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UNIVERSIDAD PONTIFICIA

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GRADO EN INGENIERÍA DE TECNOLOGÍAS INDUSTRIALES

TRABAJO FIN DE GRADO

ANÁLISIS DEL IMPACTO EN LA RED DE DISTRIBUCIÓN ELÉCTRICA DE DIFERENTES ESTRATEGIAS DE RECARGA INTELIGENTE PARA VEHÍCULOS ELÉCTRICOS

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Madrid

Julio 2023

Declaro, bajo mi responsabilidad, que el Proyecto presentado con el título

Análisis del impacto en la red de distribución eléctrica de diferentes estrategias de recarga inteligente para vehículos eléctricos en la ETS de Ingeniería - ICAI de la Universidad Pontificia Comillas en el

curso académico 2022/2023 es de mi autoría, original e inédito y

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El Proyecto no es plagio de otro, ni total ni parcialmente y la información que ha sido

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Fdo.: Lucas Damotte Huedo Fecha: 10/ 07/ 2023

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RESUMEN DEL PROYECTO

I. Introducción

La motivación para este proyecto proviene de la necesidad imperativa de identificar nuevas fuentes de energía como sustitutos de los combustibles fósiles, dados su considerable contribución a la contaminación atmosférica. La electricidad parece ser la alternativa más viable, elevando la importancia de los vehículos eléctricos (VE) en esta transición energética. Sin embargo, esta transición trae consigo numerosos desafíos que deben abordarse, principalmente relacionados con la demanda de carga. Para entender estos desafíos, se ha realizado un análisis del impacto de varias estrategias de carga inteligente de VE en una gran red urbana en España.

La creación de vehículos eléctricos (VE) se remonta a alrededor de 1830, un período sorprendentemente anterior a la aparición de los coches de motor de combustión en 1890. Sin embargo, debido a la popularización de los vehículos de gasolina, la industria de los VE pasó por una fase de estancamiento, denominada 'viaje del desierto', entre 1920 y 1990.

Los coches con motor de combustión, aunque populares, tienen significativas desventajas medioambientales, principalmente relacionadas con los gases tóxicos emitidos durante el proceso de combustión. Tales preocupaciones ambientales han llevado a las organizaciones internacionales a promulgar regulaciones estrictas sobre las emisiones de CO2, con visiones futuras como 'Emisiones Netas Cero' para 2050 [1]. Esto ha llevado al resurgimiento de los VE, con las principales compañías automotrices desarrollando sus propios modelos 100% eléctricos. El recuento de VE en Europa ha aumentado a 250 millones y se prevé que continúe creciendo [2].

Sin embargo, este cambio en la industria automotriz presenta sus propios desafíos, particularmente en lo que respecta a la creciente demanda de electricidad. Para soportar una demanda tan alta, los elementos de la red deben ser reemplazados, pero esto conlleva un alto precio y dificultad. Por eso, la 'Recarga Inteligente' de los VE parece ser la solución que ayudaría a la red con las congestiones.

La recarga inteligente ofrece varios beneficios, como el 'peak shaving' para reducir la carga de potencia pico y aplanar la demanda, la provisión de servicios auxiliares para el equilibrio en tiempo real de la red, y la 'optimización detrás del medidor' y 'energía de respaldo' para reducir la dependencia de la red [3].

Hay tres categorías principales de técnicas de carga inteligente: carga controlada unidireccional (V1G), vehículo a red (V2G) y vehículo a casa/edificio (V2H/B). Actualmente, la técnica más adoptada es V1G o time of use (TOU), que anima a los consumidores a desplazar sus horarios de carga de las horas pico a las horas de menor demanda a través de diferencias de precios significativas (recorte de picos) [3].

Técnicas más sofisticadas como V2G y V2H/B, que consideran los VE como consumidores y generadores de energía, todavía están en desarrollo. Estas técnicas permiten que los VE proporcionen energía durante períodos de alta demanda y sirvan como fuentes de energía de respaldo para ayudar a la red en escenarios de alta congestión. Sin embargo, como estos procedimientos de carga inteligente aún no están completamente maduros, la mayoría de los métodos utilizados actualmente son técnicas V1G.

II. Estado del Arte

La urgente necesidad de encontrar fuentes de energía alternativas para reemplazar los combustibles fósiles hace que este sea un tema actualizado. Muchos proyectos como [3],[4] se enfocan en explicar todos los problemas asociados con la recarga no controlada, seguido de una descripción de todas las técnicas de recarga inteligente y las necesidades necesarias para implementarlas.

Otros proyectos se centran en comparar el impacto de la recarga no controlada con una estrategia de recarga inteligente. En [5], estudian el impacto de aplicar una tarifa TOU en una red urbana y rural australiana. En [6], lo comparan en una red grande pero esta vez con diferentes estrategias, una de ellas asumiendo que durante las horas pico el 10 % de los vehículos pueden operar en modo V2G.

Estos tipos de proyectos presentan una falta de datos sobre los comportamientos de los conductores de VE, por lo que tienen que hacer muchas suposiciones. Debido a eso, muchos proyectos se enfocan en desarrollar modelos confiables del comportamiento de los conductores de VE, como [7] y [8].

Finalmente, hay proyectos que intentan estudiar el impacto de estrategias más complejas. Sin embargo, estos estudios a menudo se realizan en redes pequeñas, ya que la tecnología para introducir completamente estas estrategias aún no está desarrollada. Es el caso de [9] y [10].

Este proyecto tiene como objetivo comparar diferentes estrategias de recarga inteligente en el mismo proyecto, ya que la mayoría de los trabajos realizados en el campo a menudo solo comparan uno, confiando en modelos bien definidos para obtener el resultado más realista posible.

III. Metodología

Esta sección presenta los diferentes procedimientos realizados para desarrollar el algoritmo de capacidad de alojamiento de VE para un escenario de recarga no controlada, una tarifa TOU y una estrategia mixta.

Recarga no controlada

El término "recarga no controlada" se refiere a un escenario donde los VE se recargan inmediatamente después de completar su último viaje del día y se recargan a su máxima capacidad. En otras palabras, este proceso ocurre durante las horas pico de consumo de electricidad, sin ninguna consideración para optimizar la carga de la red o reducir los costos de energía.

El modelado de este algoritmo depende en gran medida de los perfiles de demanda del vehículo eléctrico (VE), que constituyen un componente crucial del proceso. Estos perfiles se derivan de los datos presentados en estudios previos [5], [7], [8]. Los parámetros clave que influyen en estos perfiles de demanda incluyen:

• Hora de salida y llegada diaria: estos datos son cruciales ya que determinan la hora de inicio de la recarga en este escenario. Se utiliza el modelo de [7], que utiliza datos de la Encuesta Nacional de Viajes de los Hogares (NHTS) para generar distribuciones de probabilidad que modelan las horas de salida y llegada de los conductores de VE.

• Distancia recorrida (km): este es otro parámetro vital ya que determina la demanda de energía necesaria para la recarga, y por lo tanto, el tiempo de recarga. Esta información se obtuvo de [8], donde los datos de la Encuesta Nacional de Viajes de Dinamarca se utilizan para modelar los comportamientos de los conductores de VE, resultando en un promedio de 34 km recorridos por día por conductor.

• Factor de conexión diario y estado de carga (SOC): esto modela la cantidad de veces que los VE se recargan durante el día y su estado de carga. En este proyecto, se asume que los conductores de VE solo hacen un viaje durante el día, por lo que solo se conectan una vez y cargan completamente para satisfacer su demanda, resultando en un 100% de SOC.

• Tamaño del cargador de VE: el tamaño del cargador de VE (3.7 kW o 7.4 kW) determina el tiempo requerido para recargar la batería.

• Factor de potencia: los cargadores de VE poseen un factor de potencia bastante pequeño, pero debe considerarse para un escenario realista. Siguiendo la suposición de [5], se considera un factor de potencia de 0.99.

Para explicar la creación del algoritmo, profundicemos en los diversos componentes. El algoritmo comienza introduciendo los datos de la red, seguido por el usuario especificando la penetración de VE deseada para el escenario. La penetración de VE es esencialmente un porcentaje del número total de VE en la red. Dada la penetración de VE, el algoritmo calcula el número de VE en la red (N) y luego está preparado para comenzar a generar los perfiles de demanda de VE. Para cada VE, se necesita generar una hora de salida (dt) y una hora de llegada (at), siendo esta última particularmente significativa en este contexto, ya que determina la hora de inicio de la recarga. Para modelar un escenario realista, todos los autobuses de recarga tienen un máximo de 3 VE, por lo que el algoritmo debe verificar que haya menos de 3 VE en ese autobús antes de asignar la demanda de VE a él. Las horas de salida y llegada se generan utilizando el modelo de [7]. Basándose en las distribuciones obtenidas, extrajeron una función que proporciona la hora de llegada en función de una probabilidad generada aleatoriamente. Esta es la función:

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

Los parámetros son obtenidos de la siguiente tabla:

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

Tabla 1: Parámetros asociados a las distribuciones de horas de salida y llegada. Fuente: [7]

En este proceso, una vez obtenidos los datos y se confirma que la hora de salida (dt) es menor que la hora de llegada (at), los datos pueden asignarse al autobús. Para lograr esto, el algoritmo selecciona aleatoriamente un cargador, ya sea de 3.7 kW o de 7.4 kW, con una probabilidad de 0.5. En este proyecto, se asume que hay una distribución equitativa de ambos cargadores dentro de la red. La distancia recorrida se fija en 34 km y el consumo de energía de la batería se establece en 180 Wh/km. Esta métrica de consumo de energía corresponde a la batería del Nissan Leaf, uno de los automóviles eléctricos más populares en el mercado. En este proyecto se asume que todos los conductores de la red poseen este modelo específico de VE. Utilizando estos parámetros, se calcula el perfil de recarga y se añade al bus. Este proceso se replica para todos los VE en la red, por lo que se repite 'N' veces, donde 'N' es el número de VE en la red.

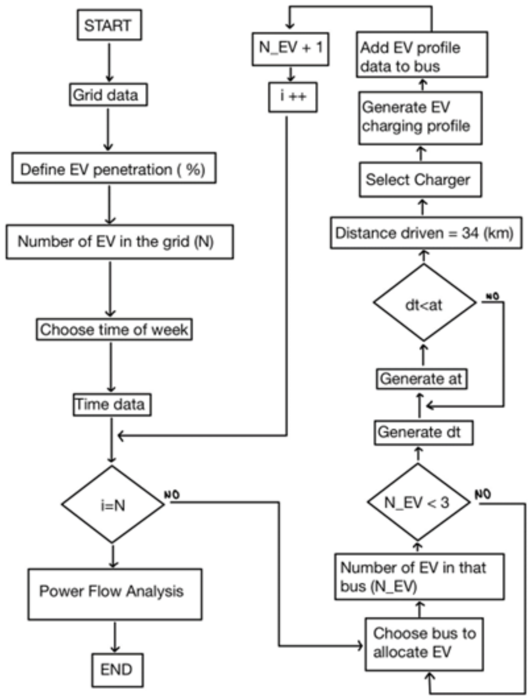

Figura 1: Algoritmo para carga no controlada

El proyecto continúa ahora con la evaluación de la capacidad de acogida de los VE. Esencialmente, este paso tiene como objetivo examinar el impacto de la recarga de los VE en la red en función de la penetración de los VE. Esto ayuda a determinar el número umbral de VE en el que la red comienza a encontrar problemas. La evaluación se realiza revisando los resultados obtenidos del análisis del flujo de potencia al final del algoritmo, enfocándose específicamente en varios parámetros clave:

- Potencia Aparente Agregada (MVA): Es la suma de toda la potencia aparente en cada demanda del circuito.

- Porcentaje de Sobrecarga (%): Es el nivel de utilización del elemento de la red en función de su capacidad nominal.

- Subtensión (%): Es el número de buses con un nivel de tensión fuera del límite definido, que suele ser de 0.9 a 1.1 pu, en función del total de buses.

Tarifa de Tiempo de Uso (TOU)

La estrategia de Tiempo de Uso (TOU) tiene como objetivo desplazar la recarga de los VE de las horas pico a las horas fuera de pico implementando un esquema de precios. Este esquema ofrece beneficios significativos de costos para los clientes que alteran su horario de recarga en consecuencia. La estrategia comparte el mismo objetivo que la anterior, que es realizar una evaluación de la capacidad de acogida de los VE y comparar el impacto con la estrategia anterior. Esto ayuda a entender los beneficios de implementar estas estrategias. Los parámetros que definen los perfiles de demanda de los VE permanecen sin cambios. Sin embargo, la introducción de un problema de optimización de programación lineal diseñado para minimizar el costo de recarga requiere suposiciones adicionales. En este algoritmo revisado, la recarga del VE no comienza inmediatamente después del último viaje del día del conductor. En cambio, durante las horas fuera de pico, el algoritmo determina el momento más rentable para recargar el VE. Para hacerlo, el programa necesita saber la duración durante la cual el VE está en casa y disponible para cargar. Esto requiere una suposición sobre la hora de salida. Se asume que la hora de salida se refiere al primer viaje del próximo día después de la hora de llegada. En consecuencia, todas las horas entre la hora de llegada (at) y la hora de salida (dt) representan la ventana durante la cual el VE está disponible para cargar. El proceso de generación de perfiles de demanda de los VE es idéntico al anterior y se repite para todos los VE (N) en la red. Los perfiles resultantes se incorporan luego en el problema de optimización de programación lineal para determinar las horas de recarga más rentables. Una vez determinadas estas horas, la demanda correspondiente se añade al bús apropiado. El último paso implica llevar a cabo un análisis de flujo de potencia para evaluar el impacto de los horarios de recarga definidos en el rendimiento y la capacidad de la red.

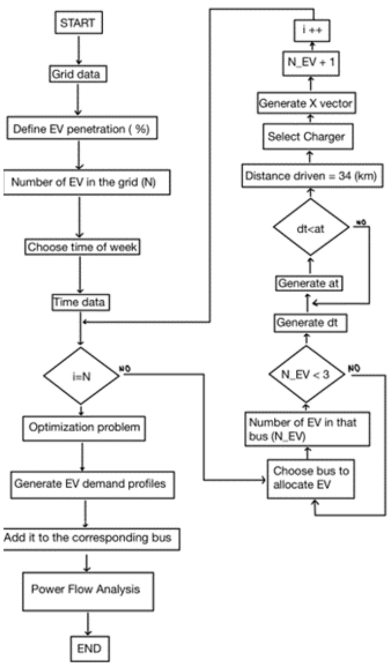

Figura 2: Algoritmo para TOU

La Tarifa de Tiempo de Uso con proporción

Esta estrategia representa una combinación de los dos métodos previamente discutidos: Tarifa de Tiempo de Uso (TOU) y Rearga no controlada. Aunque la TOU se considera una estrategia de recarga inteligente, en esencia sigue siendo no controlada ya que no hay un medio fiable para predecir el número de clientes que se adaptarán a ella. Esta imprevisibilidad puede potencialmente conducir a complicaciones, que se discutirán en secciones subsiguientes, y podría aumentar finalmente los problemas existentes. Por lo tanto, investigar los límites de la TOU es crítico en términos de optimización del rendimiento de la red. Específicamente, determinar la proporción mínima de usuarios de TOU requerida en cada escenario de recarga no controlada puede contribuir a optimizar la capacidad de los elementos de la red y mejorar la satisfacción general del consumidor. Para ello, el algoritmo se modifica para preguntar al usuario la proporción de usuarios de TOU que quiere establecer para cada penetración, pero el resto es igual ya que incorpora las partes de los dos algoritmos anteriores.

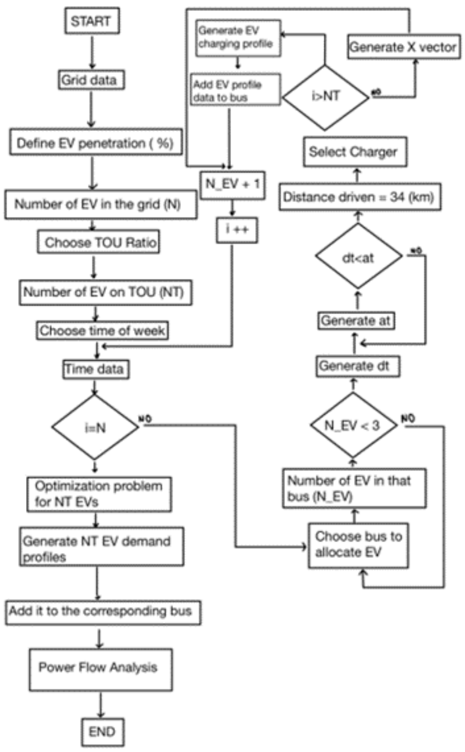

Figura 3: Algoritmo para estrategia mixta

IV. Caso de Estudio

Esta sección está dedicada a describir los componentes de la red, así como el perfil de los consumidores y el esquema de precios utilizado para la TOU.

Red

La siguiente tabla describe los componentes de la red:

Componentes	Cantidad
Buses	5322
Demandas	4905
Líneas	5126
Transformadores	209

Tabla 2: Componentes de la red

La red referenciada es una gran red urbana donde los alimentadores están situados muy cerca uno del otro, y no sigue un diseño completamente radial, con una de las líneas creando un bucle. Estos dos factores son cruciales ya que resultan en caídas de voltaje muy bajas, haciendo que las fluctuaciones de voltaje sean una preocupación menos significativa en el análisis de los impactos de la recarga inteligente.

Perfil de los consumidores

Estos perfiles de consumidores son básicamente la demanda inicial de la red sin demanda de vehículos eléctricos. Se calculan calculando la potencia activa pico para cada bus de la red, que depende de la capacidad instalada y del factor de simultaneidad. El factor de simultaneidad es un coeficiente, siempre inferior a 1, que representa el uso real de la capacidad disponible de cada sistema energético. Para la parte de Baja Tensión (BT), tiene un valor de 0.4 y para la Media Tensión (MT) un valor de 0.8. Esto multiplicado por la capacidad instalada da la potencia activa pico.

Para terminar, los perfiles unitarios horarios reflejan la variación de la energía para cada tipo de cliente durante el día y deben tenerse en cuenta:

hours	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
LV coefficients	0.67	0.49	0.37	0.32	0.30	0.30	0.31	0.42	0.52	0.53	0.57	0.61	0.68	0.73	0.77	0.76	0.73	0.73	0.77	0.81	0..87	0.97	1.00	0.86
MD coefficients	0.37	0.35	0.35	0.34	0.35	0.37	0.44	0.50	0.59	0.83	0.98	1.00	0.98	0.81	0.61	0.59	0.62	0.67	0.69	0.69	0.65	0.53	0.45	0.41

Tabla 3: Perfiles unitarios horarios

Esquema de precios de la TOU

El esquema de precios de Tarifa de Uso del Tiempo (TOU) introducido es el plan de 'Iberdrola' llamado 'Plan Vehículo Eléctrico' que ofrece una tarifa de 0.03 €/kWh para las horas fuera de pico (01:00 - 06:59) y una tarifa de: 0.349874 €/kWh para el resto (07:00 - 12:59).

V. Resultados

Recarga No Controlada:

La Figura 4 muestra cómo la potencia aparente agregada varía con respecto a la hora, en función de la penetración de vehículos eléctricos (EV). A medida que aumenta la penetración de EV, la potencia aparente también se eleva, escalando de 14 MVA al 0% de penetración de EV a 16 MVA al 160% de penetración de EV. Este aumento crea un pico durante las horas pico, lo que puede provocar problemas en la red.

