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Analysis and Operation of Smart Grids with Electric Vehicles

PhD Dissertation

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Dr. José Antonio Aguado Sánchez y Dr. Sebastián de la Torre Fazio, profesores doctores asociados al departamento de Ingeniería Eléctrica de la Universidad de Málaga y directores de la tesis de título "Analysis and Operation of Smart Grids with Electric Vehicles" realizada por el doctorando Miguel Ángel López Pérez, DNI 74853854D, dentro del programa de doctorado en Ingeniería Mecatrónica, certifican que:

- Han procedido con la revisión del texto completo de la tesis arriba mencionada.
- Autorizan su presentación para la lectura y defensa de la misma.

JOSÉ ANTONIO AGUADO SÁNCHEZ	SEBASTIÁN DE LA TORRE FAZIO
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Abstract

Nowadays, the growing concern about environmental issues is leading many countries to take measures that allow a more rational energy usage and for a more sustainable future. The improvement on systems efficiency and the use of renewable sources are some points to work on to reduce anthropogenic greenhouse gas emissions, the main cause of climate change. In this respect, the electric sector is one of the most important sources of harmful emissions in the atmosphere, followed by the transportation sector. This statement is justified if the strong dependency of these sectors on fossil fuels, specifically petrol and its derivatives, is taken into account. That is why electric mobility is drawing the attention of companies, countries and research groups, as an important measure to face the negative consequences derived from the current energy usage.

It is clear that the inclusion of electric vehicles will strongly affect the operation, management and planning of current electric power systems. Firstly, an additional load will have to be considered, the electric vehicles' charging. In an initial stage, when the deployment of electric vehicles is not significant, special measures will not be required. However, in the future with thousands of vehicles in operation, a bad electric vehicle management can lead to line congestion or voltage limits violation. Moreover, an update of the current electric power systems regarding more advanced information and communication technologies, better metering devices, an appropriate charging and discharging infrastructure, as well as the presence of more renewable sources are required for the suitable integration of electric vehicles. In brief, electric systems have to incorporate more intelligence and be more sustainable, efficient and secure, in other words, they have to tend to the smart grid concept.

Thus, this thesis is intended to cover relevant points regarding a satisfactory integration of electric vehicles in the future electric grids. It deals with three aspects, namely demand-side management, technical problems' corrections and the role of a new entity

managing electric vehicles, the agreggator.

Demand-side management refers to specific strategies intended to change current consumption patterns towards other behaviours that allow a more efficient operation of the power system. Thus, they aim at reducing the general electricity demand or, instead, shift the demand to other more favourable time periods. To this end, it is necessary to encourage consumers to modify their habits or plan their activities in a different way. In this thesis, the use of price signals is proposed to evoke these changes. The result is a flatter demand curve that allows makes the most of the existing infrastructure and available generation resources, postponing ulterior reinforcements. From the consumer point of view, the energy costs are reduced.

In the absence of corrective measures, the presence of electric vehicles will cause technical problems in the electricity system. In order to provide a solution for the most common technical problems, two tools are developed in this thesis: a centralised approach that dispatches the generators within the grid, and an algorithm that makes use of electric vehicles. Both approaches permit the avoidance of line congestion problems effectively in certain situations. In particular, the electric vehicle charging or power injection in specific buses in the grid is proposed as way to lead the system to a secure state.

Finally, a particular strategy is set to allow an electric vehicle aggregator to maximise its benefits, managing electric vehicle charging and discharging. As a consequence of its application, electric vehicle drivers satisfy their mobility requirements and reduce the cost of charging the batteries. Thus, the charging will take place during night hours when the costs are typically lower while the discharging will be performed at the demand peaks. Such a strategy allows aggregators to have useful tool at their disposal to participate in electricity markets. Its application is illustrated through a market-clearing algorithm in which along with the traditional agents present nowadays in the electricity markets, the introduction of aggregator agents is also taken into account.

Resumen

Hoy en día la creciente preocupación por temas medioambientales está llevando a muchos países a tomar medidas que permitan un uso más racional de la energía y un futuro más sostenible. La mejora de la eficiencia de los sistemas y el uso de recursos renovables son algunos puntos sobre los que se debe trabajar para poder atajar las consecuencias de los gases de efecto invernadero, principal responsable del cambio climático. En relación con esto, el sector eléctrico es el uno de los más importantes responsables de emisiones nocivas a la atmósfera seguido por el sector del transporte. Su fuerte dependencia en los combustibles fósiles, particularmente el petróleo y sus derivados, justifica esta última afirmación. Por este motivo, la movilidad mediante vehículos eléctricos está atrayendo la atención de empresas, países y grupos de investigación, como una medida importante para poder hacer frente a las consecuencias negativas derivadas del uso actual de la energía.

Resulta claro que la introducción del vehículo eléctrico afectará de manera importante a la operación, gestión y planificación de los sistemas eléctricos actuales. En primer lugar, será necesario tener en cuenta un consumo eléctrico adicional, la carga de las baterías de los vehículos eléctricos. En una primera etapa, donde el número de vehículos desplegados por las ciudades sea reducido no serán necesarias medidas especiales. Sin embargo, en un futuro con miles de vehículos, una mala gestión de la carga puede llevar a problemas técnicos de congestión en las líneas o niveles de tensión no admisibles. Por otra parte, su adecuada integración requiere que los sistemas eléctricos existentes tiendan a incorporar las tecnologías de la información y comunicación más avanzadas, mejores dispositivos de medida, una adecuada infraestructura para carga y descarga así como una mayor presencia de energías renovables. En definitiva, los sistemas eléctricos han de incorporar más inteligencia, ser más sostenibles, eficientes y seguros, en otras palabras, han de tender hacia el concepto de "smart grid".

De esta forma, esta tesis trata de cubrir puntos relevantes en relación la integración

satisfactoria de los vehículos eléctricos en las redes eléctricas del futuro. Los aspectos tratados son la gestión de la demanda, la resolución de problemas técnicos y el papel de una nueva entidad gestora de vehículos eléctricos, el agregador.

La gestión de la demanda hace referencia a estrategias específicas que tratan de cambiar los patrones de consumo actuales hacia otros comportamientos que permitan un funcionamiento más eficiente del sistema eléctrico. De esta forma, se tiene como objetivo reducir la demanda de electricidad de forma general o bien desplazar dicha demanda hacia otros periodos de tiempo más favorables. Para conseguir esto, es necesario proporcionar algún tipo de incentivo a los consumidores para que puedan modificar sus hábitos o planificar sus actividades de otra manera. En esta tesis, se propone usar señales de precio para provocar ese cambio. El resultado es una curva de demanda más plana que permite aprovechar mejor la infraestructura existente y los recursos de generación disponibles, retrasando ulteriores planificaciones. Desde el punto vista del consumidor, los costes de la energía son menores.

En ausencia de medidas correctoras, la presencia de vehículos provocará en el futuro problemas técnicos en el sistema eléctrico. Con vistas a proporcionar solución los problemas más comunes de índole técnica, dos herramientas se desarrollan en esta tesis, un problema centralizado que despacha a los generadores de la red y un algoritmo que hace uso de los vehículos eléctricos. Ambos enfoques permiten aliviar las congestiones de manera efectiva en determinadas situaciones. En particular, la inyección de potencia o la carga de los vehículos en ciertos nudos de la red se propone como una medida posible para llevar al sistema a un estado seguro.

Finalmente, se plantea una estrategia que permite la maximización de los beneficios de un agente agregador que gestiona la carga y la descarga de los vehículos. Como consecuencia de su aplicación, los conductores ven sus necesidades de movilidad satisfechas a la vez que los costes de carga se reducen. De esta forma, la carga se producirá en las horas nocturnas donde los costes de la energía son normalmente más pequeños y la descarga tendrá lugar en las horas donde hay picos de demanda. Dicha estrategia permite a los agregadores disponer de una herramienta útil a la hora de participar en los mercados de energía eléctrica. Su aplicación es ilustrada a través de un algoritmo de liquidación de mercado en el que además de los elementos comunes presentes hoy en día en los mercados eléctricos, la introducción de agentes agregadores es también tenida en cuenta.

Resumen ampliado

En este apartado se resumen los temas principales trabajados durante el desarrollado de la tesis y se ponen en relieve las contribuciones de la misma. La primera sección sirve de introducción y expone la motivación por el trabajo de investigación. En las secciones subsiguientes, se explica en detalle cada uno de los puntos en los que se ha incidido así como las metodologías empleadas y los resultados obtenidos. Finalmente, se presentan las contribuciones más relevantes que surgen de la tesis y los artículos publicados que la avalan.

Introducción

Hoy en día, la movilidad mediante vehículos eléctricos está atrayendo la atención de numerosos países, empresas y centros de investigación. Su principal atractivo reside en su potencial para reducir las emisiones nocivas a la atmósfera y su alta eficiencia de operación si se compara con los vehículos que utilizan motores de combustión interna. En un entorno donde el cambio climático es una de las preocupaciones más extendidas en todos los países, los vehículos eléctricos suponen una apuesta por una movilidad más sostenible. El sector eléctrico y el del transporte, en todos sus ámbitos, son dos de las fuentes más importantes de emisiones de gases de efecto invernadero a nivel global. En particular, el sector energético en España fue el que más emisiones causó en 2012, con un 78% del total, la mayor parte de ellas debidas a la generación de electricidad y al transporte por carretera. Por tanto, resulta interesante estudiar alternativas de movilidad al modelo de transporte individual de personas que actualmente es fuertemente dependiente del petróleo y sus derivados. Entre dichas alternativas, se prevé que el vehículo eléctrico juegue un papel fundamental en el medio plazo.

La integración satisfactoria del vehículo eléctrico requiere un trabajo importante con respecto a una serie de retos desde el punto de vista técnico:

- La carga de las baterías supondrá una demanda adicional de electricidad que tendrá que ser satisfecha. En un futuro donde el número de vehículos sea considerable, pueden producirse problemas técnicos en los sistemas eléctricos como consecuencia de una carga concentrada en determinadas horas. Por este motivo, resulta interesante el estudio de estrategias que permitan mover dicha carga a periodos de tiempo más favorables donde la demanda de electricidad es menor, es decir, desplazarla a las horas nocturnas.

- Su futuro está condicionado a un incremento en la participación de las energías renovables en la generación de energía eléctrica así como de una actualización de los sistemas existentes. Por una parte, la carga de los vehículos debería realizarse con tecnologías de generación renovables o al menos que sean más eficientes y menos dependientes de los combustibles fósiles. En otro caso, el problema de las emisiones persistiría ya que sería trasladado al sector eléctrico. Por otro parte, se hace necesario una evolución de los sistemas eléctricos actuales hacia el concepto de redes inteligentes o "smart grids". Además del cambio requerido en relación a las plantas de generación, es fundamental un incremento en las tecnologías de información y comunicación y el uso de dispositivos más modernos de control y medida.

- Con el objeto de explotar algunas funcionalidades asociadas a la carga y descarga de las baterías, se concibe la existencia de un agente o entidad responsable de su gestión. De esta forma, el así llamado "agregador de vehículos eléctricos" se perfila como futuro gestor de la carga de los mismos. Su labor principal será la de satisfacer las necesidades energéticas asociadas a la movilidad aunque, al mismo tiempo, tratará de aprovechar la tecnología Vehicle-to-Grid (V2G), es decir, la inyección de potencia en la red a través de la descarga de las baterías, para encontrar otras oportunidades de negocio. Por tanto, la gestión de vehículos a través de un agregador permitirá un proceso de carga más eficiente, mayores beneficios tanto para el agregador como para los propietarios de los vehículos y la prestación de servicios complementarios como la reserva o la regulación.

En esta tesis, se tratan de cubrir algunos aspectos señalados en los puntos anteriores. La gestión de la demanda, la operación técnica y el papel del agregador de los vehículos eléctricos en las redes eléctricas del futuro son abordadas desde distintas perspectivas. Asimismo, se proponen diversas herramientas susceptibles de ser usadas en la operación de las smart grids con la participación activa de los vehículos eléctricos. Dichos puntos son tratados en detalle en las secciones subsiguientes.

Gestión de la demanda

En los sistemas eléctricos actuales, la demanda de energía eléctrica suele ser elevada en las horas intermedias y finales del día mientras que tiende a ser pequeña durante las horas nocturnas. Este hecho provoca la existencia de picos importantes de la demanda que se acentúan con los cambios estacionales debido, por ejemplo, a las necesidades de calefacción o aire acondicionado. Estos picos de demanda han de ser satisfechos por generadores flexibles y de respuesta rápida, con el objecto de mantener el equilibrio entre demanda y generación, pero que llevan asociados mayores costes de operación. Sin embargo, durante aquellas horas de menor demanda existe una capacidad de generación que no se está usando. Resulta atractivo, por tanto, el aplanar la curva de la demanda de energía eléctrica para aprovechar mejor tanto las tecnologías de generación como la infraestructura eléctrica existente. La ausencia de mecanismos que gestionen la demanda de manera adecuada llevará en un futuro a incrementar el número de generadores para cubrir los picos y a tener que reforzar las líneas eléctricas para que no se produzcan congestiones.

La gestión de la demanda hace referencia a un conjunto de estrategias mediante las cuales se trata de cambiar el patrón de consumo de los usuarios finales de la energía intentando que la curva de demanda sea más plana. Existen varias formas de conseguir este objetivo pero, en cualquier caso, hace falta proporcionar algún incentivo a los consumidores para cambiar su comportamiento. Entre las distintas opciones, en esta tesis, se propone lograr un desplazamiento temporal de las cargas a través de señales de precio. Con el objeto de conseguir este comportamiento, se han definido una serie de agentes o entidades que pueden realizar este tipo de gestión. En la práctica, estos agentes pueden ser estar representados por conjuntos residenciales, complejos industriales, empresas generadoras de energía eléctrica o áreas comerciales por citar algunos ejemplos. La metodología usada se basa en problemas de optimización de manera que cualquiera de los agentes antes citados puede maximizar sus beneficios, o en su defecto minimizar los costes de la energía, valiéndose de una reorganización horaria de su demanda. Este problema de optimización puede formularse genéricamente de la siguiente manera:

$$\begin{aligned} \text{maximizar} \quad & \textit{ingresos} - \textit{costes} \\ \text{sujeto a} \quad & \mathbf{f} \leq \mathbf{0}, \quad \mathbf{g} = \mathbf{0} \end{aligned} \tag{1}$$

donde “ingresos” y “costes” son términos que dependen de los precios horarios de compra y de venta de la energía y las funciones $\mathbf{f}$ y $\mathbf{g}$ representan las restricciones de desigualdad e igualdad respectivamente. El agente obtiene ingresos vendiendo la energía sobrante de sus generadores y, en cambio, incurre en costes al comprar la energía que necesita y en la operación de sus activos de generación.

Dentro del modelo presentado, las restricciones más importantes permiten definir cómo puede desplazarse la demanda. De esta forma, se define un parámetro k que representa el máximo número de periodos que la demanda puede desplazarse hacia delante o hacia atrás en el tiempo. La cantidad de demanda que puede ser movida se define como una fracción de la demanda total en cada uno de los periodos de tiempo. Otras restricciones del problema representan límites técnicos de ciertos elementos que posee el agente, como generadores o baterías. El resultado del problema de optimización permite situar la demanda en aquellos periodos de tiempo donde el beneficio, expresado como la diferencia entre ingresos y costes, es máximo. Teniendo en cuenta que la energía eléctrica es más barata en aquellos periodos donde la demanda es menor, y viceversa, las cargas se desplazarán hacia aquellos periodos más ventajosos tanto desde el punto de vista económico como desde el punto de vista técnico. La formulación completa de este problema se presenta en la Capítulo 2.

Los resultados obtenidos, aplicados en dos casos de estudio concretos, muestran que la curva de demanda final se aplana conforme el valor del parámetro k crece, dándose un valor óptimo entre 3 y 12 para el cual los beneficios de los agentes involucrados así como los obtenidos por del sistema, en términos de pérdidas y cantidad de potencia transportada por las líneas, se encuentran compensados.

Asimismo, esta metodología puede aplicarse también a los vehículos eléctricos. En este caso, la carga se localizará en las horas nocturnas, donde el precio de compra de la energía es más bajo, mientras que la descarga se emplazará en las últimas horas del día, aprovechando los precios de venta más ventajosos. El problema de optimización incorpora restricciones en relación al nivel energético de la batería de los vehículos. Así por ejemplo, la batería debe estar completa en alguna de las primeras horas del día y se tiene en cuenta también la energía consumida en los desplazamientos del vehículo. Este problema es el que desarrollaría un agregador que tiene como objetivo maximizar sus beneficios, a través de la carga y descarga de las baterías de los vehículos, pero satisfaciendo los requerimientos energéticos de la flota que representa. Esta estrategia es comparada con distintos tipos de carga no controlada resaltando los beneficios de una gestión mediante agregador. Este problema es estudiado más en detalle en el Capítulo 4.

Dentro del Capítulo 2, también se describe un mecanismo de subasta susceptible de ser utilizado en mercados locales de energía eléctrica, es decir, aquellos mercados no mayoristas que se dan a nivel de la red de distribución. La idea de esta subasta es la de proporcionar un precio más favorable a los compradores y los vendedores por la energía que quieren comprar o vender con respecto a los precios que le ofrecería la red principal, que podría venir representada por un comerciante minorista. Partiendo de dos valores extremos, la subasta se desarrolla por rondas en las que los compradores emiten ofertas crecientes y los vendedores emiten ofertas decrecientes hasta que se produce un cruce de ofertas y la correspondiente casación. Una vez que las cantidades que se pretenden intercambiar son conocidas, el precio que se oferta se calcula de acuerdo a la siguiente función:

$$y = \frac{a}{x+b} + c \tag{2}$$

donde a, b y c son parámetros que dependen de cada agente y x es el índice de las rondas. Los valores de estos parámetros definen a los agentes compradores o vendedores además del ritmo al que el precio aumenta o disminuye con las rondas. El mecanismo de subasta queda totalmente definido por un conjunto de reglas concretas que determinan las cantidades de energía eléctrica que se intercambian y el precio en los distintos tipos de casación que puedan darse, entre dos agentes solamente (un vendedor y un comprador) o entre múltiples agentes (varios compradores con varios vendedores).

Operación técnica

Otro de los retos a los que se enfrentan los sistemas eléctricos del futuro es la corrección de problemas técnicos que puedan surgir, en particular, la congestión en algunas líneas de la red. Como consecuencia de una carga no controlada de vehículos, se prevé que las líneas puedan sobrecargarse, es decir, que lleguen a niveles de flujo de potencia no admisibles y que pueden suponer un peligro para su integridad. Además, este hecho puede agravarse por flujos bidireccionales de potencia debidos a los generadores situados a nivel de distribución. Con el objeto de dar solución a este tipo de problemas se proponen dos formas de atajarlos. La primera forma opera de manera centralizada y la segunda hace uso de vehículos eléctricos. Ambas opciones son presentadas en el Capítulo 3.

El primer método propuesto hace uso de un problema de optimización conocido como flujo de cargas óptimo. Se trata de llevar al sistema a un estado seguro tomando la potencia de salida de los generadores como variables de control. Este problema se formula de manera general de la siguiente forma:

$$\begin{aligned} \text{minimizar} \quad & \textit{incremento} \\ \text{sujeto a} \quad & \mathbf{f}_C \leq \mathbf{0}, \quad \mathbf{g}_C = \mathbf{0} \end{aligned} \tag{3}$$

donde "incremento" es una función que se expresa como una suma ponderada de las diferencias entre las potencias iniciales de los generadores (las que originan el problema técnico) y las potencias finales (resultado del problema de optimización) en valor absoluto. Los términos $\mathbf{f}_C$ y $\mathbf{g}_C$ son las restricciones de desigualdad e igualdad respectivamente, que quedan representadas por límites sobre los niveles de tensión o la capacidad de las líneas así como las ecuaciones del flujo de potencia que garantizan el balance.

Por tanto, mediante la aplicación de este problema, se intentan corregir las infactibilidades actuando sobre la potencia suministrada por los generadores pero tratando de quedarse lo más cerca posible del estado inicial. Los pesos de cada uno de los términos de la función objetivo permiten dar prioridad a modificar la potencia de algunos generadores sobre otros. De forma general, la energía proveniente de fuentes renovables será la que en el última instancia se modifique en detrimento de otras fuentes de energía menos sostenibles.

Los resultados muestran que el flujo de cargas óptimo es adecuado para aliviar congestiones siempre que la variación en la potencia suministrada, por el generador que corresponda, afecte al flujo de potencia sobre la línea en cuestión. Por este motivo, este problema falla para aquellas líneas de alimentación sobrecargadas en las que solo haya cargas. En este caso, modificar las potencias de los generadores tiene poco o ningún efecto y otras medidas, tales como el deslastre de cargas, tendrían que ser aplicadas en ausencia de otros mecanismos.

El segundo método propuesto hace uso de los vehículos eléctricos para aliviar la congestión en las líneas. Valiéndose del concepto de "factor de distribución", la capacidad de las baterías para cargar o descargar en determinados nudos de la red es aprovechada para reducir el flujo de potencia en aquellas líneas que se encuentren sobrecargadas. Los factores de distribución pueden definirse como la variación que se produce en el flujo de potencia de una línea como consecuencia de una inyección de potencia unitaria en un nudo de la red. Dichos factores pueden calcularse a partir de la topología de la red de estudio, de sus características de resistencia y reactancia así como del estado de actual o de referencia del sistema. Puesto que la potencia puede ser activa o reactiva, se obtienen cuatro grupos de factores haciendo todas las combinaciones posibles.

Los factores de distribución, de acuerdo a la definición, dan una idea de aquellos nudos que deben elegirse para provocar un cambio en el flujo de potencia en una línea. De este modo, si una línea concreta está congestionada, puede determinarse el nudo más adecuado, es decir, el que tenga el mayor valor del factor de distribución, y aliviar el flujo de potencia de la misma. La base de este método está en que la contribución de inyección de potencia, en el nudo que corresponda, se lleve a cabo por los vehículos eléctricos mediante la carga o la descarga de sus baterías. Se toma como hipótesis que los vehículos pueden modificar el flujo de potencia de una línea solamente mediante aporte de potencia activa. El cálculo de los factores de distribución y el algoritmo que define el método se desarrollan en detalle en el Capítulo 3.

El algoritmo se aplica a dos sistemas diferentes con vehículos y patrones concretos. Los resultados arrojan que un número reducido de vehículos puede resolver problemas de congestión pequeños/moderados en las líneas de manera satisfactoria. Sin embargo, dada la naturaleza lineal de la formulación, niveles más elevados de congestión pudieran no ser resueltos adecuadamente. Además, para que el problema sea corregido se ha de disponer de un número suficiente de vehículos, con un estado de carga determinado que le permita inyectar/absorber la potencia requerida y con una localización nodal adecuada, por lo que el éxito de dicha estrategia queda supeditado a garantizar estos requisitos.

El agregador de vehículos eléctricos

Tal como se ha comentado, el agregador se concibe como una futura entidad responsable de la carga de los vehículos eléctricos de forma las necesidades de movilidad de los propietarios se vean satisfechas. En esta tesis, se proponen dos problemas que involucran a los agregadores: un problema de maximización de beneficios y otro de liquidación de mercado.

El problema del agregador se plantea como una maximización de la diferencia entre los ingresos que recibe por venta de energía (V2G o descarga) y los costes de compra de la misma (carga). Puesto que los precios quedan definidos de forma horaria, su estrategia consistirá en proceder con la carga en aquellos periodos donde la energía sea más barata y realizar la descarga en los periodos de tiempo donde el precio de venta sea más favorable. Para que el agregador maximice sus beneficios, debe disponer de información adecuada respecto a los precios de venta y compra de energía así como de la disponibilidad de los vehículos con respecto a la conexión a la red. Por tanto, debe disponer de datos suficientes para estimar ambos aspectos que resultan claves para lograr sus objetivos. En el capítulo 4 se expone en detalle el problema del agregador y se estudia la influencia de los parámetros que intervienen. En particular, se aplica una herramienta basada en cadenas de Markov para determinar el estado de los vehículos (es decir, si está en movimiento o conectado a la red y el nudo de conexión) y una simulación de Monte Carlo que permite generar patrones.

Como resultados principales se obtienen no solo los periodos de tiempo más favorables para realizar la carga o la descarga sino también la cantidad de energía que se ha de comprar o vender. La estrategia del agregador es comparada con la de carga no controlada en términos económicos. De esta forma, si los vehículos cargaran de forma libre, los costes de carga serían más elevados que si la gestión de la misma la realizara el agregador. La principal aplicación de esta herramienta es la de servir de apoyo a los gestores de carga de cara a su participación en los mercados eléctricos. Estimados los precios y los patrones más comunes asociados a los vehículos, los periodos de tiempo en los que se debe ofertar más alto quedan claramente determinados. Sin embargo, se ha de tener en cuenta que los resultados obtenidos son cualitativos, en el sentido en que se sabe cuándo ofertar pero no cuánto. La magnitud concreta de la oferta debe estar basado en un estudio previo sobre los precios históricos de mercado.

Finalmente, en el capítulo 5 se desarrolla un algoritmo de liquidación de mercado con restricciones de seguridad. El objetivo de este algoritmo es determinar qué agentes se van a encargar de suministrar la energía eléctrica, cuáles van a comprar para satisfacer su demanda y también cuáles son los precios asociados a dichas transacciones. En la formulación se concretan los agentes que tradicionalmente participan en los mercados eléctricos, a saber, las compañías suministradoras, los consumidores y los contratos bilaterales. La inclusión del agente agregador de vehículos como nueva entidad participante es la principal aportación al respecto. Este algoritmo queda definido a través de un problema de optimización de la siguiente forma:

$$\begin{aligned} \text{maximizar} \quad & z_S + z_C + z_B + z_A \\ \text{sujeto a} \quad & \mathbf{f}_S \leq \mathbf{0}, \quad \mathbf{f}_C \leq \mathbf{0}, \quad \mathbf{f}_B \leq \mathbf{0} \\ & \mathbf{f}_A \leq \mathbf{0}, \quad \mathbf{g} = \mathbf{0} \end{aligned} \tag{4}$$

donde los términos z_S, z_C, z_B y z_A, por un lado, y $\mathbf{f}_S$, $\mathbf{f}_C$, $\mathbf{f}_B$ y $\mathbf{f}_A$, por otro, representan las funciones de utilidad y las restricciones asociadas a los suministradores, consumidores, contratos bilaterales y agregadores respectivamente. El término $\mathbf{g}$ tiene en cuenta las restricciones técnicas de la red que garantizan el balance entre generación y demanda.

El resultado de este problema da lugar al despacho óptimo de las unidades de producción que satisfacen la demanda del sistema de acuerdo a las ofertas emitidas por cada uno de los agentes. Los suministradores emitirán ofertas de venta de energía para proporcionar potencia y reserva y, en cambio, los consumidores emitirán ofertas de compra. De forma general, serán aceptadas aquellas ofertas de venta más bajas, es decir, la de aquellos suministradores que están dispuestos a vender su energía más barata, ocurriendo lo contrario para las ofertas de compra, que serán rechazadas si el consumidor no está dispuesto a comprar su energía a un precio suficientemente alto. Para los consumidores se ha considerado que hay una fracción de la demanda que es fija y otra que es despachable, de manera que solo se emiten ofertas para ésta última. Del mismo modo, los contratos bilaterales se resolverán de acuerdo a los precios pactados entre ambas partes. Las restricciones para cada uno de estos agentes, por citar algunas, son por ejemplo los límites de operación de los generadores o la contribución de potencia suministrada o demandada en cada uno de los nudos.

En particular, el agregador de vehículos eléctricos es un agente especial que emite ofertas de venta y de compra de energía. Las ofertas de compra se realizarán pensando en la carga necesaria requerida por las baterías mientras que las ofertas de venta perseguirán obtener ingresos adicionales. Como se dijo anteriormente, el problema de maximización de beneficios permite a los agregadores evaluar las estrategias de oferta más favorables de cara a la participación en los mercados eléctricos. Las ofertas de compra serán altas en aquellos periodos de tiempo donde se prevé que los precios de compra sean más pequeños mientras que las ofertas de venta serán bajas donde se espera que los precios ofrecidos sean más ventajosos.

El modelo propuesto se ha desarrollado para un sistema en el que participan tres agregadores con distintos vehículos y patrones de movimiento. Los resultados arrojan que una buena estimación de los precios de mercado y de la disponibilidad de los vehículos para estar conectado a la red, permite a los agregadores emplazar la compra y la venta de energía en los periodos de tiempo que le reportan más beneficios.

Contribuciones

De acuerdo a las ideas expuestas anteriormente, las principales contribuciones de la tesis se presentan a continuación:

- La formulación de una estrategia específica de gestión de demanda basada en problemas de optimización. El problema se formula como una maximización de los beneficios de cada uno de los agentes siendo el desplazamiento de las cargas el medio para lograr una reducción de los costes de la energía. El aplanamiento de la curva de la demanda reporta también beneficios al sistema eléctrico en términos de una reducción de pérdidas y un mejor aprovechamiento de los activos existentes. El emplazamiento horario de los generadores es también tenido en cuenta y se facilita la integración de los vehículos eléctricos y las fuentes de generación renovable.

- Un flujo óptimo de cargas que permite actuar sobre los generadores para corregir problemas técnicos que puedan surgir en las redes a nivel de distribución. Como herramienta centralizada permite evitar congestiones modificando los niveles de generación y favoreciendo a las fuentes renovables.

- El desarrollo de un algoritmo que hace uso de los vehículos eléctricos para alivio de congestiones aprovechando la capacidad de las baterías para cargar y descargar.

Usando los factores de distribución es posible seleccionar qué nudos con vehículos son los más adecuados.

- Aspectos técnicos y económicos desarrollados en la tesis se ponen conjuntamente, proporcionando un esquema completo caracterizado por mecanismos de subasta, problemas de optimización de los agentes, gestión de los vehículos y operación técnica centralizada.

- La implementación de un problema de maximización de beneficios que puede ser usado por los agregadores y que le permite determinar la forma óptima de participar en los mercados eléctricos.

- El desarrollo de un algoritmo de liquidación de mercado con restricciones de seguridad y que incluye a los agregadores de vehículos como nuevos agentes participantes.

Los artículos que avalan la tesis se muestran a continuación:

<u>Publicados en revista</u>

M.A. López, S. Martín, J.A. Aguado, S. de la Torre, V2G strategies for congestion management in microgrids with high penetration of electric vehicles, Electric Power Systems Research, Volume 104, Noviembre 2013, Pages 28-34.

<u>Aportaciones a congresos</u>

M.A. López, J.A. Aguado, S. de la Torre, M. Figueroa, Optimization-based market-clearing procedure with EVs aggregator participation, 4th IEEE PES Innovative Smart Grid Technologies (ISGT Europe), 2013, Pages 1-5, Octubre 2013.

M.A. López, S. Martín, J.A. Aguado, S. de la Torre, Optimal microgrid operation with electric vehicles, 2nd IEEE PES Innovative Smart Grid Technologies (ISGT Europe), Pages 1-8, Diciembre 2011.

M.A. López, S. Martín, J.A. Aguado, S. de la Torre, Market-oriented operation in MicroGrids using Multi-Agent Systems, 2011 International Conference on Power Engineering, Energy and Electrical Drives (POWERENG), Pages 1-6, Mayo 2011.

<u>Enviados</u>

M.A. López, S. de la Torre, S. Martín, J.A. Aguado, Demand-side Management in Smart Grid Operation considering EVs load shifting and V2G support, enviado a la revista International Journal of Electrical Power & Energy Systems, Febrero 2014.

List of Abbreviations

BEV	Battery Electric Vehicle
DF	Distribution Factor
DG	Distributed Generation
EV	Electric Vehicle
GHG	Greenhouse Gases
ICE	Internal Combustion Engine
ICT	Information and Communication Technologies
MAS	Multi-Agent System
MG	MicroGrid
OPF	Optimal Power Flow
PHEV	Plug-in Hybrid Electric Vehicle
SOC	State of Charge
SG	Smart Grid
V2G	Vehicle-to-Grid

Contents

List of Figures

List of Tables

Chapter 1

Introduction

This chapter presents the motivation for this thesis and the fundamentals of some concepts in relation to it. A review of the state of the art is also provided. It is concluded with the outline, its structure and the main identified contributions.

1.1 Background and Motivation

Nowadays, there is a major concern for environmental issues such as the emission of GreenHouse effect Gases (GHG), which contribute to global warming, and atmospheric pollution, which degrades the air quality in many cities. These concerns go hand in hand with others related to the use of energy and the future of existing energy resources. In particular, climate and energy legislation in the EU aims to meet certain targets related to climate change. These targets consist of a 20% reduction in GHG emission, an increase in the ratio of renewable energy to 20% of the EU's total energy consumption, and a 20% improvement in energy efficiency. Moreover, the 2030 policy framework for climate and energy presented by the European Commission at the beginning of 2014 proposes more ambitious targets to reduce GHG emissions, facilitate the integration of renewable energy sources and, in short, to make the EU's economy and energy system more competitive, secure and sustainable [1].

In this regard, the road transport sector is responsible for an important share of the total energy consumption. In the EU, it represents one third of this total contributing about one fifth of the total carbon dioxide emissions with this figure constantly on the rise year on year. This situation is similar in other countries such as the United States, where the transportation sector was the second largest contributor of GHG in 2011 after the Electricity Sector [2]. Road transport also shows a high level of dependence on petroleum-derived fuels, mainly petrol and diesel, which are foreseen to be scarce in the future. Several authors and institutions forecast a near term peak in oil production followed by a significant decline, with alternative fuels not being capable of meeting the foreseen energy requirements. Furthermore, it is agreed by some that the production of oil has actually reached or even past that peak, anticipating a much more pessimistic scenario [3–7]. These concerns are aggravated by the increasing trend and high volatility in the price of crude oil [8].

Therefore, the road to a more sustainable energy future necessitates more efficient and low carbon technologies. To this end, given the considerable impact that road transport sector has on the environment, measures to improve the current automobile fleet need to be undertaken. Although there has been noteworthy progress in fuel efficiency and CO_2 emissions in recent years [9, 10], this does not seem to be enough and there is a growing interest in a shift towards alternative types of automobiles. Among them, Electric Vehicles

(EVs) are expected to play a crucial role [11].

EVs have been around for many years, the first of that kind dating back to the end of the nineteenth century. At that time, EVs had to compete against other vehicle technologies, namely the petrol-powered Internal Combustion Engine (ICE) and the steam-powered vehicle [12]. Each of them had its advantages and shortcomings although petrol-powered ICE cars were the fastest to overcome the difficulties encountered and they finally outpaced their competitors by the first quarter of the twentieth century [13]. EVs offered appealing features: they were clean, silent, simple to operate and they did not need mechanical transmissions. Nonetheless, the lack of suitable charging power stations, the required frequent battery maintenance, the reduced range due to vehicle speed, and the premature ageing of the battery were areas in which strong efforts were made but not enough to avoid its decline. Nowadays, these still constitute issues that need working on, although the prospects are quite different given the technological developments that have since been successfully achieved. Regarding the said issues, it is mainly the high costs and technical limits of the batteries that are hampering the success of the EV today [14]. On the other hand, in the near future, a varied mix of vehicle technologies including fuel cell, plug-in hybrid and electric vehicles is expected [15, 16].

EVs offer a high energy efficiency and a cleaner mode of personal transportation. Possibly, the most important characteristic is that they run only on electricity, not producing any emissions at all. However, they rely on the energy contained in their batteries which necessarily require charging if they are close to depletion. Hence, an effective deployment should not entail the substitution of tailpipe emissions by additional emissions from the increased electricity generation [17]. In this respect, the launch of EVs has to be accompanied by a corresponding increase in the power supplied by Renewable Energy Sources (RES) to the detriment of other high carbon generation technologies. Furthermore, EVs could support large scale renewable power plants by exploiting their capability of absorbing (storing) energy in their batteries or returning stored energy to the grid, thus complementing fluctuations in the grid that result from the uncertainties or intermittency associated with wind and photovoltaic plants [18].

Additionally, the successful integration of EVs would demand changes in the way electric power systems are managed and operated nowadays. A large scale adoption of EVs will pose new challenges to system operators since their charging can cause technical problems, such as voltage limits violating or line congestion, mainly at the distribution level [19, 20]. Therefore, it is interesting to develop tools and strategies that allow tackling these or anticipate their consequences [21–24]. Furthermore, upcoming entities responsible for complying with the EVs' mobility requirements will make their way through the existing regulatory framework and business models [25]. In general, the so called "EV aggregators" will try to maximise their benefits by allocating charging to the most favourable time periods [26]. Thus, charging takes place in those time periods when it is cheaper to do so, i.e. during night hours. These time periods are also suitable from a technical point of view since the demand during the same is typically small [27, 28]. Finally, the management and exploitation of EVs' capabilities is not possible with the existing infrastructure. Adequate metering devices, information and communication technologies and control, among other things, have to be put together to enable their integration. In short, the way towards a "smarter" grid have to be paved [29].

The smart grid concept as well as some ideas about EV modelling are introduced in Sections 1.2 and 1.3. Section 1.5 presents some interesting articles and works related to the topics of study. The thesis is outlined in Section 1.7. Finally, Sections 1.4, **??** and 1.6 introduce the framework of the research study, the structure of the thesis and the contributions respectively.

1.2 The Smart Grid Concept

As discussed in the previous section, the integration of EVs relies on the upgrade of the existing electric power systems towards Smart Grids (SGs). Current power systems can be considered almost entirely AS a mechanical system in which the use of sensors, communication devices and electronic control is very limited. A SG entails the use of sensors, communications, computational ability and control in such a way that the overall functionality of the power system is enhanced. This permits several functions that allow the optimisation of the use of generation assets, storage systems, distributed energy resources and end-consumers in order to ensure reliability, mitigate the environmental impact and to make better use of the available energy [30]. Therefore, an integration of power system engineering and information and communication technologies is necessary to enable a smarter grid and, in turn, this integration can allow for advances in reliability, efficiency and operational capability [31]. Among other characteristics, it also allows for a more flexible demand and the efficient integration of renewable sources, boosted by concerns about the complete depletion of fossil fuels and the negative environmental impact of most of the current energy sources.

The transition towards SGs requires the addition of new functionalities and capabilities to the existing electricity grid. Distributed generation is a common characteristic of SGs and, in addition, the nature of these generators is varied since they can be renewable, such as wind turbines or photovoltaic panels, or otherwise, such as combined heat and power, fuel cells, microturbines or diesel-powered plants [32]. Devices which are able to store energy, such as electric fixed batteries, can help the system to smooth the intermittent behavior of renewable sources enabling an easier integration. The next generation of the electricity grid will also facilitate the electrification of transportation systems [33]. SGs comprise different entities that can interact with each other bidirectionally, allowing the establishment of commercial relationships to serve and request electric energy or to solve technical problems that could arise, thus empowering the consumer. These entities within the SG can respond to changes in the energy prices allowing them to minimise the cost of the energy they need to buy or maximise the income of the energy they can sell.

Among other interesting characteristics of SGs, the concept of Demand-Side Management (DSM) has become very important and, among DSM strategies, Demand Response (DR) is one of the most significant. DR can be understood as voluntary changes by end-consumers of their usual consumption patterns in response to price signals [34]. Along with the savings that customers procure in their electricity bills, this kind of scheme can be used to avoid undesirable peaks in the demand curve that take place during some time periods of the day, providing a more beneficial rearrangement [35–37]. Through the use of DSM, several benefits are envisioned, like the improvement in the efficiency of the investment in system infrastructure, the security of supply or the reduction in the flexibility requirements for generators, although some challenges have to be overcome starting from the lack of necessary infrastructure [38, 39]. In addition, the introduction of DSM has to be conceived as an integration with other distributed energy resource technologies under the SG paradigm [40, 41]. With regard to this, several SG projects worldwide have either been completed or are underway [42, 43]. On the other hand, DSM can also be applied to EVs and, for this reason, they may be also find themselves influenced by price signals, changing their location or their consumption pattern if needed. Thus, an optimal charging allocation can be of benefit to both EV managers and system operators.

In this context, Microgrids (MGs) are power networks that have some properties in common with SGs [44]. Microgrids can be defined as integrated energy systems comprising distributed energy resources and multiple electrical loads, operating either in parallel or 'islanded' from the main utility grid. In the most common configuration, several feeders are linked to the point of common coupling and then connected to the larger grid [45]. They are regarded as active energy networks since they are envisioned to facilitate the integration of distributed generation, with bidirectional electricity transportation, and allow the application of DSM techniques [46].

