Monday – Friday, without having to incur costs for starting up or shutting down. The less efficient 8M601 generators are used only once, at around hour 20. These four 18V46 generators are also able to handle 100% EV market penetration, and again charge the EVs on-peak, as shown in Figure 4-5. Again, overnight charging is used ensure that none of the 18V46 generators need to be shut down. During the day, EVs are clearly charged before and after their 2 PM trip (see Table 3.6).

A full accounting of weekly system costs and emissions for all simulations for the current power sector configuration can be found in the appendix, in Table A.1. These results are summarized in Figures 4-6 and 4-7, which show the percent change in costs and emissions with respect to the baseline scenario, respectively, for all three charging schemes.

Figure 4-6 shows that at 5% EV market penetration, there is little difference between the charging schemes in terms of system costs. The optimal charging scheme is actually able to reduce system costs by 0.84 kEuros, due to decreases in generator cycling and the operation of the generators at more efficient load levels. At 50% and 100% market penetration, off-peak and optimal charging have similar costs, but on-

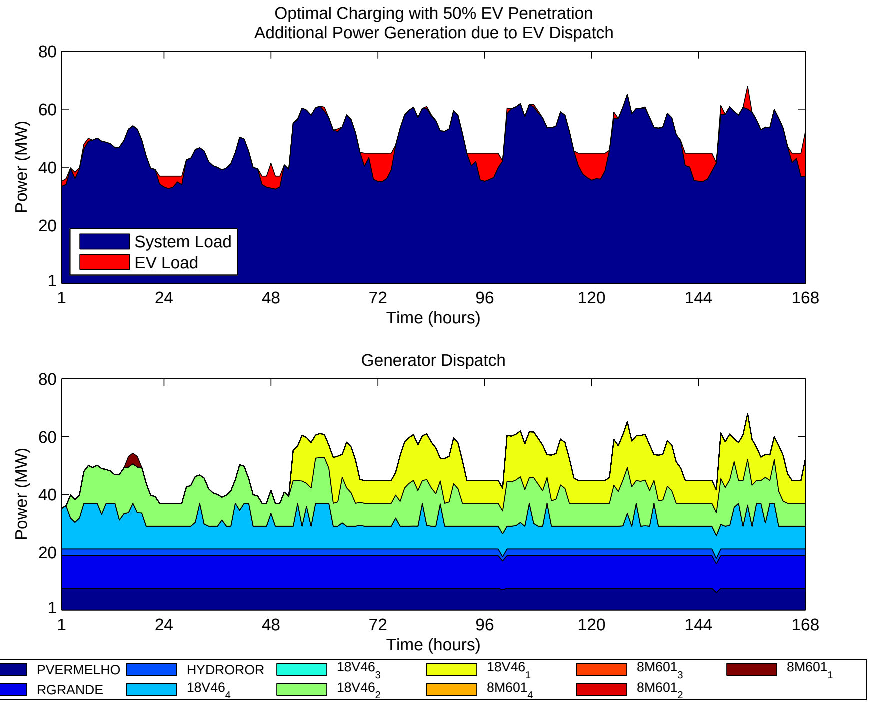


Figure 4-4: Dispatch for Current Power Sector, 50% EV Market Penetration, Optimal Charging. System costs were 824.27 kEuros, emissions were 3681.1 metric tonnes.

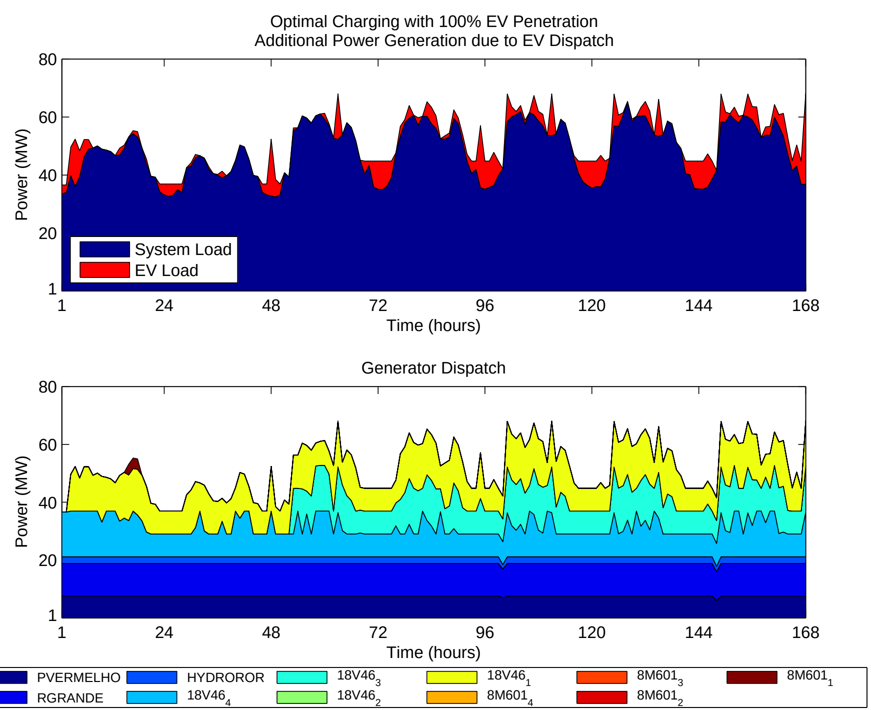


Figure 4-5: Dispatch for Current Power Sector, 100% EV Market Penetration, Optimal Charging. System costs were 854.737 kEuros, emissions were 3871.1 metric tonnes.

peak charging becomes increasingly more expensive. This is due to having to provide power using the less efficient 8M601 generators for a short period of time.

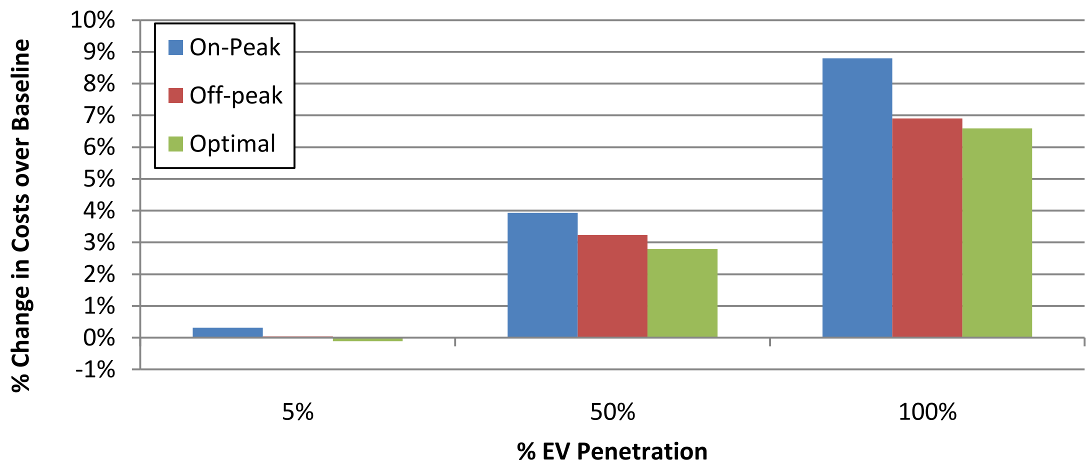


Figure 4-6: Percent change in costs for dispatches, with respect to the baseline dispatch.

Figure 4-7 shows how CO_2 emissions from the power sector increase as EV market penetration increases. Unsurprisingly, more EVs means greater emissions from the power sector. Despite the fact that optimal charging is intended to be optimal in terms of only cost, it also appears to have the lowest emissions profile. This is due to the optimal dispatch being able to schedule charging such that the 18V46 generators are used more frequently, due to their lower cost per MWh, as compared with the 8M601 generators. However, the 18V46 generators also have lower CO_2 emissions, per MWh, than the 8M601 generators, with the result being consistently lower CO_2 emissions.

It is important to note that the cost and emissions trends are not linear. That is to say, doubling from 5% to 10% EV market penetration will not necessarily double emissions or costs. This is due to the dynamics of the generation system. For instance, part of baseload is served by inexpensive renewable generation- moving from this region of generation into higher levels of generation means using more expensive and carbon intensive generators. Similarly, turning generators on and off also incurs a cost. For these reasons, attempting to interpolate between data points can often lead to misleading or incorrect conclusions.

How do EVs fare when compared with conventional ICE vehicles? In all cases, EVs produce less CO_2 emissions than ICE vehicles. But the savings vary according to how many vehicles there are, and how they are charged. Figure 4-8 compares the best (lowest) and worst (highest) case EV charging emissions savings over ICE vehicles, based on the data in Table A.1 and Table 4.4.

EVs produce far lower rates of emissions than ICE vehicles. The more vehicles that are electrified, the greater the savings. At low rates of EV market penetration, the best-case CO_2 savings are almost double those of the worst-case savings, but both quantities of savings are low on an absolute scale. As the market penetration of EVs increases to 50% and 100% (9,500 and 19,000 vehicles, respectively), the difference between the best and worst case savings narrows. This is due to the increased reliance on all available forms of generation to meet load, which brings with it an increase in absolute emissions.

Table 4.5 presents a summary of all the data presented in this section.

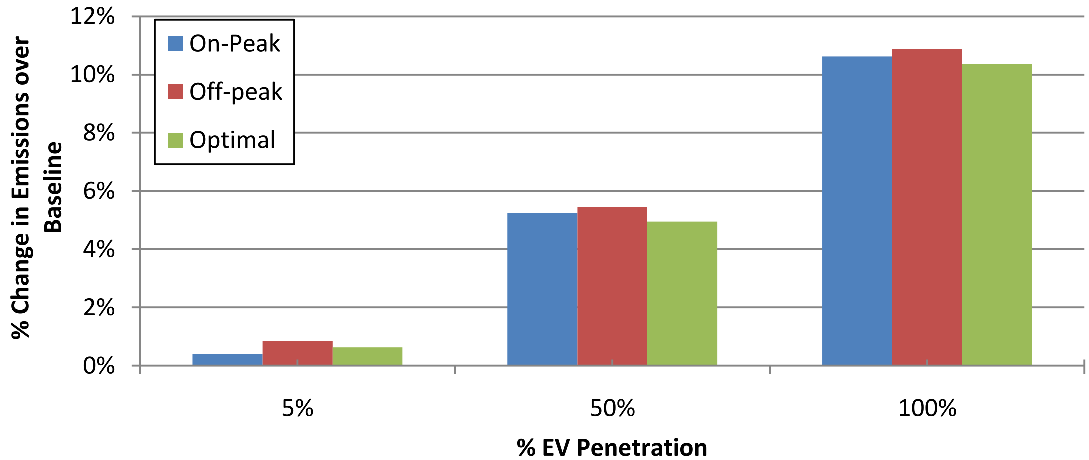


Figure 4-7: Percent change in Power CO_2 emissions for dispatches, with respect to the baseline dispatch.

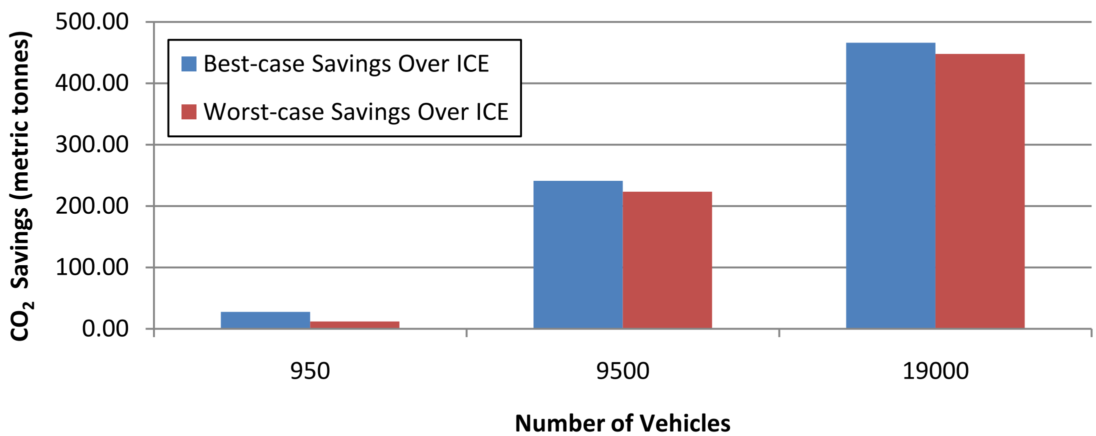


Figure 4-8: Current Power Sector, Worst and Best Case EV Charging Net CO_2Savings Compared to ICE Emissions.

		EV Electric Sector Impacts		Avoided ICE Vehicle Impacts		Savings/EV	
No. EVs	Charging Scheme	Electricity Costs	CO_2 Emissions	Gasoline Costs	CO_2 Emissions	Avoided Costs	Avoided CO_2 Emissions
950	On-Peak	2.53	14.10	24.59	41.47	23.22	28.81
950	Off-peak	0.31	29.90	24.59	41.47	25.56	12.18
950	Optimal	-0.84	22.10	24.59	41.47	26.77	20.39
9,500	On-Peak	31.51	184.10	245.93	414.71	22.57	24.27
9,500	Off-peak	25.91	191.50	245.93	414.71	23.16	23.50
9,500	Optimal	22.41	173.60	245.93	414.71	23.53	25.38
19,000	On-Peak	70.50	372.70	491.86	829.42	22.18	24.04
19,000	Off-peak	55.38	381.50	491.86	829.42	22.97	23.57
19,000	Optimal	52.88	363.60	491.86	829.42	23.10	24.52
		(+1000 Euro)	(+Metric Tonnes CO_2)	(-1000 Euro)	(-Metric Tonnes CO_2)	(Euro)	(kg CO_2)

Table 4.5: Current Power Sector Configuration Summary Table. Demand Before EVs: 8.1 GWh/week. All values are per week.

4.2 Near-term Future Power Sector

EDA is planning to install a wind farm on São Miguel, consisting of ten 900 kW Enercon E-44 turbines, within the next one to two years. The same analysis as above is repeated here, except that *wg* is now active, and uses the production data shown in Figure 4-9. Table A.2 lists all results for these scenarios.

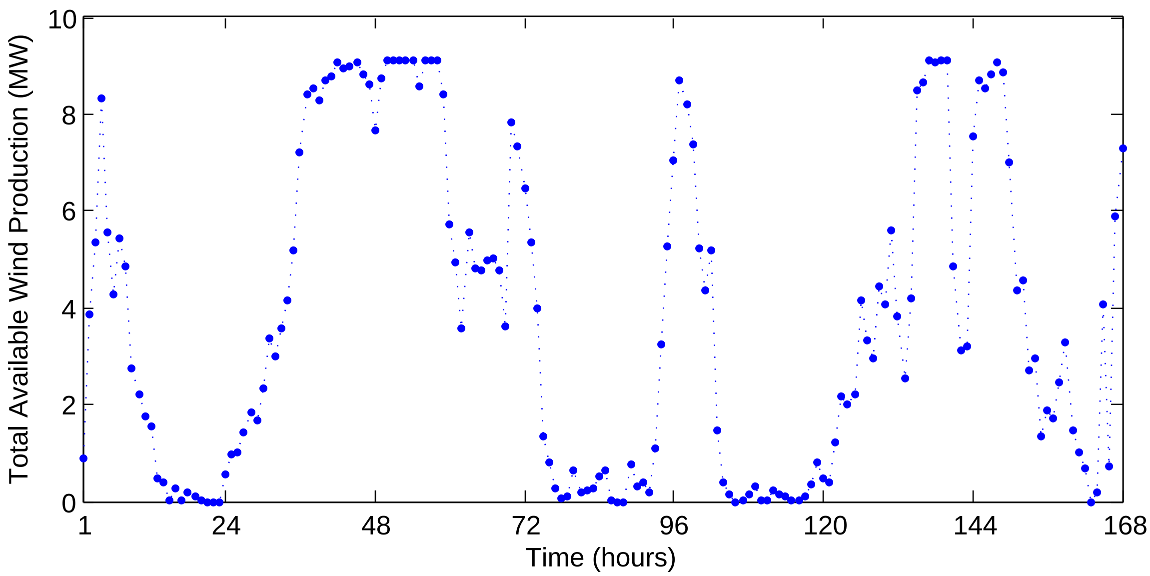


Figure 4-9: Wind Production Data for São Miguel for April, Hours 2405 – 2572. A derivation of this data is provided in the appendix.

