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GRADO EN INGENIERÍA EN TECNOLOGÍAS INDUSTRIALES

TRABAJO FIN DE GRADO

Analysis of the Spanish EV charging infrastructure. Design of a smart charging model and its integration with solar PV generation in a residential environment

Autor: Álvaro José Pérez Triay

Directores: Manuel Pérez Bravo, Miguel Martínez Velázquez

Madrid

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Analysis of the Spanish EV charging infrastructure. Design of a smart charging model and its integration with solar PV generation in a residential environment.

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Fdo.: Álvaro José Pérez Triay Fecha: 20 / Junio / 2022

Autorizada la entrega del proyecto

LOS DIRECTORES DEL PROYECTO

Fdo.: Manuel Pérez Bravo Fecha: 20 / Junio / 2022

Fdo.: Miguel Martínez Velázquez Fecha: 20 / Junio / 2022

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I would like to express my deepest appreciation to my project directors for being so involved, serving as a rational and experienced guide and having taught me so much in such a short time.

I am grateful for the roommates I have had this exchange year in the USA. Thanks for supporting during the toughest moments of the process and giving me the strength I needed to do my best at this project. They are now friends for life.

I wish to thank my friends for being such a support to everything I do.

I'm extremely thankful to my family because without them I would be nothing.

ANÁLISIS DE LA INFRAESTRUCTURA DE RECARGA DEL VEHÍCULO ELÉCTRICO EN ESPAÑA. DISEÑO DE UN MODELO DE RECARGA INTELIGENTE Y SU INTEGRACIÓN CON GENERACIÓN SOLAR EN UNA COMUNIDAD DE VECINOS

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RESUMEN DEL PROYECTO

1. Introducción

La motivación de este proyecto es promover el uso del vehículo eléctrico y las energías renovables como una potente alternativa para luchar contra el cambio climático. Para ello, se ha realizado un análisis en profundidad de la infraestructura de recarga del vehículo eléctrico (EV) en España y el diseño de un modelo de recarga inteligente para integrar la generación de energía solar con la recarga de vehículos eléctricos en un entorno residencial.

La Tierra ha experimentado un aumento constante de la temperatura media que se puede relacionar con el aumento de la concentración de gases de efecto invernadero en la atmósfera [1]. Este aumento de las temperaturas está provocando un cambio climático que tiene múltiples consecuencias y de gran importancia. Aumento del nivel del mar, intensas sequías, escasez de agua, inundaciones, deshielo de los polos, incendios graves, tormentas catastróficas y disminución de la biodiversidad. Los seres humanos están experimentando y experimentarán el cambio climático de muchas maneras. El cambio climático puede afectar a nuestra salud, a la capacidad de cultivar alimentos, a la vivienda, a la seguridad y al trabajo. El aumento del nivel del mar y la intrusión de agua salada han afectado a comunidades enteras que han tenido que reubicarse. Las personas que viven cerca de la costa pueden tener que reubicarse también debido al aumento del nivel del mar. Las sequías prolongadas ponen a la gente en riesgo de hambruna. No hay duda de que las consecuencias del cambio climático son graves y que necesitamos actuar para evitar que empeore la situación [2].

Para entender las causas que están provocando el cambio climático, es necesario explorar los diferentes factores que pueden tener algo que ver. En cuanto a las fuerzas externas más relevantes, la actividad solar y los ciclos de Milankovitch pueden ser descartadas. El clima no responde a la mayoría de variaciones en la actividad solar que ocurren en períodos tan cortos [3]. Los ciclos de Milankovitch tienen gran efecto en el clima a largo plazo, pero no pueden ser la causa de un cambio tan repentino en las temperaturas [4]. Emisores de gases de efecto invernadero como las plantas o los volcanes, podrían ser los responsables de este aumento de la concentración de dióxido de carbono (CO_2). Sin embargo, por la concentración de carbono-14 en las moléculas de CO_2 que están entrando en la atmósfera, sabemos que no es cierto. Sólo seres vivos que han estado muerto durante millones de años podrían ser la razón de esto niveles de carbono-14 [5]. Es por ello que parece razonable apuntar a la quema de combustibles como carbón, petróleo y gas. En 2019 se emitieron más de 35 gigatoneladas de CO_2 en todo el mundo. Sólo China, Estados Unidos, India y Rusia contribuyen a casi el 55% de las emisiones mundiales [6].

La actividad humana en diversos sectores es la principal causa del cambio climático. El uso de la energía en la industria, la agricultura, la silvicultura y el uso de la tierra, el uso de la energía en los edificios y el transporte son los sectores que más contribuyen [7]. Todos ellos tienen alternativas menos contaminantes, pero su despliegue es escaso. Dentro del sector del transporte, el transporte por carretera – que representa más del 70% de las emisiones – podría ser sustituido en su totalidad por alternativas verdes.

El objetivo del proyecto es ayudar a reducir esas emisiones del transporte por carretera. Los vehículos eléctricos son la alternativa actual que tenemos. Ya han sido diseñados y mejorados hasta el punto de que son competidores directos de los ICEV (vehículos con motor de combustión interna). Es necesaria una mayor penetración de los vehículos eléctricos, pero no se puede conseguir sin antes encontrar soluciones a problemas que tienen como su impacto en la red. El modelo de recarga inteligente diseñado persigue este objetivo, además de reducir los costes de recarga.

2. Estado del arte

En este capítulo se pretende mostrar cómo es la infraestructura de recarga y la regulación española, así como introducir el concepto de recarga inteligente y explicar qué tienen en cuenta los diferentes modelos existentes.

-Análisis de la electromovilidad española

La industria de la automoción desempeña un enorme papel en la economía española. Sólo la fabricación de vehículos y sus componentes supuso aproximadamente el 8% del PIB español en 2020. La capacidad de adaptación y la gran demanda de vehículos españoles hicieron que España se convirtiera en el octavo fabricante mundial y el segundo de Europa. Sin embargo, aún no está preparada para una gran penetración de la fabricación de vehículos alternativos. Sólo se fabricaron 164.821 vehículos alternativos en 2020, lo que supone el 7,3% del total [8].

El parque automovilístico español es uno de los más antiguos de Europa, con una edad media de más de 13 años. Como se puede ver en la Ilustración 1, los vehículos de bajas emisiones – clasificados como DGT CERO y DGT ECO – tienen una escasa penetración en las carreteras españolas, ya que sólo representan el 2,2% del total del parque automovilístico español. Sin embargo, las ventas de vehículos eléctricos han aumentado de forma constante en los últimos años. En 2020, las matriculaciones de vehículos eléctricos representaron casi una quinta parte del total de nuevas matriculaciones [8].

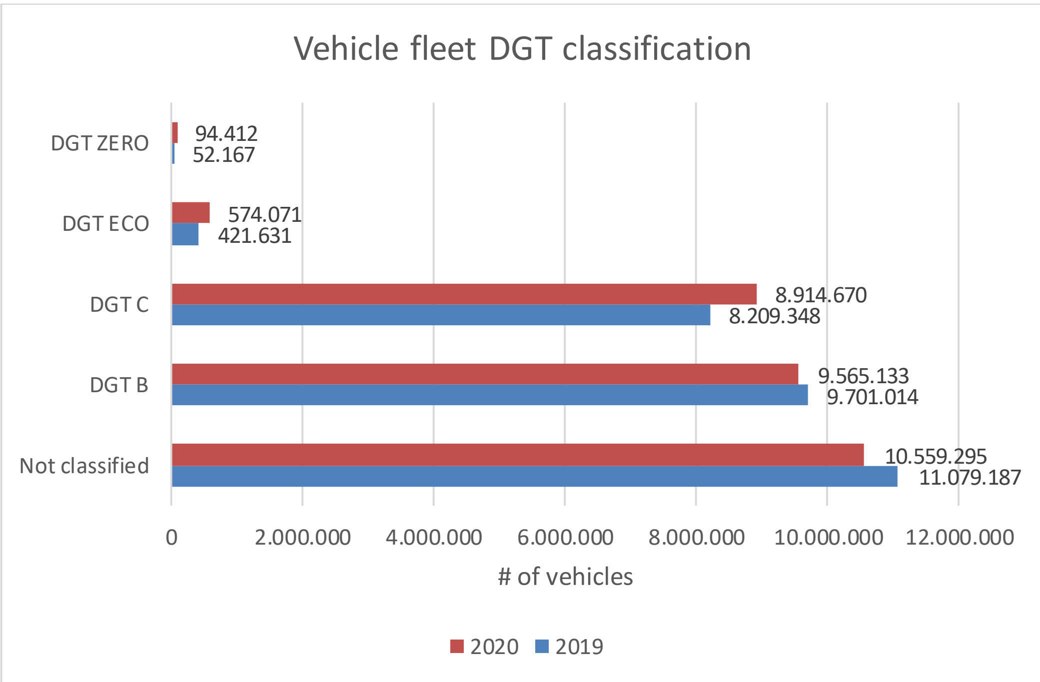

Ilustración 1: Desglose del tipo de vehículo en función de la etiqueta de la DGT. Fuente: ANFAC 2020

Si se compara con sus colegas europeos, España sale muy mal parada tanto en penetración de vehículos eléctricos como en infraestructura de recarga. España obtuvo 13,3 puntos en el índice global de electromovilidad de 100 puntos diseñado por la ANFAC, mientras que la media europea fue de 28,1 puntos. Dentro de España, Madrid, Cataluña y Navarra son las regiones con mejores resultados, mientras que Andalucía, Extremadura y Ceuta y Melilla obtuvieron las puntuaciones más bajas [8].

-Infraestructura de recarga española

Existe una percepción errónea de los vehículos eléctricos en España que dificulta su compra. En 2018, el 57% de los consumidores españoles consideraba que la mayor barrera para comprar un VE era la escasa autonomía de estos vehículos. Sin embargo, esta percepción contrasta radicalmente con el hecho de que la autonomía actual de los VE es suficiente para cubrir el 95% de los trayectos en España [9]. Esa percepción errónea, unida a la falta de infraestructura de recarga, es una gran barrera para la penetración del VE en España. Contar con una infraestructura de recarga sólida es clave para cambiar esta mentalidad y se necesitan ayudas públicas. Ya existen programas nacionales de incentivos para promover el uso del VE como el Plan MOVES – Movilidad Eficiente y Sostenible – que pretende incentivar la compra de VE y FCEVs concediendo ayudas de hasta 7.000 Eur a partir de 2021 [10]. Regulación sobre las plazas mínimas de recarga exigidas en los aparcamientos también pretende incentivar el uso del VE.

Los puntos de recarga públicos disponibles en España son muy variados: velocidades de carga de hasta 400 kW (recientemente introducidos por Porsche e Iberdrola en Elche), los cuatro modos de carga reconocidos internacionalmente – que difieren en la cantidad de información compartida entre el VE y la red – y muchos conectores diferentes – como el SAE j1772, Mennekes, Scame, CHAdeMO, CSS, etc. También hay leyes regulando los esquemas y elementos de los puntos de recarga, que pueden clasificarse en garajes privados, comunitarios y electrolineras [11].

-Carga inteligente

La recarga inteligente consiste en controlar la potencia a la que se carga el vehículo en tiempo real bajo algunas restricciones. Estas restricciones y el objetivo perseguido pueden variar mucho en función de la estrategia de recarga inteligente, pero la mayoría de ellas tienen que ver con la capacidad de conexión o de la red, las variaciones de carga, la producción local de energía, las cuotas de energía renovable, los precios de la electricidad y las necesidades de los usuarios. La recarga inteligente es una forma de gestionar las cargas de los vehículos eléctricos mediante la integración vehículo-red [12].

En un escenario de penetración masiva de vehículos eléctricos, si se cargan de forma incontrolada, muchos vehículos podrían cargarse al mismo tiempo, aumentando el pico de demanda en la red y contribuyendo a sobrecargarla. La creciente demanda de electricidad en un escenario de alta penetración de vehículos eléctricos también requerirá inversiones en la red de distribución. Además, hay un gran reto que deben afrontar los sistemas de distribución para satisfacer las necesidades de los usuarios de vehículos eléctricos: la carga rápida. Las mayores potencias requeridas por la carga rápida necesitan una mayor capacidad de las redes de distribución [12].

A nivel de sistema, los vehículos eléctricos cargados de forma inteligente pueden ayudar a reducir el pico de demanda y, por lo tanto, evitar inversiones en aumento de la capacidad de generación. Como baterías de almacenamiento conectadas a la red que los vehículos eléctricos son, pueden ofrecer muchos servicios a la red: control de la frecuencia a través de la reserva primaria, secundaria y terciaria; rellenar los valles de carga, gestionando la variabilidad del voltaje o aumentar el consumo de energías renovables variables (VRE) mediante el desplazamiento de sus tiempos de carga a los tiempos de generación de energías renovables. A nivel local, se pueden proporcionar servicios similares. La reducción de la congestión local y el aumento del autoconsumo de VRE se consideran los mejores usos. Los vehículos eléctricos también pueden almacenar energía de reserva en caso de cortes de la red local [12].

-Modelos de recarga inteligente existentes

La recarga inteligente puede implementarse utilizando diferentes estrategias y especificaciones técnicas. Las estrategias varían en función de los objetivos (minimización de costes, minimización de la variabilidad de la carga, maximización del consumo de VRE, etc.) y de las restricciones (capacidad de la red, rangos de tensión de la red, especificaciones de los puntos de recarga, capacidades de los VE, necesidades de los usuarios y tecnología utilizada) [13]. Entre las formas de implementar la recarga inteligente, algunos mecanismos de control directo – necesarios a niveles de penetración de VE más altos – destacan sobre otros:

- Control unidireccional de los VE (también conocido como V1G): permite controlar la tasa de potencia, desde 0 hasta la máxima potencia disponible.

- Control bidireccional de los vehículos eléctricos (también conocido como vehicle-to-everything, o V2X): los vehículos pueden cargarse y descargarse a un ritmo de energía controlado para ofrecer más flexibilidad

Existen dos corrientes principales para la implementación de la carga inteligente basada en la arquitectura de control: el enfoque centralizado y el enfoque descentralizado. En un esquema centralizado, la carga de todos los vehículos es optimizada por un único agregador con el fin de alcanzar un objetivo. En un esquema descentralizado, cada vehículo eléctrico tiene un programa de carga optimizado diferente que se establece de forma independiente una vez que el vehículo se enchufa con el fin de alcanzar el objetivo específico de los usuarios [14].

Los diferentes modelos de recarga inteligente también varían en su planteamiento. Hay algunos modelos que establecen las potencias para cada vehículo en cada momento antes del periodo de tiempo en el que se van a utilizar. Esto se hace asumiendo los estados de carga iniciales y las horas de llegada y salida, basándose en previsiones muy precisas [15]. Por otro lado, algunos modelos emplean la programación en tiempo real. La potencia para cada vehículo se establece justo en el momento en el que el vehículo llega, por lo que no se hacen suposiciones sobre las horas de llegada, y se pregunta a los conductores las horas esperadas de salida [16].

3. Descripción del modelo

Los dos modelos que se presentan en este estudio establecen horarios óptimos de recarga en función de los objetivos perseguidos: el modelo 1 es un problema de programación lineal (LP) que persigue la minimización del coste de recarga, mientras que el modelo 2 es un problema de programación cuadrática (QP) que persigue la minimización de la variabilidad de la carga. Se compararán en profundidad los resultados obtenidos en función de los diferentes objetivos perseguidos y se analizará la sensibilidad de los resultados de ambos modelos añadiendo una restricción de la variabilidad máxima de la carga y del coste de recarga a los modelos 1 y 2 respectivamente. En el modelo también se considera la generación de energía solar.

Las variables empleadas en este modelo son: consumo de energía de cada VE en cada periodo, estado de carga de cada VE en cada periodo, cantidad de energía solar generada vendida a la red en cada periodo, cantidad de energía solar generada utilizada para satisfacer la demanda interna.

Los parámetros empleados son: las horas de llegada y salida y los estados de carga de cada VE, la capacidad, la eficiencia del cargador y la potencia máxima de cada VE, los estados de carga máximos y mínimos de cada VE, y el precio de la electricidad, el precio de la energía inyectada en la red, la carga de la demanda y la generación de energía solar en cada periodo.

Las restricciones utilizadas son: la potencia máxima, el requisito de carga del usuario del VE, las coincidencias del estado de carga, la capacidad mínima y máxima de la batería del VE, la actualización dinámica del estado de carga, la capacidad máxima de la red, la energía solar total generada y el valor máximo de la energía solar generada para satisfacer la demanda interna.

4. Resultados

-Caso de estudio

Este modelo se ha probado en un entorno residencial de 20 vehículos eléctricos en El Puerto de Santa María, España, que tiene instalada energía solar fotovoltaica. Se han estudiado seis escenarios diferentes.

Los valores de los parámetros fueron modelados – como las horas de llegada y salida, asumidos – capacidad máxima del alimentador y eficiencia del cargador, o tomados de datos históricos – capacidades de los vehículos eléctricos, demanda de electricidad, precios de la electricidad y de la energía inyectada y generación de energía solar.

Los seis escenarios explorados son abril de 2022, abril de 2022 sólo días laborables, abril de 2022 sólo días no laborables, abril de 2019, julio de 2019 y enero de 2020. El motivo de la elección de estos escenarios es explorar el cambio en los patrones de recarga debido a los diferentes precios, demandas de electricidad y generación de energía solar en: día de la semana frente a fin de semana, prepandemia frente a postpandemia y verano frente a invierno frente a primavera/otoño.

-Escenario 1 (abril de 2022) resultado de todos los modelos

Los resultados de todos los modelos para el primer escenario se muestran en la siguiente figura. El porcentaje representa la desviación máxima permitida del valor óptimo (que se ha calculado utilizando los modelos 1 y 2) de la característica restringida para el modelo 3a (minimización del coste con una restricción en la desviación de la variabilidad de la carga) y del modelo 3b (minimización de la variabilidad de la carga con una desviación máxima del coste de carga que el usuario del VE está dispuesto a pagar). Por ejemplo, en el modelo 3a el 5% significa que el modelo minimizará los costes de carga restringidos a tener una variabilidad de la carga inferior al 105% de la mínima variabilidad de la carga posible.

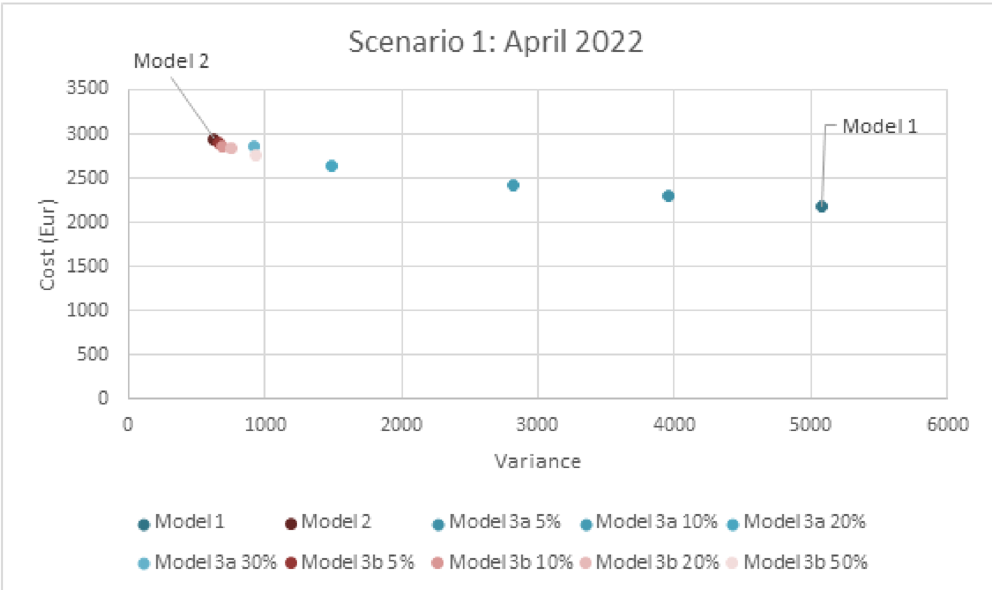

Ilustración 2: Compensación entre el coste y la varianza obtenida de los diferentes modelos en abril de 2022

La Ilustración 2 muestra las compensaciones entre el coste y la varianza que experimentan los resultados de todos los modelos estudiados para el Escenario 1. En primer lugar, se observa una relación inversa entre el coste y la varianza. Cuanto menor es el coste, mayor es la varianza. Sin embargo, un pequeño aumento de los costes reduce mucho la varianza.

En segundo lugar, como era de esperar, los resultados de los modelos 1 y 2 se sitúan en los extremos y los de los modelos 3a y 3b entre medias. Como los modelos 3a y 3b tienen restricciones en el coste de carga o en la variabilidad de carga, sus valores objetivo aumentan en función del porcentaje elegido en la restricción. Por ejemplo, la variabilidad de carga del modelo 3b aumenta con respecto al modelo 2, pero su coste disminuye, acercándose al resultado del modelo 1.

En tercer lugar, se observa que los resultados del modelo 3b son todos muy próximos entre sí, ya que la baja varianza mínima hace que el porcentaje extra en las restricciones de varianza para este modelo sea casi imperceptible, con muy poca diferencia respecto a lo que se observa en los resultados del modelo 1 y del modelo 3a.

-Análisis de variables

El escenario 4 (abril de 2019) se utiliza como referencia dadas las condiciones estándar vividas en ese mes. Los precios de la electricidad fueron normales, la generación solar es importante pero no tan alta como durante el verano y la demanda de electricidad se acerca a la media anual.

- Modelo 1 (Coste 814,62 Eur; 5057,88)

El resultado de este modelo tiene un coste muy bajo pero una variabilidad de la carga muy alta.

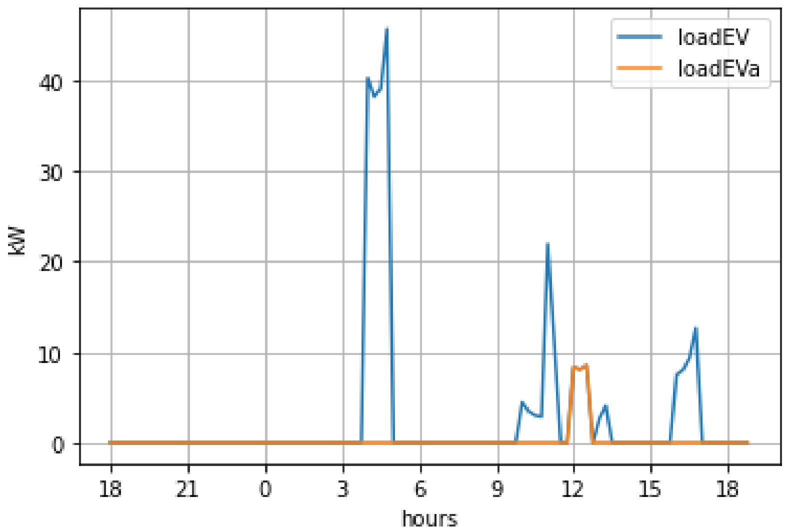

Ilustración 3: Resultados de la evolución de la carga de VE para el modelo 1 en abril de 2019

La Ilustración 3 permite entender mejor cómo se organiza el horario de carga. Se produce un gran pico que alcanza los 40 kW de potencia de carga en torno a las 4-5 de la madrugada, dado que es a esa hora cuando el precio de la electricidad es más bajo. También se produce una parte de la carga antes de la tarde y por la noche, beneficiándose de la energía solar producida. El vehículo elegido se carga a mediodía, cuando no se está cargando ningún otro vehículo, y lo hace casi a la máxima potencia.

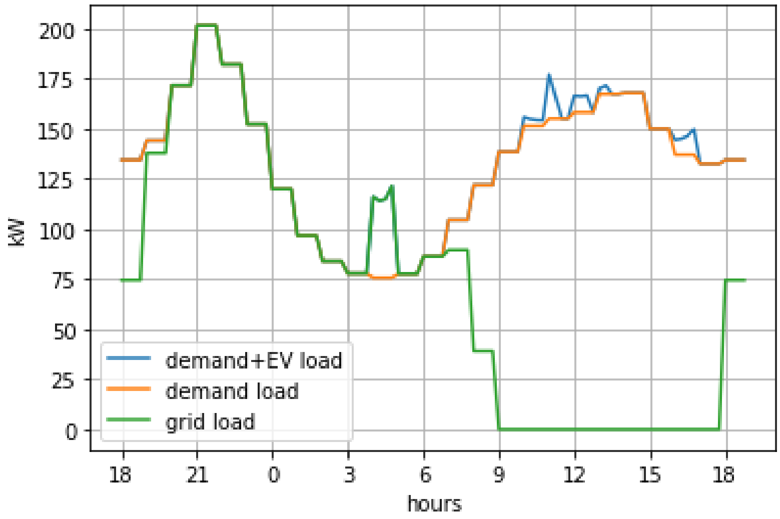

Ilustración 4: Evolución de la demanda, carga de VE y la demanda a la red para el modelo 1 en abril 2019

La Ilustración 4 ayuda a entender cuál es la potencia demandada a la red, así como la forma en que el horario de carga modifica la carga de la demanda. El pico antes de la medianoche contrasta con el valle durante el día, aunque la demanda sigue siendo alta durante el día. El pico de carga es sólo un pequeño pico a las 4-5 de la mañana, dado que los 40 kW máximos alcanzados por la potencia de carga son relativamente pequeños en comparación con la demanda de electricidad, que alcanza valores de 200 kW.

- Modelo 2 (Coste: 1371,55 Eur; Var: 616,47)

El resultado de este modelo tiene un 168% de costes de carga y una varianza de sólo el 12% del resultado del modelo 1.

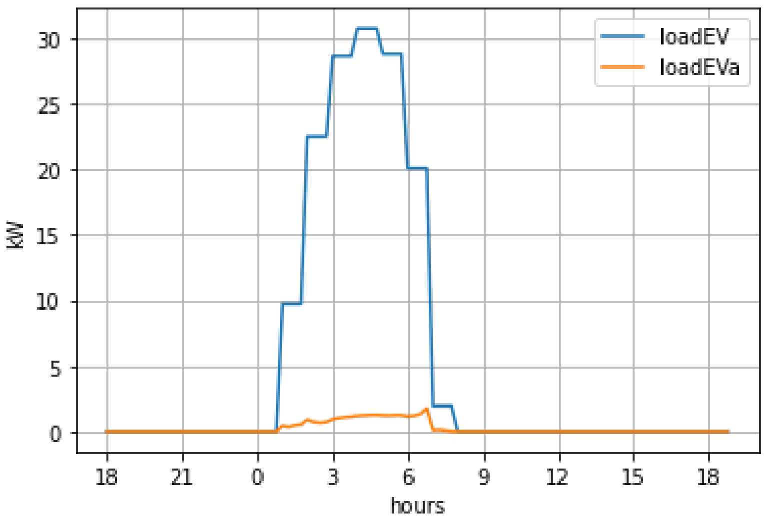

Ilustración 5: Resultados de la evolución de la carga de VE para el modelo 2 en abril de 2019

La primera diferencia que se aprecia en la Ilustración 5 con respecto a la Ilustración 3 es que el pico que se produce por la noche no es tan pronunciado. La carga máxima alcanzada por el VE es algo superior a los 30 kW. La carga sólo tiene lugar por la noche. La minimización de la varianza desplaza las cargas a las horas nocturnas – cuando los precios de la electricidad son más bajos – de forma natural, sin ninguna restricción de costes. La carga del vehículo elegido se reparte por todo el rango de horas de carga – desde la 1 de la madrugada hasta las 8 de la mañana aproximadamente.

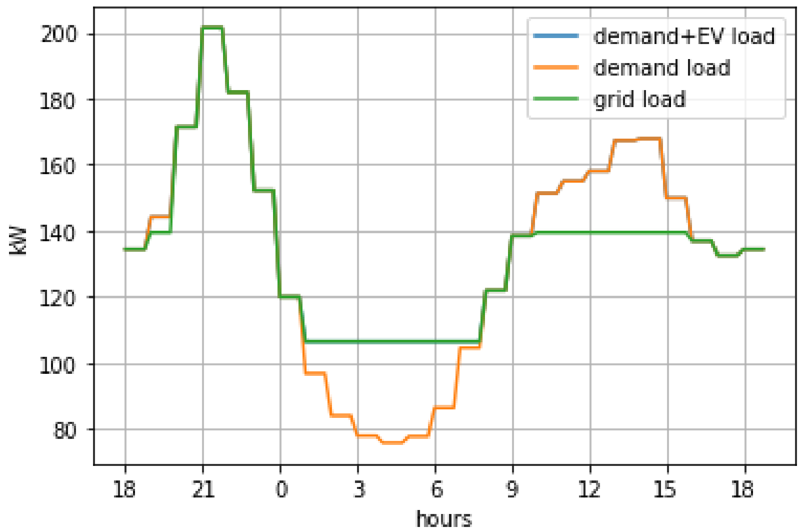

Ilustración 6: Evolución de la demanda, carga de VE y la demanda a la red para el modelo 2 en abril 2019

La Ilustración 6 muestra que la minimización de la variabilidad impone una demanda a la red mucho más plana. El pico antes de medianoche no puede reducirse más, ya que no hay producción de energía solar y la demanda de electricidad no puede modificarse. El valle de demanda de electricidad se rellena con la carga de los vehículos eléctricos para que la carga de red sea mucho más plana.

5. Conclusión

España carece de la infraestructura de recarga necesaria para permitir una mayor penetración de los vehículos eléctricos en las carreteras españolas.

A pesar de ser uno de los principales fabricantes de automóviles – el octavo del mundo y el segundo de Europa – todavía no se ha producido la electrificación de la producción ni de la flota de vehículos. Sólo el 2,2% de toda la flota de vehículos es eléctrica. Sin embargo, las ventas de vehículos eléctricos han aumentado de forma constante durante los últimos años, pero a un nivel más lento que el de otros países europeos. En concreto, España es el tercer país con peores resultados de Europa según el índice global de electromovilidad de ANFAC.

La percepción errónea que tienen los españoles sobre las capacidades de los VE es otra barrera para su penetración. Los incentivos nacionales como el Plan MOVES parecen ayudar, pero no son suficientes. La recarga inteligente podría ser útil para disminuir los costes de recarga o promover la compensación por participar en los servicios auxiliares, como forma de hacer más atractiva la compra de un VE.

Los modelos diseñados cumplen claramente los objetivos planteados. Los costes de carga y la variabilidad de la carga pueden reducirse en gran medida gracias al método de optimización empleado. Además, se optimiza el uso de la energía solar generada para reducir al máximo los costes. Ningún conductor lleva su coche con menos del 80% de la capacidad de la batería, no se perjudica al alimentador ya que nunca se alcanza la capacidad máxima y no se desperdicia la energía solar generada. Sin embargo, algunas limitaciones hacen que estos modelos sean imperfectos.

La primera y mayor limitación de este modelo es la suposición que se hace sobre las horas de llegada y salida. Aunque el modelo empleado para estimarlas da aproximaciones muy cercanas a la realidad, los resultados no dejan de ser estimaciones. No hay certeza de que esas horas sean correctas, y casi seguro que no lo serán. Además, se supone que la generación de energía solar se da el día anterior, pero el problema es que sólo se pueden hacer previsiones muy precisas, nunca valores exactos.

Por último, no hay una solución única. Según la importancia que se dé a cada atributo – costes o variabilidad de la carga – el modelo dará una u otra solución.

El resumen del diseño de este modelo no podía terminar sin insistir de nuevo en la importancia de la recarga inteligente para abordar los futuros problemas que provocará la mayor penetración de los vehículos eléctricos.

La carga incontrolada puede afectar gravemente a la distribución de electricidad y a la infraestructura de la red. Al aumentar incontroladamente el pico de demanda, no sólo de forma agregada sino también en zonas locales, el sistema podría fallar y miles de personas sufrirían los efectos sociales, económicos y políticos. Además, se necesitarían inversiones en la generación de energía, el hardware de la red y las redes de distribución.

Para resolver todos estos problemas, la recarga inteligente es una solución inmejorable. Desplazar las cargas de recarga de los vehículos eléctricos para minimizar los problemas explicados anteriormente es el camino a seguir. No sólo se pueden reducir en gran medida las inversiones en capacidad de generación de energía o en capacidad de la red, sino también los costes de recarga para los consumidores. Además, se puede maximizar el uso de las energías renovables.

Todas estas ventajas hacen de la recarga inteligente la solución ideal que permitiría una mayor penetración del VE.

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ANALYSIS OF THE SPANISH EV CHARGING INFRASTRUCTURE. DESIGN OF A SMART CHARGING MODEL AND ITS INTEGRATION WITH SOLAR PV GENERATION IN A RESIDENTIAL ENVIRONMENT

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ABSTRACT

1. Introduction

The motivation behind this project is to promote the use of electric vehicles and renewable energies as a powerful alternative to fight against climate change. In order to do so, an in-depth analysis of the Spanish charging infrastructure and the design of a smart charging model for integrating solar energy generation with electric vehicles (EVs) on a residential environment have been carried out.

The Earth has experienced a steady rise in average temperatures, which can be related to the increase in the concentration of greenhouse gases in the atmosphere [1]. This rise in temperatures makes the climate change and the consequences are multiple and of high importance. Rising sea levels, intense droughts, water scarcity, flooding, melting polar ice, severe fires, catastrophic storms and declining biodiversity. Humans are experiencing and more will experience climate change in many ways. Climate change may affect our health ability to grow food, housing, safety and work. Rising sea levels and saltwater intrusion have affected whole communities who have had to relocate. People living near the coast may have to relocate too due to the increasing sea level. Protracted droughts put people at risk of famine. There is no doubt that the consequences of climate change are severe and that action must be taken [2].

To understand the causes behind climate change, it is necessary to explore the different factors that might be playing a role. As external forces, solar activity and the Milankovitch cycles can be discarded. Climate does not respond to most of the variations in solar activity that occur in a timely, shorter-period manner, as they are too small [3]. The Milankovitch cycles have great effect on long-term climate, but they cannot make up for such a sudden

change in global temperature [4]. Other sources of greenhouse gases, like volcanoes or plants, could be responsible for this abundance of greenhouse gases molecules in the atmosphere. However, thanks to concentration levels of carbon-14 in CO_2 molecules entering the atmosphere, we know that it is not true. Only living beings that have been dead for millions of years could be the reason of the concentration levels of carbon-14 in CO_2 molecules entering the atmosphere [5]. Therefore, it seems reasonable to point coal, oil and gas as responsible. More than 35 gigatons of CO_2 were emitted worldwide in 2019. Only China, US, India and Russia contribute to almost 55% of the world's emissions [6].

Human activity in a variety of sectors is the main cause of climate change. Energy use in industry, agriculture, forestry and land use, energy use in buildings, and transport are the most contributing sectors [7]. All of them have less-polluting alternatives, but their deployment is low. Within the transport sector, road transport – which accounts for more than 70% of the emissions – could be entirely replaced by green alternatives.

The focus of the project is to help on cutting those road transport emissions. Electric vehicles are the current alternative we have. They have already been designed and improved to the point that they are direct competitors of ICEVs (internal-combustion engine vehicles). Higher penetration of electric vehicles is needed, but it cannot be achieved before solutions to issues they have like their impact on the grid are found. The smart charging model designed pursues this objective, as well as reducing charging costs.

2. State of the art

In this chapter the purpose is to show what the Spanish charging infrastructure and regulation looks like, as well as introduce the concept of smart charging and explain what the different existing models take into account.

-Analysis of the Spanish electromobility

The automotive industry plays a huge role in the Spanish economy. Only the manufacturing of vehicles and their components accounted for approximately 8% of the Spanish GDP in 2020. The adaptation capacity and the high demand of Spanish vehicles made Spain become the 8th biggest manufacturer in the world and the 2nd in Europe. However, it is not yet prepared for a huge penetration of manufacturing of alternative vehicles. Only 164,821 alternative vehicles were produced in 2020, accounting for 7.3% of the total [8].

The Spanish fleet is one of the oldest in Europe, with an average age of more than 13 years old. As can be seen in Illustration 1, low-emissions vehicles – classified as DGT ZERO and DGT ECO – have poorly been introduced into Spanish roads, as they only account for 2.2% of the total Spanish vehicle fleet. Nevertheless, EV sales have steadily increased for the past years. In 2020, EV registrations accounted for almost a fifth of the total new registrations [8].

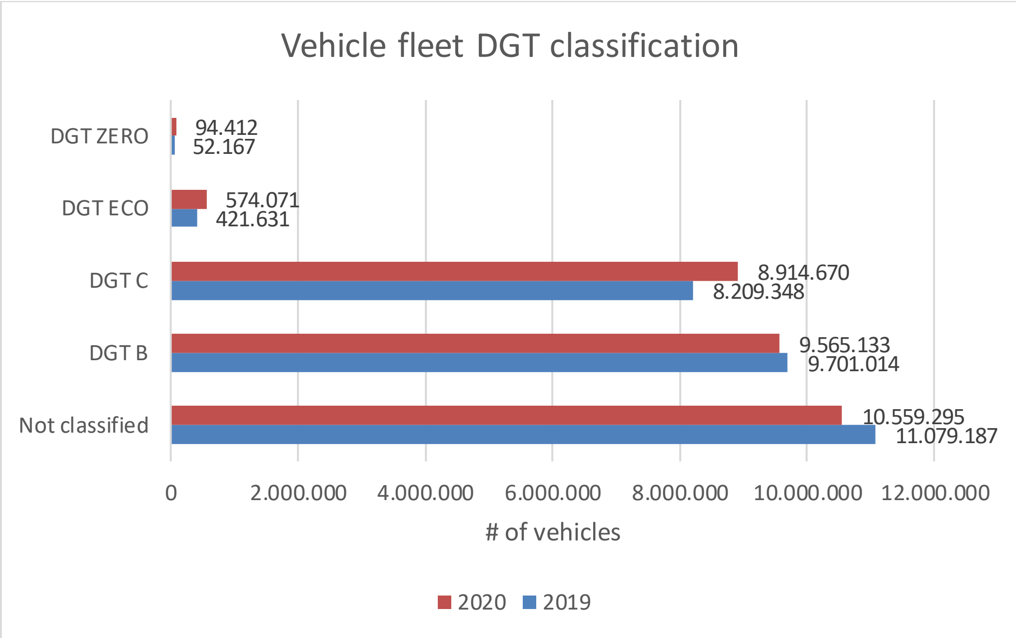

Illustration 1: Breakdown of vehicle type depending on DGT classification. Source: ANFAC 2020 [8]

When compared to its European colleagues, Spain performs really badly in both EV penetration and charging infrastructure. Spain got 13.3 points in the 100-point global electromobility index designed by the ANFAC, while the European average was 28.1 points. Within Spain, Madrid, Catalonia, and Navarra are the best performing regions, while Andalusia, Extremadura, and Ceuta and Melilla got the lowest punctuations [8].

-Spanish charging infrastructure

There is a huge misperception of electric vehicles in Spain that make it difficult for people to buy them. In 2018, 57% of the Spanish consumers felt that the biggest barrier towards buying an EV was the low autonomy of these vehicles. However, this perception radically contrasts with the fact that current EV autonomy is enough for covering 95% of the rides in

Spain. That misperception, combined with the lack of charging infrastructure, is a huge barrier for EV penetration in Spain [9]. Having a solid charging infrastructure is key to change this mindset and public help is needed. National incentive programs to promote EV use like the MOVES Plan – which stands for Efficient and Sustainable Mobility in Spanish – already exist. This Plan aims to incentivize EVs and FCEVs purchases by conceding aids up to 7,000 Eur as of 2021 [10]. Some regulation regarding minimum charging spots in parkings also try to incentivize EV use.