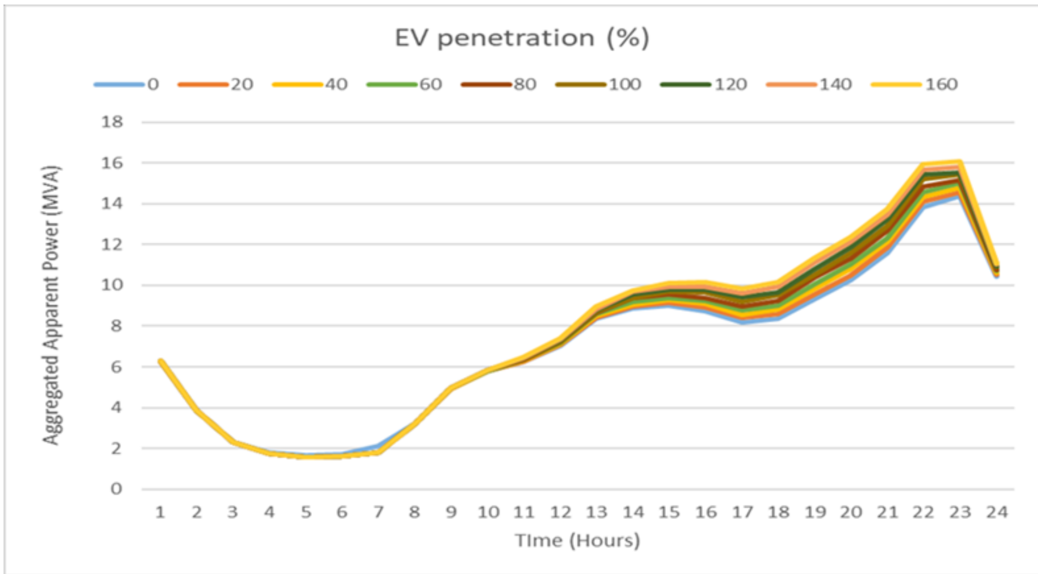

Figura 4: Potencia Aparente Agregada en función de la hora durante días de la semana

El aumento de la demanda conduce principalmente a la sobrecarga de elementos como muestra la Figura 5. Desde el 50 % de penetración de vehículos eléctricos ya hay 10 elementos sobrecargados.

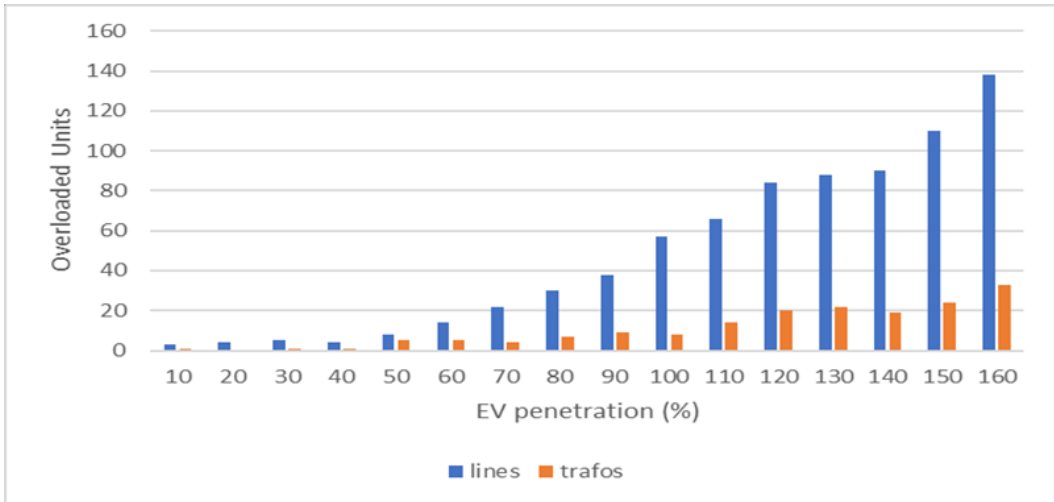

Figura 5: Número de líneas y transformadores saturados en función de la penetración de Ves durante días de la semana

Tarifa TOU:

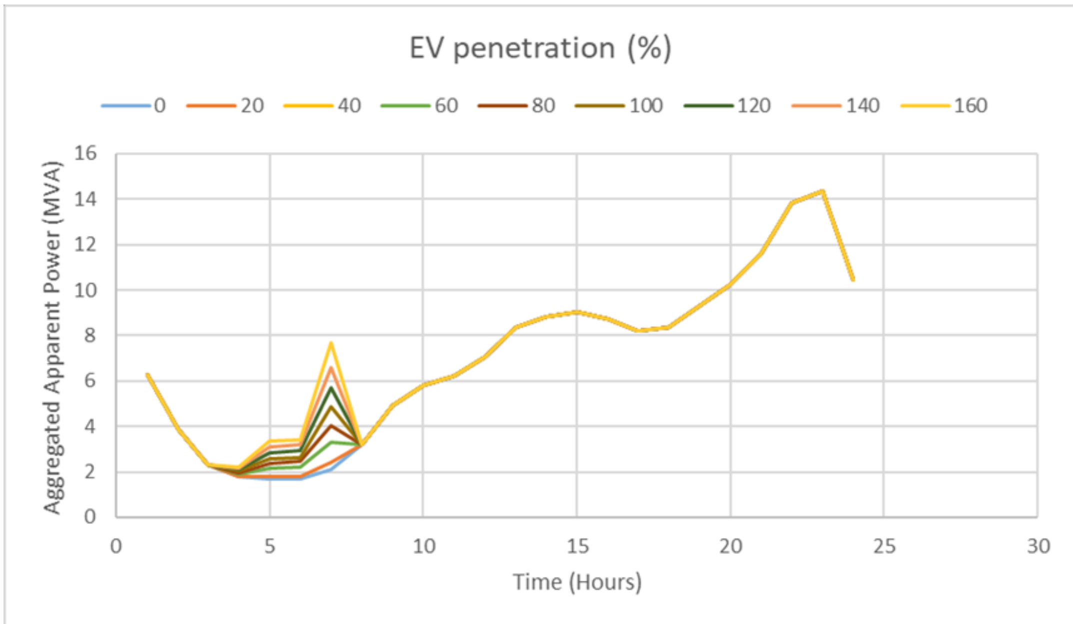

Figura 6: Potencia Aparente Agregada en función de la hora usando una TOU durante días de la semana

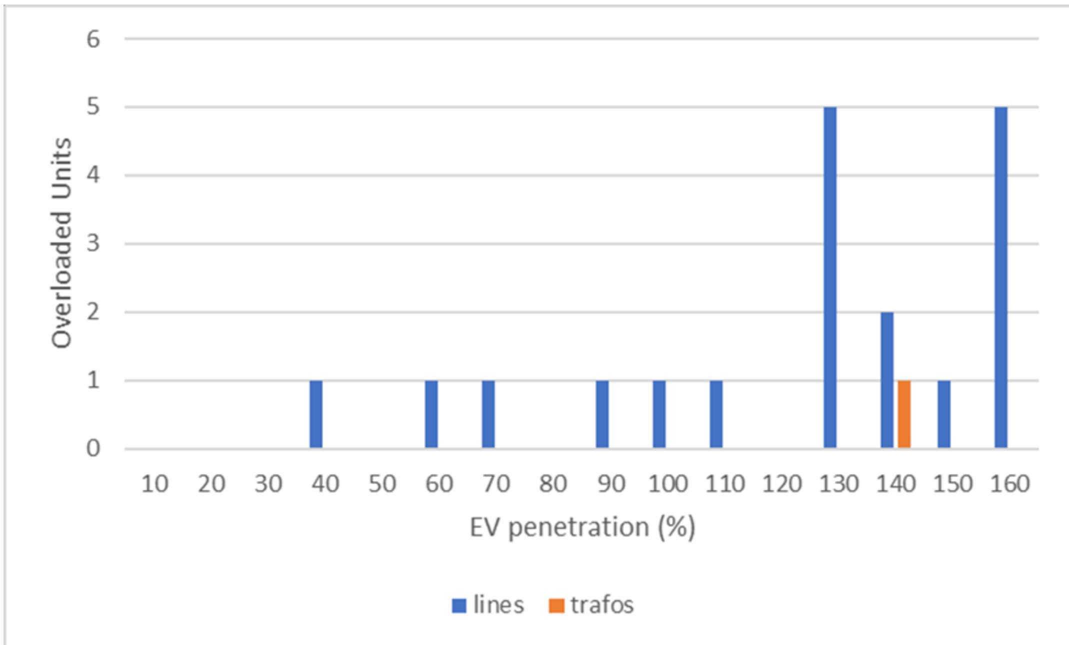

Figura 7: Número de líneas y transformadores saturados en función de la penetración de Ves usando una TOU durante días de la semana

La Figura 6 indica que el pico durante las horas pico ahora se ha eliminado, y casi todas las instancias de sobrecarga de elementos se eliminan, como se ilustra en la Figura 7. Sin embargo, debido a la impredecibilidad de este sistema, aparece un pico durante las horas no pico, que aumenta de 2 MVA a casi 8 MVA en el escenario más exigente, marcando un incremento del 300%.

TOU with adoption ratio:

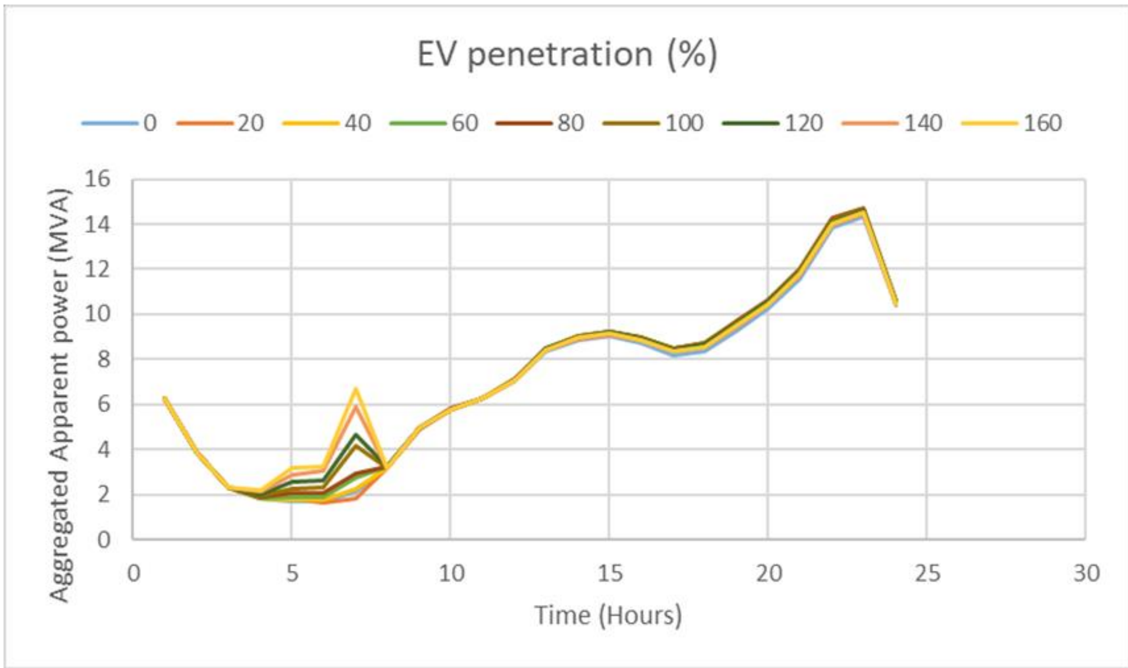

Figura 8: Potencia Aparente Agregada en función de la hora usando una estrategia mixta durante días de la semana

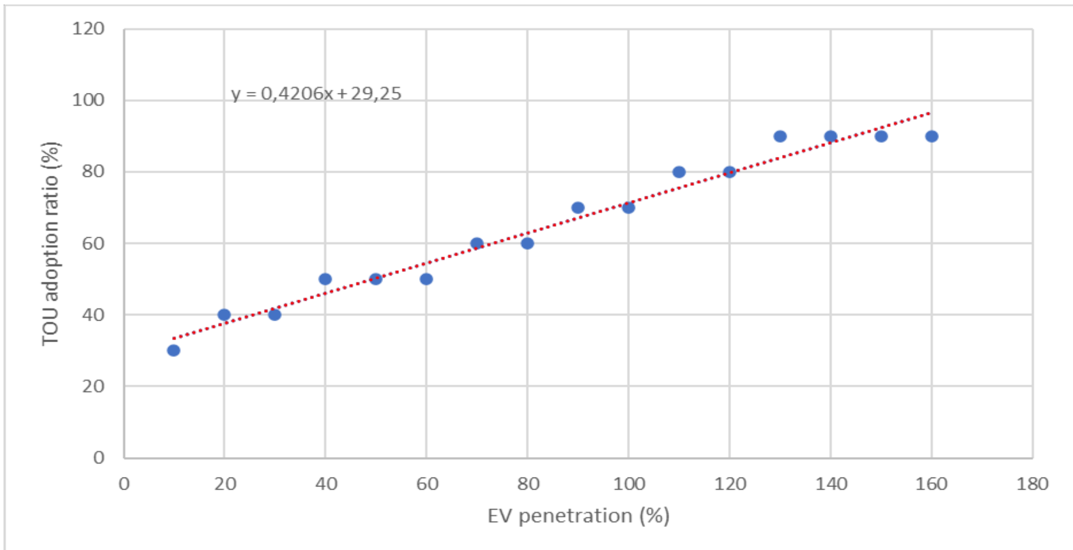

Figura 9: Adopción de proporción de TOU en función de la penetración de Ves durante días de la semana

La implementación de una estrategia mixta ayuda a reducir el segundo pico que aparece debido al Tiempo de Uso (TOU), aunque no de manera dramática. Como se indica en la Figura 8, la potencia aparente aumenta de 2 MVA a alrededor de 6 MVA, lo que denota un aumento del 200%, que es menor que el 300%, pero sigue siendo significativo. Esto sucede porque la proporción de adopción de TOU aumenta rápidamente con el incremento de la penetración de los vehículos eléctricos (VE), como se muestra en la Figura 9. Como resultado, para escenarios de baja penetración de VE, esta estrategia funciona excelentemente. Sin embargo, a medida que aumenta la penetración de VE y la proporción también aumenta, los problemas anteriormente asociados con el TOU (como el segundo pico) comienzan a surgir nuevamente.

VI. Conclusiones

En conclusión, las estrategias de recarga inteligente ayudan a reducir el estrés causado por la recarga no controlada, reduciendo prácticamente a cero las unidades sobrecargadas. Sin embargo, estas estrategias también son, en cierto sentido, incontrolables, ya que no es posible predecir con precisión cuántas personas adoptarán estas técnicas. En consecuencia, nuevos desafíos como el segundo pico para el Tiempo de Uso (TOU) pueden crear más problemas que los encontrados anteriormente.

La estrategia mixta ayuda a reducir el segundo pico y optimiza la utilización de la capacidad de los componentes de la red. Sin embargo, esto solo es aplicable para niveles bajos de penetración de EV. A medida que aumenta la penetración de EV, también aumenta rápidamente la necesidad de adoptar una proporción más grande.

En general, las técnicas de recarga inteligente estudiadas en este proyecto ofrecen una solución, pero solo a corto plazo, ya que la red no podría sostener tales estrategias frente a una alta demanda de EV. Los proyectos futuros examinarán más a fondo estrategias más complejas que dependen de una comunicación más fuerte entre los Operadores del Sistema de Distribución (DSOs), los Operadores del Sistema de Carga (CSOs), los cargadores de EV y los conductores de EV, a medida que las tecnologías para estas estrategias continúan evolucionando.

VII. Bibliografía

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ANALYSIS OF THE IMPACT ON THE ELECTRICAL DISTRIBUTION GRID OF DIFFERENT SMART CHARGING STRATEGIES FOR ELECTRIC VEHICLES

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ABSTRACT

I. Introduction

The motivation for this project comes from the imperative need to identify new energy sources as replacements for fossil fuels, given their substantial contribution to atmospheric pollution. Electricity appears to be the most viable alternative, elevating the importance of Electric Vehicles (EVs) in this energy transition. Nevertheless, this transition brings numerous challenges that need to be addressed, primarily related to charging demand. To understand these challenges, an analysis of the impact of various EV smart charging strategies has been carried out on a large urban grid in Spain.

The creation of electric vehicles (EVs) dates back to around 1830, a time period surprisingly earlier than the appearance of combustion engine cars in 1890. However, due to the popularization of gasoline vehicles, the EV industry underwent a stagnation phase, referred to as the 'desert travel', between 1920 and 1990.

Combustion engine cars, while popular, have significant environmental drawbacks, mainly related to the toxic gases emitted during the combustion process. Such environmental concerns have driven international organizations to enact stringent regulations on CO2 emissions, with future visions like 'Net Zero Emissions' by 2050 [1]. This has led to the resurgence of EVs, with major automobile companies developing their own 100% electric models. The EV count in Europe has surged to 250 million and is predicted to continue growing [2].

However, this shift in the automotive industry presents its own challenges, particularly regarding the increased demand for electricity. To support such a high demand, grid elements

must be replaced, but this comes at a high price and difficulty. Because of that ‘Smart Charging’ of EVs appears to be the solution which would help the grid with congestions.

Smart Charging offers several benefits, such as 'Peak shaving' to reduce power peak load and flatten demand, provision of ancillary services for real-time balancing of the grid, and 'Behind the meter optimization' and 'back-up power' to reduce grid dependency [3].

There are three primary categories of smart charging techniques: Unidirectional controlled charging (V1G), Vehicle to grid (V2G), and Vehicle to home/building (V2H/B). Currently, the most widely adopted technique is V1G or Time of use tariffs (TOU), which encourages consumers to shift their charging times from peak hours to off-peak hours through significant price differences (peak shaving) [3].

More sophisticated techniques such as V2G and V2H/B, which consider EVs as both consumers and generators of power, are still under development. These techniques allow EVs to provide power during high-demand periods and serve as backup power sources to help the grid in high congestion scenarios. However, as these smart charging procedures are not yet fully mature, most currently used methods are V1G techniques.

II. State of the Art

The urgent need to find alternative energy sources to replace fossil fuels make this an up-to-date topic. Many projects such as [3],[4] focus on explaining all the problems associated with uncontrolled charging followed by a description on all the smart charging techniques and the necessities needed to implement them.

Other projects focus on comparing the impact of uncontrolled charging with a smart charging strategy. In [5], they study the impact of applying a TOU tariff in an Australian Urban and Rural Grid. In [6], they compare it in a large grid but this time with different strategies, one of them assuming that during peak hours 10 % of the vehicles can operate in V2G mode.

These types of projects present a lack in EV drivers behaviours data, so they have to make a lot of assumptions. Because of that many projects focus on developing reliable models of EV drivers’ behaviours such as [7] and [8].

Finally, there are projects that try to study the impact of more complex strategies. However, these studies are often made in small grids since the technology to fully introduce these strategies is not yet developed. It is the case of [9] and [10].

This project aims to compare different smart charging strategies in the same project, as most the works done in the field often compare only one, relying on well defined models to get the most realistic result possible.

III. Methodology

This section presents the different procedures realized in order to develop the EV hosting capacity algorithm for different an uncontrolled charging scenario, a TOU tariff and a mix strategy.

Uncontrolled Charging

The term "uncontrolled charging" refers to a scenario where EVs are charged immediately upon completion of their last trip of the day and are charged to their full capacity. In other words, this process occurs during peak electricity consumption hours, without any consideration for optimizing grid load or reducing energy costs.