As discussed in Section 3.2, this is an *upper bound* on the power that can be produced by wind. The model is able to use the full amount, zero, or any value in between. This same production data is used for all the simulations in this and the following sections. Of course, it is very unlikely that wind production would be the same on any two days, let alone across several years. However, the goal of this chapter is not to produce a series of very accurate dispatches according to varying wind conditions, but rather to show the cost and environmental impact of EVs on a hypothetical future São Miguel power sector that has been modified to include wind power. By using the same wind production across all the scenarios in this section, it it possible to draw some general conclusions about the effect of including wind power and EVs in the same dispatch.

The wind production data shown in Figure 4-9 has a weekly capacity factor of

42%, which is quite close to the yearly capacity factor of 44%.[2] Additionally, it has the benefit of being quite varied: Wind power is available for part of the weekend. It is also available on-peak and off-peak for different days. Thus, this sample production data forces the model to meet the demand for power under a variety of conditions. The baseline cost (without EVs) for meeting demand for this week was 955.256 kEuros, with CO_2 emissions amounting to 4193.5 metric tonnes.

The addition of wind has the potential to reduce emissions and costs, but the growth in demand – from 8.1 GWh for the simulated week in April 2010 to a projected 9.68 GWh for the simulated week in the near-term future – offsets these reductions. Overall, there is an increase in both system costs and emissions, owing primarily to this increase in demand. Some of it is met with wind power, but the bulk of this new demand is met using thermal units. However, as before, low penetration rates of EVs make very little difference on the overall dispatch, as shown in Figure 4-10.

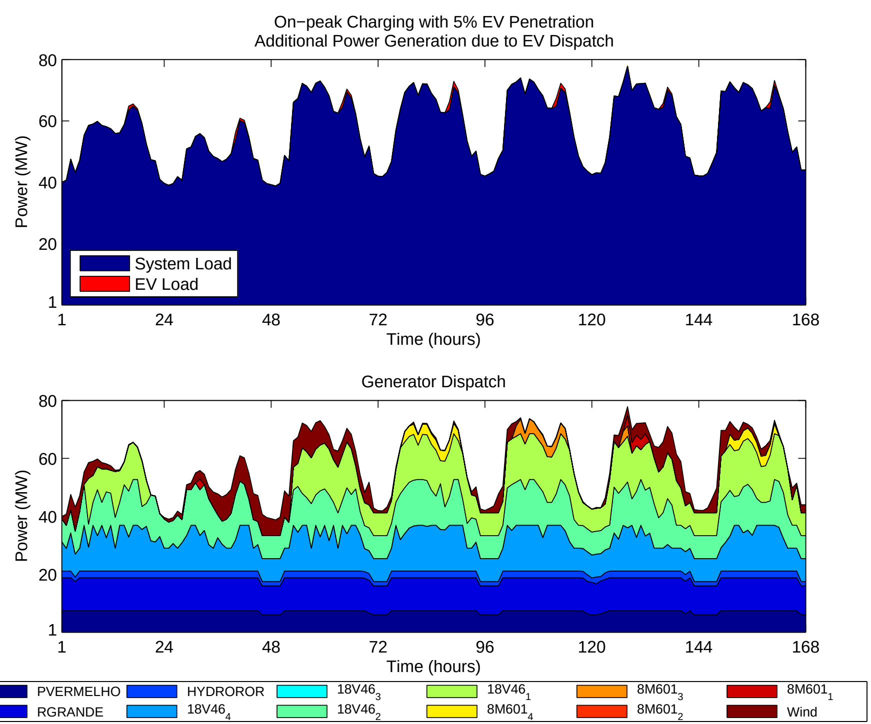


Figure 4-10: Dispatch for Short-term Future Power Sector, 5% EV Market Penetration, On-peak Charging. System costs were 958.245 kEuros, emissions were 4212.4 metric tonnes.

[2]Wind production data for hours 2405 – 2572 was not used because that week has a capacity factor of 56%, which is higher than average.

Optimal charging uses a combination of overnight wind power and thermal generators, as shown in Figure 4-11. Note that wind power provides for a substantial amount of overnight charging.

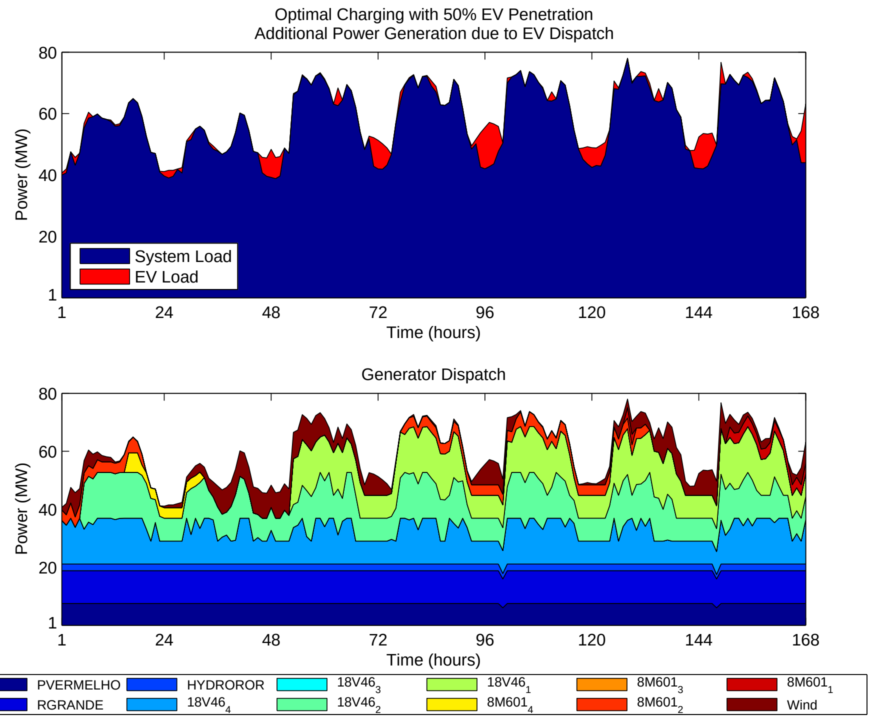


Figure 4-11: Dispatch for Short-term Future Power Sector, 50% EV Market Penetration, Off-peak Charging. System costs were 982.01 kEuros, emissions were 4279.9 metric tonnes.

This charging configuration is able to capture a fair amount of wind resources that would have otherwise not been used to serve demand. However, if the wind were to blow at another time, the effectiveness of off-peak charging in capturing available wind power might change. Wind power tends to be at its strongest during the night time, which is when off-peak charging occurs, so there may be a natural synergy between off-peak EV charging and wind power.

Overall, the optimal charging scheme makes the best use of wind power. Because charging can happen at any time, with the exception of when the EVs are moving, optimal charging is able to reduce system costs (and typically emissions as well) by shifting EV charging to times when wind power is available.

There is, however, a problem with this approach: It assumes that the there is perfect knowledge of when there is going to be wind power, and in what quantity it will be available. It also assumes that there would be a means for charging an EV at any time and in any location. In reality, it would probably not be the case that drivers can charge in any location. In practical terms, optimal charging is only as optimal as its ability to make accurate predictions about the availability of wind power during times when EVs would be able to use that power for charging.

Figures 4-12 and 4-13 show the changes in costs and emissions, respectively, over the baseline dispatch for the short-term future power sector. Note that, as compared with the current power sector, on-peak charging is more expensive and emissions-intensive (as a percentage), but only for higher levels of EV market penetration. This is due to off-peak and optimal charging taking more advantage of inexpensive wind power. In fact, there tends to be very little difference, in terms of both costs and emissions, between these two charging schemes. Optimal charging emissions and costs are always slightly lower than off-peak charging, but by only a very small amount.

As before, at 5% market penetration, there is hardly any difference between the three charging schemes. And even at 100% EV market penetration, the percent change in costs over baseline for on-peak charging are less than those for the equivalent scenario using the current power sector composition – but this is in part due to the fact that the denominator is larger in the case of near-future power sector.

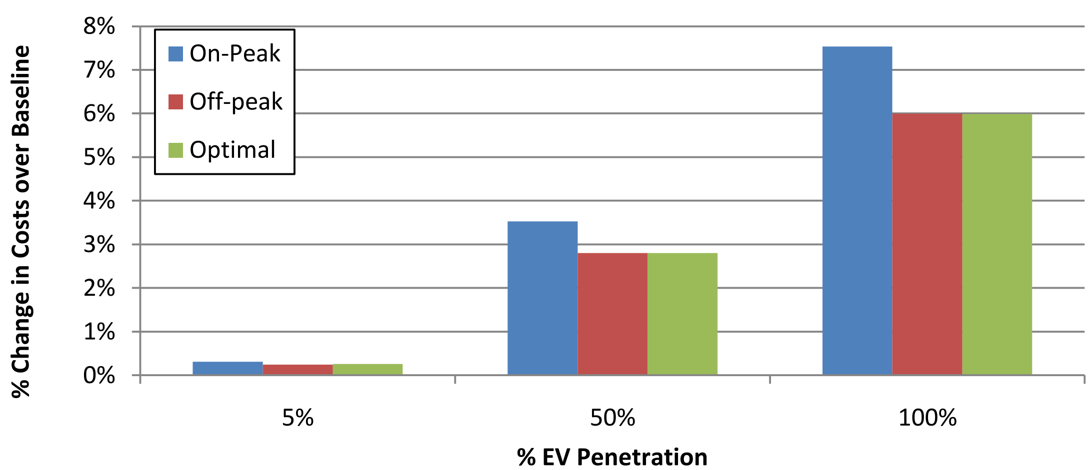


Figure 4-12: Percent change in costs for dispatches, with respect to the baseline dispatch.

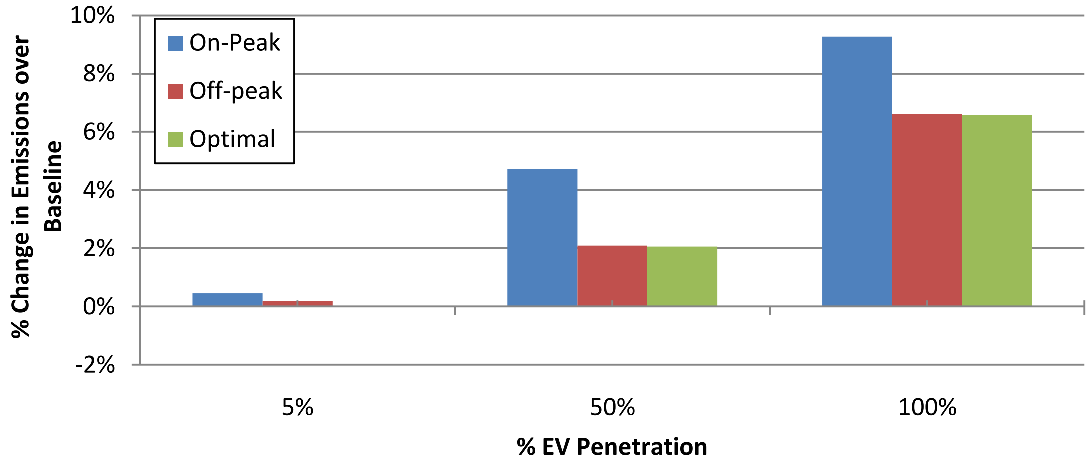


Figure 4-13: Percent change in Power CO_2 emissions, with respect to the baseline dispatch.

Figure 4-14 shows emissions savings of the best and worst-case charging scenarios over emissions that would be produced by an equivalent number of ICE vehicles. Interestingly, although overall system emissions have gone up, due to exogenously increasing levels of demand for power, the CO_2 emission reduction of EVs has increased, as compared with those shown in Figure 4-8. This is accounted for by the introduction of wind power into the system, which is able to provide entirely CO_2-free charging to vehicles. As long as the vehicles can charge using this power, they can reduce their CO_2 emissions. In the Current power sector configuration, vehicles always receive their marginal kWh from a thermal unit; here, in the Near-term future configuration, they can get it from a wind turbine. Note the disparity between the best and worst case emissions savings over ICE vehicle emissions – this difference is due to on-peak charging's inability to take advantage of wind power when it is available, which is frequently at night.

Table 4.6 presents a summary of all the data presented in this section.

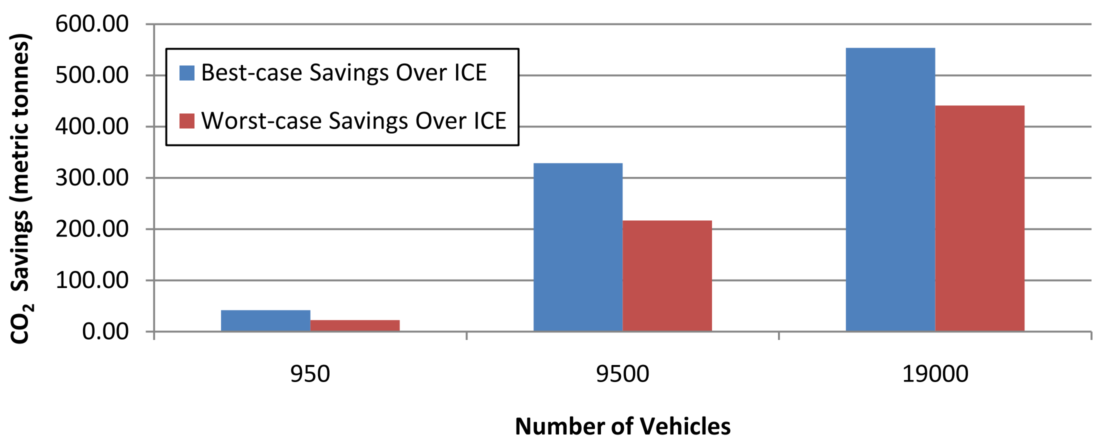


Figure 4-14: Short-term Future Power Sector, Worst and Best Case EV Charging Net CO_2Savings Compared to ICE Emissions.

		EV Electric Sector Impacts		**Avoided ICE Vehicle Impacts**		**Savings/EV**	
No. EVs	Charging Scheme	Electricity Costs	CO_2 Emissions	Gasoline Costs	CO_2 Emissions	Avoided Costs	Avoided CO_2 Emissions
950	On-Peak	2.99	18.90	24.59	41.47	22.74	23.76
950	Off-peak	2.34	8.10	24.59	41.47	23.43	35.13
950	Optimal	2.50	-0.10	24.59	41.47	23.26	43.76
9,500	On-Peak	33.70	198.40	245.93	414.71	22.34	22.77
9,500	Off-peak	26.80	87.70	245.93	414.71	23.07	34.42
9,500	Optimal	26.75	86.40	245.93	414.71	23.07	34.56
19,000	On-Peak	71.98	388.70	491.86	829.42	22.10	23.20
19,000	Off-peak	57.25	277.20	491.86	829.42	22.87	29.06
19,000	Optimal	57.21	275.70	491.86	829.42	22.88	29.14
		(+1000 Euro)	(+Metric Tonnes CO_2)	(-1000 Euro)	(-Metric Tonnes CO_2)	(Euro)	(kg CO_2)

Table 4.6: Near-Term Future Power Sector Configuration Summary Table. Adds 9MW of wind power. Demand Before EVs: 9.68 GWh/week. All values are per week.

4.3 Long-term Future Power Sector

This sector scenario is meant to represent a hypothetical power sector further in the future. According to EDA, by 2014 the Pico Vermelho geothermal plant on São Miguel will be expanded to produce an additional 10 MW. No potential production data is available for this plant expansion and, as Figure 3-5 shows, there is often variation in Pico Vermelho's output. The current output of the Pico Vermelho plant in the GAMS model is simply increased by 10 MW, and costs per MWh are kept the same. The same wind power profile used in the Near-future Power Sector section is used again here. Demand for electric power is also certain to have increased by this time, and is projected using the same method described in the Near-future Power Sector section. The baseline dispatch for this power sector composition, without any EVs, has a system cost of 997.839 kEuros and emits 3574.4 metric tonnes of CO_2. A full list of all emissions and costs associated with this power sector configuration may be found in Table A.3.