The available public charging points in Spain are very varied: charging speeds of up to 400 kW (recently introduced by Porsche and Iberdrola in Elche), all four charging modes – which differ in the amount of information shared between the EV and the grid, and many different connectors – like the SAE j1772, Mennekes, Scame, CHAdeMO, CSS, etc. There is modern regulation regarding the charging points schemes and elements, which can be classified into private garages, community garages, and charging stations [11].

-Smart charging

Smart charging consists of controlling the power rate at which the vehicle is being charged in real time under some constraints. These constraints and the objective chased can vary a lot depending on the smart charging strategy, but most of them have something to do with connection or grid capacity, load variations, local energy production, renewable energy shares, electricity prices and user needs. Smart charging is a way of managing electric vehicle loads through vehicle-grid integration [12].

Under a massive penetration of EVs scenario, if charged uncontrolledly, many EVs could be charging at the same time increasing the peak demand on the grid and contributing to overloading it. More energy capacity generation and upgrades at the distribution level could be needed. The increasing demand for electricity in a high-penetration-of-EVs scenario will also require distribution grid investments. In addition, there is a great challenge that must be encountered by distribution systems in order satisfy EV users' needs: fast charging. The higher powers required by fast charging need of higher capacity of the distribution networks [12].

That is why smart charging is needed. At a system level, EVs charged smartly can help shaving the peak demand and therefore avoid investments in upgrading peak generation capacity. As grid-connected storage batteries, EVs can offer many services to the grid:

frequency control through primary, secondary, and tertiary reserve; fill load valleys, managing the variability in voltage or increase the variable renewable energies (VRE) consumption by shifting their charging times to renewable energies generation times. At a local level, similar services can be provided. Reducing local congestion and increasing the VRE self-consumption are seen as best uses. EVs can also store back-up power in case of local grid shutdowns [12].

-Existing smart charging models

Smart charging can be implemented using different strategies and technical specifications. Strategies vary depending on the objectives (cost minimization, variability of the load minimization, maximization of VRE consumption, etc.) and constraints (feeder capacity, grid voltage ranges, charging point specifications, EV capabilities, user needs and technology used) [13]. Among the technical ways of implementing smart charging, some direct control mechanisms – necessary at higher EV penetration levels in the long-run – stand out from others:

- Unidirectional control of EVs (also known as V1G): it allows to control the power rate – from 0 to the maximum power rate available.
- Bidirectional control of EVs (also known as vehicle-to-everything, or V2X): EVs can both be charged and discharged at a controlled power rate in order to provide more flexibility

Two mainstreams for smart charging implementation based on control architecture exist: centralized approach and decentralized approach. In a centralized scheme, the charging of all vehicles is optimized by a single aggregator in order to reach an objective. In a decentralized scheme, each EV has a different optimized charging schedule that is established independently once the vehicle is plugged in order to reach the users' specific objective [14].

The different smart charging models also vary in approach. There are some models that establish the power rates for each vehicle at each time prior to the time period in which they will be used. This is done by assuming starting state-of-charges and arrival and departure times, based on very accurate forecasts [15]. On the other hand, some models employ real-time schedule. The power rate for each vehicle is established just when the vehicle arrives.

Therefore, no assumptions of arrival times are made, and the departure times are asked to the drivers [16].

3. Description of the model

The two models presented in this study establish optimal charging schedules depending on the objectives pursued: model 1 is a linear programming (LP) problem that pursues a charging cost minimization, while model 2 is a quadratic programming (QP) problem that pursues load-variability minimization. An in-depth comparison will be made among the results obtained based on the different objectives pursued. Furthermore, an analysis of the sensibility of the outcomes of both models will be made by adding a restriction on maximum load-variability and charging cost to models 1 and 2 respectively. Solar energy generation is also considered in the model.

The variables employed in this model are: power consumption of each EV at each period, state of charge of each EV at each period, amount of solar energy generated sold to the grid at each period, amount of solar energy generated used to satisfy internal load.

The parameters employed are: arrival and departure times and states of charge of each EV, capacity, charger efficiency and maximum power rate of each EV, maximum and minimum states of charge of each EV, and electricity price, price of energy injected into the grid, demand load and solar energy generation at each period.

The constraints used are: maximum power rate, PEV user charging requirement, state-of-charge matches, PEV minimum and maximum battery capacity, dynamic charging update, maximum feeder capacity, total solar energy generated, and solar-energy-generated-used-to-satisfy-internal-demand maximum value.

4. Results

-Case study

This model is proved in a 20-electric-vehicle residential environment in El Puerto de Santa María, Spain, which has solar PV installed. Six different scenarios were studied.

The values of the parameters were either modelled – like the arrival and departure times, assumed – maximum feeder capacity, power charging rate and charger efficiency, or taken from historic data – EV's capacities, demand load, electricity and injected energy prices and solar energy generation.

The six scenarios explored are April 2022, April 2022 only working days, April 2022 only non-working days, April 2019, July 2019, and January 2020. The reason behind the choices of these scenarios is to explore the change in charging patterns due to the different prices, demand loads, and solar energy generation in: weekday vs. weekend, pre-pandemic vs. post-pandemic, and summer vs. winter vs. spring/fall.

-Scenario 1 (April 2022) output of all models

The outputs of the model of all models for the first scenario are shown in the below figure. The percentage represents the maximum allowed deviation from the optimal value (which has been computed using models 1 and 2) of constrained characteristic for model 3a (cost minimization with a constraint on the load variability deviation) and of model 3b (load variability minimization with a maximum charging cost deviation that the EV user is willing to pay). For example, in model 3a 5% means that the model will minimize charging costs constrained to having a load variability less than 105% that of the minimal load-variability possible.

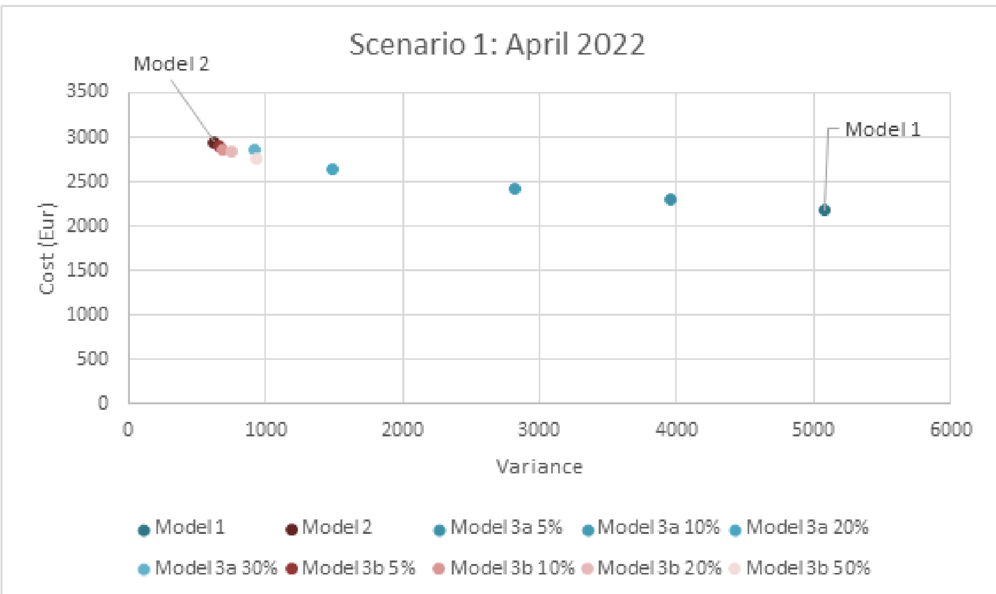

Illustration 2: Tradeoff between cost and variance experienced by the output of the different models in April 2022

The Illustration 2 shows the tradeoffs between cost and variance experienced by the outputs of all studied models for Scenario 1. Firstly, an inverse relationship between cost and variance can be seen. The lower the cost the greater the variance. However, a small increase in costs reduces much variance.

Second, as expected, model 1 and model 2 outcomes are at the extremes and model 3a and 3b outcomes are in between. As model 3a and 3b have constraints on either charging cost or load-variability, their objective values increase depending on the percentage chosen on the constraint. For example, model 3b's load-variability increases with respect to model 2, but its cost decreases, coming closer to model 1's outcome.

Third, it is noticeable that the model 3b outcomes are all very close to each other, as the low minimum variance makes the extra percentage in variance constraints for this model almost useless, with very little different relative to what is seen in model 1 and model 3a outcomes.

-Variable analysis

Scenario 4 (April 2019) is used as a benchmark given the standard conditions lived on that month. The electricity prices were normal, the solar generation is important but not as high as during summer and the electricity demand is close to an annual average.

- Model 1 (Cost 814.62 Eur; 5057.88)

This model's outcome has a very low cost but a very high variability of the load.

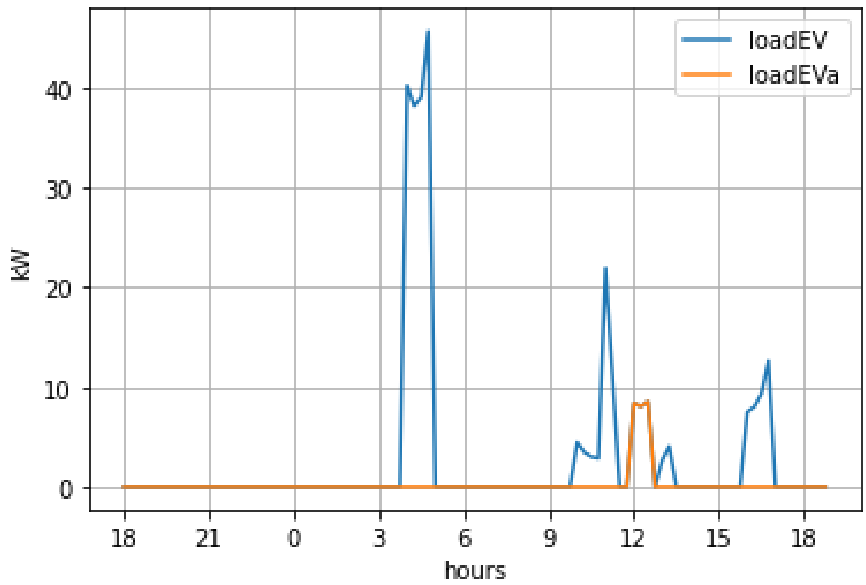

Illustration 3: LoadEV and LoadEVa evolution output using model 1 in Scenario 4

Illustration 3 gives a better understanding of how the charging schedule is organized. A huge spike reaching the 40 kW charging power rate at around 4-5 am occurs, given that it is at that time when the electricity price is lowest. Some charging also occurs before afternoon and in the evening, benefiting from the solar energy produced. The chosen vehicle is charged at noon when no other vehicle is being charged. This car is charged at almost maximum power.

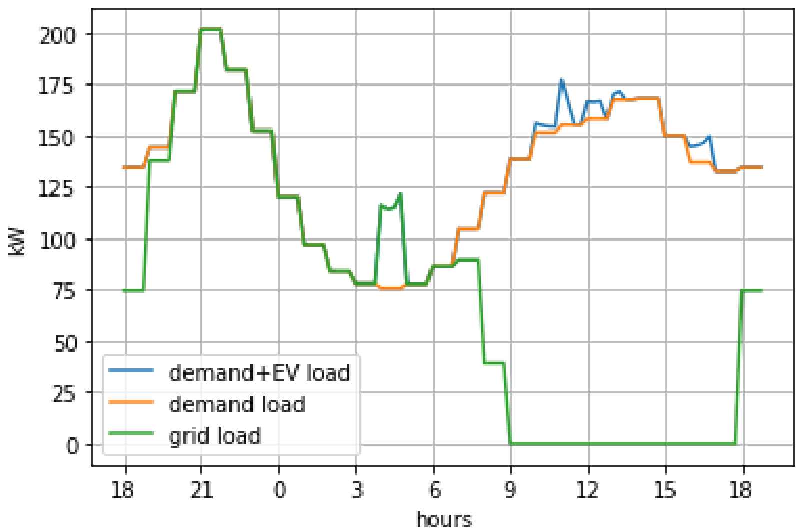

Illustration 4: Demand, demand+loadEV and grid load evolution using model 1 in Scenario 4

Illustration 4 helps understand what is the power demanded to the grid, as well as how the charging schedule modifies the demand load. As there is no restriction on variability, the peak before midnight contrasts with the valley during the day, even though the demand is still high during the day. The charging spike is just a little peak at 4-5 am, given that the maximum 40 kW reached by the charging power rate is relatively small compared to the electricity demand – which reaches values of 200 kW.

- Model 2 (Cost: 1371.55 Eur; Var: 616.47)

This model's outcome has a 168% charging costs and a variance of just 12% of the outcome of the model 1.

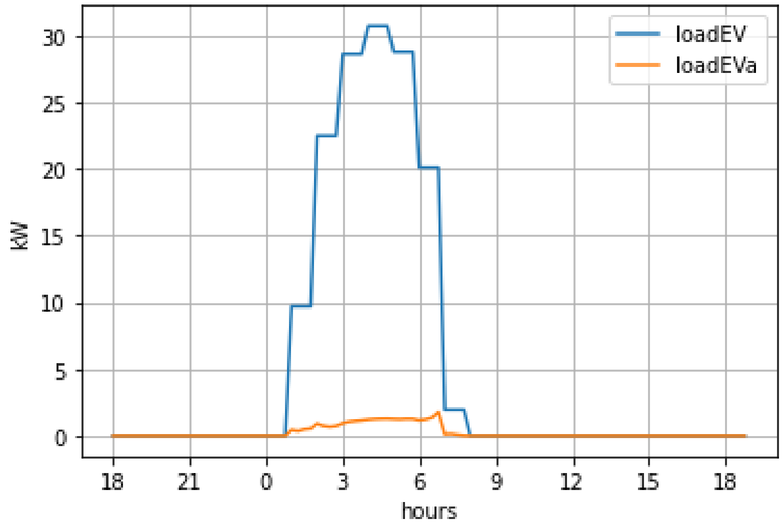

Illustration 5: LoadEV and LoadEVa evolution output using model 2 in Scenario 4

The first difference that can be seen in Illustration 5 with respect to Illustration 3 is that the spike that occurs at night is not that steep. The maximum EV load reached is a little higher than 30 kW. The charging only takes place at night. The variance minimization shifts the loads to night times – when the electricity prices are lower – in a natural way, without any cost restriction. The charge of the chosen vehicle is spread all around the charging times range – from around 1 am to around 8 am.

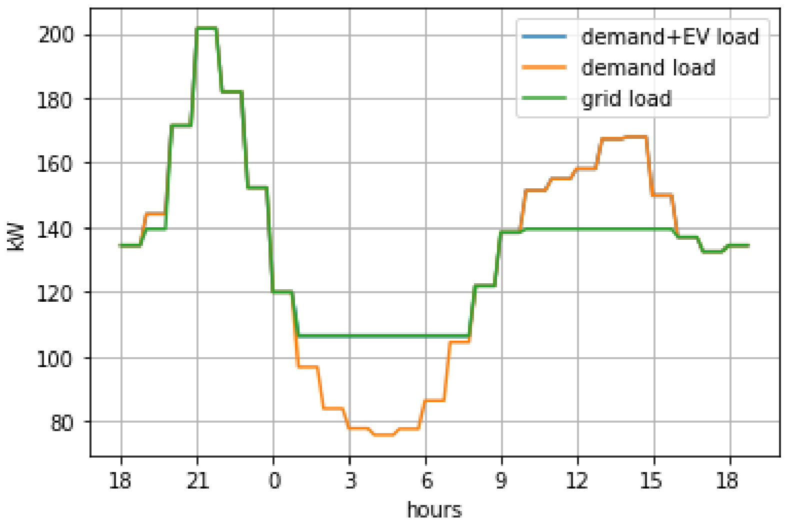

Illustration 6: Demand, demand+loadEV and grid load evolution using model 1 in Scenario 4

Illustration 6 shows that the variability minimization imposes a much plainer grid load. The peak before midnight cannot be further reduced as there is no solar energy production and the electricity demand cannot be changed. The electricity demand valley is filled with EV load in order to make the grid load much plainer.

5. Conclusion

Spain lacks of the necessary charging infrastructure in order to allow for a higher penetration of EVs on Spanish roads.

Although being a major car manufacturer – 8th in the world and 2nd in Europe – the electrification of neither the production nor the vehicle fleet has not happened yet. Only 2.2% of the entire vehicle fleet is electric. However, the EVs sales have steadily been increasing for the past years – but at a slower level than other European countries. To be concrete, Spain is the third worst performing country in Europe according to the ANFAC global electromobility index.

The misperception Spanish people have on EVs' capabilities is another barrier for their penetration. National incentives like the MOVES Plan seem to help, but they are not enough. Smart charging could be helpful in order to decrease charging costs or promote the compensation for participating in ancillary services, as a way of making the investment more attractive.

The designed models clearly accomplish the objectives set. Charging costs and the variability of the load can be greatly reduced thanks to the optimization method employed. Also, the use of generated solar energy is optimized so as to reduce costs as much as possible. No driver takes their car with less than 80% of the battery capacity, no harm is done to the feeder as the maximum capacity is never reached and no generated solar power is wasted. However, some limitations make these models imperfect.

The first and biggest limitation of this model is the assumption made about the arrival and departure times. Although the model employed to estimate them gives very accurate approximations of reality, the outcomes are still estimations. There is no certainty that those times will be correct, and almost for sure they will not. Also, solar power generation is assumed to be given the day before, but the problem is that only very accurate forecasts can be made, never exact values.

Finally, there is not a unique solution. Depending on the importance given to each attribute – costs or load variability – the model will give one or other solution

This model design could not be finished without emphasizing again on the importance of smart charging in addressing future problems that higher penetration of EVs will cause.

Uncontrolled charging can seriously impact the electricity distribution and the grid infrastructure. By uncontrollably increasing the demand peak, not just in an aggregate way but also in local areas, the system could fail and thousands of people suffer from social, economic and political effects. In addition, investments in power generation, grid hardware and distribution networks would be needed.

To solve all these problems, smart charging is an unparalleled solution. Shifting EV charging loads in order to minimize the problems explained above is the way to go. Not only investments in power generation capacity or grid capacity could be highly reduced, but also charging costs for consumers. Furthermore, renewable energy use can be maximized.

All these benefits make smart charging the ideal solution that would allow a higher EV penetration.

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Index

Chapter 1. INTRODUCTION

In this chapter a broad introduction explaining the motivation behind the project is made in order to arouse interest in the reader.

1.1 MOTIVATION BEHIND THE PROJECT

Since I realized the impact of the climate change on our planet, I have always wanted to help to mitigate its severe mid- and long-term consequences. I believe that the great opportunity I have of making a full individual project at my senior year in college must not be missed.

Along my undergraduate experience I have had plenty of interesting classes, but those related with electricity and energy – like Electrotechnics, Electric Power Systems, Electromagnetic fields, etc. – have especially caught my attention.

When exploring how to combine these two interests I had, two things came to my mind: renewable energies and electric vehicles (EVs). They were, and still are, two of the most relevant solutions to make the transition towards a greener planet. By leveraging these two alternatives, the share of renewables in the energy mix and the penetration of electric vehicles in the transportation system would both increase and hence reduce the greenhouse gases emissions that keep warming our planet.

However, most of the topics to which I could bring something new with my research were either too complex or not very motivating for me. I tried to change my mind and realized that electric vehicles are still in a very early stage of penetration into the current vehicle fleet. When searching for reasons, I noticed that costs were a huge barrier. There was one way to reduce their operational costs that I did not know: smart charging. That is when I knew what my project was going to be about. Smart charging is crucial for the future of electric vehicles, but it is still under development. It could also be combined with the generation of renewable energies: I had the opportunity of killing two birds with one stone. And I did not miss it.

1.2 CLIMATE CHANGE AND TRANSPORT

The importance of climate change is of general knowledge. But what are its main drivers? How can we stop it? Is there any planned action? All these issues will be explored in this section.

1.2.1 WHAT IS CLIMATE CHANGE? CAUSES AND EFFECTS

Climate change refers to long-term changes in weather patterns. Earth's climate is always changing and there are many possible causes to these changes, both external and internal. However, for the last 200 years, Earth has experienced a steady rise in average temperatures, and this rise can be related to the increase in the concentration of greenhouse gases, as Figure 1-1 illustrates in the case of carbon dioxide (CO_2) [1]. This sudden climate change is not like others and its consequences are severe and diverse.

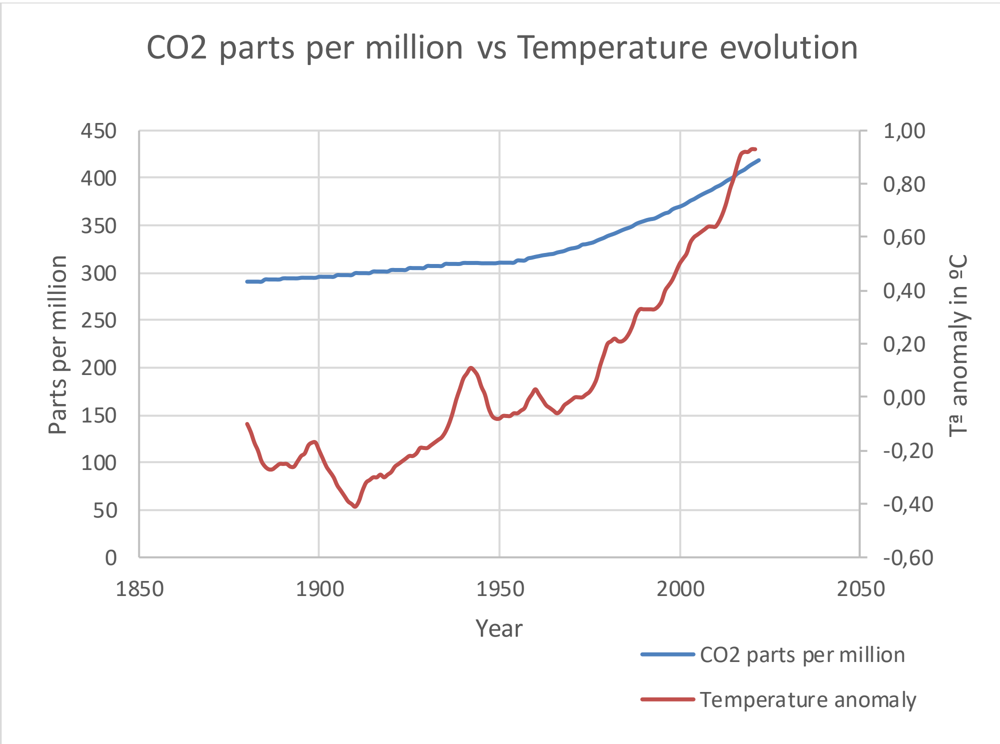

Figure 1-1: CO2 parts per million vs temperature evolution. Source: NASA [1] and EEA [2]

The consequences of climate change are multiple and of high importance. Because the Earth is a system in which everything is connected, changes in one area can influence changes in all others. The consequences of climate change include rising sea levels, intense droughts, water scarcity, flooding, melting polar ice, severe fires, catastrophic storms and declining biodiversity. Humans are experiencing and will experience climate change in many ways. Climate change may affect our health ability to grow food, housing, safety and work. Rising sea levels and saltwater intrusion have affected whole communities who have had to relocate. People living near the coast may have to relocate too due to the increasing sea level. Protracted droughts put people at risk of famine. There is no doubt that the consequences of climate change are severe and that action must be taken [3].

To know which are the causes for the global warming, it is necessary to better understand the greenhouse effect. The greenhouse effect is a process through which the energy coming from the sun warms the planet's surface and the atmosphere prevents the heat from returning back to space. Sunlight goes through the atmosphere and warms the surface, which then radiates heat. This heat is absorbed by greenhouse gases. Without this natural greenhouse effect, life on Earth as we know it would not exist, as the planet would be much colder, with an average temperature of Earth's surface of about -18ºC [4]. However, too much of these greenhouse gases could make the Earth warm above sustainable levels. The main greenhouse gases in Earth's atmosphere are water vapor, carbon dioxide, methane, nitrous oxide and ozone, being carbon dioxide the biggest contributor to global warming [4].

As illustrated in Figure 1-1, there is a high correlation between CO_2 concentration in the air and global temperature. However, simple correlation is not enough for implying a cause-and-effect relation. As stated before, there are many potential causes of global warming, both external and internal. Among the external forces, solar activity and the Milankovitch cycles have the highest importance on climate. There are internal sources of greenhouse gases emissions apart from human activity, such as volcanoes or plants that could be accounting for most of these greenhouse gases emissions.

Solar activity is the first external force explored. The sun is the source of most of our energy. Small variations in solar radiation could have huge impact in global climate. There are some little variations in solar radiation that occur approximately every 11 years. However, our climate does not respond to these variations because they are too small (<0.1%) and too quick. There could exist longer and bigger cycles which could impact the Earth's climate that we cannot notice using the direct data of the past 50 years. Nevertheless, using indirect measures, such as the level of carbon-14 in the tree trunks – the lower the level of carbon-14, the higher the solar radiation – we find other bigger cycles that have occurred periodically for the last ten thousand years. The most relevant cycle is the one that takes place every 200 years. Apparently, we should be living a colder period due to this cycle, but temperatures are rising. Therefore, solar activity cannot be a cause for the current global warming [5].

Another external force is the Milankovitch cycles, which include: the shape of Earth's orbit (eccentricity), the angle Earth's axis is tilted with respect to Earth's orbital plane (obliquity) and the direction Earth's axis of rotation is pointed (precession). These changes on Earth's movements have a great effect on long-term climate, but they are so slow – they take tens of thousands of years to be completed – that they cannot be making up for such a sudden change in global temperature [6].

There are other sources of greenhouse gases emissions, especially CO_2, such as volcanoes and plants. It is also known that volcanoes have caused other climate changes in past times. How do we know that all of the greenhouse gases emitted are our responsibility? The response is in the different concentration levels of the carbon isotopes in the air. The concentration level of the carbon-12 respect to carbon-13 or carbon-14 in the air is increasing with the increase in CO_2 in the atmosphere. This change in the concentration levels can only come from living beings, as volcanoes do not make distinctions between carbons[7]. However, the concentration level of carbon-14 in CO_2 molecules that are entering the atmosphere is almost null. Plants do emit carbon-14 in little quantities, hence they are not the huge source of CO_2 that is being emitted to the atmosphere. Only living beings that have been dead for millions of years do not have carbon-14 in their molecules. Therefore, it seems reasonable to think that the source of the massive amounts of CO_2 that are being emitted to the atmosphere is the burning of fossil fuels like coal, oil and gas [8].

Once human activity seems the most reasonable cause for the climate change, an analysis comparing countries CO_2 emissions and their emissions' drivers is done.

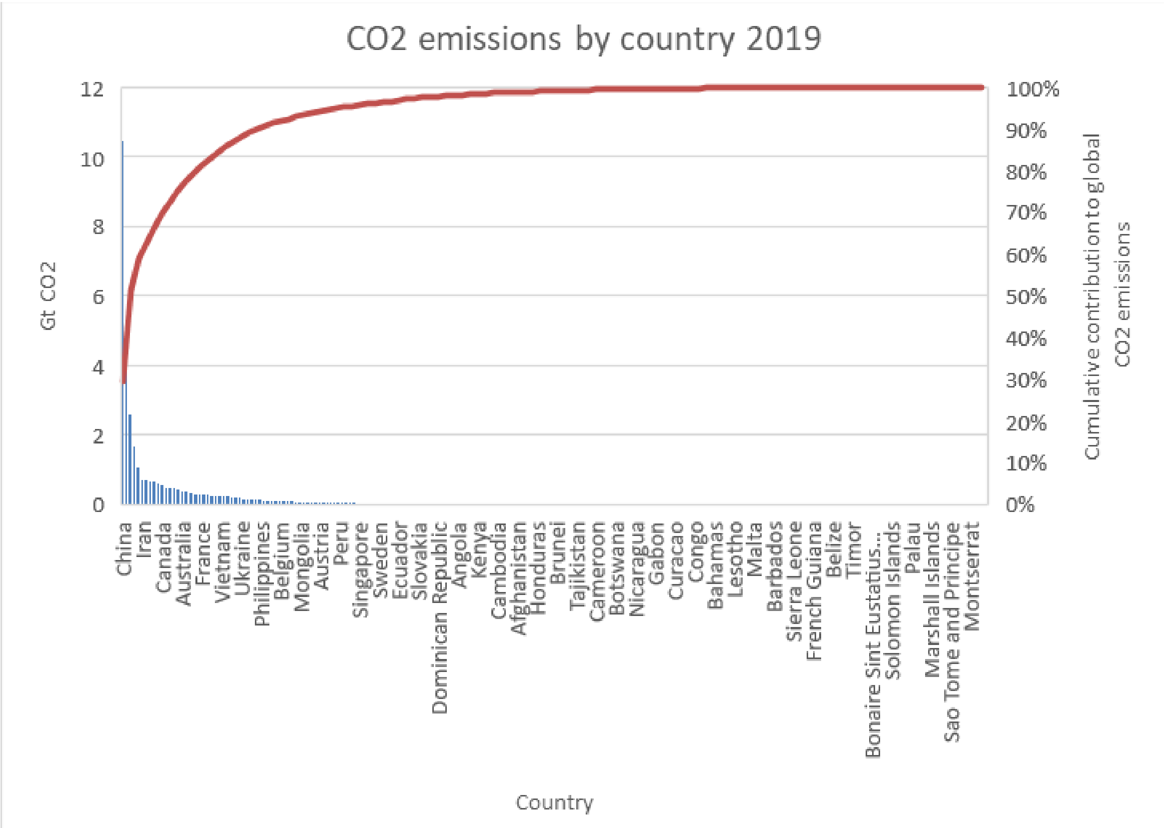

Figure 1-2: Countries' contribution to global CO2 emissions. Source: International Energy Agency [9]

The total worldwide CO_2 emissions during 2019 were around 36.72 gigatons [9]. It is easy to see from Figure 1-2 that CO_2 emissions by country follow a Pareto distribution. Few countries account for almost all global emissions, while most of the countries barely contribute in relation. Only China, the US, India and Russia – the four biggest contributors – alone, make up for almost 55% of the worldwide emissions.

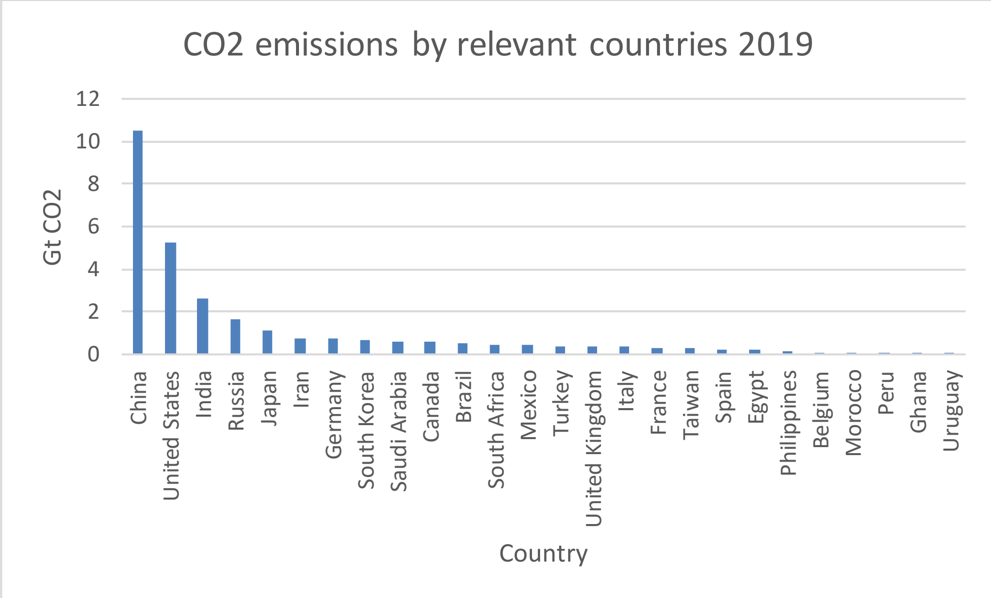

Figure 1-3: Relevant countries' contribution to global CO2 emissions. Source: International Energy Agency [9]

Figure 1-3 shows the CO_2 emissions of just some relevant and top-contributor countries. Industrialized and economically developed countries like the US, Japan and European countries have a huge impact on emissions relative to their size. BRIC countries (Brazil, Russia, India and China) all have emerging and very polluting economies, and it will be analyzed later that their impact is worrying. Big oil exporting countries such as Iran or Saudi Arabia also play a huge role. Unlike these ones, slower developing economies barely contribute to the total CO_2 emissions when compared to the formers.

But, why are there these differences among countries? The Kaya identity may answer this question. It is an identity stating that the total emission level of the greenhouse gas CO_2 of a country or region can be expressed as the product of four factors: human population, GDP per capita, energy intensity (energy consumption divided by GDP) and carbon intensity (grams of CO_2 that it takes to produce a kWh). Below, graphs of changes of these factors over time using the year 2000 as a benchmark (value 100 in year 2000) are provided.

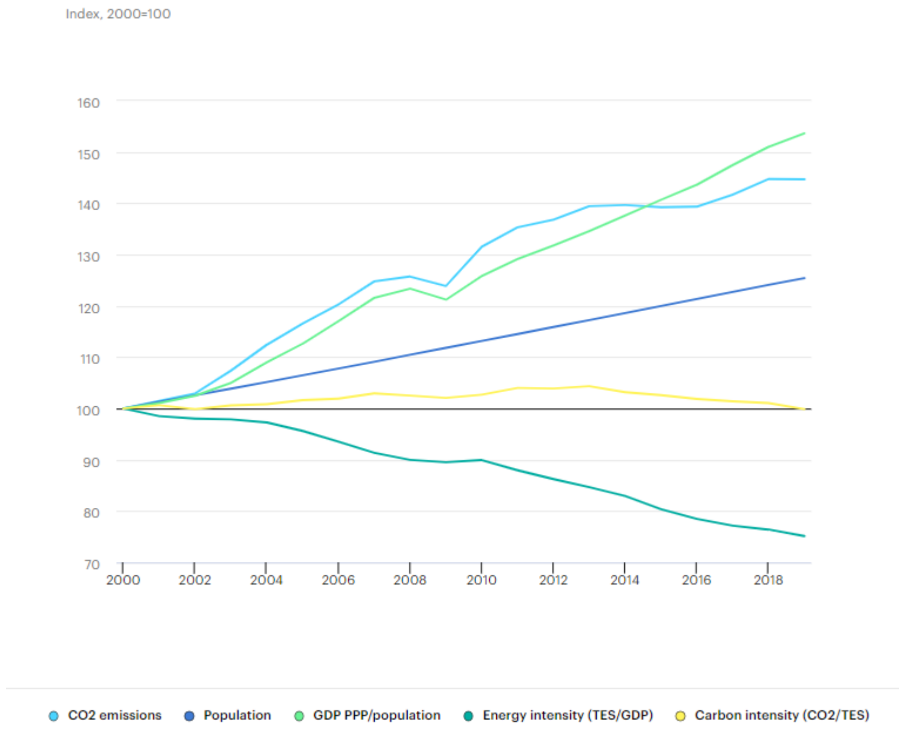

Figure 1-4: World's drivers of CO2 emissions over time. Source: International Energy Agency [9]

As Figure 1-4 shows, since 2000, global CO_2 emissions and GDP per capita have both increased by around 50%. Population increases approximately linearly with time, while carbon intensity has barely changed. However, energy intensity has decreased more than 20% – probably because GDP increases is increasing faster than energy consumption.

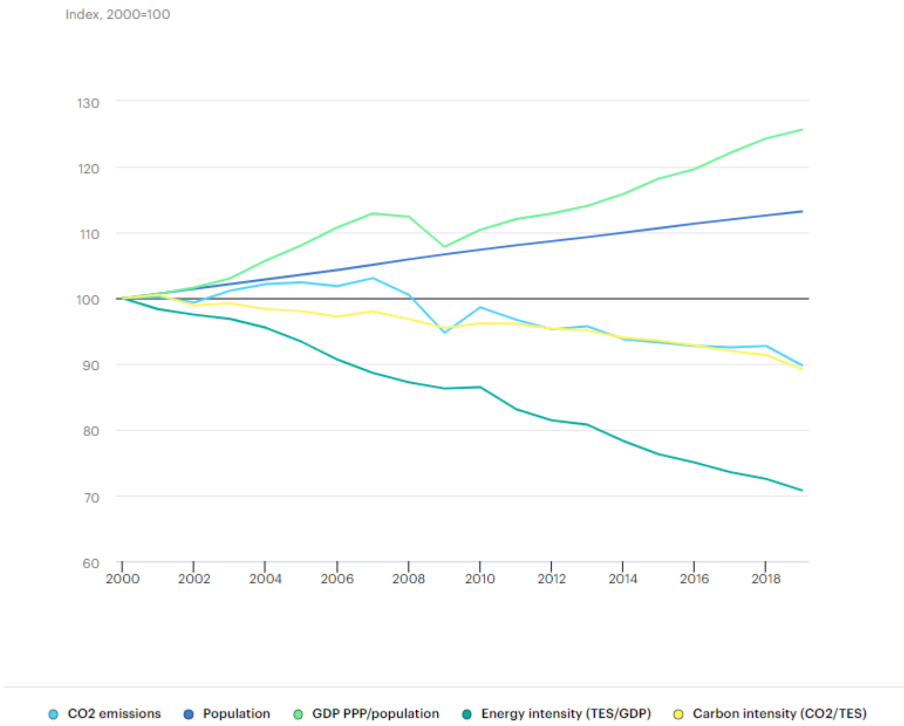

Figure 1-5: OECD's drivers of CO2 emissions over time. Source: International Energy Agency [9]

In Figure 1-5 only OECD countries are shown. The OECD includes the US, most European countries, Japan and other modern economies. It is easy to see that, while GDP per capita has steadily increased– except for the Great Recession shock – CO_2 emissions, carbon intensity and energy intensity have all decreased. Innovations in new power generation methods, effective cost reductions and efficiency due to great investments in R&D have helped reduce carbon intensity and energy intensity, as less greenhouse gases are emitted in order to produce the same amount of energy, and less energy is required to do the same activities.