The modelling of this algorithm heavily relies on the electric vehicle (EV) demand profiles, which constitute a crucial component of the process. These profiles are derived from data presented in prior studies [5], [7], [8]. Key parameters influencing these demand profiles include:

- Daily departure and arrival time: This data is crucial as it determines the starting charging time in this scenario. The model from [7] is utilized, which uses data from the National Household Travel Survey (NHTS) to generate probability distributions that model EV drivers' departure and arrival times.
- Distance driven (km): This is another vital parameter as it determines the energy demand needed for charging, and thus, the charging time. This information was obtained from [8], where data from the Danish National Travel Survey is used to model EV drivers' behaviours, resulting in an average of 34 km driven per day per driver.

- Daily Plug-in factor and State of Charge (SOC): This models the number of times EVs charge during the day and their state of charge. In this project, it is assumed that EV drivers only make one trip during the day, so they only plug in once and charge to fully meet their demand, resulting in 100% SOC.
- EV charger size: The EV charger size (3.7 kW or 7.4 kW) determines the time required to charge the battery.
- Power Factor: EV chargers possess a rather small power factor, but it needs to be considered for a realistic scenario. Following the assumption of [5], a power factor of 0.99 is considered.

To explain the algorithm creation, let's delve into the various components. The algorithm begins by inputting the network data, followed by the user specifying the desired EV penetration for the scenario. The EV penetration is essentially a percentage of the total number of EVs in the network. Given the EV penetration, the algorithm calculates the number of EVs on the grid (N) and is then prepared to start generating the EV demand profiles. For each EV, a departure (dt) and an arrival time (at) need to be generated, with the latter being particularly significant in this context, as it determines the starting charging time. In order to model a realistic scenario, all load buses have a maximum of 3 EVs, so the algorithm must verify that there are fewer than 3 EVs on that bus before assigning the EV demand to it. The departure and arrival times are generated using the model from [7]. Based on the distributions obtained, they extracted a function that provides the arrival time based on a randomly generated probability. This is the function:

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

The parameters are obtained from the following table:

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

Table 1: Departure and arrival times distribution's parameters. Source: [7]

In this process, once the data is obtained and it's confirmed that the departure time (dt) is less than the arrival time (at), the data can then be allocated to the bus. To achieve this, the algorithm randomly selects a charger, either 3.7 kW or 7.4 kW, with a 0.5 probability. In this project, it is assumed that there's an equal distribution of both chargers within the network. The distance driven is fixed at 34 km and the battery energy consumption is set at 180 Wh/km. This energy consumption metric corresponds to the battery of the Nissan Leaf, one of the most popular electric cars in the market. It is assumed in this project that every driver in the network owns this specific model of EV. Using these parameters, the charging profile is calculated and added to the bus. This process is replicated for all EVs in the network, hence it's repeated 'N' times, where 'N' is the number of EVs on the grid.

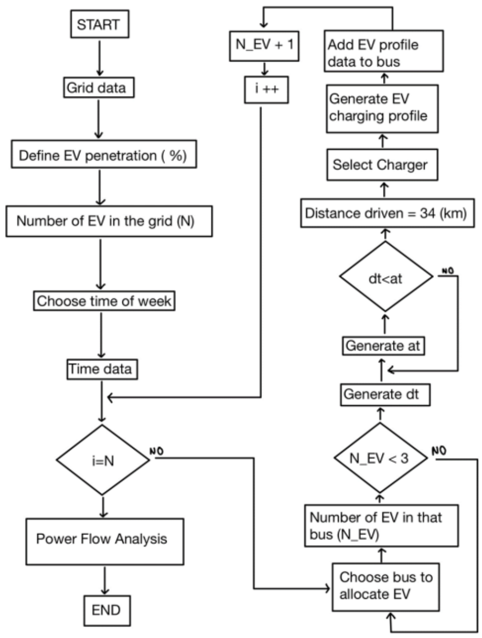

Figure 1: Uncontrolled Charging algorithm

The project now proceeds with the hosting EV assessment. Essentially, this step aims to examine the impact of EV charging on the grid as a function of EV penetration. This helps to determine the threshold number of EVs at which the grid begins to encounter issues. The assessment is accomplished by reviewing the results garnered from the power flow analysis at the conclusion of the algorithm, focusing specifically on various key parameters.:

•Aggregated Apparent Power (MVA): It is the sum of all the apparent power in each load of the circuit.

•Overloading percentage (%): It is the utilization level of the asset in function of their rated capacity.

•Undervoltage (%): It is the number of buses with a voltage level out of the defined boundary, which is usually 0.9 to 1.1 pu, in function of the totality of buses.

Time of Use Tariff (TOU)

The Time of Use (TOU) strategy aims to shift EV charging from peak hours to off-peak hours by implementing a pricing scheme. This scheme offers substantial cost benefits to customers who alter their charging schedule accordingly. The strategy shares the same goal as the previous one, which is to perform an EV hosting capacity assessment and to compare the impact with the prior strategy. This helps in understanding the benefits of implementing these strategies. The parameters defining the EV demand profiles remain unchanged. However, the introduction of a linear programming optimization problem designed to minimize the cost of charging necessitates additional assumptions. In this revised algorithm, EV charging does not begin immediately after the driver's final trip of the day. Instead, during off-peak hours, the algorithm determines the most cost-effective time to charge the EV. To do so, the program needs to know the duration for which the EV is at home and available for charging. This necessitates an assumption about the departure time. It is assumed that the departure time refers to the first trip of the next day after the arrival time. Consequently, all the hours between the arrival time (at) and departure time (dt) represent the window during which the EV is available to charge. The process of generating EV demand profiles is identical to the previous one and is repeated for all the EVs (N) on the grid. The resultant profiles are then incorporated into the linear programming optimization problem to determine the most cost-effective charging hours. Once these hours are determined, the corresponding demand is added to the appropriate bus. The final step involves conducting a power flow analysis to assess the impact of the defined charging schedules on the grid's performance and capacity.

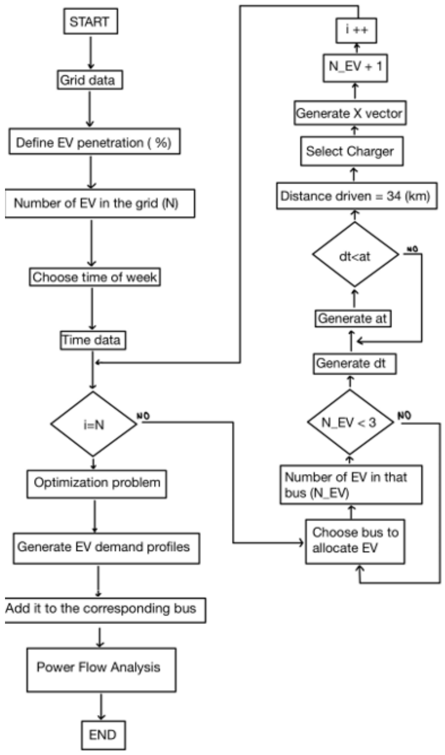

Figure 2: TOU algorithm sequence

Time of Use Tariff with ratio

This strategy represents a blend of the two previously discussed methods - Time-of-Use (TOU) and Uncontrolled Charging. Although TOU is considered a smart charging strategy, it inherently remains uncontrolled as there is no reliable means to predict the number of customers who will adapt to it. This unpredictability can potentially lead to complications, which will be discussed in subsequent sections, and could ultimately increase existing issues. Therefore, researching the limits of TOU is critical in terms of optimizing grid performance. Specifically, determining the minimum ratio of TOU users required in each uncontrolled charging scenario can contribute to optimizing the capacity of grid elements and enhancing overall consumer satisfaction. For that, the algorithm is modified to ask the user the ratio of TOU users it wants to set for each penetration, but the rest is the same as it incorporates the parts of the precious two algorithms.

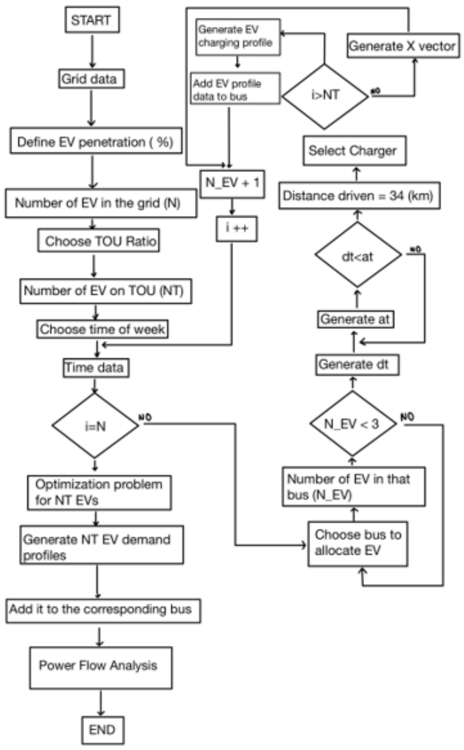

Figure 3: TOU adoption ratio algorithm sequence

IV. Case study

This section is dedicated to describing the network components, as well as the consumers profile and the pricing scheme used for the TOU.

<u>Network</u>

The following table describes the components of the network:

Components	Numbers
Bus	5322
Load	4905
Line	5126
Transformer	209

Table 2: Network's components

The referenced network is a large urban grid where the feeders are closely situated to one another, and it doesn't follow a completely radial design, with one of the lines creating a loop. These two factors are crucial as they result in very low voltage drops, rendering voltage fluctuations a less significant concern in the analysis of smart charging impacts.

Consumer’s profile

These consumers profile are basically the initial demand of the network with no EV demand. There are made calculating the peak active power for each bus of the network which is dependent on the installed capacity and the simultaneity factor. The simultaneity factor is a coefficient, always inferior to 1, that represents the real usage of the available capacity of each energy system. For the Low voltage (LV) part it has a value of 0.4 and for the Mid Voltage (MV) a value of 0.8. This times the installed capacity gives the peak active power.

To finish hourly unit profiles reflects energy variation for each type of customer during the day and needs to be taken into account:

hours	0	1	2	3	4	5	6	7	8	9	10
LV coefficients	0.67	0.49	0.37	0.32	0.30	0.30	0.31	0.42	0.52	0.53	0.57
MD coefficients	0.37	0.35	0.35	0.34	0.35	0.37	0.44	0.50	0.59	0.83	0.98

11	12	13	14	15	16	17	18	19	20	21	22	23
0.61	0.68	0.73	0.77	0.76	0.73	0.73	0.77	0.81	0..87	0.97	1.00	0.86
1.00	0.98	0.81	0.61	0.59	0.62	0.67	0.69	0.69	0.65	0.53	0.45	0.41

Table 3: Hourly unit profiles

TOU pricing scheme

The TOU pricing scheme introduced is the plan for ‘Iberdrola’ called ‘Electric Vehicle Plan’ which gives a rate of 0.03 €/kWh for off-peak hours (01.00 – 06:59) and a rate of : 0.349874 €/kWh for the rest (07:00 – 12:59).

V. Results

Uncontrolled Charging:

Figure 4 demonstrates how the aggregate apparent power varies with respect to the hour, based on the EV penetration. As the EV penetration increases, the apparent power also elevates, escalating from 14 MVA at 0% EV penetration to 16 MVA at 160% EV penetration. This surge creates a peak during the peak hours, which can instigate issues in the grid.

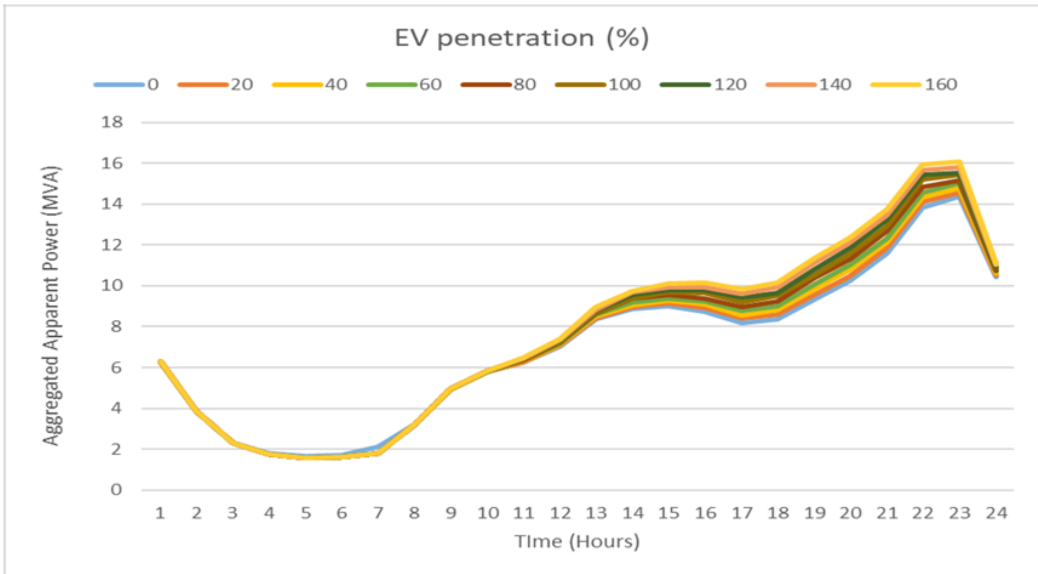

Figure 4: Aggregated Apparent Power in function of the hour during weekdays

The increase in demand leads to mostly elements overloading as Figure 5 shows. From 50 % EV penetration there is already 10 elements overloaded.

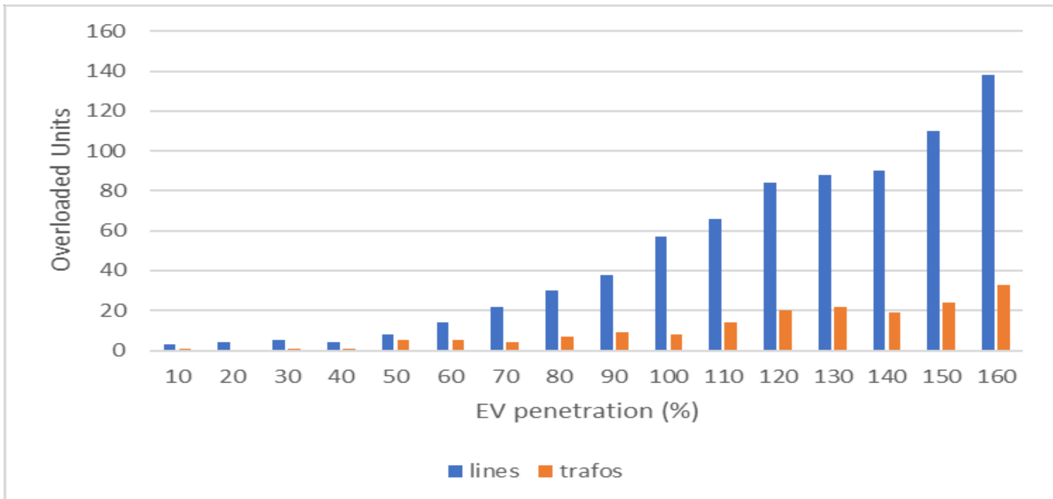

Figure 5: Number of overloaded lines and transformers in function of the EV penetration during weekdays

TOU tariff:

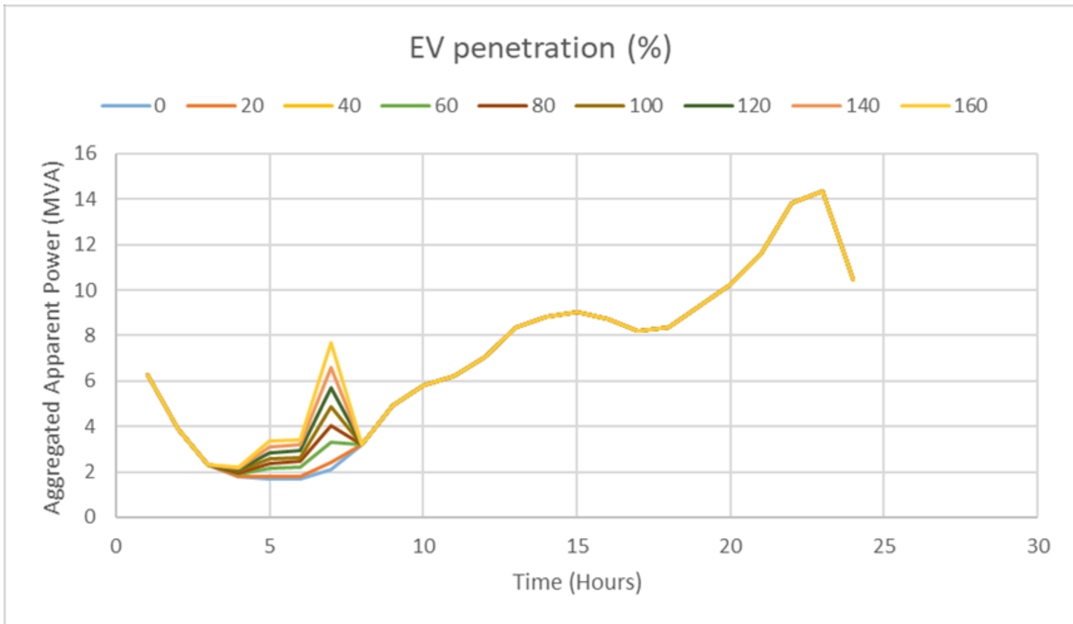

Figure 6: Aggregated Apparent Power in function of the hour using a TOU during weekdays

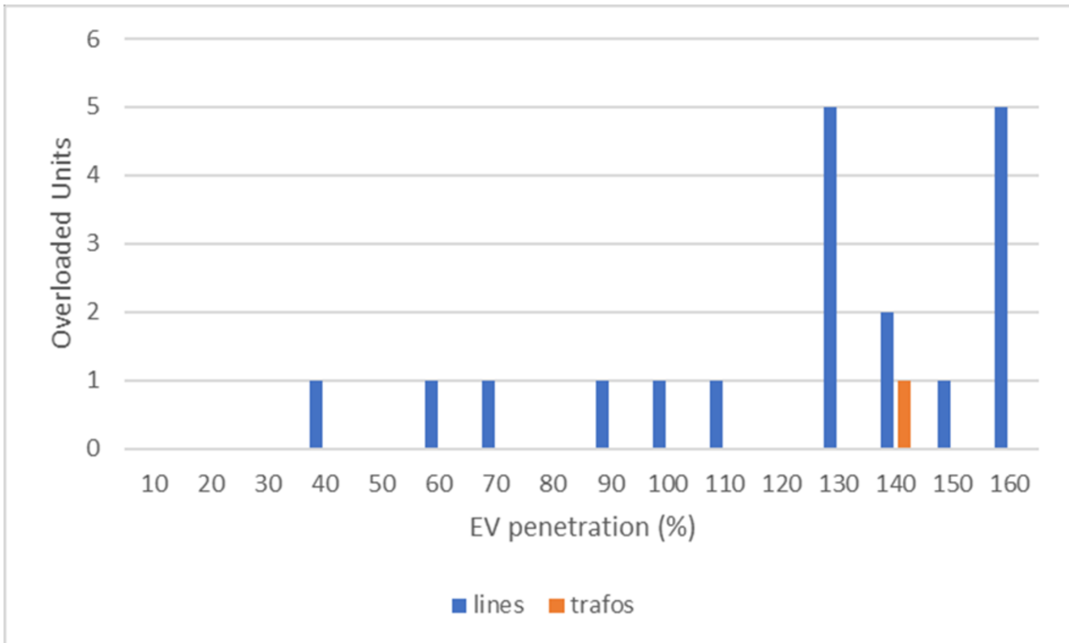

Figure 7: Number of overloaded lines and transformers in function of the EV penetration using a TOU during weekdays

Figure 6 indicates that the peak during peak hours is now eliminated, and almost all instances of element overloading are removed, as illustrated in Figure 7. However, due to the unpredictability of this system, a peak emerges during the off-peak hours, which rises from 2 MVA to nearly 8 MVA in the most demanding scenario, marking a 300% increase.