Overall, system costs are higher, due to increased demand for electric power, but emissions are lower than those in the near-future power sector scenario. The Pico Vermelho expansion is able to meet a great deal of the new demand, which has increased from a weekly demand for 8.1 GWh in 2010 to a projected demand of 10.38 GWh in the Long-term future sector. The expanded geothermal helps meet growth in baseload demand, and does so with zero CO_2 emissions. As in all previous scenarios, low EV penetration, even with on-peak charging, does not present an environmental or economic challenge for the power system, as shown in Figure 4-15.

As in the previous two power sector configurations, 100% EV market penetration with optimal charging sometimes results in charging on-peak. In general, because of the constant increase in the availability of geothermal power at all times, off-peak charging and optimal charging tend to have the same cost, as shown in Figure 4-16.

As in all previous scenarios, on-peak charging tends to be the most expensive charging scheme, particularly at 100% EV market penetration. Because of the increase in exogenous demand for electric power, charging on-peak with an entirely

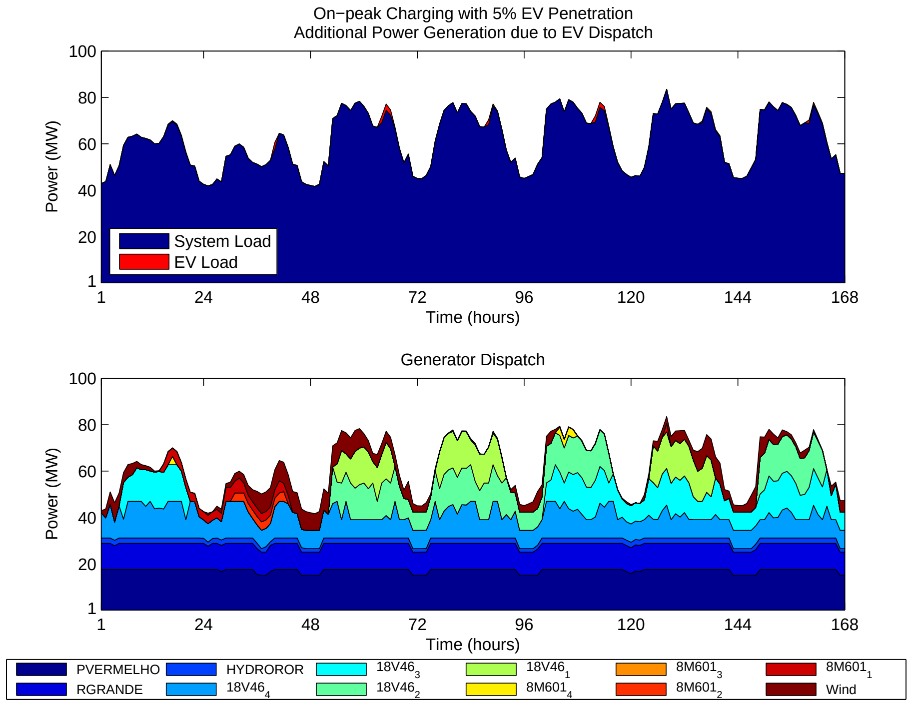


Figure 4-15: Dispatch for Long-term Future Power Sector, 5% EV Market Penetration, On-peak Charging. System costs were 1000.795 kEuros, emissions were 3593.1 metric tonnes.

electrified LDV fleet requires the full dispatch of hydropower, geothermal, and either all of the 18V46 units, or a combination of two-three 18V46 generators, plus available wind power or 8M601 units. One interesting change is that, at 50% EV market penetration, off-peak charging has higher levels of CO_2 emissions than optimal or on-peak charging, as shown in Figure 4-17. Although the difference between the two is only 0.63% over baseline, it is still surprising: In previous power sector configurations, on-peak charging consistently had the highest CO_2 emissions for all levels of EV market penetration. This anomalous result is due to the off-peak charging scheme's decreased use of geothermal and hydropower resources overnight, in order to avoid incurring the cost of shutting down and restarting one of the 18V46 generators.

Finally, Figure 4-18 shows the CO_2 emissions of EVs over an equivalent number of ICE vehicles. Note that, as in the near-term future power sector configuration, the introduction of higher levels of renewable generation reduces mobility related emissions, but that there is a significant difference between the best and worst-case

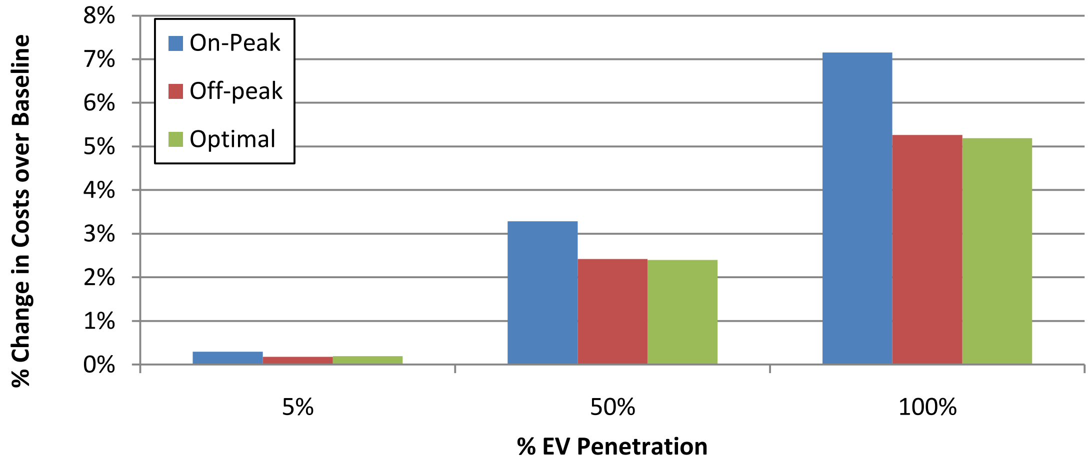


Figure 4-16: Percent change in costs for dispatches, with respect to the baseline dispatch.

scenarios. Table 4.7 presents a summary of all the data presented in this section.

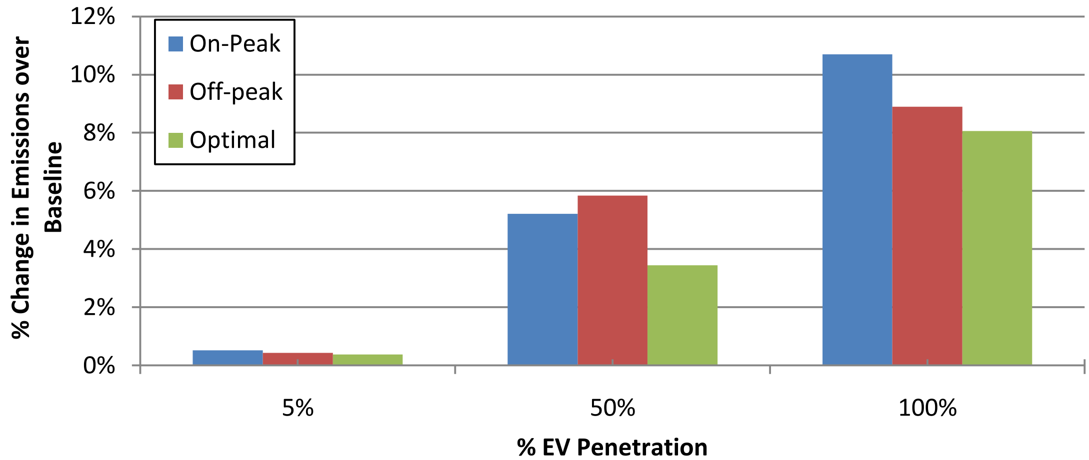


Figure 4-17: Percent change in Power CO_2 emissions for dispatches, with respect to the baseline dispatch.

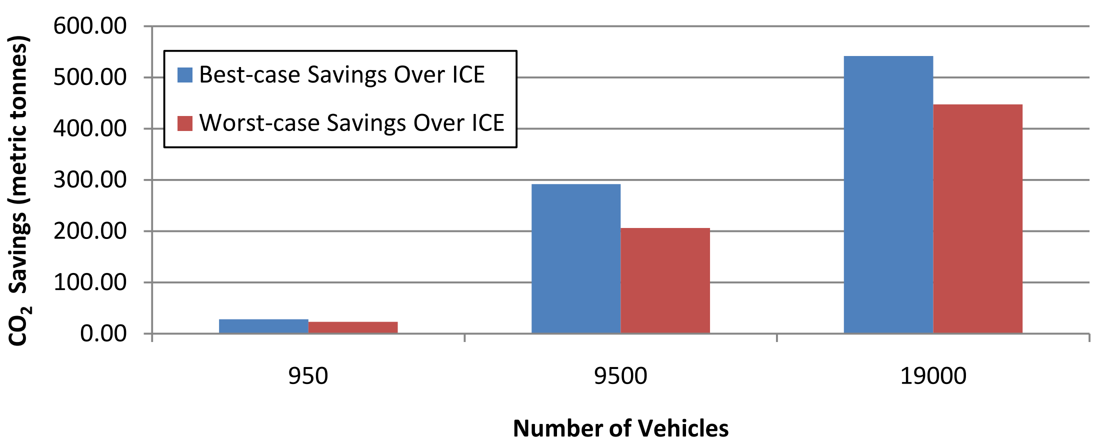


Figure 4-18: Long-term Future Power Sector, Worst and Best Case EV Charging Net CO_2Savings Compared to ICE Emissions.

		EV Electric Sector Impacts		Avoided ICE Vehicle Impacts		Savings/EV	
No. EVs	Charging Scheme	Electricity Costs	CO_2 Emissions	Gasoline Costs	CO_2 Emissions	Avoided Costs	Avoided CO_2 Emissions
950	On-Peak	2.96	18.70	24.59	41.47	22.78	23.97
950	Off-peak	1.81	15.30	24.59	41.47	23.99	27.55
950	Optimal	1.91	13.60	24.59	41.47	23.88	29.34
9,500	On-Peak	32.81	186.30	245.93	414.71	22.43	24.04
9,500	Off-peak	24.13	208.60	245.93	414.71	23.35	21.70
9,500	Optimal	23.93	123.30	245.93	414.71	23.37	30.67
19,000	On-Peak	71.40	382.50	491.86	829.42	22.13	23.52
19,000	Off-peak	52.54	318.00	491.86	829.42	23.12	26.92
19,000	Optimal	51.77	288.10	491.86	829.42	23.16	28.49
		(+1000 Euro)	(+Metric Tonnes CO_2)	(-1000 Euro)	(-Metric Tonnes CO_2)	(Euro)	(kg CO_2)

Table 4.7: Long-Term Future Power Sector Configuration Summary Table. Adds 9 MW of wind and 10 MW of additional geothermal. Demand Before EVs: 10.38 GWh/week.

4.4 Results Synthesis

Tables 4.5, 4.6, and 4.7 show that there are slight differences in cost and emissions depending upon how vehicles are charged. This is due to some forms of charging, particularly optimal, being able to take greater advantage of inexpensive renewable energy than on-peak charging, which typically charges uses additional thermal generators.

In general, EVs can save their owners about 23 Euros per week in mobility costs due to vehicle operation. In the 5% penetration case for the Current power sector configuration, the optimal charging scheme can save as much as about 27 Euros per week. This is due to the optimal charging scheme's ability to charge throughout the day. In the Short-term and Long-term future power sector configurations, the variation in cost savings from scenario to scenario is typically less than one Euro per week. This is due to higher overall levels of demand for electricity. In some cases, charging EVs get their marginal kWh from a thermal unit, meaning that there is no advantage to charging off-peak as opposed to on-peak, since their electricity source is always the same. This also plays a role in the reduction in cost savings.

Avoided CO_2 emissions vary more widely, from about 24 kg to 44 kg per vehicle, per week. This large disparity is due to the intermittency of wind, of which optimal charging is best able to take advantage from both a cost and emissions reduction perspective.

Note that neither the CO_2 emissions nor cost savings scale with the number of EVs in the system. There are no "economies of scale" of which to take advantage of; more EVs means a higher need for energy, which is simply shifted from ICE vehicle tailpipes to the electric power sector. Because São Miguel's diesel generators have a higher thermal efficiency than an ICE, CO_2 emissions and costs are reduced. The addition of renewable electric power generation somewhat enhances the reduction of CO_2 emissions in the Near-term and Long-term future power sector configurations, but the extent depends greatly upon when the EVs are able to charge.

But do these cost and CO_2 emissions reductions justify the expense, including capital costs, of EVs? The following chapter explores this question in greater detail.

Chapter 5

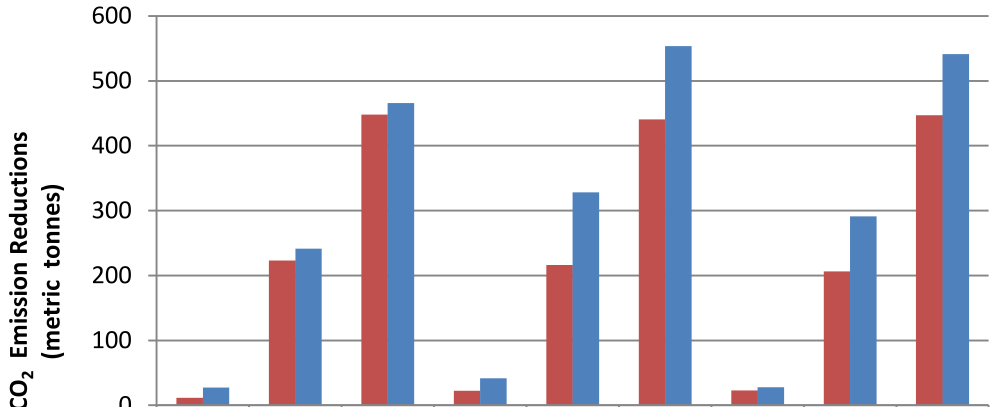
Policy Analysis and Conclusions

What are the economic and environmental impacts of EVs in São Miguel? Results from the model are synthesized to produce costs of electric vs. ICE mobility. A discounted cash flow model is created to demonstrate the capital costs required to purchase EVs and complementary infrastructure. Previous results show that, in general, optimal charging tends to provide the greatest emissions reductions for the lowest cost. But implementing optimal charging on a significant number of EVs could prove to be expensive, and that charging EVs overnight could have an impact on electric grid infrastructure.

5.1 Emissions Reductions and Mobility Costs

From the perspective of a policy maker concerned with the deployment of EVs on São Miguel, there are two useful metrics through which to view this deployment: The ability of EVs to reduce CO_2 emissions and petroleum use, and the cost/savings of doing so. Figure 5-1 shows the best and worst-case weekly avoided emissions of EVs, compared with an equivalent number of conventional ICE vehicles. Worst-case are the minimum amount of emissions that could be avoided, while best-case are the maximum amount that could be avoided, as measured in metric tonnes of CO_2. These values were tabulated and condensed from Tables A.1, A.2, and A.3.