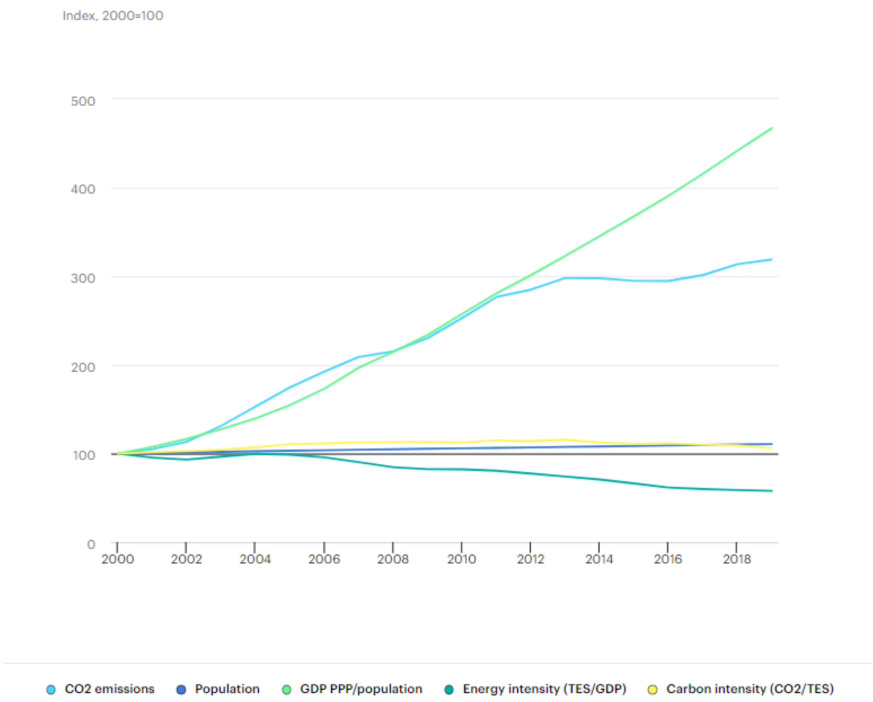

Figure 1-6: China's drivers of CO2 emissions over time. Source: International Energy Agency [9]

Figure 1-6 shows China's factors evolution. This evolution is similar to the ones of developing countries, such as India and Brazil. As stated before, these countries' CO_2 emissions are worrying as they have increased by more than 200% since 2000, almost linearly to their increase in GDP per capita. Their bumping economies and big populations need of so many resources. As the big-capacity power generation plants are the easiest and most feasible way of sourcing the energy needed to move these economies and most of those have a high-polluting nature, developing countries emit huge quantities of CO_2 with an increasing trend. Population and carbon intensity have not changed a lot in China (population has increased a lot in India). Only energy intensity has shown a decreasing trend, almost halving its 2000 value. The explanation for this is again that GDP increase in China clearly outpaces energy consumption increase.

The Kaya identity approximately holds for the shown cases, as increasing and decreasing factors counterbalance each other for CO_2 emissions to keep in between these factors' extremes.

1.2.2 BREAKDOWN OF SECTORS THAT CONTRIBUTE TOWARDS CLIMATE CHANGE

Although the drivers of greenhouse gases emissions and countries' contributions are clear, it is relevant to study what concrete human activities are the main sources of greenhouse gases emissions. A detailed breakdown of sectors and processes that contribute to global emissions is provided below.

According to the latest breakdown of global emissions by sector (2016), published by Climate Watch and the World Resources Institute, the many sectors that contribute to global emissions can be divided into the following categories: energy (electricity, heat and transport), direct industrial processes, waste and agriculture, forestry and land use [10].

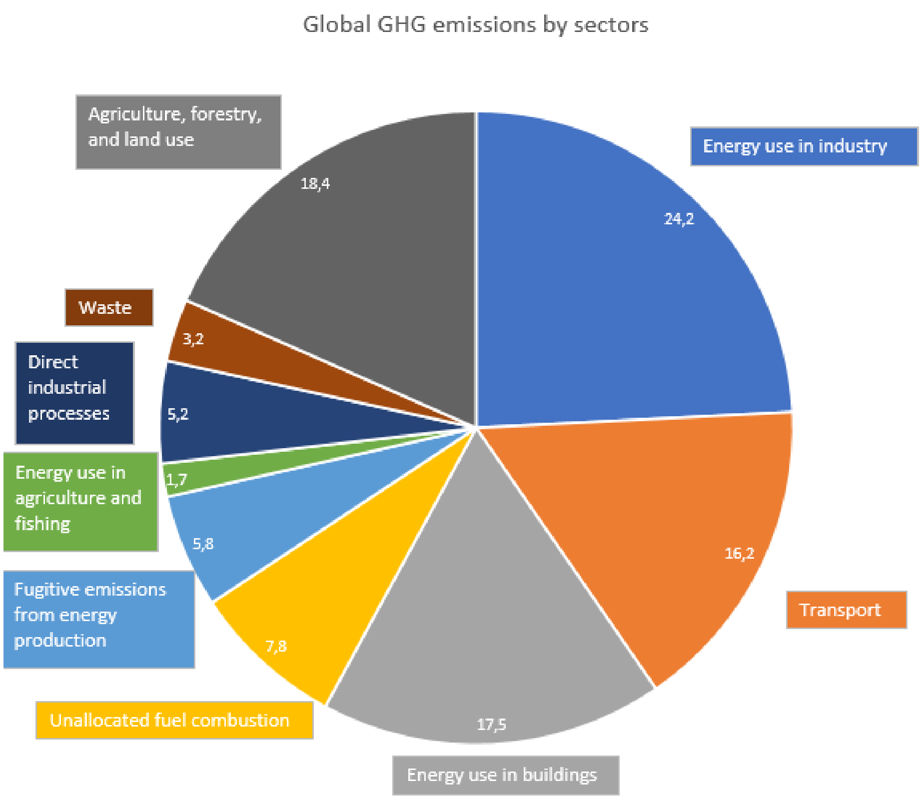

Figure 1-7: Global CO2 emissions by sectors. Source: Our World in Data [10]

As shown in Figure 1-7 energy is the biggest contributor to global emissions with a 73.2%, followed by agriculture, forestry and land use with a 18.4%, direct industrial processes with a 5.2% and waste with a 3.2%. A more detailed approach follows.

Energy is the biggest contributor, but it encompasses many varied sectors.

First, the energy use in industry – which accounts for 24.2% of the total – includes the energy-related emissions from manufacturing iron and steel (7.2%), chemicals and petrochemicals such as fertilizers or pharmaceuticals (3.6%), food and tobacco (1%), non-ferrous metals (0.7%), paper and pulp (0.6%), machinery (0.5%) or others such as mining and quarrying, construction, textiles, wood products and transport equipment (10.6%).

Second, the energy use in buildings account for 17.5% of total emissions and includes energy-related emissions from the generation of electricity for lighting, appliances, cooking, etc. and heating from both residential (10.9%) and commercial buildings (6.6%).

Third, the transport sector – which accounts for 16.2% of the total – includes a small amount of electricity (indirect emissions) as well as direct emissions from burning fossil fuels to power transport activities. Road transport (11.9%) – which includes the emissions from the burning of petrol and diesel from both passenger travels (cars, motorcycles and buses) that account for 60% of the road transport emissions and road freight (lorries and trucks) that account for the remaining 40% – plays an important role in transport. It is followed by aviation (1.9%), which includes emissions from passenger travels (81% of aviation emissions) and freight (19% of aviation emissions), shipping (1.7%), rail (0.4%) and pipeline (0.3%).

Following these bigger sectors are unallocated fuel combustion (7.8%), fugitive emissions from energy production (5.8%), and energy use in agriculture and fishing (1.7%).

The second biggest contributor – agriculture, forestry and land use (18.4%) – includes grassland (0.1%), cropland (1.4%), deforestation (2.2%), crop burning (3.5%), rice cultivation (1.3%), agricultural soils (4.1%) and livestock and manure (5.8%) – what is to say – the food system as a whole.

Direct industrial processes (5.2%) include cement (3%) and chemicals and petrochemicals (2.2%), which both produce greenhouse gases as a byproduct of the chemical processes.

Finally, waste (3.2%) includes wastewater (1.3%) and landfills (1.9%), from which methane and nitrous oxide is produced when the organic matter decomposes.

Although the data might seem a bit outdated, in fact relative emissions by sector have barely changed over the last few years, with energy in all its uses remaining as the top emitter by far [11].

The biggest insight that can be gained from this data is that there is no single solution to tackle global warming. It is not enough to focus on electricity, transport or food alone. Even just within the energy sector, if decarbonizing the total electricity supply, there would be a need to electrify transport and heating. Low-carbon technologies exist for most sectors, but have not been implemented yet due to unfeasibility, unprofitability or entry barriers. For other sectors, low-carbon technologies have not been developed yet.

1.2.3 PLANNED ACTION TOWARDS MITIGATING CLIMATE CHANGE

In order to tackle climate change and its terrible impacts, leaders from all around the world reached a historic agreement at the United Nations Climate Change conference on 12 December 2015: the Paris Agreement. The Agreement sets long-term goals to guide all nations:

- reduce global greenhouse gas emissions to limit the global average temperature to 2ºC above pre-industrial levels while pushing stronger to limit the increase even further to 1.5ºC;
- review countries' commitments and actions they will take to reduce their greenhouse gas emissions based on what stated on their Nationally Determined Contribution

(NDC) – an updated national climate action plan that each country is expected to submit every five years;

- provide finance support to developing countries to mitigate global warming and to enhance abilities to adapt to climate impacts.

The Paris Agreement serves as a useful and long-term framework for guiding each countries' efforts. It is also seen as the beginning of a shift towards a net-zero emissions world [12].

In order to reach the marked goal of keeping global average temperature below the 1.5ºC increase, cutting on 30 gigatons of greenhouse gas emissions annually by 2030 is necessary. Global greenhouse gas emissions were about 52.4 gigatons in 2019, of which 36.72 gigatons were CO_2 emissions [13].

But how? On the Paris Agreement the UNEP identified some potential ways to reduce emissions by 30 gigatons annually. First, humanity can cut 12.5 gigatons on energy generation by shifting to renewable energy and using less energy. Next, industry can cut 7.3 gigatons by introducing passive or renewable energy-based heating and cooling systems, improving energy efficiency and mitigating methane leaks. Innovative food production solutions can cut 6.7 gigatons by reducing food loss and waste or shifting to plant-rich or more sustainable diets. If halting deforestation and ecosystems degradation, the world could reduce emission by 5.9 gigatons. In addition, this would help restore ecosystems, improve air quality and give water security for rural population. Transport needs an electrification as soon as possible and around 4.7 gigatons of emissions can be reduced by using actual technology. Shifting to electric vehicles, encouraging people to walk, cycle or using other forms of non-motorized transport are all key to achieve the goal. Finally, by updating cities and homes infrastructures so as to improve efficiency and use low-carbon alternatives, emissions can be cut by 5.9 gigatons. The world has the numbers, now it is time to achieve them [14].

1.2.4 EVS AND RENEWABLE ENERGY AS A KEY SOLUTION

Although the UNEP sets the goal of cutting greenhouse gas emissions by 4.7 gigatons annually with the transport electrification, in Europe, the aim is to reach a net-zero scenario by 2050 in which transport would have to cut emissions by more than 90%. In this context, electric vehicles are the actual and feasible solution that humanity has. A higher penetration of these vehicles is needed in order to achieve the goals marked by the Paris Agreement. Pure electric vehicles could become zero-emitters if they were charged with electricity generated from non-emmiting generation, such as renewables. However, their batteries could be harmful to the environment [15], so additional efforts needs to be taken in order to successfully recycle them. A high penetration of electric vehicles into existing power systems is also challenging due to the massive electricity demands of these emerging loads. Uncoordinated charging of electric vehicles could result in power losses, voltage deviations or transmission and distribution risks [16]. Nevertheless, controlling the charging of these vehicles so as not to overload power systems – what is called smart charging – is seen as a solution and it will later be further explored.

Table 1-1 and Figure 1-8 show a comparison outlining the principal differences among the principal technologies used in Spanish road transportation in terms of cost, efficiency and emissions.

	BEVs	PHEVs	HEVs	Gasoline	Diesel
Autonomy (km)	160-450	31-73	1-4	385-911	800-1000
Avg energy cost (Eur/100km)	1,36	3,34	8,65	11,17	7,85
Maintenance cost (Eur/100km)	6,3	6,7	7,3	3,2	3,2
Noise impact (dB)	56-75	56-90	56-90	84-90	84-90
Avg energy efficiency	75%-80%	45%-50%	40%-45%	20%-25%	30%-35%
Emissions (g CO2/100km) with current energy mi	6000	9150	12500	14300	10700

Table 1-1: Comparison among different technologies. Adapted from: OBS [15]

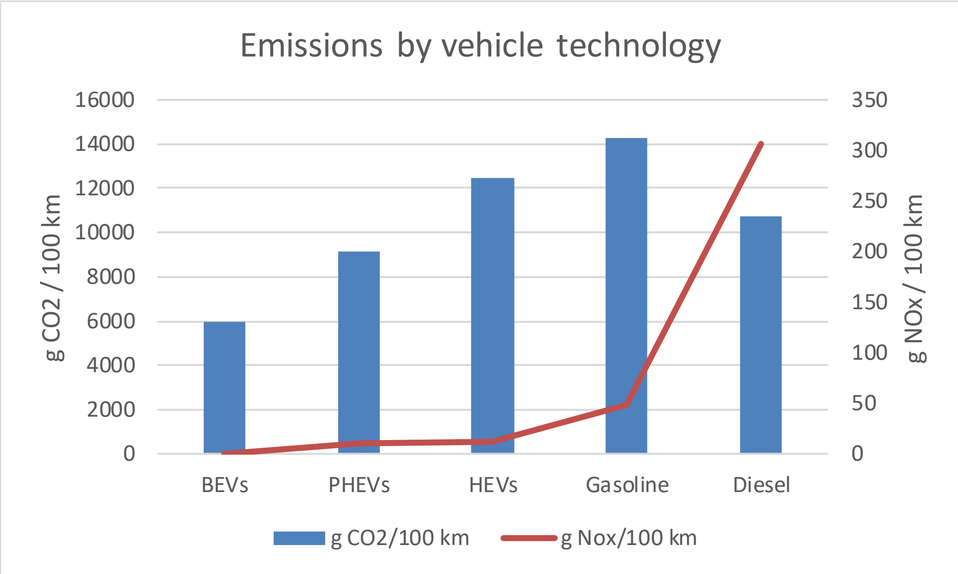

Figure 1-8: Emissions of CO2 and NOx classified by technology. Source: OBS [15]

Both Table 1-1 and Figure 1-8 support the statements made above. BEVs are the least polluting and most efficient ones, followed by PHEVs and HEVs.

However, even when electrifying the entire fleet of vehicles, they can still be indirectly polluting, as can be seen in Figure 1-8. The electricity consumed by these vehicles may have been produced in a highly polluting coal-fired plant or in a thermal power station. In order to cut emissions on electricity generation, a transition to renewable energies must be taken. Upscaling solar, wind and hydro generation – which only account for around the 25% of the world's electricity supply – is key [17]. The problem here is the generation-demand balance as solar or wind can only generate electricity when the sun is shining or the wind is blowing and may not coincide with demand. Low-carbon alternatives to this issue are being developed.

Electric vehicle charging and renewable energy use can both be combined in a try to maximize the reduction in greenhouse gases emissions. The objective of the case study analyzed in this project is to study how can smart charging increase the penetration of EVs and solar photovoltaic (PV) generation at a residential level.

The rest of the document is organized as follows: the state of the art is revised, in which an analysis of the Spanish electromobility and charging infrastructure is carried out, as well as an introduction to smart charging, its objectives, and different existing models. After that, the model is described, and its objective functions and constraints shown. Then, the results obtained from the different models and chosen scenarios are analyzed. Finally, a conclusion is made.

Chapter 2. STATE OF THE ART

2.1 SPANISH ELECTROMOBILITY ANALYSIS

2.1.1 INTRODUCTION

The automotive industry plays a huge role in the Spanish economy. Only the manufacturing of vehicles and their components accounted for approximately 8% of the Spanish GDP in 2020. When taking into account other services related to the automotive industry – such as distribution, insurance, financial services – this participation reaches 11% of the Spanish GDP. As a consequence, it also gives jobs to more than 9% of the total Spanish workforce [18].

In 2020 Spain produced 2,268,185 vehicles, a 19.6% less than the previous year due to the pandemic restrictions. However, the adaptation capacity and the high demand of Spanish vehicles made Spain become the 8th biggest manufacturer in the world and the 2nd in Europe [18].

Although the modernity and development of the Spanish automotive industry is undoubtable, it is not yet prepared for a huge penetration of manufacturing of alternative vehicles. Only 164,821 alternative vehicles were produced in 2020, accounting for 7.3% of the total [18]. The lack of charging infrastructure, the lack of effective policies that incentivize the alternative vehicles use, the lack of investments and the slow transition of consumers towards more innovative technologies make it difficult for the Spanish automotive industry to achieve the higher levels of growth of the manufacturing of alternative vehicles seen in other countries.

A deep analysis of the Spanish vehicle fleet, of the new registered vehicles and of the Spanish electromobility is made in this section.

2.1.2 VEHICLE FLEET

In 2020 the Spanish vehicle fleet increased by 0.8%, reaching the 29.7 millions of total vehicles. The vehicle average age kept its increasing trend reaching the 13.1 years old. Spain has one of the oldest vehicle fleets in Europe, whose vehicle average age is 10.8 years old [18].

The great recession in the new vehicles market produced by the pandemic and the forced shutdowns of car dealerships worsened the renovation situation, with 2020 Renove Plan having little impact. On the other hand, old vehicles unit sales have increased and even overpassed new vehicles unit sales. More than 50% of the used vehicles unit sales were vehicles over 10 years old [18].

The low-emissions vehicle fleet, with vehicles classified as DGT ECO – including hybrid electric vehicles (HEVs) and plug-in hybrid electric vehicles (PHEVs) with an electric autonomy under 40 km – or DGT CERO – including battery electric vehicles (BEVs) and PHEVs with over 40 km of electric autonomy – has enjoyed a great increase during 2020. The DGT CERO vehicles have increased by 81%, reaching the 94,412 units while the DGT ECO vehicles have increased by 36%, overpassing the half million units. This low-emissions vehicle fleet only accounts for 2.2% of the total Spanish vehicle fleet [18].

Figure 2-1 shows a comparison between total vehicle fleet, plug-in electric vehicles (PEVs) and HEVs percentages broken down by type.

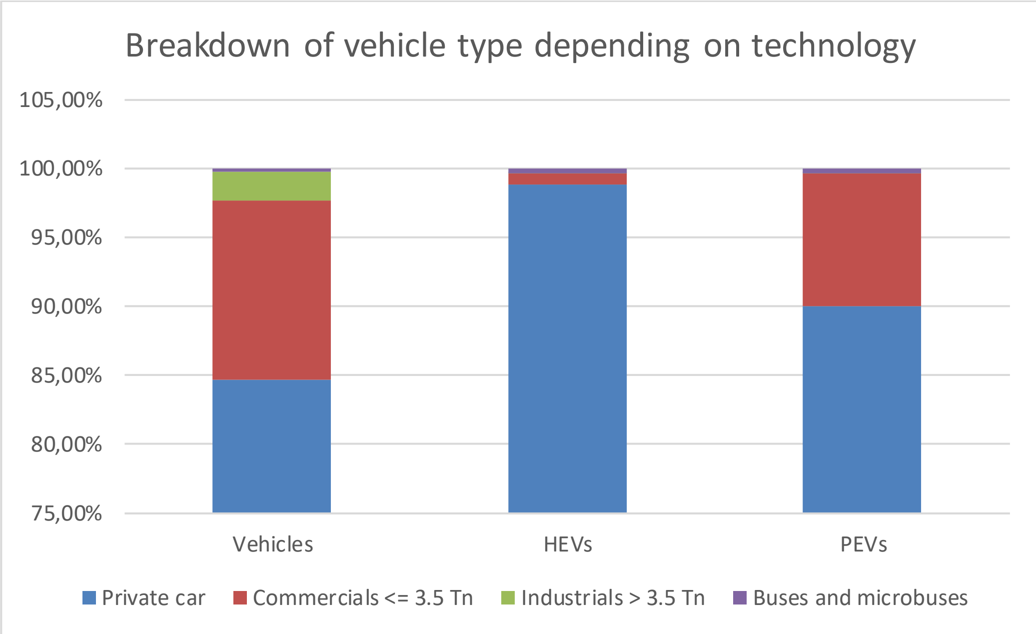

Figure 2-1: Breakdown of vehicle type depending on technology. Source: ANFAC 2020 [18]

Although it is important to take into account that HEVs and PEVs only represent a very small fraction of the entire vehicle fleet, some insights can be gained from Figure 2-1. Private cars are the most common vehicle type – accounting for more than 80% on each technology – but it is remarkable the incredible representation of private cars among HEVs. Not many commercial, industrial vehicles or buses use the hybrid technology. Commercial vehicles – those that weight less than 3.5 tons – account for more than 12% of the total vehicle fleet and almost 10% of the PEV fleet [18]. Industrial vehicles and buses using hybrid or plug-in electric technology barely exist. Lower autonomy, lack of charging infrastructure in highways and higher purchasing price might be some possible explanations for that.

Figure 2-2 shows a breakdown of the entire Spanish vehicle fleet by DGT categories. DGT B includes gasoline vehicles registered after 2000 and diesel vehicles registered after 2006. DGT C includes those gasoline vehicles registered after 2006 and diesel vehicles registered after 2014. The rest of the vehicles are not classified and are the most polluting ones. As explained before DGT ECO include hybrid electric vehicles (HEVs) and plug-in hybrid electric vehicles (PHEVs) with an electric autonomy under 40 km and DGT CERO include battery electric vehicles (BEVs) and PHEVs with over 40 km of electric autonomy [19].

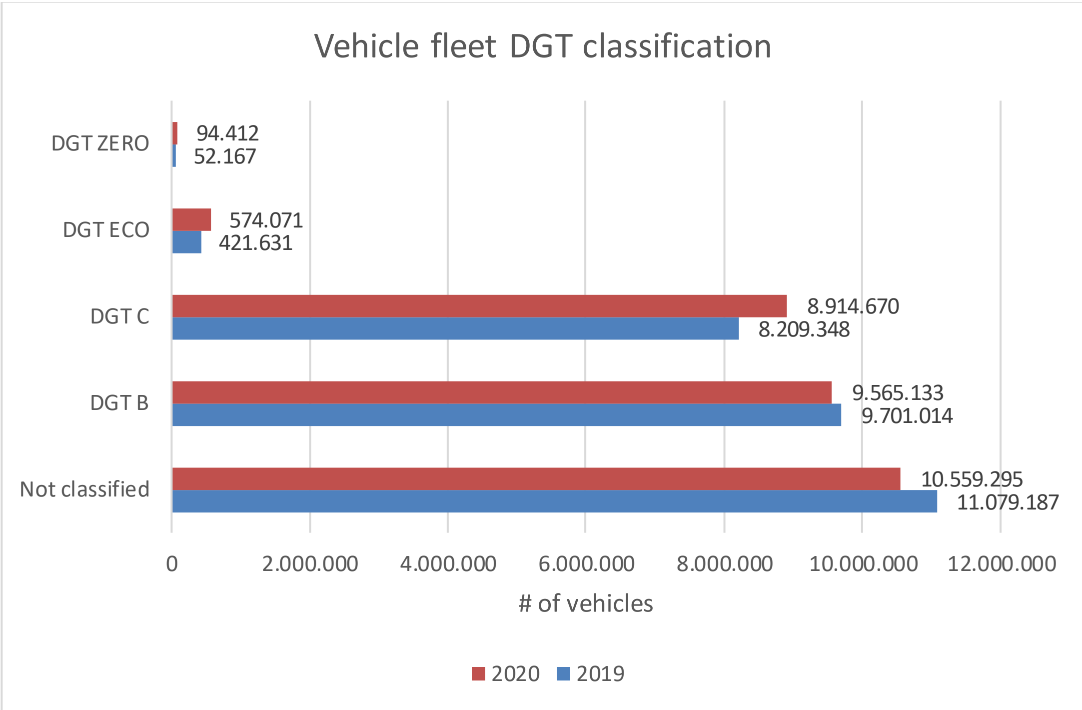

Figure 2-2: Vehicle fleet classified by DGT. Source: ANFAC 2020 [18]

As expected, most of the cars are not classified as DGT ZERO or DGT ECO, given the low fraction of cars using alternative technologies. The age of the Spanish vehicle fleet is quite impressive. Most cars are not even classified, while there are more DGT B than DGT C (newer than DGT B). However, the evolution is on the right trend, with a decreasing number of not-classified or DGT B vehicles and an increasing number of DGT ZERO and DGT ECO.

2.1.3 NEW EV REGISTRATIONS

The COVID-19 pandemic seriously affected the car industry in Spain during 2020, with a great decrease in sales. For instance, private cars sales dropped by 32.3%, the greatest drop since 2014. This decrease in sales took place in all Spanish regions and in most countries in the world [18].

During 2020 the alternative vehicles registrations accounted for 19% of the total new registrations with 201,412 units in total. Its growth was 30.7% [18].

Although overall new vehicle sales have decreased due to the pandemic, the growth trend shown by the electromobility demand stayed for another year. PEVs unit sales doubled, reaching the 43,317 units and accounting for a 4.2% of the new vehicles market share. Of those, the PHEVs experienced the highest increase (213%) with 23,3268 units sold. BEVs unit sales increased by 65.5% with 19,949 units sold [18].

On the other side, HEVs keep consolidating as the strongest option of alternative mobility, with 140,869 units sold and a 28.3% increase with respect to 2019. Their new vehicles market share is 13.6% and their new alternative vehicles market share is 69.9% [18].

It is the strong commercial effort made by car brands the main responsible of the alternative vehicles' sales growth. Without public aids to mitigate the price differences between traditional and alternative vehicles and without a great charging infrastructure, car brands have reached the benchmark of 200,000 alternative vehicles sold [20].

Figure 2-3 shows the evolution of EV registrations from 2019 to 2020 by type of technology.

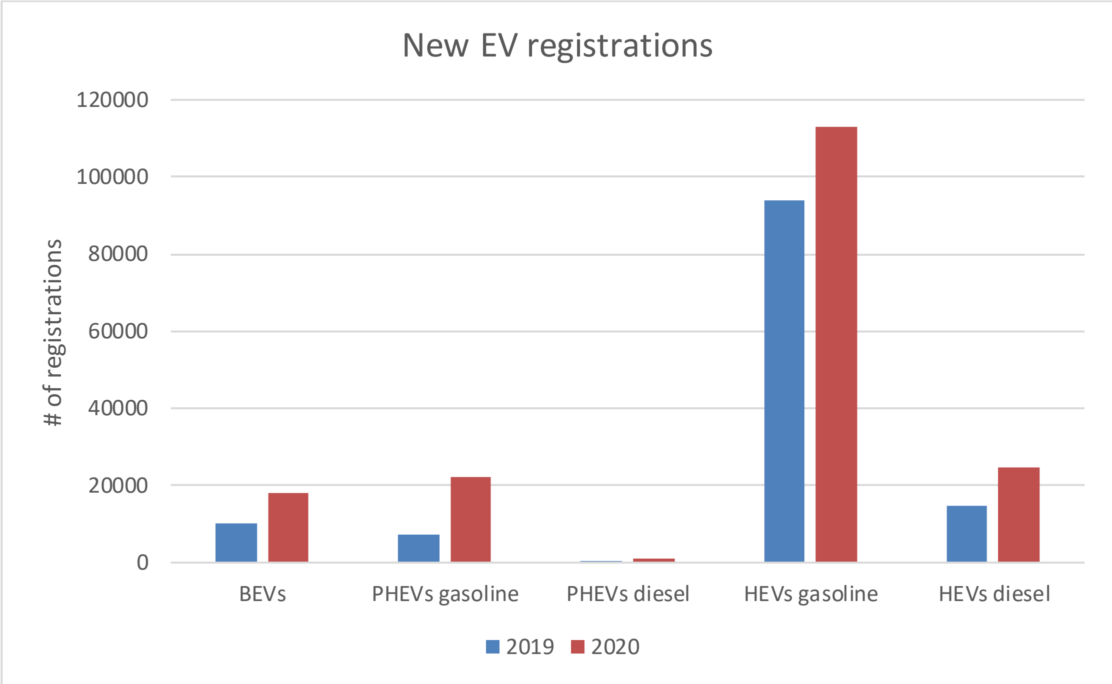

Figure 2-3: New EV registrations in 2019 and 2020. Source: ANFAC 2020 [18]

A general increase in the new registrations is seen in all technologies. It is interesting to notice that gasoline is much more used regarding the hybrid technology. According to [21] it is a matter of reliability over time. BEVs and PHEVs gasoline are the ones with greater increase in registrations in 2020 with respect to 2019. The diesel sales enjoy a sustained growth but are still less than a quarter of gasoline sales.

2.1.4 ELECTROMOBILITY INDEX

Spain is slowly increasing the electrification of its transport sector. Though it has improved its performance by 1.4 points in 2022-Q1 with respect to 2021-Q4, Spain is still among the worst performing European countries in the global electromobility index made by ANFAC [22].

This trimestral global electromobility index analyzes the evolution of the electrification of the transportation in Spain and its communities relative to its European peers. This index has base 100 and evaluates the electrification of the transportation in a territory based on the following objectives for 2030: (a) PEVs reach a 40% vehicle fleet share, (b) BEVs reach a

70% market share within PEVs and (c) reach 10.3 charging points per thousand people aged 18+ – which is the necessary amount of charging points for accomplishing (a) and (b) – and have 10% of these charging points to be over 50 kW. Territories are evaluated based on the accomplishment grade of these objectives [23].

As Figure 2-4 shows, Spain got 13.3 points in the global electromobility index, very far away from the European average: 28.1 points. Although demand is increasing, the progression rhythm is insufficient in both the penetration of electric vehicles and the charging infrastructure. Norway and the Netherlands are the models to follow reaching both more than 50 points. However, their market structure and playing conditions differ a lot from the Spanish ones. More similar countries like France, Portugal, the UK or Germany all get much better ratings than Spain in both EV penetration and charging infrastructure.

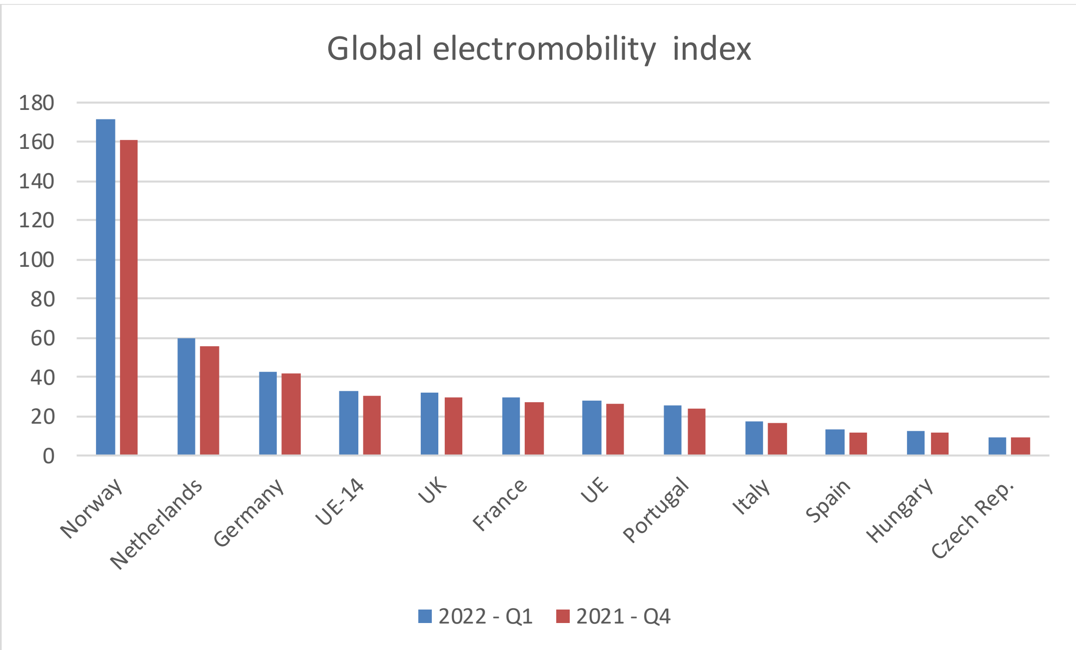

Figure 2-4: European countries performance on the global electromobility index. Source: ANFAC 2022 [22]

As Figure 2-5 shows, Spain gets 21.7 points regarding EV penetration, only above Hungary and Czech Republic. The European average is more than 20 points above. The commercial effort made by the main car brands and the MOVES Plan helped increase EVs sales a lot during the first quarter of 2022. However, this was still insufficient.

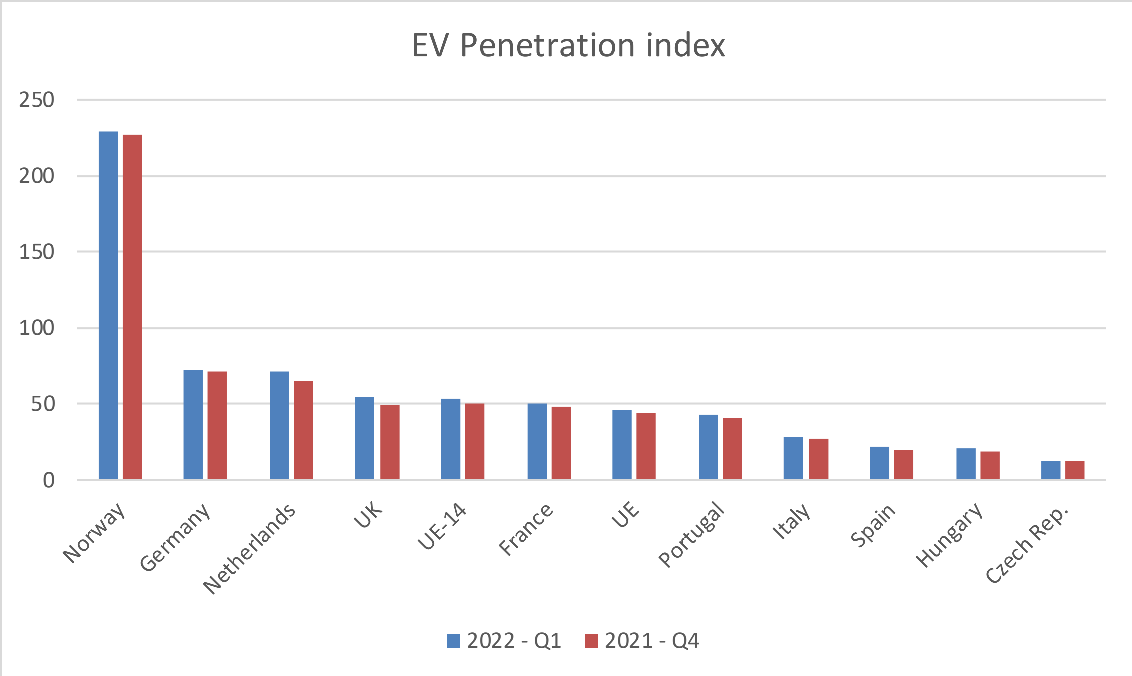

Figure 2-5: European countries performance on the EV penetration index. Source: ANFAC 2022 [22]

The charging infrastructure development – which is key for further improvement of the electromobility – is Spanish Achilles' heel. Only about 833 new charging points have been installed during this first quarter of 2022. There are 14,244 charging points in the national territory, positioning Spain as the second worst performing European country in the charging infrastructure index with just 4.8 points out of 100. Figure 2-6 shows a more detailed breakdown of the performance of other European countries.

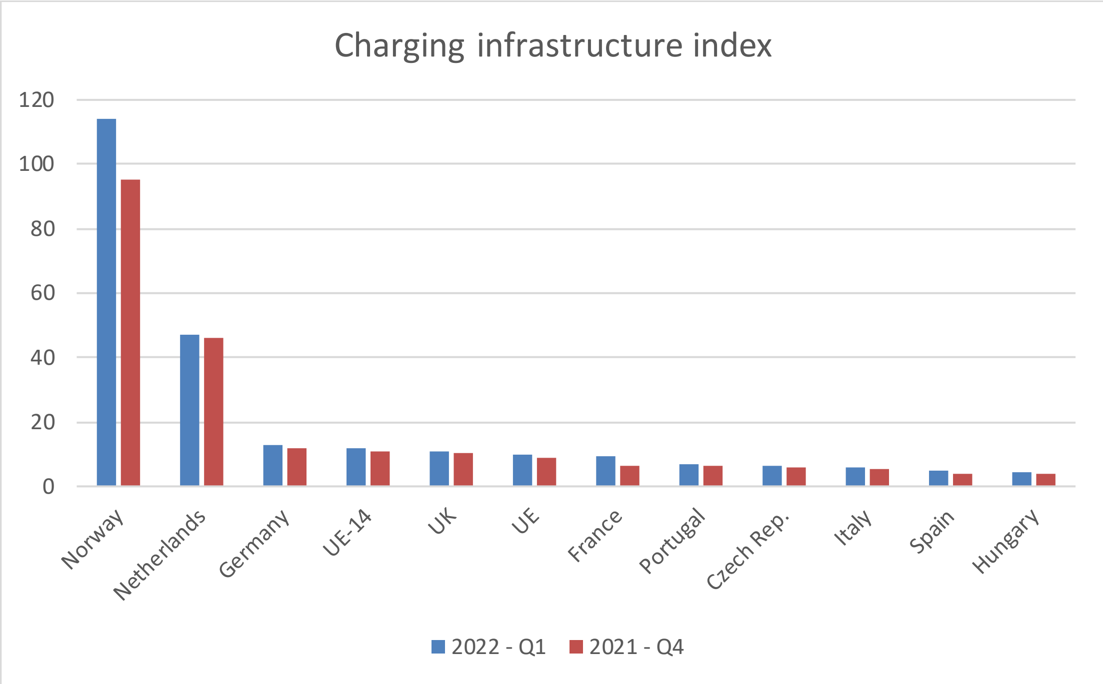

Figure 2-6: European countries performance on the charging infrastructure index. Source: ANFAC 2022 [22]

There exist big differences among regions in Spain. While Madrid gets 20.1 points, Ceuta and Melilla only get 4.9 points. Only Madrid, Catalonia, Navarra, Balearic Islands, and Canary Islands overpass the Spanish average. Andalusia, Extremadura and La Rioja are the worst performing communities, just above Ceuta and Melilla, as shown in Figure 2-7.

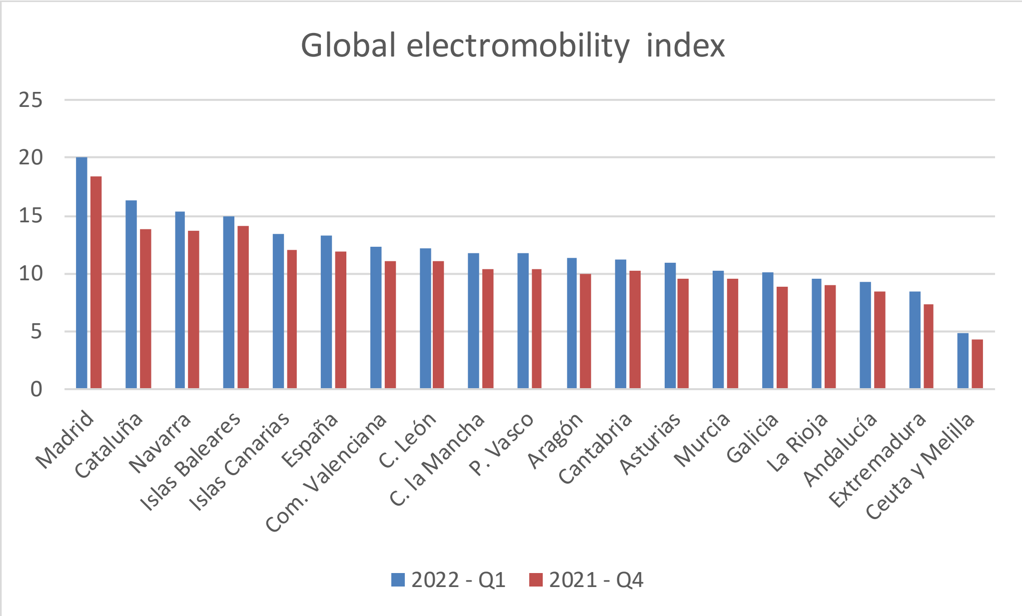

Figure 2-7: Spanish regions performance on the global electromobility index. ANFAC 2022

Figure 2-8 illustrates that, regarding EV penetration, Madrid gets 36.4 points, followed by Navarra with 24.2 points while the worst performing regions still are Ceuta and Melilla, Extremadura, La Rioja and Andalusia.