Although MGs are mainly conceived as low voltage systems [47], some authors support the idea of a MG operating at medium voltage depending on the capacities of the distributed generation [48, 49]. In any case, these systems have adhere to certain characteristic features [45]: i) they can be grid-tied or off-grid remote systems, ii) MGs can operate 'islanded' from the main grid, iii) MGs require some level of storage, iv) they typically exploit their distributed energy resources at the retail distribution level. Additionally, MGs offer different kinds of benefits: technical, economical and environmental [50]. From the technical point of view, they have the potential to improve energy efficiency, increase reliability and reduce dependency on the utility grid. Economical benefits are represented by the reduction in line losses, due to the small distances between generators and loads, and the minimisation of fuel costs among others. Finally, the environmental benefit is owed to lower emissions given the incorporation of cleaner energy sources. MGs can also integrate EVs satisfactorily. Regarding this, several authors have presented works in which EVs' impact is analysed under different approaches [51–53].

1.3 Electric Vehicles Modelling

As stated previously, the growing interest in EVs and their impact in electric power systems is based on environmental issues, energy dependence and fossil fuel scarcity for satisfying future transportation needs. The integration of EVs into electric power systems brings new challenges to be overcome, but it also brings new opportunities. To this end, EVs modelling is essential to identify and to be ready for the new operational problems that could arise. In this section, the main issues and characteristics with respect to EVs are presented.

In order to model EVs in steady-state operation, the most widely used tool is the power flow as a means for verifying the grid security state with respect to voltage limits violation and lines overload as a consequence of a moderate or high penetration of EVs. The analyses are usually performed on a hourly basis during a day, week, month or a complete year for low voltage and medium voltage networks. The correct EV modelling includes the knowledge or at least the estimation of several parameters affecting their behaviour. In general, these parameters are known with a certain degree of uncertainty, i.e., they are enclosed in a certain confidence interval [54]. Some of the most important data that have to be taken into account for EV studies are, but not limited to, the following:

- When EVs charge, remain idle or undertake a journey - time periods
- Where EVs charge - bus location
- How EVs charge and which is the charging rate - charge mode
- What is their State of Charge (SOC), the efficiency of the charging process and the battery energy consumption during journeys - battery energy level tracking

These data can be assumed for the purpose of the corresponding analysis either because a common behaviour of EVs is expected or because it represents a less favourable situation in which the study can be justified. One possible way to build EV patterns comes from the analysis of survey responses. This is the methodology used in projects like Merge and G4V [55, 56]. Examples of questions made to the survey respondents are related to:

- Personal data: birthplace, place of residence, job, age,...
- Main vehicle usage: work, shopping, leisure.
- Regularity of usage.
- Preferred moment for charging: whenever it is possible, at the end of the day, only when the battery is about to deplete, whenever it is convenient and there is time.
- Preferred place for charging: at home, at work, at charging station.

- Intention for changing the time of charging depending on specific tariffs.
- Vehicle location when not in use: at home (own private garage), at home (public street), at home (communal parking lot), at work, other place (train station, shopping centre).
- Possibility to access a socket for vehicle charging.
- Predicted mileage covered on weekdays and weekends.
- Time periods when the first journey of the day and the return journey are made.

With these data it is possible to extract some important information about the EVs' patterns and behaviours that can be used in different studies. Other authors make use of the data of surveys developed in some countries, e.g., the National Household Trade Survey in United States [57].

One of the most important research issues is the possibility of incorporating the charging of EVs into existing electric power systems. In order to carry out this kind of study it is firstly necessary to characterize the hourly demand curve of the system under investigation. The strategy usually consists in taking reference load curves based on historical data, extracted from grid operators or those data previously established in the case studies. The EV charging is added to this base load under different scenarios of EVs' behaviour or operation.

To give a forecast for the number of EVs that could be present in a particular system, when large scale adoption is considered, the number of conventional vehicles is firstly estimated for the current date and it is assumed that a percentage of those are electric. Such a percentage is commonly known as penetration and its value is usually chosen between 5% and 20% [58, 59]. For small systems, it is usually enough to select this number based on the load levels. Generally, the starting point is to admit a small EV penetration and increase this number until grid technical problems, like congestion or voltage limits violating, are detected. Once this happens, several viable alternatives may be proposed to enable EV integration securely, with or without additional grid reinforcements, whilst at the same time satisfying the mobility requirements. Other authors, like [19], develop a particular algorithm to determine the maximum number of EVs that can be incorporated in a system starting from some assumptions regarding EV patterns and charging levels.

The EV charging power is given depending on the availability of a charging point with the suitable infrastructure to supply the power for which it has been designed. The coexistence of three different charging levels is widely adopted [60–62]:

- slow charging (Level 1): around 3.0 kW (one phase, 230V AC–16A)
- slow charging (Level 2): up to 19.2 kW (one or three phase, 400V AC–80A)
- fast charging (Level 3): up to 100 kW (three phase, 600V AC or 300-600V DC–from 150A to 400A)

Slow charging (level 1) is considered the one that can be performed "at home", with charging times that can be around eight hours depending on the type of EV. Slow charging (level 2), sometimes also called semi-fast charging, is suitable for commercial areas or public places with smaller charging times and where several charging points are grouped in common accessible zones where people who visit these buildings for leisure, business, etc. can park their EVs. Finally, fast charging (level 3) takes place in medium voltage connection points in AC or, at specific locations in DC. The latter way of charging is intended for gas stations, which can integrate EV charging points, and for charging times not higher than thirty minutes.

For these charging modes different connectors have been developed and proposed from the common Schuko socket to other connectors that incorporate both the feeding and communication cables [63–65].

One of the most important issues related to the EV pattern is to know when the charging takes place, e.g., at what time EVs charge during the day. In that regard, many authors differentiate among different charging behaviours directly related with the moment of the day when EVs are charging [19, 55, 66, 67]. It is generally accepted that they can follow different behaviours conditioning their charging pattern, however, regardless of the charging strategy considered, they have to fulfil particular requirements to meet their daily SOC needs.

If EVs operate freely, i.e. the EV charging pattern cannot be changed and there is no control action from an external entity, it is said that the charging is uncontrolled or sometimes referred to informally as "dumb charging". If EVs operate under an uncontrolled charging, EVs are considered as normal loads like any other electric device or appliance. Under this concept, different EV behaviours can be distinguished corresponding to some expected EV hourly patterns; some of them include the charge after the last journey of the day or the charge whenever possible [55]. Thus, uncontrolled charging encompasses those EV patterns that depend on the owners' convenience for charging and, therefore, they are subject to an important uncertainty. It is envisaged that this will become a typical charging mode for many consumers during the development of better EV technologies.

Uncontrolled charging often means that EVs charge as soon as they arrive from the last journey of the day, which according to surveys is frequently between 17h and 20h [55, 68]. Thus, under uncontrolled charging it is common to assume a substantial demand during the latter period of the day, occurring at the same time as the peak of the demand curve. This charging mode provides a base scenario to study the impact of EVs on electric power systems. Some typical impacts under consideration by authors are, but not limited to: peak of the demand increase, congestion in lines and losses in the grid [27].

However, EVs can react to price signals and change their original charging schedule, if it is in their best economical interest. The prices for buying energy can be different in each time period or there may be two or three different prices during the day, commonly referred to in the literature as a multiple tariff scheme. Nevertheless, if the scheduling depends on the EV owner's willingness to take advantage of this feature, this charging strategy is regarded as an uncontrolled charging.

When the EV charging or discharging is managed through an external agent it is said that the operation is controlled. This so called controlled charging relies on demand-side strategies by which EV charging can be allocated to other more convenient time periods based on a predefined contract or agreement between EV owners and the external agent. Among them, the strategy based on price signals has been studied deeply [55, 56]. The idea under this approach is to move the EV charging to those time periods when economical conditions are more favourable. "Smart charging" refers to specific controlled charging strategies for allocating EV charging based on algorithms to shift the charging to valley hours or, instead, altering the initial charging pattern [27].

In a controlled charging framework, an external control agent is responsible for the allocation of EVs. This external agent is envisioned to be an EV agreggator or a grid operator and it can also incorporate Vehicle-To-Grid (V2G) capabilities, that is, EVs are allowed to inject energy to the grid by drawing energy from the battery [55]. The most important reasons to change the EV initial pattern are economical, although there may be technical reasons as well.

Regarding the point of connection, the maximum power that an EV can supply, or absorb, is conditioned by the location of the charging point. In the simplest case, the EV location is a known parameter of the problem. On the other hand, to account for the uncertainties in EV owner behaviour, Monte Carlo simulations or Markov chains based techniques [54] can be employed to determine the node of connection to the grid. In this last case, each EV is assumed to have a certain "state", e.g. driving or charging, and the transition from one state to another is carried out according to transition probabilities. These probabilities are determined by statistically analysing some data extracted from surveys or mobility studies. For instance, it is highly probable that the EV stays at home during night hours or that it performs the first departure in the early hours of the morning. Regardless of the way of modelling EV movement, it is necessary to take into account those time periods in which EVs are moving or not connected to the grid since it may be necessary to update the state of charge despite EV not being associated to any node.

From the grid point of view, EVs can be mainly classified as plug-in hybrid electric vehicles (PHEV) or battery electric vehicles (BEV) [69]. PHEVs usually rely on an Internal Combustion Engine (ICE) used either for driving or to charge the battery which capacity typically is less than 15 kWh, however, BEVs only have the battery at their disposal to perform journeys with manifold capacities ranging from 15 kWh to 60 kWh. There are other types of EVs cited in the literature such as Extended Range Electric Vehicles (EREVs) or Fuel Cell Electric Vehicles (FCEVs) although they can either be considered as particular cases of the two main groups mentioned above or they are not of interest in the field of study. In general, EVs can be considered as mobile batteries that can charge or discharge.

According to different research studies and manufacturers datasheets, the battery consumption when EVs are in movement is around 0.15 kWh/km. In stochastic analyses, this consumption is modelled using typical random distributions which statistical data are taken from adequate patterns [54]. The studies carried out from several universities and research centres show that at least 50% of EV users could perform their daily mobility needs with only 30 kilometres of travel.

With respect to dynamic studies, interesting works have been developed [27, 55, 70].

These kind of studies analyze situations in which a quick EVs' response is required under the occurrence of certain circumstances. For example, regulation is needed to balance supply and demand and it requires fast responses taking typically less a minute. Compared to steady-state studies, dynamic studies are performed over a smaller time scale, commonly a few hundreds of seconds. They are related to the services that EVs are able to provide in the future like reserve, primary and secondary frequency control or renewable generation integration [18, 71].

Finally, it is important to remark the actions taken, with respect to EVs, regarding several initiatives launched in different countries. For instance, in Grid For Vehicles (G4V) [56] and Mobile Energy Resources in Grids of Electricity (MERGE) [55], both European projects, different studies were carried out on EV control strategies, challenges, impacts and opportunities, provision of services, or supporting of renewable energy sources through EVs. EDISON is another interesting project that pursued EV integration including aspects related to network operation, market issues and the contribution of different energy technologies [72]. In the United States, the largest deployment of EVs and charging infrastructure in the world is taking place under the EV Project [73]. Furthermore, in Spain there have been developing plans to foster the integration of EVs [74], projects that involve EV deployment [75] and specific normative has been issued dealing with charging infrastructure, requirements and protection measures based in international standards [76].

1.4 Framework, Electric Energy Systems

In this section, the framework regarding electric energy systems is introduced.

The field of application is an electric power system which can be regarded as a SG. Hence, the necessary ICTs are assumed to be developed and, in addition, the generators can be considered as DG. Thus, the system is composed of generators of different nature such as microturbines, combined heat and power plants, fuel cells or diesel-powered generators, although with a significant share of renewable generators such as wind turbines or photovoltaics. In addition, storage systems can be present in the form of fixed batteries, flywheels, pump storage hydroelectric plants or mobile batteries such as EVs. Finally, the existence of several owners, or entities, is considered. They are responsible for the necessities in different areas of the grid comprising loads, generators or storage systems. These entities are assumed to be intelligent agents and, thus, have some specific characteristics like reactivity, pro-activity and social abilities [77]; they will be referred to SG agents hereafter. Other more specific like the SG operator, main grid agent and EV aggregator are also taken into consideration, Fig. 1.1. The role of these agents will be clarified later and throughout the thesis.

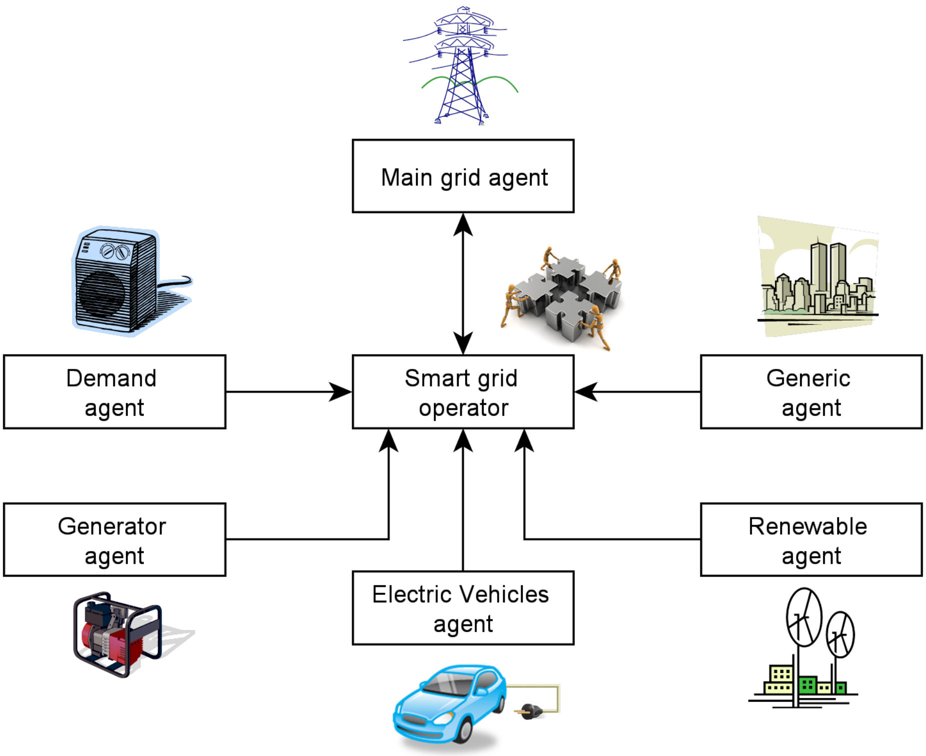

Figure 1.1: Framework of the research study

According to the ideas mentioned above, SG agents can comprise different elements or assets, with several combinations. The following types of agents are possible:

- Demand agents: they only own loads located in certain buses in the grid. They can represent residential areas where some electrical needs have to be satisfied.

- Generator agents: they have loads and generators of non-renewable nature. They can represent industrial complexes where both generation and demand can be present at the same time.

- Renewable agents: these specific agents own renewable generators and fixed batteries but loads are also part of them. They can be regarded as a company with an important number of investments in renewable technologies.

- EV aggregator agents: they can be thought of as an entity responsible for the whole set, or a small group of EVs, in a grid. Hence, they manage the EV charging in order to satisfy their mobility requirements and they pursue new business opportunities to make the most of the services that EVs can provide.

As stated earlier, in order to generalise the approach, generic agents with loads, non-renewable and renewable generators, fixed batteries, EVs or any combination of these can be defined. Some have already been introduced, namely demand agents, generators agents, renewable agents and EV aggregators. However, the possibility of considering any kind of SG agent with the elements or assets that have been mentioned is stressed here. This distinction is important because it will affect the optimisation problem for DSM as will be explained in Chapter 2.

Finally, two specific entities have been considered in this research study. Firstly, the SG operator, responsible for the market and technical operation of the grid. On the one hand, it is conceived to collect the SG agents bids to clear the market using any suitable auction scheme. On the other, it watches over the grid making use of tools to prevent it from technical limits violating. Secondly, the main grid agent takes responsibility for balancing supply and demand in the grid regulating the power through the point of connection of the SG with the upstream system. These agents have to be coordinated with each other in order to maintain overall grid stability, for this purpose, the bidirectional communication is important.

1.5 State of the art

There are several interesting works regarding EVs and other related areas, all of them trying to focus on particular characteristics or fields of interest. In this section, some of these works are described stressing the goals pursued, the applied methodologies and the results presented.

Several works have proposed the use of optimisation problems applied to situations in which EVs and SGs are considered together. Authors in [78, 79] use an OPF to coordinate EV charging with the objective of minimising the grid losses, the cost of GHG emissions or the total energy costs. Results show that EVs can have different impacts depending on the objectives considered. The benefits of using fixed storage systems together with

EVs for minimising operating costs and harmful gas emissions in commercial buildings is analysed in [80]. The results indicate that EVs are appealing for supplying electric energy in those time periods in which energy is more costly. An OPF for optimising operating generation costs and EV charging is used in [81] to determine the magnitude and time period in which the EV charging should take place. In [82], PHEVs impact for different charging levels and the use of DSM strategies is studied in detail for a particular case study. It is shown that EV charging can be moved to night hours giving benefits for both the EV owner and the grid; presenting the results through representative coefficients.

For future electricity systems, DSM and related techniques are expected to become very important. In [83], an optimisation model is described to maximise the utility of a consumer responding to uncertainty in electricity prices. In order to ensure secure operation of the grid under important peaks of demand, a voluntary household load shedding model is studied in [84]. Using two different methodologies, the benefits of DSM for both the consumers and utilities are shown in [85, 86], stressing the importance of identifying the flexible loads. In [87], a DSM strategy is implemented with the aim of bringing the final load curve as close to an objective load curve as possible.

EVs' impact on the demand profile is analysed in [88] and, in [89], the authors try to integrate EVs with DR strategies involving the consumer. In [90], an interesting game theoretic approach is proposed to schedule EV charging for peak shaving and valley filling while, in [91], V2G is also considered for this purpose; developing an optimisation problem that aims to obtain a final load profile close to a target load curve. In [92], a coordination mechanism is proposed to allocate EV charging efficiently stressing the role of renewable energy. Other authors consider a specific smart load management approach that can be applied to EVs but focusing in technical aspects like losses minimisation or voltage limits [93]. In [94], the authors identify, through a broad review, which are the most important aspects that determine the impact of EVs on distribution grids such as driving patterns, charging characteristics, charge timing and vehicle penetration. Areas left for improvement include the addition of more stochasticity into models and the calculation of reliability indices considering EV load and V2G.

Multi-Agent Systems (MAS) have been proposed as a suitable approach in power engineering applications [95, 96], in particular when EVs are included. In [97] a MAS-based modelling is combined with a particular OPF to determine the optimal bus location for EVs and their SOC in a problem in which losses are minimised. In [98], the MAS systems theory is used for modelling market operation and integrate EVs in a specific grid where they are managed by an aggregator. In [99], an agent based analysis tool is developed to assess the impact of a large scale adoption of EVs. The proposed tool is used to analyse interesting scenarios in which EVs can perform valley filling and peak shaving, balancing power from renewable sources or take voltage stability measures meanwhile a comprehensive vehicles, individual transportation behaviour and power system modelling is given.

Numerous authors have dealt with the joint integration of EVs and renewable energy sources, particularly when they are used to balance the intermittent power output associated to renewable generators. A complete stochastic process modelling is proposed in [66] to alleviate congestion in lines and maintain adequate voltage levels, where EVs are allowed to absorb energy from renewable sources. In [67], a framework is proposed with the purpose of integrating PHEVs into the existing electric power systems. The paper deals in detail with the current configuration of these systems, a state scheme for EVs and an application example for that framework considering controlled charging and V2G. The combined integration of renewable distributed generation, photovoltaic panels, store devices and EVs is analysed in [100]. The study shows how storage devices can be used to mitigate generation losses from PVs and coordinate with EVs.

Another issue studied by researchers is the effect of different EV charging strategies. For different penetration levels, the impact of uncontrolled charging and coordinated charging is analysed in terms of voltage levels and grid losses in [58]. A way for assessing the impact of PHEVs in electric power systems is proposed in [59] under different penetration levels and EV charging hypothesises. In [19], dynamic and steady-state studies are presented extracted from the European Project MERGE. The study is developed under an illustrative framework involving market and technical operations. Other authors propose specific tariffs in the daily market applied to EVs in order to charge them in those time periods in which congestion in lines can be avoided [88]. A medium voltage real distribution grid is used to put into practice different EV charging strategies in [24]. These strategies are analysed and compared on a daily basis in relation to grid losses, voltage limits and line active power flow. The maximum number of EVs that the grid is able to support, without additional reinforcements, is determined by means of an optimisation procedure. Four different EV charging strategies are investigated from both economical and technical points of view in [101]. The impact of different types of EVs, with several charging levels and percentages of penetration is studied in [89]. The use of a DSM strategy is applied to avoid undesired demand peaks and line congestion in a distribution grid. The integration of EVs in distribution grids is analyzed in [102]. Their technical impacts and specific charging strategies to achieve different objectives are proposed under a complete framework. In [103], several optimisation problems to determine EV charging are formulated from the perspective of three different entities: consumers, system operators and wind power producers. Results stress the importance of the chosen objectives in final EVs' profiles.

V2G has been taken into consideration in many works. In [104] an optimisation-based model permits a practical implementation of V2G as a part of the energy management system in MGs. A complete study of the impact of EVs capable of V2G is developed in [105]. The operation framework uses the independent Spanish system operator data carrying out an economic dispatch including EVs in the formulation. Different scenarios for renewable sources, generators, EV penetration and patterns, and demand curves are included as input parameters. Results show that an increase in EV penetration, along with the renewable share leads to reduction in costs. In regard to V2G, one of the most attractive aspects related to EVs is their suitability to provide ancillary services [71]. The authors of [106, 107] propose the use of EVs as an storage system that can be used in buildings whenever convenient considering DSM strategies. In [108], the provision of energy and ancillary services through V2G is studied via an algorithm to maximise EV aggregator's benefits. It is shown that the algorithm makes possible reduce the charging costs and provide the system with additional flexibility.

Many works present in the literature show the relevance of the aggregator role for allowing EVs to participate actively in the electricity market. In [26], the role of the EV aggregator is described in detail along with a complete bibliography survey. With respect to the inclusion of an aggregator in a market environment several approaches have been developed. An algorithm to forecast EV demand and prices, is used to determine optimal scheduling in [109]. Two different approaches for allowing an aggregator agent to participate in day-ahead markets are presented in [110] and [111], showing advantages and drawbacks of both and supporting the optimisation formulation with a complete numerical analysis. Charging and discharging of EVs are optimised in [112] where an aggregator agent allows an EV fleet to participate in the market. Specific algorithms are used to avoid technical problems arising from EV charging in [113]. Authors in [114] propose an EV charging planning to avoid congestion in grid lines while minimising the electricity costs. The effects of two scheduling models for EV charging on the day-ahead market is analysed in [115]. In [116], authors propose a model where an EV aggregator can coordinate EV charging and it can also offer services like V2G, energy and reserve. Finally, EV regulation services are investigated under three different strategies in [117].

With respect to uncertainty in EV pattern of mobility, in [118], authors analyse the impact of EVs considering a particular battery model and Monte Carlo techniques to describe the EVs' movements taking mobility patters from Barcelona. The model takes into account the uncertainty both associated with the EVs and the load of the grid. Results, developed in an adapted distribution grid, compare the impact of two different battery recharging models. Authors in [54] make use of Monte Carlo simulation and Markov chains to model the EV motion and charging in a grid. The battery consumption in journeys or the EV charging, for example, are calculated through probability distributions depending on the EV state. The impact is assessed in terms of technical issues such as losses, power flows levels or voltages. In [119], an OPF aiming at minimising system costs is proposed. The uncertainties associated to driving behavior are implemented in the form of chance constraints [120] and it is shown that it is possible to reduce the probability of violating grid constraints at small additional costs with respect to a deterministic approach.

1.6 Contributions

The main contributions of the thesis can be identified through the following achievements:

- The formulation of a DSM strategy based on optimisation problems where the profits maximisation of the different agents is pursued. Load shifting is proposed as a means of both reducing energy costs and benefiting the power system through the flattening of the demand curve. The allocation of the power supplied by generators is also considered, facilitating also the EVs and renewable sources integration.

- A specific OPF acting on generators power output is proposed as a centralized tool to avoid or correct technical problems that can take place in distribution networks. It can be carried out in a way that renewable sources production is encouraged.

- A novel algorithm that uses EVs for congestion management taking advantage of charging and discharging, i.e. V2G, has been developed. Through DFs the most adequate EVs are selected in order to alleviate congestions.

- Technical and economic issues applicable to MGs and distribution grids can be linked providing a comprehensive scheme characterized by an auction mechanism, agents optimisation problems, EV management and centralized technical operation.

- A particular optimisation problem that can be used by EV aggregators to maximise their benefits has been proposed. It can be applied to assess the participation of EV aggregators in both local and wholesale electricity markets.

- A market-clearing procedure including technical security constraints and the role of EV aggregators has been presented.

1.7 Outline and structure of the Thesis

The thesis is organized into six chapters which address different issues regarding EV integration and their impact in future electric power systems, i.e. SGs.

The current chapter (**Chapter 1**) presents the motivation for the thesis along with a review of state of the art and some aspects in relation to the SG concept and EV modeling. The specified framework and the general structure that support the work developed within the scope of the thesis are also given.

Chapter 2 deals with DSM strategies that can be applied to SGs including EVs. Load shifting is proposed to rearrange the hourly demand and make the most of the existing infrastructure through changes in the scheduled consumption patterns. This methodology can also be applied to EVs that can take advantage of the most favorable time periods for charging and discharging, maximising their expected benefits.

Chapter 3 provides two different ways to manage technical problems in SGs. Firstly, a centralized OPF that can be performed by a system operator is presented. Acting on generation assets, it is attempted to lead the system to a secure state regarding voltages and line power flows. Secondly, an algorithm that manages EVs is proposed to relieve line congestion using the EVs' batteries capabilities to charge/discharge. This algorithm makes use of Distribution Factors (DFs) to calculate how much the EVs should contribute and which are the most suitable buses to carry out an injection that solves line congestion problems.

Chapter 4 describes a specific optimisation problem that can be used by EV aggregators. It aims at maximising the expected profits but satisfying the mobility requirements of all the EVs under their management. The effect of some input parameters on the optimal charging/discharging allocation is analyzed in detail.

Chapter 5 introduces a market-clearing procedure to assess the EV aggregators' participation in electricity markets taking security constraints into account. Starting from the assumption that they can be responsible for the EVs contained in the MGs and areas in which they operate, EV aggregators can bid for buying or selling energy competing with other consumers and suppliers. Regarding this, adequate EVs' patterns and price forecasts are needed in order to bid efficiently.

Chapter 6 gives the main conclusions drawn from this thesis and outlines the potential future work.

The structure of the thesis is now described and clarified. Fig. 1.2 shows the different topics included within the scope of this work.

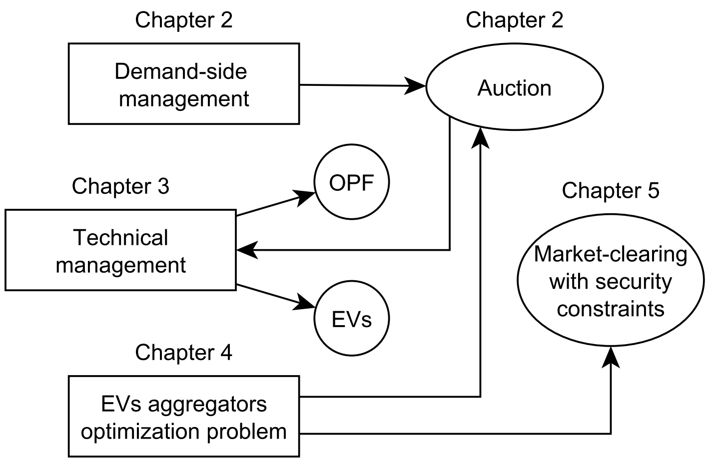

Figure 1.2: Contents within the scope of the thesis

As can be seen, three main issues are addressed. Firstly, a particular DSM strategy that can be applied to SG agents is developed in Chapter 2. Performing an optimisation problem aiming at maximising benefits, or minimising costs, agents are able to allocate their demand and generation according to their own restrictions and taking into account the energy prices. Over a time horizon of 24 hours, in steps of 1 hour, loads can be shifted to periods when energy costs are lower while the generators can operate in those time periods when the energy prices are higher. The power provided/drawn by/from fixed batteries can be also calculated.

The participation of these agents in a local energy market defined by an auction scheme is also developed in Chapter 2. Thus, the amount of demand allocated and the energy surplus from generators in the current time period are put to bid and cleared. This auction allows agents to obtain a better price for the energy they are willing to buy/sell with respect to those prices offered by the main grid that ultimately clear the unmatched quantities.

Two interesting tools that allows to protect the system from technical problems that could arise are proposed in Chapter 3, making use of an OPF and EVs respectively as stated in the outline of the thesis. These tools can be linked with DSM strategies leading to a complete procedure running on a predefined time horizon.

An optimisation problem developed for EV aggregators is introduced in Chapter 2 although further details are considered in Chapter 4. This tool is conceived to support EV aggregators in their participation in both local and wholesale electricity markets. The optimal hourly EV charging and discharging are determined with the purpose of maximising the expected profits. Provided that energy prices are cost-reflective, charging will take place in time periods when the demand is typically low and, instead, discharging will be performed in time periods when the demand is high, hence, providing additional benefits to the power system. Depending on the scope of operation regarding EV aggregators, they can manage a small number or large amounts of EVs conditioning their participation in either one or another type of market.

In Chapter 5, a market-clearing procedure considering security constraints is presented. Along with the traditional actors in electric power systems, EV aggregators are included in the formulation and they can bid for buying/selling energy. Unlike local markets, in which a maximum amount of about a few hundreds of EVs managed by the EV aggregator is expected, in this case, they are responsible for the management of thousands of EVs or, otherwise, a quantity big enough that permits them to compete against other consumers and suppliers. Using the results from the optimisation problem in Chapter 4, they can know in advance which are the most suitable time periods for charging and discharging the EVs and, hence, have a guidance on how to bid.

Chapter 2

Demand-side Management Strategies and Electric Vehicles

Demand-side management refers generally to those strategies that try to change the pattern of energy consumption of end consumers of electricity either by shifting it to other more convenient time periods through price signals or by promoting behaviours of a better and more efficient use of energy. The objective is to reshape the demand curve so that it is distributed uniformly in time. Techniques that follow this philosophy include load shifting, valley filling, strategic conservation, peak clipping or flexible load shaping. In this chapter, a specific optimisation problem that considers load shifting, which can be applied to smart grids, is proposed. Firstly, the generic objective function is introduced and the meaning of every term is explained in detail. Secondly, the constraints presented divided into characteristic groups based on the different elements considered: load buses, non-renewable generators, renewable generators, batteries and electric vehicles. Decentralised approaches, for different values of input parameters, are compared. A particular auction that completes the market operation, is described and analysed. Finally, two cases of study are presented showing the adequacy of the proposed methodology.

2.1 Introduction

DSM is one of the most important characteristics associated to future electric power systems. It allows customers to reduce the costs of the energy they need and help the system to reduce the peak of the demand, increase the grid sustainability and make a better utilization of the existing electrical infrastructure. DSM techniques focus on changing electricity consumption patterns in order to modify the shape of the load curve. There are six methods that can be applied: valley filling, peak clipping, load shifting, strategic conservation, load growth, and flexible load shape [87], see Fig. 2.1.

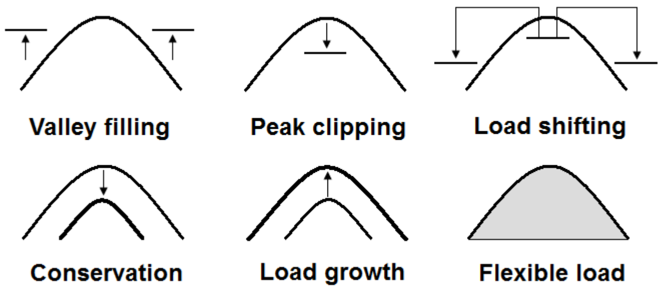

Figure 2.1: Demand-side management techniques

Valley filling and peak clipping try to reduce the difference between the valley and peak load levels in order to increase the security of the smart grid. Strategic conservation and load growth aim to achieve load shape optimisation through reducing and increasing the demand respectively. Flexible load refers to the identification of some customers which have loads with a certain degree of flexibility and which let the SG management system to control those loads during critical periods. Load shifting allows to move the demand from some time periods, typically during peak time, to other more favourable time periods taking advantage of time independence of loads. Load shifting is considered as the most effective DSM technique in current distribution grids. A particular DSM strategy based on optimisation problems and considering load shifting is proposed here.

2.2 Demand-side management optimisation problem

The optimisation function for each SG agent is aimed at maximising its benefit, expressed as the difference between the income and the costs, but satisfying its demand at the same time. The objective function consists of three clearly differentiated terms:

1. The first term considers the revenue obtained from selling energy.
2. The second term computes the payments due to the energy bought.
3. The third term is associated with the generation costs from non-renewable sources.

These ideas are expressed in the following equation:

$$\underset{\{P_t^{S,e},P_t^{B,e},C_{t,i}^{G,e}\}}{\text{maximise}} \quad \sum_{e=1}^{n_e} W^e \cdot \sum_{t=t_0}^{t_f} \left(\hat{\lambda}_t^b \cdot P_t^{S,e} - \hat{\lambda}_t^s \cdot P_t^{B,e} - \sum_{j=1}^{n_g} C_{t,j}^{G,e} \right) \tag{2.1}$$

where $\hat{\lambda}_t^b$ and $\hat{\lambda}_t^s$ are the hourly forecasted buying and selling market prices (parameters), $P_t^{B,e}$ and $P_t^{S,e}$ are the hourly power bought and sold respectively (variables) and $C_{t,j}^{G,e}$ represents the function of generation costs for non-renewable generator j, further described in Section 2.2.2, and n_g is the total number of non-renewable generators belonging to the agent. The superscript $e = 1, 2, ...n_e$ refers to the scenarios considered, W^e is a scenario weight, t_0 is the initial time period, t_f is the final time period, and $t = 1, 2, ...T$ is the index for the time periods. The set of scenarios models the uncertainty associated with renewable generators; details about these scenarios are provided in Section 2.2.3.

Equation (2.1) is valid for any agent regardless of the specific assets it owns. This way, according to the framework presented in Section 1.4, several cases can be found:

- For demand agents, the terms associated to hourly power sold and generation costs are zero since these agents do not have generators and, therefore, it is not possible for them to sell energy. For the same reason, scenarios can also be omitted. The function is converted into a costs minimisation problem:

$$\underset{\{P_t^B\}}{\text{maximise}} \quad \sum_{t=t_0}^{t_f} -\hat{\lambda}_t^s \cdot P_t^B \equiv \underset{\{P_t^B\}}{\text{minimise}} \quad \sum_{t=t_0}^{t_f} \hat{\lambda}_t^s \cdot P_t^B \tag{2.2}$$

- For generator agents, all the terms have to be taken into consideration but the set of scenarios can be narrowed so that renewable generators are not part of their assets:

$$\underset{\{P_t^S,P_t^B,C_{t,i}^G\}}{\text{maximise}} \quad \sum_{t=t_0}^{t_f} \left(\hat{\lambda}_t^b \cdot P_t^S - \hat{\lambda}_t^s \cdot P_t^B - \sum_{j=1}^{n_g} C_{t,j}^G \right) \tag{2.3}$$

- For renewable agents, the terms related to non-renewable generation costs are not included:

$$\underset{\{P_t^{S,e},P_t^{B,e}\}}{\text{maximise}} \quad \sum_{e=1}^{n_e} W^e \cdot \sum_{t=t_0}^{t_f} \left(\hat{\lambda}_t^b \cdot P_t^{S,e} - \hat{\lambda}_t^s \cdot P_t^{B,e} \right) \tag{2.4}$$

- For an EV aggregator, when only the EV's charging is managed, the function is similar to that considered for demand agents and only the term associated to the energy bought is considered. When V2G capability is available, the only terms that are rejected correspond to those associated to the non-renewable generation costs. Additionally, the set of scenarios can be ignored unless the agent is responsible for renewable generators:

$$\underset{\left\{P_t^S, P_t^B\right\}}{\text{maximise}} \sum_{t=t_0}^{t_f} \left(\hat{\lambda}_t^b \cdot P_t^S - \hat{\lambda}_t^s \cdot P_t^B\right) \tag{2.5}$$

Henceforth, the superscript e will be used to consider the most general case. Unless otherwise stated, the time period step will be assumed to be one hour. Once the objective function is defined, additional relations applicable to any kind of agents are introduced.

The overall hourly power bought and sold, $P_t^{B,e}$ and $P_t^{S,e}$, are related to the power supplied from generators, the bus load and the power absorbed or delivered by batteries, or EVs, for each SG agent:

$$\begin{aligned} P_t^{S,e} - P_t^{B,e} =& \sum_{i=1}^{n_{rg}} P_{i,t}^{rg,e} + \sum_{j=1}^{n_g} P_{j,t}^{nrg,e} + \\ & \sum_{b=1}^{n_b} (P_{b,t}^{d,e} - P_{b,t}^{c,e}) + \sum_{v=1}^{n_v} (P_{v,t}^{d,e} - P_{v,t}^{c,e}) - \sum_{n=1}^{n_a} \Phi_{n,t}^e \quad \forall t, \forall e \end{aligned} \tag{2.6}$$

where $P_{i,t}^{rg,e}$, $P_{j,t}^{nrg,e}$, $P_{b,t}^{d,e}$ and $P_{v,t}^{d,e}$ are the hourly power supplied by renewable generator i, non-renewable generator j, battery b and EV v, $P_{b,t}^{c,e}$ and $P_{v,t}^{c,e}$ are the hourly power absorbed by the battery b and EV v, and $\Phi_{n,t}^e$ is the total demand in node n. All these variables are referred to a particular agent that owns these elements in time period t and scenario e. The summations are extended to the number of renewable generators n_{rg}, non-renewable generators n_g, fixed batteries n_b, EVs n_v, and agent's demand nodes n_a respectively.

From (2.6) it can be seen that agents that do not have generators will buy the energy they need from other agents or from the grid. However, agents with generators will buy or sell energy based on their own demand and their capacity to supply energy economically in the current time period, as well as on the nature of its generators and the presence of others elements such as fixed batteries or EVs. In general, an agent that owns generators will try to satisfy its demand in the most economical way and, if favourable, it will sell its energy surplus.

In addition, variables representing power sold and bought are positive and cannot be different from zero at the same time, that is, an agent is not allowed to buy and sell during the same time period. These variables are important since they define the agent's role in the electricity market, buyer or seller, and the amount of energy offered. Hence, two binary variables yb_t^e and ys_t^e are defined according to the following equations to comply with this condition:

$$P_t^{B,e} \leq yb_t^e \cdot X \quad \forall t, \forall e \tag{2.7}$$

$$P_t^{S,e} \leq ys_t^e \cdot X \quad \forall t, \forall e \tag{2.8}$$

$$yb_t^e + ys_t^e \leq 1 \quad \forall t, \forall e \tag{2.9}$$

where X is a large enough parameter that must be chosen conveniently. Equations (2.7) to (2.9) constitute an application of the Big-M method. This formulation can be simplified considering that only one binary variable is needed:

$$P_t^{B,e} \leq yb_t^e \cdot X \quad \forall t, \forall e \tag{2.10}$$

$$P_t^{S,e} \leq (1 - yb_t^e) \cdot X \quad \forall t, \forall e \tag{2.11}$$

2.2.1 Demand-side management strategy

In this work, load shifting is presented as the proposed DSM strategy. It is implemented making use of particular optimisation problems and it can be considered as an upgrade of the formulation introduced in [28]. The main idea behind the strategy is to provide customers with the possibility to obtain a better price at which to buy the energy they need in those time periods when the system conditions are more favourable. If electric energy is consumed in those time periods, i.e. during the night, the system can be more economically and securely operated.