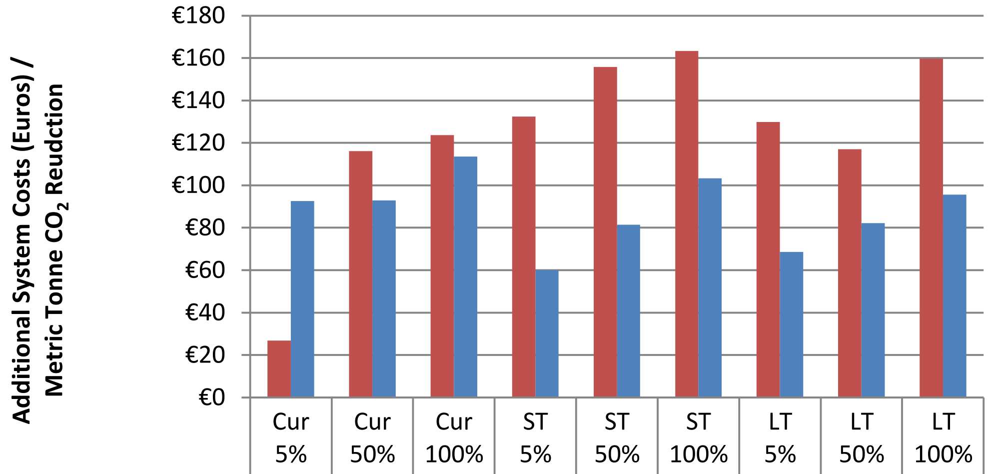
In general, best-case emissions reductions resulted from the optimal charging scheme, while worst-case were either the off-peak or on-peak charging schemes. It is worth noting that, for the Near-term future configuration, emissions and costs of the optimal and off-peak charging schemes were almost identical, with optimal being slightly lower. For the Long-term future scenario, the costs of the optimal and off-peak charging schemes almost the same, but the emissions of the optimal charging scheme were much lower than off-peak charging.



	Cur 5%	Cur 50%	Cur 100%	ST 5%	ST 50%	ST 100%	LT 5%	LT 50%	LT 100%
Worst Case Reductions	11.6	223.2	447.9	22.6	216.3	440.7	22.8	206.1	446.9
Best Case Reductions	27.4	241.1	465.8	41.6	328.3	553.7	27.9	291.4	541.3

Figure 5-1: Best and Worst Case Weekly Emissions Reductions. The three power sector scenarios, Current (Cur) Short-term Future (ST), and Long-term Future (LT) are shown.

However, avoided emissions are only one element in the decision making process. Figure 5-2 shows the abatement costs (Euros) per tonne of avoided metric tonne of CO_2, using the same best and worst-cases mentioned above. These costs are the difference between the system cost for each scenario and baseline dispatch for each power sector configuration. This provides the cost of charging EVs, which reduce CO_2 emissions by a certain amount, for each scenario. With the exception of the current power sector configuration scenario with 5% EVs, the worst-case reductions are always the most expensive, per tonne of CO_2, form of abatement. This is because the worst-case reductions tend to charge EVs using more expensive thermal power plants, for reasons explained in the previous chapter, while best-case charging uses the less expensive renewable resources.



	Cur 5%	Cur 50%	Cur 100%	ST 5%	ST 50%	ST 100%	LT 5%	LT 50%	LT 100%
Worst Case GHG Reductions	€ 26.8	€ 116.1	€ 123.6	€ 132.4	€ 155.8	€ 163.3	€ 129.8	€ 117.1	€ 159.8
Best Case GHG Reductions	€ 92.5	€ 92.9	€ 113.5	€ 60.0	€ 81.5	€ 103.3	€ 68.5	€ 82.1	€ 95.6

Figure 5-2: Cost of Abatement, per Scenario. The three power sector scenarios, Current (Cur) Short-term Future (ST), and Long-term Future (LT) are shown.

In general, the abatement costs (per tonne) increase as the number of vehicles in the system increase. With a relatively low number of EVs in the system, they can be charged using spare generation capacity, or even charged in a fashion that allows the system to run more efficiently. But in cases where there are many EVs in the system, the presence of these EVs results in significant changes to the dispatch. Depending on the charging scheme used, another 18V46 generator will have to run full-time, or a combination of18V46 and 8M601 generators will have to cycle to meet load. With this additional need for electric power comes higher system costs, as would be the case for any increase in demand.

In this model of São Miguel's power sector, if the EV gets its marginal kWh from a wind turbine, that marginal kWh still has a cost. However, in a liberalized market, this might not be the case. It is quite possible that for certain periods, typically during the night, the market price of power could be zero. EVs would be able to consume power for free, although they would still need to pay for transmission and distribution (T&D) costs. In some cases, such as when there is excess capacity, EVs could even be paid to charge, minus T&D costs. Thus, computing the cost of abatement can be difficult, and depend greatly upon the existence of a market for power and how that market is structured.

An alternate way to calculate abatement costs might be the additional cost incurred by the power sector in charging EVs, minus the cost of gasoline consumed by an equivalently sized ICE vehicle fleet. This produces negative cost abatement values ranging from 150 to 2000 Euros per metric tonne of CO_2. The negative value indicates that, from a societal perspective, it is cost saving to drive electric vehicles. This is in part due to the high price of gasoline in Portugal, which, owing to a variety of governmental taxes, costs around 1.5 Euros/liter.[1]

The gasoline ICE LDVs on São Miguel produce 0.14 kg CO_2 per km driven, and cost 0.24 Euro cents per km driven, based solely on the cost of gasoline. Based on the data presented in Tables 4.5, 4.6, and 4.7, EV travel costs per km are between one and two Euro cents, based solely on the costs of the additional electric power generated for their travel.

EV CO_2 emissions reductions per km traveled range from a minimum of 0.07 kg (off-peak charging, 5% EV penetration, Current power sector configuration) to a maximum of 0.17 kg CO_2(optimal charging, 5% EV penetration, Near-term future power sector configuration). It is important to keep in mind that "optimal" means "lowest cost", which is not necessarily the same as "lowest emissions."

5.2 Vehicle and Infrastructure Costs

But analyzing only mobility expenses (both electric and gasoline) does not provide a complete picture of all the costs associated with EVs. There are two other factors to consider: The first is the price difference between a conventional ICE vehicle and an EV, which is accounted for primarily by the added expense of the large and specialized battery in the EV. The second is the cost of installing charging stations. One way of analyzing the addition of these costs is via spreadsheet analysis, accounting for the time-value of money from a societal perspective. This is similar in nature, although not as thorough, as the analysis done in [22].

[1] Approximately $8/gallon.

A simple discounted cash flow spreadsheet model is built to quantify the costs of EV vs. conventional ICE vehicle ownership over a ten year period, for a 950 vehicle fleet on São Miguel. Clearly, it is unlikely that 950 EVs would appear overnight in São Miguel. It is similarly unlikely that the EV fleet would stay the same size for ten years. However, this model provides a starting point in thinking about the costs of vehicle electrification on São Miguel.

The cost of electricity for each year, from 2010 – 2019, is the difference between the baseline and 5% EV market penetration with on-peak charging scenario for each respective year, according to the power sector configuration listed in Table 1.1. Costs for years 2012 – 2014 come from Near-term power sector configuration, and the Long-term power sector configuration costs are used for years 2014 – 2019. Because these are weekly costs, they are multiplied by 52 in order to be used as yearly costs. As stated in Section 3.3, system costs vary through the year, but these average values provide a useful working estimate. Other parameters are listed in Table 5.1. Note that V2G is not included in this model, for the reasons described in Chapter 1.

Cost of Nissan LEAF with after rebate (Euros)	30,250
Cost of Conventional ICE Vehicle (Euros)	22,000
Vehicle Lifetime (Years)	10
Charging Stations/Vehicle	1
Cost of Charging Stations (Euros)	300
Discount Rate (Percent)	15
Gas Price (Euro/Liter)	1.53

Table 5.1: Values Used for Discounted Cash Flow Calculations

The spreadsheet model shows that, under these assumptions, EVs have a societal cost 1.59 million Euros at the end of ten years. The main reason for this cost is because of relatively high capital cost of buying EVs in the initial year, as compared with the cost of conventional ICE vehicles. Future savings associated with EVs, stemming from the low costs of electric vs. gasoline mobility, are discounted, thereby playing a lesser role. In order to break-even by the end of the tenth year, a discount rate of just 8.24% is required. This is a low discount rate from the perspective of a consumer, but not from a governmental perspective. However, the cost of the EV already has a rebate worth several thousand Euros. Decreasing the number of charging stations per vehicle has relatively little effect on costs.

If the CO_2 reductions of the EVs were considered under a carbon trading mechanism, such as the Clean Development Mechanism, it might be possible to slightly reduce the costs of EVs from a societal perspective. For instance, a cost of five euros/tonne CO_2 emissions reduces the costs to 1.55 million Euros. Higher emissions prices further decrease societal costs, but because they occur in the future, they too are discounted. The energy security benefits of using EVs is difficult to quantify, but may still be valuable from a geopolitical perspective. It should be noted that the Nissan LEAF, a BEV, has a 24 kWh battery. This large battery likely accounts for some its high price, which has been attenuated by a government rebate. Given the short distances traveled on São Miguel, this battery may appear to be over capacity. It is true that a smaller battery would likely suffice for the average LDV driver on the island, but it seems unlikely that any vehicle manufacturer would design an EV with a small battery, just for the purposes of catering to a very limited niche market. Modeling results showed that the extent to which EVs are able to rely upon renewable forms of energy depends upon how and when they are charged. Having a large battery is useful in charging, as it allows vehicles to charge a great deal when inexpensive and clean power is available. The introduction of a wind farm and increased geothermal production on São Miguel represents a chance to operate vehicles with greatly reduced emissions, as compared with an equivalent ICE vehicle fleet. From the perspective of a regional government concerned with reducing CO_2 emissions, this represents an excellent opportunity. And, in general, Figure 5-2 shows that the least-expensive abatement aligns directly with the greatest overall reduction in emissions.

5.3 The Best Case is Not the Easiest Case

But getting to the best case scenario, which is almost always provided by optimal charging, is not simple. As described in the previous chapter, optimal charging allows vehicles to charge anywhere, anytime, except when traveling. This means that charging stations would need to be installed not only in homes, but also in workplaces and perhaps in supermarkets, on the roadside, and so on. The capital and installation costs of public-use electric vehicle supply equipment (EVSE) are higher than those of EVSE intended to be used by only one private owner. For this reason, the costs described in the above spreadsheet model should be considered a lower bound.

Optimal charging, as implemented in this model, relies upon exact knowledge of when renewable electric power will be available. This knowledge, combined with the ability to charge vehicles anywhere, as well as data on exactly how far vehicles will drive, is what allows the optimal charging scheme to produce the lowest-cost (and, frequently, lowest emission) charging program. In practice, this would mean excellent forecasting capabilities. In the case of geothermal, this is not a major concern. Wind power, however, could prove to be more challenging, as its production can be difficult to predict far into the future. Another source of uncertainty is driving patterns. For all these reasons, the best-case emissions reductions shown in Figure 5-1 should be considered an upper bound, while the abatement costs shown in Figure 5-2 for the best-case scenario should be considered a lower bound.

In order to employ optimal charging, additional costs would need to be considered, including: The installation and maintenance of public EVSE, the required communications system between charging points and EDA, and any potential upgrades to grid infrastructure (such as transformers or substations) that may be necessary due to new sources of load on the T&D system. Studies, such as [12, 52], show that infrastructure impact depends upon the number of vehicles in the area, the rate at which they charge, when they charge, and the kind of load that the infrastructure in the area was initially designed to handle.

For instance, many distribution system transformers have been designed to cool overnight. But a high concentration of EVs in a single area using an off-peak charging scheme would keep the transformers loaded during the night, resulting in reduced equipment lifespan. Cost-allocation for potential upgrades would only be a significant issue in cases where there was widespread deployment of EVs, but utilities would likely want to keep track of any potential charging "hot-spots." Therefore, the sharing of information between EV owners and utilities on charging location is an important consideration in any policy that targets widespread use of EVs. And regardless of the kind of charging scheme used, permitting and installation procedures for the installation of EVSE would also have to be considered and addressed by the appropriate authorities. By standardizing this process, the time and cost involved in the installation of EVSE could likely be reduced.

Fortunately, in terms of system costs, off-peak charging is frequently almost as good as optimal charging in both the Near-term and Long-term power sector configurations. And because it would require only some form of timer in the EV, a feature which the Chevrolet Volt and Nissan LEAF already possess, it is far easier and less expensive to implement than optimal charging. Nevertheless, off-peak charging used in conjunction with a large number of EVs still faces the same infrastructure related issues that optimal charging would. Although the capital costs associated with installation of EVSE are attenuated, as compared with optimal charging, the impact on T&D is amplified, because charging always takes place overnight, when transformers are designed to cool down.

5.4 Conclusions

EVs represent an opportunity to greatly reduce transportation sector CO_2 emissions in São Miguel. Simulations from Chapter 4 show that even in the worst-case scenario, with on-peak charging, EVs stand to roughly halve emissions, as compared with an equivalent number of ICE vehicles. And as the power sector in São Miguel further incorporates renewables, emissions reductions will only increase. It is certainly possible for the power sector to support 19,000 EVs, although it seems unlikely that so many EVs would be deployed in the near future.

But calculating the exact cost for doing so is difficult. The capital costs for EVs are higher than those of conventional ICE vehicles, while costs for mobility per kilometer traveled are the opposite. In addition, EVs require infrastructure, which itself has costs. The model implemented in this thesis shows that certain ways of charging EVs produce lower per kilometer emissions and costs than other ways, but these charging schemes will incur higher infrastructure costs. Additionally, they will also require more information about renewable generation, particularly with regard to wind power, and to travel patterns on São Miguel. Acquiring this data will also have costs. Further studies should be done to assess these costs, as well in gauging the impact of EV charging on T&D on São Miguel. The model also shows that, in cases where there are many EVs in the system, some charging of EVs during the day time may be preferable to charging during the night, when additional generators would have to be dispatched to meet the load from charging EVs. This is contrary to conventional wisdom about charging EVs, which states that always should be charged at night, and is a result of the small size of the power system on São Miguel.

Market distortions further complicate quantifying the costs of EVs. The Portuguese government currently subsidizes the purchase of EVs, while it taxes the cost of gasoline. The internal rate of return for a 950 EV deployment on São Miguel would likely be too low to attract the average consumer, but might be high enough to attract a regional government that is interested in reducing emissions. And because the regional government in the Azores is going ahead with a 10 MW wind farm, there may already be excess wind power during some nights of the week, which EVs could use to charge.

Charging EVs in a "smart" way means using some form of timed charging, in which EVs charge off-peak. Ideally, EVs would charge according to price or environmental signals sent out by EDA, but doing so would require further investment in the grid. Results from modeling, shown in Chapter 4, illustrate that, in general, off-peak is almost as good as the "optimal" charging scheme from a cost perspective. But overnight charging may still have a significant impact on electric grid infrastructure, if many EVs charge on the same transformer. For this reason, EDA should be kept aware of any charging "hot-spots."

Should the regional government choose to encourage the deployment of EVs in the Azores, it should take these factors into account. With a full understanding of the benefits and drawbacks of vehicle electrification, including cost and grid impact, EVs on São Miguel could greatly reduce transportation sector related emissions.

Appendix A

Dispatch Figures

This appendix section displays all the dispatches for all the scenarios presented in Chapter 4. For commentary on this data, please see Chapter 4.