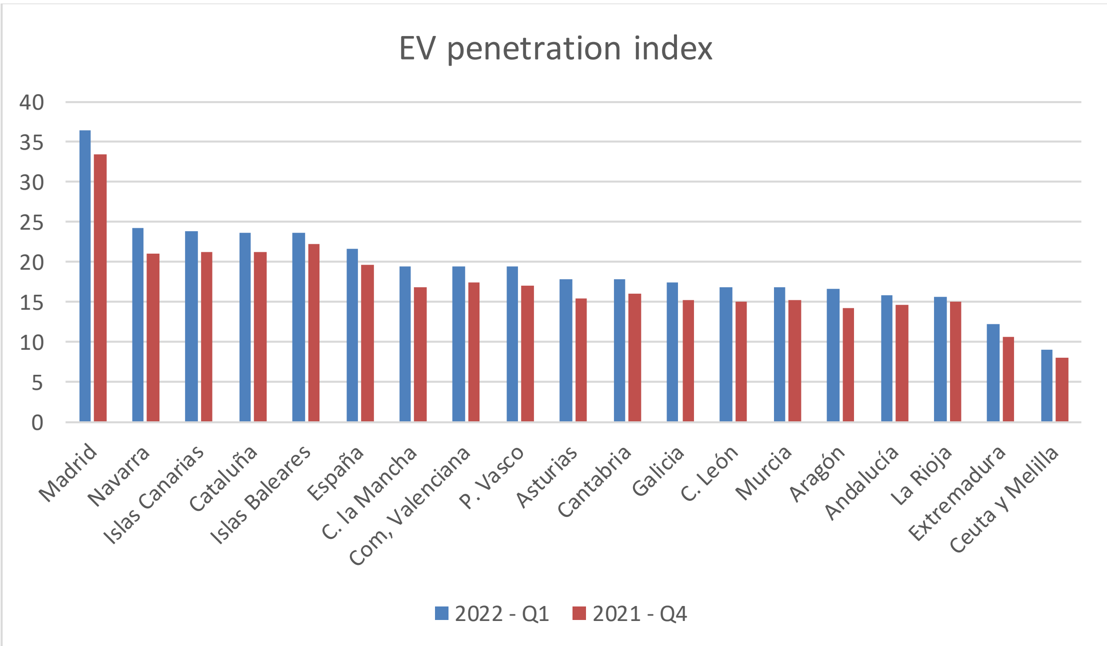

Figure 2-8: Spanish regions performance on the EV penetration index. Source: ANFAC 2022 [22]

Figure 2-9 shows that, regarding charging infrastructure, Catalonia and Castilla y León are the top leaders, both with more than 7 points. It is surprising that Madrid only gets 3.7 points, below the Spanish average. A possible explanation is the higher population of Madrid with respect to other communities.

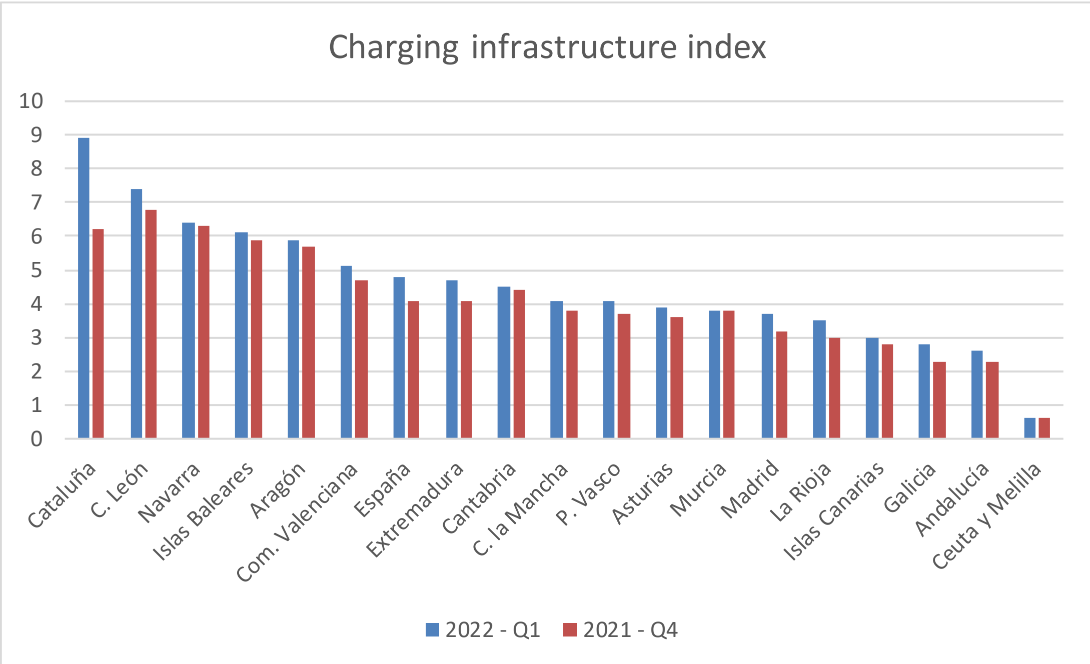

Figure 2-9: Spanish regions performance on the charging infrastructure index. Source: ANFAC 2022 [22]

2.1.5 SPANISH CHARGING POINTS

The Spanish public charging infrastructure is clearly insufficient. The 14,244 public charging points are not enough to reach the minimum objectives of 120,000 charging points for 2025 and 350,000 for 2030 established by the AUTO 2020 Plan of ANFAC [18].

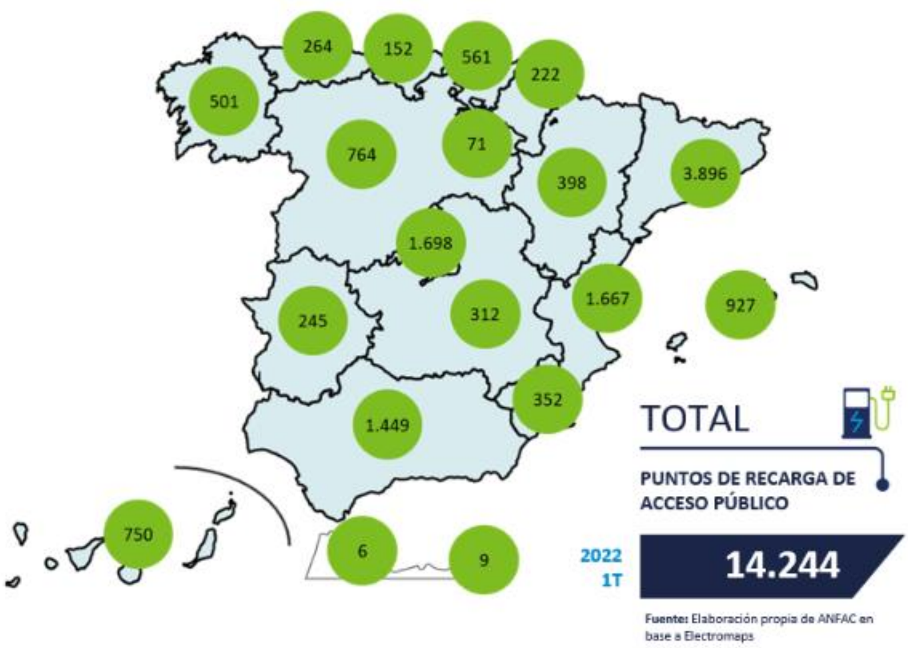

Figure 2-10: Public access charging points by region. Source: ANFAC 2022 [22]

As illustrated in Figure 2-10, Catalonia, Madrid, Andalusia and Valencian Community are the regions with most public access charging points due to their higher necessities demanded by bigger populations.

8,108 charging points are situated in urban environments, whereas the other 6,136 are situated in interurban environments. It is interesting to see in Figure 2-11 and Figure 2-12 that the two strongest economic regions – Madrid and Catalonia – have about double urban charging points than interurban charging points.

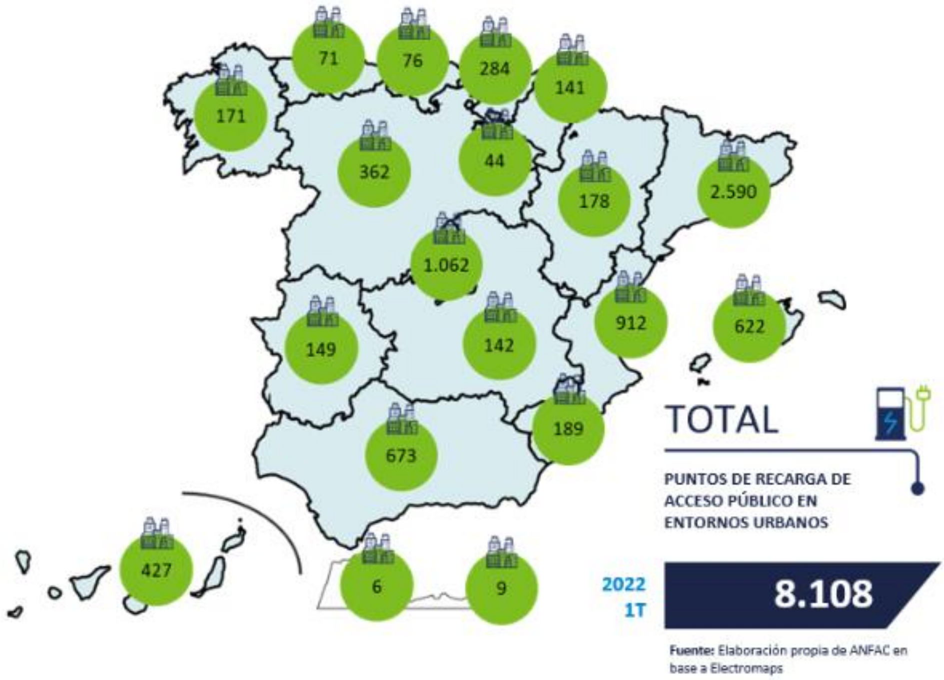

Figure 2-11: Public access urban charging points by region. Source: ANFAC 2022 [22]

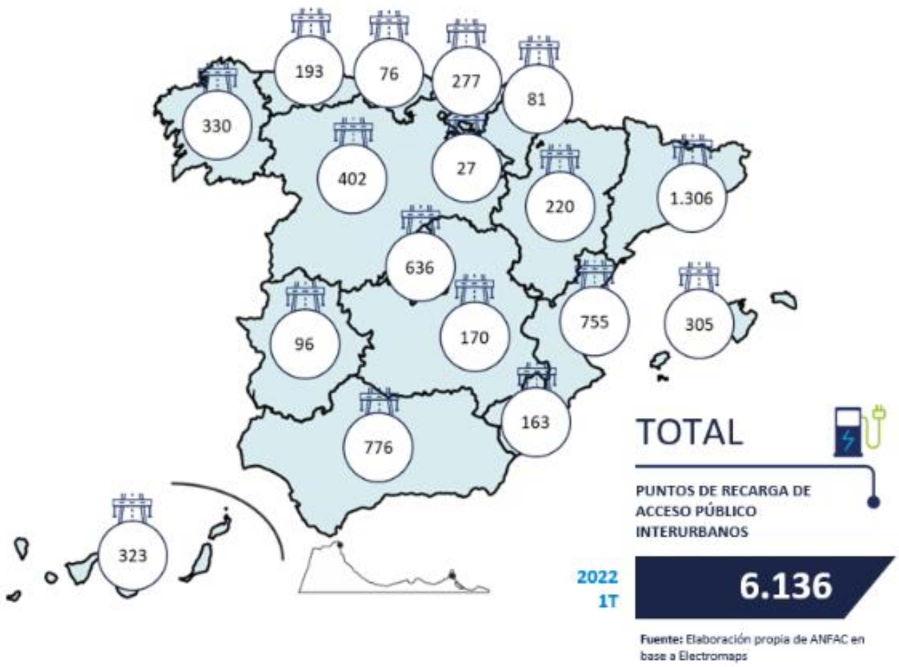

Figure 2-12: Public access interurban charging points by region. Source: ANFAC 2022 [22]

There are very few ultrafast charging points in Spain. A lot of them are concentrated around Madrid, while the rest are all spread around the territory as can be seen in Figure 2-13. There are long distances without ultrafast charging points in highways on Northwestern Spain.

Figure 2-13: Public access interurban ultrafast charging points by region. Source: ANFAC 2022 [22]

2.2 ANALYSIS OF THE SPANISH CHARGING INFRASTRUCTURE

2.2.1 INTRODUCTION

As explained in last section, Spain is far behind its European colleagues in terms of both EV penetration and charging infrastructure. It is obvious that both are linked to each other and Spain must find the way to avoid that endless spiral.

Along this section, the importance of enjoying of a great charging infrastructure to incentivize EV penetration, the regulatory framework for Spanish electromobility, the classification of charging points, the legal charging schemes and elements, charging points installation costs, and charging times will be explored.

2.2.2 IMPORTANCE OF THE CHARGING INFRASTRUCTURE ON THE EV PENETRATION

It is obvious that the deployment of charging infrastructure is key for the increase of the EV fleet in Spain and that a greater public charging offer will encourage EV use. Nevertheless, it is not the only factor causing a lower EV penetration in Spain than in other countries. The misperception that Spanish consumers have on EV features is another major factor.

In 2018, 57% of the Spanish consumers felt that the biggest barrier towards buying an EV was the low autonomy of these vehicles [24]. However, this perception radically contrasts with the fact that current EV autonomy is enough for covering 95% of the rides in Spain [24]. In addition, although the lacking charging infrastructure is a reality, the densification of charging points process in urban areas is real and the different projects aiming to increase the offer of charging points in inter-urban areas will help mitigate the fear to the lack of autonomy that Spanish customers perceive.

Another key aspect is the scarce offer of EV models. Although European policies regarding greenhouse gases emissions have pushed manufacturers to increase their PEVs offer, it is still not enough to satisfy all customers' needs [25].

In relation to this, another of the biggest barriers towards the electrification of road transport is the great initial investment needed. The purchase of an EV is on average a 40-50% more expensive than the purchase of an ICEV, even when public aids are present [26]. Furthermore, this initial investment is even greater if the installations costs of a charging point are taken into account. However, the Total Ownership Cost for vehicles that make more than 20,000 kilometers per year is between 2000 and 4000 Eur less annually for EVs [25]. This amount could reach the 20,000 Eur in a ten-year period, which is easily achievable, as most vehicles last more than ten years [25]. The savings come from significantly lower maintenance costs and the lower charging costs – the purchase cost of electricity needed to ride 100 km is much lower than those of gasoline or diesel. In addition, the reduction in the acquisition price that will be seen over the years will help overcome the economic barrier. The speed of charge is also relevant for customers. A more varied offer of chargers is necessary to match customers' needs.

A huge debate exists among those that defend the charging infrastructure deployment to promote the EVs sales and those that think it is better to wait and let the market evolve. The situation can be seen as a vicious circle, as the lack of charging points prevent from a higher penetration of EVs. The reality is that the low demand for electricity from the current vehicle fleet make it difficult for infrastructure investors to be profitable [25].

With all that said, the charging infrastructure is key for the penetration of EVs in the Spanish market and a higher deployment of charging infrastructure is needed to break the barriers imposed by consumers and to support the future needs of the electromobility in Spain. In parallel to this, it is necessary to increase customers' awareness regarding the benefits of electromobility [27].

2.2.3 REGULATORY FRAMEWORK FOR THE SPANISH ELECTROMOBILITY

The transport sector is both socially and economically very important in the Spanish society. In order to achieve the electrification goals, regulation policies that enable, ease and promote the EV use are necessary. These policies include EV regulation and charging infrastructure regulation.

National incentive programs to promote EV use like the MOVES Plan – which stands for Efficient and Sustainable Mobility in Spanish – already exist. This Plan aims to incentivize EVs and FCEVs purchases by conceding aids up to 7,000 Eur as of 2021. The Plan also aims to incentivize efficient mobility in workplaces, charging infrastructure and electric bicycles sharing services deployment [28].

Teresa Ribera, the fourth VP of Spain and the Ecologic Transition and Demographic Challenge Minister announced that "increasing inter-urban charging infrastructure" is key to those "citizens concerned with not finding enough charging points" [28].

The government of Spain is working in this direction and a Royal Decree was established to regulate the EV charging points. The Construction Technical Code is modified following the EU Directive 2018/844 that modifies the Directive 2010/31/EU regarding the buildings' energetic efficiency and the Directive 2012/27/EU regarding energy efficiency and establishing conditions on the minimum necessary infrastructure for the smart charging systems in parking lots in buildings and modifying the Complementary Technical Instruction (ITC) BT-52 from the Electrotechnical Rules for Low Tension. These charging infrastructure conditions translate into the obligation to new buildings of having a pre-channeling for all its parking spots if the building is for private residential use and of 20% of all its parking spots if the building is for other use. For those buildings that are not for private residential use there must be one charging point for every 40 parking spots and those buildings administered by the State there must be one charging point for every 20 parking spots [25].

The National Federation of Installation Businessmen in Spain (FENIE) believes that mechanisms aiming to help the deployment and renovation of charging infrastructure are key towards the electromobility development. Furthermore, the FENIE considers that not only more charging points must be deployed, but they must also work well and be periodically maintained. There is a need to modify the tariff system to promote savings and energy efficiency given that the current system does not promote the charging infrastructure deployment [25].

2.2.4 PEV CHARGING POINTS CLASSIFICATION

The charging points can be classified based on different aspects: charging speed, charging modes and connector types.

2.2.4.1 Charging speed types

In Spain it is possible to distinguish three basic charging speeds: slow, fast and rapid. These represent the power outputs, and therefore charging speeds, available to charge an EV. There are some authors that divide rapid speed between rapid and ultra-rapid speed [29]. Charging times vary depending on the charging unit, the EV and its battery capacity.com

- Slow speed

It is thought to be used domestically. Most slow charging units are carried out between 2.3 kW and 6 kW, though the most common slow chargers are rated at 3.7 kW (16A).

Slow charging is a very common method of charging EVs, used by many owners to charge at home overnight. However, slow units aren't necessarily restricted to home use, with workplace chargers and public points also to be found. The longer charging times make slow public charge points less common and are usually older devices. This charging method is available for all types of EVs [30].

- Fast speed

Fast chargers are typically rated at either 7.4 kW (single-phase 32A) or 22 kW (three-phase 32A). Most of them provide AC charging, but some networks are installing 25 kW DC chargers. Fast chargers tend to be found at social destinations in where you usually spend more than one hour, like supermarkets, car parks, or leisure centers. It is also a pretty common way of home charging. Charging rates depend on the car's on-board charger because not all models accept 7 kW or more. These models are still allowed to be plugged in to the charge point, but the power rate will be limited to the maximum power accepted by the on-board charger [30].

- Rapid speed

Rapid chargers are the fastest way to charge an EV. Their power rate is higher than 50 kW, with some new chargers reaching 350 kW. They are often found at motorway services or locations close to main routes. They supply high power DC or AC. When using rapid chargers, most EVs are limited to reach a state-of-charge of 80% in order to help protect the battery and to maximize charging efficiency. The power from a unit represents the maximum charging speed available. Furthermore, the car will reduce charging speed as the battery gets close to full charge [30].

2.2.4.2 Charging modes

The charging modes are classified in the IEC 61851 standard based on the amount of information between the EV and the grid. There exist four modes and they are all explained below.

- Mode 1

It consists in the direct connection of the EV to the normal current sockets (using Schuko connectors in Spain) without special safety systems. The protection is given by the electrical network to which the vehicle is connected, as the charging cable does not provide any added protection. Mode 1 is typically used for electric scooters and bikes. It is not recommended its use for larger vehicles due to the circuits heating excessively because of the longer charging times. The rated values for current and voltage shall not exceed 16A and 230V in single-phase and 400V in three-phase [31].

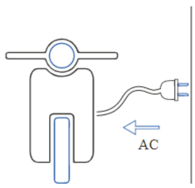

Figure 2-14: Mode 1 representation

- Mode 2

This mode requires the presence of a specific safety system between the point of connection to the electrical network and the car in charge. The system is placed on the charging cable and is called the Control box. The Control box tracks the state-of-charge and provides with a differential protection system. Mode 2 can be used with domestic and industrial sockets and is usually installed on EV portable chargers. The rated values for current and voltage shall not exceed 32A and 230V in single-phase and 400V in three-phase [31].

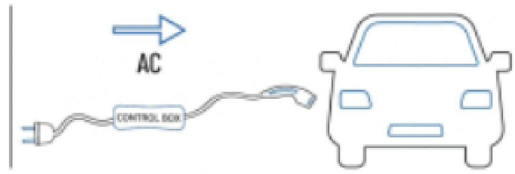

Figure 2-15: Mode 2 representation

- Mode 3

This mode requires that the vehicle is charged through a power supply system permanently connected to the electrical network. The Control box is directly integrated into the dedicated charging point and has control and protection features. This is the most complete and most popular charging mode and is usually used in commercial charging points, wallboxes and all automatic charging systems in AC. The rated values for current and voltage shall not exceed 32A and 230V in single-phase and 400V in three-phase [31].

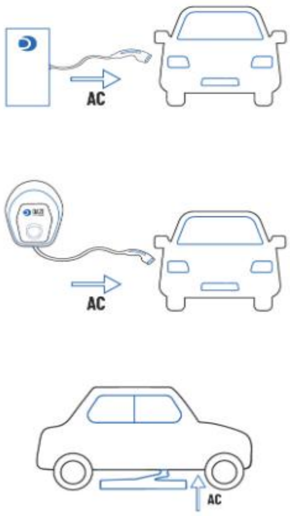

Figure 2-16: Mode 3 representation

- Mode 4

This mode provides DC and hence requires a current converter external to the vehicle to which connect your charging cable. These charging points are usually more voluminous than previous modes due to the presence of the AC-DC converters. They are almost always found on EV charging stations. As in mode 3, the control and protection features are the charging points' responsibility. Charging stations that charge in mode 4 allow up to 200A and 400V [31].

2.2.4.3 Connector types

There are many different connectors currently available in the market. Each connector is used with a compatible charging mode. The IEC 62196 standardizes the types of EV-specific connectors for both AC and DC charging. The most common ones are described in Table 2-1.

Connector type	Description	Picture
Schuko	Conventional connector to monophasic house circuits, compatible with Mode 1 and Mode 2 (monophasic), up to 16 A and 230 V	
SAE j1772 (Type 1)	Type 1 according to IEC 62196-2; compatible with Mode 3; up to 32 A and 230 V	
Mennekes (Type 2)	Type 2 according to IEC 62196-2; compatible with Mode 3; up to 70 A and 230 V or 63 A and 400 V	
Scame (Type 3)	Type 3 according to IEC 62196-2; compatible with Mode 3; up to 32 A and 400 V	
CHAdeMO (Type 4)	Type 4 according to IEC 62196-2; compatible with Mode 4; up to 200 A and 500 V in DC	
CSS (Combined Charging System)	Used in Mode 4; up to 200 A and 850 V in DC	

Table 2-1: Connector types. Adapted from: Junta de Andalucía [32]

2.2.5 LEGAL CHARGING POINTS SCHEMES AND ELEMENTS

In this section the different elements and charging schemes applicable to private garages, residential neighborhoods garages and business parking lots will be explained. The information here outlined is based on the Complementary Technical Instruction (ITC) BT-52 (Royal Decree 1053/2014, Dec 12th 2014) [32]. A deeper analysis of all these schemes and elements is done at the Annex (Section 7.2).

2.2.5.1 Private garages:

The charging points installations in private garages must follow what the ITC BT-52 states about private garages in single-family households: "In new single-family households that have a parking spot for an EV, an exclusive circuit will be installed for the EV charging. This circuit will be known as C13 – according to ITC BT-25 nomenclature – and will follow the 4a installation scheme. In those existing households that wish to install a charging point will also follow this section. Single- and three-phase power can be used [32].

2.2.5.2 Community garages

The ITC establishes four big groups of charging points schemes:

1. Collective scheme with a primal counter at the origin of the installation
2. Individual scheme with a common counter for the house and the charging point
3. Individual scheme with a counter for each charging point
4. Scheme with additional circuits [32]

2.2.5.3 Charging stations

A charging station is a public charging point. They can be installed in existing gas stations to take advantage of the existing services offered, like café or restrooms. They must follow the 4b scheme but given their increasing importance a whole section is given to them [32].

2.2.6 INSTALLATION OF CHARGING POINT PRICES DEPENDING ON POWER RATE

In this section the approximated prices for the purchase and installation of charging points with the most common power rates are presented. Those range from domestic use to big charging stations:

- Slow charge (up to 3.7 kW), Schuko connector: it is usually given by car manufacturers when purchasing an EV. There is no need for installation. It can be bought for less than 10 Eur in Amazon [33].
- 7.4 kW AC charge: there exist multiple alternatives in the market. Wallbox – the leading charging point Spanish manufacturer – has very interesting alternatives. Among the 7.4 kW AC options found in the online vendor ecity charge website, always choosing the single-phase 20 meters long cables: Wallbox Pulsar (1446 Eur), Wallbox Copper SB (1926 Eur), Policharger In (1516 Eur), eNext (1542 Eur) and EVBox BusinessLine G4 (1942 Eur) [34].
- 22 kW AC: a 22-kW charger is the fastest charger you can get for the home, but a three-phase electricity supply is needed [35]. Also, the car itself will need to be able to accept such power rate. Always choosing the 20 meters long cables, among the most interesting options found in ecity charge: Wallbox Pulsar Plus (1736Eur), Wallbox Copper SB (1926Eur), Wallbox Commander 2 (2166Eur), EVBox Elvi Basic (1647Eur) and EVBox Iqon Hub 2x22 kW (5342Eur) [34].
- Charging stations: according to [36] the investment required to install a 300-sq-meter charging station with 15 to 20 charging points in Spain would approximately be 165,000 Eur. That includes charging infrastructure, informatic systems, control and safety systems and land adequation. If adding licenses, taxes, establishment costs and initial cash the total investment amounts to 200,000 Eur.

2.2.7 CHARGING TIMES OF MOST POPULAR EV MODELS

2.2.7.1 Charging times

Although charging times vary a lot depending on external conditions, quality of chargers and the car itself, a comparison among the charging times of the most popular EVs in Spain in 2020 is presented in order to have a more realistic view of how long it takes to charge a vehicle. It is important to take into account that the rapid charge time is only for charging from 20% to 80%. The comparison is shown in Table 2-2.

Model	Capacity (kWh)	Autonomy in favorable conditions (km)	Rapid charge (50 kW DC)	Wallbox 11 kW AC	Wallbox 7.4 kW AC	Slow charge 3.7 kW
Renault Zoe	52	395	1h29'	5h48'	9h33'	18h48'
Hyundai Kona LR	64	660	1h13'	10h18'	10h18'	25h
Peugeot e-208	50	362	1h	5h15'	8h	31h
Tesla Model 3	54	580	50'	8h	10h	18h
Volkswagen ID.3 Pro	62	415	52'	6h35'	9h	18h

Table 2-2: Comparison of charging times between the most popular EV models in Spain in 2020. Source: different manufacturers' websites

Although the credibility of this data is at least debatable, as it comes from each vendors' websites, some insights can be gained. The capacity is clearly the driver of autonomy, although consumption also plays a huge role there. The Tesla Model 3 apparently makes a better use of energy than the Volkswagen ID.3 Pro as it has a smaller battery but greater autonomy. However, bigger capacities take longer times to charge when it is not rapid charge. In the case of rapid charge those two models mentioned above are the quickest charged. Better charging technology or a better charging curve (the evolution of the power charging rate over the state-of-charge) may be some explanations for that.

2.2.7.2 Standardized P3 Charging Index

Nevertheless, all these charging times were provided by the vendors themselves or some motor magazines and may vary a lot under different conditions. Furthermore, in both fast and slow charging the charging rate significantly decreases once the 80% state of charge has been reached. As stated before the maximum charging capacity of the vehicles is often reached just for a few minutes during the entire charging process [37].

In order to better understand how the real charging process is seen from the customer's perspective, two important questions are prompted below:

What range is needed to get to the next stop?

How long will it take for the charging process to recharge for this range?

This second question introduces an important parameter not discussed yet: the consumption of the EV. This parameter is very relevant as the charged energy will cover a certain mileage depending on the EV's consumption. The inclusion of this parameter in the analysis leads to a more realistic comparison.

A standardization of the charging process used for a more transparent and "use case" comparison is set by the P3 charging index. The P3 charging index measures the actual distance recharged in 20 minutes divided by 300 km. The actual distance recharged not only depends on the charging rate, but also on the vehicle's consumption. Consumption values have been obtained from WLTP and ADA Ecotest. A vehicle that is able to charge a range of 300 km in just 20 minutes would reach a P3 Charging Index of 1.0. This form of standardization is very practical as usual long-distance driver would take a short break every 200-300 km [37].

$$P3\ Charging\ Index = \frac{Actual\ recharge\ in\ 20\ minutes\ starting\ at\ 10\%\ SoC}{300\ km}$$

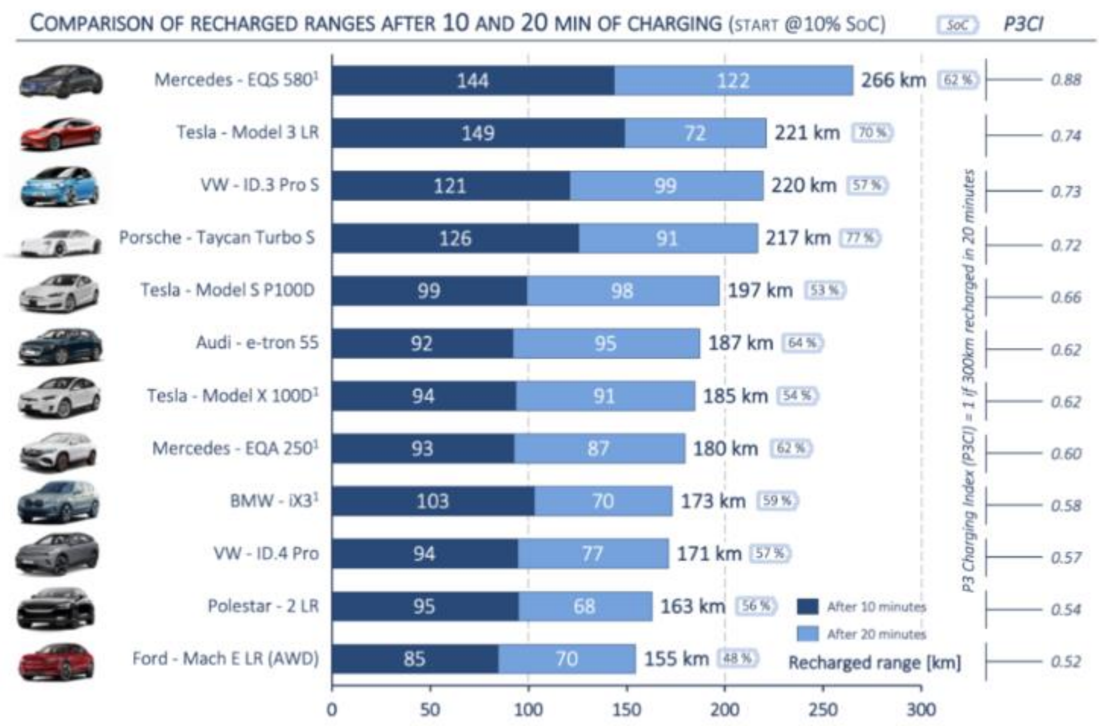

Figure 2-17: Comparison of P3 Charging Index performance of some popular models. Source: P3 [37]

As can be seen in Figure 2-17, none of the electric vehicles available in the market in 2021 reaches the optimal value of 1.0. However, the top 4 vehicles (Mercedes-EQS 580, Tesla-Model 3 LR, VW-ID.3 Pro S and Porsche-Taycan Turbo S) already achieve over 70% of the optimal value. Other vehicles are a little behind these top 4. This means that electric vehicle drivers need to calculate one or more charging stops on usual long-distance trips. Only data about 3 out of the top 5 EVs sold in Spain in 2020 is available: the Tesla Model 3 LR gets a 0.74, the VW-ID.3 gets a 0.70, and the Hyundai Kona gets a 0.41 [37].

The P3 Charging Index does not only establish a comparison of actual and realistic charging performances of electric vehicles, but also claims that the development of vehicles should focus on a mix between charging performance and efficiency of the vehicle.

2.3 SMART CHARGING

2.3.1 SMART CHARGING POTENTIAL

Extensive research has found that cars are parked for about 95% of their lifetime [24], including electric vehicles. EVs also have storage capacity in their batteries that can serve as a flexibility solution to support system operation. They could offer many different services to the grid when connected to it (e.g., congestion management, balancing, etc.).

Using current EV models typical consumption data, an EV consumes around 3000 kWh annually when driving 15000 km per year. To provide this annual energy, the car can be charged in about 10% of the time it is parked, giving a broad "flexibility window". Charging at times when electricity is cheaper is highly valuable for both EV owners and the power system [16].

However, this flexibility may be lower in practice due to fast charging, vehicle parked but not plugged in, or EV users' time constraints.

2.3.1.1 Flexibility today

In the present, the EV fleet is very limited compared to the ICEV fleet. Therefore, the flexibility offered to the grid is still very low.

The factors that condition the flexibility provided by EVs to the power system are plenty, but the most important ones are vehicles' plugged-in times, type of vehicle, available charging infrastructure and drivers' needs.

Depending on the type of vehicle and its usage, plugged-in times vary a lot:

- Individual EVs: their charging times are easy to forecast and have two different charging patterns. Long-duration (more than 4 h) offers the highest flexibility and usually takes place at the drivers' residence at night or at the workplace during the day. Medium-duration (30 min to 2 h) includes charging at leisure places or shopping centers and short-duration (15 min to 1 h) offer very little flexibility.

- Shared and commercial cars: their charging times may vary a lot depending on the business performed. Transport services like taxis need to reduce their idle time to maximize revenue and hence providing little flexibility to the grid. Cargo transport might take place at night and hence be charged during the day.
- Electric bus: their charging times depend a lot on where it is being charged. When charging at the bus depot, expected charging times can be long (more than 4 h). When charging at the end-of-line, charging times may last up to 15 min. When charging at each bus stop, flash charging (30 seconds) might take place [16].

In densely populated areas with not many private charging points, most of the charging could take place in public, while less densely populated areas most of the charging could take place at home or at the workplace. Nevertheless, in reality most charging takes place at home and at the workplace given the individual ownership of EVs and the economic suitability of charging like that. The IEA estimated in 2017 that the proportion of private chargers to public chargers is more than six to one. However, fast charging points have increased exponentially in the last years [16].

The battery capacity of the vehicles is critical to understand the flexibility provided to the grid. E-bikes (0.5 kWh), e-motorbikes (3-20 kWh) or PHEV (8-16 kWh) cannot store much energy. Even among the BEVs great differences can be seen: entry BEVs (20-40 kWh), standard BEVs (40-60 kWh) and premium BEVs (60-100 kWh). Bigger vehicles like buses (100-600 kWh) offer much more energy flexibility [16].

Finally, drivers need of a sufficient state of charge of their vehicle so they can use it without distance range issues. With increasingly large EVs' batteries, the relevance of this state of charge might decrease.

2.3.1.2 Flexibility in 2030

The availability of flexibility will increase a lot, as a higher penetration of EVs is likely to occur. As today, by 2030 car sharing will be an option but outnumbered by individual ownership of EVs. The increase of flexibility can be explained by the following reasons:

- EVs cost is likely to decrease due to falling battery cost and public incentives. Hence, more electric vehicles will be on the roads.
- These EVs will also have larger batteries, enabling longer driving distances and giving more availability to the grid.
- More charging points will be available both at the workplace and at leisure or shopping centers, providing EV users with more charging place choices.
- Fast charging will still be limited to long-distance trips, given that charging at home remains cheaper [16].

2.3.1.3 Flexibility in 2050

Some experts point out that between 2030 and 2050 new mobility business models such as mobility-as-a-service (Maass) and new technologies such as autonomous vehicles might appear. This could lead to less individual ownership and more shared vehicles. The availability of flexibility to the grid might decrease under these emergences due to the following reasons:

- Distance driven by cars would increase. Hence, they would be less time connected to the grid.
- In case of an advanced MaaS ecosystem, the number of EV sales would decrease after many years of growth. Therefore, in the long term less EVs would be available to provide grid services.

However, these trends might only be noticed in urban areas – where around 75% of the world population is expected to live by 2050. In suburban or rural areas, the current individual ownership model would prevail.

Moreover, the autonomous vehicles penetration will depend on regulation and infrastructure and hence will not be implemented in great proportion until some years after a reliable technology is launched [16].

A summary of the EV flexibility over the years is shown in Table 2-3.

	Today	2030	2050
	Low penetration	High penetration	High penetration
	Small batteries (30-60kWh) → Low driving range (150-300km)	Large batteries (90-200kWh) → High driving range (600-1000km) (?)	Large batteries (90-200kWh) → High driving range (600-1000km)
	Standing still 90% of time	Still high parking time	Reduced parking time
	Home & office charging	Still mostly home & office charging	Hubs in city suburbs (mostly night)
	Smart charging in testing phase Only ToU more common	Smart charging implemented, market-dependent potential	Smart charging implemented, market-dependent potential

Positive for EV flexibility *Negative for EV flexibility* *Less positive impact than in 2030*

Table 2-3: Summary of the EV flexibility Today, in 2030, and in 2050. Source: IRENA [16]

2.3.2 SMART CHARGING OUTLOOK

2.3.2.1 Impact on electricity capacity and demand

And, why smart charging? Let's first discuss the impact that uncontrolled charging – charging at maximum charging rate once the vehicle is plugged in until fully charged – can have on electricity capacity and demand.

Under a massive penetration of EVs scenario, if charged uncontrolledly, many EVs could be charging at the same time increasing the peak demand on the grid and contributing to overloading it. More energy capacity generation and upgrades at the distribution level could be needed. Most studies classify the impact of EVs on the electricity capacity and demand in three main points:

- Electricity demand will not be highly impacted:

Many trials conducted globally show that even with 100% EV penetration, the demand for electricity would not reach a worrying portion of total electricity production, as Eurelectric

(2015) showed for the Europe case – EV electricity demand would be no more than 15% of total electricity production. Nevertheless, local grid issues might occur [16].

- Peak demand can be highly impacted in an uncontrolled charging scenario:

-Peak demand could increase by 3 GW in the UK when having an EV fleet of 10 million. By using smart charging, this increase could be reduced to only 0.5 GW.

-Peak demand could increase by 18% in New England when having a 25% share of EVs. By using smart charging, this increase could be reduced to less than 6% [16].

- Local distribution grids can also be highly impacted in an uncontrolled charging scenario:

-A 50% increase in transformer and low-voltage distribution systems costs in Germany could take place when having an EV fleet of 10 million. By using smart charging these costs could be avoided.