<u>TOU with adoption ratio:</u>

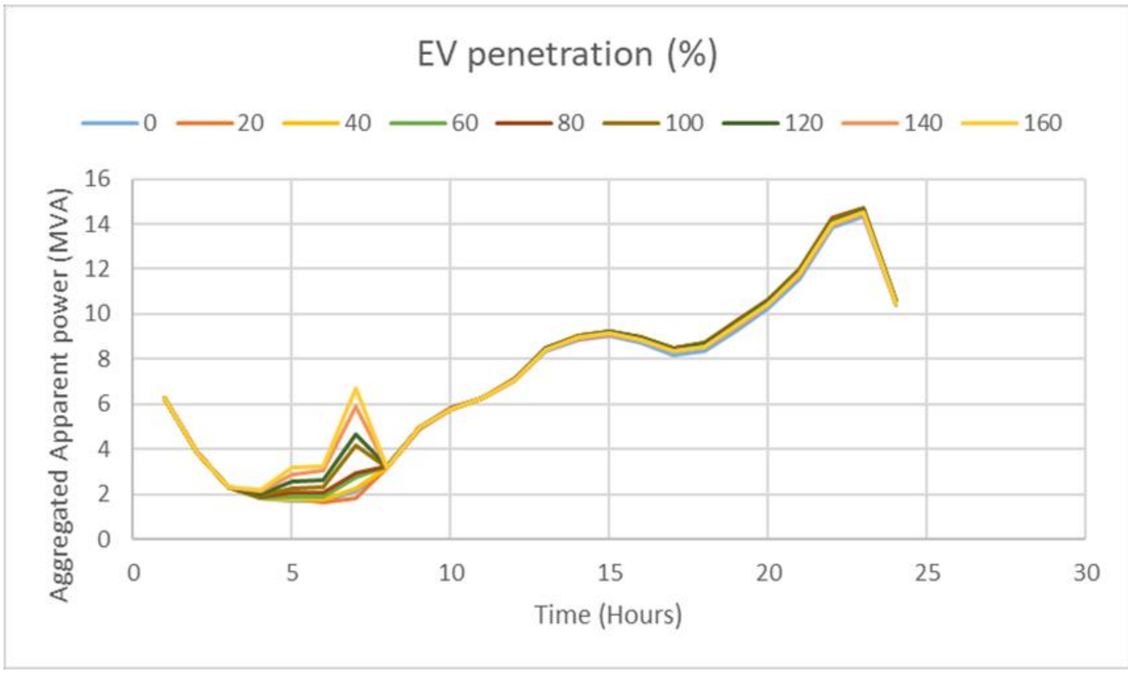

Figure 8: Aggregated Apparent Power in function of the hour using a mix strategy during weekdays

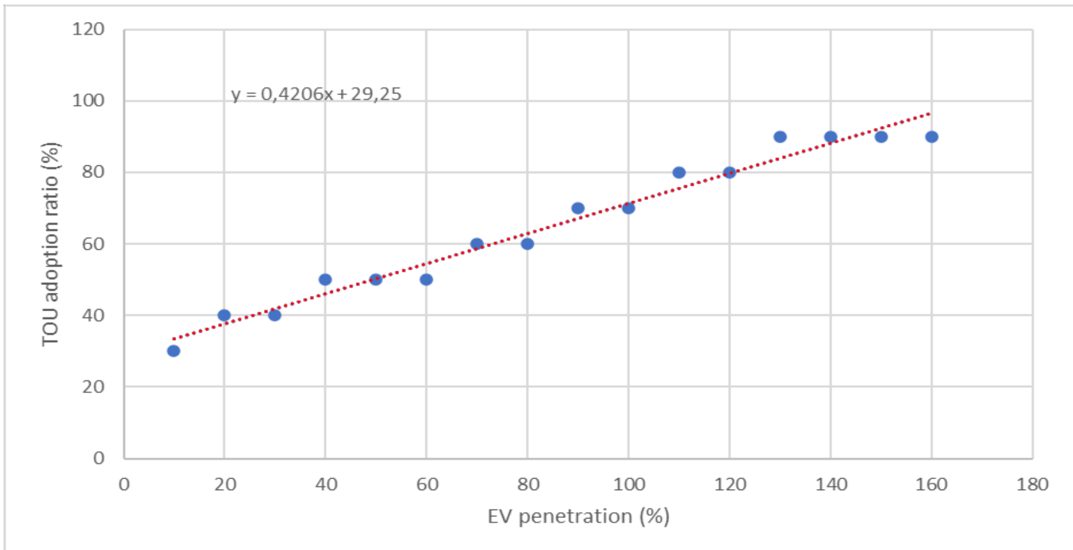

Figure 9: TOU adoption ratio in function of the EV penetration during weekdays

Implementing a mixed strategy helps reduce the second peak that appears due to the Time of Use (TOU), although not dramatically. As indicated in Figure 8, the apparent power increases from 2 MVA to around 6 MVA, denoting a 200% rise, which is less than 300% but still significant. This happens because the TOU adoption ratio escalates quickly with the increase in EV penetration, as shown in Figure 9. As a result, for low EV penetration scenarios, this strategy works excellently. However, as EV penetration increases and the ratio also increases, the problems previously associated with TOU (such as the second peak) start to emerge again.

VI. Conclusions

In conclusion, smart charging strategies help reduce the stress caused by uncontrolled charging, reducing overloaded units practically to zero. However, these strategies are, in a sense, also uncontrolled since it's not possible to accurately predict how many people will adopt these techniques. Consequently, new challenges such as the second peak for the Time of Use (TOU) can create more problems than those previously encountered.

The mixed strategy helps reduce the second peak and optimizes the capacity utilization of the grid's components. However, this is only applicable for low EV penetration levels. As EV penetration increases, the need to adopt a larger ratio also rises rapidly.

Overall, the smart charging techniques studied in this project offer a solution, but only a short-term one since the grid could not sustain such strategies in the face of high EV demand. Future projects will look deeper into more complex strategies that rely on stronger communication between Distribution System Operators (DSOs), Charging System Operators (CSOs), EV chargers, and EV drivers, as the technologies for these strategies continue to evolve.

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CHAPTER 1. INTRODUCTION

This section provides context for the history of Electric Vehicles (EVs) as well as the increasing significance of smart charging techniques. It also explains the motivation behind undertaking this project and outlines the objectives it seeks to achieve.

1.1 BACKGROUND

The history of electric vehicles started around 1830 when the first vehicle appeared. Surprisingly enough their history begins before the combustion engine car, which only appeared around 1890. Even though it appeared first, EV suffered what is called the 'desert travel' that happened between 1920 and 1990 because of the popularity of gasoline cars.

However not everything associated with combustion engine cars was ideal since the combustion necessary to create the mechanical energy to move the car releases toxic gases which are harmful to the environment and for our health. All the problems related to combustion engine cars led all the different World Organizations to create laws and regulations for CO2 emissions, as well as future scenarios involving a massive or even total reduction of CO2 emissions, such as the 'Net Zero Emissions' by 2050[1].

Electric Vehicles regained importance mostly due to these facts. Lots of companies started developing their 100% electric car, such as Ford with the 'Ford E-Transit', Nissan with the 'Nissan Leaf', Volvo with the 'Volvo C40', and many more. Electric cars are becoming the answer to be able to reach that 'Net Zero Emissions' scenario. Right now, there is 250 million EVs only in Europe and this number will not stop increasing [2]. But this major change in the automobile industry raises questions of its own. Figure 1 shows the massive evolution of EVs between 2005-2016.

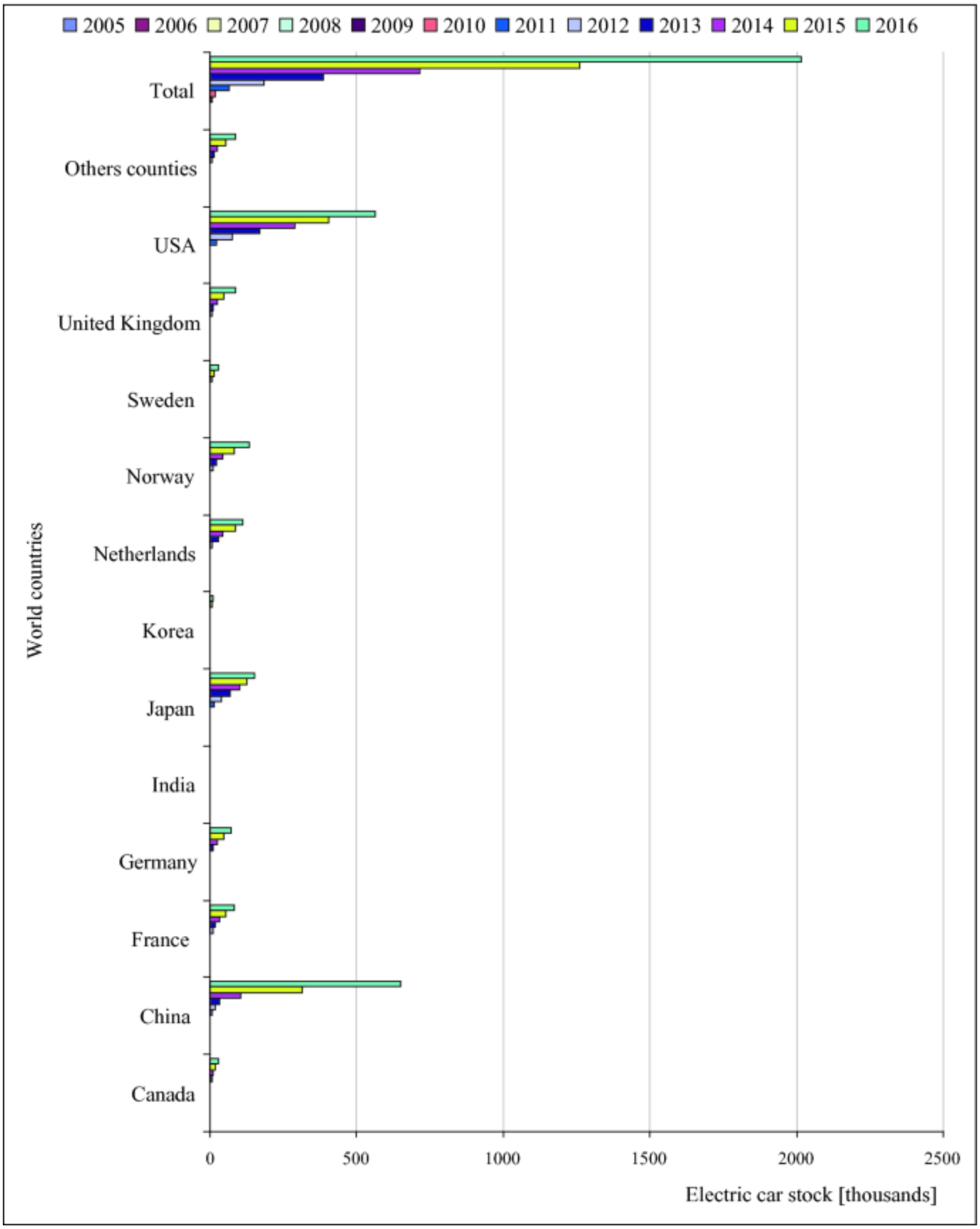


Figure 1: Number of Electric vehicles in individual countries from 2005-2016. Source: [3]

One is now confronted with questions about electricity consumption and demand, as the requirement for electricity is set to increase dramatically. This uptick in demand must be matched by an enhancement of the electrical grid, since the current grid infrastructure may not be capable of supporting the colossal quantities of energy that will be needed.

However, such an enhancement is prohibitively expensive and challenging, compelling the need to explore alternative solutions. 'Smart Charging' appears to be the promising solution to this predicament.

In essence, Smart Charging establishes communication between the charger of the electric vehicle, the grid, charging stations, and even the utility company. This allows for the regulation of energy usage to charge the car, based on the grid's requirements and energy needs, thereby optimizing the charging process. The ensuing description is primarily based on a referenced article [4], as it provides a highly accurate description.

Smart Charging will allow the provision of different services, for instance:

- <u>Peak shaving</u>: the objective of peak shaving is basically to flatten the demand by reducing the peaks in power, which can cause grid failures, and by filling the ‘valleys. The valleys are periods of the day where there is very low load demand, so it is interesting to shift electric vehicle charging demand to these hours.
- <u>Ancillary services</u>: the communication between all the systems involved in the charging will allow to do a real time balancing of the grid. EV will help in frequency regulation of the grid, preventing the short-term changes of the 4 grid, reducing congestion, EV vehicles located near the congested area will help reach the demand by discharging and sending electricity and many more.
- <u>Behind the meter optimization and ‘back-up power’</u>: smart charging will allow increased production of locally produced renewable electricity. This will reduce the electricity bills as well as the dependence on the grid.

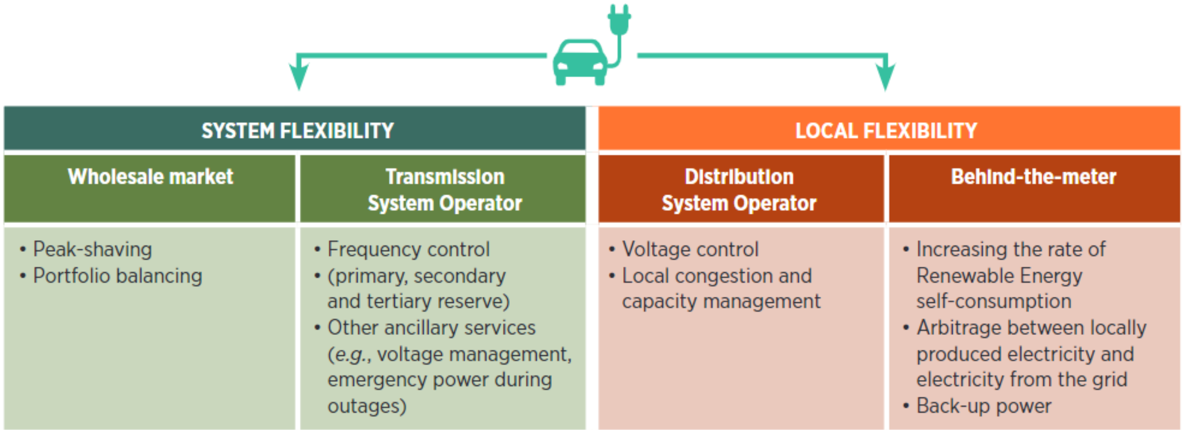


Figure 2: Potential Range of flexibility services by EVs. Source: [4]

There are different ways to apply smart charging techniques nowadays. Some are more difficult and less 'mature' than others; however, they allow for more applications. They divide approximately in 3 categories:

1) Unidirectional controlled charging (V1G)

2) Vehicle to grid (V2G)

3) Vehicle to home/building (V2H/B)

The first one, as the name states, is a one-way flow of electricity. EV receive electricity from the grid and charge. The techniques that are part of this category are mainly 'Time of use tariffs'.

The second and third ones are more sophisticated options still under development. EV in these options are seen as both generators and consumers of power. In V2G the customers will provide services to the grid when the electric vehicle is in discharge mode, such as providing a source of power during periods of high-power demands (peak shaving).

In V2H/B the electric vehicle is also used as a back-up power source but for behind the meter services optimizing the energy use in buildings. For example, increasing self-consumption from PV. Not all these smart charging procedures are applied nowadays. Most of what we use are V1G techniques or time of use tariffs. Let's explain more in depth in what each of them consists of:

- Time of use tariffs: This technique is simple and the most used. The objective is to encourage consumers to change their charging period from peak hours to off-peak hours by creating big price differences between those two periods.
- V1G: Projects involving V1G techniques are being tested. These projects involve a mix between V1G and dynamic pricing. Dynamic charging means the real-time regulation of the energy used to charge the car depending on the energy resources and the state of the grid. As renewable energies improve these projects try to recommend charging while the renewable energy disposal is bigger, so the price is smaller.
- V2X: Vehicle to everything is still a pre-commercial solution; however, this is the most promising solution today. V2G technologies will help in all sectors, such as real states, power grid and even consumers. V2G technology will help balance out electricity demand [4] so there would be no unnecessary costs for building an electric system as well as provide help to the grid.

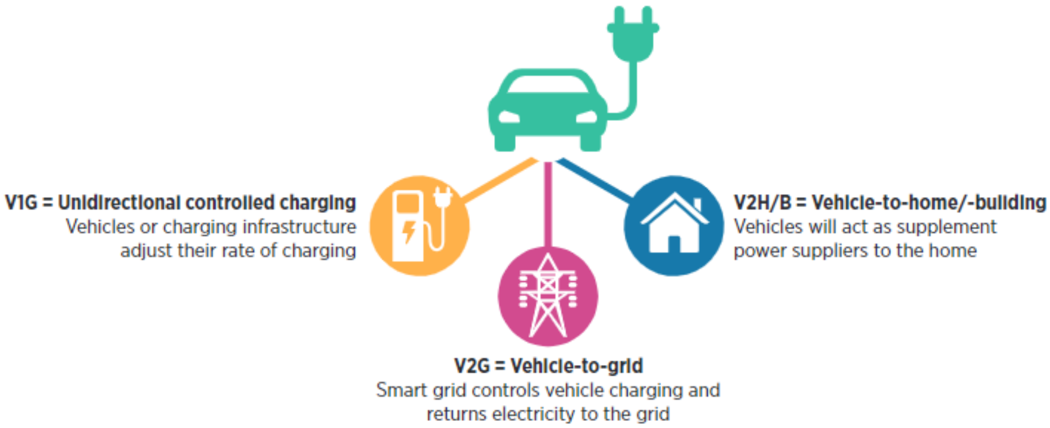


Figure 3: Forms of smart charging. Source: [4]

1.2 PROJECT MOTIVATION

This subject captivated me completely the first time I scrolled through it. There are so many dimensions to this project that as an industrial engineer, specialized in the electrical branch, can be approached.

First, as an engineer I am very interested in cars and their way of functioning. This invention has been one of the keys of modern society and has allowed us to live much more comfortably, so understanding all its way of functioning has always been very fascinating to me. Electric cars have yet to travel a long road to be at the same level as combustion engine cars, but we keep progressing and discovering new ways to make them work. Learning about these new technologies and their way of working is one of the main reasons why this subject was so attractive.

Second is the energy part. The main reason why I decided to specialize as an electrical engineer is the energy sector. The need to discover new reliable energy sources is now more important than ever with the CO2 problem we are going through. One of the key factors to solve this problem is the complete change in the automobile industry from combustion engine cars to electric ones. So, the fact that this is a current issue made it really interesting to me since I may be able to contribute to the issue and, in the future maybe be able to work on this as well.

Third is the optimization part. Comparing different strategies because of their impact, costs, benefits to reach a conclusion is something that I really appreciate. I have always been a person who likes to see everything from every possible angle to be able to reach a more accurate solution. I felt because of the different smart charging strategies that we are going to study throughout this project that I was going to be able to do that which motivates me a lot.

1.3 PROJECT OBJECTIVES

In this project the main focus is to understand the benefits that the grid receives from using different smart charging techniques. Initially we will select those strategies to then study them separately and observe the different impacts that each of them causes. With this we will try to understand what benefits the grid receives by increasing the complexity of those strategies.