An important equation relating different components of the demand is introduced next. The initial total demand, $\Theta_{n,t}$, is expressed as the sum of a fixed demand, $\phi_{n,t}$, and the maximum load shifting, $\gamma_{n,t}$. In turn, the latter is a fraction, f_e, of the total demand, in every node and time period; this can be written as:

$$\Theta_{n,t} = \phi_{n,t} + \gamma_{n,t} = \phi_{n,t} + f_e \cdot \Theta_{n,t} \quad \forall t, \forall n \tag{2.12}$$

Eq. (2.12) is a relation among parameters, they are not variables of the optimisation problem. The parameter $\phi_{n,t}$, referred to as fixed demand, represents the demand that cannot be shifted to other time periods and, therefore, is the minimum quantity of energy consumed that remains unchanged for a particular bus n in the corresponding time period t. By contrast, the parameter $\gamma_{n,t}$ denotes the maximum amount of demand that can be shifted to other time periods. It can be said that, for the proposed framework, this fraction of demand is sensitive to prices, in other words, it is a price responsive demand with a certain degree of flexibility to be moved. The electric energy required to operate a washing-machine, a dish-washer or an air-conditioning unit can be viewed as a potential price responsive demand.

The demand management problem is formulated with the following equations which are included as constraints for each agent:

- The total demand $\Phi^e_{n,t}$ (variable) that is actually consumed in time period t, is expressed as the sum of the fixed demand $\phi_{n,t}$ and the variable which represents the final amount of price responsive demand $\Gamma^e_{n,t}$:

$$\Phi^e_{n,t} = \phi_{n,t} + \Gamma^e_{n,t} \quad \forall t, \forall n, \forall e \tag{2.13}$$

- The total demand for node n and period t can be also written in terms of the amount of energy that moves from other periods t' to the current period t, $M^e_{n,t',t}$, minus the amount of energy that leaves period t to other period t', $M^e_{n,t,t'}$, for each node n and scenario e. Alternatively, this can be expressed in terms of the price responsive demand:

$$\Phi^e_{n,t} = \Theta_{n,t} + \sum_{t'} M^e_{n,t',t} - \sum_{t'} M^e_{n,t,t'} \quad \forall t, \forall n, \forall e \tag{2.14}$$

$$\Gamma^e_{n,t} = \gamma_{n,t} + \sum_{t'} M^e_{n,t',t} - \sum_{t'} M^e_{n,t,t'} \quad \forall t, \forall n, \forall e \tag{2.15}$$

  In the optimisation problem either (2.14) or (2.15) can be used. Note that t and t' represent specific time periods of the day, they are not exactly equations' indexes.

- The total amount of energy that can be shifted to other time periods has to be less than the limit imposed by the maximum load that can be shifted:

$$\sum_{t'} M^e_{n,t,t'} \leq \gamma_{n,t} \quad \forall t, \forall n, \forall e \tag{2.16}$$

- The variable $M^e_{n,t,t'}$ has to satisfy some logical relations for load shifting given by the following conditions:

$$M^e_{n,t,t'} = 0 \ \text{ if } \begin{cases} \text{a)} \ \ t = t', \\ \text{b)} \ \ t + k < t', \\ \text{c)} \ \ t' < t \ \ \textit{and} \ \ t + k < t' + 24. \end{cases} \qquad \forall n, \forall e, \forall t, \forall t' \tag{2.17}$$

  Condition (2.17.a) assures that the demand cannot be shifted to the same time period. Condition (2.17.b) states that the demand cannot be shifted more than k periods forward for all t and t' belonging to the same day. Finally, condition (2.17.c) includes the possibility that demand might move to the following day.

The formulation of the problem presented so far guarantees that price responsive demand can only be moved up to k periods of time forward. If time periods t and t' are swapped, the new constraints limit demand shifting k time periods backwards. If both sets of equations are included, load shifting will be limited to k periods in either direction. Thus, Eq. (2.17) can be rewritten as follows:

$$M^e_{n,t',t} = 0 \ \text{ if } \begin{cases} \text{a)} \ \ t' = t, \\ \text{b)} \ \ t + k < t', \\ \text{c)} \ \ t' < t \ \ \textit{and} \ \ t + k < t' + 24. \end{cases} \qquad \forall n, \forall e, \forall t, \forall t' \tag{2.18}$$

According to (2.12), (2.13) and (2.14)/(2.15), the final configuration of the demand curve will be determined by the hourly fixed demand plus the amount of electric energy demand left to make up to the total demand, but distributed differently in time with respect to the initial configuration. In other words, the total demand before and after load shifting are the same, see Fig. (2.2).

To allow for a smooth transition for the final demand curve, some conditions are imposed. These conditions are represented by a bound in the demand that can be shifted and bounds for the slope of the curve expressed by equations (2.19), (2.20) and (2.21) respectively:

$$\Gamma^e_{n,t} \leq k_\epsilon \cdot \phi_{n,t} \quad \forall t, \forall n, \forall e \tag{2.19}$$

$$\Gamma^e_{n,t+1} - \Gamma^e_{n,t} \leq k_\delta \quad \forall t, \forall n, \forall e \tag{2.20}$$

$$\Gamma^e_{n,t+1} - \Gamma^e_{n,t} \geq -k_\delta \quad \forall t, \forall n, \forall e \tag{2.21}$$

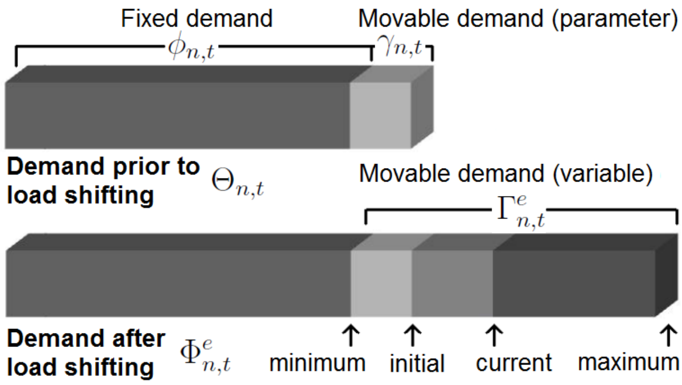

Figure 2.2: Parameters and variables related to the demand

where k_ϵ and k_δ are parameters that should be chosen adequately. Equation (2.19) limits the price responsive demand $\Gamma^e_{n,t}$ through the fixed demand $\phi_{n,t}$ and the parameter k_ϵ. Equations (2.20) and (2.21) affect the demand curve slope through parameter k_δ.

2.2.2 Non-renewable generators modelling

Constraints and equations for agents with non-renewable generators are given next. The first aspect is the generation cost for a non-renewable generator which was introduced in Section 2.2. For unit j, this cost is made up of a variable operational cost, expressed as the product of a marginal cost vc_j and the power output $P^{nrg,e}_{t,j}$, a fixed cost fc_j, a start-up cost yc_j and a shut-down cost sc_j in the following way:

$$C^{G,e}_{t,j} = vc_j \cdot P^{nrg,e}_{t,j} + fc_j \cdot v^{G,e}_{t,j} + yc_j \cdot y^{G,e}_{t,j} + sc_j \cdot s^{G,e}_{t,j} \quad \forall t, \forall j, \forall e \tag{2.22}$$

where $v^{G,e}_{t,j}$ / $y^{G,e}_{t,j}$ / $s^{G,e}_{t,j}$ are equal to one in the case that, during the current time period, the generator: is running / has started / has stopped, and zero in any other case. Thus, if a non-renewable generator is running in a particular time period the operation cost is composed of a variable cost depending on the generation level, or power output, and a fixed cost that does not depend on it. The start-up and shut-down costs have to be included whenever the generator starts or stops respectively in the considered time period.

In Fig. 2.3, the operation costs for three different generators are depicted. As it can be observed, the operation costs follow a linear function, according to (2.22), although depending on the power output it is more economically favourable to run one or other generator. Therefore, generators with a high fixed operating cost but with a low variable operating cost typically will start up for high power output, like NRG1, and vice versa, like NRG2 . On the other hand, generators with intermediate values for the operating costs will start up for in-between power outputs, like NRG3. In addition, the relation

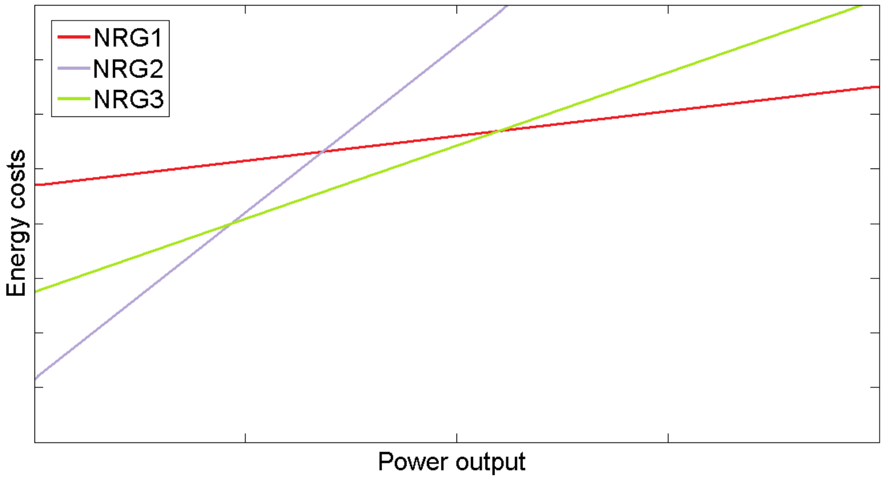

Figure 2.3: Non-renewable generators costs

between binary variables which represent start, stop and operation for a generator j can be written as [121]:

$$y_{t,j}^{G,e} - s_{t,j}^{G,e} = v_{t,j}^{G,e} - v_{t-1,j}^{G,e} \quad \forall t, \forall j, \forall e \tag{2.23}$$

The four possibilities that can take place along with the corresponding values of the binary variables are given in Table 2.1: 1) the generator was running in time period $t-1$ and it remains running in the following time period t (State R-R), 2) the generator was stopped in time period $t-1$ and it remains stopped in the following time period t (State S-S), 3) the generator starts in time period t (State S-R), and 4) the generator stops in time period t (State R-S). Thus, it is proved that Eq. 2.23 stands true for all the possible states.

Table 2.1: Values of binary variables related to non-renewable generators operation

State	$v_{t-1,j}^{G,e}$	$v_{t,j}^{G,e}$	$y_{t,j}^{G,e}$	$s_{t,j}^{G,e}$
R-R	1	1	0	0
S-S	0	0	0	0
S-R	0	1	1	0
R-S	1	0	0	1

Finally, the power output $P_{t,j}^{nrg,e}$ has to lie between a maximum and a minimum value due to technical reasons:

$$v_{t,j}^{G,e} \cdot P_{g,j}^{min} \leq P_{t,j}^{nrg,e} \leq v_{t,j}^{G,e} \cdot P_{g,j}^{max} \quad \forall t, \forall j, \forall e \tag{2.24}$$

where $P_{g,j}^{max}$ and $P_{g,j}^{min}$ are the maximum and minimum power output limits for non-renewable generator j, respectively. The binary variable $v_{t,j}^{G,e}$ has to be included to avoid power outputs below the minimum permissible limit and to allow a value of zero.

2.2.3 Renewable energy sources modelling

In this work, the power output from photovoltaic panels and wind turbines are the only modelled, as they represent the most typical renewable sources. The specific values to determine the power supplied by renewable generators have been calculated using real values of wind speed and solar radiation as input parameters in real generator models.

The hourly power output $P_{i,t}^{PV}$ for a photovoltaic panel i is determined by the following equation:

$$P_{i,t}^{PV} = \eta \cdot A \cdot I_t \tag{2.25}$$

where η is the global efficiency, A is the surface area of the array in m^2 and I_t is the hourly solar radiation in kW/m^2. In addition, it is considered that PV panels can supply energy between zero and their nominal power.

The hourly power output $P_{i,t}^{WT}$ for a wind turbine i is calculated according to:

$$P_{i,t}^{WT} = k_w \cdot v^{k_v} \tag{2.26}$$

where k_w is a proportionality coefficient that depends on the air characteristics and the swept area of blades, v is the wind speed in m/s and k_v is a coefficient which value typically is between 2 and 3. It is also considered that wind turbines can supply energy from wind speeds higher than a minimum (cut-in speed) up to their nominal power.

Hereby, a set of scenarios for each renewable source has been devised and these values have been combined to get an overall number of different scenarios corresponding to representative situations that could take place during the year. In Fig. 2.4, an example is shown with three scenarios for each renewable source and nine total scenarios. In this way, it is possible to analyse situations in which the power output contribution from renewable sources is varied. In general, the total number of scenarios is equal to the product of the number of scenarios considered for each renewable source.

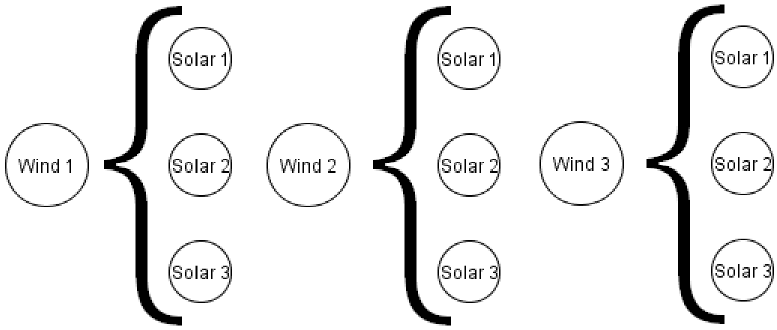

Figure 2.4: Example of scenarios generation

These types of generators are considered to work regardless of costs, which is a reasonable assumption if subsidy policies are applied. Thus, each generator power output obtained using the methodology previously described is introduced as a parameter of the corresponding optimisation problem affecting some variables such as the total demand or the value of the objective function. The aim of this methodology is to facilitate their integration in the electricity system. Additionally, the expected value of those variables depending on renewable scenarios, for instance ψ^e, can be determined assuming a value for the probability of each scenario considered represented by the scenario weight W^e introduced in Section 2.2:

$$\mathbb{E}[\psi] = \sum_{e=1}^{n_e} W^e \cdot \psi^e \tag{2.27}$$

2.2.4 Storage systems modelling

As stated in previous sections, storage systems are manifold so they can be represented by electric fixed batteries, flywheels, hydroelectric plants with pump devices or even mobile batteries, e.g. EVs. In this work, electric fixed batteries and EVs are considered.

Fixed Batteries

For agents which own electric fixed batteries, the following constraints are applied.

There is a maximum and minimum charging and discharging power:

$$0 \leq P_{b,t}^{c,e} \leq y_{b,t}^{c,e} \cdot P_b^{c,max} \quad \forall t, \forall b, \forall e \tag{2.28}$$

$$0 \leq P_{b,t}^{d,e} \leq y_{b,t}^{d,e} \cdot P_b^{d,max} \quad \forall t, \forall b, \forall e \tag{2.29}$$

where $P_{b,t}^{d,e}$ and $P_{b,t}^{c,e}$ are the hourly power supplied and drawn for battery b, $P_b^{d,max}$ and $P_b^{c,max}$ are the maximum discharging and charging power. The binary variables $y_{b,t}^{d,e}$ and

$y_{b,t}^{c,e}$ have to comply with:

$$y_{b,t}^{c,e} + y_{b,t}^{d,e} \leq 1 \quad \forall t, \forall b, \forall e \tag{2.30}$$

With Eqs. (2.28) to (2.30), it is assured that the power for a battery is kept within the limits and it cannot simultaneously charge and discharge in the same time period.

In addition, some constraints related to the battery energy level, or SOC, $S_{b,t}^{e}$ are needed. Equation (2.31) represents the update of the SOC of a battery b between two consecutive time periods when it is charging or discharging:

$$S_{b,t}^{e} - S_{b,t-1}^{e} = \eta_C \cdot P_{b,t}^{c,e} - (1/\eta_D) \cdot P_{b,t}^{d,e} \quad \forall t, \forall b, \forall e \tag{2.31}$$

where η_C and η_D are the charging and discharging efficiencies.

The SOC has to lie between S_b^{min} and a maximum value S_b^{max} due to technical reasons:

$$S_b^{min} \leq S_{b,t}^{e} \leq S_b^{max} \quad \forall t, \forall b, \forall e \tag{2.32}$$

Finally, the initial and final battery energy level are considered to be identical:

$$S_{b,t_0}^{e} = S_{b,t_f}^{e} \quad \forall b, \forall e \tag{2.33}$$

where S_{b,t_0}^{e} and S_{b,t_f}^{e} are the initial and final states of charge in time periods t_0 and t_f respectively. This condition avoids non-realistic solutions as, for example, the complete discharging of the battery at the end of the time horizon.

Electric vehicles

From the point of view of the network, EVs are another means of storing electric energy, although with the ability to change their location in the electric system, e.g. they can be present in different nodes in the grid for different time periods. Although in accordance with the defined framework, EVs can be part of agents with several assets, the idea of an EV manager, or EV aggregator, is being considered by the research community [26].

Another important issue regarding EVs is the way they can behave with respect to the grid. On the one hand, if EVs operate freely without any centralised control action, it is said that EVs charge in an uncontrolled way, sometimes also called ‘dumb charging’. Thus, EV owners choose when and where they wish to charge their EVs. Although multiple charging patterns are possible, many surveys carried out in Europe and U.S. suggest typical behaviours for EV charging. Hence, regarding the time period, EVs either can charge only at the end of the day; whenever possible and convenient or whenever the battery is about to deplete as expressed in [55]. EVs can also charge at home, at commercial areas or at work, for example, also depending on the time period considered. On the other hand, if EVs operate under the control of an external entity or an EVs aggregator, it is said the EVs charge in a controlled manner. In this case, the EV aggregator pursues new business lines that benefit both it and the EVs owners. EV aggregators can find more favourable charging time periods, i.e. when the energy is cheaper, or, at the same time, they can exploit the abilities that EVs could offer through V2G. Regarding the latter aspect, some ancillary services have been considered as suitable for EV services provision. However, some important problems have not been overcome such as battery degradation. The optimisation problem for an EV aggregator is presented here and it is analysed in depth in Chapter 4.

In this work, it is proposed that EV owners can react to price signals and change their original charging schedule, if it is in their best economical interest, by means of a more advanced charging pattern controlled externally. The prices for buying energy can be different in each time period or there may be two or three different prices during the day, this is commonly referred to in the literature as a multiple tariff scheme [27]. EVs are also allowed to discharge if necessary or economically advantageous (V2G). When EVs operate under an uncontrolled charging pattern, the EV charging is added to the total demand in the corresponding previously established nodes and time periods with no possibility to change this behaviour. On the other hand, if the EVs can respond to electricity prices, the EV charging, or discharging, is set according to the results of the corresponding optimization problem as described in Section 2.2. However, EV daily mobility needs must be satisfied in any case. Therefore, although they can reduce the costs for charging, they must have enough energy in their batteries to perform the journeys they have planned for the day.

This optimisation problem for EV aggregators is subject to the same constraints as defined for fixed batteries in Eqs. (2.28) to (2.33). However, some additional constraints related to the EV mobility requirements are needed as previously stated.

The EV battery energy level has to be maximum in the early morning, represented by time period t_e:

$$S_{v,t}^{e} = S_{v}^{max} \quad for \quad t = t_e, \quad \forall v \tag{2.34}$$

where S_v^{max} is the maximum SOC for the EV v. However, this equation may not be applicable for those EVs with higher battery capacities, that is, the EV could have enough energy in the battery for several days. Therefore, the use of (2.34) assumes implicitly that an important fraction of the battery capacity has been used and it is necessary to charge to perform the journeys planned for the day.

If the EV is moving during time period t_m, that is, in transition between two connections to the grid, the EV battery energy level is reduced according to:

$$S_{v,t}^{e} = S_{v,t-1}^{e} - km_c \cdot C_{km} \quad for \quad t = t_m, \quad \forall v, \forall e \tag{2.35}$$

where km_c is the amount of kilometres covered and C_{km} the energy consumption in kWh/km. Equation (2.35) can be considered as a modification of (2.31) for the reduction in EV battery energy level when it is not connected to the grid.

2.2.5 Complete formulation

The agent's optimisation problem is formulated according to the following objective function and constraints:

$$\underset{\{P_t^{S,e}, P_t^{B,e}, C_{t,i}^{G,e}\}}{\text{maximise}} \quad \sum_{e=1}^{n_e} W^e \cdot \sum_{t=t_0}^{t_f} \left(\hat{\lambda}_t^b \cdot P_t^{S,e} - \hat{\lambda}_t^s \cdot P_t^{B,e} - \sum_{i=1}^{n_g} C_{t,j}^{G,e} \right)$$

$$C_{t,j}^{G,e} = vc_j \cdot P_{t,j}^{nrg,e} + fc_j \cdot v_{t,j}^{G,e} + yc_j \cdot y_{t,j}^{G,e} + sc_j \cdot s_{t,j}^{G,e} \quad \forall t, \forall j, \forall e$$

$$P_t^{S,e} - P_t^{B,e} = \sum_{i=1}^{n_{rg}} P_{i,t}^{rg,e} + \sum_{j=1}^{n_g} P_{j,t}^{nrg,e} + \sum_{b=1}^{n_b} (P_{b,t}^{d,e} - P_{b,t}^{c,e}) - \sum_{n=1}^{n_a} \Phi_{n,t}^{e} \quad \forall t, \forall e.$$

$$P_t^{B,e} \le yb_t^e \cdot X; P_t^{S,e} \le ys_t^e \cdot X; yb_t^e + ys_t^e \le 1 \quad \forall t, \forall e$$

$$\Phi_{n,t}^{e} = \phi_{n,t} + \Gamma_{n,t}^{e} \quad \forall t, \forall n, \forall e$$

$$\Gamma_{n,t}^{e} = \gamma_{n,t} + \sum_{t'} M_{n,t',t}^{e} - \sum_{t'} M_{n,t,t'}^{e} \quad \forall t, \forall n, \forall e$$

$$\sum_{t'} M_{n,t,t'}^{e} \le \gamma_{n,t} \quad \forall t, \forall n, \forall e$$

$$M^{e}_{n,t,t'} = 0 \;\; \text{if} \begin{cases} \text{a)} \;\; t = t', \\ \text{b)} \;\; t + k < t', \\ \text{c)} \;\; t' < t \;\; and \;\; t' + 24 > t + k. \end{cases} \qquad \forall n, \forall e$$

$$\Gamma^{e}_{n,t} \leq k_{\epsilon} \cdot \phi_{n,t} \quad \forall t, \forall n, \forall e$$

$$\Gamma^{e}_{n,t+1} - \Gamma^{e}_{n,t} \leq k_{\delta} \quad \forall t, \forall n, \forall e$$

$$\Gamma^{e}_{n,t+1} - \Gamma^{e}_{n,t} \geq -k_{\delta} \quad \forall t, \forall n, \forall e$$

$$y^{G,e}_{t,j} - s^{G,e}_{t,j} = v^{G,e}_{t,j} - v^{G,e}_{t-1,j} \quad \forall t, \forall j, \forall e$$

$$v^{G,e}_{t,j} \cdot P^{min}_{g,j} \leq P^{nrg,e}_{t,j} \leq v^{G,e}_{t,j} \cdot P^{max}_{g,j} \quad \forall t, \forall j, \forall e$$

$$0 \leq P^{c,e}_{b,t} \leq y^{c,e}_{b,t} \cdot P^{max}_{b} \quad \forall t, \forall b, \forall e$$

$$0 \leq P^{d,e}_{b,t} \leq y^{d,e}_{b,t} \cdot P^{max}_{b} \quad \forall t, \forall b, \forall e$$

$$y^{c,e}_{b,t} + y^{d,e}_{b,t} \leq 1 \quad \forall t, \forall b, \forall e$$

$$S^{e}_{b,t} - S^{e}_{b,t-1} = \eta_C \cdot P^{c,e}_{b,t} - (1/\eta_D) \cdot P^{d,e}_{b,t} \quad \forall t, \forall b, \forall e$$

$$0 \leq S^{e}_{b,t} \leq S^{max}_{b} \quad \forall t, \forall b, \forall e$$

$$S^{e}_{b,t_0} = S^{e}_{b,t_f} \quad \forall b, \forall e$$

$$S_{ev,t} = S^{max}_{ev} \quad for \quad t = t_e, \quad \forall ev$$

$$S_{ev,t+1} = S_{ev,t} - km_c \cdot C_{km} \quad for \quad t = t_m, \quad \forall ev$$

2.3 Proposed Auction Scheme

As a part of the market operation, this thesis proposes an auction is proposed by means of SG agents exchanging electric energy. Thus, the available supply and demand are balanced and, as a result, an economic deal mutually advantageous for all the involved parties is achieved [28]. The idea behind the auction is to give the agents the possibility to get a better price for the energy they are willing to buy/sell with respect to those offered by the main grid agent. The objective of the auction is to compute the matching among buyers and sellers as well as the amount of energy exchanged at the current time period.

It is assumed that the auction is coordinated by the SG operator, who knows the electric energy supply and demand, while the only data available to all the participants are the buying and selling market prices.

The buyers and sellers as well as the amount of energy on stake are defined hourly according to the results from each agent optimisation problem. Thus, for example, agents that do not own generators can participate in the auction in order to buy the amount of energy defined by their optimisation problem in order to serve their loads. Agents that have non-renewable generators will offer them if they expect to get a good price for the energy produced. Conversely, in those time periods when market prices are low, they will go to the auction to buy so as to satisfy their own loads. The amount of energy offered by agents with generators in the auction constitutes a surplus since each agent will try, first, to use the energy produced for their own convenience as explained in Section 2.2.

Once the amount of energy for trading is known, an iterative auction begins. Each agent calculates its bid, for round x, with an expression of the form:

$$y = \frac{a}{x+b} + c \tag{2.36}$$

where x is the index for the number of rounds and y is the auction bid in monetary units (e.g. cents of €/kWh). Parameters a, b and c define the shape of the bidding curve for each particular agent.

The value of c is the auction bid when the number of rounds is large enough. Typically, it can be defined as the buying market price for the current time period t for sellers, $\hat{\lambda}_t^b$, and as the selling market price for the current time period t for buyers, $\hat{\lambda}_t^s$:

$$\lim_{x \to +\infty} \frac{a}{x+b} + c = c; \quad c = \hat{\lambda}_t^b \;\; for \;\; sellers, \quad c = \hat{\lambda}_t^s \;\; for \;\; buyers \tag{2.37}$$

Applying the condition that in the first round, the auction bid is known, a relation between the parameters a, b and c can be obtained. The values for the auction bids at this point mark the beginning of the auction. Conversely, for $x \to 0$, the auction bid is defined as the selling market price for sellers and as the buying market price for buyers:

$$\lim_{x \to 0} \frac{a}{x+b} + c = \frac{a}{b} + c = y_0; \quad y_0 = \hat{\lambda}_t^s \;\; for \;\; sellers, \quad y_0 = \hat{\lambda}_t^b \;\; for \;\; buyers \tag{2.38}$$

Conditions defined by (2.37) and (2.38) assure that the agents obtain a better price for the energy with respect to the price they would obtain if it was bought or sold from the main grid so the buyers and sellers auction curves will intersect at an intermediate point

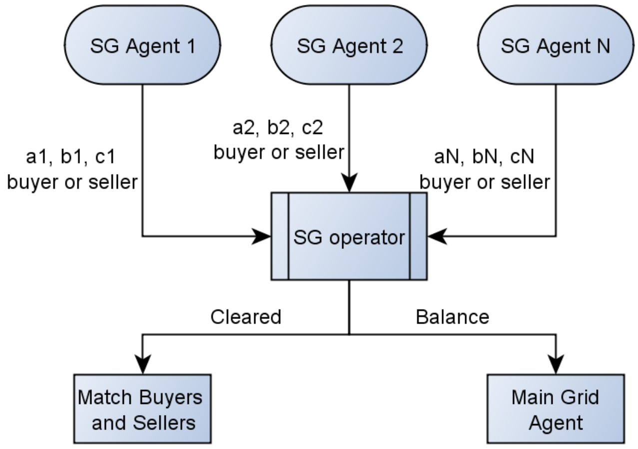

Figure 2.5: Auction procedure

where the clearing price is mutually advantageous. Finally, one condition is left to be applied and it represents the pace with which an agent bids or, in other words, it defines the slope of the curve as the number of rounds increases. For the sake of simplicity, this condition could be chosen randomly between suitable bounds or, alternatively, it could be based on auction historical data. In this work, it is chosen depending on the amount of energy at stake from each agent. Thus, buyers with high amounts of energy will bid more aggressively for fear that their demand is not served while sellers in the same conditions will behave in the opposite way. A diagram describing the main steps of the process can be seen in Fig. 2.5. Similar auction procedures have been described in the technical literature [122, 123].

In Figure 2.6, a graph is shown where six different auction bid curves are presented for different values of the parameters, four for buyers and two for sellers. The highest and the lowest limit represent the maximum and minimum auction bids for buyers and sellers respectively, that is, the value of parameter c. The initial known data are the amount of energy to buy and sell for each agent and the chosen values of the parameters corresponding to the auction curves. The clearing process is developed according to these rules:

- For the initial round number 0, buyers bid at the buying market price $\hat{\lambda}_t^b$ and sellers bid at the selling market price $\hat{\lambda}_t^s$.

- In successive rounds, each agent bids at the price defined by its corresponding function, in Eq. (2.36), with buyers increasing their bids and sellers decreasing them for every round. Demand and supply are considered to be cleared when the price at which the supply is willing to sell is less or equal to the price at which the demand is willing to buy.

- If there is only one buyer and one seller that match their bids, the amount of energy traded is equal to the minimum between the energy demanded and the energy offered.

- If more than one buyer clear their bids with only one seller, the energy is taken in descending order of buyer bid price, until there is no energy to supply or, instead, all the demands have been satisfied. The amount energy exchanged is equal to the minimum between the energy demanded for each buyer and the energy offered by the supplier.

- If more than one seller clears their bids with only one buyer, the energy is taken in ascending order by the sellers with the lowest bids until there is no energy to supply or the only buyer gets its demand satisfied. The amount energy exchanged is equal to the minimum between the energy demanded for the buyer and the energy offered by each supplier.

- If several buyers and sellers are simultaneously cleared, the energy traded is shared between them according to the ideas mentioned in the two previous points.

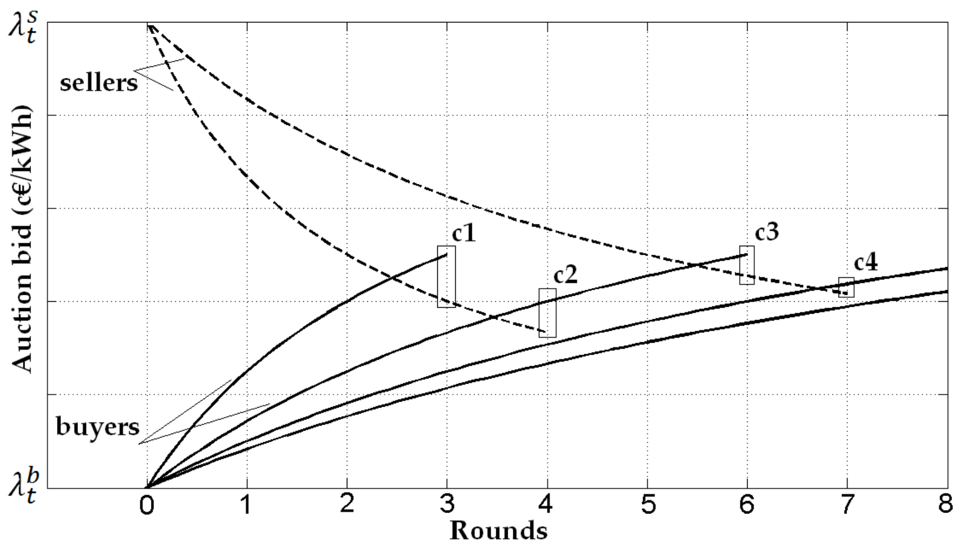

Figure 2.6: Auction bid curves

- The auction finishes when either the energy offered by buyers or the energy offered by sellers has been completely allocated. The clearing price is set in every case as the price offered by the buyer.

2.4 Case study

The case study presented in this section is based on the low voltage MG given in [124] and it is depicted in Fig. 2.7. The network under study is composed of seventeen buses and sixteen lines and it is connected to the medium voltage grid through the transformer between buses 1 and 17. Three feeders branch out from the point of common coupling at bus 1. The three feeders are devoted to residential, industrial and commercial loads, serving areas with different consumption characteristics. Additional data are provided in the next sections.

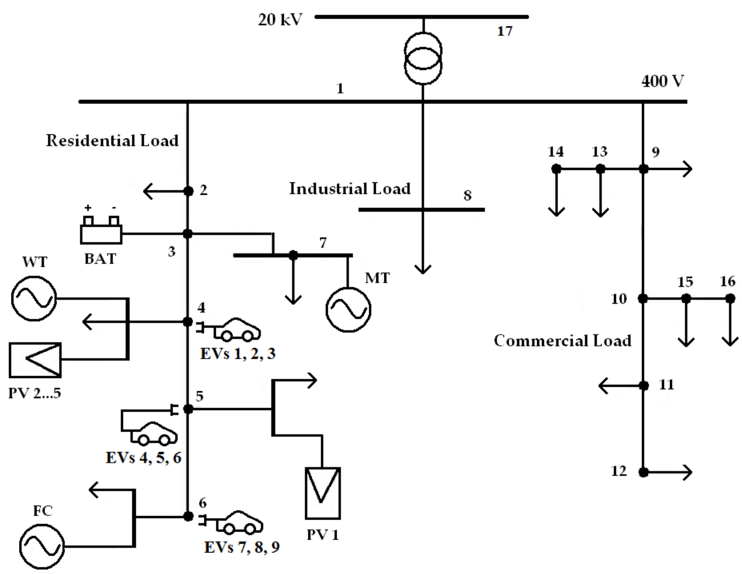

Figure 2.7: Microgrid considered for case study

2.4.1 Main data for the case study

The generators are all placed in the residential feeder and the rest of feeders only have loads. Renewable generators are represented by a single Wind Turbine (WT) and six PhotoVoltaic (PV) units whilst non-renewable generators are comprised of a single Fuel Cell (FC) and a MicroTurbine (MT). In addition, an electric Battery (BAT), located on the same feeder, allows the storing and drawing of energy as and when required.

The bus loads are represented by arrows and the total load is distributed hourly among the feeders as shown in Fig. 2.8. The load is small during night hours but steadily increases for later time periods showing different maximum values depending on the feeder considered. For the industrial feeder the load is higher around midday but for residential and commercial feeders there is a maximum in the evening hours. These loads are shared among the nodes in the same feeder according to the nature of the corresponding circuits that interconnect them.

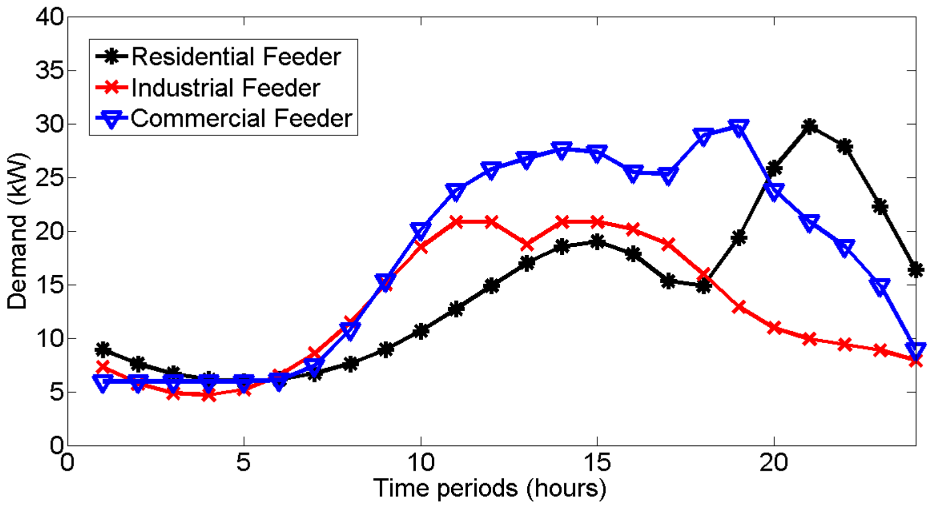

Figure 2.8: Electricity Loads in the MG Feeders

The data used to test the proposed model are given in Appendix A, namely the line characteristics and both costs and technical data regarding generators and batteries. They have been obtained from the information provided in [124–126].

Additional comments regarding these data are provided next. Firstly, as it can be seen from the tables presented, shut-down costs for non-renewable generators are assumed to be zero so they are small compared to other costs and their influence is not very important.

On the other hand, another relevant assumption is that renewable generators work regardless of costs although some operating costs can be considered as stated, for example, in [125]. Thus, the power output for renewable generators will be injected into the grid directly as a known parameter without depending on the results of the agent's optimisation problem. This assumption relies on subsidy policies that allow agents in charge of renewable sources to operate them without any sensitive costs so that their investment is appropriately funded. It is also a way to suitably consider the integration of renewable sources into the system. The same idea is applicable to batteries since they commonly are considered coupled together with renewable generators to compensate for the excess or lack of energy produced by these.

Scenarios considered for the 10.00 kW-WT and the 2.50 kW-PV renewable generators are represented in Fig. 2.9. The power output for the remaining 3.00 kW-PV generator follows a similar configuration with respect to the 2.50 kW-PV generator. For each renewable generator four scenarios have been devised representing realistic situations that could take place when solar and wind conditions vary along the day and through the seasons. These values have been obtained through real historical data [69, 127] and by applying the model defined by Eqs. (2.25) and (2.26) from Section 2.2.3. Note that the power output is higher around midday due to the influence of the sun in both the wind and solar radiation [128, 129]. Combining these scenarios an overall number of 16 scenarios are obtained.

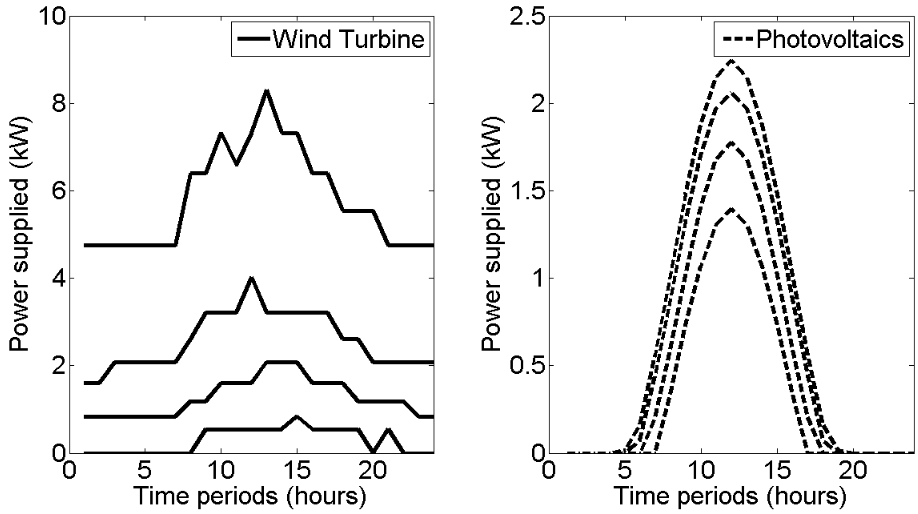

Figure 2.9: Renewable sources power output scenarios

2.4.2 Electric vehicles data and strategies

For the purpose of this work, nine EVs have been considered as a first approach. This amount of EVs can be considered as high given the grid topology and the demand level although their impact depends on the charging power and also the bus location, as will shown later. Their main characteristics are given in Table 2.2. The parameters S^{min} and S^{max} are the minimum and maximum SOC of the EVs and η_C and η_D are the charging and discharging efficiencies. The charging and discharging efficiencies are assumed for the purpose of this work, although the values taken are close to real values [130].

Table 2.2: EVs technical characteristics

S^{min} (kWh)	S^{max} (kWh)	η_C	η_D
2.00	16.50	0.90	0.95

In this work, the following charging strategies are tested:

- Uncontrolled charging - three different patterns.
- Controlled charging considering price response - hourly prices.
- Controlled charging taking into account hourly price response and V2G capabilities.

The hourly charging patterns for the uncontrolled charging strategies considered are represented in Fig. 2.10. These data are complemented with the hourly bus locations of the EVs and the journeys performed by them given in Tables A.5, A.6 and A.7 in Appendix A.