A.1 Current Power Sector

Charging Scheme	EV Penetration	System Cost (kEuros)	Generator Emissions (metric tonnes)
Baseline	0%	801.86	3507.50
Peak	5%	804.391	3521.60
Peak	50%	833.368	3691.60
Peak	100%	872.355	3880.20
Off-peak	5%	802.169	3537.40
Off-peak	50%	827.770	3699.00
Off-peak	100%	857.241	3889.00
Optimal	5%	801.021	3529.60
Optimal	50%	824.270	3681.10
Optimal	100%	854.737	3871.10

Table A.1: Current Power Sector Weekly System Costs and Emissions

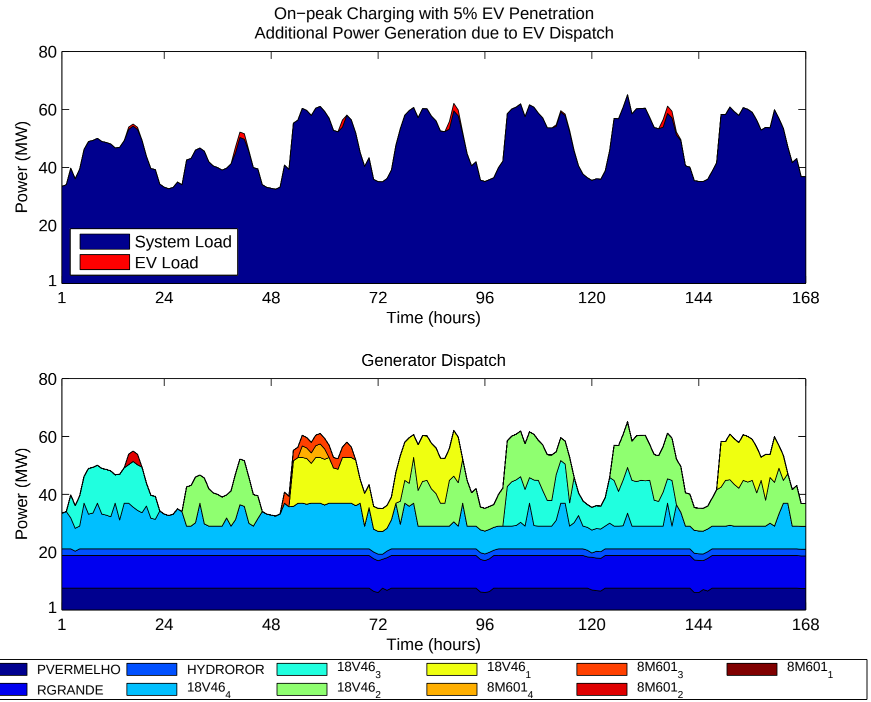


Figure A-1: Dispatch: Current Power Sector, 5% EV Market Penetration, On-peak Charging

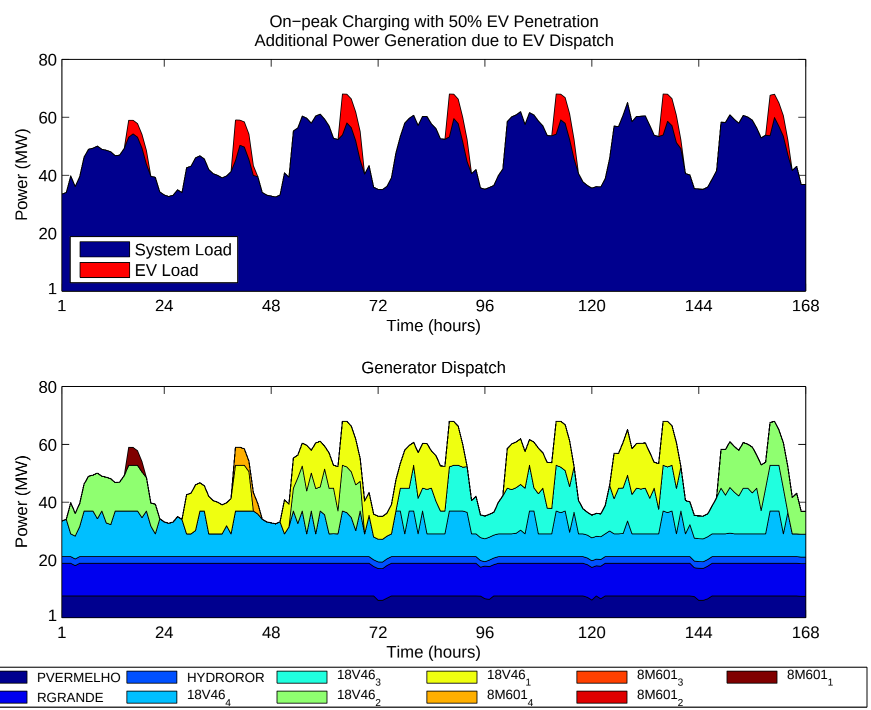


Figure A-2: Dispatch: Current Power Sector, 50% EV Market Penetration, On-peak Charging

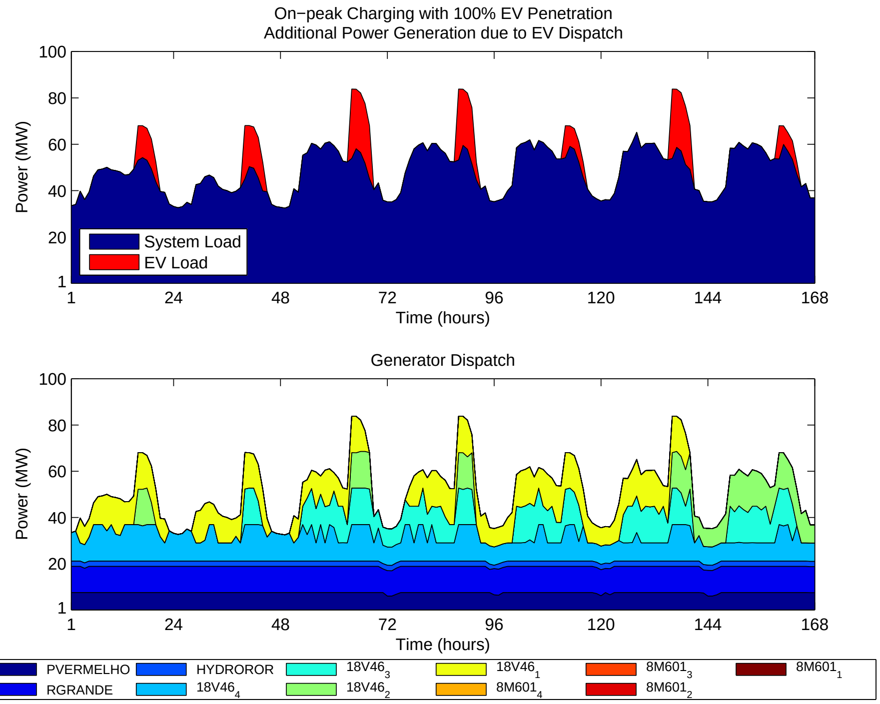


Figure A-3: Dispatch: Current Power Sector, 100% EV Market Penetration, On-peak Charging

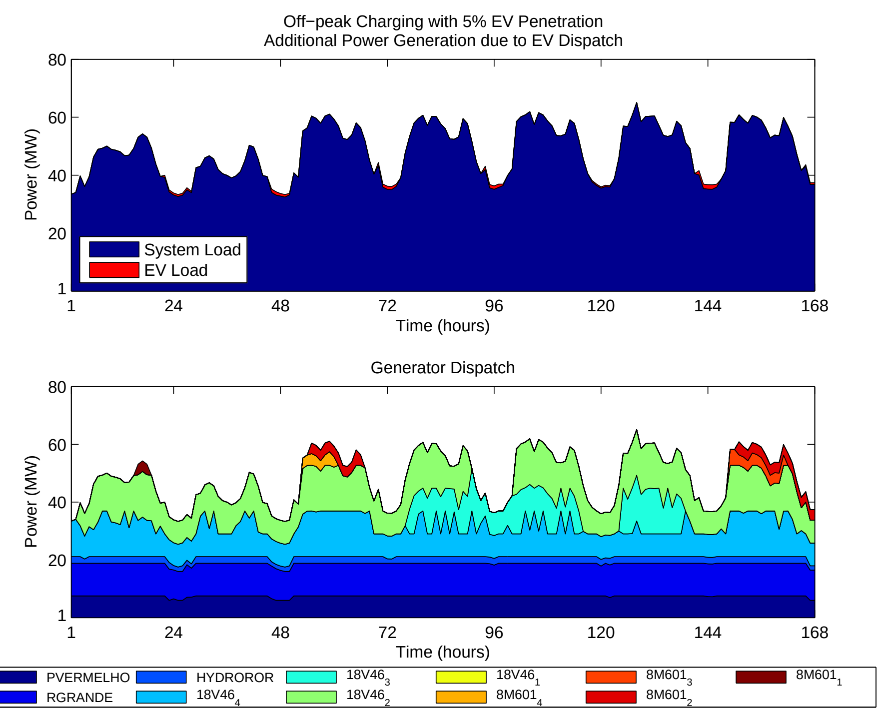


Figure A-4: Dispatch: Current Power Sector, 5% EV Market Penetration, Off-peak Charging

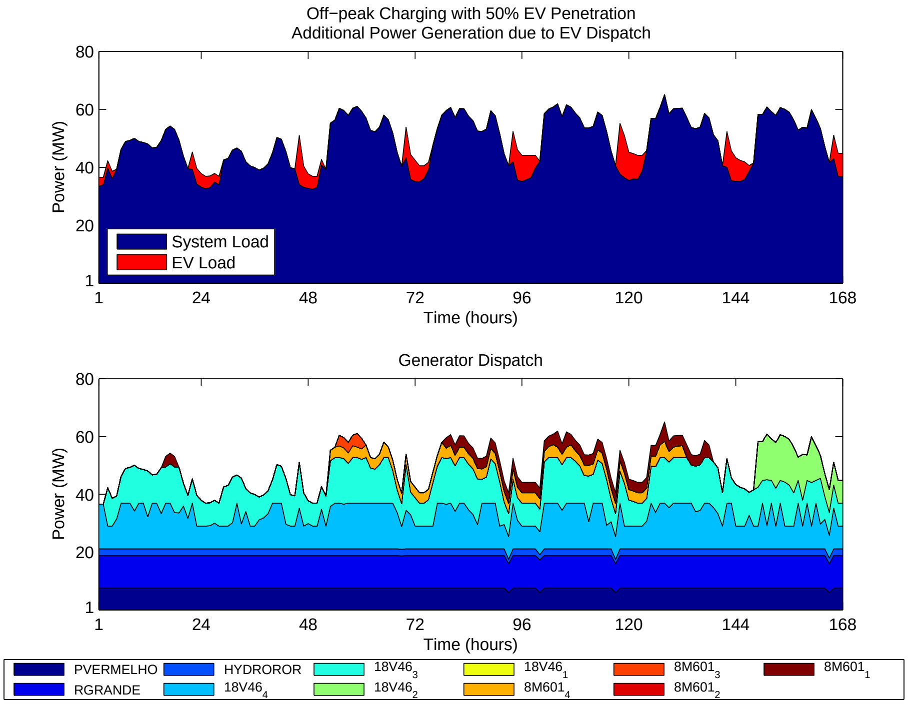


Figure A-5: Dispatch: Current Power Sector, 50% EV Market Penetration, Off-peak Charging

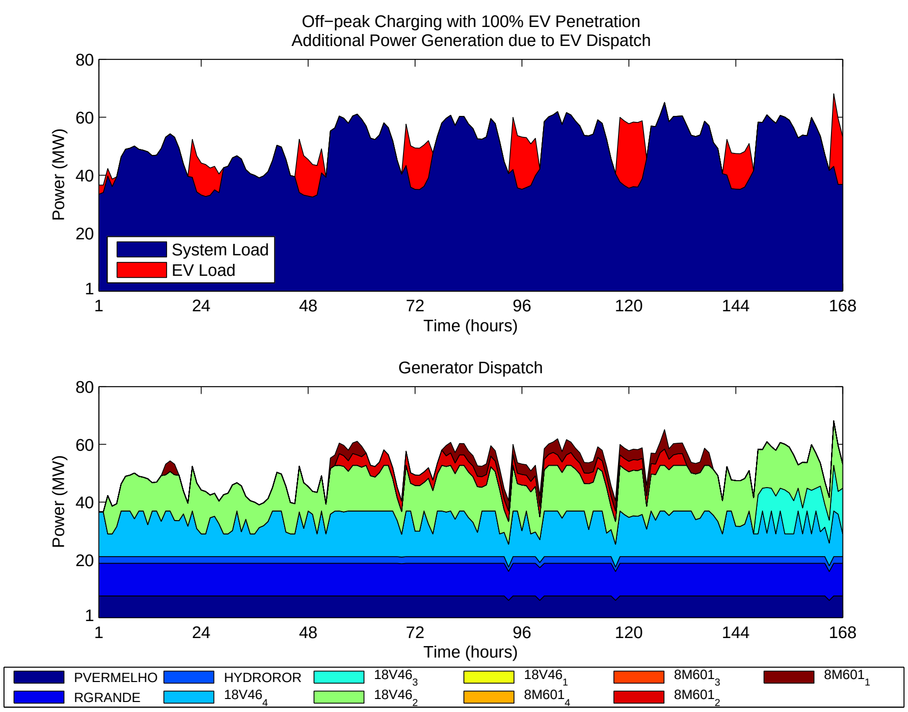


Figure A-6: Dispatch: Current Power Sector, 100% EV Market Penetration, Off-peak Charging

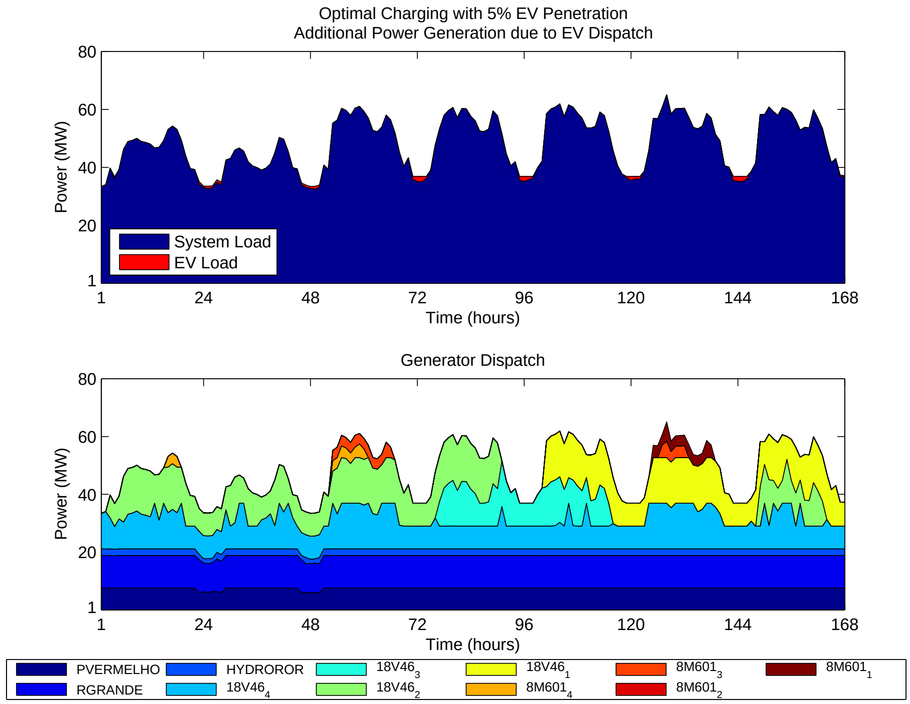


Figure A-7: Dispatch: Current Power Sector, 5% EV Market Penetration, Optimal Charging

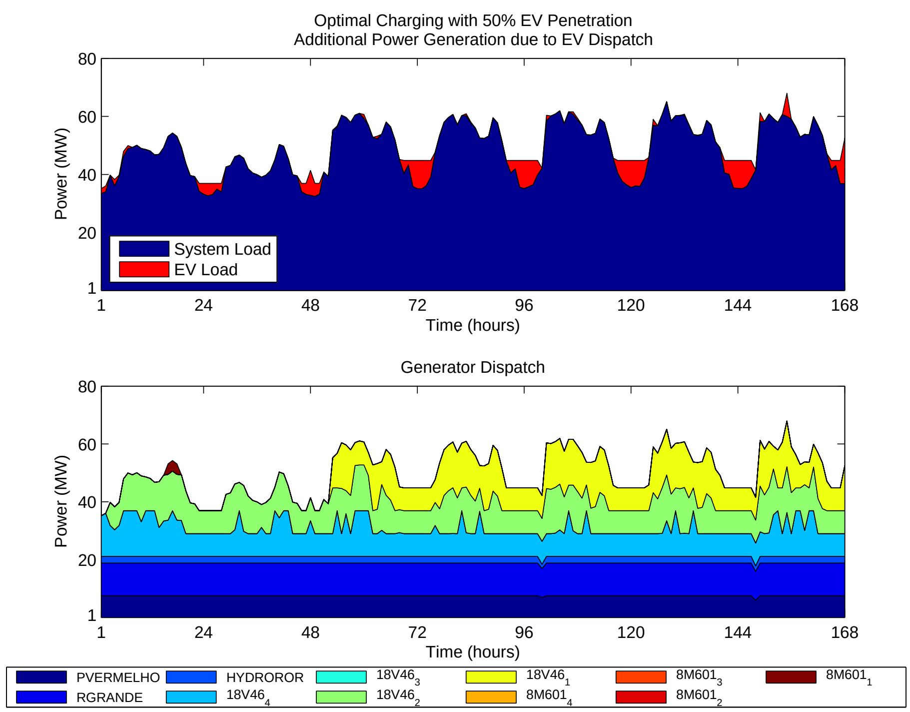


Figure A-8: Dispatch: Current Power Sector, 50% EV Market Penetration, Optimal Charging