- Quantify the impact of electric vehicles on our actual grid: If we want to be able to appreciate what smart charging techniques bring to the grid, we must know their impact on the grid and the problems they may cause . For that reason, we will study at which point of EV penetration the grid starts having problems and then specify what would need to be done to increase EV penetration.
- Model the smart charging techniques: Once the data regarding EV impact is collected the smart charging techniques that are going to be applied have to be modelled. More precisely the strategies modelled will be a Time-of-Use Tariff (TOU) with and without ratio integration.
- Study and observe the different benefits that come from applying to the grid different smart charging strategies: Once we know the flaws of the grid, we can start applying different smart charging techniques to study the different benefits we get from them. For example, a decrease in voltage drops and in grid congestions.
- Understand the benefits that more complex smart charging solutions bring to the grid: After collecting all the data from the previous steps, we can now compare their benefits to more complex but also more expensive techniques.

1.4 SUSTAINABLE DEVELOPMENT PROJECT GOALS

Our project objectives follow the spirit of the Sustainable Development Goals (SDG) [5], most precisely these following:

- **SDG 13**: Climate Action: This is the goal number 13 out of the 17. Out of all the listed below this is the most important one. The need to study the impact of smart charging techniques on the grid is because we can no longer use combustion engine cars if we want to keep living on Earth. CO2 emissions that come from those cars are increasing the effects of climate change dramatically and are leading us to a catastrophe. EV transition is one of the actions needed to live in a healthy planet.
- **SDG 7**: Affordable and clean energy: This goal follows the spirit of the first one. We are transitioning to an Earth where we want to be only using renewables energies. EV have a massive impact in that aspect since they are going to allow more self-production of renewable energy such as photovoltaic energy. That change is also going to increase electricity usage, so improving the grid is becoming essential for affordable electricity.
- **SDG 9**: Industry innovation and infrastructure: The objective with this goal is to improve our current infrastructure to build a more resilient and sustainable one as well as promote innovation. With this project we are going to be studying the impact of different techniques on the grid for its future adequate improvement, so we are clearly following the spirit of that goal.

1.5 PROJECT STRUCTURE

This project is divided into six parts. The first part, the introduction, presents the context of EVs and the objectives of this project. This is followed by the state of the art section, where the current literature relating to the impact of EVs and the integration of smart charging techniques on the grid is reviewed. The methodology section comes next, explaining all the procedures needed to develop various charging scenarios and smart charging techniques.

The case study section then reviews all the characteristics of the grid, the consumers, and some strategies, related to this specific project. Following this, the results section compares and reviews the findings from the simulation of different strategies.

The project concludes with a summary of all the conclusions drawn from the project and a discussion about future projects.

CHAPTER 2. STATE OF THE ART

This section is dedicated to reviewing the existing literature related to the topic of this project in order to gain a deeper understanding of how this work complements and extends current knowledge in the field.

With the urgent need to find alternative energy sources to replace fossil fuels, electricity has emerged as the most viable solution for decarbonizing the energy consumption in several sectors (e.g., transportation, heating and cooling, etc.). Road transport is responsible of 10 % of global greenhouse gas emissions [6]. EVs are expected to represent 40 % of total car sales in the United States by 2030 and optimistic projections forecast the sale surpassing 50 % by 2030 as well [7]. An uncontrolled deployment of high shares of EVs can be a challenge for their integration in distribution networks [8], making smart charging a relevant research topic. There are a number of projects studying the impact of electric vehicle penetration on the power grid, each featuring different premises that distinguish it from the others. Such different research perspectives highlight the complexity of this topic and the diversity of possible solutions to the challenges associated with the integration of electric vehicles into the power grid.

The existing literature is primarily focused on exploring the wide range of flexibility services that EVs can offer to the grid, while also investigating various smart charging strategies that can be implemented. The authors of the study in [4] describe how uncontrolled charging of electric vehicles can lead to problems such as voltage drops, overloading of transmission lines and transformers, and congestion. All of these can affect distribution quality and potentially lead to grid failures. However, it also describes smart charging strategies that can mitigate these problems, the conditions necessary for their implementation, and the requirements for EVs to support such charging methods. The authors of [9] emphasize the necessity of using EV flexibility services related to smart charging, mostly V2G which has shown the technical benefits to the grid in numerous projects even though the technology is still not entirely developed. They also focus on identifying and discussing the economic and institutional barriers that currently pose challenges to the implementation of these strategies.

Some studies, such as [10] [11], emphasize on the specific requirements necessary for various smart charging strategies to be implemented. For instance, in [11], after highlighting the risks of grid failure due to uncontrolled EV integration and arguing that the cost of replacing current transformers and lines with higher capacity ones is prohibitive, the authors introduce the Open Smart Charging Protocol (OSCP). This protocol is designed to facilitate communication between Distribution System Operators (DSOs), Charging Station Operators (CSOs), charging stations, and EVs. The authors propose an algorithm capable of sending 24-hour forecasts about the grid's capacity. These forecasts provide information about available and backup capacities to manage excess demand. DSOs can then adjust capacity based on EV demands. Implementing a unified protocol for EV integration can potentially expedite the adoption process.

Numerous studies, aside from the technical requirements, primarily aim to evaluate the impact of high EV penetration scenarios under various charging strategies, both uncontrolled and controlled. The objective of these studies is to maximize EV penetration without jeopardizing grid stability and minimizing necessary investments. The primary distinctions among these projects arise from the varying assumptions made about driver behaviours. For instance, [12] investigates the impact of increased EV penetration on Australia's low-voltage and medium-voltage grids, assuming that electric vehicles can be plugged in multiple times a day. Contrastingly [13], assumes that EV drivers only charge their vehicle once a day, immediately following their final trip of the day. In [14], EV charging profiles are determined assuming a constant daily driving distance of 32.7 km, while [8] assumes that during peak hours, 10% of the vehicles can operate in Vehicle-to-Grid (V2G) mode. A majority of these studies reach similar findings about uncontrolled charging. For instance, the study in [12] concludes that without any congestion or failure, the grid can only tolerate a maximum EV penetration of 40%. Similarly, in [8], a scenario where Plug-in Electric Vehicles (PEVs) charge during peak hours necessitates significant investments. The research indicates that to sustain a 62% EV penetration scenario, the required investment in the grid increases by 19% of the network total cost, underscoring the imperative for smart charging strategies to facilitate the transformation in the automotive sector.

As a potential solution for that issue, these papers evaluate smart charging strategies to increase the EV penetration on the grid and, thus, reducing the investment needed on grid reinforcements to accommodate the increasing number of EVs. In most of them they either propose a Time-of-Use (TOU) pricing strategy or simply move the EV charging from peak to off-peak hours, also known as peak-shaving. In [12], is concluded that implementing TOU strategies can be advantageous for mitigating peak loads, thereby lessening the strain on transformers during these periods, which was shown to be the first grid unit affected by the increase of EV penetration. However, it doesn't serve as a sustainable solution in the long run, especially when faced with high EV penetration during the designated TOU intervals. This situation can result in another load peak, giving rise to additional grid-related issues. One of the critical limitations with TOU strategies lies in the uncertainty of customer behaviour change, meaning that the outcomes of smart charging procedures aren't entirely under the control of the Distribution System Operators (DSOs). A similar conclusion is reached in [8] where implementing smart charging strategies and moving charging from peak to off-peak hours reduces up to 70 % of the investment needed.

In [15] it is argued that many projects tend to overvalue the potential of smart charging capabilities due to inaccuracies in EV demand profiles and the failure to acknowledge the random nature of EV charging. To address this, they analyse a case study in Shanghai, a city experiencing rapid growth in EV usage. The findings from uncontrolled charging scenarios align with previous studies, highlighting the significant load peak that occurs in the evening. As a smart charging solution, they propose a Time of Use (TOU) approach, which should be specifically tailored after understanding the charging habits of the city's drivers. They emphasize that each driver has a unique charging pattern, and TOU strategies should be designed to adapt to these individual behaviours.

Continuing with the idea of understanding user behaviour, many projects aim to develop an accurate algorithm to model EV drivers' habits. In [16], the social patterns of Internal Combustion Engine Vehicle (ICEV) drivers are investigated to extrapolate the behaviour for Plug-in Electric Vehicle (PEV) drivers, due to the lack of data for the latter. They assume that the behavioural differences will not be a result of the type of vehicle being used. Utilizing the data collected, they create an algorithm that generates EV charging profiles under eight different scenarios, considering both the season of the year and the day of the week. In study [17], individual EV charging profiles are constructed based on Danish data, which are then used to examine the impact of uncontrolled charging on the electrical grid.

In order to offer real-time grid data, other research projects use more sophisticated methodologies that establish connection between the Charging Station Operator (CSO) and the Distribution System Operator (DSO). This provides information about the demands of the grid and modifies charges as needed. In study [18], they simulate three alternative algorithms to examine the effects of expanding photovoltaic (PV) energy self-consumption utilizing smart charging for EVs, mostly Vehicle-to-Grid (V2G) technology. According to the findings, employing V2G technology aids in boosting PV self-consumption and lowering demand peaks. However, it is noted that more study is required because V2G significantly increases battery usage, which could shorten the battery's lifespan. Additionally, it should be mentioned that this study was done on a very small scale, therefore in order to completely comprehend the impacts, it needs to be replicated on a larger scale. In study [19], researchers examine the impact of EVs and Vehicle-to-Grid (V2G) technology on the Brazilian electricity sector. To conduct this study, they run a V2G charging simulation on MATLAB, observing the results following two different strategies. The first one focuses on profit maximization, and the second one aims for grid stabilization. The findings from both strategies reveal that V2G plays a significant role in grid management and peak shaving.

The existing literature still has many gaps. The impact of EV smart charging is not yet fully quantified due to a lack of data and because many smart charging techniques are still under development, which makes it impossible to acquire real-world data (like V2G).

Not many papers compare different strategies, often focusing only on Time of Use (TOU), which yields certain results but all end with the same conclusion on unpredictability. The aim of this paper is to compare the benefits of different smart charging techniques to understand the advantages that each of them brings.

In order to accurately model these, data regarding EV driver patterns such as the time of the first journey, the time of the last journey, charging times, and the type of charger used are needed. This is done in a large urban network, which is important as many studies only consider small grids and therefore do not reflect real-world scenarios.

CHAPTER 3. METHODOLOGY

This section is dedicated to elaborating on the range of procedures utilized for conducting simulations related to the hosting capacity of EV under diverse circumstances, such as different charging methods. It starts by presenting the uncontrolled charging strategy followed by a series of smart charging procedures to reduce the impact of EVs on the grid.

3.1 UNCONTROLLED CHARGING

In this project, uncontrolled charging refers to an EV charging event where EVs are charged to meet their demand as soon as they arrive home after the last journey. This entire charging process takes place during peak hours.

3.1.1 EV DEMAND PROFILES

One of the keys of the project is to create EV demand profiles as close as possible to reality so that the results can be useful. But this is not an easy task since EV drivers behaviours are very variable.

The data required to accurately model social patterns is scarce, hence numerous assumptions must be made to minimize errors as much as possible. There is no available data for Spanish PEV drivers' behaviours, so some aspects of the demand profiles will contain data from previous works done about this subject. The factors that will influence the profiles are as follows [12], [16]:

- **Departure and Arrive time (hours):** Modelling this parameter correctly is critical since the charging behaviour of the drivers mostly depends on this. For uncontrolled charging, arrival times are very important since it is assumed that

EVs will start charging as soon as they arrive. Later, when analysing smart charging strategies, departure times will also be required to define the time windows where the EV are available for charging.

- **Distance driven (km):** This parameter is crucial in developing the behavioural model of our drivers. The distance driven is used to estimate the charging demand for each EV, which will determine the length of the charging sessions.

- **Daily Plug-in factor and SOC:** This models the number of times EV charge during the day and the initial State of Charge (SOC) of the battery.

- **EV charger size:** EV charger size (3.7 kW or 7.4 kW) greatly influences the charging of the battery since with more power comes a reduction in the time of charging.
- **Power Factor**: Even though EV chargers possess a small power factor, it needs to be represented for a realistic simulation.

3.1.1.1 Departure and arrive time

This part of the profile is done thanks to the data provided in [16] which uses data from the National Household Travel Survey (NHTS). The NHTS is a periodic national survey to assist transportation planners and policy makers who need comprehensive data on travel and transportation patterns in the United States. The data used from this survey is from 2009. The data taken comes from 4 different documents and the characteristics of these documents are summarized in the following table:

Variable	**Description**
DWELTIME	Calculated time at destination
ENDTIME	End time of the trip
HHVEHCNT	Count of household vehicles
STRTTIME	Start time of the trip
TDWKND	Trip on weekend
TDAYDATE	Date of travel day
TDTRPNUM	Travel day trip number
TRPMILES	Calculated trip distance in miles
TRPTRANS	Transportation mode used on trip
TRVLCMIN	Calculated travel time
URBRUR	Household is in rural or urban area
VEHID	Vehicle number used for trip

Table 1: Description of the variables from the data. Source: [16]

For the departure and arrive time only a handful of variables are useful such as STRTTIME, ENDTIME and TDTRPNUM. For the departure time only the first trip counted and for the arrive time the last trip, so the first assumption was that there is only 1 trip during the day.

The following figures represent the departure and arrive time distributions for the different 8 analysed cases which depend on the type of day (weekday or weekend) and the season:

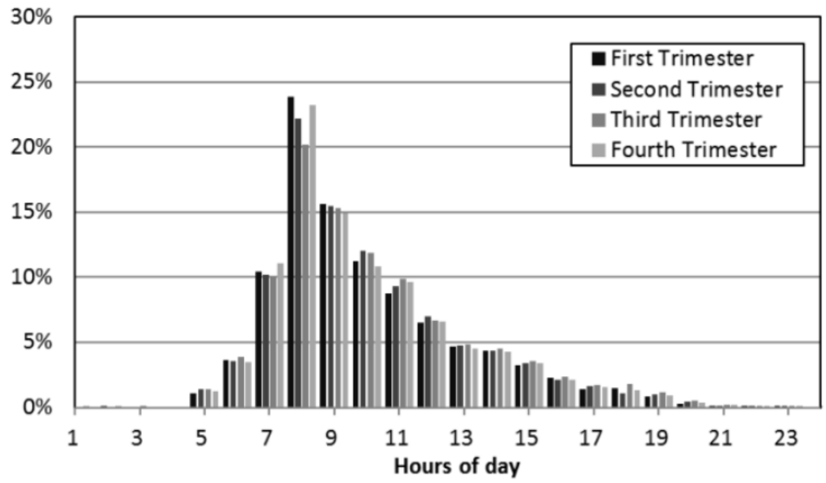


Figure 4: Distribution of departure time in weekdays. Source: [16]

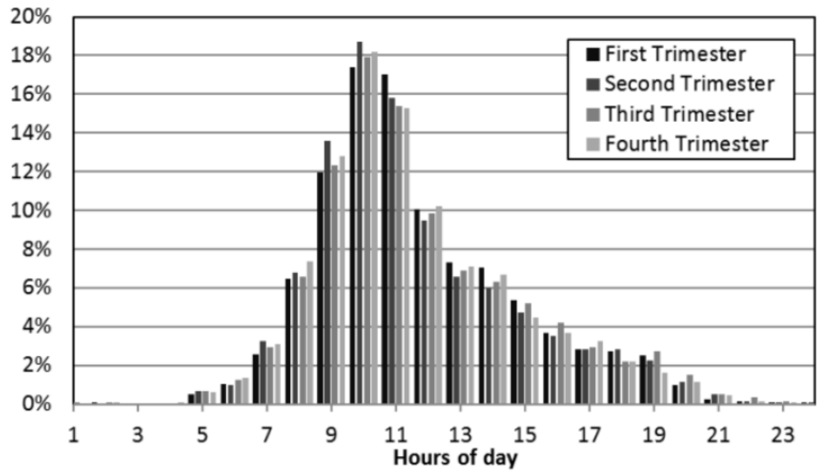


Figure 5: Distribution of departure time in weekends days. Source: [16]

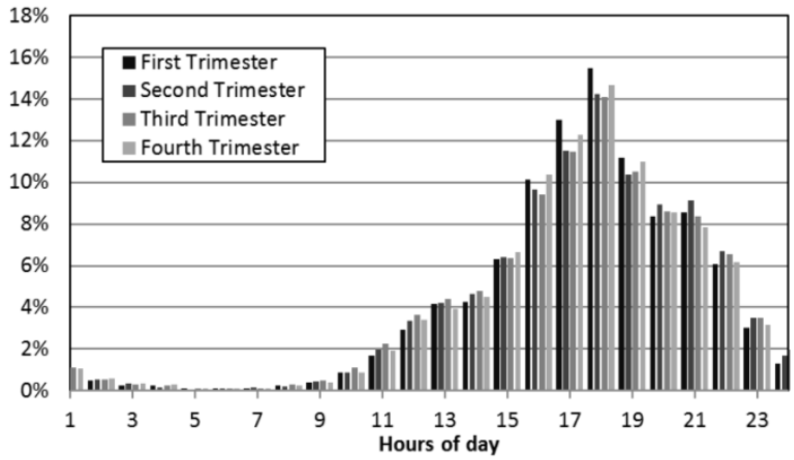


Figure 6: Distribution of arrive time in weekdays. Source: [16]

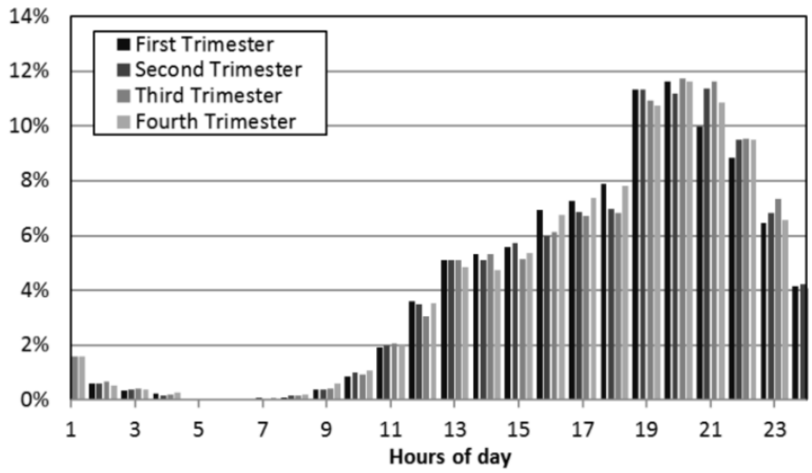


Figure 7: Distribution of arrive time in weekend days. Source: [16]

At first glance the main difference between weekdays and weekends for both departure and arrival time, is a delay of approximately 2 hours in the distribution peak. For Figures 4 and 5 the peak goes from 8 to 10 and in Figures 6 and 7 from 18 to 20.

The main parameters that could be extracted from these distributions are on the following table:

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

Table 2: Departure and arrival time distributions parameters. Source: [16]

This project aims to examine the effects of uncontrolled charging under the most challenging conditions, with the ultimate goal of preparing for any possible scenarios in the future. It is recognized that the most intense electrical peaks often occur in winter, driven by increased utilization of heating systems. Consequently, the parameters employed for this analysis will correspond to those observed during the fourth quarter, aligning with the winter season, and will account for both weekdays and weekends.

3.1.1.2 Daily travel distance

The daily distance driven by an electric car user is one of the most important variables used in the model's formulation. However, the information is both limited and very dependent on EV driver's behaviours in the area of interest, just like the data for arrival and departure times, necessitating the use of a great deal of assumptions.

In [17] they use data from Danish National Travel Survey to model the travel behaviour of EV owners. This information corresponds to gasoline car drivers. However, it is assumed that EVs will replace gasoline powered cars and that the behaviours of their owners should remain the same. So, assuming that the EV will be drove in the same way the distance driven parameter is estimated based on gasoline car data from [17].

As explained in [17], the data is obtained by interviewing many people, in this case 110 000, in Denmark during a ten-year period. This data is only taking into account drivers and not passengers in the car to get as close to possible to reality.