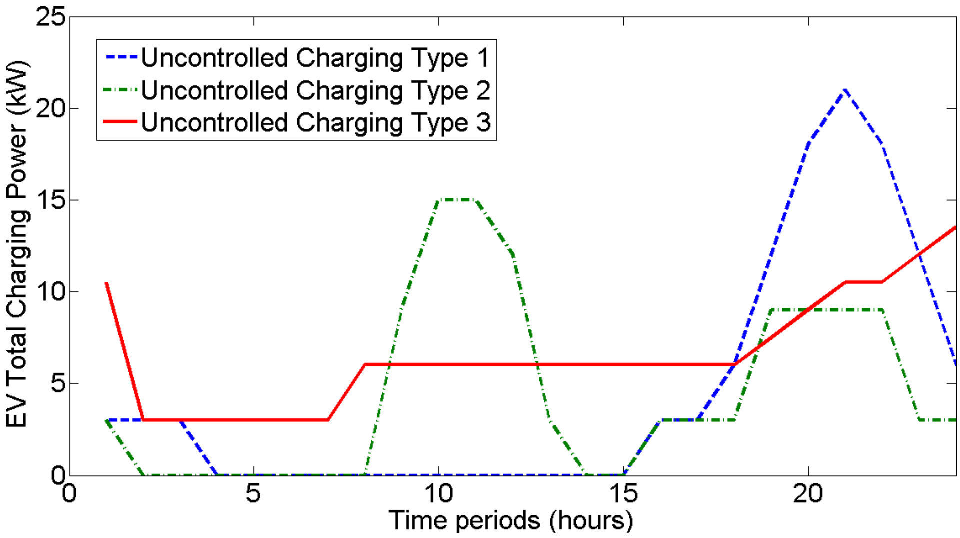

Figure 2.10: Uncontrolled Charging Strategies - EVs Total Charging Power

It can be observed that the total charging power is significant since there are some intermediate time periods in which EV charging would represent more than 20% of the peak of the demand. For the first charging pattern, EVs charge at a rate of 3.0 kW during four time periods, as soon as they return from the last journey of the day, after which they stay idle for the remaining time periods. For the second charging pattern the charging power is similar to the first one but the EVs charge during two time periods after they arrive at the desired destination until full charge, thereafter remaining idle. Both strategies differ in the time period in which the charging takes place although the hourly bus location is the same. These two charging strategies would correspond to some of the expected behaviours that EVs would follow when no control actions or price signals are applied [55].

The bus location shown in Fig. 2.7 corresponds to one of the places where EVs are supposed to charge, that is, the parking place where the EV owner has at his/her disposal the powerpoint to connect the vehicle to. It is considered that each EV performs two journeys, or transitions, and each one is attached to a particular time period. During transitions, EVs consume a certain amount of energy equal to half the total individual EV charging. In the tables provided in Appendix A, the connection node at the first time period and the commuting node are given along with the charging and transition time periods and the initial SOC for each EV.

The third charging pattern is based on the uncontrolled charging pattern introduced in [19]. It can be considered an extreme scenario where EVs charge at different levels. The values used are based on the charging levels and specific reviews shown in [60–62]. The most important charging takes place in the last periods of time, that is, EV drivers tend to charge their vehicles as soon as they arrive from the last journey of the day. The EV pattern considered as well as the initial SOC are given in Table A.7. Time periods that do not appear in the table are transitions with a 2 kWh energy consumption. The maximum SOC is assumed to be 40 kWh in contrast to the 16.5 kWh for the other charging patterns since these charging levels cannot be undertaken with low EV battery capacities.

In this work, a specific controlled operation is proposed in which EVs can respond to electricity prices by charging or discharging based on the signals provided by an external EV aggregator. In this scenario, EV operation is set according to the results of the corresponding optimisation problem introduced in Section 2.2. The objective function aims at maximising the benefits of the EV group considered, as specified in Eq. (2.5). In the case where only the charging is managed, the objective function turns out to be a minimisation of the costs. The controlled charging strategies differ one from another in: i) the hourly price configuration, and ii) the consideration of V2G. Thus, a triple tariff scheme and different hourly prices for a whole day considered. Likewise, the latter case is studied both under V2G operation and without including it.

The performed journeys, and the battery energy consumption, can be taken from one of the uncontrolled charging strategies defined above as parameters of the problem. However, the hourly charging power, and consequently the SOC, will be calculated because they are variables in the corresponding optimization problem. Hence, the optimisation problem searches for an optimal charging pattern for each EV in a way that the overall benefits are maximised, or the overall costs are minimised, whilst satisfying the mobility requirements. The comparison among these strategies is provided in Section 2.4.4.

2.4.3 Smart grid agents specification

Regarding the seven agents considered in the case study, relevant data are given in Table 2.3. For each agent, the agent identifier, *agent ID*, and nodes belonging to it, *Nodes*, are given. In the same fashion, their assets, namely non-renewable generators, *NRG*, renewable generators, *RG*, batteries, *BAT* and EVs, *EV*, are indicated.

Table 2.3: Agents defined in the case study

Agent ID	*Nodes*	*NRG*	*RG*	*BAT*	*EV*
1	2-5	–	WT, PVs 1-6	BAT	–
2	6	FC	–	–	–
3	7, 8	MT	–	–	–
4	9, 13, 14	–	–	–	–
5	11, 12	–	–	–	–
6	15, 16	–	–	–	–
7	–	–	–	–	EVs 1-9

In practice, SG agents can be represented by groups of residential customers, small industries, commercial areas, service companies or EV managers.

Finally, one of the most important data that agents have to know are the hourly selling and buying prices, as these have a significant effect on their decisions. In this work, these prices are assumed to be information that every agent has at its disposal, that is, they are data that all the agents have in common. In local markets, like those which can take place among agents within MGs, it makes sense to have different prices for buying energy with respect to those for selling it. That is why the agents' optimisation problem distinguishes these two kinds of prices. Additionally, this assumption supports and gives value to the proposed auction model. This is a strong difference with respect to wholesale markets in which there is only one hourly clearing price and the exchanged energy amounts are also much higher.

In Fig. 2.11, the hourly buying market prices are depicted. These prices correspond to those offered by the main grid to purchase energy from the MG. To consider a more general model, they are set to represent three different scenarios; hourly reference intermediate values for prices are defined along with two hourly extreme values of +/-10%. The same configuration is considered for the hourly selling market prices, that is, those prices offered by the main grid to sell energy to the MG. Admittedly, selling prices are double the purchase prices. This is a reasonable assumption taking into account that these prices could be established by a retailer that pursues benefits.

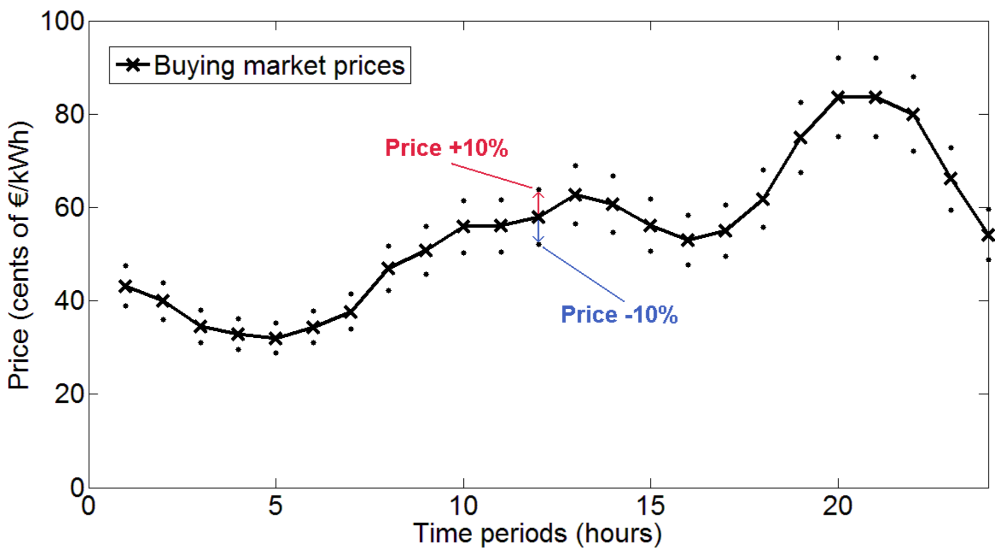

Figure 2.11: Demand curve and price scenarios

2.4.4 Results and Discussion

In this section, the proposed DSM model is applied to the MG case study described previously in order to illustrate its performance. The results presented are mainly related to the following aspects:

- Form of the final electricity load curve when DSM is used for different values of the parameter k related to the maximum number of periods that loads can be shifted.
- Contribution of each agent's assets with respect to generators and batteries.

- Impact of the different EV charging strategies considering also V2G.
- SOC comparison among the EV charging strategies.
- Economical and technical features of the scenarios taken into account.

In every case, suitable values of some relevant parameters related to DSM, tested on the computer simulations, are the following: a) f_e and k are strictly positive values not higher than 0.15 and 12 hours respectively and b) k_ϵ and k_δ are 1.00 kWh and 0.75 kWh.

The effect of the number of periods k that loads can be shifted by in order to flatten the demand curve is shown in Fig. 2.12. For four different values of k, the final hourly demand is represented by a bar diagram. These values are obtained once the corresponding optimisation problems, described in Section 2.2, are performed for each agent. The daily electricity curves without DSM and with DSM for k=12 are also highlighted.

Results reveal that higher values of this parameter allocate the demand more efficiently, in other words, the total grid load is more uniformly distributed along time periods. The load is shifted from time periods when higher prices are expected, for instance the end of the day, to time periods with lower expected prices, e.g. nighttime and some afternoon time periods. This latter idea emphasises the importance of the hourly prices configuration since, in general, the DSM approach will tend to move the loads towards the time periods where price valleys are present. That is the reason why the demand levels during the peak time periods after midday, decrease with increasing values of k.

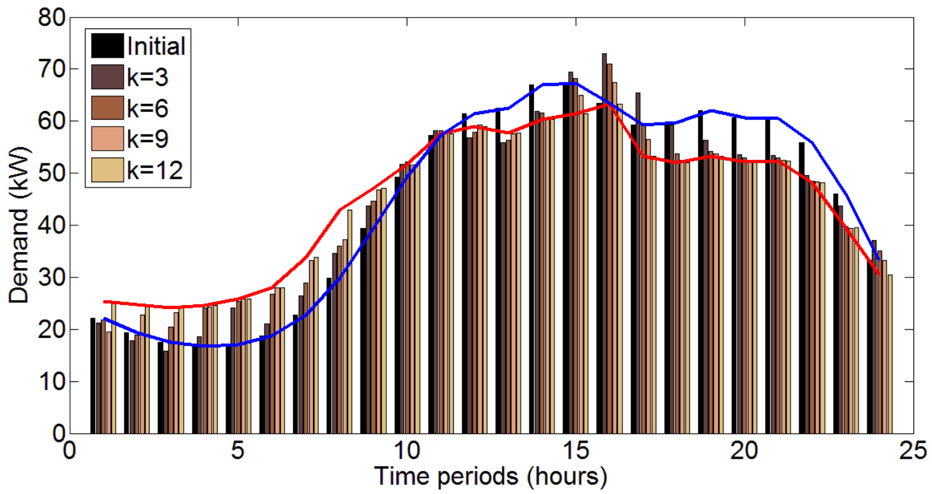

Figure 2.12: Daily electricity demand for several values of parameter k

To compare the final demand curve for different values of the parameter k, the standard deviation σ_k and demand range D^r_k, defined as the difference between the hourly maximum and minimum values of the demand, are given in Table 2.4. It is evidenced that as the value of k is increased the standard deviation is reduced and, on that account, the hourly loads in the MG are more homogeneously distributed. However, the demand range for small and medium values of k is higher compared to the value of the demand range for k=0. Thus, when a small value of parameter k is used, the agent optimisation problem cannot "see" subsequent time periods with better expected prices and tends to allocate the demand before.

Table 2.4: Standard deviation and demand range for different values of k

k	0	3	6	9	12
σ_k (kW)	19.20	17.98	16.10	15.01	13.79
D_k^r (kW)	50.46	57.16	52.13	48.57	39.17

Regarding the demand and generation share, Figs. 2.13 and 2.14 show the total MG power demand and the total MG power supplied for the scenario that considers DSM with k=12. The identical form of these diagrams evidence the balance between demand and generation in the network.

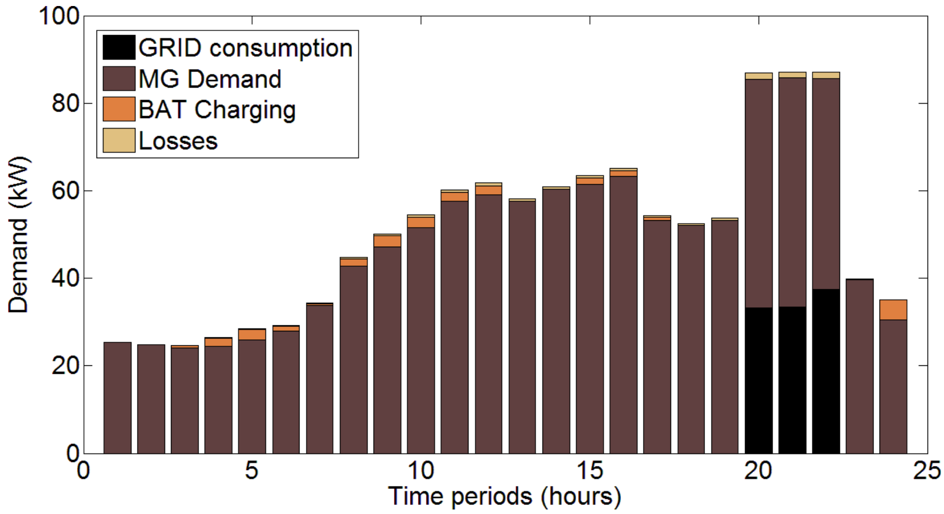

Figure 2.13: Microgrid power demand with DSM, k=12

As it can be observed, for the proposed approach, the MG cannot operate autonomously since there are several time periods in which the main grid is supplying power. Only in some evening hours, the main grid is absorbing power because the FC and the MT generators are running at maximum power taking advantage of higher prices for selling their energy. Active power losses are not very significant and roughly represent 1% of the total demand, with higher values at the end of the day.

Whereas the MT is almost running in every time period, the FC only starts at the end of day due to the comparative high fixed costs. With respect to the battery, it operates by charging when low prices are expected and discharging in the opposite case. Renewable generators power output is determined as stated in Section 2.2.3.

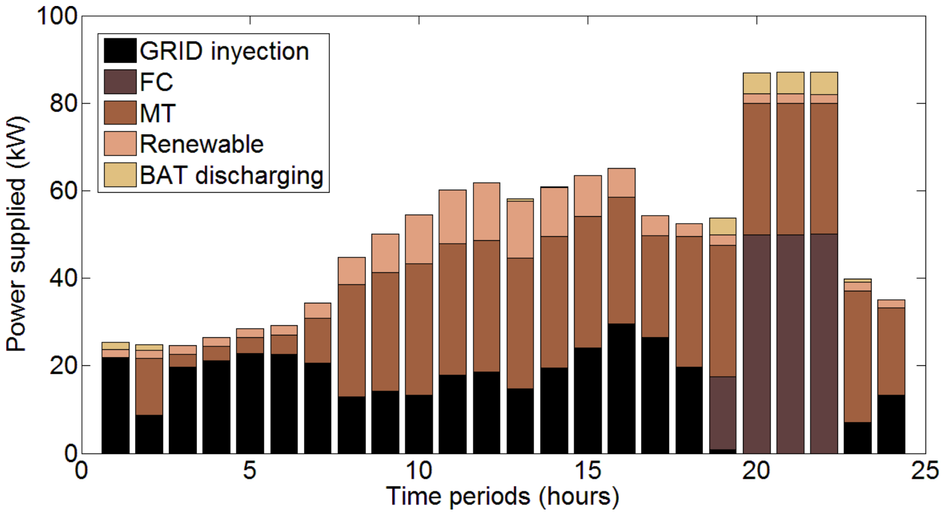

Figure 2.14: Microgrid power supply with DSM, k=12

The combined impact of EVs and DSM strategies on the load curve is analysed next. For EVs operating under uncontrolled charging, considering the charging pattern strategies introduced in Section 2.4.2, the daily electricity curves are represented in Fig. 2.15. The demand peak is increased in every case with respect to the initial load curve when DSM is not applied. For the uncontrolled charging strategies 1 and 3 the maximum is at the end of the day while for the uncontrolled charging strategy 2 the maximum takes place at noon.

In addition, the MG cannot hold out against these EV charging configurations and it has one congested or heavily loaded line in time period t_{19}, Table 2.5. As it can be seen, the apparent power flow for the line considered goes beyond the maximum allowable for the uncontrolled charging strategy 1 and for the rest it is close to the limit. Because of the characteristics of the feeder that contains the line, which only contains loads, the only way to tackle the congestion is by reducing the loads. Common and EV load shifting are considered next in this section as a means to avoid this kind of technical problem. Chapter 3 is devoted to technical management, and two additional tools to address congestion are

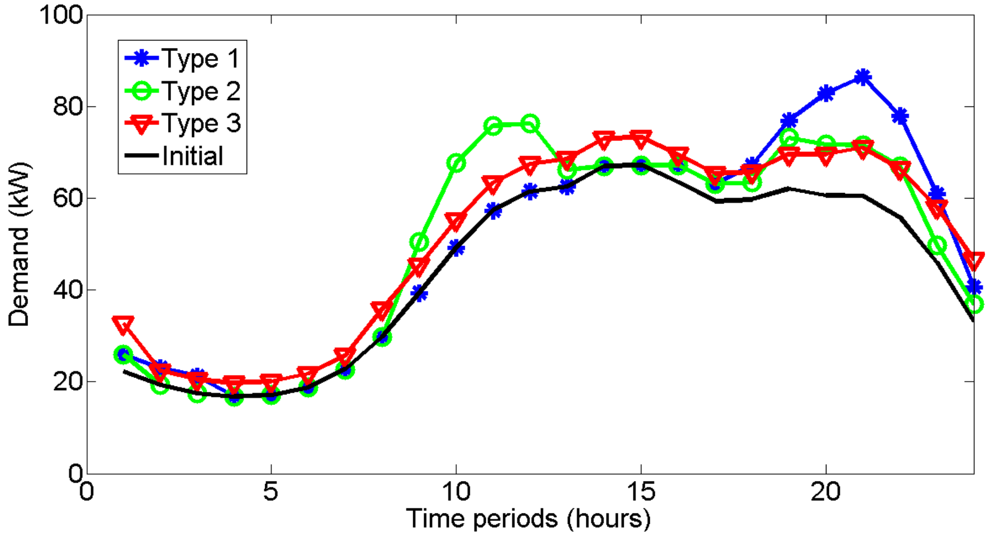

Figure 2.15: Daily electricity demand without DSM and EVs uncontrolled charging strategies

presented. The first one makes use of an OPF and the second one manages the EVs to lead the system to a secure state.

Table 2.5: Apparent power flow for line 1-9 at time period 19 for uncontrolled charging strategies - Without DSM

$S_{1,9}^{max}$(kVA)	$S_{1,9}^{st,1}$(kVA)	$S_{1,9}^{st,2}$(kVA)	$S_{1,9}^{st,3}$(kVA)
46.00	48.67	45.22	41.91

When DSM is applied and the EVs' charging is maintained, the hourly maximum grid load is smaller although a significant peak remains for every uncontrolled strategy. However, no lines are congested but the line considered is still supporting a significant load for the first type of uncontrolled charging considered, Table 2.6.

Table 2.6: Apparent power flow for line 1-9 at time period 19 for uncontrolled charging strategies - Applying DSM

$S_{1,9}^{max}$(kVA)	$S_{1,9}^{st,1}$(kVA)	$S_{1,9}^{st,2}$(kVA)	$S_{1,9}^{st,3}$(kVA)
46.00	43.41	37.98	36.62

The results presented so far suggest that the combination of load shifting and EV management can lead to a more efficient usage of the MG. When EVs are charged responding to hourly prices, and DSM is performed at the same time, the load shifting makes it possible to reduce the demand peak and flatten even more the final load curve; moving the charging to the night hours when prices are more favourable. In Fig. 2.16, the final daily electricity curve is depicted for two different scenarios with a different battery consumption in journeys.

In order to allow a smooth progress of the load curve, a condition on the total number of EVs charging, and discharging, has been added to the optimisation problem. This is needed to avoid an undesired level of EVs charging during the early-morning time periods. The included constraint imposes an hourly limit of 11.10 kW which is roughly equates to restricting to three the number of EVs that can charge in the same time period.

On the other hand, if V2G is allowed, i.e. EV discharge is permitted in the optimisation problem, for a battery energy consumption during transitions equal to 2.70 kWh, no V2G is finally carried out (see curve "'DSM with EVs no V2G). Similar results can be obtained if this consumption is increased. This result can be justified taking into account that the constraints affecting the SOC are satisfied if the SOC of the EVs is high enough to perform the arranged journeys and V2G. In other words, if consumption in transitions and the maximum SOC for EVs are not sufficiently different, there is no flexibility for allowing V2G in a economical way. If consumption in transitions is reduced to 1.80 kWh, V2G takes place in the most favourable time periods (see curve "'DSM with EVs V2G"). As it can be seen, the EV charging is very similar in both cases except for at time period t_7. Similar results could have been obtained increasing the capacity of the battery of the EVs and maintaining the previous battery energy consumption in journeys.

To compare the progression of the battery energy level the SOCs of four different EVs for the uncontrolled charging strategy type 1, labelled "unc 1", uncontrolled charging strategy type 2, "unc 2", and controlled charging/discharging managed by the EV aggregator, "cont", are depicted in Fig. 2.17. In every case, the EV maximum charging power is 3.7 kW and the battery consumption during journey is assumed to be 6.66 kWh for the uncontrolled scenario and 1.80 kWh for the controlled one. When EVs are free to charge, it can be seen that EV charging takes place either at the end of the day or after midday, according to the charging pattern defined for these strategies. SOC is also maximum at the beginning and at the end for all the EVs.

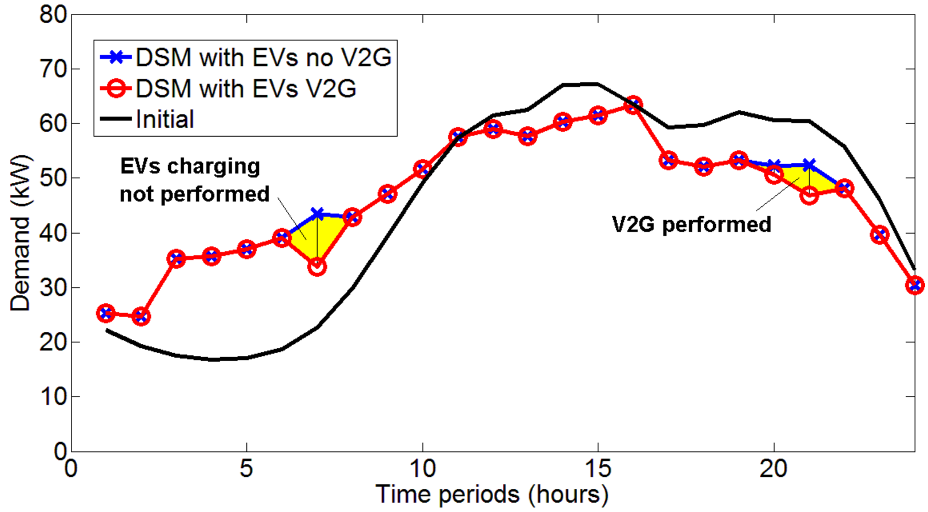

Figure 2.16: Daily electricity demand with DSM and EVs controlled charging strategy

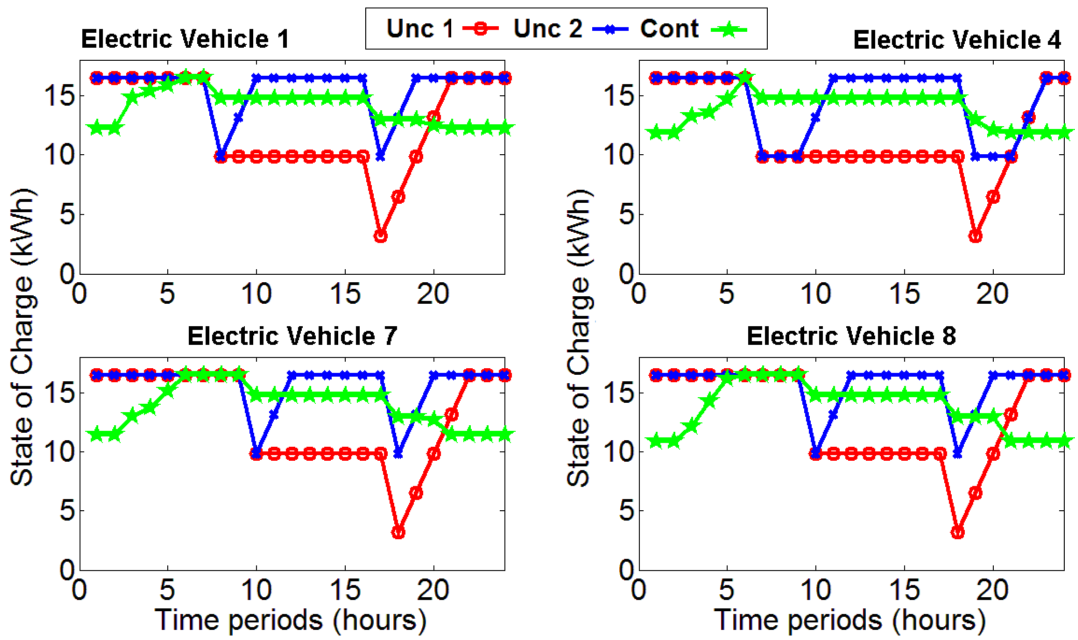

Figure 2.17: EVs SOC for different strategies

Conversely, the SOC for the controlled strategy is equal at the beginning and at the end too but it is an optimal value determined by the corresponding optimisation problem. EV charging takes place during night hours while discharging is performed in the evening time periods based on the most beneficial values of the buying and selling market prices. The time periods with transitions are the same in all the scenarios although V2G is fulfilled for the controlled strategy if battery energy consumption in journeys is sufficiently small. This latter assumption leads EVs to carry out V2G but it does not cover more general situations in which EVs cannot reach the specified value for the SOC or they can perform longer distances. It is clear that the EV aggregator optimisation problem results depend on many parameters not taken totally into account here. These situations are addressed in Chapter 4.

Table 2.7 shows some economical results regarding the proposed model when DSM is considered. For different values of the parameter k, the total income, the costs of the energy bought and the costs of non-renewable generation, labelled as NRG costs, are given. The benefits expressed as the difference between the income from energy sold and the total costs are also provided, where the minus sign indicates that on average a disbursement is required by the agents to acquire the energy they need.

Table 2.7: Economical aspects of the DSM model

k	**0**	**3**	**6**	**9**	**12**
Income(€)	228.82	178.80	220.40	207.58	215.12
NRG costs(€)	53.87	56.81	61.54	56.80	57.33
Energy costs(€)	661.37	620.32	601.45	609.28	605.25
Benefits(€)	-486.42	-498.33	-442.59	-458.50	-447.46

It may be suspected that as the parameter k is increased, the overall benefits for all the agents should increased. However, this idea is not so clear in view of the results presented. In fact, the highest benefits take place for the case in which k is equal to 6. Moreover, for k equal to 3 the benefits are below the case when DSM is not considered.

It makes sense that for demand Agents 4 to 6, the energy costs decrease when there is more flexibility to shift the demand since it can be easily allocated in those time periods where the energy is cheaper. Actually, this is the trend. Even for the renewable agent 1 this statement stays true because this agent can take advantage of its "costless" assets to satisfy its demand more economically through DSM. In contrast, for agents with non-renewable generators this is not so evident. These agents have to find an optimal hourly configuration for their generator's power output in such a way that their own demand is satisfied and they obtain profits by selling the surplus. The allocation for the power supplied depends not only on the generation costs but also on the hourly demand conditioned by the value of parameter k and also the initial demand configuration. As such, there is a value for this parameter that produces the best results. As it can be seen, for k equal to 6 the costs of the energy bought are the smallest and, in addition, the difference between the income and the generation costs are the best among the cases with DSM.

Regarding technical aspects, Table 2.8 shows the maximum apparent power in the MG along with the time period and the line in which it takes place. Total active losses are also given. It is evidenced that as parameter k increases, the maximum apparent power in the MG grows although at a slow pace. A similar tendency for the losses can be appreciated. These results can be justified taking into account the particular characteristics of the MG under study and the level of non-renewable generator power output for the latest time periods of the day.

Table 2.8: Losses and maximum apparent power of the DSM model

k	**0**	**3**	**6**	**9**	**12**
Losses(kW)	9.69	10.98	10.86	11.01	11.47
$\boldsymbol{S_{m,n}}$**(kVA)**	63.63	62.33	65.68	66.15	66.47
Line and period	2-3, t_{20}	2-3, t_{21}	2-3, t_{20}	2-3, t_{20}	2-3, t_{20}

When DSM is considered, the demand in the residential feeder is in part shifted to other time periods. On the other hand, the power flow in that feeder goes towards the slack bus due to the significant power supplied from generators. Hence, although the demand is reduced in the considered time periods because of load shifting, the power outputs do not experience an important variation and, as a consequence, the power flow become greater. Nevertheless, it is important to keep in mind the benefits of DSM through the total demand rearrangement. In general, load shifting leads to a better usage of the existing electric power systems and, if necessary, the generators can reduce the power supplied through the SG operator signals in case the security of the system could be jeopardised.

Finally, in regard to the current case study, it is interesting to compare the prices for EV charging in the charging scenarios presented (Table 2.9). To establish a comparison among them in identical conditions a total charging of 133.20 kW during the whole day has been chosen, equivalent to four time periods charging at a rate of 3.7 kW. Thus, an EV with a capacity of 16.5 kWh would be close to the full charge.

It can be seen that the controlled charging strategy offers the best price for charging the EVs in relation to the uncontrolled charging strategies. Because the EV charging

Table 2.9: EVs charging periods and average prices

	Unc 1	**Unc 2**	**Unc 3**	**Cont**
Average price(€)	21.29	18.97	17.57	12.70
Main charging periods	t_{21}	t_{10}, t_{11}	t_{24}	t_3, t_4, t_5

is allocated in the most favourable time periods, the price is significantly reduced. The uncontrolled charging type 1 produces the most expensive prices since the EV charging takes place at the end of day when hourly buying prices are higher. For the remainder of scenarios, the average price is between these extreme cases so that the EV charging is more distributed among the different time periods.

2.4.5 Auction results and performance

Two cases referred to the auction scheme results are demonstrated next in Tables 2.10 and 2.11 corresponding to time period t_{21}. DSM is performed in both scenarios but in the first one the EV uncontrolled charging type 3 is used while in the second one the EV charging managed by an EV aggregator with V2G activated is performed.

In Table 2.10, a summary of the participants' energy is given. For each agent, its role as buyer or seller and the energy at stake are shown. The amount of energy for Agents from 1 to 6 are the same in the two cases presented since they are results from each agent optimisation problem. However, EVs, represented by Agent 7, bid to charge their batteries in the first case (EV charging is a parameter) and, instead, EVs bid to supply energy in the second case (EV charging/discharging are variables of the corresponding optimisation problem). Hence, Agent 7 representing EVs participates as a buyer in the first case and as a seller in the second case.

In Table 2.11, the different energy transactions between agents regarding the amount of energy sold, the number of rounds for clearing and the agreed price are given. As it can be observed, all the agents clear their energy in the auction, although Agent 2, in both cases, has to sell its remaining energy to the external grid, since the total energy that it needs to sell is higher than the total demand before the auction.

With respect to the clearing prices, as was explained in Section 2.3, these have to lie between the current buying market price, equal to 8.36 cents of €/kWh in this example,

Table 2.10: Auction bids for time period 21

First case: DSM with EVs uncontrolled charging pattern			
Buying bids		*Selling bids*	
Agent	**Energy(kWh)**	**Agent**	**Energy (kWh)**
1	3.40	2	43.20
4	9.67	3	12.65
5	5.24	—	—
6	2.79	—	—
7	10.50	—	—
Second case: DSM with EVs and V2G			
1	3.40	2	43.20
4	9.67	3	12.65
5	5.24	7	5.55
6	2.79	—	—

and the current selling market price, equal to 16.32 cents of €/kWh. All the clearing prices are established from the buyer bid when it is higher with respect to the seller bid. In case several buyers are cleared simultaneously with only one seller (see first case round 10), the best buyer bid clears first. Conversely, when several sellers are cleared at the same time with only buyer, the best seller bid is cleared before (see second case round 8). The buyers bid price is respected in any case.

Regarding the number of required rounds, the auction is designed to finish in a maximum number of 12 rounds. However, other possibilities can take place since the auction duration depends on the magnitude of the bid increment in successive rounds for buyers and sellers. Thus, sellers with high amounts of energy available to sell at the auction with respect to their maximum capacity will tend to bid in subsequent rounds more slowly compared to other sellers. That is why, Agent 3 clears the rest of its energy with the main grid in both cases. On the contrary, buyers with highs amounts of energy to buy in relation to their maximum along the day will tend to clear later. To make the results more general, the ratio energy/maximum has been weighted with a random number to obtain the pace of the buyers bids. For instance, this effect can be noticed in the different rounds in which Agents 4 and 5 clear in the two cases presented.

Table 2.11: Auction results for time period 21

Agents		Energy(kWh)	Rounds	Price(c€/kWh)
First case: DSM with EVs uncontrolled charging pattern				
3	1	3.40	7	12.96
3	4	9.25	8	12.69
2	4	0.42	10	13.21
2	5	5.24	10	13.13
2	7	10.50	11	13.14
2	6	2.79	11	13.14
2	grid	24.25	—	8.36
Second case: DSM with EVs and V2G				
7	1	3.40	6	13.18
3	5	3.09	8	12.64
7	5	2.15	8	12.64
3	4	9.56	9	12.49
2	4	0.11	11	12.96
2	6	2.79	12	12.99
2	grid	40.30	—	8.36

2.5 Case study based on the IEEE-37 system

In order to illustrate the proposed method, an additional network has been analyzed, based on the IEEE 37-bus distribution grid given in [131]. The line characteristics in p.u. quantities are given in Tables A.8 and A.9. It is a simplified reference system that is envisaged to represent future SGs due to its size and the type of agents considered. A typical demand curve from a real distribution grid is assumed and selling/purchase hourly market prices are set to represent three different scenarios in the same fashion as stated for the MG case study, Fig. 2.18.

Load buses, generators, batteries and EVs considered in the case study are represented in Fig. 2.19, where grid areas belonging to the seven defined SG agents are labelled with circled numbers. Another agent acts as an EV aggregator responsible for complying with EV mobility requirements. The operating costs for non-renewable generators and other

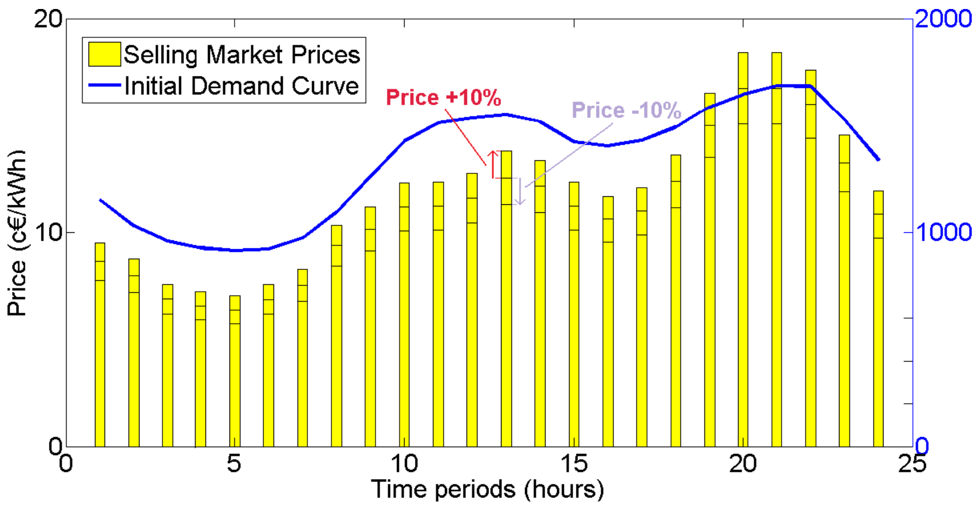

Figure 2.18: Demand curve and price scenarios

technical data regarding the considered assets can be found in Tables A.10, A.11 and A.12, from Appendix A. These data are based on the information contained in [132–134]. The assumed values of the generators' installed power is sufficient to supply the demand peak in the case that all of them were running at maximum power output with a renewable share of 25%. In this case, the same values for f_e and k used in the MG case study were chosen, whilst the parameters k_ϵ and k_δ were set to 2.5 kWh and 0.75 kWh respectively.

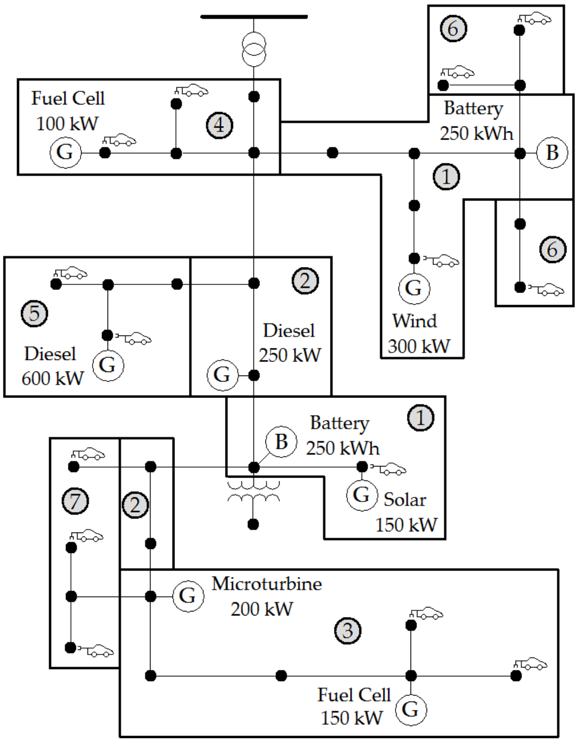

Figure 2.19: IEEE 37-bus distribution case study

In relation to renewable generators, the hourly power output for the wind and the photovoltaic plants follow a similar configuration as shown in Fig. 2.9. However, the scenarios are scaled up to adapt the corresponding values to the installed power of each generator.

With respect to the EVs, a total number of 14 EVs is considered here. An uncontrolled charging pattern is assumed in which EVs charge at a rate of 3.7 kW during four time periods at the end of the day, as soon as they arrive from the last journey of the day; then the EVs remain idle for the remaining time periods. It is also considered that each EV performs two journeys, each one attached to a particular time period like for the previous case study. During transitions, EVs consume a certain amount of energy equal to half the total individual EV charging and they commute between the initial node represented in Fig. 2.19 and the closest node. The battery capacity is 16.5 kWh for each EV and charging and discharging efficiencies are assumed to be 0.90 and 0.95 respectively. Table A.13 shows the time periods for which either a transition or a charging operation takes place. The initial SOC for all the EV batteries corresponds with the full charge state. In addition, a controlled operation where EVs respond to prices is considered. The performed journeys and the battery energy consumption are the same as specified in Table A.13 for the uncontrolled charging.

For the current system under study, some results referred to the final load curve, when DSM is considered, are presented. Firstly, the effect of the parameter k is illustrated in Fig. 2.20. For four different values of k, the final load curves are represented, obtained once the corresponding optimisation problems are performed for each agent according to the ideas presented in Section 2.2. EV loads are not included in these cases. As it can be observed, higher values of the parameter allows to rearrange the load more efficiently along the day since the final load curve tends to be flatter in comparison to the initial load curve.

The values of the standard deviation σ_k and demand range D_k^r, calculated for the hourly demand determined by each value of the parameter k, are given in Table 2.12. Both magnitudes decrease as the value of k is increased, confirming that the load curve is flatter.