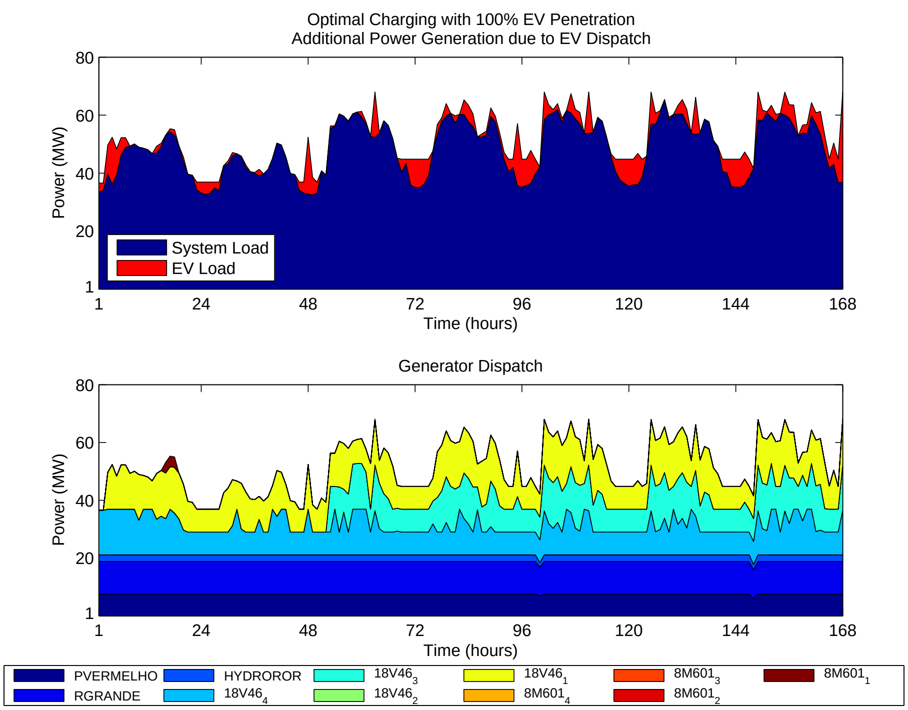


Figure A-9: Dispatch: Current Power Sector, 100% EV Market Penetration, Optimal Charging

A.2 Short-term Future Power Sector

Charging Scheme	EV Penetration	System Cost (kEuros)	Generator Emissions (metric tonnes)
On-Peak	5%	958.245	4212.40
On-Peak	50%	988.952	4391.90
On-Peak	100%	1027.232	4582.20
Off-peak	5%	957.595	4201.60
Off-peak	50%	982.053	4281.20
Off-peak	100%	1012.508	4470.70
Optimal	5%	957.752	4193.40
Optimal	50%	982.009	4279.90
Optimal	100%	1012.471	4469.20

Table A.2: Short-term Power Sector Weekly System Costs and Emissions

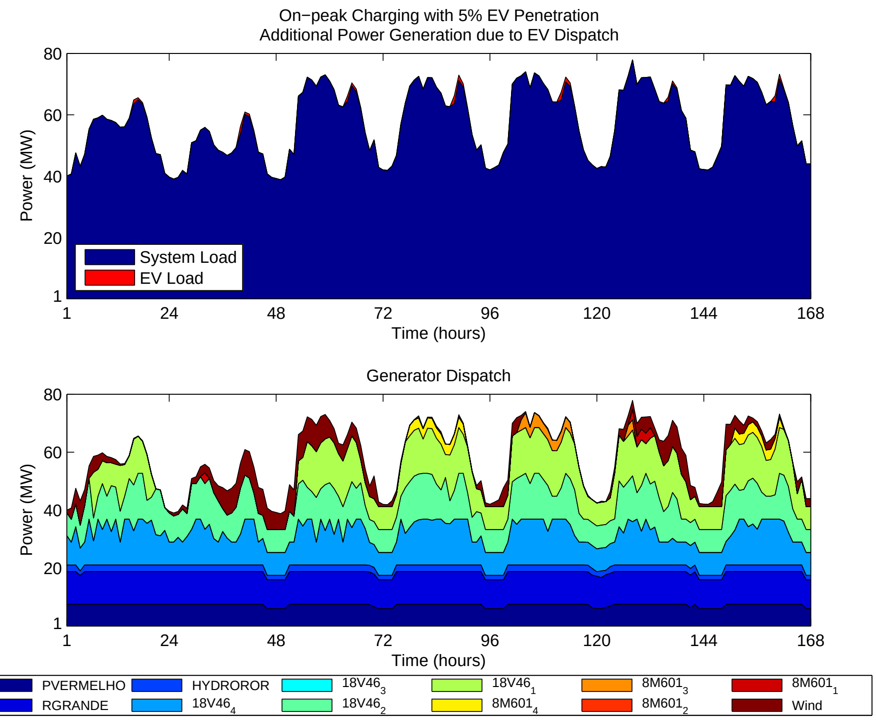


Figure A-10: Dispatch: Short-term Future Power Sector, 5% EV Market Penetration, On-peak Charging

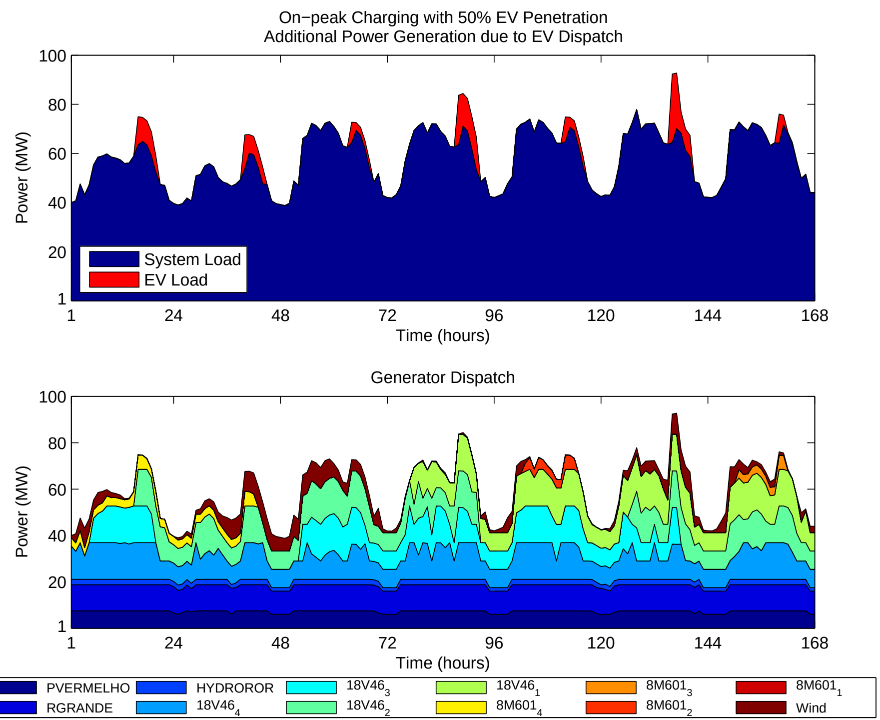


Figure A-11: Dispatch: Short-term Future Power Sector, 50% EV Market Penetration, On-peak Charging

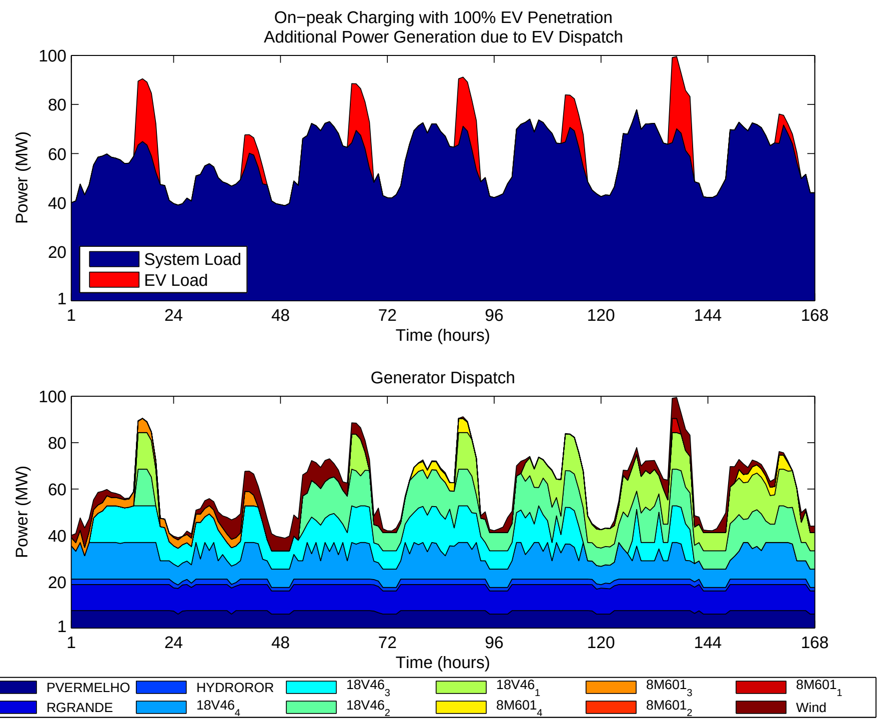


Figure A-12: Dispatch: Short-term Future Power Sector, 100% EV Market Penetration, On-peak Charging

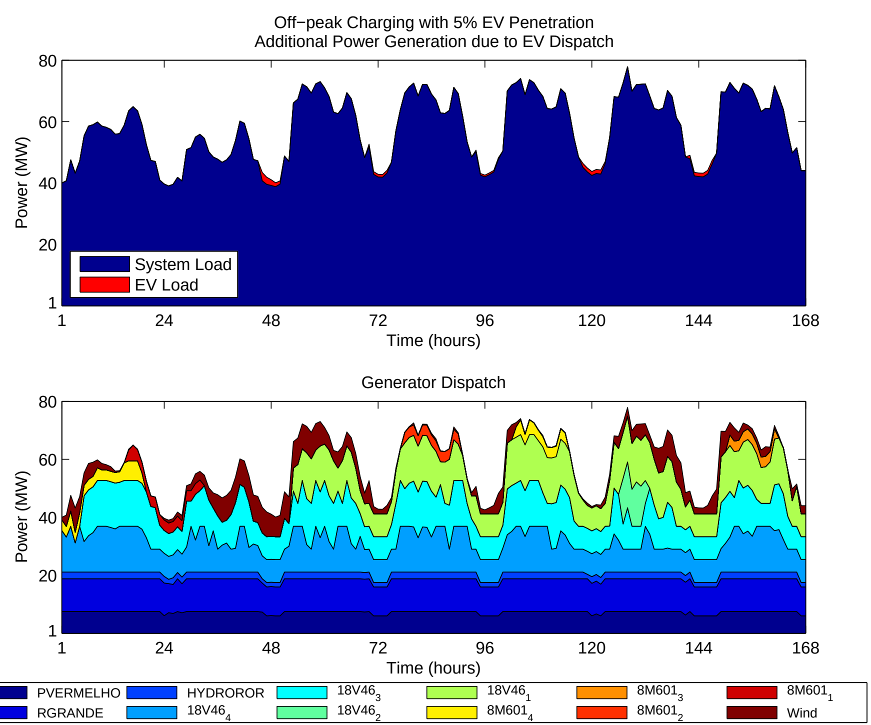


Figure A-13: Dispatch: Short-term Future Power Sector, 5% EV Market Penetration, Off-peak Charging

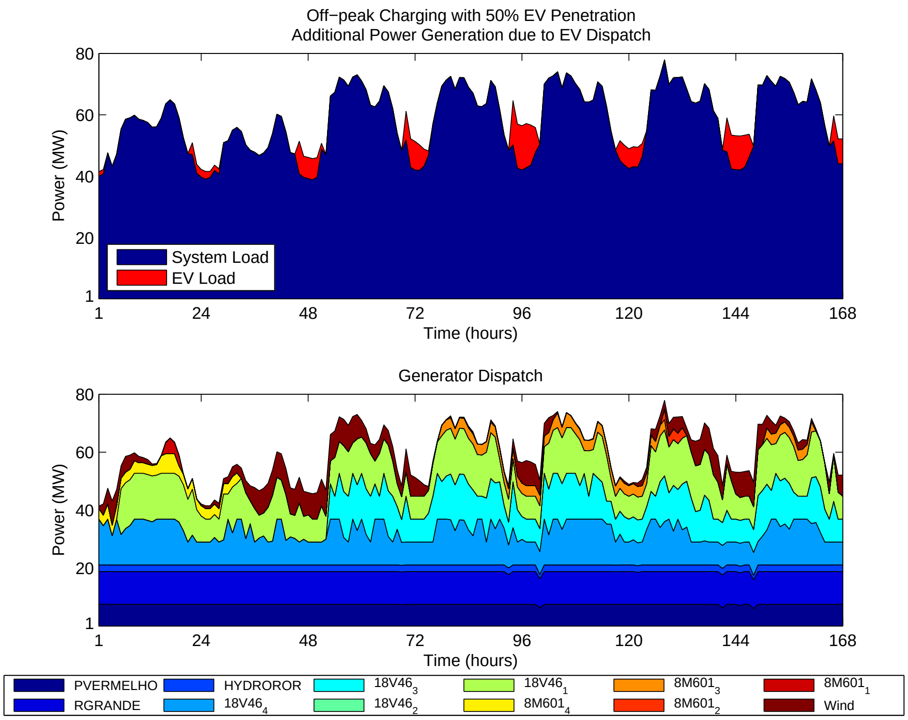


Figure A-14: Dispatch: Short-term Future Power Sector, 50% EV Market Penetration, Off-peak Charging

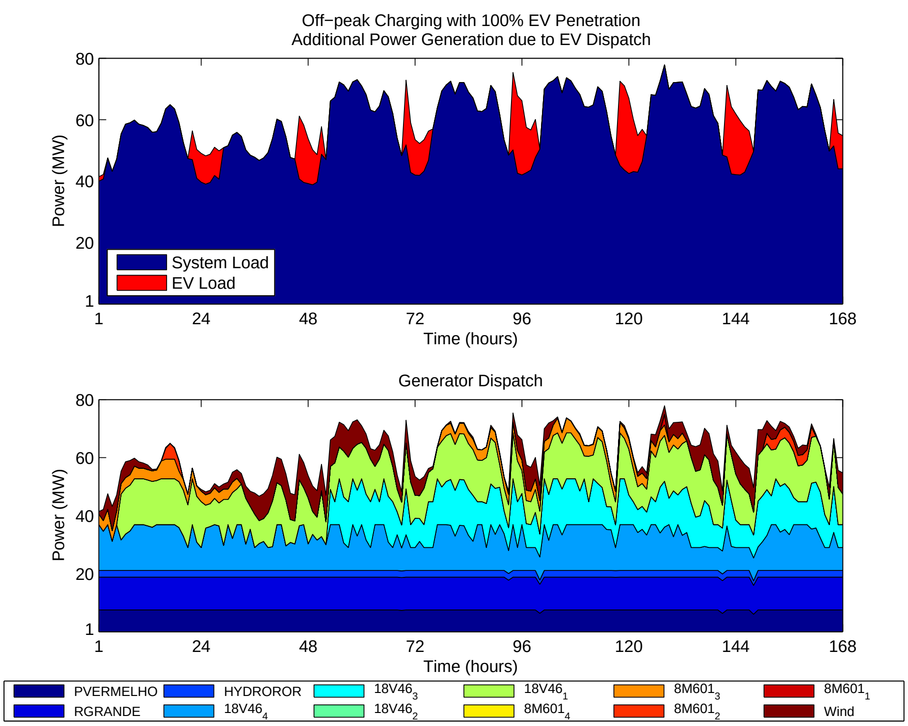


Figure A-15: Dispatch: Short-term Future Power Sector, 100% EV Market Penetration, Off-peak Charging