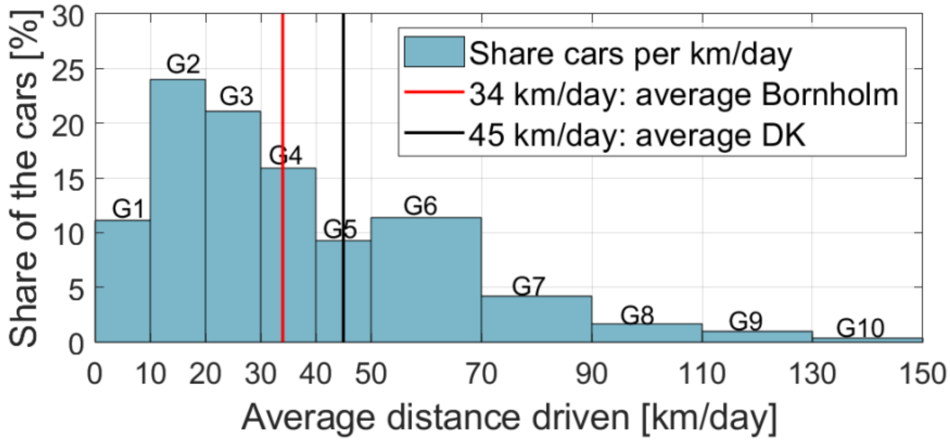


Figure 8: Daily driven distance per share of cars in Bornholm divided in ten groups. Source: [17]

Looking at Figure 11, the average distance driven in Bornholm is of 34 km a day whereas in Denmark it is of 45 km. Knowing this project's network is located in Spain getting the data closer to Spanish average is more interesting. To accomplish this, the data from Spanish drivers used in this paper [20] is employed for comparison. The data is summarized in the following table and was acquired thanks to the information gathered from a group of 1205 drivers, of which 44.6% are women and 55.4% are men, ranging from 18 to 65 years old.

Characteristics of the study sample.

Feature	Category	Frequency	Percentage
Gender	Female	538	44.6%
	Male	667	55.4%
Educational level	Primary studies	91	7.5%
	Secondary-high school	514	62.7%
	Technical studies	198	16.4%
	University studies	402	33.4%
Driving experience	< 5 years	123	10.2%
	5–10 years	185	15.4%
	> 10 years	897	74.4%
Driving frequency	Less than once a week	136	11.3%
	1–3 days a week	198	16.4%
	4–6 days a week	334	27.7%
	7 days a week	537	44.6%
Daily driving (distance)	< 10 Km/day	263	21.8%
	10–30 Km/day	510	42.3%
	31–70 Km/day	313	26.0%
	> 70 Km/day	119	9.9%
Type of vehicle	Private car	1112	92.3%
	Motorcycle/moped/two-wheeled	54	4.4%
	Van	28	2.3%
	Heavy vehicle (truck, bus, freight)	11	1.6%

Table 3: Spanish data sample characteristics. Source: [20]

The data of primary interest from Table 9 pertains to the daily driving distance. The aim is to calculate the average from this data and juxtapose it against the corresponding figures from Denmark. The initial step involves determining the average across the four categories:

- $\bar{x}$ of '<10 km/day' = 5 km
- $\bar{x}$ of '10-20 km/day' = 20 km
- $\bar{x}$ of '31-70 km/day' = 50 km
- $\bar{x}$ of '>70 km/day' = 80 km

$$\bar{X} = 5 \times 0.218 + 20 \times 0.423 + 50 \times 0.260 + 80 \times 0.099 = 30.47\ km$$

In Spain, a daily driving distance of 30.47 km is the cumulative average. This amount is very similar to Bornholm's average of 34 km. Consequently, an assumed daily average of 34 km/day has been selected in order to represent the daily driving distance of electric vehicle owners.

3.1.1.3 Daily plug-in factor and state of charge

In this project, the State of Charge (SOC) stands for the percentage of battery charge, and the term "daily plug-in factor" denotes how frequently electric vehicles are charged each day. Assumptions for these two characteristics are necessary in order to construct the relevant profiles.

First, it should be highlighted that the daily plug-in factor was based on the presumption that drivers made one long trip every day, which implied that electric vehicles were charged once every day. This charging assumption is also backed by [21] where it is said that PEV drivers will charge their vehicle once per day. Furthermore, the assumption is that charging starts at t=at, or soon after arrival, in the absence of explicit data regarding the precise plug-in time and when taking into account the modelling of uncontrolled charging.

Pertaining to the state of charge of the battery, the premise assumes that all vehicles are charged daily, making it counterintuitive not to charge them to reach a 100% SOC. Consequently, it is always the case that the vehicle commences its journey with a 100% SOC and is recharged to the maximum upon its return.

3.1.1.4 EV charger size and power factor

The main feature that's being compared between the chargers is their nominal power. This feature is really important because it decides how long it takes to charge the vehicle. With the model treating all vehicles as having the same daily drive distance and the same type of vehicle (more details are in section 3.1.2), the time taken to recharge will be the same for all vehicles that use the same type of charger. If the charger is rated at 7.4 kW, it will charge faster than a 3.7 kW one, but it will use more power. As shown in [12], it's necessary to consider a power factor, even a small one, to represent how much reactive power the network absorbs. For both chargers, a power factor of 0.99, lagging, is used.

3.1.2 ALGORITHM

Now that the profiles are explained, this section focuses on explaining in depth, the process followed by the algorithm to develop and introduce in each bus the profiles and finally get a power flow result.

As Figure 9 shows, it starts by introducing the grid data corresponding to the network, so that the user can introduce the desired EV penetration, which is no more than a percentage of the total number of EV that are going to be introduced. Then the time of week has to be provided, as explained before, the season is not necessary since the study is searching for the worst-case scenario which is on winter.

Now everything is ready to obtain the time data which are the departure (dt) and arrival time (at) of each EV, so this operation is going to have to be repeated the number of EV that there is on the grid (N). Before allocating an EV to a bus and getting its profile the bus must have 'free space' meaning that no more than three EVs can be placed on the bus (section 3.1.3), if this condition is not fulfilled the bus has to be reselected. Once this condition is met it is time to get the data using the distributions [16] from before (section 3.1.1.1). To generate random numbers associated with the distributions the technique used is the quantile function. This function is calculated inversing CDF function, then a random number y is generating simulating the probability of the distribution. Finally, the value associated to that EV is calculated using a function that depends on the random probability computed and the parameters displayed in Table 8. The function is:

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

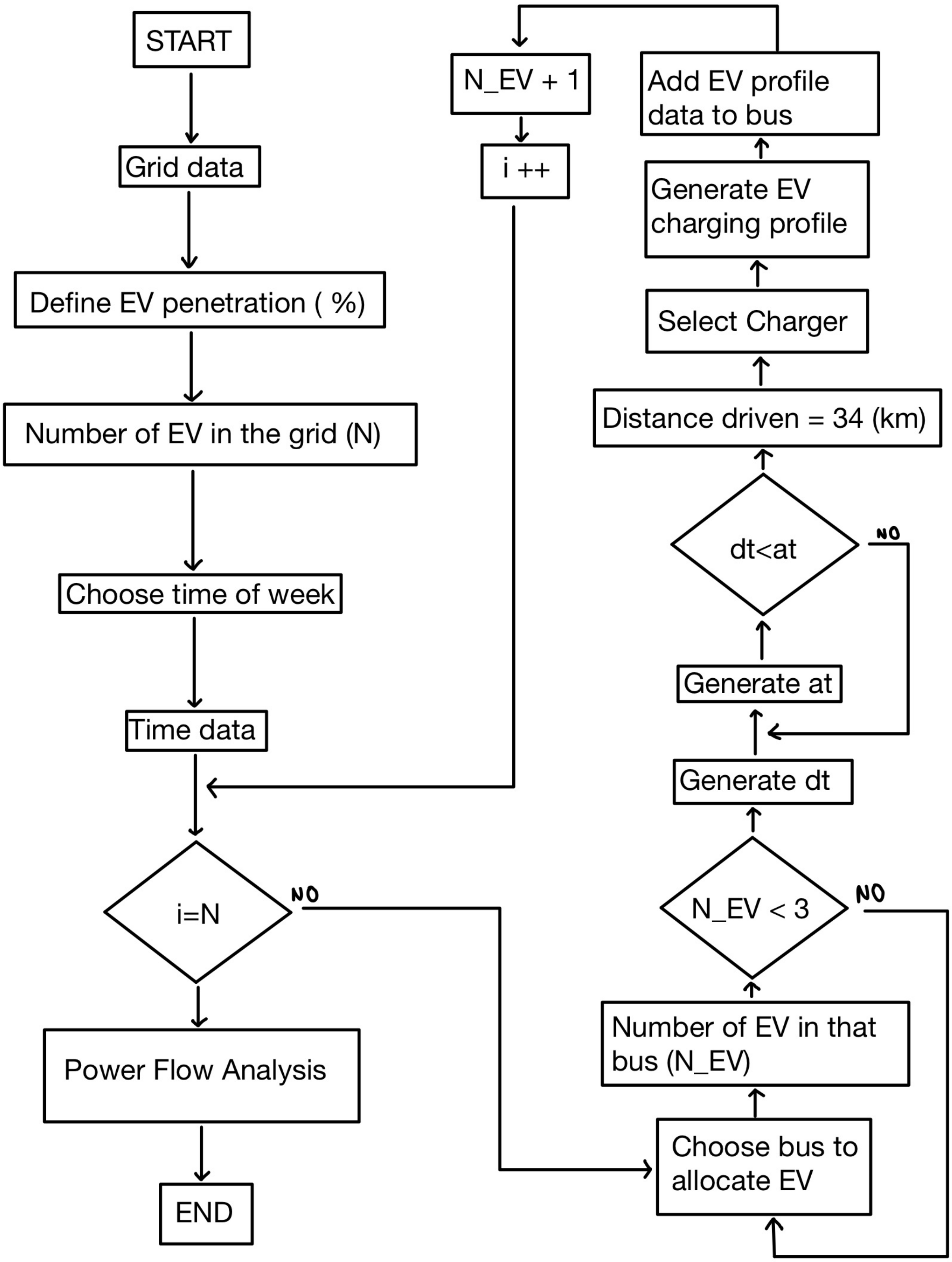


Figure 9: Uncontrolled charging algorithm sequence

- μ represents the location of the distribution function
- σ represents the scale of the distribution function
- ξ represents the shape of the distribution function

To check the fitting of the distribution the next figure shows the distribution and the quantile function of the departure time data in weekdays during the first semester:

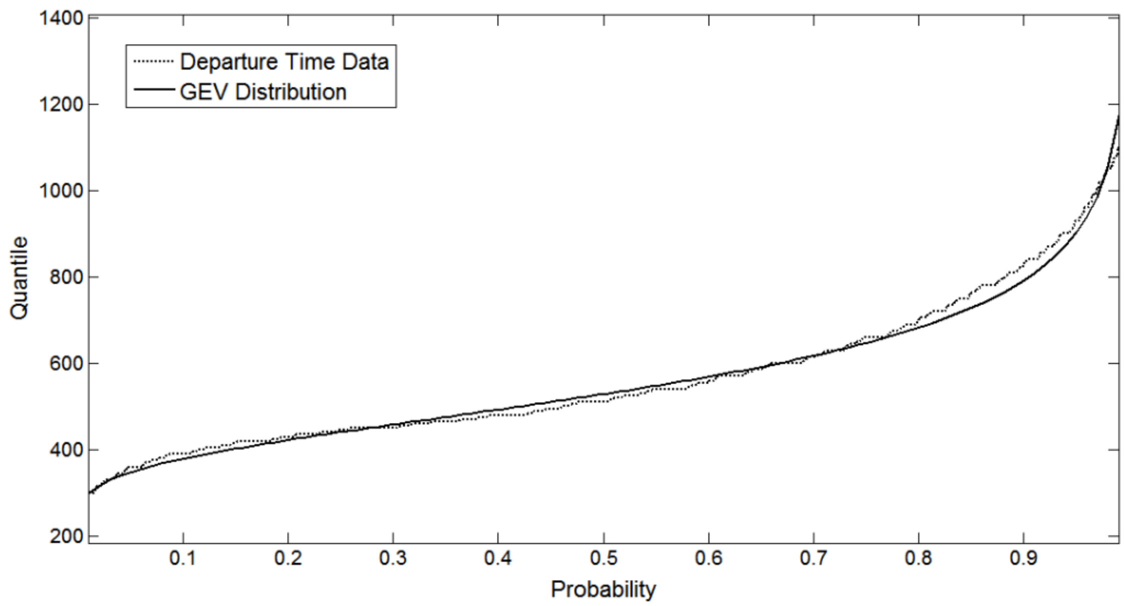


Figure 10: Quantile function fitted to departure time data. Source: [16]

The parameters between departure time and arrival time differ so this must be done twice. Before adding the charging parameters, the algorithm must check that $dt < at$, if this condition is not fulfilled the algorithm calculates the arrival time until the condition becomes true.

Now comes the part where the charging data is added to create the profile. It starts by randomly selecting a charger for the EV, the percentage, in the end, of EVs with each type of charger must be 50 %. The charging time can now be calculated.

The charging time depends on three factors, the daily distance driven by the cars which is 34 km/day, the charger of the EV and finally the energy consumption of the car. The only element missing is then the energy consumption of the car, in [16] they present a table with 3 different models.

	Battery Capacity	Energy Consumption *	Charge Power (AC Level 2)
Nissan Leaf	24 kWh	180 Wh/km	3.3/6.6 kW
Tesla Roadster	53 kWh	155 Wh/km	16.8 kW
Chevrolet Volt	16 kWh	186 Wh/km	3.3 kW

Table 4: Popular electric vehicles characteristics. Source: [16]

This project objective is not to compare the impact of different EV, so instead of using different ones all the EV have the same properties. In this case the chosen one was the more neutral, the Nissan Leaf.

Because all vehicles have the same properties, and they travel the same distance the only factor which changes the charging time is the charger.

- 3.7 kW charger: For this charger with a travelled distance of 34 km and an energy consumption of 180 Wh/km, the total energy consumption will be:

$$E = 34\ km \times 180\ \frac{Wh}{km} = 6120\ Wh$$

So, the charging time is:

$$t = \frac{6120\ Wh}{3700\ W} = 1.65\ h\ \times 60\frac{min}{h} = 99\ min$$

- 7.4 kW charger: For this charger with a travelled distance of 34 km and an energy consumption of 180 Wh/km, the total energy consumption will be the same E = 6120 Wh but the charging time:

$$t = \frac{6120\ Wh}{7400\ W} = 0.83\ h\ \times 60\frac{min}{h} = 50\ min$$

With this information the charging profiles are now complete, and the algorithm just has to add that to the selected bus to complete that EV profile. Now it has to repeat that for all the remaining EVs to then run the power flow and finish with the algorithm.

3.1.3 EV HOSTING CAPACITY ASSESSMENT

The objective of this algorithm is to analyse the impact of EV charging demand on the grid by adding them to residential loads. This problem is formulated following the example of different previous works.[12], [16]

The in-depth process followed to analyse the impact of EV charging demand is explained on Figure 9 (Section 3.1.2) but in a simple way, it consists of introducing the EV penetration wanted and selecting the time of the week where the analysis is going to be done, then the algorithm randomly chooses the buses to allocate the different EV and randomly selects a charger. Then to the buses selected it adds the EV demand profiles and then executes a power flow analysis to visualize the impact.[16]

Each load in the network in this analysis was considered a "house", meaning a residential load, capable of hosting an EV. The average amount of EV in a Spanish household are 1.6 EV's per house. Following that, EV penetration in this work was defined as the percentage of EV per household, meaning that at 100 % there is an average of 1.6 EV per house [22].

When implementing this algorithm, various levels of EV penetration are examined. The levels range from 0%, representing no EVs on average in each household, to 160%. If 100 % EV penetration corresponds to 1.6 EVs per house, then 160 % corresponds to:

$$1.6\ \frac{EV}{House} \times \frac{160}{100} = \ 2.56\ \frac{EV}{House}$$

This higher level of EVs per house will illustrate the impact future expectations on EV will have on the actual grid.

In order to accommodate the demand for that EV, a bus is chosen at random after specifying the desired EV penetration and calculating the total number of EVs for that scenario. There could be more than one vehicle per home, thus several aspects were taken into account. According to [22], of the total number of families that now have electric vehicles which is 74.7%, 42.2% have just one, 25.1% have two, and 7.4% have three . Due to the fact that any number above three would be an exception, the algorithm caps the number of electric vehicles per home at three. It must make sure that the limit is not exceeded before choosing a bus at random.

After checking on the bus availability comes the decision on the type of charger and charger size. The charger assigned to each EV is a random choice from a variety of chargers that fit Spain's actual situation.

The situation with public chargers is not of relevance in this study because the emphasis is on modelling residential charging. The bulk of Spain's domestic electric chargers have a nominal power of 3.7 kW in 2021 [23]. The most popular chargers available right now have a nominal output of 7.4 kW. Therefore, the algorithm's charger bank will consist of two chargers with differing power levels, assuming that prior consumers did not replace their charger. It is assumed that there are 50% of each sort of charger in relation to the proportion of chargers.

The chosen chargers for each power level, according to the French multinational 'Leroy Merlin', which are also the most popular in Spain, are as follows:

Figure 11: Cargador Wallbox Pulsar Plus blanco de potencia hasta 7,4 kW y manguera de 5m

Characteristics:

- Nominal power (in kW): 7.36
- Plug type: Type 2 plug
- Charging mode: Mode 3
- Protection rating (ip+ik): IP54

Figure 12: Cargador portatil Ksix para vehículo eléctrico

Characteristics:

- Nominal power (in kW): 3.7
- Plug type: Type 2 plug
- Charging mode: Mode 2
- Protection rating (ip+ik): IP66 + IK08

Once EV and chargers are randomly allocated it is time to introduce the EV profiles to each EV. Then a power flow analysis is done in the circuit for each penetration comparing both power levels, assets congestion (lines, transformers) and voltage levels using the following metrics [12]:

- **Aggregated Apparent Power (MVA):** It is the sum of all the apparent power in each load of the circuit.
- **Overloading percentage (%):** It is the utilization level of the asset in function of their rated capacity.

- **Undervoltage (%):** It is the number of buses with a voltage level out of the defined boundary, which is usually 0.9 to 1.1 pu, in function of the totality of buses.

The objective of this algorithm is to study the level of EV penetration at which the network begins to experience significant congestion so that there is a starting point for the comparison with smart charging strategies.

3.2 TIME OF USE TARIFF

The uncontrolled charging of electric vehicles (EVs) can induce substantial strain on the electricity grid. It is widely recognized that such an uncontrolled approach is ill-suited for scenarios where EV penetration reaches 100%, with the onset of grid-related issues appearing at even 40% penetration levels [12]. Time-of-use tariffs emerge as a plausible solution that requires minimal technological investment [4]. Essentially, these tariffs aim to shift charging from peak to off-peak hours, significantly mitigating the intensity of peak demand — a strategy commonly referred to as 'peak shaving'. [4]

The principal objective in the present analysis is to introduce an assessment of the EV hosting capacity. This assessment is intended to scrutinize the impact of time-of-use tariffs on the grid. The ultimate goal is to discern the EV penetration level at which the grid begins to grapple with congestion issues. There is a particular interest in identifying if such a shift could give rise to the emergence of a secondary peak.

3.2.1 TOU ALGORITHM SEQUENCE

The assessment of EV hosting capacity is also going to be conducted, but this time, it'll be done utilizing a Time of Use (TOU) tariff, which slightly reduces the uncontrolled aspect, given that there's still no control over the clients during TOU hours. The first part of the algorithm remains unchanged, where the grid data is defined, followed by setting the EV penetration and the time of the week - these inputs still need to be provided by the user. Also, the creation of the consumer's profile works in the same way, so there's no change until that point. However, the major difference arises when dealing with the EV demand profiles. Their generation and subsequent addition to the buses will be handled differently.