Fig. 2.21 illustrates the joint effect of EVs and DSM on the final load curve. The initial and the final load curves are represented also considering two kinds of EV charging

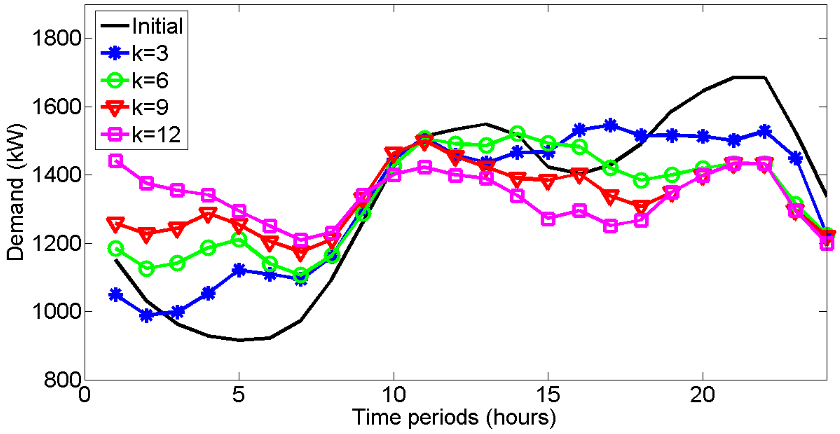

Figure 2.20: Daily electricity load curves for several values of k

Table 2.12: Standard deviation and demand range for different values of k

k	0	3	6	9	12
σ_k (kW)	264.99	203.40	144.93	94.74	74.81
D_k^r (kW)	769.69	556.58	414.40	324.40	241.56

strategies. Uncontrolled charging is determined according to the data given in Table A.13 regarding charging and transition periods. When EVs respond to hourly prices, the charging is allocated in those time periods where the energy is cheaper, allowing the EV manager to minimise the charging costs. As can be observed, the uncontrolled charging increases the demand peak, while the price-response charging allows filling of the valleys in the load curves during the first time periods of the day.

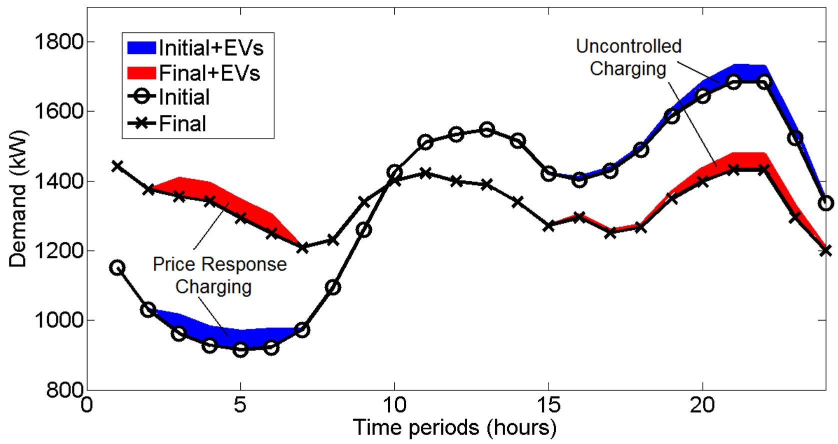

Figure 2.21: Daily electricity load curves with EVs charging

If V2G is allowed in the EV aggregators' optimisation problem, as stated in Section

2.4.4, a decrease in the battery energy consumption during the predefined journeys is needed to ultimately make possible and economical EV battery discharging. Fig. 2.22 depicts the optimal EVs charging and V2G when this consumption is reduced by half. In this case, as it will shown next, the hourly EV charging power is exactly the same with respect to the problem in which V2G is disabled. In this latter scenario the charging allows to perform the planned journeys, whereas in the former case the charging is shared to perform both the journeys and V2G.

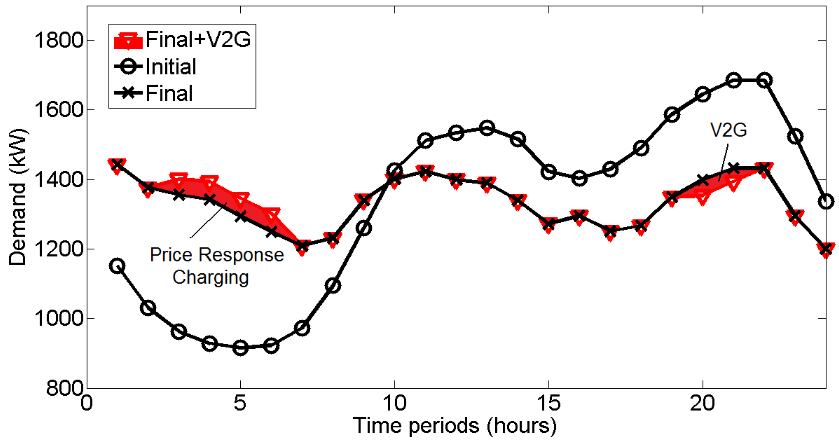

Figure 2.22: Daily electricity load curves with V2G allowed

In Fig. 2.23, the SOC for EV 1 is shown for different charging strategies.

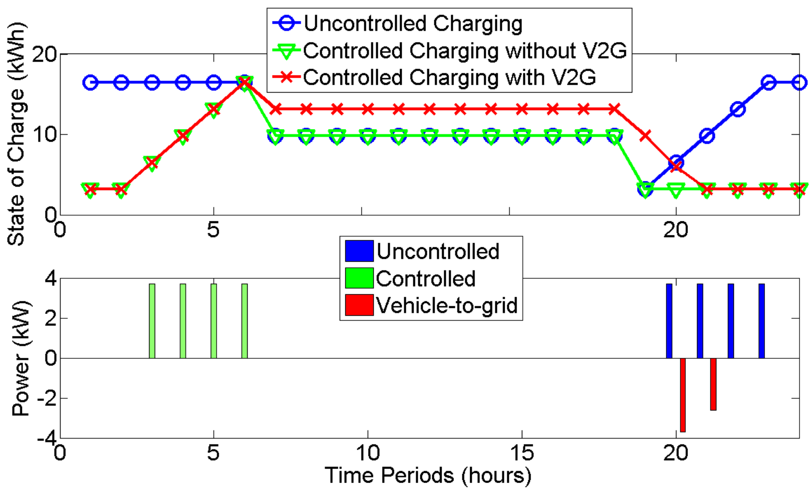

Figure 2.23: State of Charge for different strategies EV 1

As in the previous examples, the uncontrolled charging takes place at the latest time periods of the day until the EVs' battery is fully charged. When the EV is managed by an aggregator, it charges at the beginning of the day and, if V2G is permitted, it discharges in the evening time periods. The hourly allocation for the EV charging/discharging allows the manager to maximise its benefits taking advantage of cheaper prices for charging and obtaining additional income from discharging in the most advantageous periods.

Finally, some economical and technical aspects of the proposed model are presented. For the tested values of the parameter k, total income and costs of non-renewable generation are represented in Fig. 2.24. The costs of the energy bought, considering hourly selling prices from the main grid, are also given. Although the non-renewable generation cost increases as k grows, the income and costs increase and decrease respectively at a higher pace. Hence, the overall profits, considering all the involved agents, are improved through the use of load shifting.

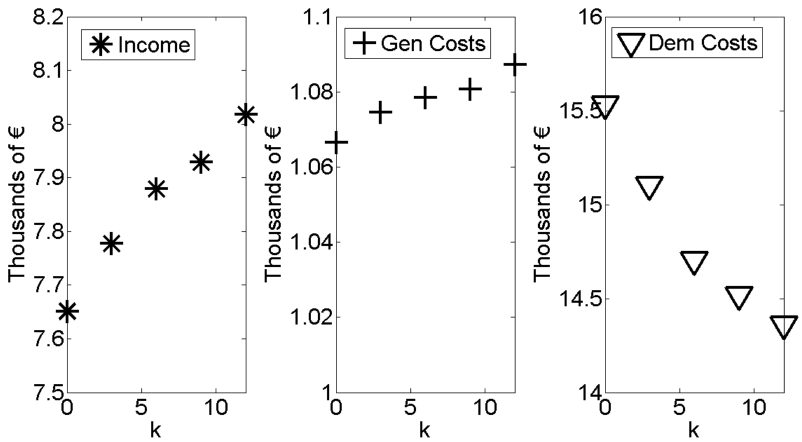

Figure 2.24: Total Income and Costs

From a technical point of view, total active losses slightly decrease as parameter k increases while average maximum apparent line power is reduced until a certain limit, Fig. 2.25. The effect of DSM on losses is important at first but the variation is not very clear based on the value of k so that the power flow in lines is of similar magnitude in the different cases. However, the grid is less stressed during the last hours of the day when DSM is applied although high values of k may cause the opposite behaviour.

With regard to EVs, an average price for charging is given in Table 2.13 for the different cases considered. When EVs charge under the uncontrolled approach the average cost for an EV battery is higher compared to the in controlled charging. The controlled approach when V2G is enabled produces a similar cost although part of the charging is precisely dedicated to perform V2G. The lower prices in relation to the previous studied system are justified take into account that the hourly EV charging was not limited due the load

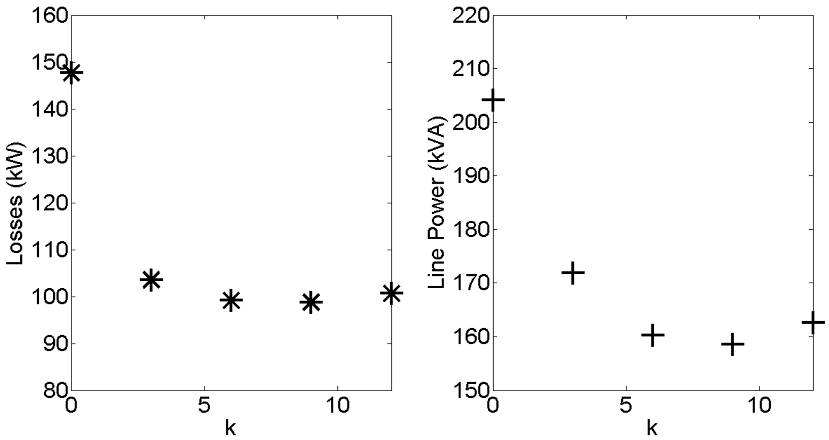

Figure 2.25: Total losses and maximum power

curve and other input parameters considered.

Table 2.13: EVs charging periods and average prices IEEE 37-bus system

	Unc	**Cont**	**Cont V2G**
Average price(€)	22.30	9.90	9.60
Main charging periods	t_{21}, t_{22}	t_3, t_4, t_5, t_6	t_3, t_4, t_5, t_6

Chapter 3

Congestion management through Vehicle-to-Grid

Modern electric power systems will face new operational challenges due to the influence of a high penetration of EVs. In this context, power system operators may take advantage of EVs equipped with V2G technologies to deal with technical problems. Thus, it is possible to have a more reliable electric grid counting on the additional support to the existing security infrastructure. In this chapter, a specific algorithm is proposed to address V2G strategies to solve congestion management issues. Power distribution factors are used to determine the amount of energy that a specific EV should contribute to relieve the congestion in a given line. It is assumed that EVs can decrease or increase their state of charge, stop their charging or even inject energy with the object of securing the integrity of the system. This approach is tested for a reference grid containing several EVs and it is shown to be suitable to solve this kind of technical problem. A particular OPF, acting on generation assets, completes the proposal of the technical operation.

3.1 Technical Operation

As it was stated in Chapter 1, an OPF is proposed as a way to solve the technical infeasibilities that could arise in the grid regarding, for example, voltage limits violating or inadmissible power flows through the lines. This tool is presumed to be the first course of action to take in order to preserve the security of the grid. The control variables are the power outputs of each generator, taking into account the power contribution from the point of connection to the grid. The OPF does not modify the loads but it searches for an optimal rearrangement of the active power injections trying to preserve the initial configuration established by the rest of the agents. A complete description of this OPF is given next. It is formulated as a single-period non-linear programming problem which is applied when a previously performed power flow detects breaches of security. Equations and constraints shown below are assumed to be valid for the current time period so the subscript associated to the time period is omitted for the sake of clarity.

The objective function for the OPF is formulated as the sum of three absolute value terms, related to the active power supplied from renewable generators, P_i^{rg}, non-renewable generators, P_j^{nrg} and the main distribution grid, P^{grid}:

$$\underset{\{\Delta P_i^{rg}, \Delta P_j^{nrg}, \Delta P^{grid}\}}{\text{minimise}} \quad \sum_{i=1}^{n_g} k_{1,i} \cdot |\Delta P_i^{rg}| + \sum_{j=1}^{n_{rg}} k_{2,j} \cdot |\Delta P_j^{nrg}| + k_3 \cdot |\Delta P^{grid}| \tag{3.1}$$

where $k_{1,i}$, $k_{2,j}$ and k_3 are positive parameters which add to 1, and sets $I = 1, 2, ...n_{rg}$ and $J = 1, 2, ...n_g$ refer to the renewable generators and non-renewable generators respectively. The relative weights among these values shows the tendency to vary one or another of these power sources and, in general, these values are lower for renewable generators to give priority to the use of renewable sources against other types of generation technologies. Given the initial result from each agent optimisation problem regarding active power generation, as stated in Chapter 2, the SG operator tries to take the grid to a feasible situation minimising the difference between the final power resulting from the OPF and the initial power resulting from the particular agent optimisation problems. With respect to the terms in absolute value from the objective function, those can be expressed in the following way:

$$|\Delta P_i^{rg}| = |P_i^{rg} - \widehat{P_i^{rg}}|, \quad \forall i \tag{3.2}$$

$$|\Delta P_j^{nrg}| = |P_j^{nrg} - \widehat{P_j^{nrg}}|, \quad \forall j \tag{3.3}$$

$$|\Delta P^{grid}| = |P^{grid} - \widehat{P^{grid}}| \tag{3.4}$$

where the terms affected by the "hat" symbol refer to the initial values of the active power, taken as parameters, and the remaining ones are the control variables of the SG operator.

The resulting optimisation problem, as it is shown next, turns out to be non-linear although Eqs. (3.2) to (3.4) have been appropriately linearised in order to reduce the number of non-linear terms in the formulation. Thus, each absolute value is expressed as the sum of two positive variables, indicated by the superscripts "+" and "-", and the final power is expressed as the sum of the initial power and the difference between these two variables:

$$|\Delta P_i^{rg}| = P_i^{rg,+} + P_i^{rg,-}; \quad P_i^{rg} = \widehat{P_i^{rg}} + (P_i^{rg,+} - P_i^{rg,-}), \quad \forall i \tag{3.5}$$

$$|\Delta P_j^{nrg}| = P_j^{nrg,+} + P_j^{nrg,-}; \quad P_j^{nrg} = \widehat{P_j^{nrg}} + (P_j^{nrg,+} - P_j^{nrg,-}), \quad \forall j \tag{3.6}$$

$$|\Delta P^{grid}| = P^{grid,+} + P^{grid,-}; \quad P^{grid} = \widehat{P^{grid}} + (P^{grid,+} - P^{grid,-}) \tag{3.7}$$

The power supplied from non-renewable generators or the main grid can be increased or decreased; however, note that the power from renewable sources can only be reduced. For this latter case it is not necessary to use the absolute value although it was used to maintain the same linearisation as the remaining variables. In practice, when the power output of some generators is modified, the contribution from the main grid guarantees the power balance. The constraints taken into account for the OPF are presented next.

- **Bounds for generators power output**

  The active and reactive power output for generators cannot be higher, or lower, than a fixed quantity due to technical reasons:

$$P_{g,k}^{min} \leq P_k^g \leq P_{g,k}^{max}, \quad \forall k \tag{3.8}$$

$$Q_{g,k}^{min} \leq Q_k^g \leq Q_{g,k}^{max}, \quad \forall k \tag{3.9}$$

  where $P_{g,k}^{min}$ and $P_{g,k}^{max}$ are the minimum and maximum active power output; while $Q_{g,k}^{min}$ and $Q_{g,k}^{max}$ are the minimum and maximum reactive power output for generator k. In addition, P_k^g and Q_k^g are the variables representing the current active and reactive power generation respectively. The subscript k and the superscript g have been used to index all the generators regardless of their nature.

- **Bus voltage limits**

  The node voltages have to lie in a range of values between a maximum and a minimum:

$$V_n^{min} \leq V_n \leq V_n^{max}, \quad \forall n \tag{3.10}$$

  where V_n^{min} and V_n^{max} are the lower and upper limits for node voltages; and V_n is the current voltage for node n.

- **Maximum apparent power**

  There is a limit in the line power flow due to physical conditions related to the maximum heating that conductors can withstand:

$$P_{m,n}^2 + Q_{m,n}^2 \leq (S_{m,n}^{max})^2, \quad \forall m, \forall n \tag{3.11}$$

  where $P_{m,n}$ and $Q_{m,n}$ are the active and reactive power flows of the line connecting nodes m and n, while $S_{m,n}^{max}$ is its maximum apparent power flow.

- **Power flow**

  The AC power flow equations are represented by:

$$P_n = V_n \cdot \sum_{m=1}^{M} V_m \cdot (G_{n,m} \cdot \cos\theta_{n,m} + B_{n,m} \cdot \sin\theta_{n,m}), \quad \forall n \tag{3.12}$$

$$Q_n = V_n \cdot \sum_{m=1}^{M} V_m \cdot (G_{n,m} \cdot \sin\theta_{n,m} - B_{n,m} \cdot \cos\theta_{n,m}), \quad \forall n \tag{3.13}$$

  where P_n and Q_n are the active and reactive power injections at bus n. The parameters $G_{n,m}$ and $B_{n,m}$ represent the conductance and the susceptance of the line connecting buses n and m, and M is the total number of grid buses.

From the OPF results, active and reactive power flow in lines can be calculated according to [135]:

$$P_{m,n} = V_n \cdot V_m \cdot (G_{n,m} \cdot \cos\theta_{n,m} + B_{n,m} \cdot \sin\theta_{n,m}) - G_{n,m} \cdot V_n^2, \quad \forall m, \forall n \tag{3.14}$$

$$Q_{m,n} = V_n \cdot V_m \cdot (G_{n,m} \cdot \sin\theta_{n,m} - B_{n,m} \cdot \sin\theta_{n,m}) + B_{n,m} \cdot V_n^2, \quad \forall m, \forall n \tag{3.15}$$

where $\theta_{n,m}$ is the difference between the phase angles of buses n and m.

Thus, the OPF problem is completely formulated as follows:

$$\underset{\{\Delta P_i^{rg}, \Delta P_j^{nrg}, \Delta P^{grid}\}}{\text{minimise}} \quad \sum_{i=1}^{n_g} k_{1,i} \cdot |\Delta P_i^{rg}| + \sum_{j=1}^{n_{rg}} k_{2,j} \cdot |\Delta P_j^{nrg}| + k_3 \cdot \Delta P^{grid}$$

$$|\Delta P_i^{rg}| = |P_i^{rg} - \widehat{P_i^{rg}}|, \quad \forall i$$
$$|\Delta P_i^{rg}| = P_i^{rg,+} + P_i^{rg,-}, \quad \forall i$$
$$P_i^{rg} = \widehat{P_i^{rg}} + (P_i^{rg,+} - P_i^{rg,-}), \quad \forall i$$

$$|\Delta P_j^{nrg}| = |P_j^{nrg} - \widehat{P_j^{nrg}}|, \quad \forall j$$
$$|\Delta P_j^{nrg}| = P_j^{nrg,+} + P_j^{nrg,-}, \quad \forall j$$
$$P_j^{nrg} = \widehat{P_j^{nrg}} + (P_j^{nrg,+} - P_j^{nrg,-}), \quad \forall j$$

$$|\Delta P^{grid}| = |P^{grid} - \widehat{P^{grid}}|$$
$$|\Delta P^{grid}| = P^{grid,+} + P^{grid,-}$$
$$P^{grid} = \widehat{P^{grid}} + (P^{grid,+} - P^{grid,-})$$

$$P_{g,j}^{min} \leq P_j^{nrg} \leq P_{g,j}^{max}, \quad \forall j$$
$$Q_{g,j}^{min} \leq Q_j^{nrg} \leq Q_{g,j}^{max}, \quad \forall j$$
$$V_n^{min} \leq V_n \leq V_n^{max}, \quad \forall n$$
$$P_{m,n}^2 + Q_{m,n}^2 \leq (S_{n,m}^{max})^2, \quad \forall m, \forall n$$
$$P_n = V_n \cdot \sum_{m=1}^{M} V_m \cdot (G_{n,m} \cdot \cos\theta_{n,m} + B_{n,m} \cdot \sin\theta_{n,m}), \quad \forall m, \forall n$$
$$Q_n = V_n \cdot \sum_{m=1}^{M} V_m \cdot (G_{n,m} \cdot \sin\theta_{n,m} - B_{n,m} \cdot \cos\theta_{n,m}), \quad \forall m, \forall n$$

3.2 Congestion Management

EVs are suitable to provide several grid services such as spinning reserve or frequency regulation as shown in [67, 71]. In this work, the capability of EVs to help avoid line congestion is shown through a well-defined algorithm using the concept of power Distribution Factors (DFs) [136]. In this section, firstly, DFs are introduced. Then, the different steps of the algorithm are presented. Finally, the main equations and fundamentals of the approach are analysed in detail.

Given a specific electricity system, DFs are parameters that depend on the grid topology, the values of impedance of the different lines that constitute it and the current state of the grid, namely the bus voltages and angles. They can be defined as linear factors that represent the increment of the power flow in each line due to a unit change in power injection at a particular bus. They are currently used as a tool for contingency analysis [135]. Because both the power flow and the power injection at a bus can be active and reactive, it is possible to distinguish four different types of DFs. Hence, two groups of DFs represent the change in active power flow in a line due to unit change in power injection at a bus while the other two represent the change in reactive power flow. Mathematically, they can be expressed as:

$$\alpha_{m,n}^{a,k} = \frac{\Delta P_{m,n}}{\Delta P^k}; \quad \alpha_{m,n}^{r,k} = \frac{\Delta P_{m,n}}{\Delta Q^k}, \forall k \tag{3.16}$$

$$\rho_{m,n}^{a,k} = \frac{\Delta Q_{m,n}}{\Delta P^k}; \quad \rho_{m,n}^{r,k} = \frac{\Delta Q_{m,n}}{\Delta Q^k}, \forall k \tag{3.17}$$

In Eqs. (3.16) and (3.17), the Greek letter α has been used to refer to active power flow and ρ to refer to reactive power flow. In the same fashion, the superscript a represents the active power injection and the superscript r represents the reactive power injection. Indices m and n are the buses connected by line and k is a generic bus where the power injection is modified.

DFs can be calculated by expanding the equations that define the power flow in a line and the power injection at a bus using Taylor series approximations [137]. Thus, if active power injection at bus n from (3.12) is expanded using a first order Taylor's series, then it can be expressed as:

$$\Delta P_n = \frac{\partial P_n}{\partial \theta_n} \cdot \Delta\theta_n + \frac{\partial P_n}{\partial \theta_m} \cdot \Delta\theta_m + \frac{\partial P_n}{\partial V_n} \cdot \Delta V_n + \frac{\partial P_n}{\partial V_m} \cdot \Delta V_m \tag{3.18}$$

Similarly, reactive power injection at bus n from (3.13) can be also expanded leading to:

$$\Delta Q_n = \frac{\partial Q_n}{\partial \theta_n} \cdot \Delta\theta_n + \frac{\partial Q_n}{\partial \theta_m} \cdot \Delta\theta_m + \frac{\partial Q_n}{\partial V_n} \cdot \Delta V_n + \frac{\partial Q_n}{\partial V_m} \cdot \Delta V_m \tag{3.19}$$

Taking the active and reactive power injections as well as the angles and magnitudes in each bus of the grid, except for the slack bus, the following matrix relation can be found:

$$\begin{pmatrix} \Delta P \\ \Delta Q \end{pmatrix} = \begin{pmatrix} j_{11} & j_{12} \\ j_{21} & j_{22} \end{pmatrix} \cdot \begin{pmatrix} \Delta\theta \\ \Delta V \end{pmatrix} \tag{3.20}$$

where ΔP and ΔQ are the active and reactive power increment injection vectors, $\Delta\theta$ is the bus angles increment vector and ΔV is the bus voltage magnitude increment vector. Terms j_{11}, j_{12}, j_{21} and j_{22} constitute the jacobian matrix J and they can be calculated computing the corresponding partial derivatives at the linearisation point. In matrix form, this can be written as:

$$\Delta I = J \cdot \Delta\Theta_V \tag{3.21}$$

where ΔI and $\Delta\Theta_V$ are the vectors containing bus power injections and bus angles/voltages respectively.

Active and reactive power flow, from (3.14) and (3.15), can be expanded in a similar way as it was shown for bus power injections:

$$\Delta P_{m,n} = \frac{\partial P_{m,n}}{\partial\theta_n} \cdot \Delta\theta_n + \frac{\partial P_{m,n}}{\partial\theta_m} \cdot \Delta\theta_m + \frac{\partial P_{m,n}}{\partial V_n} \cdot \Delta V_n + \frac{\partial P_{m,n}}{\partial V_m} \cdot \Delta V_m \tag{3.22}$$

$$\Delta Q_{m,n} = \frac{\partial Q_{m,n}}{\partial\theta_n} \cdot \Delta\theta_n + \frac{\partial Q_{m,n}}{\partial\theta_m} \cdot \Delta\theta_m + \frac{\partial Q_{m,n}}{\partial V_n} \cdot \Delta V_n + \frac{\partial Q_{m,n}}{\partial V_m} \cdot \Delta V_m \tag{3.23}$$

Taking the active and reactive power flow of every line in the grid as well as the angles and magnitudes in each node, except for the slack bus, the following matrix relation can be obtained:

$$\begin{pmatrix} \Delta P_k \\ \Delta Q_k \end{pmatrix} = \begin{pmatrix} j^f_{11} & j^f_{12} \\ j^f_{21} & j^f_{22} \end{pmatrix} \cdot \begin{pmatrix} \Delta\theta \\ \Delta V \end{pmatrix} \tag{3.24}$$

where ΔP_k and ΔQ_k are the active and reactive power flow vectors considering every line k connecting buses m and n. Terms j^f_{11}, j^f_{12}, j^f_{21} and j^f_{22} constitute the flow jacobian matrix J^f that relates angles and voltages with the power flow vector ΔF; in matrix form:

$$\Delta F = J^f \cdot \Delta\Theta_V \tag{3.25}$$

Combining Eqs. (3.21) and (3.25) it is possible to derive a relation between power flows and power injections, defining this way the DFs:

$$\Delta F = J^f \cdot \Delta\Theta_V = J^f \cdot J^{-1} \cdot \Delta I = D^f \cdot \Delta I \tag{3.26}$$

where D^f is the distribution factors matrix. This matrix can be divided into four elements:

$$D^f = \begin{pmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{pmatrix} \tag{3.27}$$

where submatrices d_{11}, d_{12}, d_{21} and d_{22} include the different DFs introduced in (3.16) and (3.17). Therefore, to calculate the DFs it is necessary to define a Taylor expansion point and compute the product of the flow jacobian matrix and the inverse of the jacobian matrix, according to (3.26). As it will be stated next, the basis of the proposed methodology consists of selecting the most suitable buses, based on the values of the corresponding DFs inside matrix D^f, to avoid congestion in the lines.

Once the concept of DFs has been presented, the main steps of the EV management algorithm will be described. In this work, EVs can be all managed together to change the power flow in a line when charging, or discharging, their batteries at the bus where they are located. It remains to be noted that the process begins under the assumption that a power flow has been performed previously and congestion is present in at least one line of the grid.

The main steps of the EV congestion management algorithm, depicted in Fig. 3.1, are given next:

STEP 1. Data regarding the congested lines are stored and DFs are calculated.

STEP 2. The most overloaded line is taken first into consideration and the most suitable bus with EVs is selected. To do this, if the congested line is represented by nodes m and n, then, the chosen bus "k" is the one with the highest value of DF $\alpha^{a,k}_{m,n}$ in absolute value.

STEP 3. The demand in the specified node is decreased, or increased, in order to remove the congestion using the EVs' batteries. The amount of demand increment is chosen taking the level of congestion into account, contributing in terms of active power injection.

STEP 4. A power flow is carried out to verify the absence of congestion at the line under study. Some corrections may be needed in case the change in reactive power flow is important. For this correction, the value of the DF $\alpha^{r,k}_{m,n}$ will be needed.

STEP 5. The process is repeated for the following line and finishes either when there are no lines with congestion in the grid or, instead, all the EVs have been used.

The equations that make up the iterative algorithm to remove congestion problems using EVs are now described in more detail:

1. The amount of power injection required ΔP^k to alleviate the congestion in a specific line defined by buses m and n can be obtained through the difference between the extreme active power flow $P^l_{m,n}$, which is the active power that equals the maximum line apparent power $S^{max}_{m,n}$, and active power flow $P^c_{m,n}$, resulting from the previous

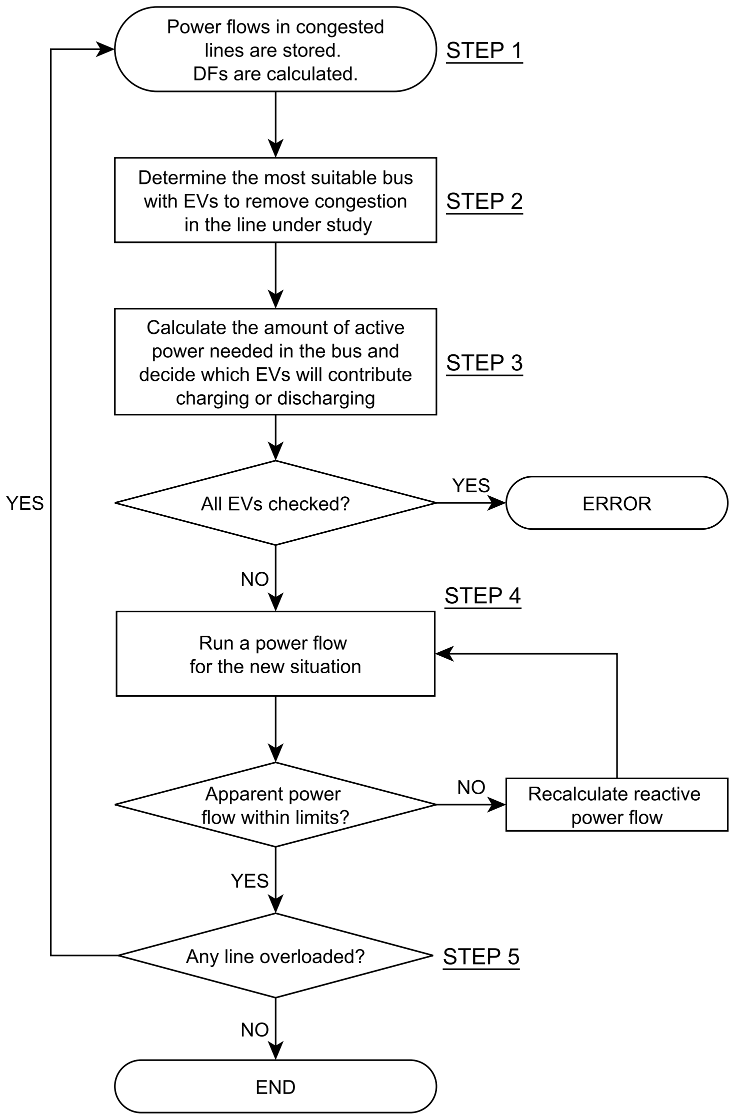

Figure 3.1: EV Management Algorithm

power flow, divided by the DF $\alpha^{a,k}_{m,n}$ as expressed in (3.28):

$$\Delta P^k = \left(P^c_{m,n} - P^l_{m,n}\right) / \alpha^{a,k}_{m,n} \tag{3.28}$$

Extreme active power flow, cited above, is defined as:

$$P^l_{m,n} = \sqrt{(S^{max}_{m,n})^2 - (Q^c_{m,n})^2} \tag{3.29}$$

where $Q^c_{m,n}$ is the reactive power flow resulting from the previously performed power flow. ΔP^k is calculated for the line with highest level of congestion assuming that reactive power flow $Q^c_{m,n}$ does not undergo changes in the first step. This way, it is attempted to take the line to a secure state only through changes in active power flow using active power injections.

2. A new power flow must be performed now, considering the contribution of ΔP^k; it is checked if the apparent power flow is within an interval, for which the width can be chosen, according to:

$$(1-\epsilon)\cdot S_{m,n}^{max} < S_{m,n}^{c} < S_{m,n}^{max} \tag{3.30}$$

The parameter ϵ defines an interval, related to the maximum apparent power flow so that the value for the final apparent power $S_{m,n}^{c}$ lies inside it. If this inequality is satisfied, ΔP^k is accepted and the process reiterates with the next most heavily congested line. Otherwise, $Q_{m,n}^{c}$, stated in (3.29), has to be recalculated in the following step to consider its contribution.

3. The change in reactive power flow for the corresponding line is calculated using the DFs $\alpha_{m,n}^{r,k}$, as shown in (3.31):

$$Q_{m,n}^{w} = Q_{m,n}^{w-1} + \alpha_{m,n}^{r,k}\cdot \Delta P^{k,w-1} \tag{3.31}$$

where $w = 1, 2, 3, ...$ refers to the iteration number. For consecutive iterations, the amounts $Q_{m,n}^{w-1}$ and $\Delta P^{k,w-1}$ are calculated from the most recent power flow which has been performed while $Q_{m,n}^{w}$ is take to be as the updated reactive power flow which variation was overridden in the first step.

4. The reactive power flow calculated above, $Q_{m,n}^{w}$, is used to estimate a new bus contribution from EVs:

$$\Delta P^{k,w} = \Delta P^{k,w-1} + n^w \cdot \Delta x^w \tag{3.32}$$

where n^w is a decreasing weight lower than 1 and Δx^w is a correction term calculated according to:

$$\Delta x^w = \pm(\Delta P^{k,up} - \Delta P^{k,0}) \tag{3.33}$$

where the positive/negative sign is chosen if the apparent power flow is above/below the endpoints defined by the interval in (3.30), $\Delta P^{k,up}$ is that given in (3.28) but calculated with the reactive updated power flow and $\Delta P^{k,0}$ is the power injection in the first step of the process.

5. The amount $\Delta P^{k,w}$ is used to re-check the apparent line power in step 2. Steps 2, 3 and 4 are repeated successively, until all the apparent power flows are within the

limits. The algorithm is repeated for each line until there is no congestion in the grid.

In order to clarify some steps of the process, additional comments regarding the algorithm are provided next:

- To select the most adequate bus, for correcting the congestion in a line, the algorithm chooses the available EV that is located in the bus with the most favorable DF, that is, the one in which an injection causes the highest variation in active power flow in the considered line. It is also assumed that EVs cannot change the location in the current time period.

- EVs will contribute depending on their current SOC. Based on this idea, discharging will be carried out by EVs with higher SOC if possible and likewise, charging will be allocated to EVs with lower SOC. Whether an EV should charge or discharge will depend on the sign of the DF.

- Maximum hourly discharging and charging rates are defined to reflect real situations which may take place. Therefore, in order to be able to remove a grid congestion, the system must have enough EVs, suitably located and with the right SOC. Unfortunately, this will not always be the case and hence, some overloads will not be tackled by EV management. If all EVs are checked and there is still congestion in the grid the algorithm will give an error signal, see Fig. 3.1.

- In addition, the power balance before and after each change in the injections is not altered because the total load changes by the same quantity as the injections. Thus, if we begin with a balanced system, then the system remains balanced after the changes in the injections by the EVs.

- EVs that injected energy by drawing energy from their batteries, recover it in later time periods thus preserving the required energy for mobility.

3.3 Results and discussion - Optimal power flow approach

In this section, the OPF introduced in Section 3.1 is analysed and applied to the MG case study of Chapter 2. As it was stated, the OPF constitutes a tool by which the system operator can correct technical infeasibilities that could arise. The control variables of the OPF are basically the power output of the generators belonging to the MG and the active power from the main grid bus. An adequate choice of the weights affecting the terms in the objective function should give priority to maintain the renewable generation contribution, although other choices are possible.

In order to understand how the OPF works, the measures taken by the MG operator, when the technical limits of some lines are modified, and DSM is not performed, are presented in Tables 3.1 and 3.2. The initial state is taken from each agent optimisation following the ideas developed in the previous chapter. The limits in bus voltages are set in 0.9 p.u and 1.1 p.u for the lower and upper bounds respectively. The limits adopted for the reactive power are given in Table A.14. Bus number 17 was selected as the slack bus.

In the current case, the agents' decisions are the origin of the infeasibilities and more specifically the level of non-renewable generation at the latest time periods of the day. Since these (time periods) are the most beneficial for the agent at which to sell its energy, the residential feeder, where the generators are located, is significantly loaded with a power flow that goes toward the slack bus while the bus voltages remain within the limits. This bidirectional character of the power flow through some lines is a remarkable characteristic of grids with distributed generation and, in particular, for the MG under study. Because of the special features of this MG, with a radial configuration, the line congestion problems are analysed only for the residential feeder. Unfortunately, the OPF cannot lead the system to a secure state when the industrial or commercial feeders are overloaded since its control variables over the generators have no effect so that the generators are located on a different feeder. Therefore, the congestion in lines belonging to feeders with only buses, and without generators, have to be tackled from the demand point of view, performing DSM or managing EVs.

The change in the FC power output when the technical limit of the lines belonging

Table 3.1: Generators power output, OPF-FC chosen

Case	$\boldsymbol{S_{1,2}^{max}}$(kVA)	$\boldsymbol{S_{1,2}^{f}}$(kVA)	$\boldsymbol{P_{FC}}$(kW)	$\boldsymbol{P_{MT}}$(kW)	$\boldsymbol{P_{grid}}$(kW)	$\boldsymbol{P_{rg}}$(kW)
Case 1	80.5	67.63	50.00	30.00	-23.07	2.49
Case 2	61.5	59.61	43.63	30.00	-16.65	2.49
Case 3	6.0	54.19	37.99	30.00	-11.24	2.49
Case 4	49.5	47.78	31.36	30.00	-4.82	2.49

to the residential feeder and, concretely, for line 1-2, are presented in Table 3.1. For the initial case, with a technical limit $S_{1,2}^{max}$ of 80.5 kVA, the apparent power flow for line 1-2 $S_{1,2}^{f}$ is equal to 67.63 kVA and both the FC and the MT are running at a maximum power of 50 kW, P_{FC}, and 30 kW, P_{MT}, respectively. The main grid consumes 23.07 kW, P_{grid}, and the overall renewable generators' power output P_{rg} is 2.49 kW. When the technical limit is decreased, as the power output of the FC is reduced, the main grid consumption, through the slack bus, decreases thus giving a feasible result. This case corresponds to the situation in which the weight affecting the FC generator is the smallest and, therefore, this generator is the first one selected to remove the congestion. The chosen values of the weights in the different cases are provided in Table A.15.

Table 3.2: Generators power output, OPF-MT and RES chosen

Case	$\boldsymbol{S_{1,2}^{max}}$(kVA)	$\boldsymbol{S_{1,2}^{f}}$(kVA)	$\boldsymbol{P_{FC}}$(kW)	$\boldsymbol{P_{MT}}$(kW)	$\boldsymbol{P_{grid}}$(kW)	$\boldsymbol{P_{rg}}$(kW)
Case 1	80.5	67.63	50.00	30.00	-23.07	2.49
Case 5	61.5	59.61	50.00	23.76	-16.65	2.49
Case 6	56.0	54.19	37.99	18.22	-11.24	2.49
Case 7	61.5	59.61	26.24	30.00	-16.65	0.00

However, similar results can be obtained if the MT is chosen as the preferred generator to decrease its generation level. Table 3.2 shows the modification in the MT power output in this latter case and an additional scenario where the renewable generators are stopped. Fig. 3.2 summarises the results presented.