-A 32% distribution circuit upgrades in the UK when having a 40-70% share of EVs [16].

2.3.2.2 Impact on grid infrastructure

The increasing demand for electricity in a high-penetration-of-EVs scenario will require distribution grid investments. There are many factors to take into account in order to estimate the magnitude of the required investments – essentially cables and transformers:

- Congestion: in the local grid prior to electric vehicles penetration.
- Simultaneity factor: which measures the odds of having to replace a specific part of the equipment at the same time as another part of the equipment. It depends on the size of the distribution grid.
- Load characteristics: like locations with common use of electric heating.
- Generation capacity at low voltage level: in countries like Germany with a high share of solar PV at a residential level, smart charging will help the integration of charging with solar generation.

- Regulations: like national grid code limits, which establish voltage and frequency variations that cannot be exceeded [16].

There is a great challenge that must be encountered by distribution systems in order satisfy EV users' needs: fast charging. The higher powers required by fast charging need of higher capacity of the distribution networks. Also, charging cables and cars must be prepared for this power. The negative impacts of this technology are outlined below:

- Electric vehicles need of more expensive protection devices.
- Fast charging points require more expensive cables, transformers, electronics, cooling and protection devices.
- With the increasing number of EVs, increasing demand will require even more charging power [16].

2.3.3 SMART CHARGING

2.3.3.1 Definition

Smart charging consists of controlling the power rate at which the vehicle is being charged in real time under some constraints. These constraints and the objective chased can vary a lot depending on the smart charging strategy, but most of them have something to do with connection or grid capacity, load variations, local energy production, renewable energy shares, electricity prices and user needs. Smart charging is a way of managing electric vehicle loads through vehicle-grid integration (VGI) [16].

Smart charging can help both the system flexibility and the local flexibility in many ways as outlined in Figure 2-18: Smart charging flexibility benefits. Source: IRENA [16]. At a system level, EVs charged smartly can help shaving the peak demand and therefore avoid investments in upgrading peak generation capacity. As grid-connected storage batteries, EVs can offer many services to the grid: frequency control through primary, secondary, and tertiary reserve; fill load valleys, managing the variability in voltage or increase the variable renewable energies (VRE) consumption by shifting their charging times to renewable energies generation times. At a local level, similar services can be provided. Reducing local congestion and increasing the VRE self-consumption are seen as best uses. EVs can also store back-up power in case of local grid shutdowns [16].

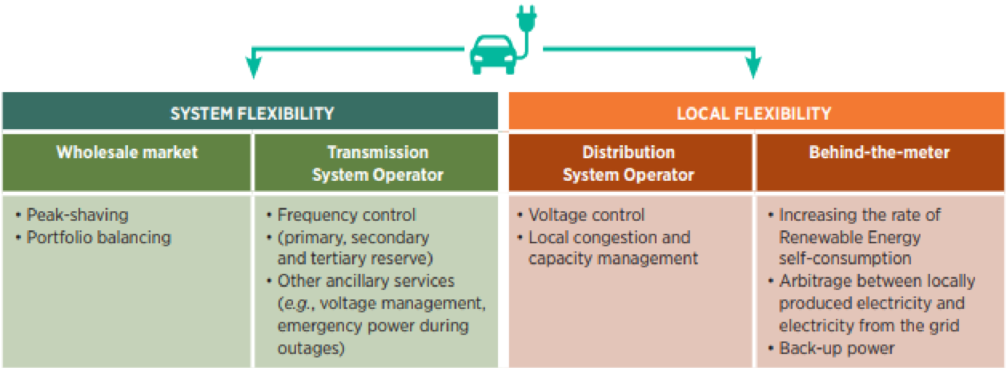

Figure 2-18: Smart charging flexibility benefits. Source: IRENA [16]

2.3.3.2 Contributions

All these contributions that smart charging can make both at a system and local level are further explained below:

- Peak shaving (wholesale market): by incentivizing shifting some charging patterns the peak demand could be reduced and the valley could be filled. In systems with much solar production, charging at afternoon could be a solution to this. In systems with much wind production, charging at night when wind production is greater could help fill the load valley as well as increase VRE consumption. Charging at peak demand times, like early evening, would be deferred.
- Ancillary services (system and local levels): EVs serve as spread energy storages that can help balance the grid in terms of voltage and frequency through ancillary services. This could help improving the distributed energy resources integration with the grid.
- Consumers' optimization and back-up power (at local levels): smart charging can help reduce the household's electricity bill by charging the EV at cheaper times and by increasing the locally produced VRE consumption [16].

2.3.3.3 Types of smart charging

Smart charging can be implemented using different strategies and technical specifications. Strategies vary depending on the objectives (cost minimization, variability of the load minimization, maximization of VRE consumption, etc.) and constraints (feeder capacity, grid voltage ranges, charging point specifications, EV capabilities, user needs, and technology used). Among the technical ways of implementing smart charging, some direct control mechanisms – necessary at higher EV penetration levels in the long-run – stand out from others:

- Unidirectional control of EVs (also known as V1G): it allows to control the power rate – from 0 to the maximum power rate available.
- Bidirectional control of EVs (also known as vehicle-to-everything, or V2X): EVs can both be charged and discharged at a controlled power rate in order to provide more flexibility. Two different forms of bidirectional charging are especially important:

  -Vehicle-to-building (V2B) or vehicle-to-home (V2H): EVs are used in order to maximize self-generated power and decrease the dependance on the grid or as back-up power sources. They do not affect directly the grid performance.

  -Vehicle-to-grid (V2G): EVs can both receive and transmit power to the grid, serving as a more useful tool for providing ancillary services. The ability of selling energy to the system provides much more flexibility than when using V1G, in which the power rates can only be decreased to zero, as Figure 14 shows. Therefore, V2G has the potential of shaving peak demand and balancing voltage and frequency through ancillary services in a much easier and effective way than other methods.

Unidirectional charging is already a market solution and enjoys certain maturity. However, V2X is yet in a experimental phase, with very specific commercial alternatives like the V2H in Japan, available since 2012. Figure 2-19: V1G vs V2G power range availability example. Source: IRENA [16] better illustrates the main difference between V1G and V2G: power range availability [16].

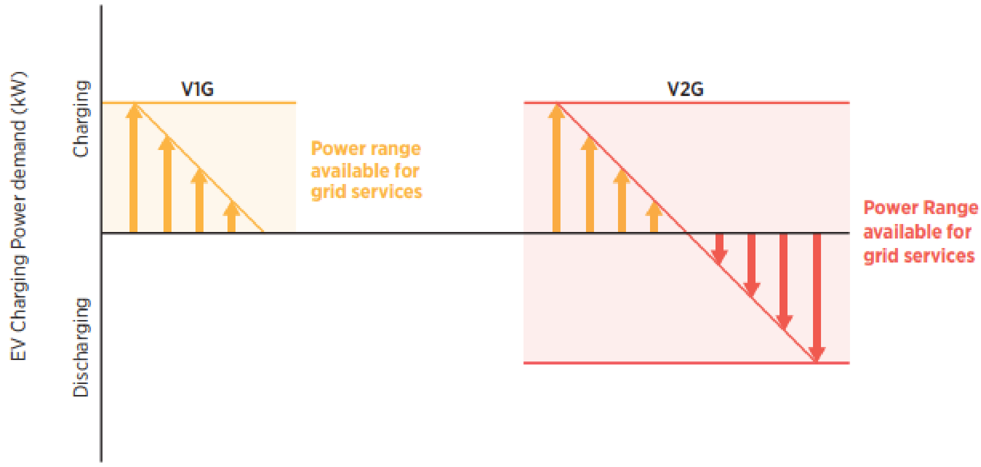

Figure 2-19: V1G vs V2G power range availability example. Source: IRENA [16]

2.3.3.4 Practices

Now, some charging practices are explained in further detail:

- Time-of-use tariffs

This is a widely used practice that does not necessary rely on smart charging. Most people set the times they want the car to be charged at through a mobile app or through the car's on-board system. The charging times usually match off-peak hours, in which the price of electricity is cheaper. The more difference in price found between peak and off-peak times, the better this practice. An example showing the difference in electricity prices depending on time in California is presented in Figure 2-20: Example of time-of-use tariffs. Source: IRENA [16].

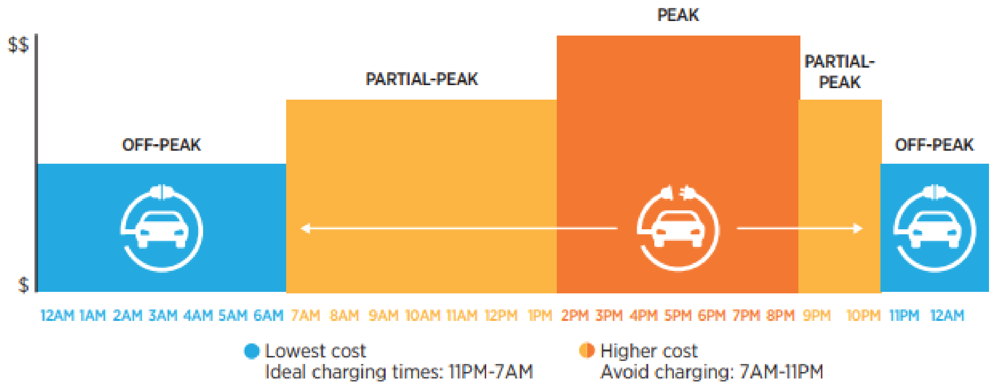

Figure 2-20: Example of time-of-use tariffs. Source: IRENA [16]

- V1G and dynamic pricing

Real-time cost of energy, as well as VRE generation signals are both used as inputs to determine the charging rates at each time period. This is commonly used in the Netherlands, but not yet implemented in most countries [38].

- V2X charging experience

The experience using V2X is also very poor. However, as stated before, Japan has enjoyed the V2H technology since 2012. Using the CHAdeMO connector – the only international standard connector available for V2X use – a single vehicle with around 40 kWh of capacity (like the Nissan LEAF, the most popular one) can provide more than three days of power to a single household, as average daily consumption is about 12 kWh.

Nevertheless, V2G is very superior to V2H in all aspects. Apart from providing back-up power to the household, it can provide ancillary services that become a new source of revenue for EV users. But, in order to provide those ancillary services, many EVs need to be aggregated. Specifically, around 500 EVs available and connected to 7.3 kW charging points would be needed to provide from 1 MW to 2 MW [16].

- VGI with fast charging

There is no much potential for VGI with fast charging, as the available times are short and therefore not flexible enough. In addition, fast charging may become a problem for the grid that will need to be mitigated by locating the charging points in areas with low congestion and local peak demands.

However, fast charging of heavy-duty vehicles, like electric buses or electric trucks, may make much more sense. The larger batteries they have longer time they take to charge even with fast charging, providing some flexibility. This alternative is being further explored by ASSURED [39].

Another way of providing more flexibility to the grid is through fast charging with stationary batteries and locally installed VRE combination. By using energy from the stationary batteries -charged during suitable periods, especially off-peak – and from the local VRE, the power extracted from the grid is minimized, avoiding adding stress on the grid.

A summary of the studies smart charging forms is provided on Table 2-4.

Type of application	Smart control over charging power	Possible uses	Maturity
Uncontrolled but with time-of-use tariffs	None	Peak shaving with implicit demand response; long-term grid capacity management (both transmission and distribution system operators)	High (based on changes in charging behavior only)
Basic control	On/off	Grid congestion management	High (partial market deployment)
Unidirectional controlled (V1G)	Increase and decrease in real time the rate of charging	Ancillary services, frequency control	High (partial market deployment)
Bidirectional vehicle-to-grid (V2G) and grid-to-vehicle (G2V)	Instant reaction to grid conditions; requires hardware adjustments to most vehicles and EVSE	Ancillary services including frequency control and voltage control, load following and short-duration integration of renewable energy	Medium (advanced testing)
Bidirectional vehicle-toX (e.g., V2H/V2B)	Integration between V2G and home/building management systems	Micro-grid optimisation	Medium (advanced testing)
Dynamic pricing with EVs	EVSE-embedded meters and close-to-real-time communication between vehicle, EVSE and the grid	Load following and short-duration integration of renewable energy	Low

Table 2-4: Types of smart charging. Adapted from: IRENA [16]

2.3.3.5 Smart charging enablers

- Consumer behavior:

There are two very different group of consumers: the technology enthusiasts and the ordinary customers. While the former is willing to help achieve a more sustainable society and willing to try any new technology release, the latter – and also much bigger – group just wants easy and affordable alternatives. However, this gap is being reduced thanks to technology improvements, increased awareness and marketing efforts.

EVs have been gaining a much greater acceptance over time due to the increasing distance autonomy of EVs. This is still a great barrier, but future improvements in batteries and consumption will mitigate its effect in consumers' attitudes. But even under a high EV penetration scenario, availability of flexibility is not guaranteed. There needs to be incentives that encourage users to participate in smart charging schemes and that leave their vehicles plugged in for longer times in order to achieve the full potential of flexibility [16].

- Big data and artificial intelligence:

Big data allows customers to interact with market complexity and energy mixes in real time. This allows customers to decide when they want their vehicle to charge or what smart charging scheme to adopt and helps them realize the positive effect of their decisions and improve their EVs' perceptions.

Also, artificial intelligence (AI) algorithms can help match EV user needs. By monitoring and interpreting specific parameters, maintenance decisions can be made [40].

Finally, digitalization will be key to both new business models and the match between transport service and grid services. Management of charging stations, remote maintenance and efficiency optimization across different charging points are just some of the new business models that are being developed. Finding the optimal locations for charging points, as well as matching mobility patterns with power supply will be easier with data analytics [16].

- Blockchain technology:

A blockchain is a distributed database that is shared among the nodes of a computer network. The information is stored electronically in a digital format. Their decentralized essence makes blockchain a very secure and cheap way of making transactions that do not need to be supervised by any third party. Hence, blockchain has all the potential to become a great tool for charging transactions (current transactions take longer times and have higher fees). Blockchain could be used tor peer-to-peer solutions: sharing a private charger when nobody is using it could be beneficial for both the user (finds a place to charge their car) and the charger owner (earns some revenue while not using it). Blockchain would enable this operation with simple user identification [16].

2.3.4 Regulation needed for VGI

As studied before, the opportunity for EV and VRE integration will have great potential in the following years due to the increasingly higher penetration of EV and of VRE in the energy mix. Improvements on batteries, consumption, smart charging technologies and digitalization will greatly contribute to this integration.

On the other hand, charging infrastructure is a major slowdown that needs to be overcome by public support as no successful business model exists yet. Also, smart charging schemes need to be incentivized in order to minimize the greater demand impact of more EVs on the roads and also to integrate EVs and VRE in a more efficient way. Policy regulation needs to help overcome these challenges through economic and non-economic incentives, regulatory measures, public procurements and public relations.

Three major points of focus for governments are outlined below:

- Decarbonization of the power system and of mobility must be promoted together in order to leverage their gains:

This must be done by setting ambitious road transport targets and GHG reductions targets for transport; by supporting charging infrastructure through incentives, installation of public charging, etc.; by introducing temporary incentives for EVs like price reduction of EV purchase or emission-free zones where only BEVs can drive on; and by deploying more renewables through more ambitious targets where they are not yet in place [16].

- Leverage the use of smart charging, especially in solar-based systems:

This must be done by standardizing and ensuring interoperability between electric vehicles and smart charging points; by implementing smart charging first in isolated systems with high shares of VRE as there will be less competition and can serve as real-world examples of smart charging success; by developing and better regulating the electricity market design for smart charging with, for example, the elimination of double taxes for getting and reinforcing energy in the grid with V2G; and by promoting the design of smart charging strategies that take into account the energy mix and the grid performance [16].

- Study impact of long-term evolution of mobility on smart charging

This must be done by supporting battery and charging R&D; research the potential implications of MaaS for EV flexibility; and by installing charging hubs in the most optimal locations to avoid useless infrastructure investments [16].

2.3.5 EXISTING SMART CHARGING MODELS

2.3.5.1 Objectives and constraints

There are several smart charging models that have already been developed and some of them even proven in real life. However, they differ in objectives, constraints, and approaches.

Two mainstreams for smart charging implementation based on control architecture exist: centralized approach and decentralized approach. In a centralized scheme, the charging of all vehicles is optimized by a single aggregator in order to reach an objective. In a decentralized scheme, each EV has a different optimized charging schedule that is established independently once the vehicle is plugged in order to reach the users' specific objective [41].

These two approaches are played slightly differently by the main agents: PEV users, PEV aggregators, and grid operators. In a centralized scheme, PEV users just require convenient low charging costs, grid operators keep their focus on grid performance and operational costs reduction, and PEV aggregators act as intermediaries. In a decentralized scheme, the charging schedule of each vehicle, although optimized independently, is indirectly controlled by electricity price signals [42]. PEV aggregators forecast the PEV charging demands for the period and use that information to make a competitive bid. After that, grid operators must approve the bidding strategy, just like in a centralized approach. Then, the broadcasted price will be shown to PEV users and each user will schedule their vehicle charging. This usually ends in PEV loads being induced from high demand hours to least congested hours [42].

Among the smart charging models that already exist, three objectives are especially relevant and usually pursued: economic objective, grid performance objective, and environmental objective [42].

The economic objective can be seen from two different perspectives: PEV users and PEV aggregators. While PEV users want to minimize their charging cost and make their batteries live the longest, PEV aggregators want to maximize their profit. PEV users get their charging costs minimized by shifting their charging times towards lower-electricity-price hours. They can also participate in grid ancillary services to cut more their costs or even make some profit. PEV aggregators make an optimal bidding strategy the day ahead based on charging demand and then sell that purchased energy to the PEV users [42].

In order to achieve a great grid performance, smart charging models focus on some type of objective that pursue this goal. The main objectives that can be found are: load variance minimization – that minimizes the variance of the total load: demand load plus charging load – peak load minimization – that makes the maximum load to be minimal – and power loss minimization – which focuses on minimizing the losses incurred in the power transmission wires [42].

The last objective is the environmental one. The idea is to maximize charging when the energy mix generated is mostly renewable so as to reduce the GHG emissions, which is usually done by shifting PEV loads towards hours at which the marginal carbon emissions rate per kWh is lowest [42].

Smart charging models need from some constraints that can be classified into two groups: constraints from the grid, and constraints from PEVs.

Constraints from the grid focus on ensuring a safe operation of the system. They restrict the values node voltages, feeder capacity, and transmission power can take to a range of values [42].

Other constraints related to PEVs are those that protect their battery life or that match user requirements. Among the former constraints, maximum charging and discharging rates and battery capacity constraints (most commonly between 20% and 80%) are thought to be the most relevant ones. Among the latter constraints, require departures times or desired ending state of charge are the most relevant ones.

Other models also integrate smart charging with solar PV generation so as to maximize renewable energy use in PEV charging [43]. However, most of these models are based on workplace charging.

There are also some models that integrate decentralized energy generators (mostly solar) with smart charging in order to have a greener energy in the PEVs' batteries. Nevertheless, these models are usually based on workplace charging, as solar generation matches better with times at work. There are models that employ energy storage to improve energy loss minimization in the presence of solar PV generation [44].

2.3.5.2 Approaches

Not only the existing smart charging models differ in the objectives they pursue and the constraints used, but also in the approach they use.

- Day-ahead

There are some models that establish the power rates for each vehicle at each time prior to the time period in which they will be used. This is done by assuming starting state-of-charges and arrival and departure times, based on very accurate forecasts.

Among them, some approach the problem by establishing some order of priority to charging the EVs based on some characteristics like remaining charging time, price of electricity and state-of-charge. This approach aims to ensure fairness among the different vehicles connected. [45] employs a fuzzy interference scheme to determine these priority levels while reducing the charging cost and is solved using a linear programming approach. [46] uses a moving horizon optimization technique and focuses on valley filling and charging cost reduction.

Other models just consider some input data – mostly forecasted data – and then optimize the charging schedule based on some objective. [47] uses a Genetic Algorithm-based optimization model that minimizes the system peak, while satisfying the physical and operational constraints of the system. A mixed-integer linear programming models is employed in [48] in a try to solve the unbalanced electrical distribution systems problem, and in [49] in order to maximize renewable energy use. [50] presents two model predictive control algorithms that schedule the charging minimizing electricity bills and peak powers.

- Real time

On the other hand, some models employ real-time schedule.

The power rate for each vehicle is established just when the vehicle arrives. Therefore, no assumptions of arrival times are made, and the departure times are asked to the drivers. The optimization program is executed every time a vehicle arrives, and the load is actualized every time a charging schedule is made. [51] presents a EV smart charging model that minimizes the net load variability in a residential environment with installed solar PV. A real-time energy management algorithm is used in [52] in order to minimize the charging cost, the impact on the grid, and the power peaks.

Chapter 3. DESCRIPTION OF THE MODEL

The two models presented in this study establish optimal charging schedules depending on the objectives pursued: model 1 is a linear programming (LP) problem that pursues a charging cost minimization, while model 2 is a quadratic programming (QP) problem that pursues load-variability minimization. An in-depth comparison will be made among the results obtained based on the different objectives pursued. Furthermore, an analysis of the sensibility of the outcomes of both models will be made by adding a restriction on maximum load-variability and charging cost to models 1 and 2 respectively. Solar energy generation is also considered in the model.

N is the number of EVs (20), m is the number of periods per hour and T the number of periods for which the model is proved (36*m). The model was proved in a one day and a half (i.e., 36 hours) time period starting at 12 pm of day 1 and ending at 12 am of day 2 in order to account for those vehicles that arrive before 12 pm of day 1 or departure after 12 pm of day 2. However, the results only the period in between 6 pm of day 1 and 6 pm of day 2, in order to make them clearer.

3.1 NOMENCLATURE

3.1.1 VARIABLES

Name	Symbol	Description
P_EV	$P_{t,n}^{EV}$	Power consumption of EV n at period t in kW
SoC_EV	$SOC_{t,n}$	State of charge of EV n at period t

PV_grid	P_t^{PVg}	Amount of solar energy generated sold to the grid at period t in kW
PV_load	P_t^{PVl}	Amount of solar energy generated used to satisfy load of PEV demand at time t in kW

Figure 3-1: All variables-used-in-the-model's names, symbols, and descriptions

All variables are defined as nonnegative.

3.1.2 PARAMETERS

Name	Symbol	Description
t_EV_s	t_n^s	Arrival time of EV n
t_EV_e	t_n^e	Departure time of EV n
C_EV	C_n	Battery capacity of EV n
charger_eff_EV	η_n	Charger efficiency of EV n
P_EV_max	$P_{max,n}^{EV}$	Maximum power rate EV n can be charged at
SoC_EV_s	SOC_n^s	Arrival state-of-charge of EV n
SoC_EV_e	SOC_n^e	Desired departure state-of-charge of EV n

SoC_EV_max	$SOC^{EV}_{max,n}$	Maximum state-of-charge that EV n can achieve
SoC_EV_min	$SOC^{EV}_{min,n}$	Minimum state-of-charge that EV n can achieve
lambdRT	λ^{RT}_{t}	Electricity price at period t in Eur/kWh
lambdRT_PV	λ^{RT-PV}_{t}	Price of energy injected into the grid in Eur/kWh
P_load	P^{l}_{t}	Demand load at period t in kW
PV	P^{PV}_{t}	Solar energy generation at period t in kW

Figure 3-2: All parameters-used-in-the-model's names, symbols, and descriptions

3.2 OBJECTIVES

For this project, the following objective functions have been considered.

- Cost minimization:

$$min \sum_{t=1}^{T} \left[\left(\sum_{n=1}^{N} P^{EV}_{t,n} + P^{l}_{t} - P^{PVl}_{t} \right) \cdot \lambda^{RT}_{t} - P^{PVg}_{t} \cdot \lambda^{RT-PV}_{t} \right] \tag{1}$$

- Load variability minimization:

$$min \frac{1}{T} \cdot \sum_{t=1}^{T} \left(P^{l}_{t} + \sum_{n=1}^{N} P^{EV}_{t,n} - P^{PVl}_{t} - \mu^{H}_{t} \right)^{2} \tag{2}$$

where

$$\mu_t^H = \frac{1}{T}\sum_{t=1}^{T}\left(P_t^l + \sum_{n=1}^{N} P_{t,n}^{EV} - P_t^{PVl}\right) \tag{3}$$

In the proposed models different approaches are used. One only minimizes costs without considering load variability (**model 1**). The second one only minimizes the load variability, without considering the costs (**model 2**). The extra ones that analyze the sensibility have different constraints and objectives: one minimizes costs but also has a constraint that limits the variability up to some percentage over the minimal (**model 3a**). The fourth one minimizes the variability but also has a constraint that limits the costs up to some percentage over the minimal (**model 3b**).

Hence, the tradeoff between costs and load variability will be well understood and conclusions about which model works best for each case will be obtained.

3.3 CONSTRAINTS

- Maximum power rate: too high charging power will accelerate the ageing of the PEVs' batteries under the current battery technology. Also, chargers have a maximum power rate that cannot be overpassed.

$$P_{t,n}^{EV} \leqslant P_{max,n}^{EV} \; \forall t, n \tag{4}$$

- PEV user charging requirement: the state-of-charge required by the users must be achieved before the end of the charging period so as to ensure the next journey, and the total energy given to the vehicle must match the raise in the state of charge of the vehicle. Therefore, in order to improve charging satisfactions, the PEV user charging requirement should be satisfied by:

$$\eta_n \sum_{t=t_n^s}^{t_n^e} P_{t,n}^{EV} = (SOC_n^e - SOC_n^s) \cdot C_n \ \ \forall n \tag{5}$$

- Initial and final state-of-charge matches: the state-of-charge at the period in which the vehicle arrives must match the forecasted starting state-of-charge and the state-of-charge at the period in which the vehicle departs must match the desired ending state-of-charge, as required by:

$$SOC_{t_n^e,n} = SOC_n^e \ \ \forall n \tag{6}$$

$$SOC_{t_n^s,n} = SOC_n^s \ \ \forall n \tag{7}$$

- PEV minimum and maximum battery capacity: the battery life is related to the depth of charge/discharge and therefore, it is best to keep PEVs batteries' capacity within a reasonable range, usually between 20% and 80% [53],as required by:

$$SOC_{t,n} \leqslant SOC_{max,n}^{EV} \ \forall t,n \tag{8}$$

$$SOC_{t,n} \geqslant SOC_{min,n}^{EV} \ \forall t,n \tag{9}$$

- Dynamic charging update: the stored energy in the battery at period t+1 must equal the stored energy in that same battery at period t plus the energy transmitted to the battery at period t:

$$C_n \cdot SOC_{t+1,n} = C_n \cdot SOC_{t,n} + \eta_n \cdot P_{t,n}^{EV} \quad \forall n, \forall t \in [t_n^s, t_n^e) \cup [0, T-1] \tag{10}$$

- Maximum feeder capacity: there is always a maximum load allowed by each feeder, and cannot be exceeded:

$$P_t^l + \sum_{n=1}^{N} P_{t,n}^{EV} - P_t^{PVl} \leqslant P_{l,max}\ \forall t \tag{11}$$

- Total solar energy generated: the solar energy sold to the grid plus the solar energy used to satisfy internal demand must equal the total solar energy generated:

$$P_t^{PVl} + P_t^{PVg} = P_t^{PV}\ \forall t \tag{12}$$

- Solar PV maximum consumption: the solar energy used to satisfy internal demand cannot be greater than the internal demand. This internal demand is composed of electricity demand of the households and of EVs charging loads:

$$P_t^{PVl} \leqslant P_t^l + \sum_{n=1}^{N} P_{t,n}^{EV}\ \forall t \tag{13}$$

Chapter 4. RESULTS

Firstly, a comparison between the different outcomes of each model in each scenario will be made, regarding the tradeoff between cost and variance of the electricity load demanded from the grid. Then, an analysis of the evolution of the variables over the studied period will be made for one scenario using the models 1 and 2 in order to see the differences in charging patterns followed by the models, as restrictions for models 3a and 3b make the outputs in between those of model 1 and model 2. Finally, the outcomes obtained for different values of the parameter R will be shown, in order to evaluate how different installed solar capacity affects the charging patterns.

4.1 CASE STUDY

This model is proved in a residential environment in El Puerto de Santa María, Spain, which has solar PV installed and 20 EVs. Six different scenarios were studied. The input data for the model parameters and the chosen scenarios are explained below.

4.1.1 ARRIVAL AND DEPARTURE TIMES

The plug-in and plug-out times of the EVs were obtained using a social patterns model that forecasts arrival to and departure from home times [54]. By using the parameters given in Table 4-1 and plugging them into Equation 4-1, the probability distribution of arrival and departure times for each scenario was obtained. It was also necessary to impose some restrictions to the starting and ending charging times: starting times could not be lower than 0 – i.e., they cannot take place before 12 pm – and ending times could not be greater than 36*4 – i.e., they cannot take place after 12 am the following day; starting times also had to take place before ending times. The outcome of the probability function was expressed in minutes, and was therefore rounded to 15-minute intervals.

	Departure time		Arrive time	
	Weekday	Weekend day	Weekday	Weekend day
1st Trimester	μ = 481.66 σ = 126.83 ξ = 0.07216	μ = 586.9 σ = 153.93 ξ = -0.06192	μ = 953.88 σ = 240.14 ξ = -0.4962	μ = 989.48 σ = 282.96 ξ = -0.6292
2nd Trimester	μ = 485.34 σ = 131.46 ξ = 0.045	μ = 576.03 σ = 156.24 ξ = -0.05644	μ = 953.72 σ = 251.07 ξ = -0.5163	μ = 995.59 σ = 284.93 ξ = -0.6414
3rd Trimester	μ = 489.61 σ = 136.82 ξ = 0.05572	μ = 583.88 σ = 161.67 ξ = -0.05694	μ = 947.14 σ = 258.64 ξ = -0.5246	μ = 997.77 σ = 288 ξ = -0.6524
4th Trimester	μ = 483.66 σ = 132.1 ξ = 0.04543	μ = 574.65 σ = 153.76 ξ = -0.05118	μ = 945.78 σ = 252.78 ξ = -0.5106	μ = 988.83 σ = 285.3 ξ =-0.6347

Table 4-1: Departure and arrival times parameters for different scenarios. Source: [54]

$$x = f(y|\mu,\sigma,\xi) = \mu + \sigma \cdot \left\{\frac{[-\ln(y)]^{-\xi}-1}{\xi}\right\} \quad \begin{cases} y \in [0,1] \\ \mu \in R \\ \sigma > 0 \\ \xi \in R \end{cases}$$

Equation 4-1: Calculates the cumulative probability of departure or arrival times. Source: [54]

4.1.2 EVS' BATTERY CAPACITIES

A representative sample of the Spanish EV fleet was modelled by analyzing the number of units of each model sold during 2022. Although it is obvious that this sample would not be the most representative nowadays – most EVs in the Spanish vehicle fleet were bought before 2022 – it can be a great benchmark for the years to come, during which smart charging will play a major role. Each of those EV models was given a probability of being in the sample. For example, the Tesla Model 3 was sold 1,137 times and 9,085 EVs were sold in total. Hence, the probability of a car in the neighborhood being a Tesla Model 3 was 1,137/9,085 = 12.52%. Then, the cumulative probability was calculated and N random numbers from 0 to 1 were chosen in order to get the aimed representative fleet. The steps followed are shown in Table 4-2, and the chosen fleet for the residential environment can be seen in Table 4-3.

Ranking	Modelo	Unidades	Capacidad (kWh)	Probabilidad	Probabiliad Acum.
1	Tesla Model 3	1.137	54	0,125151348	0,125151348
2	KIA e-Niro	924	64	0,101706109	0,226857457
3	Citroën ë-C4	483	50	0,053164557	0,280022014
4	FIAT 500e	443	42	0,048761695	0,328783709
5	KIA EV6	426	58	0,046890479	0,375674188
6	Hyundai IONIQ 5	410	58	0,045129334	0,420803522
7	MINI Cooper SE	358	32,6	0,039405614	0,460209136
8	Hyundai Kona Eléctrico	340	39,2	0,037424326	0,497633462
9	Tesla Model Y	299	60	0,032911392	0,530544854
10	Mercedes EQA	257	66,5	0,028288387	0,558833242
11	Peugeot e-2008	245	50	0,026967529	0,585800771
12	Volkswagen ID.4	218	52	0,023995597	0,609796368
13	Smart EQ ForTwo	208	17,6	0,022894882	0,632691249
14	Renault ZOE	206	52	0,022674739	0,655365988
15	Dacia Spring	200	27,4	0,022014309	0,677380297
16	Peugeot e-208	193	50	0,021243808	0,698624106
17	Ford Mustang Mach-E	177	68	0,019482664	0,718106769
18	Renault Twingo Electric	167	22	0,018381948	0,736488718
19	Mercedes EQB	164	66,5	0,018051734	0,754540451
20	BMW i3	164	42,2	0,018051734	0,772592185

Table 4-2: First 20 models and their respective cumulative probabilities of being bought. Source: ANFAC [22]

Nissan Leaf	40
Tesla Model 3	54
Citroën ë-C4	50
Mercedes EQC	80
Hyundai IONIQ 5	58
Renault ZOE	52
Mercedes EQA	66,5
Tesla Model 3	54
Hyundai IONIQ 5	58
Volkswagen ID.3	45
Aiways U5	63
Tesla Model 3	54
Tesla Model 3	54
Renault Twingo Electric	22
Audi Q4 e-tron	76,6
Mercedes EQA	66,5
Hyundai Kona Eléctrico	39,2
MINI Cooper SE	32,6
KIA e-Niro	64
BMW i4	80,7

Table 4-3: Chosen vehicles and their corresponding battery capacities for the case study

4.1.3 MAXIMUM FEEDER CAPACITY

Assuming 12.5 kW as maximum allowable load per household, 12.5*N = 250 kW can be assumed to be the maximum demand the grid can satisfy

4.1.4 MAXIMUM POWER CHARGING RATE

The maximum power charging rate was set to 11 kW, which is a common fast speed type of charger. Power rates higher than 11 kW reduce the flexibility given to smart charging, while power rates lower than 11 kW take too long to charge increasingly bigger batteries.

4.1.5 CHARGER EFFICIENCY

The efficiency of all chargers was set to 90%

4.1.6 DEMAND LOAD

The demand load on an hourly basis was obtained using data from REE [55]. Only less-than-10-kW consumers were considered – mostly representing households. The demand load varied between months, as expected.

4.1.7 ELECTRICITY AND INJECTED ENERGY PRICES

The prices were obtained on an hourly basis using again data from REE [56]. The PVPC (the voluntary price for the small consumers) was chosen as the electricity price, while the Energy Injected into the Grid price was chosen as the solar energy for sale price.

4.1.8 SOLAR ENERGY GENERATION

Using PVWatts Calculator [57] and using concrete data as input, solar generation on an hourly basis was estimated based on past years data. The data used as input is:

- Location: El Puerto de Santa María. This city was chosen given the great solar resource available to use and due to its almost non-existing EV charging infrastructure, in an attempt to promote EV use.
- Fixed array type: the solar panels do not move following the sun
- Standard module type: crystalline silicon, 15% nominal efficiency, glass as module cover, and -0.47%/ºC temperature coefficient of power
- Tilt angle: 20º, as the optimal angle during summer is L-15º (being L = 36.6ºN the latitude at El Puerto de Santa María), season at which the solar generation is most relevant.
- Azimuth angle: 180º – true south – in order to best capture sun rays

Also, the capacity of the solar panels was set to 2.3 kW per household, which produce 3,478 kWh annually, close to what a Spanish average household consumes throughout a year: 3,487 kWh. A parameter R is defined to be an annual solar production to annual electricity demand ratio, which in the case of 2.3 kW is very close to 1. This parameter was modified in some cases in order to show how changes in the capacity of the solar panels change charging patterns and costs. Its value was set to 0.4 in the base case study, but a sensitivity to this value is performed in Section 4.4.

4.1.9 SCENARIOS

4.1.9.1 April 2022

This month is used as a benchmark, given its proximity and its relatively normal working conditions.

4.1.9.2 April 2022 only working days

Same month as before but only taking into account working days. This, compared to only non-working days, will be helpful in determining differences in charging behaviors given the different electricity prices and social patterns related to those days.

4.1.9.3 April 2022 only non-working days

Useful to compare against only working days.

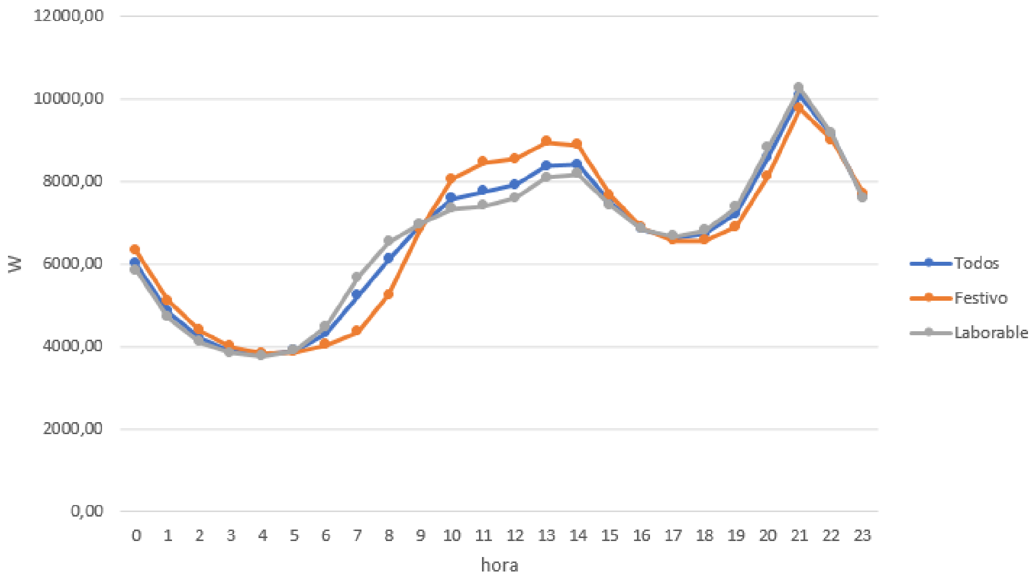

Figure 4-1: Demand load during April 2022 for all, only working, and only non-working days. Source: REE [55]

The demand – shown in Figure 4-1– during April is very intuitive. It starts to increase in the morning when people start working and there is a high demand during the most intense hours of the day, where everybody is doing something productive: either working or socializing. During and after lunch there is a valley, as people go home to eat and take a nap and go back to work around 6 pm. The peak occurs at around 9 pm, time at which most people are at home.

The demand load during non-working days is quite similar to the one during working days, with small differences. There is a higher demand during the morning and afternoon (10 am - 2 pm), a lower demand during the start of the journey (6 am - 9 am) and a lower peak at 9 pm.