The most noticeable change revolves around the scheduling of the charging sessions. In the case of uncontrolled charging, we primarily assumed that customers would begin charging their EVs immediately upon reaching home, so, the start time for charging equalled the arrival time. However, this approach isn't applicable with a TOU tariff, as charging is pushed to off-peak hours to take advantage of the lower rates offered during these hours. As shown in the following figure, arrival times tend to coincide with peak hours. Therefore, many EV users will have to delay their charging sessions to off-peak hours. The discomfort caused by delaying the charge events is compensated by a lower energy charge in the electricity bill.

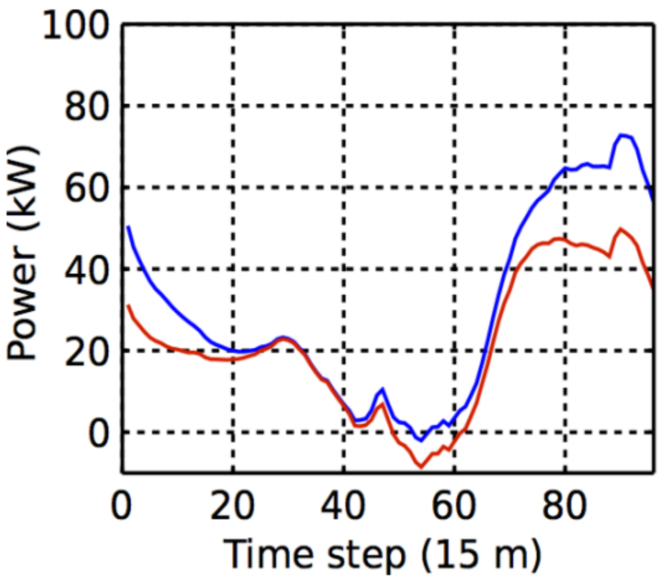


Figure 13: Daily average transformer load profile under different scenarios. Source: [24]

In [24], the impact of coordinated EV charging in a LV residential grid was studied. Figure 14 shows the daily load of a transformer in a no charging EV scenario (red) and an uncontrolled charging scenario (blue). The peak times go from around 20:00 to 00:00 which corresponds to our most probable arrival time outcomes. As well as the off-peak hours corresponds with the discounted hours from the selected plan.

So, now the key to this algorithm is to determine at which time from the discounted hours it is best to charge the EV. To solve that issue a linear programming (LP) optimization problem is introduced to the algorithm to obtain the EV charging profiles that follow from considering a TOU tariff as a smart charging strategy.

3.2.1.1 Linear programming optimization problem

The goal of the LP optimization problem is to identify the best moment during the discounted hours to start the charging process for each Electric Vehicle (EV) connected to a certain bus. The timing of the vehicle's scheduled departure and arrival, the EV's energy needs, the current Time-of-Use (TOU) pricing structures, and the charger's power capacity all play a role in determining the best time to charge the EV. Each of these initial data significantly affects the optimization process, making them essential to determining the most successful and economical EV charging approach possible given the constraints at hand.

In this optimization problem, the primary variable is the energy demand for each hour (represented as 'p'), predicated on the assumption that the EV will charge at a consistent power level. Each entry within the data set holds significant relevance in shaping the outcome of this optimization problem.

Firstly, the departure and arrival times hold a key position in this context. In the scenario of uncontrolled charging, the departure time may not have been of substantial significance; however, in this model, it assumes a critical role. It is essential that the departure time is always less than the arrival time (dt < at), given that the departure time associated with the EV now corresponds to the timing of the first trip of the next day.

This shift in understanding becomes possible because the departure and arrival times now serve to generate a binary vector (designated as 'X') which delineates the hours during which the EV is available for charging. This binary vector comprises of 'ones', representing periods when the EV is at home and can thus be charged (i.e., when the time is between the arrival time 'at' and the departure time 'dt'), and 'zeros' when the EV is not available for charging (i.e., when the time exceeds the departure time 'dt').

Following there is an example of an X vector for a random dt and at:

Times	Values	Meaning
AT	17:00	Day before last trip
DT	10:00	First day trip

Table 5: Example of EV departure and arrival time

	Day Before							Actual Day																
X	17	18	19	20	21	22	23	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0

Figure 14: Example of X vector

The energy requirements of the EV (D_i) and the charger’s power capacity (P_i) remain consistent in this optimization problem. The daily distance driven by all EVs up to the specified arrival time is maintained at 34 km. The model of the car, in this case, continues to be the Nissan Leaf, which comes with its unique energy consumption profile, as outlined in Table 4. And for the chargers the options remain unchanged, two chargers one of 3.7 kW and the other of 7.4 kW.

The chosen plan, as shown in Table 10 (section 4.3), culminates in the selection of the Electric Vehicle Plan, which determines the price vector for TOU (C).

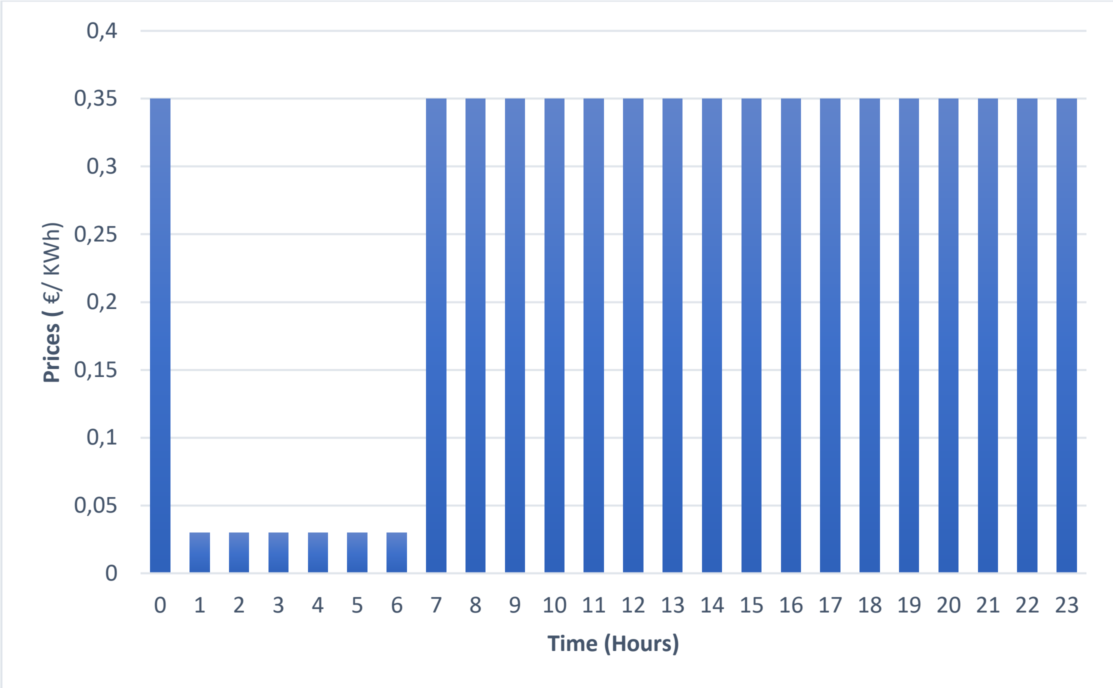


Figure 15: Electricity prices (€/KWh) in function of the hour

Now that the entry data is defined let's explain the objective function and the restraints of this problem.

The objective function of the LP optimization problem is: **minimizing the cost of charging for all EVs.** The cost of charging is formulated as the sum, for all hours, of the electricity hourly rate times the energy consumed for charging the EV. Then, the objective function is expressed as:

$$\min_{p_{i,h}} \sum_{i,h} C_h \cdot p_{i,h}$$

- i: number of EV on the grid (N)
- h: number of hours in a day
- $p_{i,h}$: energy demand for the vehicle i at the hour h
- C_h: Cost of electricity at hour h

The problem has two constraints:

1. The daily EV charging demand restriction:

$$\sum_{h} p_{i,h} = D_i \ \forall i$$

- D_i: Total Energy demand for the vehicle i

This constraint states that for all EVs the sum of all its hourly demand must be equal to the total energy daily charging needs. In other words, minimizing the cost must not prevent the EV from charging to a 100 %.

2. The EV charger power rating restriction:

$$p_{i,h} \leq X_{i,h} \cdot P_i \ \forall i, h$$

- $X_{i,h}$: Binary vector equal to 1 if the EV is available for charge and 0 if not
- P_i: Power rating of the EV charger

This constraint stipulates that for every electric vehicle and for each hour, the power allocated for charging the vehicle must not exceed the power capacity of the charger. Furthermore, the charging can only take place when the vehicle is parked at home.

With the optimization problem completed the algorithm can now create the TOU EV demand profiles to add them to each corresponding bus.

3.2.1.2 Final steps

The initial stages of the algorithm align perfectly with the uncontrolled approach, encompassing everything from extracting grid data to computing departure and arrival times using quantile functions (as detailed in section 3.1.2). The significant alteration comes with the formulation of the vector X, which is required to capture the charging availability of each electric vehicle (EV). Upon successfully storing the charging availability for each EV, the prerequisites for executing the optimization problem are satisfied, hence it can proceed to calculate the energy demand for each vehicle.

The concluding phase of the algorithm remains unaltered as well, which involves aggregating the generated EV demand profiles to their respective buses, culminating in a power flow analysis. This final step allows for the assessment of the impacts and efficiencies of the implemented charging strategy on the grid.

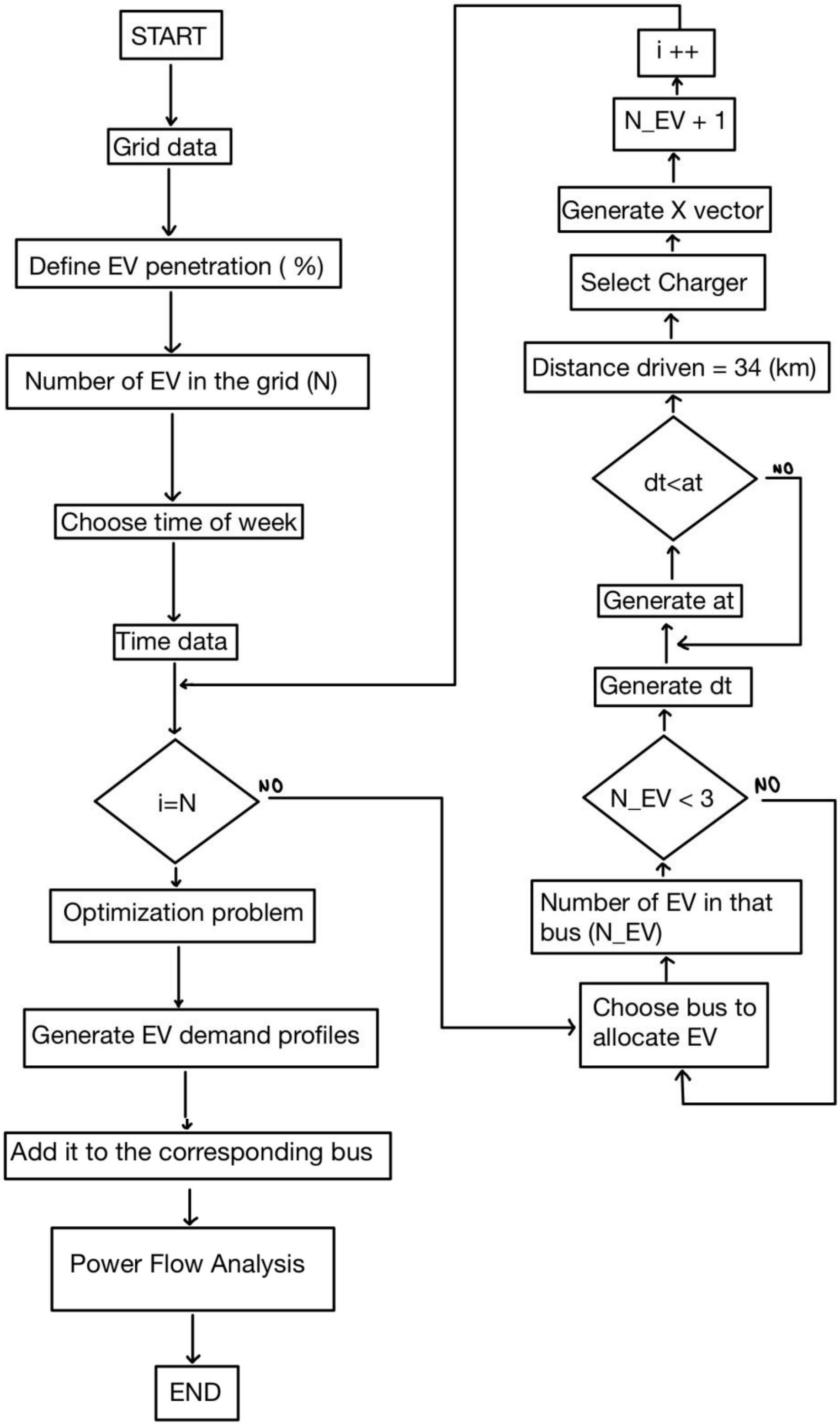


Figure 16: TOU algorithm sequence

3.3 TIME OF USE TARIFF WITH RATIO

Exploring the limits of Time of Use (TOU) pricing is a crucial step after its implementation. While TOU offers a short-term solution, it inherently encourages customers to charge at off-peak hours, which may not always align with conventional patterns of usage. This can present challenges that will be addressed in subsequent sections. The main problem with TOU tariff is that the share of EV owners who will respond to the incentive to shift their charging session to off-peak hours is unknown. An important question arises here: What is the minimum proportion of customers, at each penetration level, that would need to adopt TOU for the grid to remain stable?

To answer this, the algorithm is modified to incorporate a user-defined ratio, which represents the percentage of customers opting for the TOU pricing scheme. The remaining customers adhere to the previously outlined uncontrolled charging method. Hence, the algorithm effectively becomes a hybrid of the two preceding methods, allowing to study of a sensitivity analysis to how different proportions of TOU adoption from EVs impact the grid.

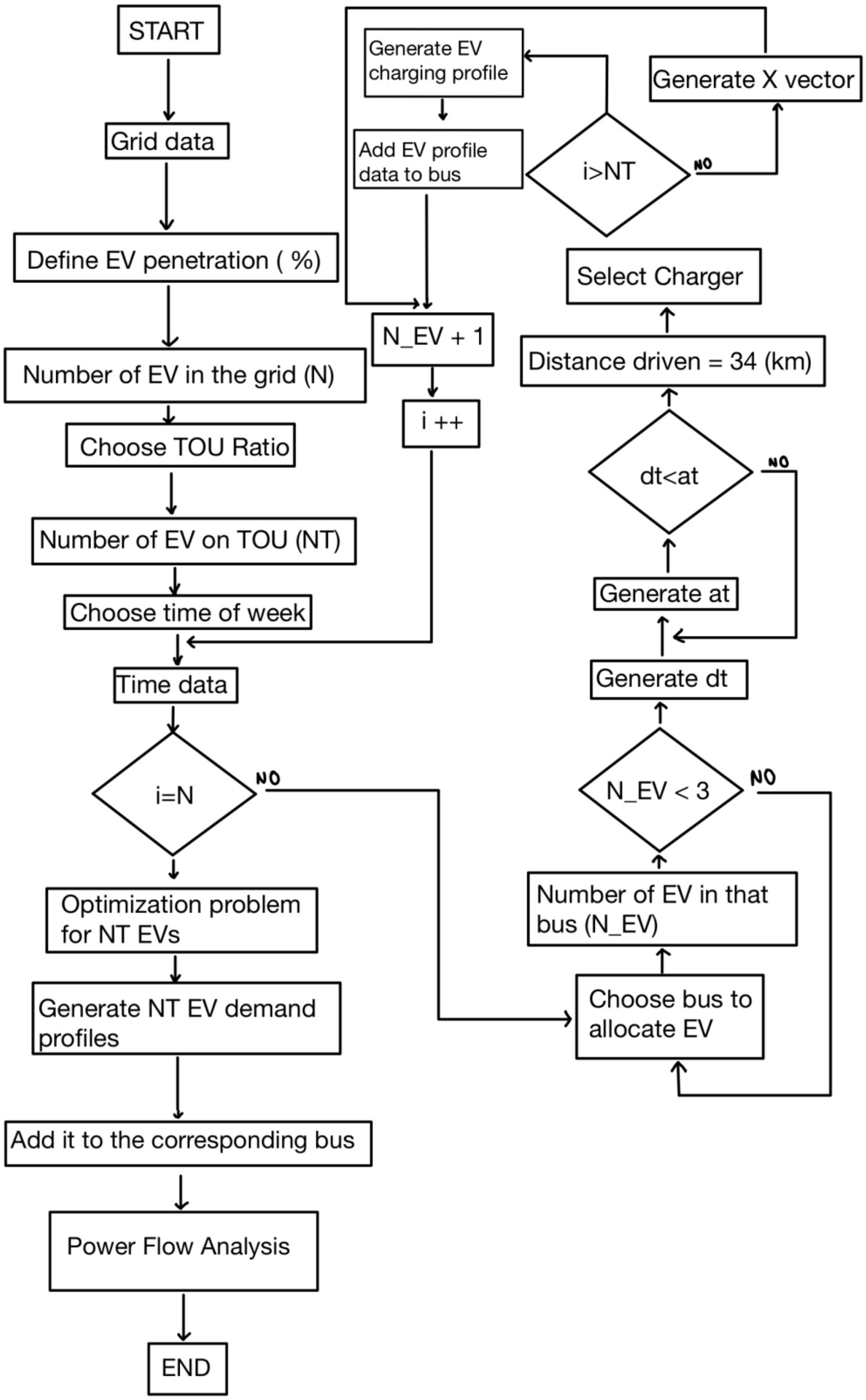


Figure 17: TOU with ratio algorithm sequence

In conclusion, this section provides a detailed exposition of the construction process behind the three distinct strategies employed to model EV charging: uncontrolled charging, Time of Use Tariff (TOU), and a mix strategy with a TOU and uncontrolled charging. Each strategy carries its unique advantages and disadvantages, all of which potentially impact the electrical grid in varying ways.

The uncontrolled strategy, though easiest to implement, puts significant strain on the electrical grid. Although the TOU strategy aims to shift charging to off-peak hours, it remains somewhat uncontrolled and unpredictable. On the other hand, the mix strategy puts together both strategies reaching a better result. However, the unpredictability is still present.

With these strategies now outlined, the following section will showcase the varied results derived from simulating these strategies.

CHAPTER 4. CASE STUDY

This section is dedicated to detailing the network components including buses, lines, and transformers, as well as the consumer profiles used in the different strategies. Additionally, the tariff used in the TOU strategy, which shifts charging from peak to off-peak hours, is also described.