Finally, it is interesting to say that these cases in which the congestion problems have been solved through a reduction in the generators' power output can be solved by increasing the bus loads in the corresponding feeder. This way, the power flow in line 1-2

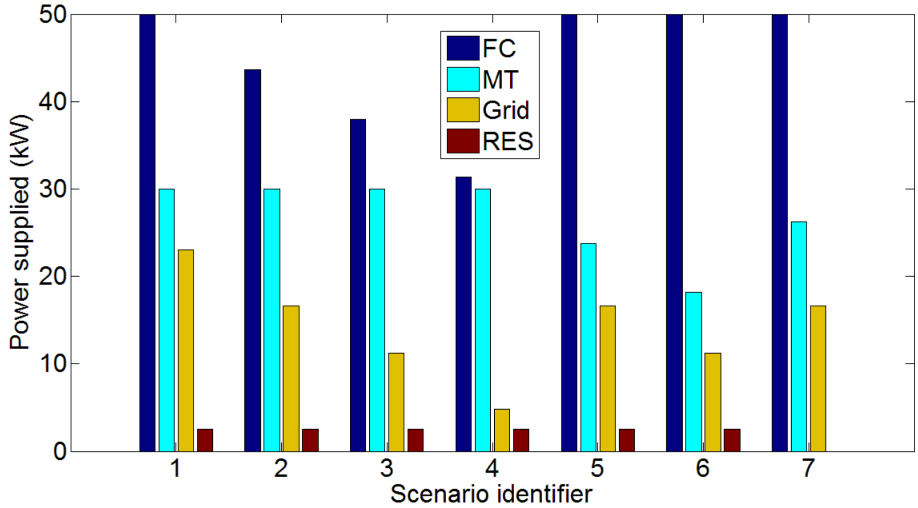

Figure 3.2: OPF correcting measures in power output

is decreased since the power is consumed before it reaches the line. This can be achieved by charging EVs in certain nodes, and constitutes the basis of the congestion management approach in the next section.

3.4 Results and discussion - Congestion management approach

Several cases are presented in this section to test the performance of the algorithm previously introduced in Section 3.2. The proposed approach allows to suitably manage EVs to avoid network congestion arising from high levels of electric energy demand or insufficient capacity of the lines that make up the electricity grids. The algorithm is applied to two different electric systems in Sections 3.4.1 and 3.4.2.

3.4.1 MG test system

In Section 2, it was shown that as a result from the combined effect of the MG loads and the charging from EVs, there is congestion in some lines of the MG which the OPF cannot correct if no additional steps are taken. In particular, lines 1-2, 2-3 and 1-9, see Fig. 2.7, are overloaded in time period 19 when uncontrolled charging strategy type 3 takes place A.7. As it can be seen in Figs. 2.13 and 2.14, the demand and generation levels are higher in the latest time periods; this causes congestion in some MG feeders; moreover this situation is aggravated with the EVs uncontrolled charging operation. In the absence of DSM strategies that can be applied to MG loads, EVs can help the system by charging or discharging energy from their batteries.

In Tables 3.3, 3.4 and 3.5, the change in the EV charging pattern that takes place if EVs are used to relieve congestion for different loads in particular buses, can be noticed. Specifically, the buses taken into consideration are buses n_2, n_4, n_5, and n_9, all belonging to the residential feeder. Two scenarios are illustrated. The first is the one in which is necessary to increase the EV charging whereas in the second situation an EV charging decrease is needed.

Table 3.3: EV charging power for several demand levels without V2G, residential feeder

Case	$\boldsymbol{D_{n2}}$(kW)	$\boldsymbol{D_{n4}}$(kW)	$\boldsymbol{D_{n5}}$(kW)	$\boldsymbol{D_{n9}}$(kW)	$\boldsymbol{\Delta P_{ev1}}$(kW)	$\boldsymbol{\Delta P_{ev9}}$(kW)
Initial	1.63	5.97	1.63	6.71	4.21	-1.50
Case 1	0.00	5.97	1.63	6.71	3.07	-1.50
Case 2	1.63	4.34	1.63	6.71	3.24	-1.50
Case 3	1.63	5.97	0.00	6.71	3.89	-1.50
Case 4	2.63	5.97	4.63	6.71	4.98	-1.50

Each EV contribution is given for several cases, that is, different bus loads, expressed in terms of active power, are considered. An initial case is considered in which EV number 1 has to increase the charging power by 4.21 kW while EV number 9 has to halt charging in 1.5 kW. This case corresponds to the initial case study taken as a reference.

EV number 1, located at bus n_4 for time period 19, represents the first scenario in which the EV consumption has to be increased. This can be understood if it is noted that the active power flow goes "from the lines to the slack bus" due to the high generation level in the current period of time in the residential feeder. That way, the active power flow in the lines with congestion is reduced because it is consumed before reaching the slack bus. It can be noticed that if the load in nodes n_2, n_4 or n_5 is decreased, Table 3.3, the EV has to charge less compared to in the initial situation, cases 1, 2 and 3. However, if the load is increased the EV will have to charge more, case 4.

For EV number 9, located at bus n_{16} for time period 19, the opposite happens: the EV charging is reduced leading to a situation where there is no charging. In this case, the active power flow goes "from the slack bus to the line" so if the energy consumed in the feeder is decreased and the congestion is alleviated. The EV consumption decrease affects the overloaded line, which now has to carry less active power. The load variation does not modify the EV contribution because the buses in which the load is modified are in a different feeder. In the situation described above only one EV was used to alleviate congestion in each feeder. However, if the demand in node n_9 is increased, more EVs will be necessary, see Table 3.4. As the demand increases the number of necessary EVs is higher, cases 6a, 7a and 8a. If the demand is small enough no EVs will contribute, case 5, although there will be also a situation in which EVs cannot tackle the congestion, case 9a.

Table 3.4: EV charging power for several demand levels without V2G, commercial feeder

Case	$\boldsymbol{D_{n9}}$(kW)	$\boldsymbol{\Delta P_{ev1}}$(kW)	$\boldsymbol{\Delta P_{ev4}}$(kW)	$\boldsymbol{\Delta P_{ev7}}$(kW)	$\boldsymbol{\Delta P_{ev8}}$(kW)	$\boldsymbol{\Delta P_{ev9}}$(kW)
Case 5	5.71	0.00	0.00	0.00	0.00	0.00
Case 6a	6.21	4.21	0.00	0.00	0.00	-0.43
Case 7a	8.71	4.21	0.00	-0.72	-1.50	-1.50
Case 8a	10.71	4.21	-1.90	-1.50	-1.50	-1.50
Case 9a	12.71	4.21	–	–	–	–

It should be said that a situation in which one or more reductions in EVs' charging are required can be carried out injecting energy to the MG making use of V2G capabilities. In the previous example EVs could be used to solve the problem of congestion by supplying energy from their batteries, Table 3.5. The use of V2G leads to a reduction in the number of EVs needed, cases 6b, 7b and 8b. In these cases, the required energy is provided by the EV and not by the main grid through the slack bus and hence a fraction of the active power flow does not have to be delivered through the lines that otherwise would be overloaded. In fact, it should be noticed that the situation mentioned before can be solved if V2G is allowed, case 9b.

EVs which help the system by performing V2G or stopping their charging, recover the energy in later time periods. For example, in case 9b, EVs number 4, 7, 8 and 9 charge their batteries in period 23 when the MG demand is small enough to allow inclusion of EV charging. The amount of energy for charging each EV is the same as that which the EV employed in the described process.

Table 3.5: EV charging power for several demand levels with V2G, commercial feeder

Case	D_{n9}(kW)	ΔP_{ev1}(kW)	ΔP_{ev4}(kW)	ΔP_{ev7}(kW)	ΔP_{ev8}(kW)	ΔP_{ev9}(kW)
Case 5	5.71	0.00	0.00	0.00	0.00	0.00
Case 6b	6.21	4.21	0.00	0.00	0.00	-0.43
Case 7b	8.71	4.21	0.00	0.00	-0.72	-3.00
Case 8b	10.71	4.21	0.00	-0.40	-3.00	-3.00
Case 9b	12.71	4.21	-0.14	-3.00	-3.00	-3.00

3.4.2 IEEE 37-bus test system

The same methodology is considered here for the IEEE 37-bus distribution test feeder introduced in Chapter 2. The main assumptions made for the analysis of the algorithm results are summarised next:

- The hourly loads and their bus distribution are the same as stated in Section 2.5.

- For the power flow studies, buses with generators are regarded as PQ buses. It is considered that all the generators are running at maximum power output with a power factor of 0.95. All the batteries are supplying energy to the grid at maximum power rate.

- The voltage magnitude at the slack bus, node of connection with the high voltage grid, is set at 1.025 p.u. to maintain the bus voltages within the limits.

- The location of the EVs and charging patterns are determined according to the data provided in Table A.13. EVs are allowed to increase the charging up to a maximum of 6.0 kW and they can discharge up to 3.0 kW. Minimum charging and discharging are set to 0.5 kW.

- Lines' maximum apparent power, given in Tables A.8 and A.9, are reduced in order to provide illustrative scenarios.

The different cases considered are shown in Fig. 3.3 where the lines under study and the EVs that contribute to relieve the congestion are highlighted. For each of them, several scenarios are analysed and time period 22 was chosen.

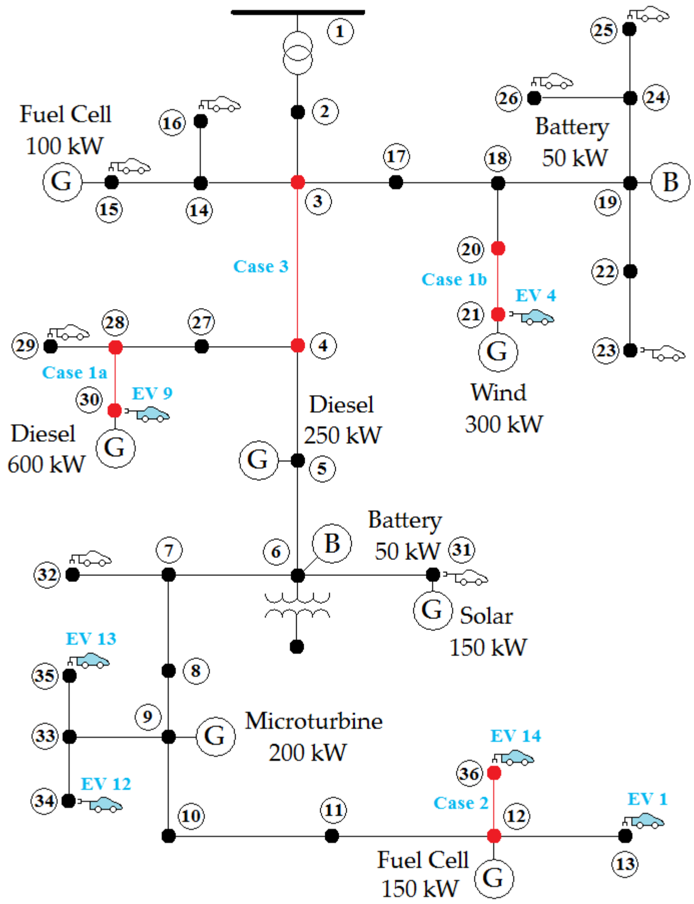

Figure 3.3: Cases of study of the IEEE 37-bus system

The results obtained after the application of the proposed algorithm are given in Table 3.6. For the different scenarios, the Congestion Level (CL) for each line, the EV identifiers, the buses where they are located and each power contribution to relieve the congestion, $\boldsymbol{\Delta P_{ev}}$, are specified. The congestion level is defined by the required increment, in terms of apparent power, to lead a particular line to a secure state. The assumed capacity of the lines were, for the purpose of this study, chosen so that they operated near the limit. These values give a measure of the levels of apparent power that EVs can confront to alleviate congested lines.

For the first case, two scenarios are presented, namely cases 1a and 1b. In both situations, the lines under study are overloaded due to the high active power supplied by the generators located on one of their buses. Thus, EVs number 9 and 4 are capable of reducing the power flow by charging their batteries. Due to they are located at the same buses as the generators, the power required for charging is consumed before reaching the line.

In the second case, three scenarios are shown for different values of congestion levels. The only EV which can help the system is the EV number 14, located at bus 36. On the other hand, the power flow goes towards that bus and, therefore, the EV, which was charging 3.0 kW, has to decrease its charging power to relieve the congestion, case 2a. When the congestion level is increased, the EV continues supporting the system by halting its charging, case 2b, or performing V2G, case 2c.

The last case illustrates how different EVs can alleviate the congestion in a particular line. For line 3-4, several EVs are available to support the system. In these scenarios, the power flow goes “from the line towards the slack bus”, in other words, the high voltage grid is absorbing power. That is why for the different congestion levels, the EVs have to increase their charging power. For case 3a, only one EV is required, while for cases 3b and 3c, two and three EVs are needed respectively. The algorithm allows to choose the EVs based on the most favourable values of the DFs. In fact, EV number 9 can also help the system but the necessary charging power is higher.

Table 3.6: EV power for the different scenarios

Case	**CL(kVA)**	**EVs Identifier**	**Location(Bus)**	$\boldsymbol{\Delta P_{ev}}$(kW)
Case 1a	3.69	9	30	4.06
Case 1b	2.81	4	21	3.09
Case 2a	1.06	14	36	-1.28
Case 2b	2.14	14	36	-3.00
Case 2c	5.38	14	36	-5.98
Case 3a	4.33	13	36	5.20
Case 3b	9.43	13, 12	35, 34	6.00, 5.06
Case 3c	12.47	13, 12, 1	35, 34, 13	6.00, 6.00, 2.36

Chapter 4

The Electric Vehicles Aggregator Case

EV aggregators are envisioned to be responsible for the acquisition of the energy required to charge those EV which accept their management rules via contracts. They can also control the V2G system to provide ancillary services and obtain additional income. In general, although patterns can be forecasted, aggregators have to face important uncertainties related to EV availability and charging requirements. Additionally, these patterns may have a different effect on the system technical performance depending on the node of connection and hourly charging power. In this chapter, a Monte Carlo simulation method along with a Markov chain random process are performed to model the uncertainties associated with EV mobility by generating multiple connection patterns and charging behaviours. This methodology is applied to the optimisation problem addressed by an EV aggregator which tries to maximise its profits through the buying and selling of energy by making use of the EVs under its management. Firstly, this optimisation problem is described in detail and the influence of the EV pattern uncertainties on the aggregator's strategy is studied. Finally, the voltage and power flow levels resulting from EVs' inclusion are analysed in a particular system, comparing uncontrolled operation and EV aggregator strategies.

4.1 Introduction

In the near future, it is expected that many EVs on the road will operate in an uncontrolled mode; thus, EV owners are free to decide a priori where and when to charge their vehicles, without any incentives. Multiple tariff schemes provide another possibility for EV owners to take advantage of better prices at which to the energy they need by charging during night hours. Both uncontrolled charging strategies, by definition, rely on the EV owner's willingness to adopt one or another behaviour. Although these EV patterns can be forecasted, in general, uncontrolled strategies may provoke undesired states for electric power systems and users will naturally have to evolve to more advanced charging strategies. Hence, with a more significant presence of EVs in the upcoming years, the way electric power systems are operated will be strongly affected and changes in regulatory and business aspects will have to be tackled.

With the imminent deployment of EVs and the adequate ICT infrastructures, many countries have set in motion initiatives to incorporate new agents responsible for managing EV charging. In particular, in Spain the so called "charging manager" is envisioned to be an agent which provides energy charging services [138] and the required infrastructure for a secure and efficient recharging process has also been regulated [76]. This concept is equivalent to the EV aggregator and it can be seen as a first step to integrate this new agent in the existing regulatory framework. Therefore, EV aggregators' main responsibility is to acquire the energy that EVs will need for their daily mobility. Other functionalities, linked to this new agent, include V2G capabilities to provide ancillary services, perform DSM approaches, support the grid or even reduce renewable energy waste. In any case, regardless of the functionalities taken into account, new tools to optimise EV management are needed.

This chapter is intended to analyse the EV aggregator optimisation problem in detail, previously introduced in Chapter 2. This problem defines the optimal charging, defined by the amount of the charging power and its hourly configuration for every EV, which an EV aggregator has to face in order to comply with the mobility needs of the EV fleet under its management. It is also considered that EVs can perform V2G, injecting this way power from their batteries. It is clear that EVs' charging requirements and availability for charging/discharging will condition EV aggregators' decisions. Thus, different EV patterns are generated through a stochastic methodology based on Markov chains theory and using Monte Carlo simulations. The interest of this model is to provide EV aggregators with adequate tools to assess their participation in electricity markets. In this thesis the participation of EV aggregators in local markets, like markets for MGs, is highlighted, although the formulation presented can be extended to wholesale markets.

This chapter is organised as follows. Firstly, the EV aggregator's principles of operation are described and the necessary data are introduced in Section 4.2. The EV aggregator optimisation problem is presented in Section 4.3. EV patterns generation is discussed in Section 4.4. Finally, the application of the proposed methodology and some technical implications are given in Section 4.5.

4.2 Operation rules of the EV aggregator

The EV aggregator, as an upcoming entity within the existing power structures, will be responsible for managing a fleet of EVs whose owners are considered as particular customers who formally adhere to its management rules. This way, the EV aggregator will operate their EVs pursuing its own goals but it also has other functions to fulfil.

For instance, although EV owners have to allow a certain degree of flexibility to draw/ store energy from/into their batteries, EV aggregators have to guarantee that their daily mobility needs are satisfied. Thus, they will have to cope with the problem of obtaining profits through EV management but always respecting the mobility needs of the fleet. In principle, it is reasonable to assume that EV aggregators represent EV owners from the perspective of electricity markets, but they have no complete control over EV behaviour regarding points of connection in the grid, journeys performed or battery energy consumption.

The proposed model aims to define the hourly EV charging/discharging power in a way that EV aggregators' benefits are maximised. This tool allows them to formulate adequate bids in the electricity market, typically defined through any suitable auction scheme. EV aggregators are assumed to act as price-takers so, in a hypothetical market participation, they would bid via energy quantities.

In order to carry out suitably its strategy, an EV aggregator must have the following information at its disposal:

- Hourly purchase and selling prices.

- EV patterns regarding available periods of connection.
- EV charging power required to perform the journeys.

In general, this information is subject to uncertainty and, hence, it should be adequately forecasted.

In this approach, the hourly prices for buying and selling energy are considered as parameters of the problem although different price scenarios are taken into account as described in Chapter 2. The EV aggregator will try to allocate EV charging in those time periods when low prices are expected whilst EV discharging will be allocated in higher price time periods. This behaviour has a double effect; on the one hand, it is clear that the maximisation of the profit is pursued so the EV aggregator takes advantage of the market prices to define its strategy; on the other hand, the system is operated more efficiently since EV charging will cover time periods in which, typically, the demand is small whereas EV discharging will take place in demand peaks.

The EV patterns deserve a special attention. Without an accurate knowledge of both hourly energy prices and EV patterns it is not possible for the EV aggregator to bid efficiently and competitively in electricity markets. However, although these data are not known exactly, in most cases it is possible to have information about the most probable values of the parameters that are needed and, to this end, valuable information can be extracted by analysing them statistically.

4.3 EV aggregator optimisation problem

In this section, the EV aggregator optimization problem proposed in this work, is described in detail. The optimisation problem aims at to maximise the EV aggregator's benefits expressed as the difference between the income from energy sold and the costs of the energy bought, taking advantage of the EVs' capabilities of supplying or absorbing energy from their batteries:

$$\underset{\left\{P_t^{S,e},P_t^{B,e}\right\}}{\text{maximise}} \quad \sum_{e=1}^{n_e} W^e \cdot \sum_{t=t_0}^{t_f} \left(\hat{\lambda}_t^{b,e} \cdot P_t^{S,e} - \hat{\lambda}_t^{s,e} \cdot P_t^{B,e} \right) \tag{4.1}$$

where $\hat{\lambda}_t^{s,e}$ and $\hat{\lambda}_t^{b,e}$ are the hourly forecasted selling and purchase prices respectively while $P_t^{B,e}$ and $P_t^{S,e}$ are the overall hourly power bought and sold. The superscript e has been used to refer to the price scenarios considered and W^e is the weight or probability of each scenario.

Variables representing power sold and bought are considered to be positive and they cannot be both different from zero at the same time, that is, an EV aggregator is not allowed to buy and sell during the same time period. In other words, it is not possible for the EV aggregator to participate in the market simultaneously as a buyer and as a seller. Hence, two binary variables yb_t^e and ys_t^e are defined according to the following equations to comply with this condition:

$$P_t^{B,e} \leq yb_t^e \cdot X \quad \forall t, \forall e \tag{4.2}$$

$$P_t^{S,e} \leq ys_t^e \cdot X \quad \forall t, \forall e \tag{4.3}$$

$$yb_t^e + ys_t^e \leq 1 \quad \forall t, \forall e \tag{4.4}$$

where X is a large enough parameter that must be chosen conveniently. Table 4.1 shows the different possibilities that Eqs. (4.2)-(4.4) can yield.

Table 4.1: EVs aggregator market participation

Market participation	yb_t^e	ys_t^e
Buyer	1	0
Seller	0	1
Neither buyer nor seller	0	0

Additionally, these variables are related to the hourly charging/discharging power for all the EVs managed by the aggregator:

$$P_t^{S,e} - P_t^{B,e} = \sum_{v=1}^{n_v} (P_{v,t}^{d,e} - P_{v,t}^{c,e}) \quad \forall t, \forall e \tag{4.5}$$

where $P_{v,t}^{d,e}$ is the hourly power supplied for EV v and $P_{v,t}^{c,e}$ is the hourly power absorbed by EV v. The summations are extended to the number of EVs n_v. Eq. (4.5) guarantees that the required power for either charging or discharging is obtained.

According to the equations presented so far, the EV aggregator can act as a seller or as a buyer depending on the time period. When hourly energy prices are low, it will participate as a buyer taking advantage of said energy prices to charge the EVs' batteries. The bid in terms of power quantities is defined by the variable $P_t^{B,e}$. In contrast, when hourly energy prices are high, it will participate as a seller, thus pursuing to make a profit by discharging the EVs' batteries. The bid in terms of power quantities would be determined by the variable $P_t^{S,e}$. In those time periods when the EV aggregator decides neither to buy nor to sell, the values of the hourly energy prices are halfway between the highest and the lowest and, additionally, there are no special energy requirements from the EV fleet. In this case, both variables are set to zero.

In order to comply with the EVs' mobility charging power requirements, the optimisation problem for EV aggregators is completed with the following constraints:

- **Maximum and minimum charging and discharging power**

  Depending on the charging and discharging rates, there is a maximum and a minimum power allowable for both processes:

$$y_{v,t}^{c,e} \cdot P_v^{c,min} \leq P_{v,t}^{c,e} \leq y_{v,t}^{c,e} \cdot P_v^{c,max} \quad \forall t, \forall v, \forall e \tag{4.6}$$

$$y_{v,t}^{d,e} \cdot P_v^{d,min} \leq P_{v,t}^{d,e} \leq y_{v,t}^{d,e} \cdot P_v^{d,max} \quad \forall t, \forall v, \forall e \tag{4.7}$$

  where $P_{v,t}^{d,e}$ and $P_{v,t}^{c,e}$ are the hourly power supplied and absorbed for EV v, $P_v^{d,max}$, $P_v^{c,max}$, $P_v^{d,min}$ and $P_v^{c,min}$ define the bounds for the maximum discharging and charging power and $y_{v,t}^{d,e}$ and $y_{v,t}^{c,e}$ are binary variables that have to comply with:

$$y_{v,t}^{c,e} + y_{v,t}^{d,e} \leq 1 \quad \forall t, \forall v, \forall e \tag{4.8}$$

  With Eqs. (4.6) to (4.8), it is assured that an EV cannot charge and discharge during the same time period. The extreme values can be typically determined depending on the characteristics of the connection point.

- **Electric vehicle state of charge - grid connection**

  When EVs are connected to the grid, the SOC $S_{v,t}^e$ for EV v in time period t is updated according to the charging/discharging power levels and the corresponding efficiencies:

$$S_{v,t}^e - S_{v,t-1}^e = \eta_C \cdot P_{v,t}^{c,e} - (1/\eta_D) \cdot P_{v,t}^{d,e} \quad \forall t, \forall v, \forall e \tag{4.9}$$

  where η_C and η_D are the charging and discharging efficiencies and $S_{v,t-1}^e$ is the SOC for EV v in the previous time period.

- **Electric vehicle state of charge - transitions**

When EVs are in transition between two nodes in the grid, for example in time period t_m, the SOC $S^e_{v,t}$ for EV v is updated subtracting the amount of energy consumed in the journey:

$$S^e_{v,t} = S^e_{v,t-1} - km_c \cdot C_{km} \quad for \quad t = t_m, \quad \forall v, \forall e \tag{4.10}$$

The battery energy consumption is expressed as the product of the amount of kilometres covered km_c and the energy consumption C_{km} usually given in kWh/km.

- **Bounds for the state of charge**

The SOC $S^e_{v,t}$ of each EV v in every time period has to lie between a minimum value and a maximum value due to technical reasons:

$$S^{min}_v \leq S^e_{v,t} \leq S^{max}_v \quad \forall t, \forall v, \forall e \tag{4.11}$$

where S^{min}_v and S^{max}_v are the minimum and maximum SOC for EV v respectively. The maximum value is given by EVs manufacturers in the corresponding technical datasheet as the EV battery capacity in kWh while the minimum value can be typically chosen to lie between 10% and 20% of the capacity.

- **State of charge in the early morning**

The SOC has to be maximum in the early morning, represented by time period t_e:

$$S^e_{v,t} = S^{max}_v \quad for \quad t = t_e, \quad \forall v \tag{4.12}$$

Eq. (4.12) allows EV owners to have enough energy to perform the daily journeys planned.

- **Initial and final state of charge**

The final SOC must be greater or equal to the initial SOC for each EV in order to avoid non-realistic solutions:

$$S^e_{v,t_0} \leq S^e_{v,t_f} \quad \forall v, \forall e \tag{4.13}$$

where S^e_{v,t_0} and S^e_{v,t_f} are the initial and final SOCs respectively. Eq. (4.13) avoids, for instance, the complete discharging of an EV at the end of the day.

In some situations, normally at the request of the system operator, EV aggregators have to adapt the EVs' charging, or discharging, to a maximum value due to safety or reliability reasons because the inclusion of EVs in the grid could jeopardize it. For this case, the following constraints are added to the EV aggregator optimisation problem:

- **Maximum overall EVs charging/discharging**

$$P_{O,t}^{c,e} = \sum_{v=1}^{n_v} P_{v,t}^{c,e} \leq \epsilon_C \quad \forall t, \forall e \tag{4.14}$$

$$P_{O,t}^{d,e} = \sum_{v=1}^{n_v} P_{v,t}^{d,e} \leq \epsilon_D \quad \forall t, \forall e \tag{4.15}$$

The threshold over $P_{O,t}^{c,e}$ and $P_{O,t}^{d,e}$, the overall EVs charging/discharging rates, are imposed through the parameters ϵ_C and ϵ_D that typically can be chosen as a percentage of the hourly peak of the demand. Eqs. (4.14) and (4.15) also allows a smooth transition for the EVs' operation.

Some comments regarding the EV aggregator optimisation problem are given next. Firstly, from the EV aggregators' point of view, it is not necessary to use the information about the nodes of connection to determine the optimal hourly EV charging and discharging. However, the EVs' availability to connect to the grid and the battery consumption during journeys are required. This information will allow to discern when Eq. (4.9) or Eq. (4.10) should be used. The EV aggregator also performs a tracking of the SOC to calculate the charging requirements. Thus, Eqs. (4.11)-(4.13) guarantee that EVs have enough energy in their batteries. However, the use of Eqs. (4.12) and (4.13) may be arguable in some particular cases. For example, if the EV has a high capacity it may not be necessary to charge the battery to its full capacity or it may even the case that the EV owner could accept a SOC at the end of the day lower than the initial SOC at the beginning.

The aggregator's optimisation problem can be formulated as follows:

$$\underset{\left\{P_t^{S,e}, P_t^{B,e}\right\}}{\text{maximise}} \quad \sum_{e=1}^{n_e} W^e \cdot \sum_{t=t_0}^{t_f} \left(\hat{\lambda}_t^{b,e} \cdot P_t^{S,e} - \hat{\lambda}_t^{s,e} \cdot P_t^{B,e}\right)$$

$$P_t^{B,e} \leq yb_t^e \cdot X; P_t^{S,e} \leq ys_t^e \cdot X; yb_t^e + ys_t^e \leq 1 \quad \forall t, \forall e$$

$$P_t^{S,e} - P_t^{B,e} = \sum_{v=1}^{n_v} (P_{v,t}^{d,e} - P_{v,t}^{c,e}) \quad \forall t, \forall e$$

$$y_{v,t}^{c,e} \cdot P_v^{c,min} \leq P_{v,t}^{c,e} \leq y_{v,t}^{c,e} \cdot P_v^{c,max} \quad \forall t, \forall v, \forall e$$

$$y_{v,t}^{d,e} \cdot P_v^{d,min} \leq P_{v,t}^{d,e} \leq y_{v,t}^{d,e} \cdot P_v^{d,max} \quad \forall t, \forall v, \forall e$$

$$y_{v,t}^{c,e} + y_{v,t}^{d,e} \leq 1 \quad \forall t, \forall v, \forall e$$

$$P_{O,t}^{c,e} = \sum_{v=1}^{n_v} P_{v,t}^{c,e} \leq \epsilon_C \quad \forall t, \forall e$$

$$P_{O,t}^{d,e} = \sum_{v=1}^{n_v} P_{v,t}^{d,e} \leq \epsilon_D \quad \forall t, \forall e$$

$$S_{v,t}^e - S_{v,t-1}^e = \eta_C \cdot P_{v,t}^{c,e} - (1/\eta_D) \cdot P_{v,t}^{d,e} \quad \forall t, \forall v, \forall e$$

$$S_{v,t}^e = S_{v,t-1}^e - km_c \cdot C_{km} \quad for \quad t = t_m, \quad \forall v, \forall e$$

$$S_v^{min} \leq S_{v,t}^e \leq S_v^{max} \quad \forall t, \forall v, \forall e$$

$$S_{v,t}^e = S_v^{max} \quad for \quad t = t_e, \quad \forall v$$

$$S_{v,t_0}^e \leq S_{v,t_f}^e \quad \forall v, \forall e$$

4.4 EV patterns generation

Apart from the hourly energy prices configuration, the most important data that EV aggregators need to know in order to determine the optimal allocation of EV charging/discharging, as it was stated in previous sections, are the EVs' availability and the battery energy consumption during journeys. Although the EV aggregators will have information about the nodes of connection in the grid, this information is not needed to solve the optimisation problem and, thus, maximise their profits.

However, for a system operator is important to know the EVs' locations in case technical problems in the grid take place, like congestion in lines or voltage limits violation. Moreover, as a consequence of the latter, the system operator could require the EV aggregators to adjust their strategy or perform a decrease in EV charging rates to lead the system to a safe state. Therefore, it is interesting to have tools to generate different EV patterns to be used by EV aggregators or system operators to assess the adequacy of the decisions they could take to comply with their own responsibilities and objectives.

In this section, a tool is presented to generate different hourly EV patterns. The general procedure including the different necessary steps is shown in Fig. 4.1. To simulate the EV movement during the established time horizon a discrete-state Markov chain has been used [54].

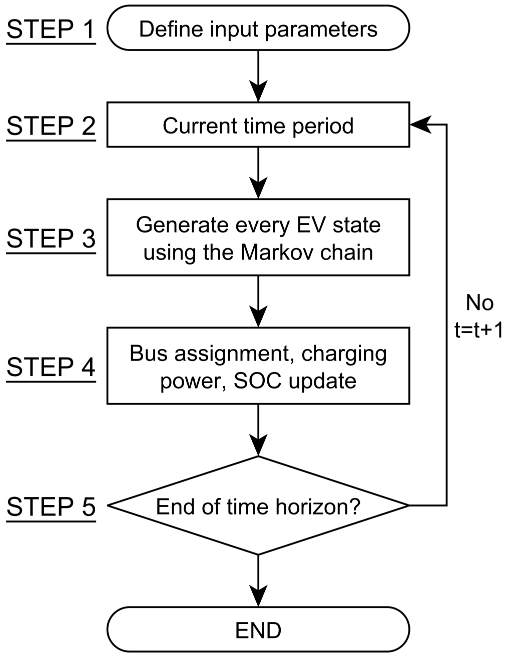

Figure 4.1: Steps of the EVs patterns generation process

STEP 1. Input parameters. The required input parameters are the following: i) the number of EVs, ii) the battery capacities, iii) the driver behaviour, iv) the grid topology, and v) the time horizon and the time step.

Additionally, an initial state for the EVs must be defined. The transition probabilities are assumed to be given.

STEP 2. Current time period. The time period under study is updated. For their use in the current time period, the previous EV states, locations, SOCs and charging/discharging power are stored.

STEP 3. EV states generation. The EV states considered are: i) in movement, ii) connected in a residential area, iii) connected elsewhere, Fig. 4.2. The magnitudes $p^t_{x \to y}$ represent the probabilities for changing to state y in time period t given that in the previous time step the state was x. Transitions between "residential" and "other" states are not considered since a movement would be needed to change the bus of connection.

Based on the previous EV states, a test is performed and depending on the transition

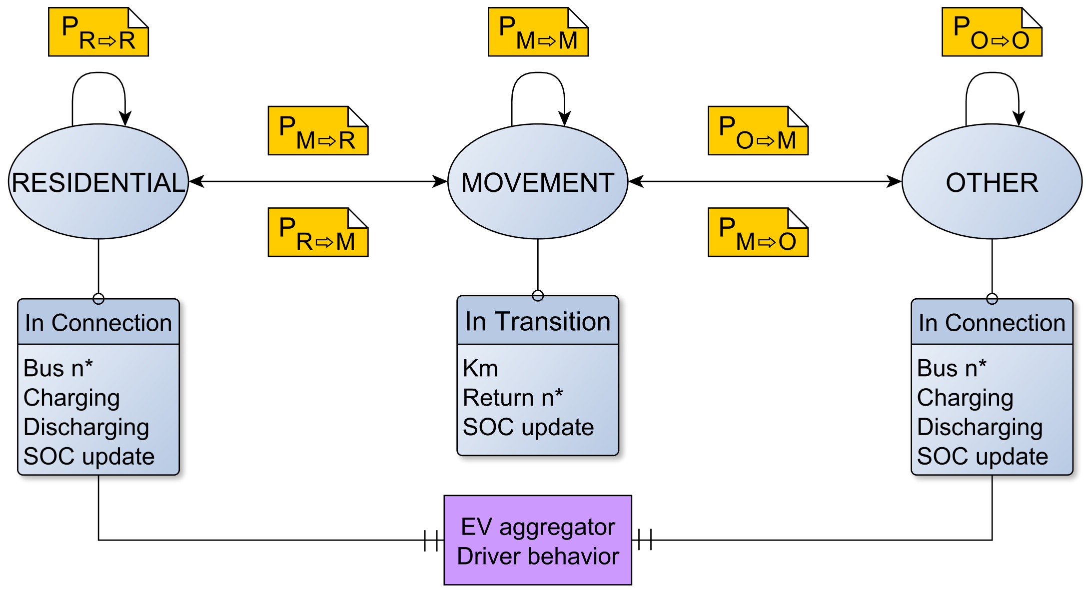

Figure 4.2: EVs states considered in the Markov chain

probabilities a new state for the current time period is calculated. The Markov property is preserved, provided that the next EV states depend only on the current state and not on the complete set of previous states.

STEP 4. Problem variables updating. For the current time period, based on the EV states, the characteristics of each EV are updated:

- If the EV is in movement, the SOC has to be updated taking into account the battery energy consumption in the journey. No bus is assigned and charging/discharging power are set to zero.

- In case the EV is connected, the SOC has to be updated considering the charging/discharging power. A bus is assigned between residential and other areas.

- The driver behaviour conditions the hourly charging/discharging configuration. Among the different possible behaviours the following have been considered: EVs charge at the end of the day, EVs charge whenever possible, EVs charge when it is needed and EVs charging/discharging subject to EV aggregator management.

STEP 5. End of the process. The characteristics of each EV are updated in the different time periods considered until the end of the time horizon is reached.

Next, the different pieces of information that result from the process are summarised:

- EVs' hourly connection to the grid, i.e., the time periods when EVs are available for charging/discharging.
- Bus locations when EVs are connected to the grid.
- EVs' hourly performed journeys, i.e., the time periods when EVs are in movement, or in transition, between two nodes in the grid.
- Battery energy consumption during journeys.
- EVs' charging/discharging power in the time horizon considered.
- State of charge of every EV.

Additional details about these EV patterns will be provided in later sections.

4.5 Economic and technical implications

In this section, the effect of the EV patterns generation methodology applied to the EV aggregator problem is discussed. To that end, a Monte Carlo simulation is performed considering the EVs patterns generation tool described previously. Firstly, the data chosen for the simulations is introduced in Section 4.5.1. Section 4.5.2 presents the implications of this modelling for the EV aggregator compared with an uncontrolled charging strategy. Finally, Section 4.5.3 deals with the technical results for both approaches.

4.5.1 Data description

The required data for input parameters stage mentioned in Section 4.4 are given here. The main EV characteristics, assumed for the purpose of this work, are shown in Table 4.2 for the 9 EVs considered. Each EV is identified by a number, the capacity of its battery and the EV driver behaviour. For the three first EVs the capacity is set to 16.5 kWh while for the rest 22.0 kWh is taken which correspond to the capacities of two commercial EVs, the Mitsubishi i-MiEV and the BMW i3 respectively [139, 140].

Three different EV drivers behaviours have been considered corresponding to those defined in the surveys of the European Project MERGE [55]. The charging power rate is chosen as 3.7 kW in every case:

Table 4.2: EVs characteristics

EV identifier	Capacity S_v^{max}(kWh)	Driver behavior
1	16.5	At the end
2	16.5	Whenever possible
3	16.5	When it is needed
4	22.0	At the end
5	22.0	At the end
6	22.0	Whenever possible
7	22.0	At the end
8	22.0	When it is needed
9	22.0	At the end

1. *At the end* - EVs charge at the end of the day. When EVs are connected to the grid and the time period is higher than 17h the EVs charge after which they remain idle for the remaining time periods.

2. *Whenever possible* - EVs charge when they are connected to the grid whenever possible, that is, without exceeding the EV capacity.

3. *When it is needed* - EVs charge when they are connected to the grid and when the SOC is lower than 30% of the EV capacity, after which they remain idle for the remainder of time periods.

In addition to these behaviours, which can be labelled as uncontrolled strategies for charging, the scenario where all the EVs are managed by an EV aggregator is also considered. In this latter case, the EVs charging is set according to the results of the EV aggregator optimisation problem defined in Section 4.3. Moreover, V2G is also permitted.

As in previous examples, the case study is the MG shown in Chapter 2 and the time horizon is 24 hours of a day in steps of 1 hour.

Regarding the transition probabilities, the corresponding values taken are represented in Fig. 4.3 and the meaning of the tags A-G is given in Table 4.3. The values are based on the work developed in [54]. The transition probabilities for passing from the state in “in movement” in a particular time period to the state “in movement” in the next period

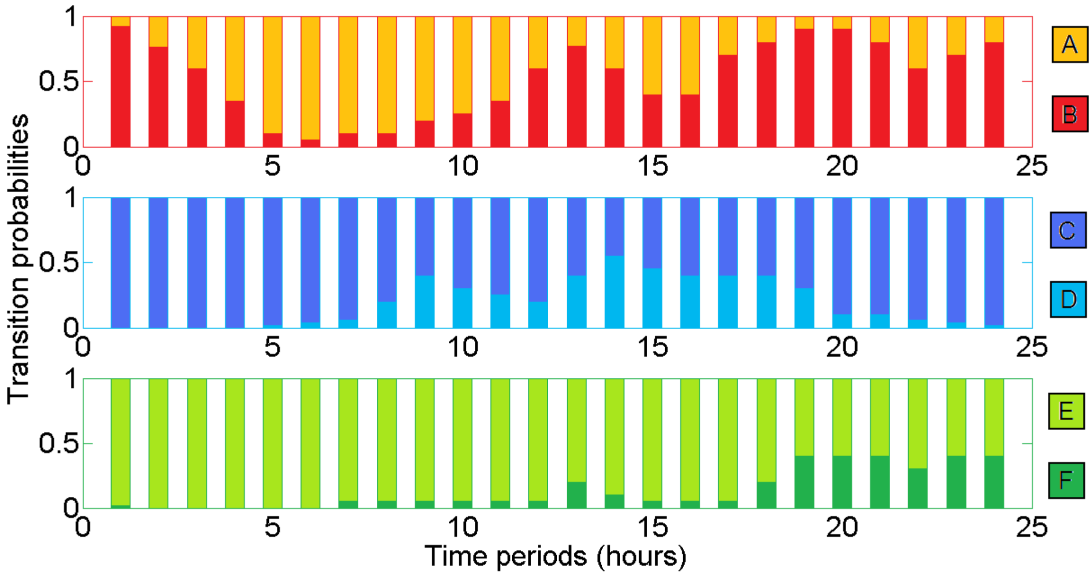

Figure 4.3: Transition probabilities for the Markov chain

are assumed to be zero, that is, an EV cannot stay in that state two consecutive periods. It is also considered that each EV can perform two journeys a day at the most.