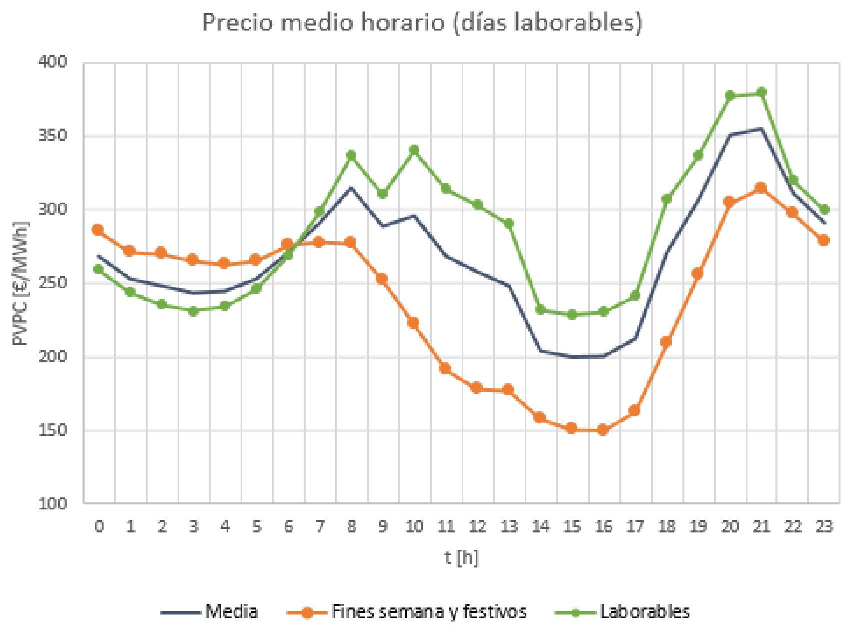

Figure 4-2: Electricity price during April 2022 for all, only working, and only non-working days. Source: REE [56]

As illustrated in Figure 4-2, the electricity price experiences two great peaks: during the start of the journey (8 am -11 am) and during dinner time (8 pm – 10 pm). A great valley can be seen after lunch (2pm – 5 pm). The electricity price is much lower the entire day during non-working days, except from night times (12 am – 6 am).

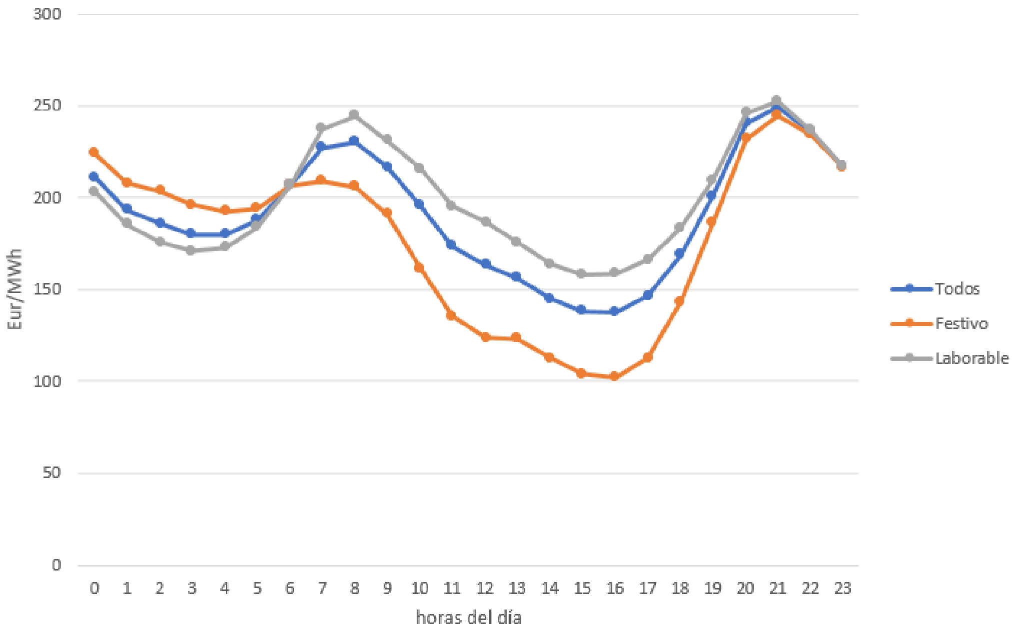

Figure 4-3: Price of energy injected into the grid during April 2022 for all, only working, and only non-working days. Source: REE [56]

The price of the energy injected into the grid follows a very similar behavior, as seen in Figure 4-3. However, it is easy to see that it is about two thirds that of the electricity price.

4.1.9.4 April 2019

Same month, but before the pandemic. Electricity prices policies have changed since then, and the situation was far more normal than it is in 2022. The post-pandemic rise in prices, combined with the war in Ukraine and the political instability, make 2022 a rather exceptional example.

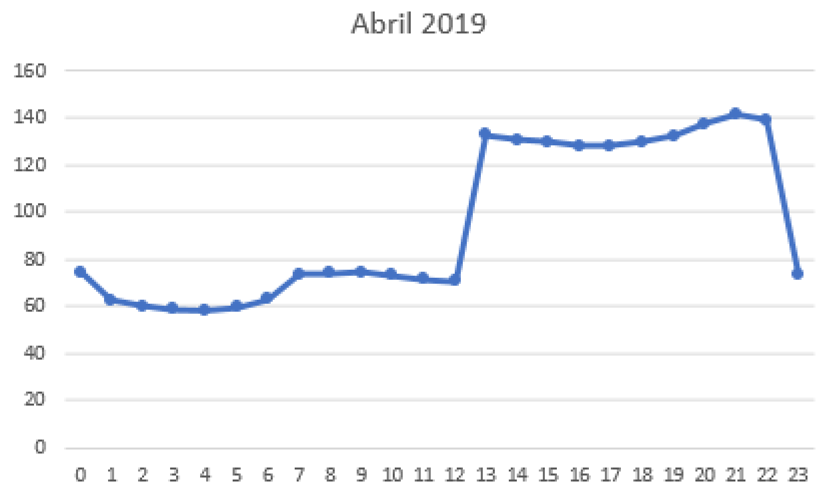

Figure 4-4: Electricity price during April 2019. Source: REE [56]

Figure 4-4 shows that there are huge differences between the electricity price in 2019 to the one in 2022. First, back in 2019, there was a different policy regarding valley, peak and plain times – although in this case only two time zones can be clearly appreciated. Then, the electricity price is about a third of the one in 2022 due to the economic and political crisis that the world is currently living.

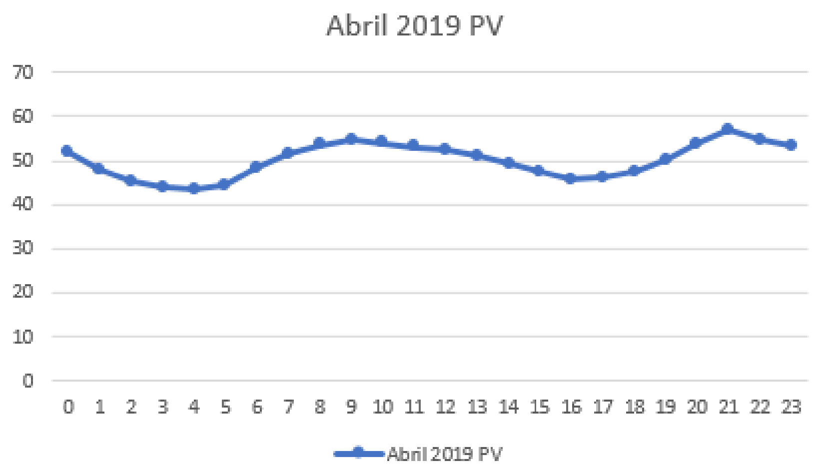

Figure 4-5: Price of energy injected into the grid during April 2019. Source: REE [56]

Again, Figure 4-5 shows that there exists a huge difference when compared to the price of energy injected into the grid in 2022. In 2019, the price was almost plain and about a third of the one in 2022. The reason behind this is that this price was settled by the energy marketer as the average electricity price minus the deviations defined in the RD 216/2014 [58].

4.1.9.5 July 2019

This scenario is situated in summer, in order to analyze the charging schedule changes given the higher solar production and the shift in peak demand times. Pre-pandemic data is used (2019), in order to avoid the extraordinary conditions of more recent years.

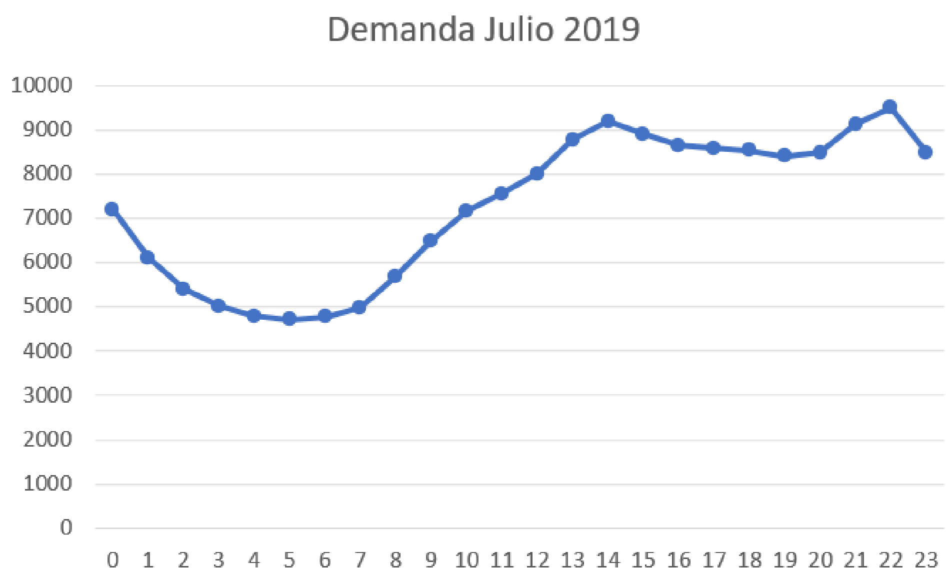

Figure 4-6: Demand load during July 2019. Source: REE [55]

As can be seen in Figure 4-6, the demand load during summer is much plainer than the one in spring. The demand starts rising around 7 am, reaching a relative peak at 2 pm, maintaining a high level during the evening before reaching the absolute peak at 10 pm, and then decreasing to almost half of its peak value at 5 am. The lower levels of work during the morning and the higher demand of air conditioning during the warmer hours could explain this behavior.

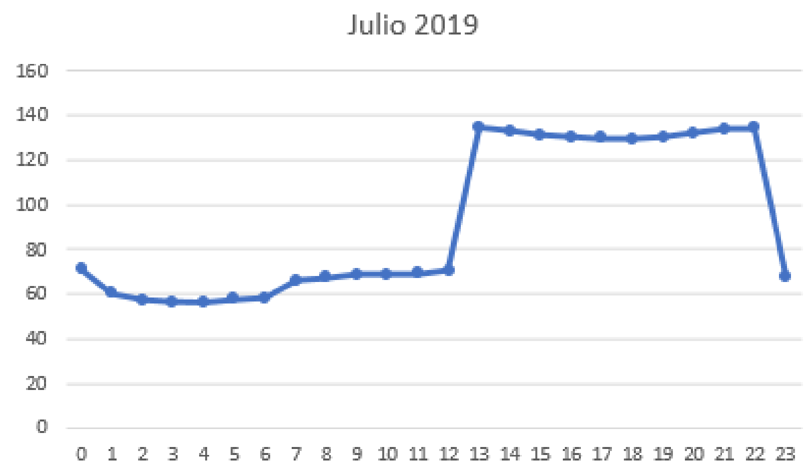

Figure 4-7: Electricity price during July 2019. Source: REE [56]

The electricity price in summer follows almost the same behavior as the one in spring, as Figure 4-7 shows. The time zones that used to characterize the electricity price for small consumers were the essence of these patterns.

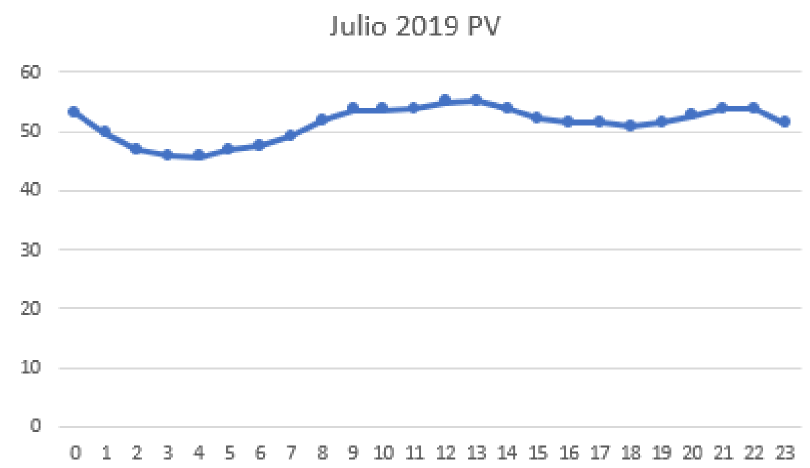

Figure 4-8: Price of the energy injected into the grid during July 2019. Source: REE [56]

Same reasoning to the one made in April 2019 can be applied to what seen in Figure 4-8.

4.1.9.6 January 2020

This scenario is situated in winter, in order to analyze the charging schedule changes given the lower solar production and the higher demands. Again, pre-pandemic data is used (2020).

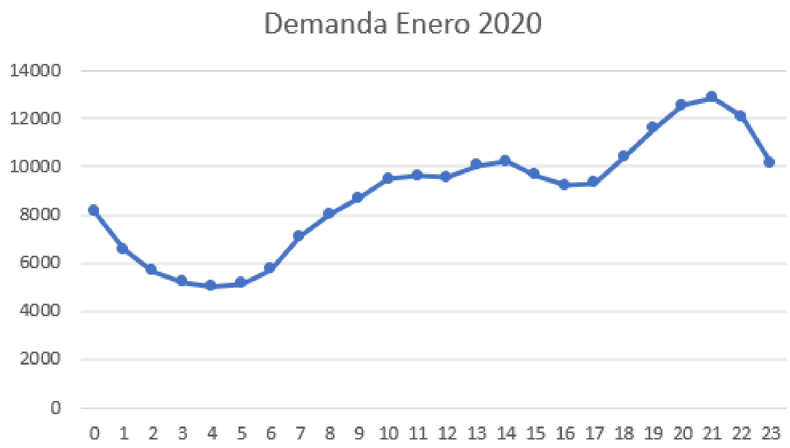

Figure 4-9: Demand load during January 2020. Source: REE [55]

Figure 4-9 shows that the demand is quite similar to other months' behaviors, but the values reached are much higher. It is relevant the high peak during night times (7 pm – 10 pm), probably caused by a huge use of electric heating.

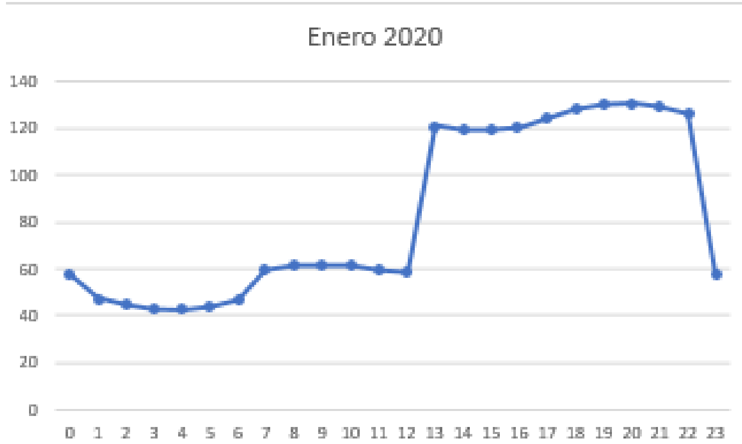

Figure 4-10: Electricity price during January 2020. Source: REE [56]

Same pattern as the ones before the pandemic can be seen in Figure 4-10, although the prices are a little lower. There is also a slightly bigger difference between valley (12 am – 6 am) and plain (7 am – 12 pm) time zone.

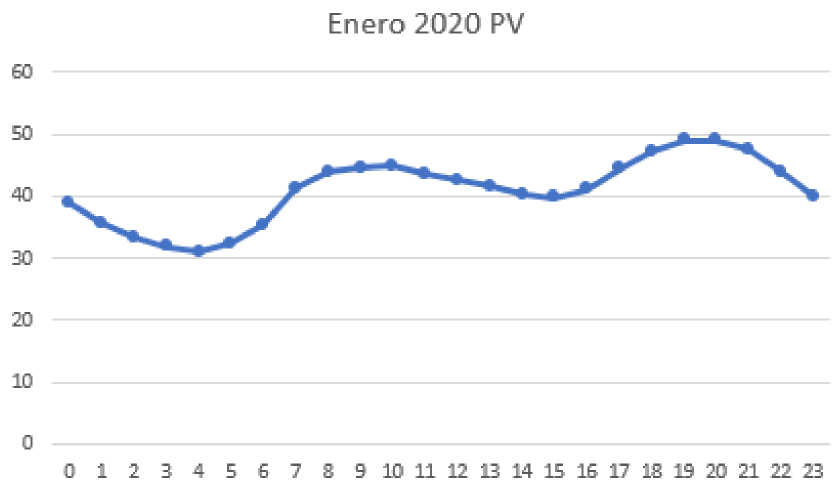

Figure 4-11: Price of the energy injected into the grid during January 2020. Source: REE [56]

Figure 4-11 shows that in winter the behavior of the prices for the energy injected into the grid is much plainer and that they are slightly lower when compared to those in summer or spring.

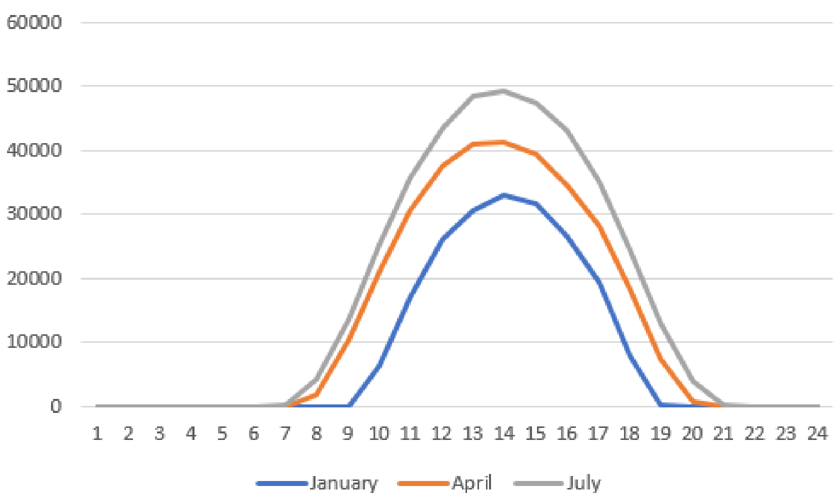

Figure 4-12: Solar energy generation during January, April, and July in El Puerto de Santa María. Source: PVWatts calculator [57]

As expected, solar energy production is greater in summer, followed by spring and winter. The peak always occurs at around 2 pm. Same behavior, but the sun stays for longer in summer than in winter. Hence, times at which solar production is 0 in winter, it is nonzero in summer or spring.

4.2 DIFFERENT SCENARIOS COMPARISON REGARDING THE TRADEOFF BETWEEN COST AND VARIANCE

The outputs of the model for the different scenarios and models are shown in the below figures. The percentage represents the maximum allowed deviation from the optimal value (which has been computed using models 1 and 2) of constrained characteristic for model 3a (cost minimization with a constraint on the load variability deviation) and of model 3b (load variability minimization with a maximum charging cost deviation that the EV user is willing to pay). For example: in model 3a 5% means that the model will minimize charging costs constrained to having a load variability less than 105% that of the minimal load-variability possible.

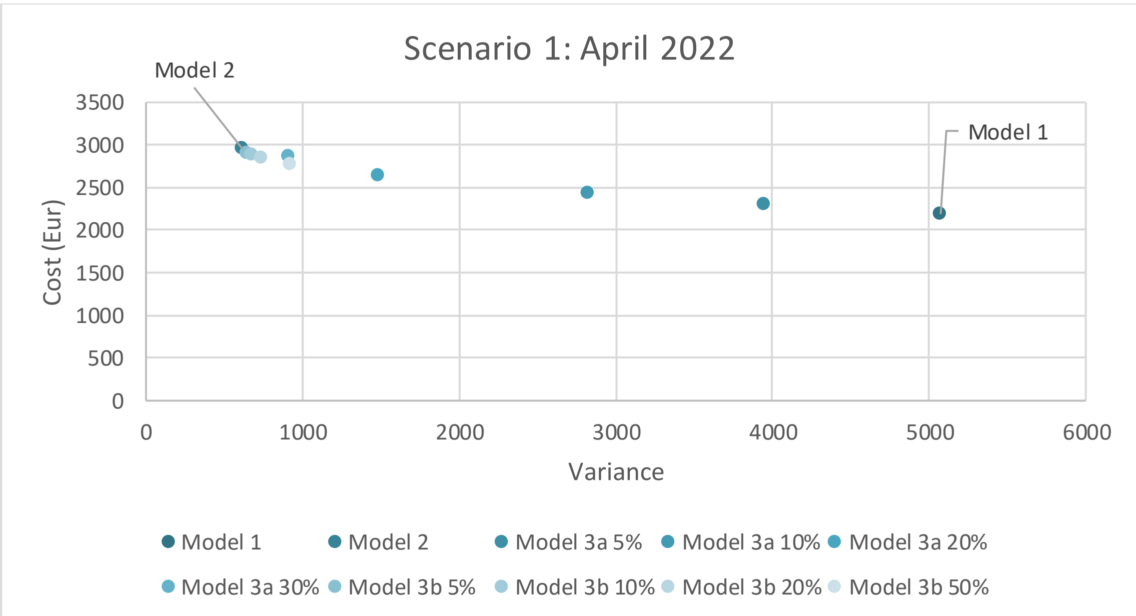

Figure 4-13: Tradeoff between cost and variance experienced by the output of the different models in April 2022

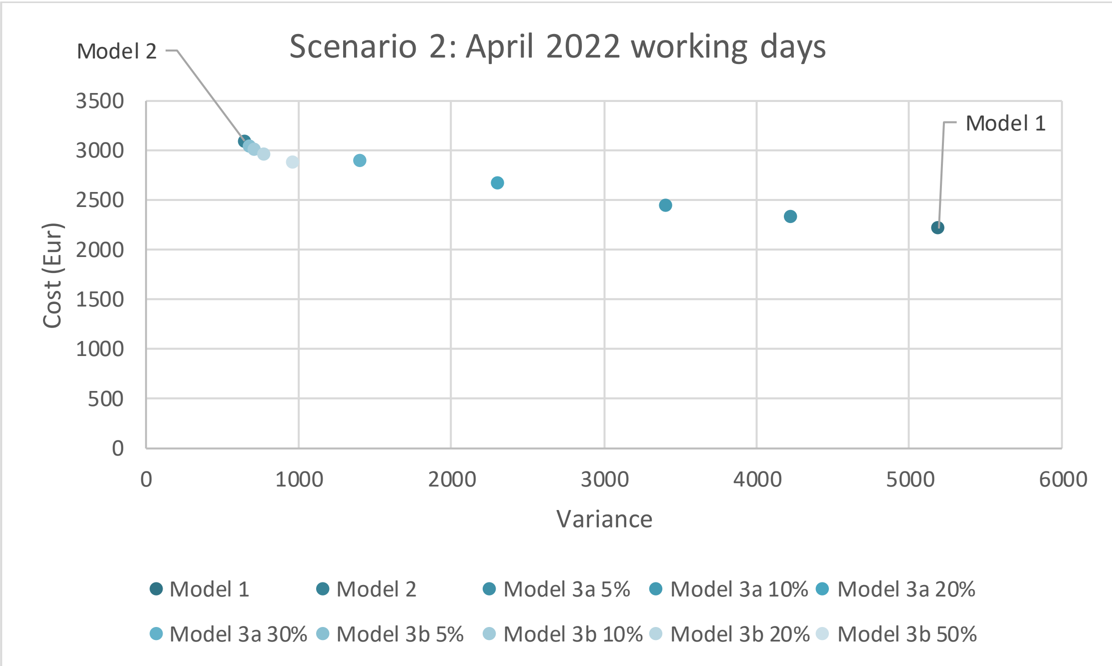

Figure 4-14: Tradeoff between cost and variance experienced by the output of the different models in April 2022 during working-days

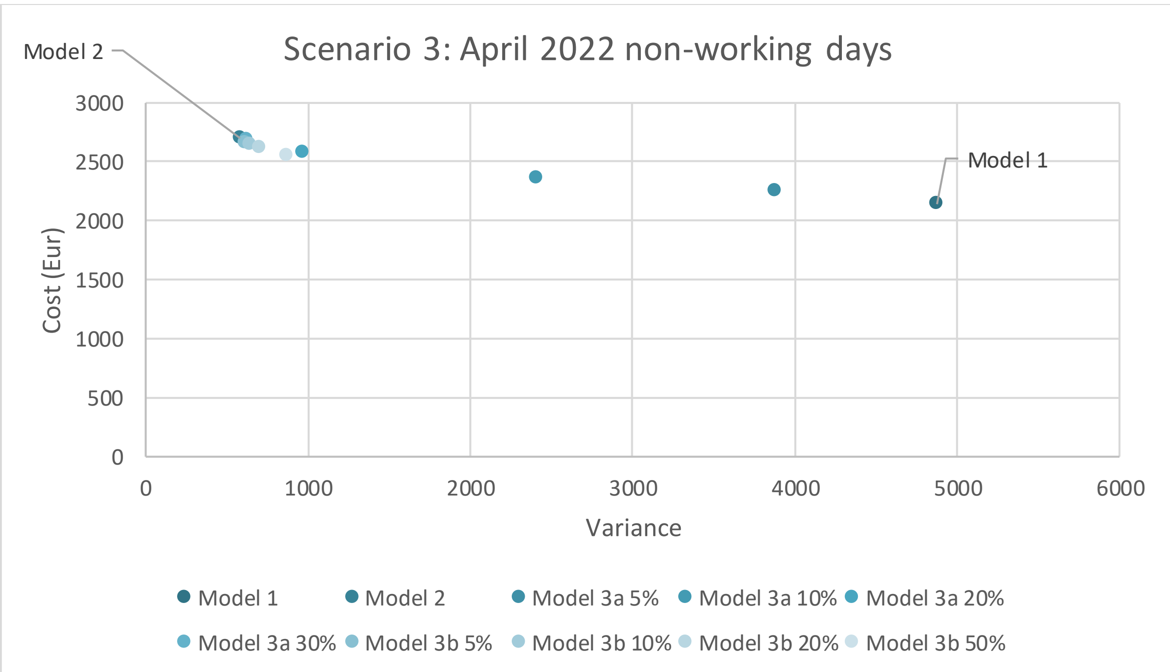

Figure 4-15: Tradeoff between cost and variance experienced by the output of the different models in April 2022 during non-working days

Figure 4-13, Figure 4-14, and Figure 4-15 show the tradeoffs between cost and variance experienced by the outputs of all studied models for Scenario 1, 2, and 3. Firstly, an inverse relationship between cost and variance can be seen. The lower the cost the greater the variance. However, the slope is almost plain: a small decrease in cost results in a great increase in variance.

Second, as expected, model 1 and model 2 outcomes are at the extremes and model 3a and 3b outcomes are in between. As model 3a and 3b have constraints on either charging cost or load-variability, their objective values increase depending on the percentage chosen on the constraint. For example, model 3b's load-variability increases with respect to model 2, but its cost decreases, coming closer to model 1's outcome.

Third, it is noticeable that the model 3b outcomes are all very close to each other, as the low minimum variance makes the extra percentage in variance constraints for this model almost useless, with very little different relative to what is seen in model 1 and model 3a outcomes.

With respect to differences among scenarios, the most relevant one is the lower charging cost and the slightly lower variance experienced during non-working days. As seen before, the lower electricity prices combined with the slightly plainer demand load can explain these differences. The scenario 1 is just a weighted average of scenario 2 and 3.

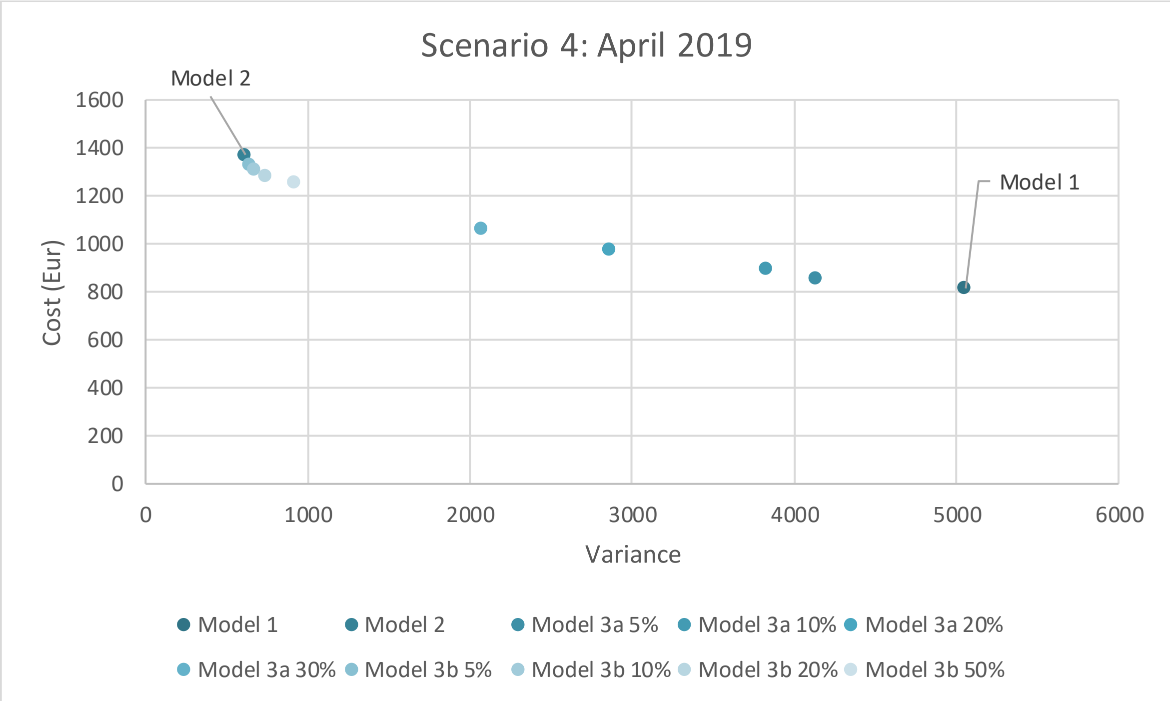

Figure 4-16: Tradeoff between cost and variance experienced by the output of the different models in April 2019

Figure 4-16 represents the tradeoff between cost and variance experienced by the outputs of all studied models in Scenario 4. The incredibly lower prices that were seen back in 2019 make scenario 4 have a much lower charging cost, even though it is in April as in the previous scenarios. Charging cost is almost reduced to a third of its 2022 value. However, the same improvements do not occur when looking at the variance even if the prices in both scenarios have very different structures. The variances are almost the same, as they basically depend on the demand load and the solar power generation, which are exactly the same for both scenario 1 and 4.

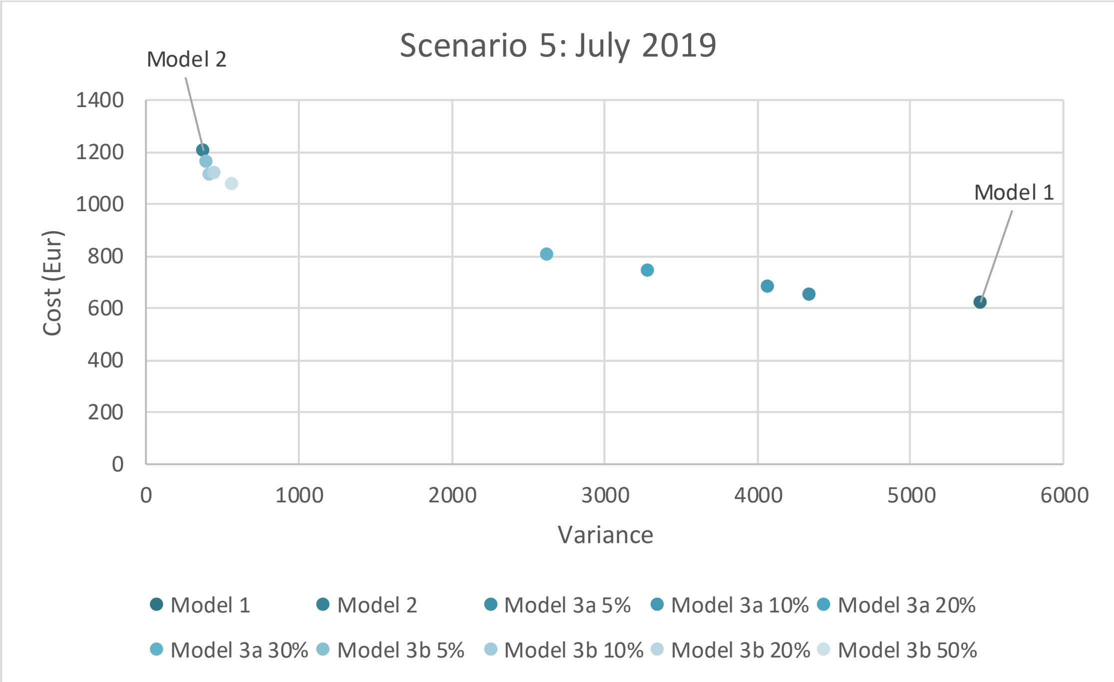

Figure 4-17: Tradeoff between cost and variance experienced by the output of the different models in July 2019

An even greater reduction in charging costs occurs during July of 2019, as seen in Figure 4-17. when electricity prices were not as high as they are now. These lower charging costs can be explained by the higher solar generation, which reduces the electricity demanded to the grid and decreases our costs by getting some revenue from the energy injected into the grid. The variance is slightly higher for model 1 and 3a outcomes and slightly lower for model 2 and 3b outcomes when compared to other scenarios. The possible explanation behind this is that in July there days are longer and solar energy is produced during a longer time which, in the case of model 1 and model 3a is mostly used to satisfy internal demand – demanding 0 kW to the grid – and hence increasing the variance.

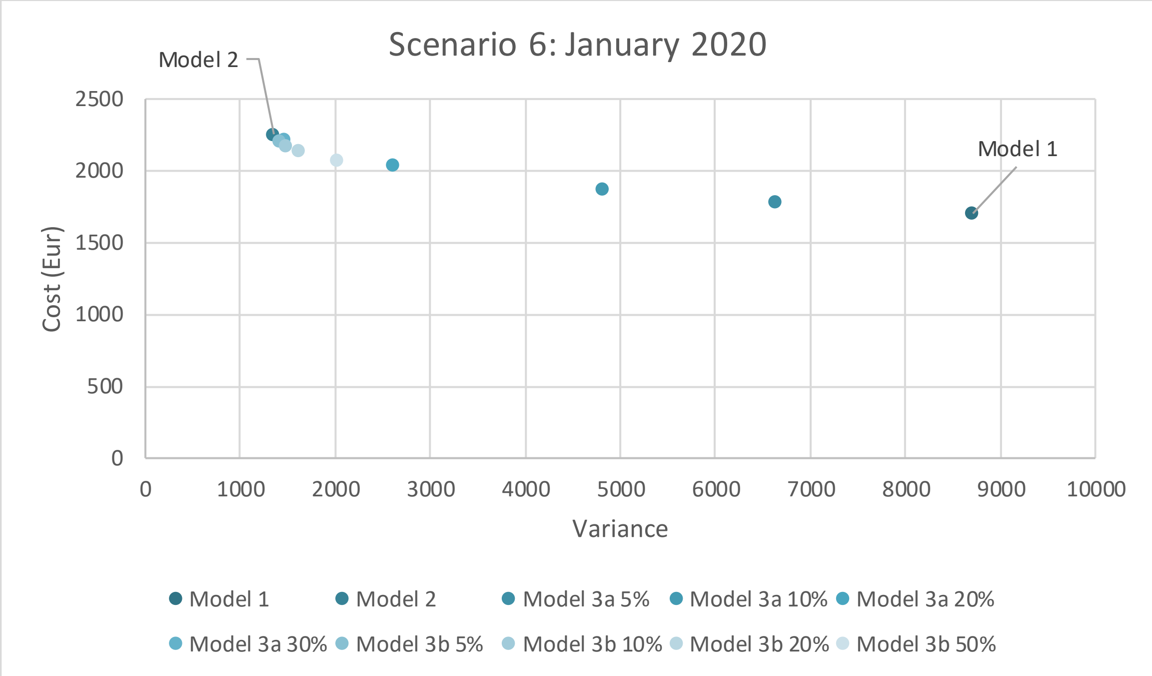

Figure 4-18: Tradeoff between cost and variance experienced by the output of the different models in January 2020

The lower solar generation and the higher electricity demand experienced in January increase the charging costs, even doubling the ones in July, as Figure 4-18 shows. The fact that the electricity prices were lower in January than they are in April or July explains the relevancy of the solar power as an alternative way of reducing charging costs. The larger electricity demand also explains the much greater variance of the demanded load to the grid.

As a general comment, it is easy to see that the lower the cost, the more assorted are the outcomes by models. E.g. in scenario 4, model 3a outcomes are all much closer together than the model 3a outcomes in scenario 2. The reason behind this is that the lower the cost, the lower additional cost in absolute value model 3a outcomes will be restricted to (30% of 600 is much less than 30% of 2200), and that is directly related to the variance outcomes, assorting the results in a natural way.

All the results are summed up in Table 4-4.

					5%		10%		20%	
	Model 1		Model 2		Model 3a (restCoste)		Model 3a (restCoste)		Model 3a (restCoste)	
Scenario	Cost	Variance	Cost	Variance	Cost	Variance	Cost	Variance	Cost	Variance
1	2189,06	5073,46	2952,89	616,47	2306,17	3954,06	2424,94	2821,08	2638,78	1485,8
2	2215,49	5194,37	3097,73	644,82	2335,35	4221,95	2447,33	3405,32	2666,08	2301,07
3	2141,45	4875,69	2700,93	581,69	2250,12	3879,02	2366,98	2407,29	2583,05	974,22
4	814,62	5057,88	1371,55	616,47	855,87	4134,19	896,91	3829,59	977,68	2862,96
5	621,63	5458,49	1204,45	377,89	652,45	4344,44	683,21	4073,26	745,03	3282,66
6	1703,2	8711,58	2255,15	1353,14	1787,62	6645,46	1872,67	4817,39	2043,49	2611,95

	30%		5%		10%		20%		50%	
	Model 3a (restCoste)		Model 3b (restVar)		Model 3b (restVar)		Model 3b (restVar)		Model 3b (restVar)	
Scenario	Cost	Variance	Cost	Variance	Cost	Variance	Cost	Variance	Cost	Variance
1	2855,34	914,24	2902,51	647,51	2878,81	678,12	2844,12	739,77	2769,93	924,64
2	2894,99	1407,66	3039,49	677,06	3010,59	709,3	2967,5	773,78	2879,22	967,22
3	2691,54	623,41	2664,8	610,77	2648,96	639,86	2622,43	698,03	2556,08	872,53
4	1061,14	2077,12	1331,46	647,3	1311,74	678,12	1283,08	739,77	1255,21	924,71
5	807,27	2629,86	1162,96	396,78	1115,7	415,67	1122,38	453,46	1077,9	566,82
6	2214,26	1474,09	2202,81	1420,79	2177,85	1488,45	2142,13	1623,76	2070,42	2029,7

Table 4-4: Summary of all outputs (all models in all scenarios)

4.3 VARIABLE ANALYSIS

Scenario 4 (April 2019) is used as a benchmark given the standard conditions lived on that month. The electricity prices were normal, the solar generation is important but not as high as during summer and the electricity demand is close to an annual average.