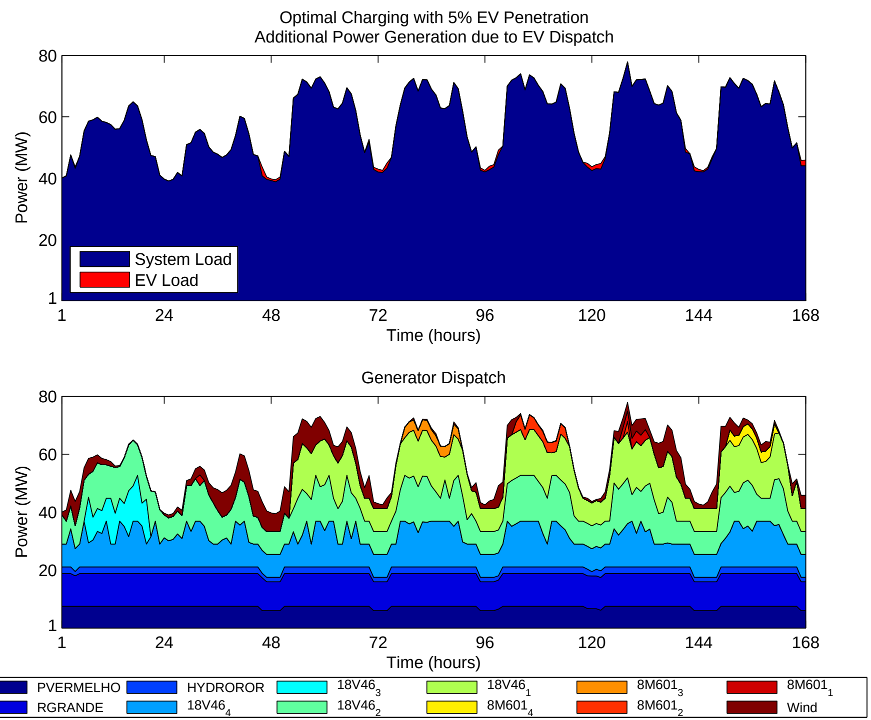


Figure A-16: Dispatch: Short-term Future Power Sector, 5% EV Market Penetration, Optimal Charging

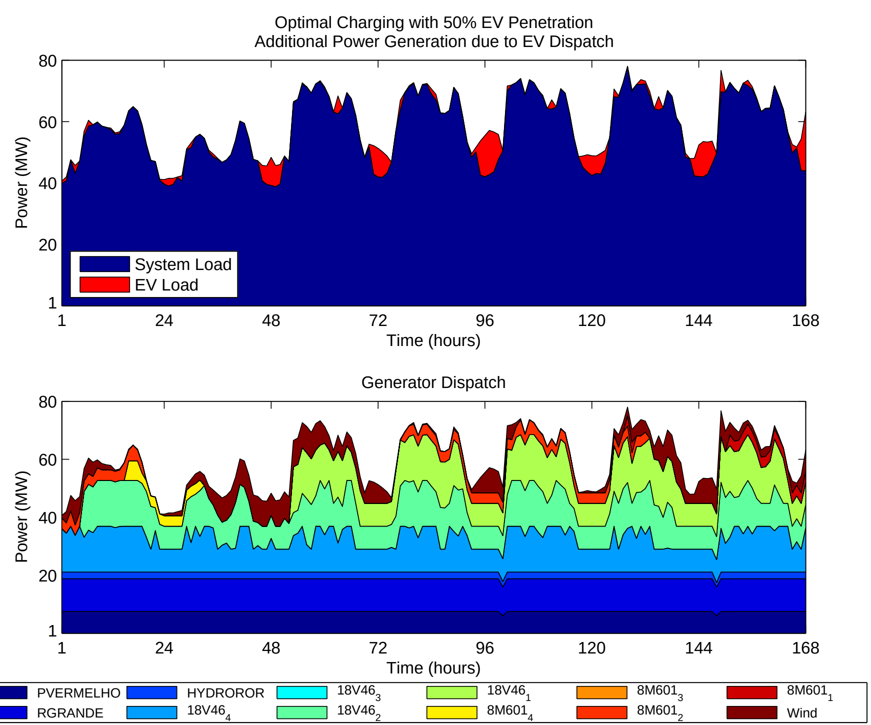


Figure A-17: Dispatch: Short-term Future Power Sector, 50% EV Market Penetration, Optimal Charging

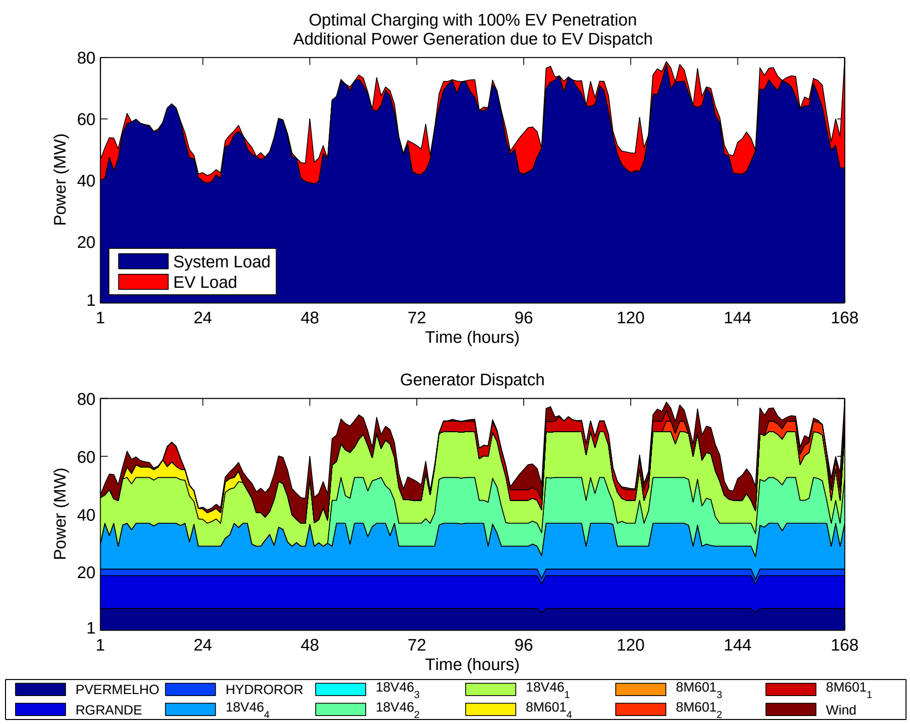


Figure A-18: Dispatch: Short-term Future Power Sector, 100% EV Market Penetration, Optimal Charging

A.3 Long-term Future Power Sector

Charging Scheme	EV Penetration	System Cost (kEuros)	Generator Emissions (metric tonnes)
On-Peak	50%	1030.651	3760.70
On-Peak	100%	1069.239	3956.90
Off-peak	5%	999.646	3589.70
Off-peak	50%	1021.968	3783.00
Off-peak	100%	1050.383	3892.40
Optimal	5%	999.749	3588.00
Optimal	50%	1021.768	3697.70
Optimal	100%	1049.608	3862.50

Table A.3: Long-term Future Power Sector Weekly System Costs and Emissions

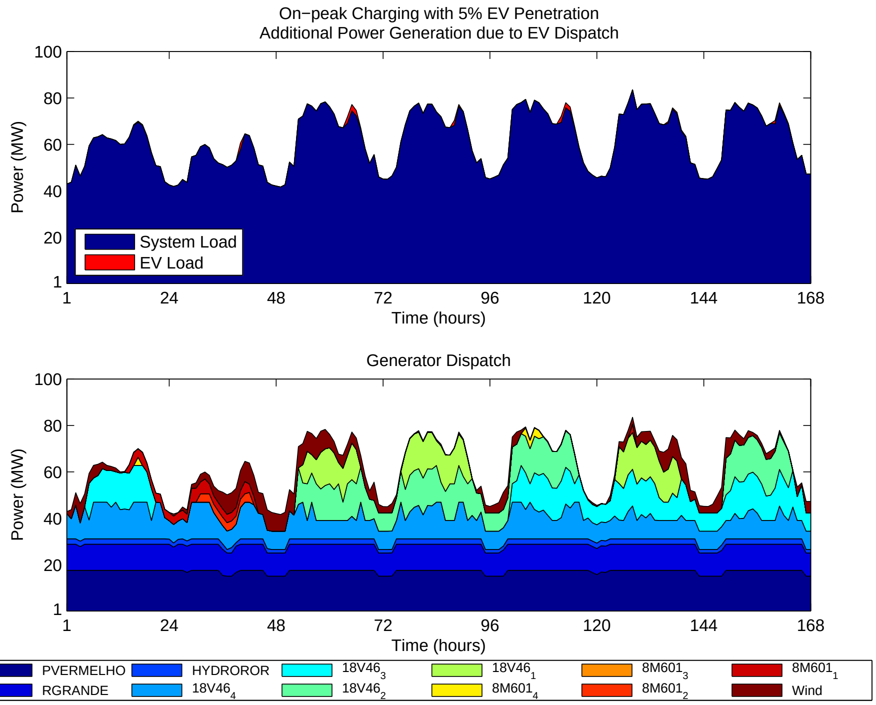


Figure A-19: Dispatch: Long-term Future Power Sector, 5% EV Market Penetration, On-peak Charging

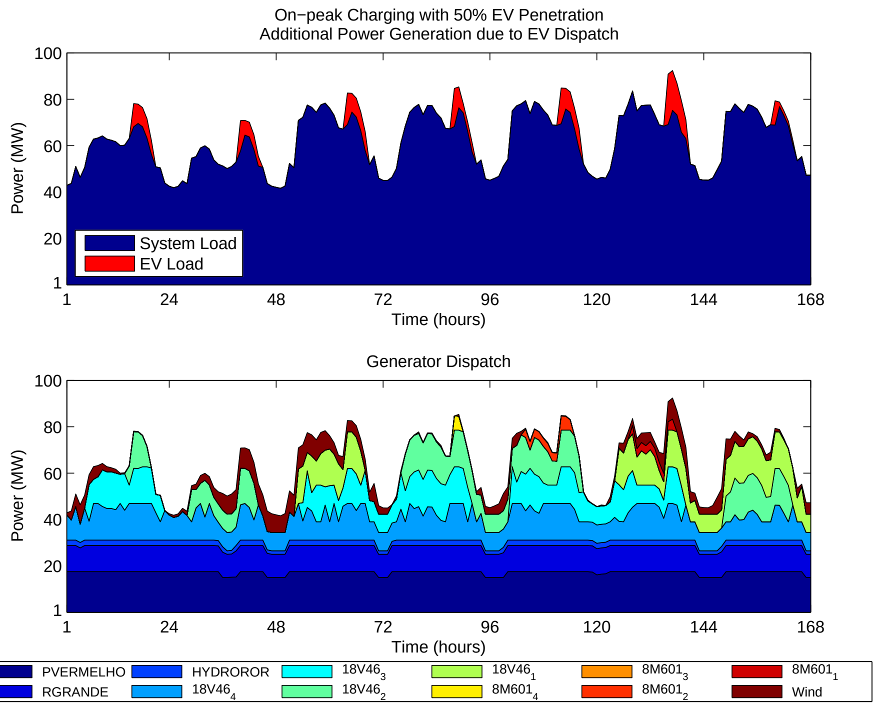


Figure A-20: Dispatch: Long-term Future Power Sector, 50% EV Market Penetration, On-peak Charging

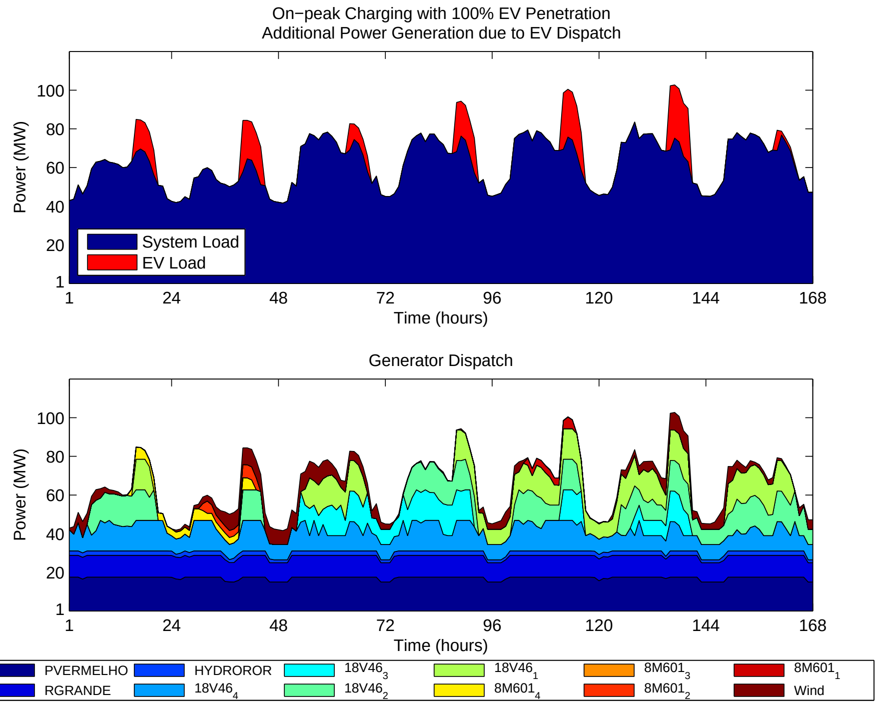


Figure A-21: Dispatch: Long-term Future Power Sector, 100% EV Market Penetration, On-peak Charging

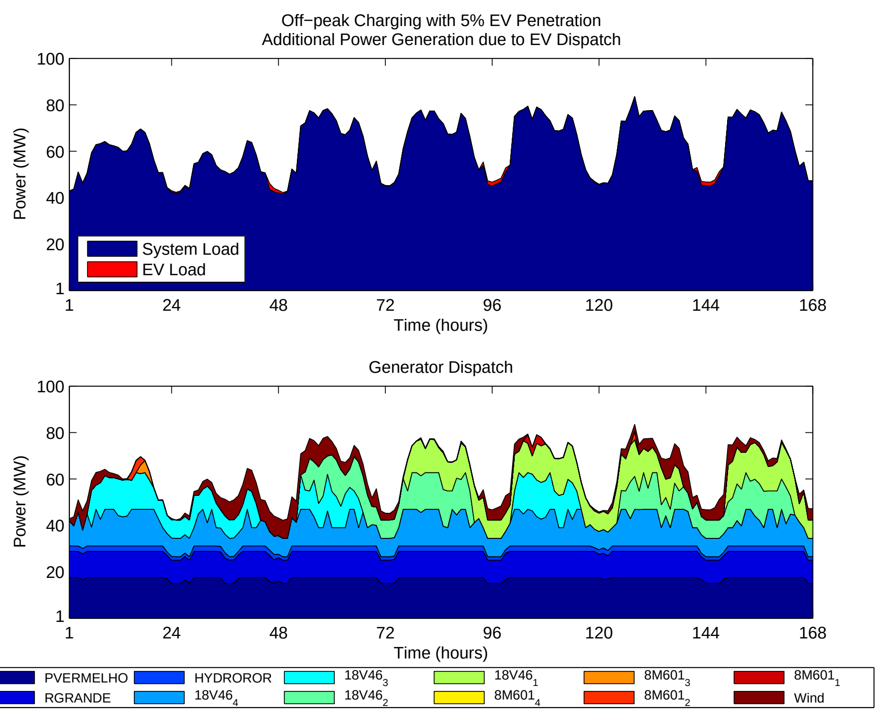


Figure A-22: Dispatch: Long-term Future Power Sector, 5% EV Market Penetration, Off-peak Charging