Table 4.3: Tags represented in Fig. 4.3

	A	B	C	D	E	F
Probability	$p^t_{M\to O}$	$p^t_{M\to R}$	$p^t_{R\to R}$	$p^t_{R\to M}$	$p^t_{O\to O}$	$p^t_{O\to M}$

Before beginning the process, an initial state and other features need to be established for every EV. It is assumed that every EV is in state "residential" for the initial time period provided that this period is usually associated with the first hour in the early morning. Thus, for that state, a bus is randomly assigned to each EV from among those belonging to the residential feeder (nodes from 2 to 7). Finally, the starting SOC is obtained from a normal distribution with mean equal to half the EV battery capacity and a standard deviation equal one-third of the mean value. The normal distribution is truncated at the top/end by the EV battery capacity and by 20% of the EV battery capacity at the bottom end.

Once the initial characteristics of each EV are determined, the EV patterns can be generated taking into account the transition probabilities and the driver behaviour. For states labelled as "residential" or "other", a bus is assigned following the same idea described in the above paragraph. EV charging is chosen based on driver behaviour and the SOC is updated consequently. On the other hand, when EVs are in the "in movement" state, no bus is assigned, EV charging is set to zero and the SOC is updated depending on the amount of kilometres covered and the battery energy consumption in the performed journey. To avoid the SOC becoming too low, it is assumed that in case it falls below the 20% threshold of the EV battery capacity, the EV driver must quickly head towards a station located in bus 8 belonging to the industrial feeder, where it can charge double the normal rate, i.e. 7.4 kW. The kilometres covered and the battery energy consumption are also set according to truncated normal probability distributions [54], Table 4.4.

Table 4.4: Normal distribution parameters

	Mean	Deviation	Max	Min
Km covered normal	9.00	4.50	27.03	0.90
Km covered fast	4.50	2.25	13.52	0.45
kWh/km consumed	0.18	0.12	0.85	0.09

In Fig. 4.4, the states, the allocated bus and the SOC are represented as an example for EVs 2 and 9 under an uncontrolled charging strategy. The three states are labelled as 1 for "movement", 2 for "residential" and 3 for "other". Each state is linked to its corresponding bus except for "movement" for which the location is set to zero. The SOC is also represented on the same axis. The differences between EV 2 that charges whenever possible and EV 9 that charges at the end of the day can clearly be observed in the figure.

4.5.2 Application to EV aggregators

As it was stated at the beginning of this section, a Monte Carlo simulation is performed to check the proposed model for the EV aggregator. With this aim in mind, the different EV patterns generated using the tool presented in Section 4.4 based on a predefined Markov chain are introduced into the EV aggregator optimisation problem and a study is undertaken on how the decisions are affected. In other words, the sensitivity of the hourly EV charging/discharging against multiple charging patterns, as a result from the EV aggregator optimisation problem, is analysed. The resulting EV charging allocations are compared to those resulting from uncontrolled charging.

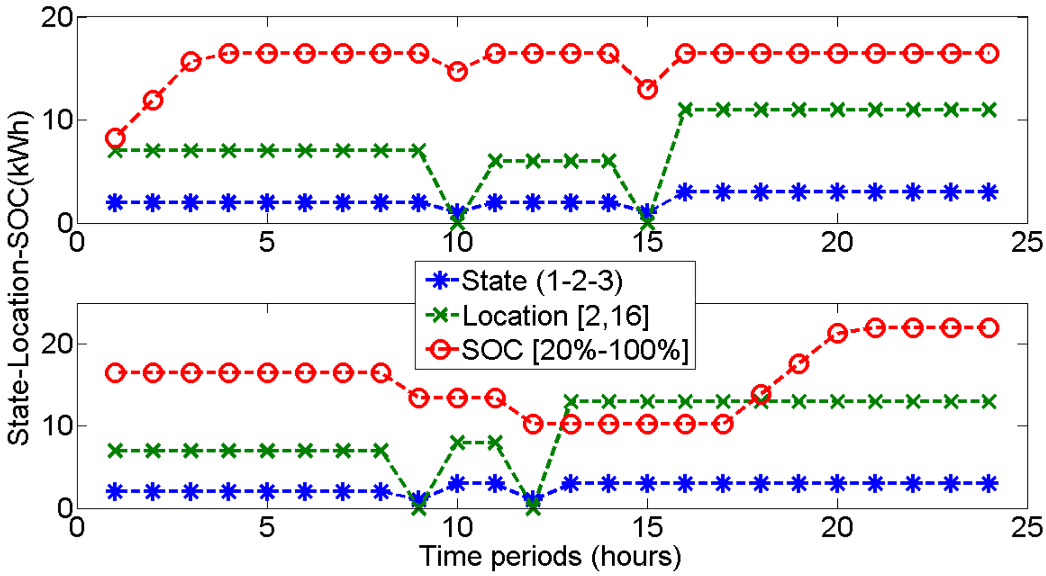

Figure 4.4: Pattern generation for EVs 2(above) and 9(below)

The process followed consists in performing several simulations according to these steps:

- The maximum number of simulations to carry out, the input parameters and the type of strategy to study are selected.
- For the current iteration, the EV patterns are generated using the described tool. With the obtained information, the hourly EV charging/discharging, bus location and transitions are taken for their posterior use.
- Making use of the EV patterns, 24 hourly power flows are carried out. The results regarding power flows and bus voltages are stored for the current iteration. Go to the following step after 10 simulations. Otherwise proceed in the same way from the previous step and next iteration.
- At every 10 simulations it is checked whether the stop criterion is met. In this latter case, the process is finished. In the opposite case, 10 new simulations are performed.

The stop criterion is based on the values of the apparent power flows resulting from the different simulations. At every 10 simulations, the hourly average and the standard deviations of the apparent power flows in every line are calculated. These values are compared in consecutive stages of the process until the differences fall below a predefined threshold. For the results presented next, the established limit was chosen as 0.1 kVA.

The generators' power output and the fixed battery contribution, used in the power flows, are taken from the problem solved in Chapter 2 when DSM is not applied.

Fig. 4.5 shows the convergence of the Monte Carlo simulation as the number of iterations performed increases. For the two cases analysed, i.e. the uncontrolled charging strategy and the charging/discharging managed by the aggregator, the percentage of values that comply with the stop criterion are shown. For the former strategy, 270 simulations were necessary while for the latter strategy 120 simulations were enough. These results show that the EV aggregators' optimisation problem produces less variations in the power flows as a consequence of a higher homogeneity of the EVs' charging/discharging.

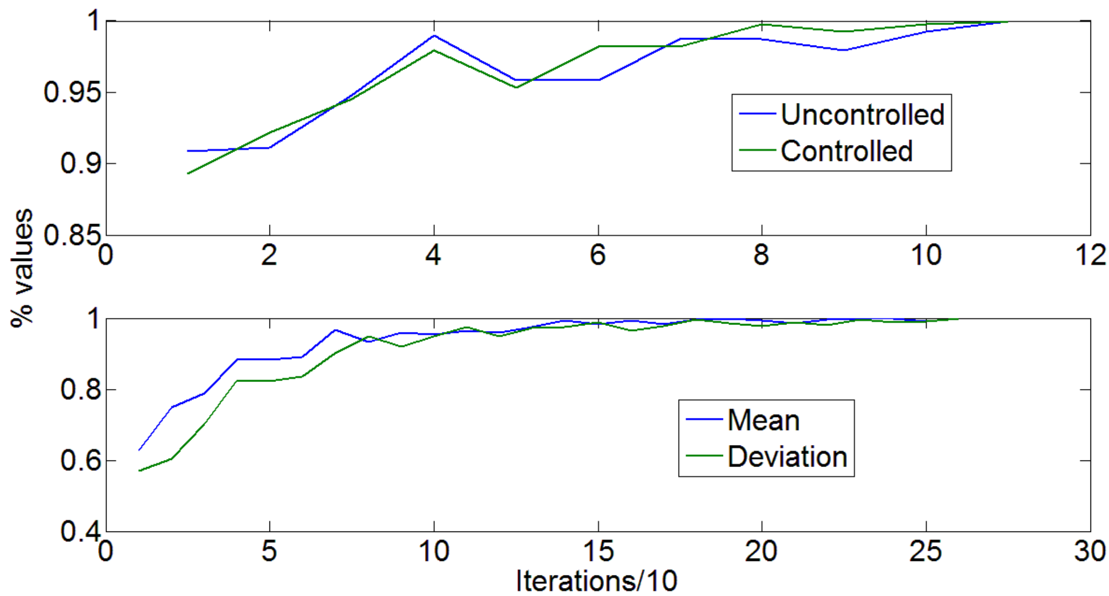

Figure 4.5: Monte Carlo simulation convergence

The average hourly charging/discharging for the two strategies considered is depicted in Fig. 4.6. As it can be observed, the EV aggregator allocates EV charging in those time periods when low prices for buying energy are expected while the opposite takes place when EV discharging is considered. Thus, according to its objective, the benefits are maximised. However, for the uncontrolled strategy, EV charging is allocated mainly at the beginning of the day and at the end of the day due to the EV drivers' behaviours taken into consideration.

If the costs for charging are evaluated for both strategies, it is found that EV aggregator strategy can reduce the costs for charging by more than four times those of the uncontrolled strategy.

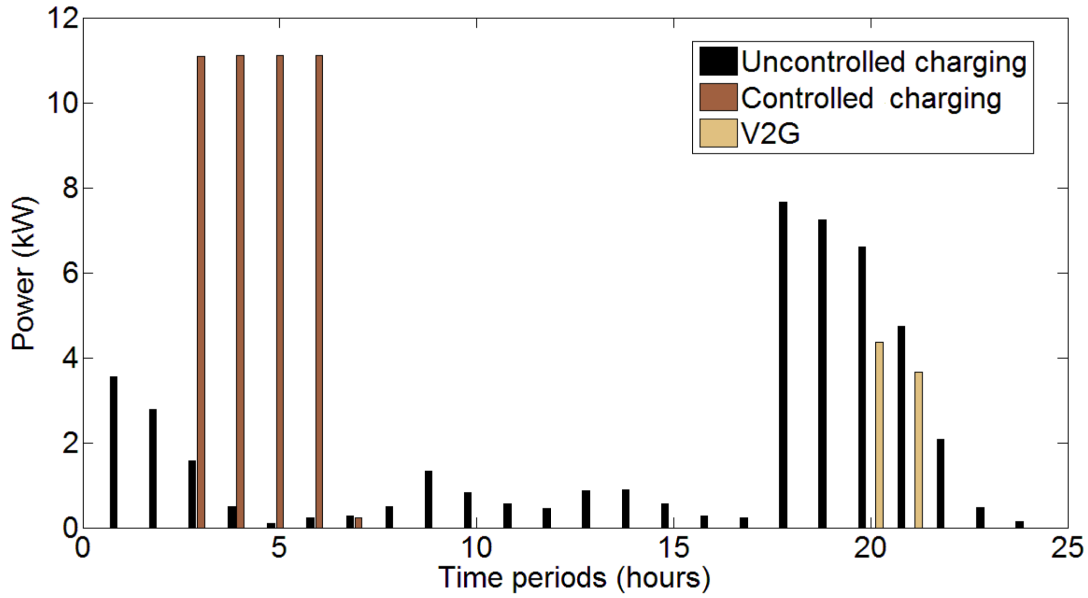

Figure 4.6: Hourly EVs charging/discharging for uncontrolled/aggregator strategies

4.5.3 System Technical Performance

In the last section it has been shown that when EV drivers adhere to the EV aggregators' management rules they can reduce the costs of charging their EVs or, at the same time, the EV aggregator maximises its benefits. However, the operation by the EV aggregator in addition leads to additional benefits from a technical performance point of view. The EVs' charging shift towards night hours allows a better usage of the grid, taking advantage of periods in which typically the grid load is small. On the other hand, V2G can support the grid providing energy in time periods when higher demands of energy are foreseen.

The MG taken as a case study system turned out to be quite robust in terms of bus voltages. Specifically, the bus voltages show little variation against changes in the EV charging patterns and in every bus the values remained within the bounds dictated by European Codes. However, if the power flows are analysed, it can be found that there are some congested lines or lines working near overload under certain EV charging patterns. Figs. 4.7 and 4.8 show the cumulative distribution function of apparent power flow in line 1-9, along with a continuous function approximation, for the two strategies considered, i.e. uncontrolled charging and charging/discharging managed by the EV aggregator.

Line 1-9, whose maximum apparent flow is 46 kVA, works far enough from the congestion limit when EV aggregator charging is applied whereas under uncontrolled charging

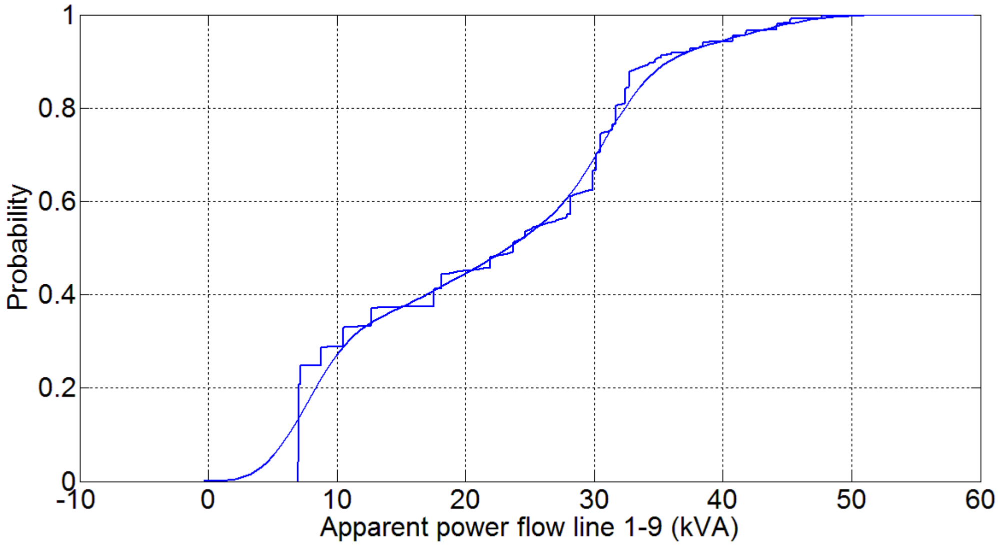

Figure 4.7: Cumulative distribution function for apparent power flow in line 1-9 Uncontrolled

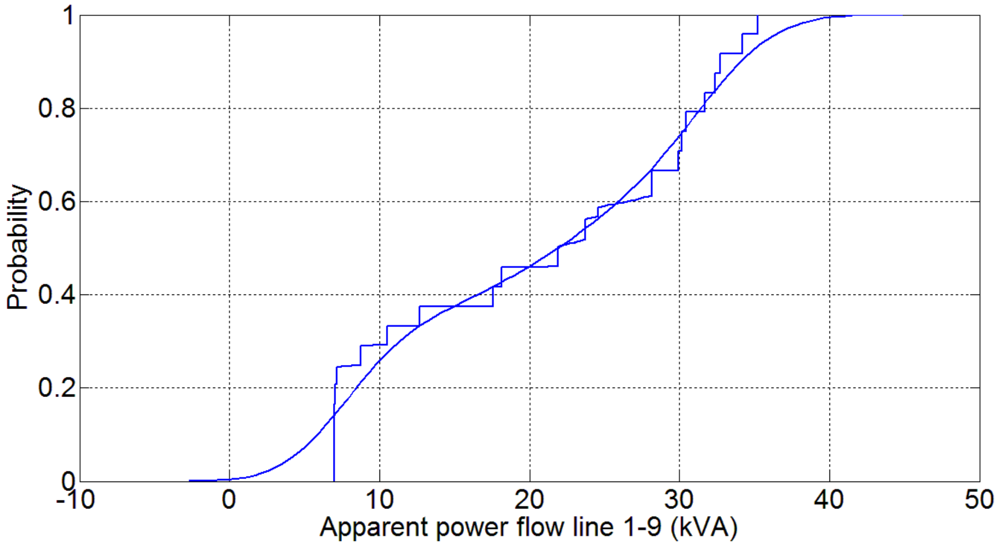

Figure 4.8: Cumulative distribution function for apparent power flow in line 1-9 Aggregator

there are some scenarios in which the line is congested. Although the probability of line 1-9 being congested is small, a change in grid load conditions may aggravate the technical problems in the grid that can however be mitigated changing the EV drivers' habits. The methodology presented herein can be used for system operators to focus their attention on those technical aspects that could jeopardize the grid and take measures in order to avoid them.

Chapter 5

Market-clearing with EV aggregators' participation

For the upcoming new generation of electric power systems, one of the most important challenges is to achieve an adequate economic and technical management involving the different agents in the process. As stated in previous chapters, the agent's market participation is possible in distributed energy systems at a local level through the use of suitable auction schemes. Smart grid operators can also watch over the security of the system. In this environment, EV aggregators are envisaged to gain importance in both issues. However, although they can take part in small electricity markets, like those within MGs, their active participation in wholesale markets makes sense when the aggregators gather EVs in groups of suitable sizes in order to bid efficiently. To this end, they can be responsible for the management of the EVs inside the system areas in which their activities take place, including MGs. In this chapter, an optimisation-based approach is proposed for clearing the market in a smart grid environment where the traditional participants in energy markets are included in the formulation, stressing the role of EV aggregators. Moreover, the proposed approach also includes security constraints. This model is applied to the IEEE-RTS 24-bus system.

5.1 Introduction

In order to facilitate the integration of EVs under the smart grid concept the development of specific tools that allow them to participate in the market whilst also complying with the necessary security restrictions in the system is an interesting prospective. EVs' incorporation in electricity markets cannot be done individually because the amount of energy they can offer is very small compared to other agents' offers. Therefore, their participation makes sense under an EV aggregator entity that can merge the individual requirements and constraints of EVs to submit bids to the market [25, 26].

In this chapter, an optimisation-based market-clearing model, including the role of EV aggregators, is proposed. The objective function aims at maximising the difference between the price the consumers are willing to pay for their energy and the price the suppliers offer for their production; clearing the market and satisfying the security requirements at the same time. Along with the traditional agents involved in a market-clearing procedure, such as suppliers and consumers, the effect, constraints and role of EV aggregators are described and studied. Thus, the formulation shown in [141] is completed through the inclusion in the model of EV aggregators that can bid for buying or selling energy although satisfying the mobility requirements of the fleet they represent.

The corresponding optimisation problem including the objective function, constraints for each participant and the model adopted for the grid, is completely described in Section 5.2.

5.2 Optimisation-based approach model

To define the optimisation problem it is necessary to take into account the contribution of the different participants of the process both in the objective function and the constraints. Hence, the problem is formulated as the maximisation of the sum of four terms:

$$\begin{aligned} \text{maximise} \quad & z_S + z_C + z_B + z_A \\ \text{s.t.} \quad & \mathbf{f}_S \leq \mathbf{0}, \quad \mathbf{f}_C \leq \mathbf{0}, \quad \mathbf{f}_B \leq \mathbf{0} \\ & \mathbf{f}_A \leq \mathbf{0}, \quad \mathbf{g} = \mathbf{0} \end{aligned} \tag{5.1}$$

where z_S, z_C, z_B and z_A are the functions that define the utility for suppliers, consumers, bilateral contracts and EV aggregators respectively and $\mathbf{f}_S$, $\mathbf{f}_C$, $\mathbf{f}_B$ and $\mathbf{f}_A$ represent the corresponding inequality constraints. Function **g** includes the equations for balancing supply and demand in the grid.

For the market to operate, as shown above, four elements have been considered:

- S, set of suppliers that submit offers for selling power and spinning-reserve, where $S = 1, 2, ..., n_s$.
- C, set of consumers that bid for buying power, where $C = 1, 2, ..., n_c$.
- B, set of bilateral agreements, where $B = 1, 2, ..., n_b$.
- A, set of EV aggregators, where $A = 1, 2, ..., n_a$.

The contribution to the objective function and constraints for each participant are described next in detail. Hereafter, the time horizon considered is a whole day in time steps of 1 hour and, thus, all the agents are considered to bid in hourly form.

5.2.1 Suppliers

To participate in the market, suppliers have to submit the power available and the power dedicated to spinning reserve, along with their offer prices, in each time period, which are typically given on a day-ahead basis. This way, the suppliers function z_S in (5.1) can be written as:

$$z_S = -\sum_{t=1}^{n_t} \sum_{i=1}^{n_s} (\mu_t^i \cdot p_t^i + \nu_t^i \cdot r_t^i) \tag{5.2}$$

where p_t^i and r_t^i are the hourly amounts of power and spinning -reserve put to bid and μ_t^i and ν_t^i are the corresponding hourly offer prices, respectively, for each supplier i and time period t in monetary units (m.u.) per MWh. The parameter n_t defines the time horizon.

Conventional generators have to conform with the following equations regarding operation:

$$0 \leq p_t^i + r_t^i \leq p_{max}^i \quad \forall i \in S, \forall t \in T \tag{5.3}$$

$$p_{t+1}^i - p_t^i \leq \triangle \bar{u}_i \quad \forall i \in S, \forall t \in T \tag{5.4}$$

$$p_t^i - p_{t+1}^i \leq \nabla \bar{u}_i \quad \forall i \in S, \forall t \in T \tag{5.5}$$

Equation (5.3) expresses that power output for generators, sum of the quantities related to power and spinning-reserve, cannot be higher than the upper technical limit p_{max}^i.

Equations (5.4) and (5.5) model generator' ramping rates through the parameters $\triangle\bar{u}_i$ and $\bigtriangledown\bar{u}_i$ representing upper and lower limits respectively.

The sum of each generator output extended over the time horizon is limited to a maximum value generally established based on technical, environmental or strategical considerations. In addition, the required power dedicated to spinning-reserve has to be satisfied. These two conditions are implemented through Eqs. (5.6) and (5.7):

$$\sum_{t=1}^{n_t} p_t^i \leq E_i^{max} \quad \forall i \in S \tag{5.6}$$

$$\sum_{i=1}^{n_s} r_t^i \leq SR^t \quad \forall t \in T \tag{5.7}$$

where E_i^{max} is the maximum production volume for unit i and SR^t is the amount of reserve in time y.

The nodal power injection $P_{t,n}^S$ for the suppliers is:

$$P_{t,n}^S = \sum_{i \propto n} p_t^i \quad \forall t \in T, \forall n \in N \tag{5.8}$$

where $i \propto n$ defines all suppliers i connected to a bus n.

5.2.2 Consumers

Consumers participating in the market bid for demand in the time horizon for buying the energy they need. However, they bid only for the dispatchable demand, that is, the amount of power/energy demand that could not be served. The remainder, the inelastic demand, is included in the power balance regardless of the price. Therefore, the consumers' function z_C in (5.1) is:

$$z_C = \sum_{t=1}^{n_t} \sum_{j=1}^{n_c} \lambda_t^j \cdot \underline{d}_t^j \tag{5.9}$$

where $\underline{d}_t^j$ is the hourly amount of dispatchable demand and λ_t^j and is the corresponding hourly offer price, respectively, for each consumer j and time period t.

The maximum hourly dispatchable demand is limited to a fraction τ_t^j of the total demand d_t^j:

$$0 \leq \underline{d}_t^j \leq \tau_t^j \cdot d_t^j \quad \forall j \in C, \forall t \in T \tag{5.10}$$

The nodal power demand $D^C_{t,n}$ for the consumers at bus n is the sum of non-dispatchable and dispatchable demand:

$$D^C_{t,n} = \sum_{j \propto n} \left((1 - \tau^j_t) \cdot d^j_t + \underline{d}^j_t \right) \quad \forall t \in T, \forall n \in N \tag{5.11}$$

where $j \propto n$ defines all consumers j connected to a bus n.

5.2.3 Bilateral agreements

For bilateral agreements it is necessary to establish the schedule for the hourly amounts that are under the contract between specific sellers and buyers:

$$z_B = \sum_{t=1}^{n_t} \sum_{b=1}^{n_b} (\varepsilon^b_t \cdot \triangledown c^b_t - \vartheta^b_t \cdot \triangle c^b_t) \tag{5.12}$$

where the quantities $(\varepsilon^b_t, \triangledown c^b_t)$, $(\vartheta^b_t, \triangle c^b_t)$ define the corresponding pairs of scheduled price and energy decremental and incremental respectively.

The amount of energy under contract is represented by E^b_t; the decremental and incremental constraints are given by:

$$0 \leq \triangle c^b_t \leq \overline{\varphi}_b \cdot E^b_t \tag{5.13}$$

$$0 \leq \triangledown c^b_t \leq \underline{\varphi}_b \cdot E^b_t \tag{5.14}$$

where $\overline{\varphi}_b$ and $\underline{\varphi}_b$ are the fractions of the contracted energy that the supplier is willing to sell or buy in the market.

The nodal contribution from bilateral contracts is:

$$P^B_{t,n} = \sum_{b \propto n} (E^b_t + \triangledown c^b_t - \triangle c^b_t) - \sum_{\overline{b} \propto n} E^{\overline{b}}_t \quad \forall t \in T, \forall n \in N \tag{5.15}$$

where $b \propto n$ and $\overline{b} \propto n$ define the seller and buyer connection buses to the grid and $E^b_t = E^{\overline{b}}_t$, i.e. the energy transactions between bilateral sellers and buyers are the same.

5.2.4 EV aggregator model

Under this model EVs can act as consumers, bidding for demand, or alternatively they can act as suppliers, submitting offers and, therefore, performing V2G; bidding through an EV aggregator agent. It is assumed that EVs are bundled in groups with similar movement patterns. The EV aggregator is responsible for satisfying the mobility requirements of the group; it also manages V2G activity whenever necessary. The hourly bids allow the allocating of the charging and discharging when it is most economically beneficial. The EV aggregator can coordinate one or several groups of EVs located in different buses of the grid although, in practice, these groups belong to the areas in which the EV aggregator carries out its activities.

The EV contribution is determined through the EV pattern, that is, the time periods when EVs are available in a particular node for charging or discharging, and the time periods when they are travelling. Assuming that a group of EVs cannot sell and buy energy in the same time period, the clearing market procedure will yield, on the one hand, the allocation of EV charging to meet mobility requirements and, on the other hand, EV discharging.

The aggregator function z_A is expressed in the following way:

$$z_A = \sum_{t=1}^{n_t} \sum_{a=1}^{n_a} (\beta_t^a \cdot p_t^{c,a} - \alpha_t^a \cdot p_t^{d,a}) \tag{5.16}$$

where $p_t^{d,a}$ and $p_t^{c,a}$ are the discharging power offered and the charging power required for EVs belonging to an aggregator a, respectively; and α_t^a and β_t^a are the corresponding offer prices.

Note that variables $p_t^{c,a}$ and $p_t^{d,a}$ represent the total hourly charging and discharging power for a group g of n_a^g EVs, belonging to an aggregator a, with identical movement pattern. Parameters β_t^a and α_t^a can depend on the bus where EVs are connected and are also the instruments to control the charging and discharging allowing flexibility to perform varied strategies. A group of EVs will behave in the same way, that is, they all will charge or discharge simultaneously, though EVs located at the same bus can also be classed in different groups. The EV aggregator will have at its disposal historical data and information provided by the owners to divide the EVs under its charge into clusters with the same patterns.

The constraints considered regarding the maximum charging and discharging power are:

$$0 \leq p_t^{c,a} \leq P_n^{max} \cdot n_a^g \quad \forall a \in A, \forall t \in T, \forall n \in N \tag{5.17}$$

$$0 \leq p_t^{d,a} \leq P_n^{max} \cdot n_a^g \quad \forall a \in A, \forall t \in T, \forall n \in N \tag{5.18}$$

where P_n^{max} is the nodal power rate.

The nodal contribution of EVs is expressed as:

$$P_{t,n}^{A} = \sum_{a \propto n} (p_t^{d,a} - p_t^{c,a}) \ \ \forall t \in T, \forall n \in N \tag{5.19}$$

where $a \propto n$ defines all EVs belonging to the aggregator a connected to bus n.

The battery SOC S_t^a for one EV in group g has to comply with the following constraints that allows for satisfying its mobility needs:

$$S_{t+1}^a = S_t^a + \eta_c \cdot \frac{p_t^{c,a}}{n_a^g} - (1/\eta_d) \cdot \frac{p_t^{d,a}}{n_a^g} - C_t^a \ \ \forall a \in A, \forall t \in T \tag{5.20}$$

$$S_{min}^a \leq S_t^a \leq S_{max}^a \ \ \forall a \in A, \forall t \in T \tag{5.21}$$

$$S_t^a = S_{max}^a \ \ if \ \ t = t^* \ \ \forall a \in A \tag{5.22}$$

$$S_{t_i}^a \leq S_{t_f}^a \ \ \forall a \in A \tag{5.23}$$

Equation (5.20) guarantees the transition of the SOC S_t^a according to the EV charging, EV discharging and consumption due to mobility C_t^a in the current time period through the corresponding charging and discharging efficiencies, η_C, η_D. The terms $p_t^{c,a}/n_a^g$ and $p_t^{d,a}/n_a^g$ are the absorbed and drawn power for a single EV respectively. Equation (5.21) limits the maximum and minimum value for the SOC in S_{max}^a and S_{min}^a. Finally, (5.22) assigns the maximum value for the SOC in time period t^*, early morning, and (5.23) establishes that the final SOC has to be higher or equal to the initial SOC.

5.2.5 Grid model

Regarding security constrains a DC power flow model has been adopted [135]:

$$P_{m,n}^t = B_{m,n} \cdot (\theta_t^m - \theta_t^n) \ \ \forall m,n \in N, \forall t \in T, m \neq n \tag{5.24}$$

where $P_{m,n}^t$ is the active power flow in line $m - n$ from bus m to bus n, $B_{m,n}$ is the line susceptance and θ_m, θ_n are the phase angles.

The limits for active power flow are defined by:

$$-P_{m,n}^{max} \leq P_{m,n}^t \leq P_{m,n}^{max} \ \ \forall m,n \in N, \forall t \in T, m \neq n \tag{5.25}$$

which has to hold for every line connecting buses m and n. Negative values mean that the power flow goes from bus n to bus m.

The power balance in every bus of the grid is guaranteed by:

$$P_{t,n}^{S} + P_{t,n}^{B} + P_{t,n}^{A} + \sum_{m \prec n} P_{m,n}^{t} = D_{t,n}^{C} + \sum_{m \prec n} P_{m,n}^{L,t} \quad \forall n \in N, \forall t \in T, m \neq n \tag{5.26}$$

where $m \prec n$ denotes all the m buses connected to n. The term related to active power losses $P_{m,n}^{L,t}$ allocates 50 % of the losses in line $m-n$ to node n and it is computed through a quadratic model [142]:

$$P_{m,n}^{L,t} = B_{m,n} \cdot (\theta_t^m - \theta_t^n)^2 \quad \forall m, n \in N, \forall t \in T, m \neq n \tag{5.27}$$

5.2.6 Complete formulation

The market-clearing algorithm with security constraints can be completely formulated with the following objective function and constraints:

$$\begin{aligned} \text{maximise} \quad & z_S + z_C + z_B + z_A \\ \text{s.t.} \quad & \mathbf{f}_S \leq \mathbf{0}, \quad \mathbf{f}_C \leq \mathbf{0}, \quad \mathbf{f}_B \leq \mathbf{0} \\ & \mathbf{f}_A \leq \mathbf{0}, \quad \mathbf{g} = \mathbf{0} \end{aligned}$$

$$z_S = -\sum_{t=1}^{n_t} \sum_{i=1}^{n_s} (\mu_t^i \cdot p_t^i + \nu_t^i \cdot r_t^i)$$

$$0 \leq p_t^i + r_t^i \leq p_{max}^i \quad \forall i \in S, \forall t \in T$$

$$p_{t+1}^i - p_t^i \leq \triangle \bar{u}_i \quad \forall i \in S, \forall t \in T$$

$$p_t^i - p_{t+1}^i \leq \triangledown \bar{u}_i \quad \forall i \in S, \forall t \in T$$

$$\sum_{t=1}^{n_t} p_t^i \leq E_i^{max} \quad \forall i \in S$$

$$\sum_{i=1}^{n_s} r_t^i \leq SR^t \quad \forall t \in T$$

$$P_{t,n}^S = \sum_{i \propto n} p_t^i \quad \forall t \in T, \forall n \in N$$

$$z_C = \sum_{t=1}^{n_t} \sum_{j=1}^{n_c} \lambda_t^j \cdot \underline{d}_t^j$$

$$0 \leq \underline{d}_t^j \leq \tau_t^j \cdot d_t^j \quad \forall j \in C, \forall t \in T$$

$$D_{t,n}^C = \sum_{j \propto n} \left((1 - \tau_t^j) \cdot d_t^j + \underline{d}_t^j \right) \quad \forall t \in T, \forall n \in N$$

$$z_B = \sum_{t=1}^{n_t} \sum_{b=1}^{n_b} (\varepsilon_t^b \cdot \triangledown c_t^b - \vartheta_t^b \cdot \triangle c_t^b)$$

$$0 \leq \triangle c_t^b \leq \overline{\varphi}_b \cdot E_t^b$$

$$0 \leq \triangledown c_t^b \leq \underline{\varphi}_b \cdot E_t^b$$

$$P_{t,n}^B = \sum_{b \propto n} (E_t^b + \triangledown c_t^b - \triangle c_t^b) - \sum_{\bar{b} \propto n} E_t^{\bar{b}} \quad \forall t \in T, \forall n \in N$$

$$z_A = \sum_{t=1}^{n_t} \sum_{a=1}^{n_a} (\beta_t^a \cdot p_t^{c,a} - \alpha_t^a \cdot p_t^{d,a})$$

$$0 \leq p_t^{c,a} \leq P_n^{max} \cdot n_a^g \quad \forall a \in A, \forall t \in T, \forall n \in N$$

$$0 \leq p_t^{d,a} \leq P_n^{max} \cdot n_a^g \quad \forall a \in A, \forall t \in T, \forall n \in N$$

$$P_{t,n}^A = \sum_{a \propto n} (p_t^{d,a} - p_t^{c,a}) \quad \forall t \in T, \forall n \in N$$

$$S_{t+1}^a = S_t^a + \eta_c \cdot \frac{p_t^{c,a}}{n_a^g} - (1/\eta_d) \cdot \frac{p_t^{d,a}}{n_a^g} - C_t^a \quad \forall a \in A, \forall t \in T$$

$$S_{min}^a \leq S_t^a \leq S_{max}^a \quad \forall a \in A, \forall t \in T$$

$$S_t^a = S_{max}^a \quad if \quad t = t^* \quad \forall a \in A$$

$$S_{t_i}^a \leq S_{t_f}^a \quad \forall a \in A$$

$$P_{m,n}^t = B_{m,n} \cdot (\theta_t^m - \theta_t^n) \quad \forall m, n \in N, \forall t \in T, m \neq n$$

$$-P_{m,n}^{max} \leq P_{m,n}^t \leq P_{m,n}^{max} \quad \forall m, n \in N, \forall t \in T, m \neq n$$

$$P_{t,n}^S + P_{t,n}^B + P_{t,n}^A + \sum_{m \prec n} P_{m,n}^t = D_{t,n}^C + \sum_{m \prec n} P_{m,n}^{L,t} \quad \forall n \in N, \forall t \in T, m \neq n$$

$$P_{m,n}^{L,t} = B_{m,n} \cdot (\theta_t^m - \theta_t^n)^2 \quad \forall m, n \in N, \forall t \in T, m \neq n$$

5.3 Case study

The case study network is based on the data and characteristics for the IEEE-RTS 24-bus system, composed of 38 lines, 10 generating units, 14 consumption units, 2 bilateral contracts and 15 buses with EVs, Fig. 5.1. The line parameters regarding resistances, reactances and capacities can be found in table number 13 in [143].

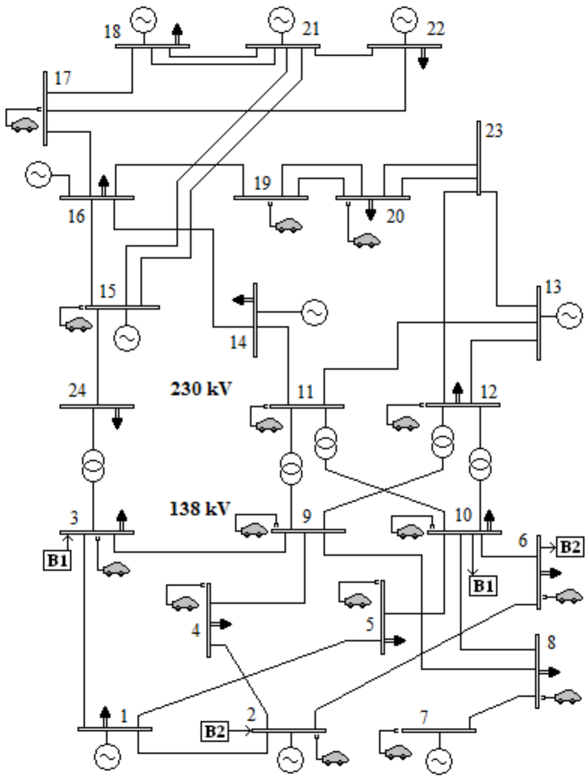

Figure 5.1: RTS 24-bus system

The technical data for each generator, namely the maximum power output and ramp rates, along with the bus location, are given in Table 5.1. In this case, the production volume is not limited, while the hourly power reserve is between 15 MW and 30 MW, being higher in intermediate and late time periods.

Table 5.1: Technical data for generating units

Bus	p_{max} (MW)	$\triangle\bar{u}$ (MW)	$\bigtriangledown\bar{u}$ (MW)
1	100	50	50
2	100	50	50
7	76	40	40
13	76	40	40
14	20	5	5
15	76	40	40
16	76	40	40
18	20	10	10
21	20	20	20
22	20	7	7

As stated previously, the model is solved for a 24 hour horizon. Thus, the hourly offer prices, regarding suppliers, for both power and reserve, have to be defined hourly. On the other hand, these prices should be cost reflective, in other words, the generation costs have to be included in some way through the corresponding offers. That is why they were obtained adapting the generation costs given in [143] depending on the different production technologies. Fig. 5.2 shows the prices for three representative suppliers corresponding to the most expensive, cheapest and intermediate cases. For the rest of suppliers, these values are between the two extreme cases represented.

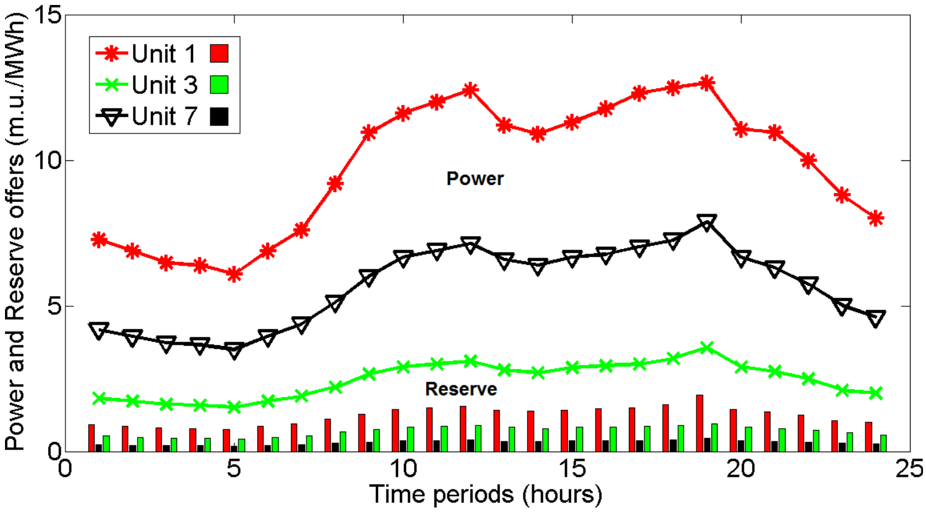

Figure 5.2: Hourly suppliers offers

In the same fashion, Fig. 5.3 depicts the hourly offer prices and the total amount of demand, dispatchable and inelastic, for the consumer located at bus 5. For the rest of the consumers the demand trend is similar with significant loads towards the end of the day. The amount of dispatchable demand depends on the time period and is between 0% and 20 %. The bidding prices for dispatchable demand are calibrated to provide illustrative results although they are of similar magnitude among consumers.