Before starting the analysis of the results, some definitions need to be made:

- LoadEV: it is the combined power rate at which all vehicles are being charged at each time.
- LoadEVa: it is the power rate at which a specific vehicle is being charged. In all these cases, the vehicle 2 was chosen.
- Demand+EV load: it is the neighborhood electricity demand plus the EV load.
- Demand load: it is the neighborhood electricity demand (it is a parameter).
- Grid load: it is the electricity demand plus the EV load minus the solar energy used to satisfy both these loads.
- PV_load: it is the part of the solar energy produced that is used to satisfy the internal demand (electricity demand plus EV load).

- PV_grid: it is rest of the solar energy produced that is injected into the grid in exchange of money.
- SoC: it is the state-of-charge of a vehicle. In all these cases, the vehicle 2 was chosen.

4.3.1 MODEL 1 (COST: 814,62 EUR; VAR: 5057,88)

This model's outcome has a very low cost but a very high variability of the load.

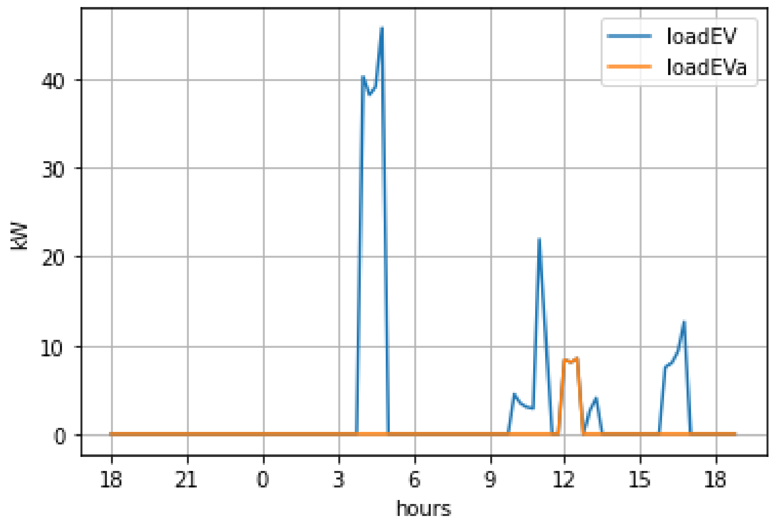

Figure 4-19: LoadEV and LoadEVa evolution output using model 1 in Scenario 4

Figure 4-19 gives a better understanding of how the charging schedule is organized. A huge spike reaching the 40 kW charging power rate at around 4-5 am occurs, given that it is at that time when the electricity price is lowest. The EV tariff in this scenario could be improved by having the exact same price during off-peak hours to avoid this spike. This time of use differentiation could also be combined with a randomized start of charging the EVs (e.g., random-in window smart charging strategy) Some charging also occurs before afternoon and in the evening, benefiting from the solar energy produced.

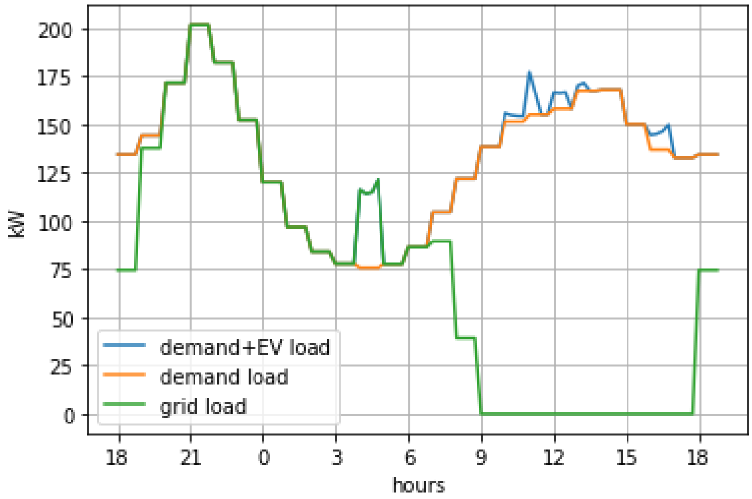

Figure 4-20: Demand, demand+LoadEV, and grid load evolution using model 1 in Scenario 4

Figure 4-20 helps understand what the power demanded to the grid is, as well as how the charging schedule modifies the demand load. As there is no restriction on variability, the peak before midnight contrasts with the valley during the day, even though the demand is still high during the day. The charging spike is just a little peak at 4-5 am, given that the maximum 40 kW reached by the charging power rate is relatively small compared to the electricity demand – which reaches values of 200 kW.

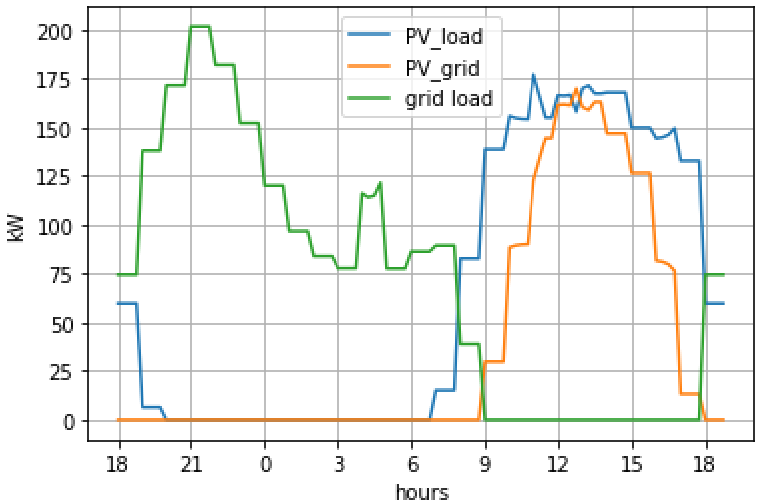

Figure 4-21: PV_load, PV_grid, and grid load using model 1 in Scenario 4

Figure 4-21 gives a view of how much solar energy is injected into the grid and how much is used to satisfy internal demand. As explained before, the lack of restriction on variance implies that all the solar power that can be used to satisfy internal demand will be used for that purpose. This happens because the charging costs are further reduced when satisfying internal demand than when selling to the grid, as the electricity price is higher than the price of injecting energy into the grid. The rest of the solar energy produced is injected into the grid.

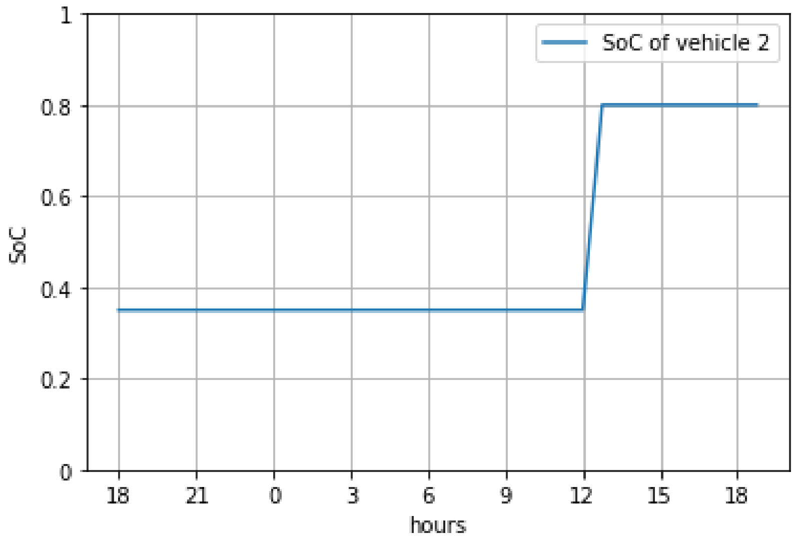

Figure 4-22: Vehicle 2 state-of-charge evolution using model 1 in Scenario 4

Figure 4-22 helps illustrate what the evolution of the state-of-charge of a random vehicle is. The state-of-charge before arriving home of all vehicles is assumed to be the starting state-of-charge. Similarly, the state-of-charge after departing from home of all vehicles is assumed to be the ending state-of-charge. The chosen vehicle is charged at noon when no other vehicle is being charged. This car is charged at almost maximum power. The quick charge can be explained by the high-power rate used – almost the maximum 11 kW – the not-huge capacity of the vehicle – 54 kWh – and the relatively high starting state-of-charge – only a 48% of the battery had to be charged.

4.3.2 MODEL 2 (COST: 1371,55 EUR; VAR: 616,47)

This model's outcome has a 168% charging costs and a variance of just 12% of the outcome of the model 1.

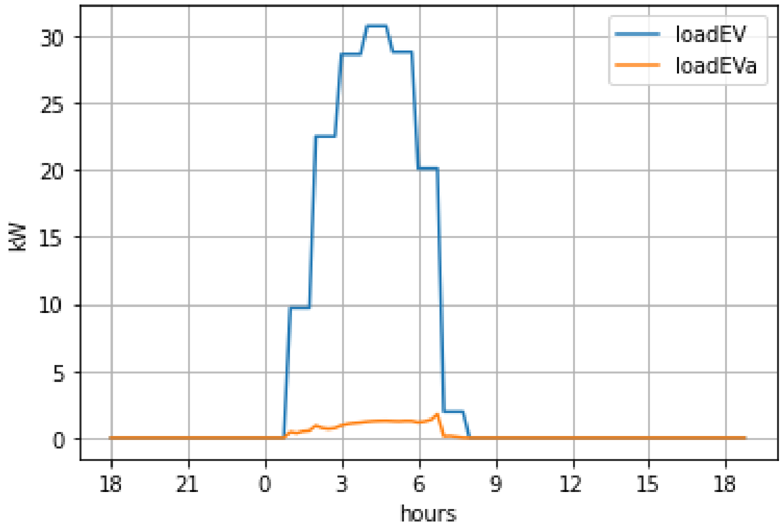

Figure 4-23: LoadEV and LoadEVa evolution output using model 2 in Scenario 4

The first difference that can be seen in Figure 4-23 with respect to Figure 4-19 is that the spike that occurs at night is not that steep. The maximum EV load reached is a little higher than 30 kW. The charging only takes place at night. The variance minimization shifts the loads to night times – when the electricity prices are lower – in a natural way, without any cost restriction. The charge of the chosen vehicle is spread all around the charging times range – from around 1 am to around 8 am.

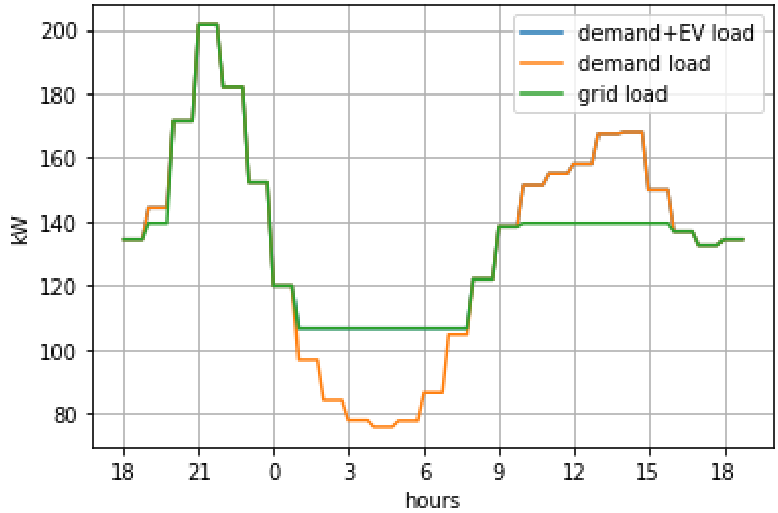

Figure 4-24: Demand, demand+LoadEV, and grid load evolution using model 2 in Scenario 4

Figure 4-24 shows that the variability minimization imposes a much plainer grid load. The peak before midnight cannot be further reduced as there is no solar energy production and the electricity demand cannot be changed. The electricity demand valley is filled with EV load in order to make the grid load much plainer.

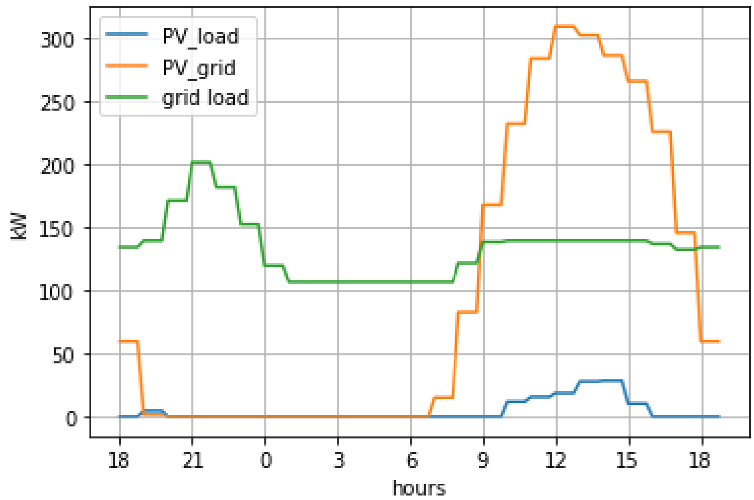

Figure 4-25: PV_load, PV_grid, and grid load using model 2 in Scenario 4

As the objective of variability minimization is approached by reducing the square difference with respect to the mean, the PV load is carefully established so as to set the grid load during the day as close to the grid load mean as possible, as illustrated in Figure 4-25. That mean is around 140 kW given that the peak before midnight and the valley at night compensate each other. The rest of the solar energy production – the vast majority – is sold to the grid.

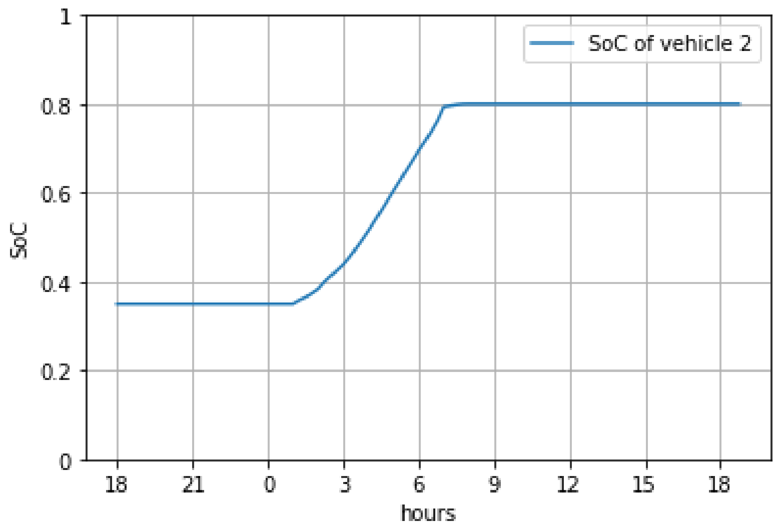

Figure 4-26: Vehicle 2 state-of-charge evolution using model 2 in Scenario 4

Figure 4-26 shows that the chosen vehicle is charged in a quite smooth way. The charge takes around 6 hours, much more than the less-than-one hour charge scheduled by model 1. As the departure time is the same as in model 1, it is easy to infer that in this case the car will remain fully charged – at the maximum state-of-charge – for more hours.

4.4 SOLAR CAPACITY INSTALLED SENSIBILITY ANALYSIS

Again, using the Scenario 4 as the base case, changes to the parameter R will be made in order to analyze how the charging pattern changes with different solar capacity installed

4.4.1 R = 0.1

4.4.1.1 Model 1 (Cost: 1801,55 Eur; Var: 1763,19)

Although the charging costs are much higher – given that less solar energy is available to reduce costs – the variance is much lower. The solar power generation could be playing the role of variance's driver.

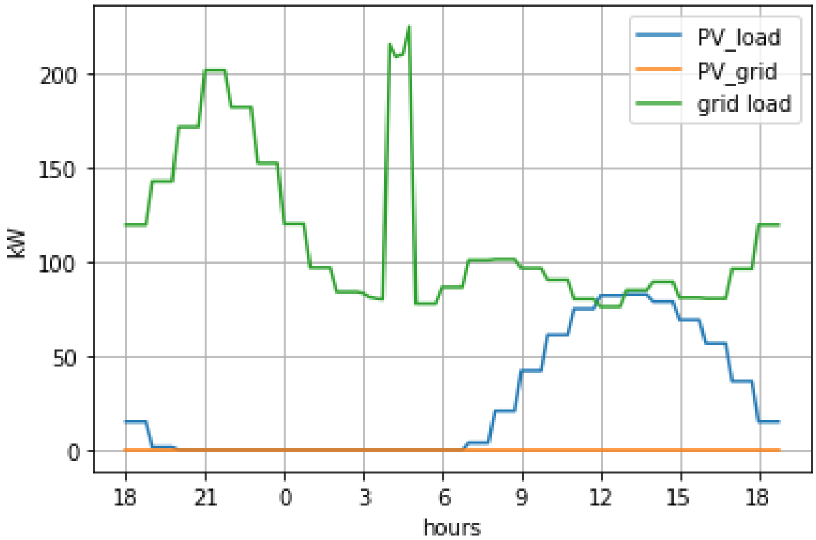

Figure 4-27: PV_load, PV_grid, and grid load using model 1 in Scenario 4 with R = 0.1

Figure 4-27 shows that a huge spike in the grid load occurs again, but in this case is bigger, as the charging only occurs at that time. It can be implied that there is no incentive to charge some cars during the day as there is no more solar energy available to use to satisfy the internal demand. All the solar energy is used for that purpose, following the same reasoning of before (further cost reduction given the different prices).

4.4.1.2 Model 2 (Cost: 2003,55 Eur; Var: 616,97)

In this case, the variance is the same as with R = 0.4 but the cost is a 46% higher.

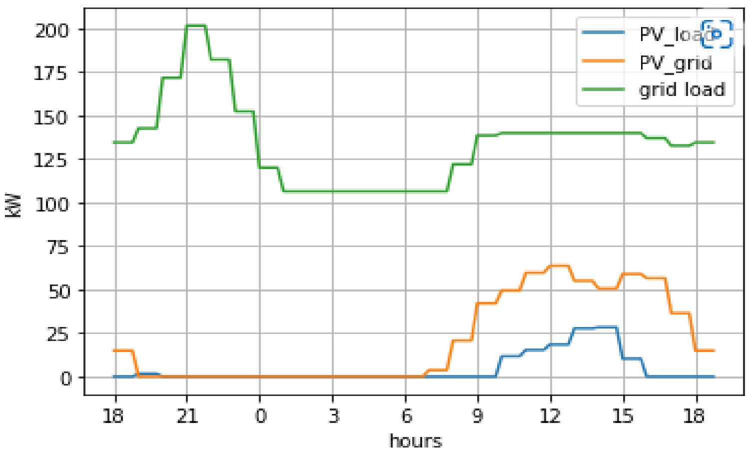

Figure 4-28: PV_load, PV_grid, and grid load using model 2 in Scenario 4 with R = 0.1

Figure 4-28 illustrates that the reason behind the increase in charging costs is the lower solar energy available to inject into the grid. While the solar energy produced was enough to satisfy the required by the load variability minimization, making the charging schedule exactly the same as before, the costs cannot be reduced that much due to the lack of produced solar energy.

4.4.2 R = 1

4.4.2.1 Model 1 (Cost: -503,61 Eur; Var: 5388,22)

In this case we have negative charging costs. The huge increase in the R parameter gives a really high solar energy production, whose excess can be sold to the grid to earn some revenue and, in this case, even profit. Nevertheless, the variance is even higher. This supports the hypothesis made above: the solar energy production is a driver of load variability.

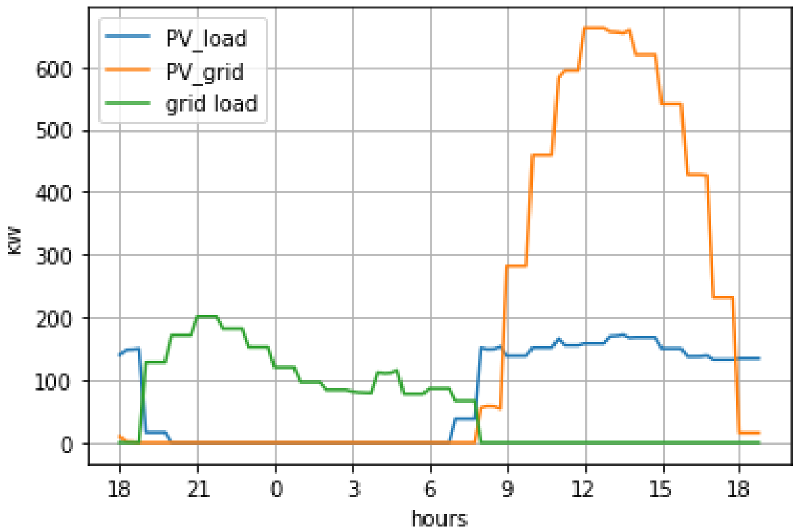

Figure 4-29: PV_load, PV_grid, and grid load using model 1 in Scenario 4 with R = 1

The solar energy is used to satisfy all the internal demand and the rest of it is sold to the grid, as shown in Figure 4-29. As the solar energy production clearly outweighs the demand, most of it is sold.

4.4.2.2 Model 2 (Cost: 112,72 Eur; Var: 616,67)

The variance remains at its minimum and the charging almost breaks even. The revenues earned by selling the excess of solar energy produced almost equals the charging costs.

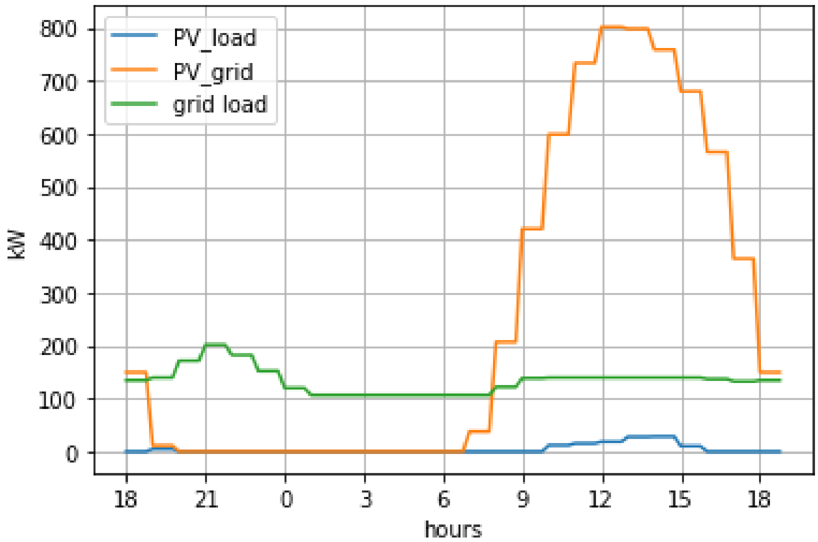

Figure 4-30: PV_load, PV_grid, and grid load using model 2 in Scenario 4 with R = 1

Figure 4-30 shows that, as before, the solar energy is used to carefully set the grid load as close to the average as possible in order to minimize the variability, while the rest of it is sold to the grid.

Chapter 5. CONCLUSION

5.1 SPANISH ELECTROMOBILITY AND CHARGING INFRASTRUCTURE

Spain lacks of the necessary charging infrastructure in order to allow for a higher penetration of EVs on Spanish roads.

Although being a major car manufacturer – 8th in the world and 2nd in Europe – the electrification of neither the production nor the vehicle fleet has not happened yet. Only 2.2% of the entire vehicle fleet is electric. However, the EVs sales have steadily been increasing for the past years – but at a slower level than other European countries. To be concrete, Spain is the third worst performing country in Europe according to the ANFAC global electromobility index.

The misperception Spanish people have on EVs' capabilities is another barrier for their penetration. National incentives like the MOVES Plan seem to help, but they are not enough. Smart charging could be helpful in order to decrease charging costs or promote the compensation for participating in ancillary services, as a way of making the investment more attractive.

5.2 SMART CHARGING MODEL

The designed models clearly accomplish the objectives set. Charging costs and the variability of the load can be greatly reduced thanks to the optimization method employed. Also, the use of generated solar energy is optimized so as to reduce costs as much as possible. No driver takes their car with less than 80% of the battery capacity, no harm is done to the feeder as the maximum capacity is never reached and no generated solar power is wasted. However, some limitations make these models imperfect.

5.2.1 MODELS' LIMITATIONS

The first and biggest limitation of this model is the assumption made about the arrival and departure times. Although the model employed to estimate them gives very accurate approximations of reality, the outcomes are still estimations. There is no certainty that those times will be correct, and almost for sure they will not. Therefore, scheduling the charging without knowing the real times can just work as a mere approximation of what would happen in reality. This problem could be limited by making drivers set the times they expect to arrive and leave before they arrive and then schedule the charging for all vehicles with some prudence – e.g. giving half an hour of margin for each of the times. As told before, others prefer to approach this difficulty by optimizing the charging per vehicle once the vehicle arrives. Nevertheless, similar costs and variances could never be reached as local optimization gives worse results and global optimization will never be made. Also, solar power generation is assumed to be given the day before, but the problem is that only very accurate forecasts can be made, never exact values. In addition, per hour data could only be obtained, losing much precision. However, the effect that small deviations on solar power generation could cause on the charging schedule are minimal.

Another big limitation to this model is its low flexibility. The model was designed for a very specific environment, in which each household has a car that has a charger always available. In cases in which there are more cars than chargers, or that people decide to buy an EV and there is not time enough to install a new charger point, the optimization problem could be infeasible. There exists an easy solution for this problem, in which one charger can be connected to more than one car at the same time and only charges one at a time. In that case, the charger could alternate cars' charging in order to satisfy drivers' requirements [59].

There is a huge issue regarding time that the algorithm takes to solve the program. The amount of variables taken into account makes a normal computer take more than 30 seconds to give a solution. Leaner programs, different algorithm solving methods or more potent computer could pull down this time.

Other less relevant limitations are that there is no restriction on grid voltage and that there is no priority given to EVs being charged with renewable energy – which in fact is not relevant, as that renewable energy that is sent to the grid will be used anyways.

Finally, there is not a unique solution. Depending on the importance given to each attribute – costs or load variability – the model will give one or other solution. This can become tricky for designers that do not know how the load variability affects the system hardware or how the price sensibility of the consumers are. However, the model was thought to be used by people that do know what ponderations to give to each attribute.

5.2.2 SMART CHARGING IMPORTANCE

This model design could not be finished without emphasizing again on the importance of smart charging in addressing future problems that higher penetration of EVs will cause.

Uncontrolled charging can seriously impact the electricity distribution and the grid infrastructure. By uncontrollably increasing the demand peak, not just in an aggregate way but also in local areas, the system could fail and thousands of people suffer from social, economic and political effects.

The necessary investments in power generation, grid hardware and distribution networks that would be needed to satisfy uncontrolled EV demand could delay its higher penetration and make society become reticent of making the change towards a more sustainable way of transporting. In that case, GHG emissions would last longer and increase the permanent negative effects on our planet.

To solve all these problems, smart charging is an unparalleled solution. Shifting EV charging loads in order to minimize the problems explained above is the way to go. Not only investments in power generation capacity or grid capacity could be highly reduced, but also charging costs for consumers. Furthermore, renewable energy use can be maximized.

Nevertheless, the sensitivity analysis in models 3a and 3b to the maximum deviation of the load variance and cost from the optimal value show that the EV users should be compensated for providing grid services such as load variability minimization. This model could be used to determine the opportunity cost of the EV user for providing load variability minimization.

All these benefits make smart charging the ideal solution that would allow a higher EV penetration.

Chapter 6. BIBLIOGRAPHY

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Chapter 7. ANNEX

7.1 ALIGNMENT WITH THE SUSTAINABLE DEVELOPMENT GOALS

The main goal of this project is to encourage PEV use by proposing a viable smart charging model and its potential integration with solar PV generation in a residential environment so as to reduce greenhouse gases emissions. Therefore, plenty of the Sustainable Development Goals adopted by the United Nations and hence world leaders more than six years ago are met within this project. The project aligns mainly with four out of the seventeen Sustainable Development Goals, having Goal 11 as the most relevant one:

Goal 9: "Industry, Innovation, and Infrastructure"

The main focus of this goal is to generate employment and income through the development and promotion of reliable, sustainable and resilient infrastructure and through domestic technology development, research and innovation.

By proposing an innovative smart charging model that tries to match the solar PV generation in a residential environment, much room for research and development is created. Supporting smart charging infrastructure, opportunities for partnerships among solar generation and PEV charging companies, creation of a legislation policy up to the smart charging challenge and research for finding even better smart charging models are just some examples of the new opportunities generated.

Goal 11: "Sustainable Cities and Communities"

The world is becoming increasingly urbanized, with more than half of the world's population living in cities. Cities act as powerhouses of economic growth, but are also highly polluting areas accounting for about a 70% of global greenhouse gases emissions. This goal aims to ensure safe, affordable and sustainable services and living conditions to all human settlements, as well as promoting resource efficiency and adaptation to climate change.

This project's focus on promoting a sustainable residential environment is clear. It does not only promote the use of a sustainable method of transportation – plug-in electric vehicles – but also promotes the use of renewable energy. Decentralized energy generation systems are a really beneficial approach to solving the issue of rapid urbanization. Uncontrolled and overburdened energy demand in slums can risk the electricity transmission systems and therefore risk energy supply – which could lead to food and other necessities shortages, no access to hot water and social disorder. By having distributed solar PV panels, dependance on the electricity grid is lowered and hence energy supply safety is increased.

By promoting the use of PEV, support to solving two major problems that the use of internal combustion engine vehicles has is given. These two major problems get even more worrying in metropolitan areas: air and noise pollution. Around 7 million people die every year due to some source of air pollution and road transport in cities is a big contributor to it. Stress related illnesses, high blood pressure, speech interference, hearing loss, sleep disruption and lost productivity are just some of the effects caused by noise pollution. With an increasing use of electric vehicles, these two major problems could be closer to being solved, and therefore, the health of millions of people could be improved.

Goal 12: "Responsible Consumption and Production"

The destructive impact that worldwide consumption and production has on the natural environment and Earth's resources could soon become no longer sustainable if population and consumption's growth rates remain at their current levels. Increasing resource efficiency and promoting sustainable lifestyles while decoupling economic growth from environmental degradation is the framework to follow if we want to keep benefiting from our planet's resources in the future.

By shifting some of the PEV charging loads to hours in which the prices are lower – when electricity demand is lower – and by trying to match the solar PV generation with PEV charging loads, the proposed smart charging model promotes the use of renewable energies and prevents the unnecessary use of resources needed to produce the energy needed to charge the PEVs.

Goal 13: "Climate Action"

Climate change is the topic that stands behind the motivation for this project and has already been discussed. The United Nations – through the Paris Agreement – aims to mark a global framework for policy making and to encourage a global response to global warming so as to keep the temperature rise this century below 2ºC.

By promoting the use of low-carbon transportation methods, renewable energies and a better use of resources, the smart charging model aims to help maintain the incredible variety of resources given by nature and to reduce the carbon footprint on our beloved planet.

SDG dimension	SDG identified	Role	Goal
Industry, Innovation, and Infrastructure	SDG 9: generate employment and income through the development and promotion of reliable, sustainable and resilient infrastructure and through domestic technology development, research and innovation	Secondary	Creation of new areas of research, support smart charging infrastructure, integration of EVs with
Sustainable Cities and Communities	SDG 11: aims to ensure safe, affordable and sustainable services and living conditions to all human settlements, as well as promoting resource efficiency and adaptation to climate change.	Primary	Promotion of sustainable residential environments, promotion of renewable energy particular use,
Responsible Consumption and Production	SDG 12: increasing resource efficiency and promoting sustainable lifestyles while decoupling economic growth from environmental degradation	Secondary	Prevents from the unnecessary use of resources needeed to produce energy to charge EVs
Climate Action	SDG 13: aims to mark a global framework for policy making and to encourage a global response to global warming so as to keep the temperature rise this century below 2ºC.	Secondary	Promotion of low-carbon transportation methods, renewable energies and a better use of resources

Table 7-1: Summary of SDGs aligned with the project objectives

7.2 LEGAL CHARGING POINTS SCHEMES AND ELEMENTS

In this section the different elements and charging schemes applicable to private garages, residential neighborhoods garages and business parking lots will be explained. The information here outlined is based on the Complementary Technical Instruction (ITC) BT-52 (Royal Decree 1053/2014, Dec 12th 2014).

7.2.1 PRIVATE GARAGES:

The charging points installations in private garages must follow what the ITC BT-52 states about private garages in single-family households: "In new single-family households that have a parking spot for an EV, an exclusive circuit will be installed for the EV charging. This circuit will be known as C13 – according to ITC BT-25 nomenclature – and will follow the 4a installation scheme. In those existing households that wish to install a charging point will also follow this section. Single- and three-phase power can be used.

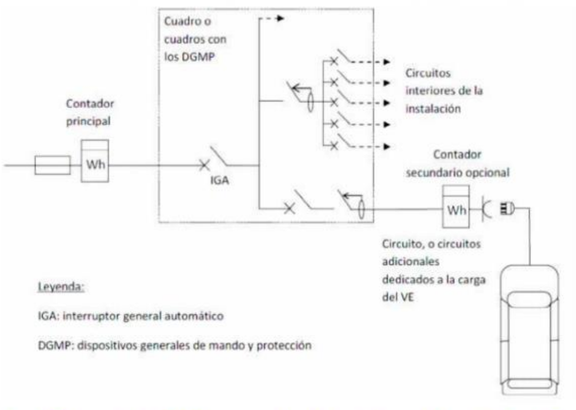

Figura 25. Esquema 4a de la ITC BT 52 para recarga de vehículo eléctrico en viviendas unifamiliares [37]

Figure 7-1: 4a scheme. Source: ITC

Figure 7-1 shows that one of the household's internal circuits is for EV charging exclusive use. Therefore, repairing can be done without affecting the rest of the house's electricity supply.

An optional secondary counter can be installed in this internal circuit and can be integrated with the Control box.

7.2.2 COMMUNITY GARAGES

It is worth mentioning two important parts from relevant norms regarding community garages:

-Law 19/2009, November 23rd, about promoting measures for the energetic efficiency of the buildings: "If you will to install a charging point in the building parking for private use in an individual parking spot, you are only required to inform the community about the installation. The installation costs are totally assumed by the interested parts".

-ITC BT-52 in the "Special goals installations. Electric vehicles charging infrastructure" part it is said that in existing garages there is no need no install any charging point. Also "when the first charging point installation in existing buildings is performed, it is a must to install the common elements needed for future charging points installation".

The ITC establishes four big groups of charging points schemes:

1. Collective scheme with a primal counter at the origin of the installation
2. Individual scheme with a common counter for the house and the charging point
3. Individual scheme with a counter for each charging point
4. Scheme with additional circuits

- 1st scheme: Collective scheme with a primal counter at the origin of the installation and secondary counters at each of the charging points

Within this scheme there exist three different cases:

1a scheme:

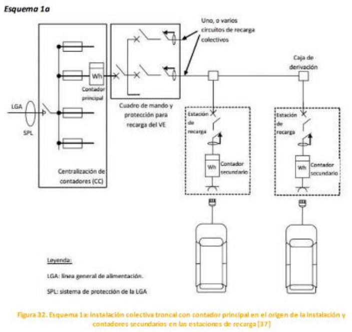

Figure 7-2: 1a scheme. Source: ITC

The collective charging points are connected to the same node in which the primal counter is at. Each charging point has its secondary counter so that EV users pay proportionally to the amount of electricity used.

1b scheme:

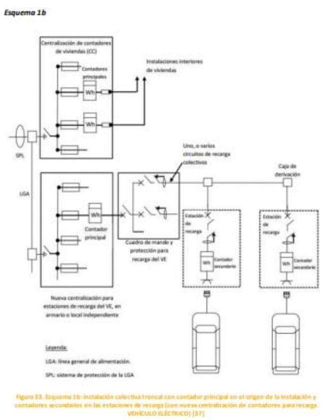

Figure 7-3: 1b scheme. Source: ITC

In this case the power source to EV charging comes from a centralized group of circuits that differs from the one that sources the internal circuits of the households.

As specified in ITC BT-52: "For choosing among 1a or 1b the following priority criteria must be followed. First, the centralized group of circuits in the existing installation will be used (1a). If it was not enough, the existing centralized group must be amplified (1a). Finally, in case of no space, new centralized group of circuits will be used (1b).

1c scheme:

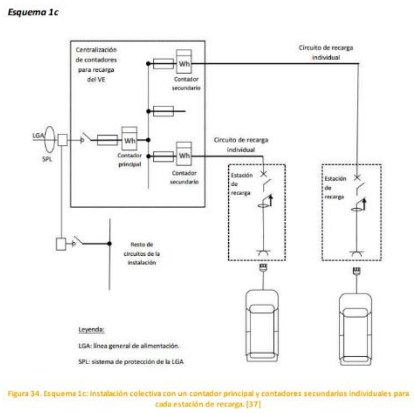

Figure 7-4: 1c scheme. Source: ITC

There is a third alternative – the 1c – in which both the primal and secondary counters are in the same centralized group of circuits. Given the access restriction, the secondary counters are safer. The ITC BT-52 says: "the centralization of counters can belong to the existing centralization or to new centralizations".

- 2nd scheme: Individual scheme with a common counter for the house and the charging point

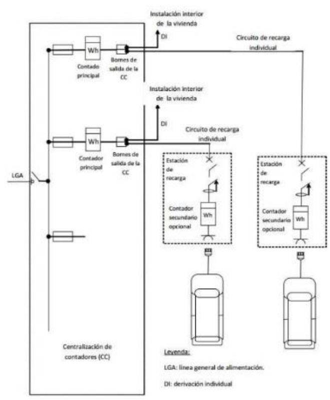

Figure 7-5: 2 scheme. Source: ITC

In this case each household has its own primal counter and then a secondary counter just for the charging point. The ITC BT-52 states that "in the design project a justification must be provided regarding the protection offered by the fuse to both the household's and the charging point's circuits in terms of short-circuits. The power control function must be performed by the primal counter without the need of installing an independent Power Control Switch (ICP)". This means that the primal counter is the one in charge of controlling that the power does not exceed the maximum contracted without the need of an external ICP.

The greatest advantage of this scheme is that only one electric supply is paid (only the rent of one counter is paid).

- 3rd scheme: Individual scheme with a counter for each charging point

There are two variations of this scheme:

3a scheme:

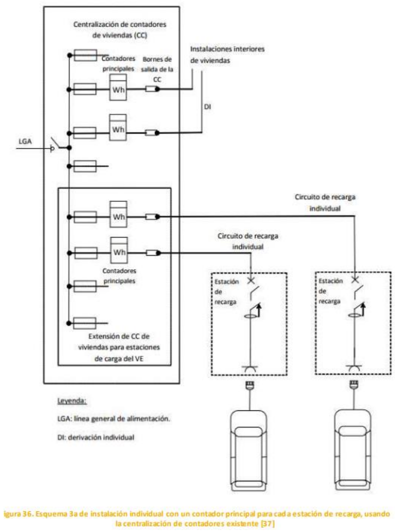

Figure 7-6: 3a scheme. Source: ITC

3b scheme:

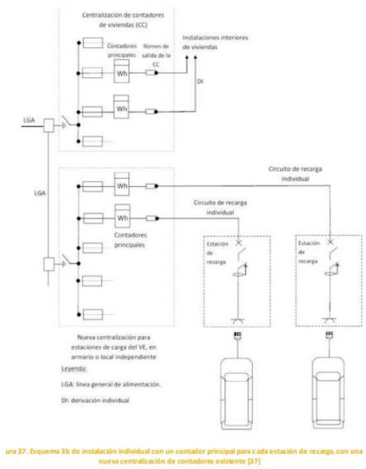

Figure 7-7: 3b scheme. Source: ITC

The ITC BT-52 establishes the priority criteria for selecting 3a or 3b. "First, the centralized group of circuits in the existing installation will be used (3a). If it was not enough, the existing centralized group must be amplified (3a). Finally, in case of no space, new centralized group or groups of circuits will be used (3b)". This means that the goal is always to use available space in the existing group of circuits and a new one will only be installed in case of no space.