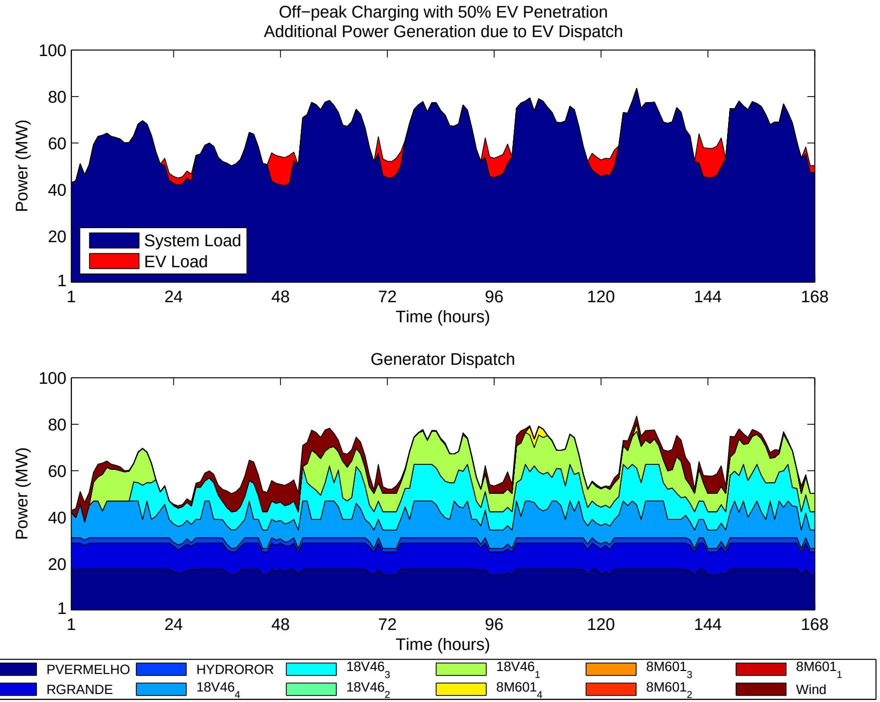


Figure A-23: Dispatch: Long-term Future Power Sector, 50% EV Market Penetration, Off-peak Charging

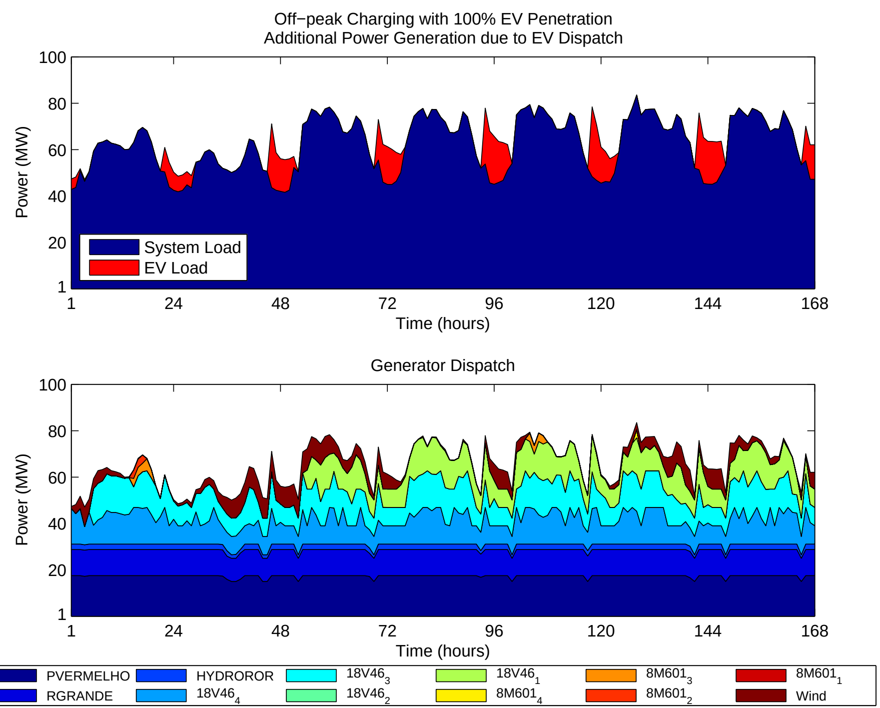


Figure A-24: Dispatch: Long-term Future Power Sector, 100% EV Market Penetration, Off-peak Charging

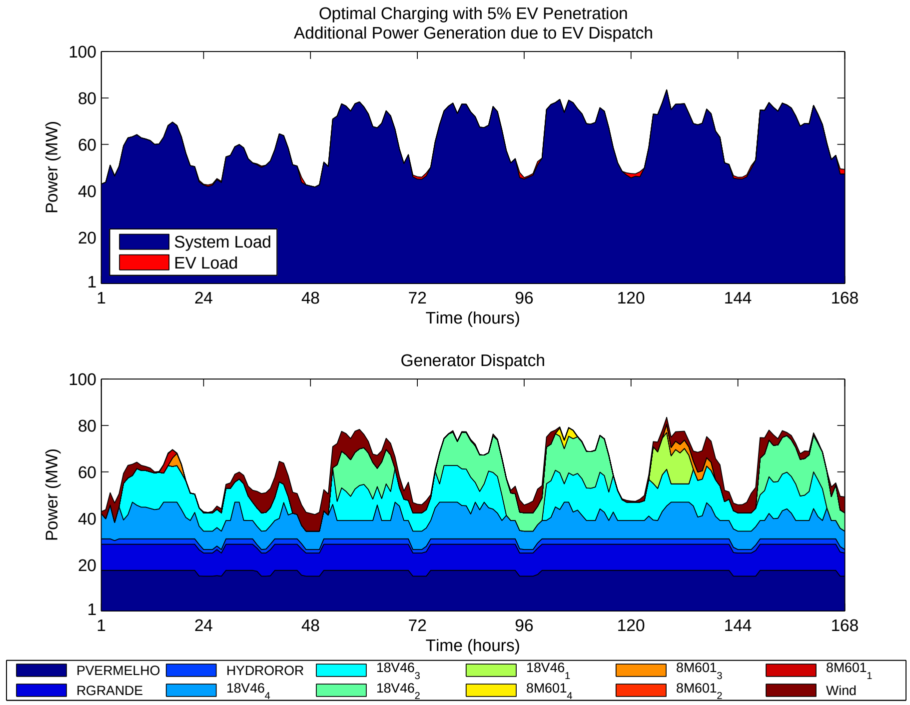


Figure A-25: Dispatch: Long-term Future Power Sector, 5% EV Market Penetration, Optimal Charging

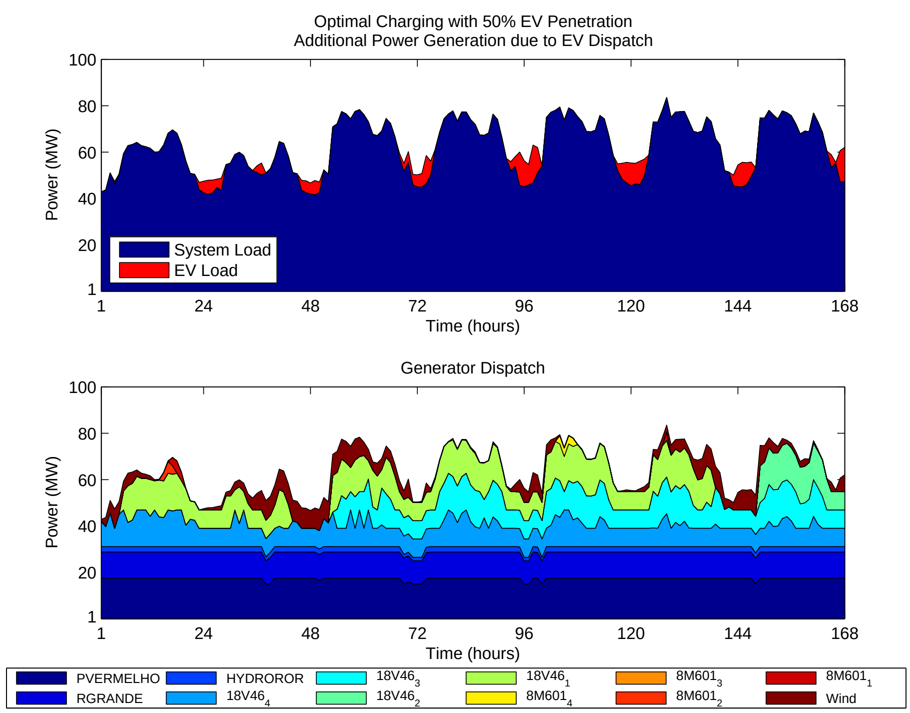


Figure A-26: Dispatch: Long-term Future Power Sector, 50% EV Market Penetration, Optimal Charging

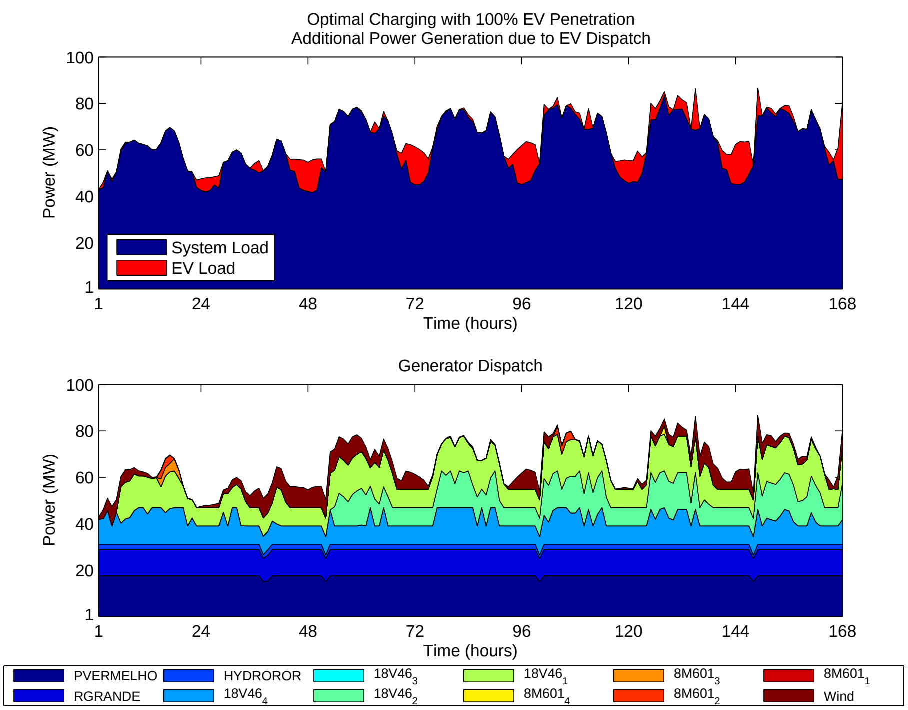


Figure A-27: Dispatch: Long-term Future Power Sector, 100% EV Market Penetration, Optimal Charging

Appendix B

Wind Power Production Derivation

As of the writing of this document, EDA had not installed any wind turbines on São Miguel. The only wind speed data for the island was taken from anemometers installed near the Ponta Del Gada (PDL) airport on the island. However, these anenometers were installed at a height of six meters, while the hub height (the height at which the blades on the turbine rotate around a fixed axis) on the Enercon E-44 turbine is 55 meters. The difference in heights leads to a difference in wind speeds. It is important to capture this difference in wind speeds, because higher wind speeds mean a greater capacity factor. The wind power law, shown in Equation B.1 is used as a rough estimation of the wind speed (u_{55}) at a height of 55 meters (z_{55}) based on wind speed and data taken at a height of six meters (z_{55}, u_{55}).

$$u_{55} = u_6 \times \left(\frac{z_{55}}{z_6} \right)^{\frac{1}{7}} \tag{B.1}$$

After "scaling up" the hourly wind speed data from PDL to a hub height of 55 meters, using Equation B.1, the next step is to adjust for the change in location. The turbines at São Miguel are going to be installed on a ridge in the middle of the island, which will be exposed to far more wind than the PDL airport, regardless of hub height. In order to approximate these weather conditions, wind speed data from wind farm on the nearby island of Terceira is used. Wind speed data naturally approximates the Weibull distribution; wind speed data from PDL (scaled up) and

Terceira are fitted to a Weibull distribution using MATLAB's WBLFIT command. The fitted curves are plotted in Figure B-1.

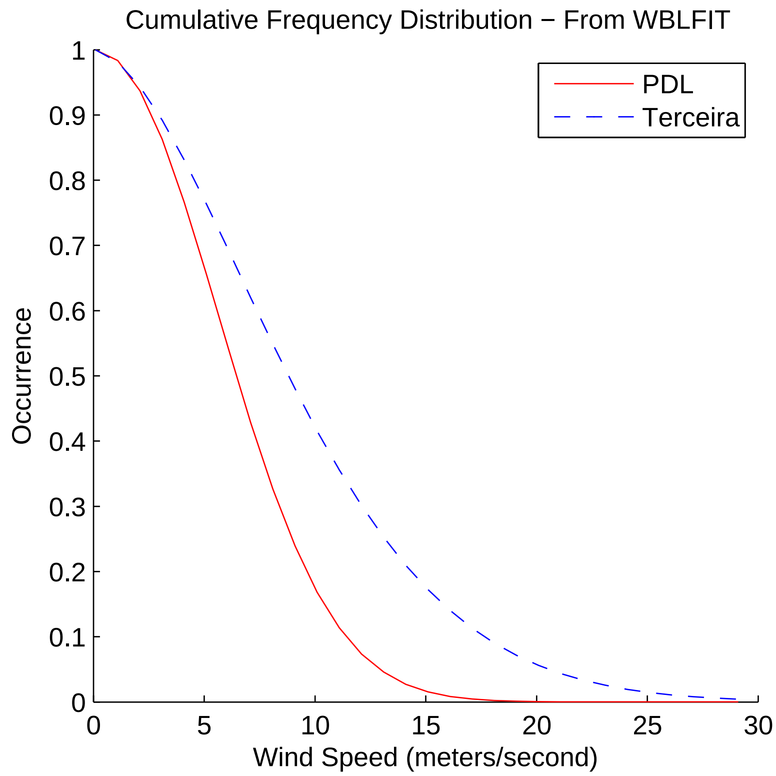


Figure B-1: Terceira and PDL Wind Speed Cumulative Frequency Distribution

The scaled up PDL data is then scaled up again, this time by matching it to an equivalent wind speed in Terceira. For instance, the 0.1 occurrence of PDL (approximately 12/ms) is converted to the equivalent 0.1 occurrence value for Terceira (approximately 16 m/s). This mapping is then used to approximate the height of an entire year of wind speed data from PDL, scaled up to a hub height of 55 meters, located on a ridge in the middle of São Miguel. The original and the scaled/mapped data are shown in Figure B-2.

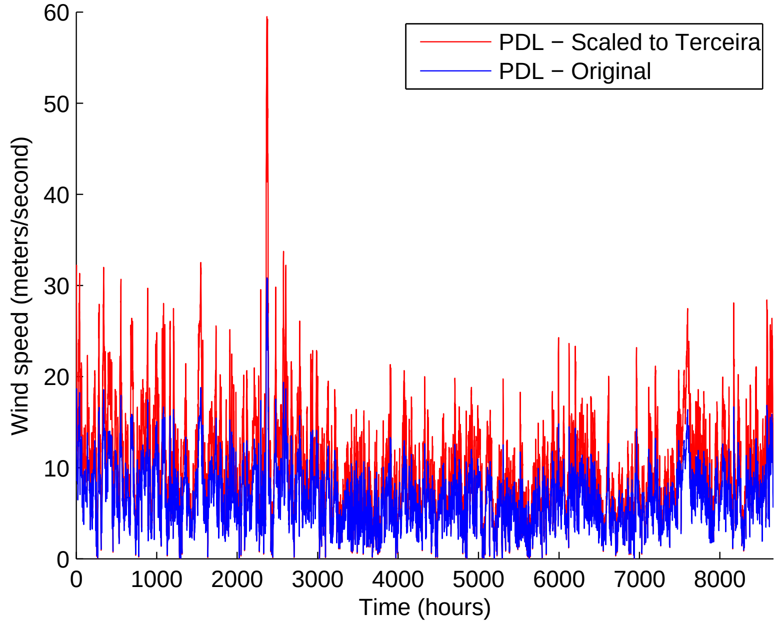


Figure B-2: PDL Data Scaled/Mapped Wind Speeds

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