Regarding the two bilateral contracts, the energy selling and purchase bids are 8, 9 and 4, 3, in $m.u./MWh$, respectively for both. The amount of energy the supplier is willing to sell or buy in the market is assumed to be 20% for both contracts. The volume of energy contracted is different for every time period and lies between 10 MW and 30 MW.

Finally, 7800 EVs have been considered in the system, roughly constituting 5 % of the system power capacity if they were all charging simultaneously in the same time

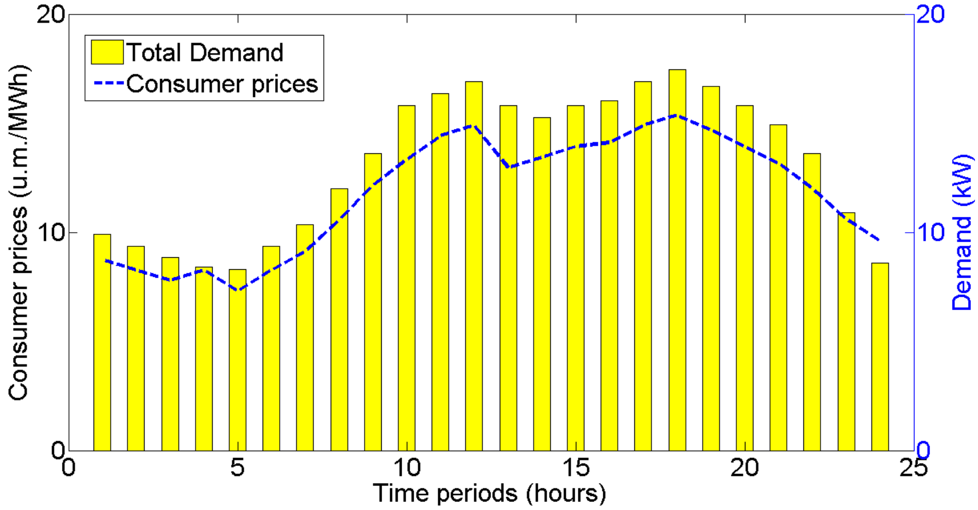

Figure 5.3: Hourly consumer load and offers

period. They have been distributed into 30 groups of 260 EVs each, with 2 groups in each bus. It is assumed that all the EVs have the same characteristics; the maximum and minimum battery levels are 16.5 kWh and 2.0 kWh respectively. A value of 3.7 kW has been chosen for the maximum individual EV charging and discharging whilst the corresponding efficiencies, η_C and η_D, are 0.90 and 0.95. These EVs are managed by three EV aggregators which operate downstream of the connection bus.

It is considered that each EV performs two journeys a day. The outward journey takes place in the early morning and the return journey in the afternoon, or evening. Fig. 5.4 gives the hourly configuration of the journeys and the total consumption in MWh for all the EVs. It is also assumed that EVs are attached to a particular bus in the system, that is, when EVs move, connection points at the origin and destination are linked to the same transmission grid bus. The battery consumption represented in Fig. 5.4 takes place when the EVs are moving; this is not a load for the grid. These patters are completely defined in Table A.16.

With respect to EV offer prices, these were chosen to represent realistic situations taking into account the results from the previous EV aggregator problem as explained in Chapter 4. Additional details are given in the next section.

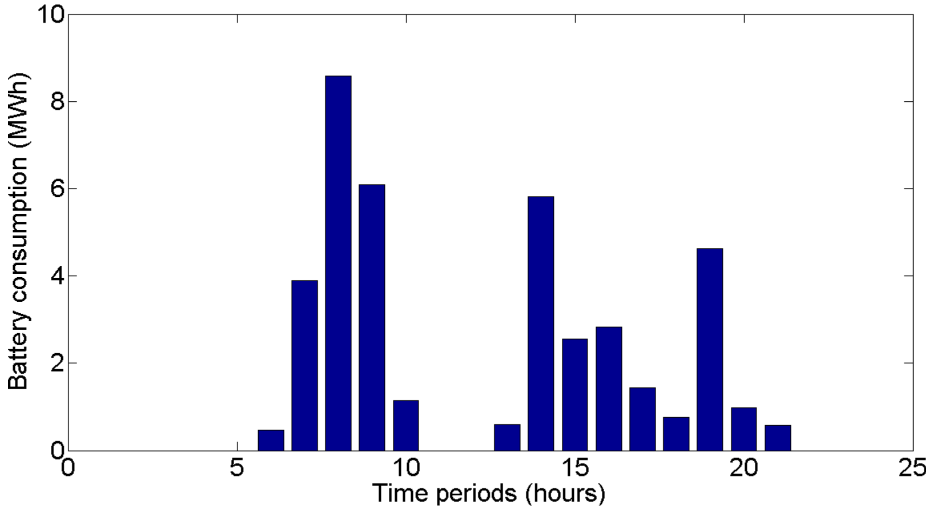

Figure 5.4: EV battery consumption in trips

5.4 Results

This section is dedicated to presenting the most relevant results of applying the proposed market-clearing model to the described system: i) Nodal prices, ii) Generators power output, iii) Dispatchable demand, iv) Bilateral contracts, v) Hourly EVs charging and discharging for each aggregator.

In relation to nodal prices, Fig. 5.5 shows by way of example the price for four different buses. In practice, nodal prices determine, for instance, the dispatch of generators

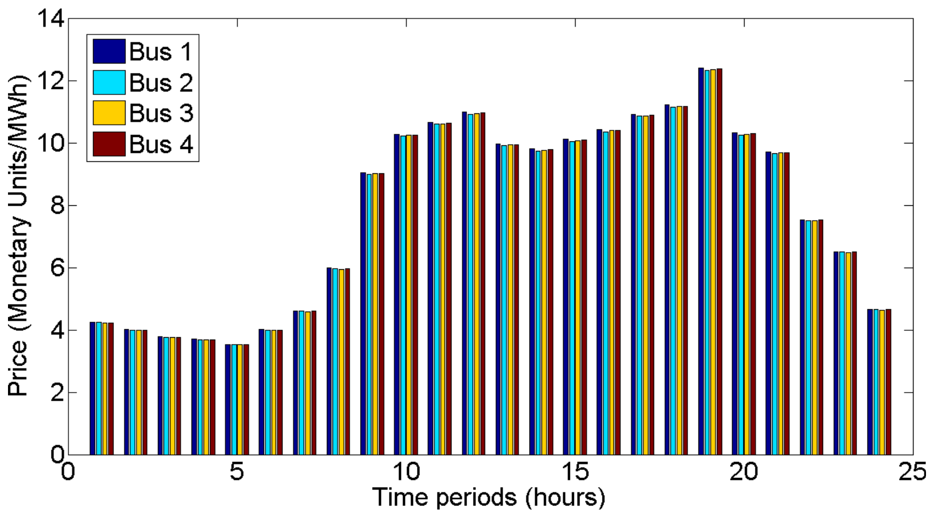

Figure 5.5: Hourly nodal price for several buses

and demand. Mathematically, they can be determined through the Lagrange multipliers associated with the nodal balance equation, see Eq. (5.26). In this work, it is assumed that the system capacity is high enough so that no congestion takes place in lines. Thus, nodal prices are very close although they are slightly different because of losses.

As an example, the hourly generation level for three representative generators is shown in Fig. 5.6. The production is higher at the end of the day due to the increased demand, which entails starting-up the most expensive generators. On the other hand, the most inexpensive generators are running the whole day.

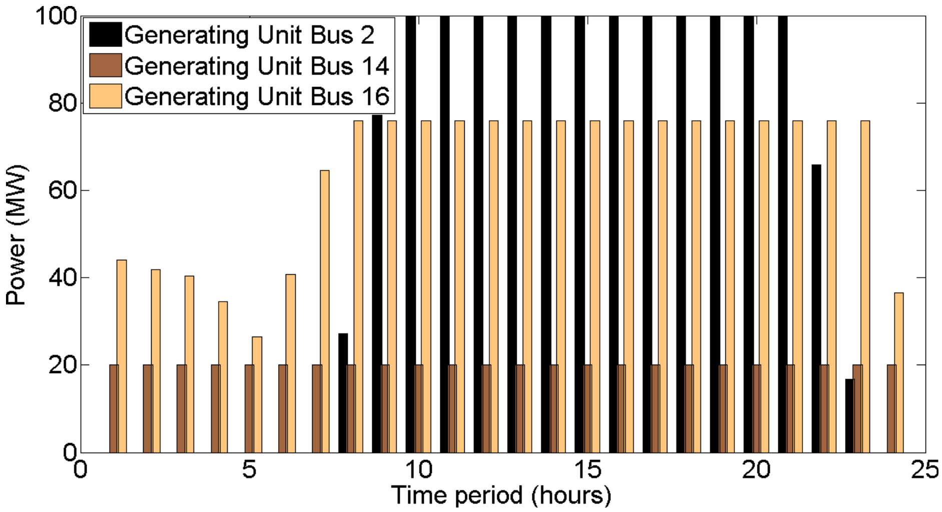

Figure 5.6: Hourly generation level

Two of these generators contribute significantly to spinning-reserve while for the remaining time periods it is provided by other ones, Fig. 5.7.

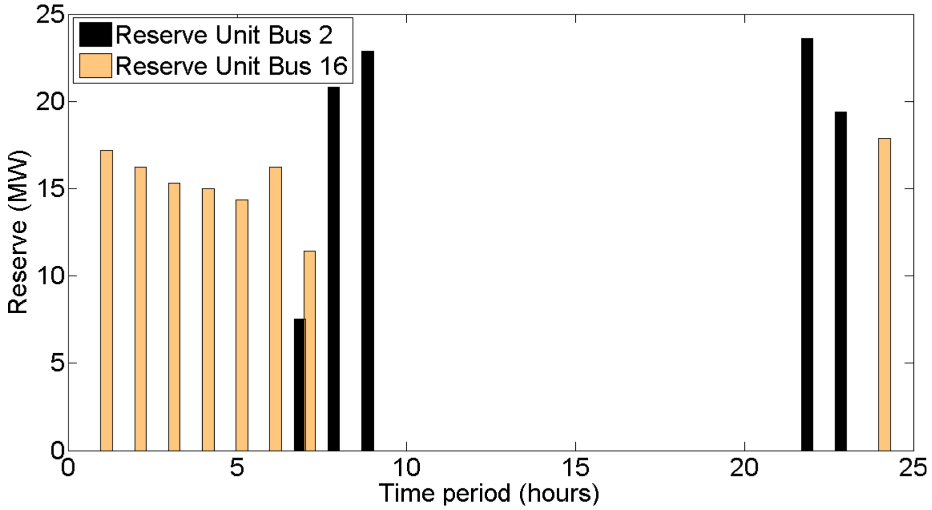

Figure 5.7: Hourly reserve level

Fig. 5.8 shows the aggregated amounts of dispatchable and inelastic demand for two consumers as a result of the market-clearing procedure. As stated previously, inelastic demand is always satisfied since the consumers do not bid for it, while the dispatchable demand may be not served. The latter represents a small percentage of the total demand.

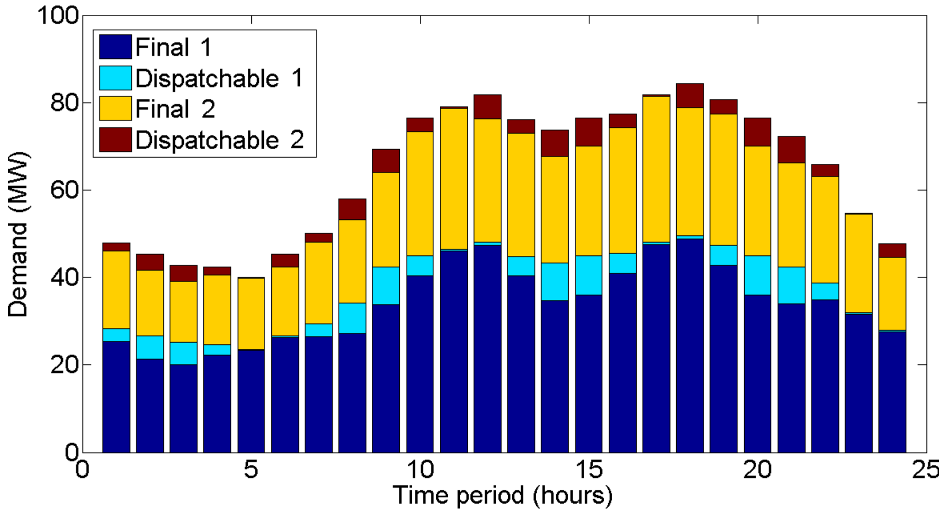

Figure 5.8: Hourly dispatchable and inelastic demand

Some results for bilateral contracts are given in Table 5.2. For contract 2, the supplier buys energy from the market in the early time periods due to the market price being lower than the limit established in the contract. However, for both contracts the suppliers sell energy to the market in the intermediate time periods since the market price is higher than the limit established in the contract.

Table 5.2: Bilateral contracts results

Bilateral contract 1				
Period	Market price	ε_t^b	ϑ_t^b	Agreement
4	3.69	4	8	Buy 2.0 MWh
14	9.77	4	8	Sell 3.0 MWh
Bilateral contract 2				
19	12.33	3	9	Sell 4.5 MWh

Finally, EV allocation for charging and discharging is described next for the three aggregators taken into consideration. Figs. 5.9 shows the results from each EV aggregators' optimisation problem as presented in Chapter 4. It is assumed that EV aggregator 1 is responsible for EVs located at buses 2, 3, 4 and 9, EV aggregator 2 for EVs located at buses 5, 6, 7, 8 and 10, and EV aggregator 3 for EVs located at buses 11, 12, 15, 17, 19 and 20. These configurations are optimal in the sense of they allow the aggregators to maximise their benefits. On the other hand, they can be used as a tool to know how to bid in the market.

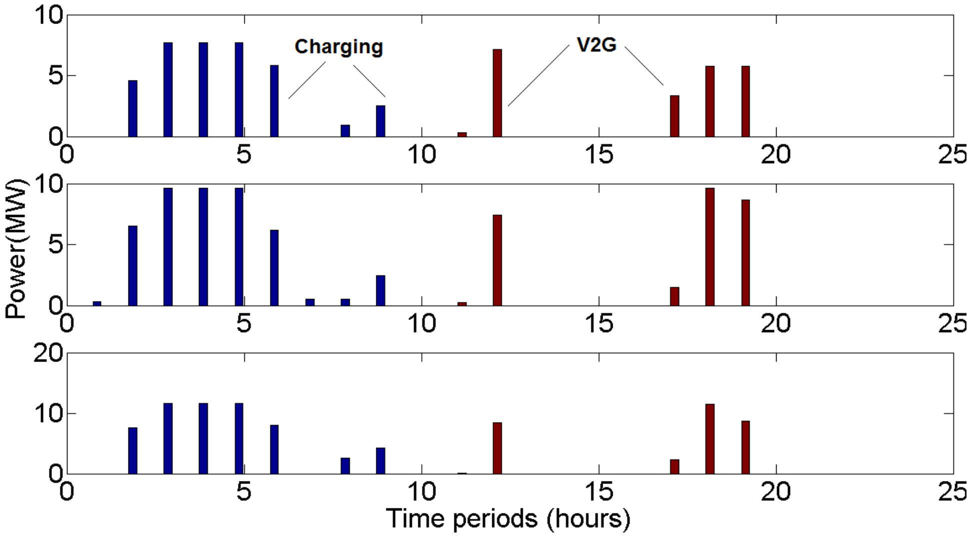

Figure 5.9: EVs total charging/discharging Aggregator problem

Fig. 5.10 depicts the EVs allocation for charging and discharging as a result of the market-clearing procedure.

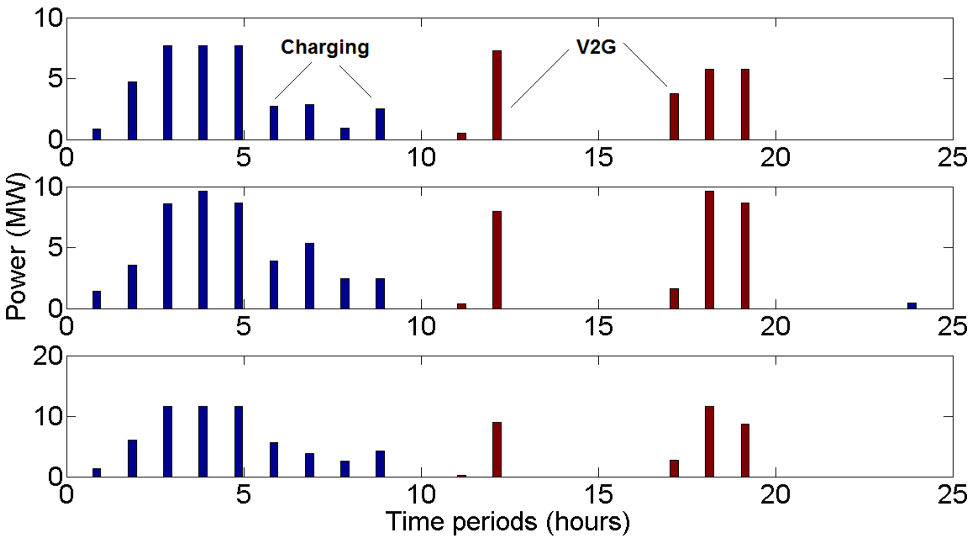

Figure 5.10: EVs total charging/discharging Market-clearing

The EV aggregator takes advantage of low purchase prices for EV charging, biding high in the early time periods. However, the EV aggregator bids high at demand peaks to get additional benefits. This behaviour conforms with the strategy adopted to maximise their profits. It is assumed that the EV aggregators have at their disposal historical data regarding market prices to perform the bids, sufficiently close to their expected values. The purchase bids have been chosen two times higher with respect to these prices while the selling bids have been reduced to half in the corresponding time periods.

The EV aggregator's offer mechanism also allows for benefits for the grid so EV charging is used to fill valleys whereas EV discharging is used for peak shaving. Fig. 5.11 shows the final load curve considering the effect of all the EVs.

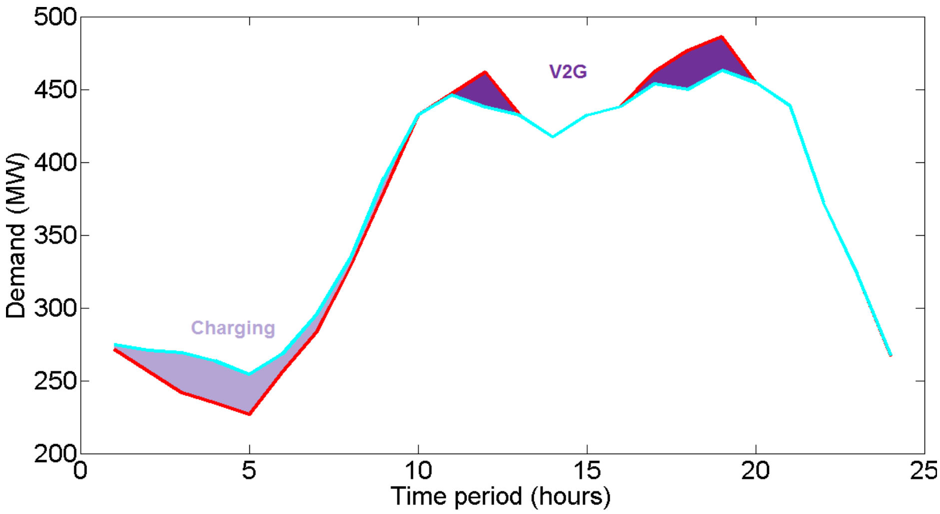

Figure 5.11: Demand curve with EVs

Chapter 6

Conclusions and Future Work

This chapter brings the thesis to an end, providing the main conclusions and the aspects of interest for future research developments.

6.1 Conclusions

A model based on DSM strategies, as a part of a comprehensive framework including economical and technical issues under the SG concept, has been developed in this thesis. This model makes use of optimisation problems to enable the flattening of the daily electricity load curve, shifting the demand from later time periods to earlier time periods in response to hourly prices. Different types of agents that own distinct elements have been considered. Through the proposed model, they can maximise their benefits or, otherwise, minimise the costs for the energy they need. It has been shown that load shifting can be applied to common grid loads and also to EV charging, thus helping to allocate the demand more efficiently and flattening even more the load curve. This effect depends strongly on the adequate selection of the parameters conditioning the results of the corresponding optimisation problem. In particular, the hourly prices configuration is one the most important factors to take into account since the load will be shifted to those time periods when lower energy prices are expected. In addition, the particular characteristics of the load curve and the elements included in the system have to be also considered. However, the parameter k that defines the maximum number of time periods that load can be shifted, forwards or backwards, has also a significant influence. Regarding this, although the system benefits from a better load rearrangement as the parameter increases, these benefits are not so clear if technical aspects such as losses or power flows are analysed. Results show that an intermediate value for k between 3 and 12 provides more favourable results from both the system's and agents' points of view.

With respect to the technical management, a centralised OPF has been developed and tested. Modifying the generators' output, control variables of the problem, it has been illustrated how the line congestion can be alleviated. However, this approach cannot give a solution in feeders that are overloaded in some of its lines and, additionally, which do not have generators. In the absence of alternative measures, load shedding should be carried out. However, a novel algorithm has been proposed to solve technical congestion problems using the capability of an EV to change its initial expected charging pattern. Using this algorithm, EVs can help the system by charging more than initially required, decreasing or interrupting the charging, or even supplying energy, that is, employing V2G to that end. In this way, EVs can alleviate line congestion regardless of the presence of generators in the feeder. The EVs' contribution, in terms of active power injection, is calculated using DFs and some specific rules to select the most suitable buses with EVs and how much energy is needed to lead a line to a secure state. For the scenarios presented, it has been demonstrated that a small number of EVs is enough to tackle line congestion although higher levels of congestion require more EVs, also taking into account the increment in reactive power flow due to the changes in bus injection.

An optimisation problem, envisaged to be used by EV aggregators, has been described and studied. This problem allows aggregators to maximise their benefits determining the most favourable time periods for charging and discharging but satisfying the EVs' mobility requirements at the same time. The influence of different parameters has been highlighted, the EV patterns and the energy prices being the most relevant. It has been shown that EV aggregators need to suitably forecast the electricity prices since they define the time periods in which the charging/discharging should be performed, but it is also necessary to have certain knowledge about the availability of the EVs for connection in those time periods. Results have revealed that EVs have to be charged during night hours whereas the discharging must take place in the latest time periods of the day to allow aggregators to maximise their profits.

Provided that there is a relation between electricity prices and load demand, the EV aggregator strategy leads to a filling of the valleys and s shaving of the peaks. This idea has been highlighted throughout the thesis showing the effect of the EVs on the load curve. Relative to this, a market-clearing procedure taking into consideration technical constraints has been presented including the role of the EV aggregators that bid for charging/discharging along with the conventional elements presented in wholesale markets. Based on the results arising from their optimisation problems, they can bid more efficiently in order to satisfy the EV energy requirements economically, applying V2G to obtain additional benefits. As stated above, this operation allows obtaining a flatter load curve.

6.2 Future work

In this section, some future research developments are suggested.

Regarding DSM strategies, results have been illustrated assuming a time horizon of 24 hours and a particular load curve in all the cases of study. The effect of considering wider time horizons has not been assessed and it is interesting to analyse how the load curve can be flattened when several days are included. On the one hand, the scope of the model through load shifting can be broadened since SG agents can adapt or improve their decisions against changes in the environment, e.g. daily electricity prices. On the other hand, parameter k can have a clearer effect on the load curve in the intermediate days since the final time period would not restrict the shift of the loads to further time periods.

In relation to the technical tools, the OPF could be extended to make possible tackle any kind of line congestion regardless the generators located at the overloaded feeder. To this end, different control variables have to be defined. Although it is possible to correct voltage limits violations, this issue has not been studied in detail. The joint consideration of these aspects would lead to a more complete formulation of the problem and to a better understanding of its capabilities. Additionally, the algorithm for EV management has proved to be effective if the congestion level is not very high. In other cases, it is necessary to evaluate the change in reactive power flow that indeed influences apparent power and, therefore, the level of congestion of the line, or increase the number of EVs considered to be able to tackle higher levels. Due to the linear nature of the model, arising the DFs formulation, the functionalities of the algorithm should be tested in different scenarios with more EVs and different congestion levels.

Other issues that deserve further research are related to the EV aggregators strategy. As stated in the corresponding chapter, an appropriate forecast of both the electricity prices and EV patterns are needed in order to maximise the benefits of the aggregators. A bad selection of these parameters can lead to undesired results. In practice, valuable information about prices and EV behaviours can be extracted from historical data, e.g. clearing prices in the market or mobility studies. However, new methodologies that allows EV managers to bid more effectively should be studied. A better comprehension and assessment of the risks that aggregators can take in economical terms requires introducing uncertainty in the optimisation problem through stochastic programming. Moreover, the proposed strategy allows determination of the most suitable time periods for the EV charging and discharging as well as the required amounts of power. Nonetheless, it does not provide information about how much the aggregators should offer, in wholesale markets, for the energy they need for charging the EVs or the energy they can supply.

In other words, they have qualitative information about the bidding process. Therefore, additional research efforts are needed to overcome these drawbacks.

Finally, it has been established that EV aggregators are responsible for satisfying EV mobility requirements and they can also take advantage of V2G capabilities. Thus, they are allowed to buy energy for EV charging and sell energy through EV discharging to obtain additional benefits. However, the provision of other services has not been considered and, therefore, new developments regarding ancillary services such as regulation or reserve can be of interest. Furthermore, considering V2G a reality in the medium/long term, the reduction in the life cycle of the EVs' batteries due to this mode of operation deserves a deeper research.

Appendix A

Main Optimisation Problems' Parameters

In this appendix, the main parameters used in the optimisation problems, described in each chapter, are given:

- System line characteristics.
- Non-renewable generators operational costs.
- Generators and fixed batteries technical data.
- Electric vehicle connection patterns.
- Chosen weights for the OPF cases.

The resistances $R_{m,n}$ and reactances $X_{m,n}$ of the line connecting buses m and n for the MG system, in per unit base power of 100 kVA, are shown in Table A.1. Their maximum apparent power $S_{m,n}^{max}$ in kVA is also given.

Table A.1: Line characteristics for the MG system

Line m-n	$R_{m,n}$(pu)	$X_{m,n}$(pu)	$S_{m,n}^{max}$(kVA)
1-17	0.002500	0.010000	400.00
1-2	0.000100	0.000100	80.50
2-3	0.012425	0.003631	80.50
3-4	0.012425	0.003631	80.50
4-5	0.012425	0.003631	80.50
5-6	0.012425	0.003631	80.50
3-7	0.021744	0.003763	53.70
1-8	0.033000	0.008875	71.30
1-9	0.007444	0.005231	46.00
9-10	0.014888	0.010463	46.00
10-11	0.021525	0.011025	36.80
11-12	0.021525	0.011025	36.80
9-13	0.010763	0.005513	36.80
13-14	0.010763	0.005513	36.80
10-15	0.022838	0.005963	22.00
15-16	0.022838	0.005963	22.00

In Table A.2, the operational costs of non-renewable generators for the MG case study: i) marginal cost vc, ii) fixed cost fc, iii) start-up cost yc, and iv) shut-down cost sc are shown. Minimum, P_g^{min}, and maximum, P_g^{max}, power output are also provided.

Table A.2: Generation Costs for the MG case study

Generator	P_g^{min}(kW)	P_g^{max}(kW)	vc(c€/kWh)	fc(c€/h)	yc(c€)	sc(c€)
FC	3.00	50.00	2.84	255.18	16.00	0.00
MT	6.00	30.00	4.37	85.06	9.00	0.00

Table A.3 shows the maximum power output P_g^{max} for renewable generators.

Table A.3: Renewable Generators Maximum Power Output for the MG case study

Generator	P_g^{max}(kW)
WT	10.00
PV 1	3.00
PV 2..5	2.50

The battery limits for charging and discharging power, $P_b^{c,max}$ and $P_b^{d,max}$, and the bounds for the state of charge, S_b^{min} and S_b^{max}, are specified in Table A.4.

Table A.4: Battery Technical Characteristics for the MG case study

Battery	$P_b^{c,max}$(kW)	$P_b^{d,max}$(kW)	S_b^{min}(kWh)	S_b^{max}(kWh)
BAT	5.00	5.00	0.00	30.00

Tables A.5 and A.6 list the data corresponding to the uncontrolled charging strategies type 1 and type 2 respectively. For each EV, the connection nodes, charging and transition periods, and the initial SOC are given.

Table A.5: Electric vehicle connection pattern for uncontrolled charging type 1

EV	**Nodes**	**Charging periods**	**Transition periods**	**Initial SOC (kWh)**
1	14-4	18-21	8, 17	16.5
2	14-4	21-24	8, 20	16.5
3	14-4	16-19	10, 15	16.5
4	15-5	20-23	7, 19	16.5
5	5-15	20-23	7, 19	16.5
6	5-15	20-23	7, 19	16.5
7	16-6	19-22	10, 18	16.5
8	16-6	19-22	10, 18	16.5
9	6-16	24, 1-3	8, 17	8.4

Table A.7 shows the connection pattern for the uncontrolled charging strategy type 3. For each EV, it provides the connection node, the time periods in which they are either charging or idling and the initial SOC. It is composed of three possible charging patterns: type A charging pattern, in which an EV charges 6.0 kWh in one hour; type B, in which it charges 3.0 kWh per hour and type C, in which this value is 1.5 kWh.

Table A.6: Electric vehicle connection pattern for uncontrolled charging type 2

EV	Nodes	Charging periods	Transition periods	Initial SOC (kWh)
1	14-4	9-10, 18-19	8, 17	16.5
2	14-4	9-10, 21-22	8, 20	16.5
3	14-4	11-12, 16-17	10, 15	16.5
4	15-5	10-11, 22-23	7, 19	16.5
5	5-15	9-10, 20-21	7, 19	16.5
6	5-15	10-11, 21-22	7, 19	16.5
7	16-6	11-12, 19-20	10, 18	16.5
8	16-6	11-12, 19-20	10, 18	16.5
9	6-16	12-13, 24, 1	8, 17	13.8

Table A.7: Electric vehicle connection pattern for uncontrolled charging type 3

<table>
<tr><th rowspan="2">EV</th><th rowspan="2">Node</th><th colspan="2">Time Period</th><th rowspan="2">Initial SOC (kWh)</th></tr>
<tr><th>Charging</th><th>Idling</th></tr>
<tr><td rowspan="2">1</td><td>4</td><td>—</td><td>9-11, 18-19</td><td rowspan="2">10</td></tr>
<tr><td>14</td><td>1-7, 20-24</td><td>13-16</td></tr>
<tr><td rowspan="2">2</td><td>4</td><td>—</td><td>9-19</td><td rowspan="2">10</td></tr>
<tr><td>14</td><td>1-7, 21-24</td><td>—</td></tr>
<tr><td rowspan="2">3</td><td>4</td><td>—</td><td>11-14</td><td rowspan="2">8</td></tr>
<tr><td>14</td><td>1, 8A, 9A, 16B, 17B, 20-24</td><td>2-7, 18-19</td></tr>
<tr><td>4</td><td>15</td><td>1, 10A, 11A, 18B, 19B, 20-24</td><td>2-6, 8-9, 12-17</td><td>8</td></tr>
<tr><td rowspan="2">5</td><td>5</td><td>23, 24</td><td>1-6, 20-22</td><td rowspan="2">10</td></tr>
<tr><td>15</td><td>12A, 13A, 16-18</td><td>8-11, 14, 15</td></tr>
<tr><td rowspan="2">6</td><td>5</td><td>23, 24</td><td>1-6, 20-22</td><td rowspan="2">10</td></tr>
<tr><td>15</td><td>14A, 15A, 16-18</td><td>8-13</td></tr>
<tr><td rowspan="2">7-8</td><td>6</td><td>—</td><td>11-17</td><td rowspan="2">15</td></tr>
<tr><td>16</td><td>1, 19-24</td><td>2-9</td></tr>
<tr><td rowspan="2">9</td><td>6</td><td>1, 24</td><td>2-10</td><td rowspan="2">15</td></tr>
<tr><td>16</td><td>19-22</td><td>12-18</td></tr>
</table>

Tables A.8 and A.9 list the resistances $R_{m,n}$, reactances $X_{m,n}$ and susceptances $B_{m,n}$ of the line connecting buses m and n, in per unit base power of 2.5 MVA and 4.8 kV for the IEEE 37 bus system. Their maximum apparent power $S_{m,n}^{max}$ in kVA is also shown.

Table A.8: Line characteristics for the IEEE-37 system - Part I

Line m-n	$R_{m,n}$(pu)	$X_{m,n}$(pu)	$B_{m,n}$(pu)	$S_{m,n}^{max}$(kVA)
1-2	0.020000	0.080000	0.000000	2500.00
2-3	0.014883	0.015390	0.000516	2269.91
3-4	0.008589	0.008937	0.000214	2039.82
4-5	0.010098	0.005758	0.000295	1579.63
5-6	0.003366	0.001919	0.000078	1579.63
6-7	0.005385	0.003071	0.000026	1579.63
7-8	0.005385	0.003071	0.000042	1579.63
8-9	0.009424	0.005374	0.000042	1579.63
9-10	0.010771	0.006142	0.000073	1579.63
10-11	0.006732	0.003839	0.000084	1579.63
11-12	0.006732	0.003839	0.000052	1579.63
12-13	0.006732	0.003839	0.000052	1579.63
3-14	0.013054	0.004197	0.000052	1080.80
14-15	0.010443	0.003357	0.000042	1080.80
14-16	0.007832	0.002518	0.000034	1080.80
3-17	0.006059	0.003455	0.000025	1579.63
17-18	0.008751	0.004990	0.000047	1579.63
18-19	0.013463	0.007677	0.000068	1579.63
18-20	0.002611	0.000839	0.000105	1080.80
19-22	0.010098	0.005758	0.000008	1579.63
19-24	0.030023	0.009652	0.000078	1080.80
20-21	0.016970	0.005456	0.000097	1080.80
22-23	0.009137	0.002938	0.000055	1080.80
24-25	0.024802	0.007973	0.000029	1080.80
24-26	0.003916	0.001259	0.000080	1080.80

Table A.9: Line characteristics for the IEEE-37 system - Part II

Line m-n	$R_{m,n}$(pu)	$X_{m,n}$(pu)	$B_{m,n}$	$S_{m,n}^{max}$(kVA)
4-27	0.007832	0.002518	0.000013	1080.80
27-28	0.004712	0.002687	0.000025	1579.63
28-29	0.009137	0.002938	0.000037	1080.80
28-30	0.006527	0.002098	0.000029	1080.80
6-31	0.010098	0.005758	0.000021	1579.63
7-32	0.010443	0.003357	0.000078	1080.80
9-33	0.016970	0.005456	0.000034	1080.80
33-34	0.006527	0.002098	0.000055	1080.80
33-35	0.041771	0.013429	0.000021	1080.80
12-36	0.006527	0.002098	0.000135	1080.80
6-37	0.004500	0.090500	0.000000	500.00

In Table A.10, the operational costs of non-renewable generators for the IEEE 37-bus case study: i) marginal cost vc, ii) fixed cost fc, iii) start-up cost yc, and iv) shut-down cost sc are shown. Minimum, P_g^{min}, and maximum, P_g^{max}, power output are also provided.

Table A.10: Generation Costs for the IEEE-37 system

Generator	P_g^{min}(kW)	P_g^{max}(kW)	vc(c€/kWh)	fc(c€/h)	yc(c€)	sc(c€)
ICE 1	50.00	250.00	3.50	102.07	16.00	0.00
MT	20.00	200.00	4.37	85.06	9.00	0.00
FC 1	15.00	150.00	2.84	255.18	16.00	0.00
FC 2	10.00	100.00	3.55	191.39	14.40	0.00
ICE 2	120.00	600.00	2.19	170.12	20.80	0.00

Table A.11 shows the maximum power output P_g^{max} for the renewable generators considered in the IEEE 37-bus system.

Table A.11: Renewable Generators Maximum Power Output for the IEEE-37 system

Generator	P_g^{max}(kW)
WT	300.00
PV 1	150.00

The battery limits for charging and discharging power, $P_b^{c,max}$ and $P_b^{d,max}$, and the bounds for the state of charge, S_b^{min} and S_b^{max}, are given in Table A.12.

Table A.12: Battery Technical Characteristics for the IEEE-37 system

	$P_b^{c,max}$(kW)	$P_b^{d,max}$(kW)	S_b^{min}(kWh)	S_b^{max}(kWh)
Batteries	50.00	50.00	25.00	250.00

In Table A.13, the data corresponding to the uncontrolled charging strategy considered in the case study based on the IEEE 37-bus test system are listed, for each EV: starting nodes, charging and transition time periods are given.

Table A.13: Electric vehicle connection pattern for uncontrolled charging for the IEEE-37 system

EVs	**Starting Nodes**	**Charging periods**	**Transition periods**
EV1-EV4	13, 15, 16, 21	20-23	7, 19
EV5-EV6	23, 25	20-23	8, 19
EV7	26	19-22	8, 18
EV8-EV9	29, 30	16-19	8, 15
EV10-EV11	31, 32	21-24	9, 20
EV12	34	20-23	9, 19
EV13-EV14	35, 36	19-22	9, 18

Table A.14 gives the generators' maximum reactive power output assumed for the cases of study related to the OPF approach. In Table A.15, the selected weights corresponding to the OPF's objective function are shown: i) $k_{1,FC}$ for the fuel cell unit, ii) $k_{1,MT}$ for the microturbine, iii) k_2 for renewable generators, and iv) k_3 for the main grid. Table A.16 provides the connection pattern assumed for the market-clearing procedure. The buses where each group of EVs are attached as well as the time periods when a transition takes place with the corresponding battery energy consumption are given.

Table A.14: Generators maximum reactive power output

	FC	MT	WT	PV 1	PV 2..5
$Q_{g,k}^{min}$(kVAr)	-32.00	-20.00	-8.00	-2.40	-2.00
$Q_{g,k}^{max}$(kVAr)	32.00	20.00	6.50	2.40	2.00

Table A.15: Chosen weights for the OPF cases

	$k_{1,FC}$	$k_{1,MT}$	k_2	k_3
Cases 2-4	0.07	0.03	0.60	0.30
Cases 5-6	0.03	0.07	0.60	0.30
Case 7	0.20	0.35	0.15	0.30

Table A.16: Electric vehicle connection pattern for the market-clearing procedure

Buses	**Group of EVs**	**Transition periods**	**Consumption (kWh)**
2	1 / 2	7, 18 / 8, 19	1.50 / 4.40
3	3 / 4	9, 19 / 7, 15	1.80 / 1.80
4	5 / 6	9, 18 / 8, 16	1.40 / 3.00
5	7 / 8	9, 17 / 10, 15	1.90 / 2.20
6	9 / 10	6, 20 / 8, 14	1.80 / 3.50
7	11 / 12	9, 16 / 8, 19	2.30 / 1.70
8	13 / 14	9, 14 / 7, 15	2.00 / 1.75
9	15 / 16	9, 14 / 8, 13	2.50 / 2.30
10	17 / 18	10, 21 / 8, 17	2.20 / 3.60
11	19 / 20	8, 19 / 9, 14	2.60 / 2.20
12	21 / 22	7, 14 / 9, 19	4.50 / 3.90
15	23 / 24	9, 16 / 7, 15	3.50 / 2.01
17	25 / 26	8, 14 / 9, 20	4.20 / 1.95
19	27 / 28	8, 16 / 8, 14	2.10 / 3.50
20	29 / 30	7, 19 / 8, 15	3.40 / 2.10

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