The first section of the ITC BT-52 states that "the objective of this Instruction is to establish applicable rules to install electric vehicle charging points. These rules are intended to apply to the electric networks needed for electric vehicles charging included in the Electrotechnical Regulation for low voltage regardless of their ownership, such as:

a) Single-family household's parking lots
b) Residential neighborhood's parking lots
c) Private fleets', businesses', offices' or car dealerships' parking lots
d) Public parking lots, with private or public ownership. BOE-A-2014-13681 OFFICIAL NEWSLETTER OF THE STATE #316, December 31st 2014, Sect. I. Page 107460
e) Public highways through which electric vehicles may ride, situated in urban zones and service areas in interurban zones as seen in the 28th article of the Law 25/1988, July 29th of Highways

Therefore, private fleets', businesses', offices', car dealerships' parking lots, public parking lots and public highways (urban zones and interurban service areas) are also regulated by this Instruction. The Instruction has provided with a very flexible scheme to those that cannot be regulated by the schemes presented before. This flexible scheme is:

- 4th Scheme: Scheme with additional circuits

The 4a was already explained in the private garages section.

4b scheme

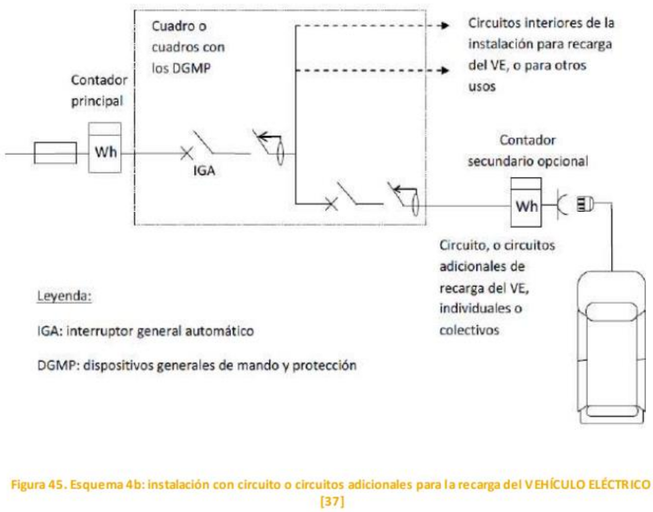

Figure 7-8: 4b scheme. Source: ITC

This 4b scheme opens the possibility of using the rest of the circuits for multiple purposes such as those in public charging stations, not just household's use.

7.2.2.1 Charging stations

A charging station is a public charging point. They can be installed in existing gas stations to take advantage of the existing services offered, like café or restrooms. They must follow the 4b scheme but given their increasing importance a whole section is given to them.

The charging stations may use mode 1, 2,3 or 4. However, mode 1, 2 and 3 usually lead to long charging times and hence mode 4 is the most interesting one in this case. By using mode

4 the charging times are very short, due to its high-power DC. As explained before, these points only charge up to an 80% to protect the batteries' life. The more-than-50-kW power rates used in these charging stations make these kind of charging points infeasible for installation in a given household, as the households' power supply never reaches these power rates.

The rapid charging is usually conceived as an exceptional charge, as a frequent use of this charge might harm the EV's battery.

The advantages of having charging stations available are multiple. The EV owner has the option of charging their vehicle almost anywhere. Therefore, there is no need to have a charging point at home. Charging stations give EV owners the confidence of making long trips knowing that they can quickly charge their vehicles. It is very similar to current gas stations ICEV use.

7.3 CODE

7.3.1 MODULES IMPORTATION

```
# Click the "Play" button on the left to import packages.
%pip install -i https://pypi.gurobi.com gurobipy;
import gurobipy
import cvxpy as cp
import numpy as np
import pandas as pd
import math
import matplotlib.pyplot as plt
import random
import io
```

7.3.2 VARIABLES AND PARAMETERS DEFINITION

```
m = 4 #number of periods per hour
T = 36*m #number of periods
N = 20 #number of EVs
P_load_max_hh = 3.45
P_load_max = 270 #maximum load supported by the feeder (in kW)

#n
C_EV = [40,54,50,80,58,52,66.5,54,58,45,63,54,54,22,76.6,66.5,39.2,32
.6,64,80.7] #capacity of the EV n (in kWh)
charger_eff_EV = 0.9 #charge efficiency of the EV n (from 0 to 1)
SoC_EV_s = [0.2,0.32,0.35,0.64,0.23,0.42,0.46,0.25,0.34,0.21,0.2,0.32
,0.35,0.64,0.23,0.42,0.46,0.25,0.34,0.21] #plugged-
in state of charge of EV n (from 0 to 1)
SoC_EV_e = [0.8,0.8,0.8,0.8,0.8,0.8,0.8,0.8,0.8,0.8,0.8,0.8,0.8,0.8,0
.8,0.8,0.8,0.8,0.8,0.8] #plugged-
out state of charge of EV n (from 0 to 1)
P_EV_max = 11 #max power rate EV n can be charged at (in kW)
SoC_EV_max = [0.8,0.8,0.8,0.8,0.8,0.8,0.8,0.8,0.8,0.8,0.8,0.8,0.8,0.8
,0.8,0.8,0.8,0.8,0.8,0.8] #maximum SoC permitted by EV n
SoC_EV_min = [0.2,0.2,0.2,0.2,0.2,0.2,0.2,0.2,0.2,0.2,0.2,0.2,0.2,0.2
,0.2,0.2,0.2,0.2,0.2,0.2] #minimum SoC permitted by EV n


"""
Scenario 1: abril 22
Scenario 2: abril 22 laborable
Scenario 3: abril 22 festivo
Scenario 4: abril 19
Scenario 5: julio 19
Scenario 6: enero 20
"""

from google.colab import files
uploaded = files.upload()
#df = pd.read_excel(io.BytesIO(uploaded['Precios y demanda.xlsx']))
df = pd.read_excel(uploaded['Precios y demanda.xlsx'],skiprows=0,name
s=['P1','S1','D1','P2','S2','D2','P3','S3','D3','P4','S4','D4','P5','
S5','D5','P6','S6','D6','RS1','RS4','RS7'])


scenario = 4
lambdRT_horas = df['P'+str(scenario)].tolist()
```

```
lambdRT_PV_horas = df['S'+str(scenario)].tolist()
P_load_hh_horas = df['D'+str(scenario)].tolist()
if scenario <= 4:
  PV_wh_horas = df['RS'+str(4)].tolist()
elif scenario == 5:
  PV_wh_horas = df['RS'+str(7)].tolist()
else:
  PV_wh_horas = df['RS'+str(1)].tolist()

lambdRT = []
lambdRT_PV = []
P_load_hh = []
PV_wh = []
for i in range(int(T/m)):
  for n in range(m):
    lambdRT.append(lambdRT_horas[i])
    lambdRT_PV.append(lambdRT_PV_horas[i])
    P_load_hh.append(P_load_hh_horas[i])
    PV_wh.append(PV_wh_horas[i])

P_load = [i*0.001*N for i in P_load_hh]

R = 1 #modificas el R y te sale la generacion de solar
PV = [i*0.001*N*R for i in PV_wh] #generacion solar en kWh en el barr
io
```

7.3.3 Arrival and departure times modelling

```
if scenario == 3: #WEEKEND
#Departure time
  mu = 576.03
  sigma = 156.24
  eps = -0.05644
#Arrival time
  muA = 995.59
  sigmaA = 284.93
  epsA = -0.6414
else: #WEEKDAY
#Departure time
  mu = 485.34
  sigma = 131.46
  eps = 0.045
```

```
#Arrival time
  muA = 953.72
  sigmaA = 251.07
  epsA = -0.5163


y = np.arange(0.01,1,0.01)
x = []
for i in y:
  x.append(mu + sigma*(((-math.log(i))**(-eps)-1)/eps))

plt.plot(y,x)
plt.show()

random.seed()

t_EV_s = []
t_EV_e = []

for n in range(N):
  t_EV_e.append(mu + sigma*(((-math.log(random.random()))**(-eps)-
1)/eps))

for n in range(N):
  t_EV_s.append(muA + sigmaA*(((-math.log(random.random()))**(-epsA)-
1)/epsA))

t_EV_s = [round(t_EV_s[n]/(60/m)) for n in range(N)]
t_EV_s = [(t_EV_s[n] - 12*m) for n in range(N)]
for n in range(N):
  if t_EV_s[n] <= 0:
    t_EV_s[n] = 0

t_EV_e = [round(t_EV_e[n]/(60/m)) for n in range(N)]
t_EV_e = [(t_EV_e[n] + 12*m) for n in range(N)]
for n in range(N):
  if t_EV_e[n] >= 36*m-1:
    t_EV_e[n] = 36*m-1

for n in range(N):
  if t_EV_s[n] >= t_EV_e[n]:
    while t_EV_s[n] >= t_EV_e[n]:
```

```
      t_EV_s[n] = round((mu + sigma*(((-
math.log(random.random()))**(-eps)-1)/eps))/(60/m)) - 12*m
      t_EV_e[n] = round((muA + sigmaA*(((-
math.log(random.random()))**(-epsA)-1)/epsA))/(60/m)) + 12*m
```

7.3.4 FORMULATION OF THE MODEL

The code shown above is common for all models, but from now on there are some little differences on objective functions, presence of auxiliar problems and added constraints among the four models.

7.3.4.1 Formulation of model 1

```
m = 4 #number of periods per hour
T = 36*m #number of periods
N = 20 #number of EVs
constraints = []

P_EV = cp.Variable((N,T),nonneg = True)
SoC_EV = cp.Variable((N,T),nonneg = True)
PV_grid = cp.Variable((T),nonneg = True)
PV_load = cp.Variable((T),nonneg = True)


objective = cp.sum(lambdRT@(cp.sum(P_EV, axis = 0) + P_load - PV_load
).T - lambdRT_PV@PV_grid.T)

for n in range(N):
  constraints += [P_EV[n] <= P_EV_max]
  constraints += [charger_eff_EV*sum(P_EV[n,t] for t in range(T)) ==
C_EV[n]*(SoC_EV_e[n] - SoC_EV_s[n])]
  constraints += [SoC_EV[n,t_EV_s[n]] == SoC_EV_s[n]]
  constraints += [SoC_EV[n,t_EV_e[n]] == SoC_EV_e[n]]
  for t in range(T):
    constraints += [SoC_EV[n,t] <= SoC_EV_max[n]]
    constraints += [SoC_EV[n,t] >= SoC_EV_min[n]]
    if t < t_EV_s[n]:
      constraints += [P_EV[n,t] == 0]
      constraints += [SoC_EV[n,t] == SoC_EV_s[n]]
    elif t > t_EV_e[n]:
      constraints += [P_EV[n,t] == 0]
      constraints += [SoC_EV[n,t] == SoC_EV_e[n]]
```

```
for n in range(N):
    for t in range(T):
        if (t < T-1)  &  (t >= t_EV_s[n]) & (t < t_EV_e[n]):
          constraints += [C_EV[n]*SoC_EV[n,t+1] == C_EV[n]*SoC_EV[n,t
] + charger_eff_EV*P_EV[n,t]]

for t in range(T):
  constraints += [P_load[t] + cp.sum(P_EV, axis = 0)[t] - PV_load[t]
<= P_load_max]
  constraints += [PV_grid[t] + PV_load[t] == PV[t]]
  constraints += [PV_load[t] <= P_load[t] + cp.sum(P_EV, axis = 0)[t]
]


problem = cp.Problem(cp.Minimize(objective),constraints)
problem.solve()


print('objective = %s' % problem.value)

for var in problem.variables():
   print('%s = %s'%(var.name(),var.value))

PEV = []
SoC = []
P_PV_grid = []
P_PV_load = []
i = 0
for var in problem.variables():
  if i == 0:
    i += 1
    for n in range(N):
      PEV.append([])
      for t in range(T):
        PEV[n].append(var[n,t].value)
  elif i == 1:
    i += 1
    for t in range(T):
      P_PV_load.append(var[t].value)
  elif i == 2:
    i += 1
    for t in range(T):
      P_PV_grid.append(var[t].value)
```

```
  else:
    for n in range(N):
      SoC.append([])
      for t in range(T):
        SoC[n].append(var[n,t].value)


loadEV = [sum(PEV[n][t] for n in range(N)) for t in range(T)] #potenc
ia acumulada EV a cada hora
vehicle = 2
loadEVa = [PEV[vehicle][t] for t in range(T)] #potencia EV[vehicle] a
 cada hora
SoCEVa = [100*SoC[vehicle][t] for t in range(T)] #SoC EV[vehicle] por
 hora
load = []
P_load_grid = []
for t in range(T):
  load.append(loadEV[t] + P_load[t])
  P_load_grid.append(loadEV[t] + P_load[t] - P_PV_load[t])

t = np.arange(0,25*m,1)
xtick_labels = [18,21,00,3,6,9,12,15,18]

plt.plot(t,loadEV[6*m:31*m],label='loadEV') #plot para potencia acumu
lada EV por hora
plt.plot(t,loadEVa[6*m:31*m],label='loadEVa') #plot para ver carga de
 EV[0]
plt.xticks(range(0,24*m+1,3*m),xtick_labels)
plt.xlabel('hours')
plt.ylabel('kW')
plt.legend()
plt.grid(True)
plt.show()

plt.plot(t,load[6*m:31*m],label='demand+EV load')
plt.plot(t,P_load[6*m:31*m],label='demand load')
plt.plot(t,P_load_grid[6*m:31*m],label='grid load')
plt.xticks(range(0,24*m+1,3*m),xtick_labels)
plt.xlabel('hours')
plt.ylabel('kW')
plt.legend()
plt.grid(True)
plt.show()
```

```
plt.plot(t,P_PV_load[6*m:31*m],label='PV_load') #plot para ver la sol
ar PV dedicada a la load and EV charge
plt.plot(t,P_PV_grid[6*m:31*m],label='PV_grid') #plot para ver la sol
ar PV inyectada a la red
plt.plot(t,P_load_grid[6*m:31*m],label='grid load')
plt.xticks(range(0,24*m+1,3*m),xtick_labels)
plt.xlabel('hours')
plt.ylabel('kW')
plt.legend()
plt.grid(True)
plt.show()


plt.plot(t,SoCEVa[6*m:31*m],label = 'SoC of vehicle '+str(vehicle))
plt.xticks(range(0,24*m+1,3*m),xtick_labels)
ytick_labels = [0,0.2,0.4,0.6,0.8,1]
plt.yticks(range(0,120,20),ytick_labels)
plt.xlabel('hours')
plt.ylabel('SoC')
plt.legend()
plt.grid(True)
plt.show()


Cost = 0.001*sum((lambdRT[i]*(sum(PEV[n][i] for n in range(N)) + P_lo
ad[i] - P_PV_load[i]) - lambdRT_PV[i]*P_PV_grid[i]) for i in range(T)
)
print('Total Cost: %s Eur'%round(Cost,2))

muH = 1/T*sum(P_load[i] + sum(PEV[n][i] for n in range(N)) - P_PV_loa
d[i] for i in range(T))
Var = 1/T*sum((P_load[i] + sum(PEV[n][i] for n in range(N)) - muH - P
_PV_load[i])**2 for i in range(T))

print('Variance: %s'%round(Var,2))
```

7.3.4.2 Formulation of model 2

```
m = 4 #number of periods per hour
T = 36*m #number of periods
N = 20 #number of EVs
constraints = []
```

```
P_EV = cp.Variable((N,T),nonneg = True)
SoC_EV = cp.Variable((N,T),nonneg = True)
PV_grid = cp.Variable((T),nonneg = True)
PV_load = cp.Variable((T),nonneg = True)

muH = 1/T*cp.sum(P_load + cp.sum(P_EV,axis = 0) - PV_load)
objective = 1/T*cp.sum((P_load + cp.sum(P_EV,axis = 0) - muH - PV_loa
d)**2)

for n in range(N):
  constraints += [P_EV[n] <= P_EV_max]
  constraints += [charger_eff_EV*sum(P_EV[n,t] for t in range(T)) ==
C_EV[n]*(SoC_EV_e[n] - SoC_EV_s[n])]
  constraints += [SoC_EV[n,t_EV_s[n]] == SoC_EV_s[n]]
  constraints += [SoC_EV[n,t_EV_e[n]] == SoC_EV_e[n]]
  for t in range(T):
    constraints += [SoC_EV[n,t] <= SoC_EV_max[n]]
    constraints += [SoC_EV[n,t] >= SoC_EV_min[n]]
    if t < t_EV_s[n]:
      constraints += [P_EV[n,t] == 0]
      constraints += [SoC_EV[n,t] == SoC_EV_s[n]]
    elif t > t_EV_e[n]:
      constraints += [P_EV[n,t] == 0]
      constraints += [SoC_EV[n,t] == SoC_EV_e[n]]

for n in range(N):
    for t in range(T):
        if (t < T-1)  &  (t >= t_EV_s[n]) & (t < t_EV_e[n]):
          constraints += [C_EV[n]*SoC_EV[n,t+1] == C_EV[n]*SoC_EV[n,t
] + charger_eff_EV*P_EV[n,t]]

for t in range(T):
  constraints += [P_load[t] + cp.sum(P_EV, axis = 0)[t] - PV_load[t]
<= P_load_max]
  constraints += [PV_grid[t] + PV_load[t] == PV[t]]
  constraints += [PV_load[t] <= P_load[t] + cp.sum(P_EV, axis = 0)[t]
]


problem = cp.Problem(cp.Minimize(objective),constraints)
problem.solve()
```

```
print('objective = %s' % problem.value)
"""
for var in problem.variables():
   print('%s = %s'%(var.name(),var.value))
"""

PEV = []
SoC = []
P_PV_grid = []
P_PV_load = []
i = 0
for var in problem.variables():
  if i == 0:
    i += 1
    for n in range(N):
      PEV.append([])
      for t in range(T):
        PEV[n].append(var[n,t].value)
  elif i == 1:
    i += 1
    for t in range(T):
      P_PV_load.append(var[t].value)
  elif i == 2:
    i += 1
    for n in range(N):
      SoC.append([])
      for t in range(T):
        SoC[n].append(var[n,t].value)
  else:
    for t in range(T):
      P_PV_grid.append(var[t].value)


loadEV = [sum(PEV[n][t] for n in range(N)) for t in range(T)] #potenc
ia acumulada EV a cada hora
vehicle = 2
loadEVa = [PEV[vehicle][t] for t in range(T)] #potencia EV[vehicle] a
 cada hora
SoCEVa = [100*SoC[vehicle][t] for t in range(T)] #SoC EV[vehicle] por
 hora
load = []
P_load_grid = []
for t in range(T):
```

```
  load.append(loadEV[t] + P_load[t])
  P_load_grid.append(loadEV[t] + P_load[t] - P_PV_load[t])

t = np.arange(0,25*m,1)
xtick_labels = [18,21,00,3,6,9,12,15,18]

plt.plot(t,loadEV[6*m:31*m],label='loadEV') #plot para potencia acumu
lada EV por hora
plt.plot(t,loadEVa[6*m:31*m],label='loadEVa') #plot para ver carga de
 EV[0]
plt.xticks(range(0,24*m+1,3*m),xtick_labels)
plt.xlabel('hours')
plt.ylabel('kW')
plt.legend()
plt.grid(True)
plt.show()

plt.plot(t,load[6*m:31*m],label='demand+EV load')
plt.plot(t,P_load[6*m:31*m],label='demand load')
plt.plot(t,P_load_grid[6*m:31*m],label='grid load')
plt.xticks(range(0,24*m+1,3*m),xtick_labels)
plt.xlabel('hours')
plt.ylabel('kW')
plt.legend()
plt.grid(True)
plt.show()

plt.plot(t,P_PV_load[6*m:31*m],label='PV_load') #plot para ver la sol
ar PV dedicada a la load and EV charge
plt.plot(t,P_PV_grid[6*m:31*m],label='PV_grid') #plot para ver la sol
ar PV inyectada a la red
plt.plot(t,P_load_grid[6*m:31*m],label='grid load')
plt.xticks(range(0,24*m+1,3*m),xtick_labels)
plt.xlabel('hours')
plt.ylabel('kW')
plt.legend()
plt.grid(True)
plt.show()


plt.plot(t,SoCEVa[6*m:31*m],label = 'SoC of vehicle '+str(vehicle))
plt.xticks(range(0,24*m+1,3*m),xtick_labels)
ytick_labels = [0,0.2,0.4,0.6,0.8,1]
```

```
plt.yticks(range(0,120,20),ytick_labels)
plt.xlabel('hours')
plt.ylabel('SoC')
plt.legend()
plt.grid(True)
plt.show()


Cost = 0.001*sum((lambdRT[i]*(sum(PEV[n][i] for n in range(N)) + P_lo
ad[i] - P_PV_load[i]) - lambdRT_PV[i]*P_PV_grid[i]) for i in range(T)
)
print('Total Cost: %s Eur'%Cost)

muH = 1/T*sum(P_load[i] + sum(PEV[n][i] for n in range(N)) - P_PV_loa
d[i] for i in range(T))
Var = 1/T*sum((P_load[i] + sum(PEV[n][i] for n in range(N)) - muH - P
_PV_load[i])**2 for i in range(T))

print('Variance: %s'%Var)
```

7.3.4.3 Formulation of model 3a

```
#AUXILIAR PROBLEM
m = 4 #number of periods per hour
T = 36*m #number of periods
N = 20 #number of EVs
constraints_aux = []

P_EV_aux = cp.Variable((N,T),nonneg = True)
SoC_EV_aux = cp.Variable((N,T),nonneg = True)
PV_grid_aux = cp.Variable((T),nonneg = True)
PV_load_aux = cp.Variable((T),nonneg = True)


objective_aux = cp.sum(lambdRT@(cp.sum(P_EV_aux, axis = 0) + P_load -
 PV_load_aux).T - lambdRT_PV@PV_grid_aux.T)

for n in range(N):
  constraints_aux += [P_EV_aux[n] <= P_EV_max]
  constraints_aux += [charger_eff_EV*sum(P_EV_aux[n,t] for t in range
(T)) == C_EV[n]*(SoC_EV_e[n] - SoC_EV_s[n])]
  constraints_aux += [SoC_EV_aux[n,t_EV_s[n]] == SoC_EV_s[n]]
  constraints_aux += [SoC_EV_aux[n,t_EV_e[n]] == SoC_EV_e[n]]
```

```
  for t in range(T):
    constraints_aux += [SoC_EV_aux[n,t] <= SoC_EV_max[n]]
    constraints_aux += [SoC_EV_aux[n,t] >= SoC_EV_min[n]]
    if t < t_EV_s[n]:
      constraints_aux += [P_EV_aux[n,t] == 0]
      constraints_aux += [SoC_EV_aux[n,t] == SoC_EV_s[n]]
    elif t > t_EV_e[n]:
      constraints_aux += [P_EV_aux[n,t] == 0]
      constraints_aux += [SoC_EV_aux[n,t] == SoC_EV_e[n]]

for n in range(N):
    for t in range(T):
        if (t < T-1)  &  (t >= t_EV_s[n]) & (t < t_EV_e[n]):
          constraints_aux += [C_EV[n]*SoC_EV_aux[n,t+1] == C_EV[n]*So
C_EV_aux[n,t] + charger_eff_EV*P_EV_aux[n,t]]

for t in range(T):
  constraints_aux += [P_load[t] + cp.sum(P_EV_aux, axis = 0)[t] - PV_
load_aux[t] <= P_load_max]
  constraints_aux += [PV_grid_aux[t] + PV_load_aux[t] == PV[t]]
  constraints_aux += [PV_load_aux[t] <= P_load[t] + cp.sum(P_EV_aux,
axis = 0)[t]]


problem_aux = cp.Problem(cp.Minimize(objective_aux),constraints_aux)
problem_aux.solve()

MinCost = problem_aux.value


#REAL PROBLEM

m = 4 #number of periods per hour
T = 36*m #number of periods
N = 20 #number of EVs
constraints = []

P_EV = cp.Variable((N,T),nonneg = True)
SoC_EV = cp.Variable((N,T),nonneg = True)
PV_grid = cp.Variable((T),nonneg = True)
PV_load = cp.Variable((T),nonneg = True)


muH = 1/T*cp.sum(P_load + cp.sum(P_EV,axis = 0) - PV_load)
```

```
objective = 1/T*cp.sum((P_load + cp.sum(P_EV,axis = 0) - muH - PV_loa
d)**2)

for n in range(N):
  constraints += [P_EV[n] <= P_EV_max]
  constraints += [charger_eff_EV*sum(P_EV[n,t] for t in range(T)) ==
C_EV[n]*(SoC_EV_e[n] - SoC_EV_s[n])]
  constraints += [SoC_EV[n,t_EV_s[n]] == SoC_EV_s[n]]
  constraints += [SoC_EV[n,t_EV_e[n]] == SoC_EV_e[n]]
  for t in range(T):
    constraints += [SoC_EV[n,t] <= SoC_EV_max[n]]
    constraints += [SoC_EV[n,t] >= SoC_EV_min[n]]
    if t < t_EV_s[n]:
      constraints += [P_EV[n,t] == 0]
      constraints += [SoC_EV[n,t] == SoC_EV_s[n]]
    elif t > t_EV_e[n]:
      constraints += [P_EV[n,t] == 0]
      constraints += [SoC_EV[n,t] == SoC_EV_e[n]]

for n in range(N):
    for t in range(T):
        if (t < T-1)  &  (t >= t_EV_s[n]) & (t < t_EV_e[n]):
          constraints += [C_EV[n]*SoC_EV[n,t+1] == C_EV[n]*SoC_EV[n,t
] + charger_eff_EV*P_EV[n,t]]

for t in range(T):
  constraints += [P_load[t] + cp.sum(P_EV, axis = 0)[t] - PV_load[t]
<= P_load_max]
  constraints += [PV_grid[t] + PV_load[t] == PV[t]]
  constraints += [PV_load[t] <= P_load[t] + cp.sum(P_EV, axis = 0)[t]
]

constraints += [cp.sum(lambdRT@(cp.sum(P_EV, axis = 0) + P_load - PV_
load).T - lambdRT_PV@PV_grid.T) <= 1.3*MinCost]

problem = cp.Problem(cp.Minimize(objective),constraints)
problem.solve()


print('objective = %s' % problem.value)
"""
for var in problem.variables():
   print('%s = %s'%(var.name(),var.value))
```

```
"""

PEV = []
SoC = []
P_PV_grid = []
P_PV_load = []
i = 0
for var in problem.variables():
  if i == 0:
    i += 1
    for n in range(N):
      PEV.append([])
      for t in range(T):
        PEV[n].append(var[n,t].value)
  elif i == 1:
    i += 1
    for t in range(T):
      P_PV_load.append(var[t].value)
  elif i == 2:
    i += 1
    for n in range(N):
      SoC.append([])
      for t in range(T):
        SoC[n].append(var[n,t].value)
  else:
    for t in range(T):
      P_PV_grid.append(var[t].value)


loadEV = [sum(PEV[n][t] for n in range(N)) for t in range(T)] #potenc
ia acumulada EV a cada hora
vehicle = 2
loadEVa = [PEV[vehicle][t] for t in range(T)] #potencia EV[vehicle] a
 cada hora
SoCEVa = [100*SoC[vehicle][t] for t in range(T)] #SoC EV[vehicle] por
 hora
load = []
P_load_grid = []
for t in range(T):
  load.append(loadEV[t] + P_load[t])
  P_load_grid.append(loadEV[t] + P_load[t] - P_PV_load[t])

t = np.arange(0,25*m,1)
```

```
xtick_labels = [18,21,00,3,6,9,12,15,18]

plt.plot(t,loadEV[6*m:31*m],label='loadEV') #plot para potencia acumu
lada EV por hora
plt.plot(t,loadEVa[6*m:31*m],label='loadEVa') #plot para ver carga de
 EV[0]
plt.xticks(range(0,24*m+1,3*m),xtick_labels)
plt.xlabel('hours')
plt.ylabel('kW')
plt.legend()
plt.grid(True)
plt.show()

plt.plot(t,load[6*m:31*m],label='demand+EV load')
plt.plot(t,P_load[6*m:31*m],label='demand load')
plt.plot(t,P_load_grid[6*m:31*m],label='grid load')
plt.xticks(range(0,24*m+1,3*m),xtick_labels)
plt.xlabel('hours')
plt.ylabel('kW')
plt.legend()
plt.grid(True)
plt.show()

plt.plot(t,P_PV_load[6*m:31*m],label='PV_load') #plot para ver la sol
ar PV dedicada a la load and EV charge
plt.plot(t,P_PV_grid[6*m:31*m],label='PV_grid') #plot para ver la sol
ar PV inyectada a la red
plt.plot(t,P_load_grid[6*m:31*m],label='grid load')
plt.xticks(range(0,24*m+1,3*m),xtick_labels)
plt.xlabel('hours')
plt.ylabel('kW')
plt.legend()
plt.grid(True)
plt.show()


plt.plot(t,SoCEVa[6*m:31*m],label = 'SoC of vehicle '+str(vehicle))
plt.xticks(range(0,24*m+1,3*m),xtick_labels)
ytick_labels = [0,0.2,0.4,0.6,0.8,1]
plt.yticks(range(0,120,20),ytick_labels)
plt.xlabel('hours')
plt.ylabel('SoC')
plt.legend()
```

```
plt.grid(True)
plt.show()


Cost = 0.001*sum((lambdRT[i]*(sum(PEV[n][i] for n in range(N)) + P_lo
ad[i] - P_PV_load[i]) - lambdRT_PV[i]*P_PV_grid[i]) for i in range(T)
)
print('Total Cost: %s Eur'%Cost)

muH = 1/T*sum(P_load[i] + sum(PEV[n][i] for n in range(N)) - P_PV_loa
d[i] for i in range(T))
Var = 1/T*sum((P_load[i] + sum(PEV[n][i] for n in range(N)) - muH - P
_PV_load[i])**2 for i in range(T))

print('Variance: %s'%Var)
```

7.3.4.4 Formulation of model 3b

```
#AUXILIAR PROBLEM
m = 4 #number of periods per hour
T = 36*m #number of periods
N = 20 #number of EVs
constraints_aux = []

P_EV_aux = cp.Variable((N,T),nonneg = True)
SoC_EV_aux = cp.Variable((N,T),nonneg = True)
PV_grid_aux = cp.Variable((T),nonneg = True)
PV_load_aux = cp.Variable((T),nonneg = True)

muH = 1/T*cp.sum(P_load + cp.sum(P_EV_aux,axis = 0) - PV_load_aux)
objective_aux = 1/T*cp.sum((P_load + cp.sum(P_EV_aux,axis = 0) - muH
- PV_load_aux)**2)


for n in range(N):
  constraints_aux += [P_EV_aux[n] <= P_EV_max]
  constraints_aux += [charger_eff_EV*sum(P_EV_aux[n,t] for t in range
(T)) == C_EV[n]*(SoC_EV_e[n] - SoC_EV_s[n])]
  constraints_aux += [SoC_EV_aux[n,t_EV_s[n]] == SoC_EV_s[n]]
  constraints_aux += [SoC_EV_aux[n,t_EV_e[n]] == SoC_EV_e[n]]
  for t in range(T):
    constraints_aux += [SoC_EV_aux[n,t] <= SoC_EV_max[n]]
    constraints_aux += [SoC_EV_aux[n,t] >= SoC_EV_min[n]]
```

```
    if t < t_EV_s[n]:
      constraints_aux += [P_EV_aux[n,t] == 0]
      constraints_aux += [SoC_EV_aux[n,t] == SoC_EV_s[n]]
    elif t > t_EV_e[n]:
      constraints_aux += [P_EV_aux[n,t] == 0]
      constraints_aux += [SoC_EV_aux[n,t] == SoC_EV_e[n]]

for n in range(N):
    for t in range(T):
        if (t < T-1)  &  (t >= t_EV_s[n]) & (t < t_EV_e[n]):
          constraints_aux += [C_EV[n]*SoC_EV_aux[n,t+1] == C_EV[n]*So
C_EV_aux[n,t] + charger_eff_EV*P_EV_aux[n,t]]

for t in range(T):
  constraints_aux += [P_load[t] + cp.sum(P_EV_aux, axis = 0)[t] - PV_
load_aux[t] <= P_load_max]
  constraints_aux += [PV_grid_aux[t] + PV_load_aux[t] == PV[t]]
  constraints_aux += [PV_load_aux[t] <= P_load[t] + cp.sum(P_EV_aux,
axis = 0)[t]]


problem_aux = cp.Problem(cp.Minimize(objective_aux),constraints_aux)
problem_aux.solve(verbose=True)

MinVar = problem_aux.value
print(MinVar)


#REAL PROBLEM

m = 4 #number of periods per hour
T = 36*m #number of periods
N = 20 #number of EVs
constraints = []

P_EV = cp.Variable((N,T),nonneg = True)
SoC_EV = cp.Variable((N,T),nonneg = True)
PV_grid = cp.Variable((T),nonneg = True)
PV_load = cp.Variable((T),nonneg = True)


objective = cp.sum(lambdRT@(cp.sum(P_EV, axis = 0) + P_load - PV_load
).T - lambdRT_PV@PV_grid.T)
```

```
for n in range(N):
  constraints += [P_EV[n] <= P_EV_max]
  constraints += [charger_eff_EV*sum(P_EV[n,t] for t in range(T)) ==
C_EV[n]*(SoC_EV_e[n] - SoC_EV_s[n])]
  constraints += [SoC_EV[n,t_EV_s[n]] == SoC_EV_s[n]]
  constraints += [SoC_EV[n,t_EV_e[n]] == SoC_EV_e[n]]
  for t in range(T):
    constraints += [SoC_EV[n,t] <= SoC_EV_max[n]]
    constraints += [SoC_EV[n,t] >= SoC_EV_min[n]]
    if t < t_EV_s[n]:
      constraints += [P_EV[n,t] == 0]
      constraints += [SoC_EV[n,t] == SoC_EV_s[n]]
    elif t > t_EV_e[n]:
      constraints += [P_EV[n,t] == 0]
      constraints += [SoC_EV[n,t] == SoC_EV_e[n]]

for n in range(N):
    for t in range(T):
        if (t < T-1)  &  (t >= t_EV_s[n]) & (t < t_EV_e[n]):
          constraints += [C_EV[n]*SoC_EV[n,t+1] == C_EV[n]*SoC_EV[n,t
] + charger_eff_EV*P_EV[n,t]]

for t in range(T):
  constraints += [P_load[t] + cp.sum(P_EV, axis = 0)[t] - PV_load[t]
<= P_load_max]
  constraints += [PV_grid[t] + PV_load[t] == PV[t]]
  constraints += [PV_load[t] <= P_load[t] + cp.sum(P_EV, axis = 0)[t]
]

muH = 1/T*cp.sum(P_load + cp.sum(P_EV,axis = 0) - PV_load)
constraints += [1/T*cp.sum((P_load + cp.sum(P_EV,axis = 0) - muH - PV
_load)**2) <= 1.2*MinVar]

problem = cp.Problem(cp.Minimize(objective),constraints)
problem.solve()


print('objective = %s' % problem.value)
"""
for var in problem.variables():
   print('%s = %s'%(var.name(),var.value))
"""
```

```
PEV = []
SoC = []
P_PV_grid = []
P_PV_load = []
i = 0
for var in problem.variables():
  if i == 0:
    i += 1
    for n in range(N):
      PEV.append([])
      for t in range(T):
        PEV[n].append(var[n,t].value)
  elif i == 1:
    i += 1
    for t in range(T):
      P_PV_load.append(var[t].value)
  elif i == 2:
    i += 1
    for t in range(T):
      P_PV_grid.append(var[t].value)
  else:
    for n in range(N):
      SoC.append([])
      for t in range(T):
        SoC[n].append(var[n,t].value)

loadEV = [sum(PEV[n][t] for n in range(N)) for t in range(T)] #potenc
ia acumulada EV a cada hora
vehicle = 2
loadEVa = [PEV[vehicle][t] for t in range(T)] #potencia EV[vehicle] a
 cada hora
SoCEVa = [100*SoC[vehicle][t] for t in range(T)] #SoC EV[vehicle] por
 hora
load = []
P_load_grid = []
for t in range(T):
  load.append(loadEV[t] + P_load[t])
  P_load_grid.append(loadEV[t] + P_load[t] - P_PV_load[t])

t = np.arange(0,25*m,1)
xtick_labels = [18,21,00,3,6,9,12,15,18]
```

```
plt.plot(t,loadEV[6*m:31*m],label='loadEV') #plot para potencia acumu
lada EV por hora
plt.plot(t,loadEVa[6*m:31*m],label='loadEVa') #plot para ver carga de
 EV[0]
plt.xticks(range(0,24*m+1,3*m),xtick_labels)
plt.xlabel('hours')
plt.ylabel('kW')
plt.legend()
plt.grid(True)
plt.show()

plt.plot(t,load[6*m:31*m],label='demand+EV load')
plt.plot(t,P_load[6*m:31*m],label='demand load')
plt.plot(t,P_load_grid[6*m:31*m],label='grid load')
plt.xticks(range(0,24*m+1,3*m),xtick_labels)
plt.xlabel('hours')
plt.ylabel('kW')
plt.legend()
plt.grid(True)
plt.show()

plt.plot(t,P_PV_load[6*m:31*m],label='PV_load') #plot para ver la sol
ar PV dedicada a la load and EV charge
plt.plot(t,P_PV_grid[6*m:31*m],label='PV_grid') #plot para ver la sol
ar PV inyectada a la red
plt.plot(t,P_load_grid[6*m:31*m],label='grid load')
plt.xticks(range(0,24*m+1,3*m),xtick_labels)
plt.xlabel('hours')
plt.ylabel('kW')
plt.legend()
plt.grid(True)
plt.show()


plt.plot(t,SoCEVa[6*m:31*m],label = 'SoC of vehicle '+str(vehicle))
plt.xticks(range(0,24*m+1,3*m),xtick_labels)
ytick_labels = [0,0.2,0.4,0.6,0.8,1]
plt.yticks(range(0,120,20),ytick_labels)
plt.xlabel('hours')
plt.ylabel('SoC')
plt.legend()
plt.grid(True)
plt.show()
```

```
Cost = 0.001*sum((lambdRT[i]*(sum(PEV[n][i] for n in range(N)) + P_lo
ad[i] - P_PV_load[i]) - lambdRT_PV[i]*P_PV_grid[i]) for i in range(T)
)
print('Total Cost: %s Eur'%Cost)

muH = 1/T*sum(P_load[i] + sum(PEV[n][i] for n in range(N)) - P_PV_loa
d[i] for i in range(T))
Var = 1/T*sum((P_load[i] + sum(PEV[n][i] for n in range(N)) - muH - P
_PV_load[i])**2 for i in range(T))

print('Variance: %s'%Var)
```