4.1 NETWORK

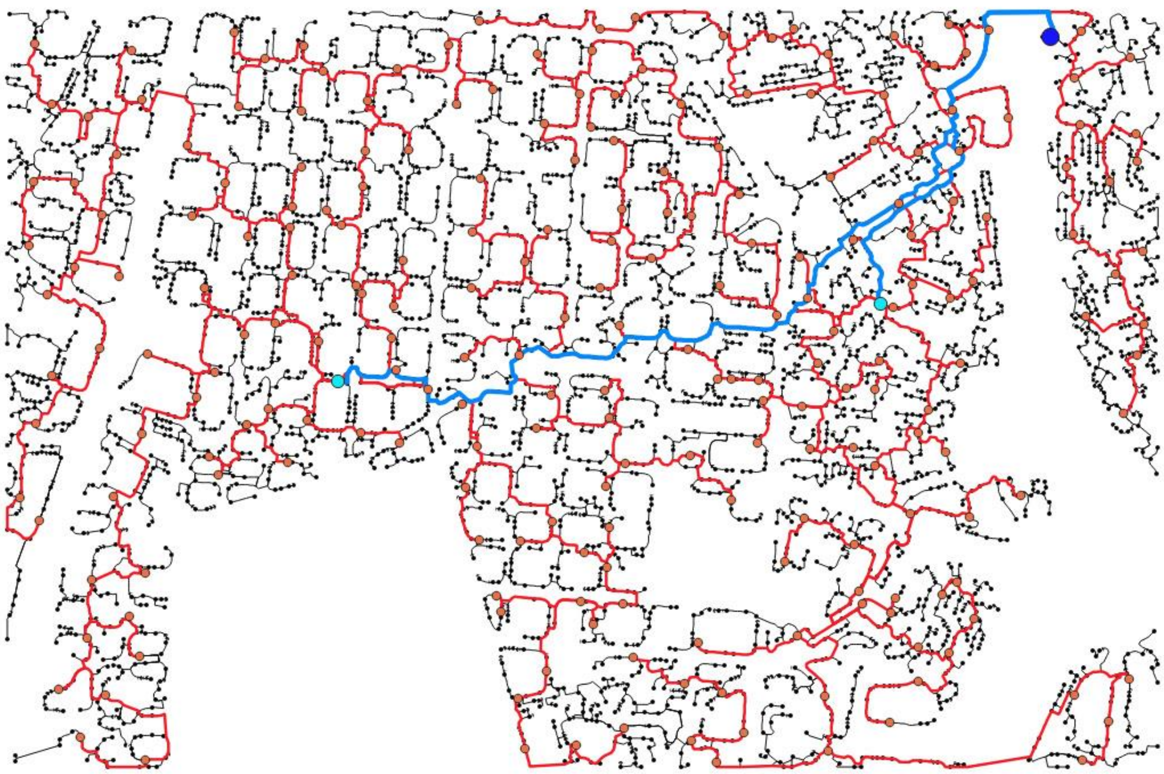


Figure 18: Grid

First and foremost, it is essential to comprehend the components of the network to subsequently analyse the impact of electric vehicles on it. The network in question is situated in Spain, therefore all the accessories and assumptions made in this study will be in correspondence with the status of electric vehicles in Spain.

These are the network components:

Components	Numbers
Bus	5322
Load	4905
Line	5126
Transformer	209

Table 6: Network's components

There is a total of 5322 buses but only 4905 loads, this is because some of the transformers are represented as 2 buses. The total of transformers is 209 and 208 of them are represented as 2 buses, making it a total of 417 buses which correspond to transformers:

$$5322 - 417 = 4905$$

There are different levels of voltage limits for the buses going from 0.4 kV to 400 kV. These exist because the grid is composed of a Low Voltage (LV) and a Mid Voltage (MV) part:

- Low Voltage (LV): This generally refers to voltages up to 1000 V or 1 kV
- Mid Voltage (MV): This generally refers to voltages going from 1 kV to 36 kV

The different voltage limits of the buses are in the Table 7:

Voltage (kV)	Number of Buses without transformers	Number of Buses with transformers
0.4	4878	5084
20	27	234
132	0	3
400	0	1
Total	4905	5322

Table 7: Buses voltage levels

The transformers which have 0.4 kV or 20 kV as their respective voltage correspond to distribution transformers which are responsible of stepping down the voltage for a safe residential, commercial or industrial use. The 132 kV and 400 kV correspond to 'Super Transformers' designed to handle very high voltages for long distances. The objective of these transformers is to distribute power at high voltages so the current flowing through the lines is low and so are the losses. Then the distribution transformers step down the voltage for the safe residential use.

4.2 CONSUMER'S PROFILE

Initially, the network was meticulously engineered such that the reactive power (Q) constituted approximately 30% of the active power (P) consumption, translating to a power factor (PF) proximate to 0.96.

a. $\sin\theta = 0.3$
b. $\theta = 16.52$
c. $\cos\theta = PF = 0.96$

Then, the next step was to get the ‘peak active power’ of each bus. The information known of each bus was the installed capacity and the simultaneity factor. The installed capacity represents the maximum generation capacity of an industry or an energy system in a precise moment. The simultaneity factor is a value always inferior to 1 which represents the real utilization of the available capacity for each energy system, when it is equal to 1 it means that everything is always using the maximum possible capacity which is highly unlikely. The product of the installed capacity with the simultaneity factor gives the peak active power, since not everybody is going to always use the maximum capacity, the result is a peak active power lower than the installed capacity.

The simultaneity factors for this project where:

Grid	Simultaneity Factor
Low Voltage (LV)	0.4
Mid Voltage (MV)	0.8

Table 8: Simultaneity Factors

To finish with the consumer´s profile, what is left are the hourly unit profiles. These are tools used in the planning and management of electrical supply networks that reflect the variation in energy consumption of different types of customers throughout the day, allowing the electric companies to create tariffs suited for each type of consumer since the energy consumption is different.

Multiplying the peak active power with these profiles gives the complete peak active power.

Depending on the grid voltage the hourly unit profile was different:

hours	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
LV coefficients	0.67	0.49	0.37	0.32	0.30	0.30	0.31	0.42	0.52	0.53	0.57	0.61	0.68	0.73	0.77	0.76	0.73	0.73	0.77	0.81	0..87	0.97	1.00	0.86
MD coefficients	0.37	0.35	0.35	0.34	0.35	0.37	0.44	0.50	0.59	0.83	0.98	1.00	0.98	0.81	0.61	0.59	0.62	0.67	0.69	0.69	0.65	0.53	0.45	0.41

Table 9: Hourly Unit profiles

4.3 AVAILABLE TARIFFS IN SPAIN

Numerous power tariffs are available on the market to accommodate the various schedules and electrical requirements of different consumers. Given these changeable rates, careful consideration of the possibilities might enable significant cost savings, lowering the overall electricity bill. Time-of-Use (TOU) tariffs, as previously indicated, are based on moving charging to off-peak times. Offering consumers much lower electricity bills if they want to charge during off-peak hours makes it easier to adopt this method. The existence of these different techniques and the corresponding price models offer a fascinating background for the goals of this research. Since these tariffs may affect both consumption habits and the overall pressure, it is crucial to think about them and their ramifications.

These are different tariffs options that fit this project:

1. **Iberdrola's Nocturnal Plan ('Plan Noche')**[25]: This particular tariff structure presents a significantly lower rate during a 14-hour window, spanning from 22:00 to 12:00 in winter, and from 23:00 to 13:00 in summer. Considering that the focus of the uncontrolled charging algorithm analysis is centered on the most challenging scenario, which occurs in winter, investigating the effect of this tariff—also primarily applicable during winter—provides valuable insights.

2. **Iberdrola’s Winter Plan (‘Plan Invierno’)**[25]: This particular plan provides a consistent rate from the 1st of December through to the 1st of March, and additionally throughout the weekend, specifically from 3 pm on Fridays until midnight on Mondays. Even though this plan aligns with the winter season, much like the focus of the project, it appears to cater more towards secondary residences than primary homes. Indeed, one cannot even opt for this plan unless they're already an existing customer of Iberdrola. Therefore, while intriguing, this plan might not be the most appropriate for the analysis as the project primarily addresses the concerns of everyday residences.
3. **Iberdrola’s electric vehicle plan (‘Plan Vehículo Eléctrico’)** [25]: This particular plan, aptly named "Electric Vehicle Plan," is specifically designed with electric vehicle owners in mind. The most significant benefit of this tariff is its incredibly low rates during the off-peak hours of 01:00 to 07:00. This means that EV owners can charge their vehicles at these hours, effectively paying far less for the kilometers they travel. It's a win-win situation as they not only get to save money but also contribute to better energy management on the grid.

The following table will show the price differences in these tariffs:

Plans	Rates
Night Plan	**Discounted hours**: 22:00 - 11:59 (Winter) **Price**: 0.159765 €/kWh **Normal hours**: 12:00 - 21:59 (Winter) **Price**: 0.209607 €/kWh
Winter Plan	**Discounted hours**: 00:00 - 23:59 (December 1st - March 1st)/ Week ends: Fridays 15:00 - Mondays 00:00 **Price**: 0.139019 €/kWh **Normal hours**: 00:00 - 23:59(rest of the year) except weekends from Fridays at 15:00 **Price**: 0.245915 €/kWh
Electric Vehicle plan	**Discounted hours:** 01:00 - 06:59 **Price**: 0.030000 €/kWh **Normal hours**: 07:00 - 00:59 **Price**: 0.349874 €/kWh

Table 10: Plans and their respective rates

Examining all the available plans, it's evident that the Electric Vehicle Plan offers the most significant discount. However, it's also worth noting that this sizable discount comes with a slightly higher price during standard hours. Nevertheless, the potential savings from charging during off-peak hours are quite remarkable with the Electric Vehicle Plan. This aspect makes the idea of adjusting charging times more appealing to customers. Thus, considering its overall features and advantages, the Electric Vehicle Plan has been chosen for this project to represent a typical time of use tariff.

CHAPTER 5. RESULTS

In this section, the results of the power flow analysis got from all of the EV penetrations for each of the strategies are analysed, focusing on voltage drops, power peaks, and overloads to define the EV hosting capacity. This helps to understand the impact each strategy has on the grid, as well as the potential benefits a smart charging strategy could bring.

5. 1 UNCONTROLLED CHARGING

In scenarios where demand increases, there is a subsequent drop in voltage and an appearance of peaks in power demand. These fluctuations negatively impact the grid as they can lead to congestion, disrupting the distribution of power, and potentially even causing grid failures.

The end of most last trips, falling between 20:00 and 22:00, contributes to a significant surge in demand. As EV penetration increases, this surge becomes more pronounced, leading to greater peaks in demand on both weekdays and weekends. This can be observed in Figures 19 and 20, which show the aggregated apparent power of the grid. At 0% penetration, the demand sits at 14 MVA. However, as EV penetration increases, the peak can reach increases of up to 20% in the most demanding scenario, which is 160% EV penetration. In the scenario representing the situation in Spain, with 1.6 EVs per house (equating to 100% EV penetration), the peak demand reaches values of 15 MVA and 15.8 MVA for weekdays and weekends respectively. This corresponds to a 13% increase in peak demand.

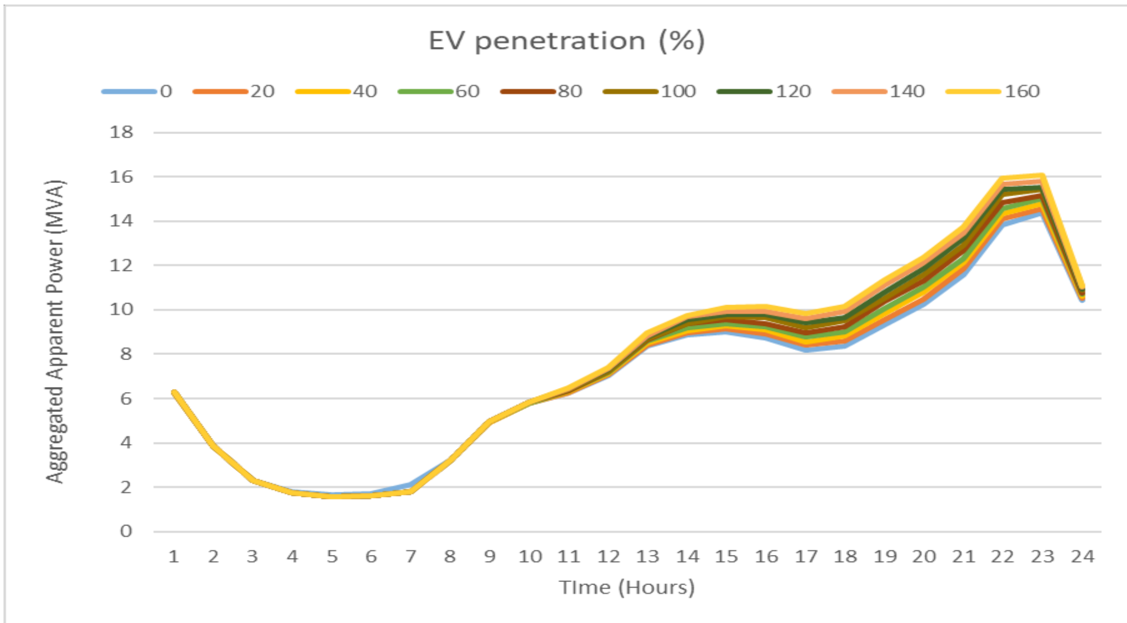


Figure 19: Aggregated Apparent Power depending on the hour during the weekdays

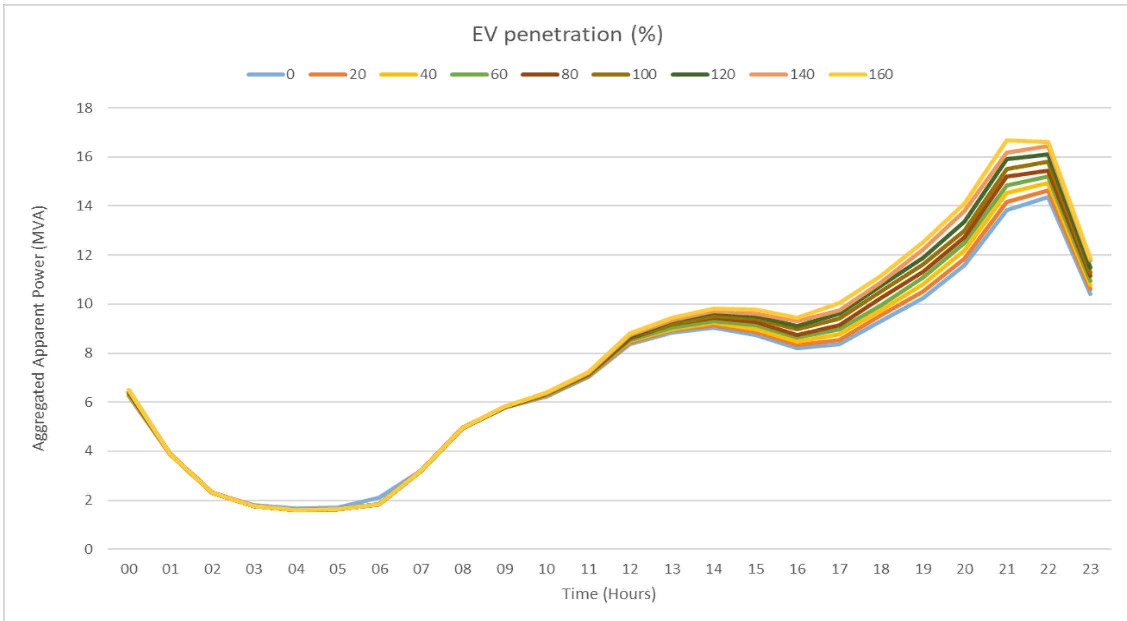


Figure 20: Aggregated Apparent Power depending on the hour during the weekend

As mentioned before this increase in the peak causes lines and transformers to overload.

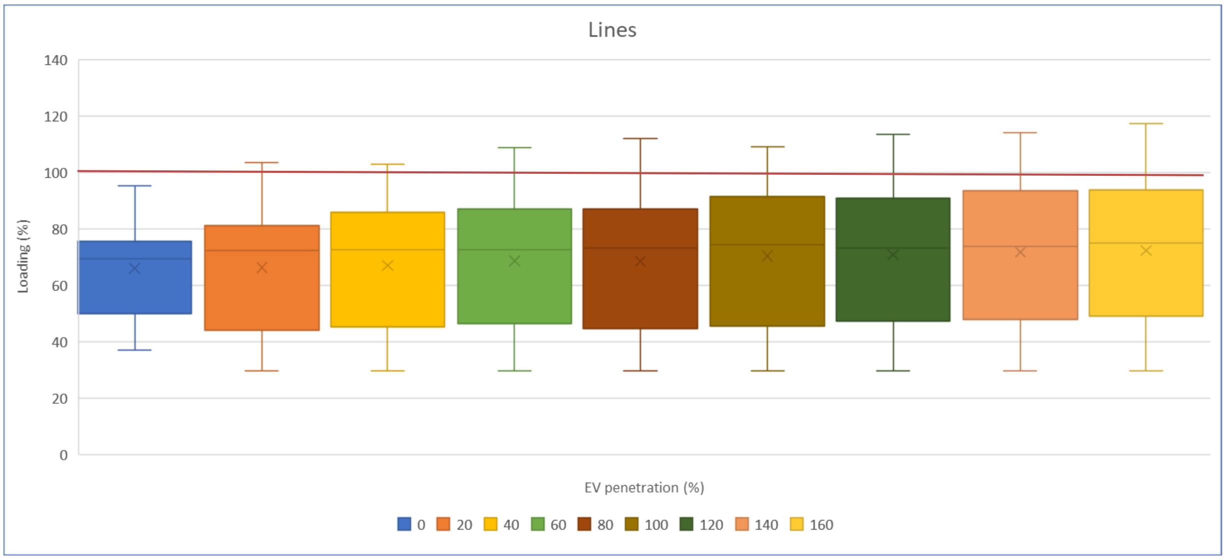


Figure 21: Lines loading value during weekdays

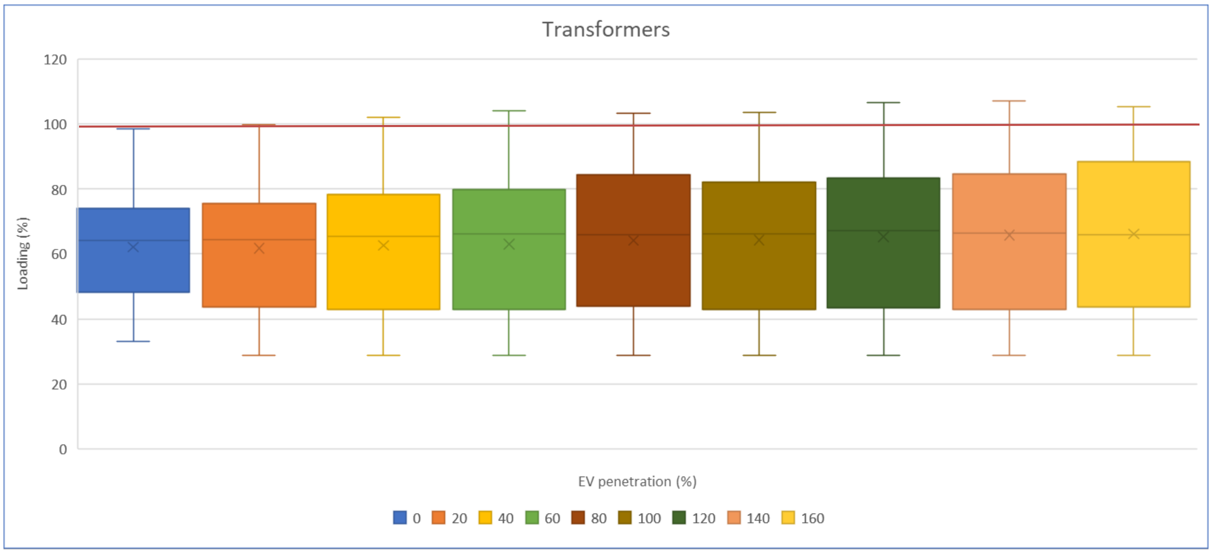


Figure 22: Transformers overloading during weekdays

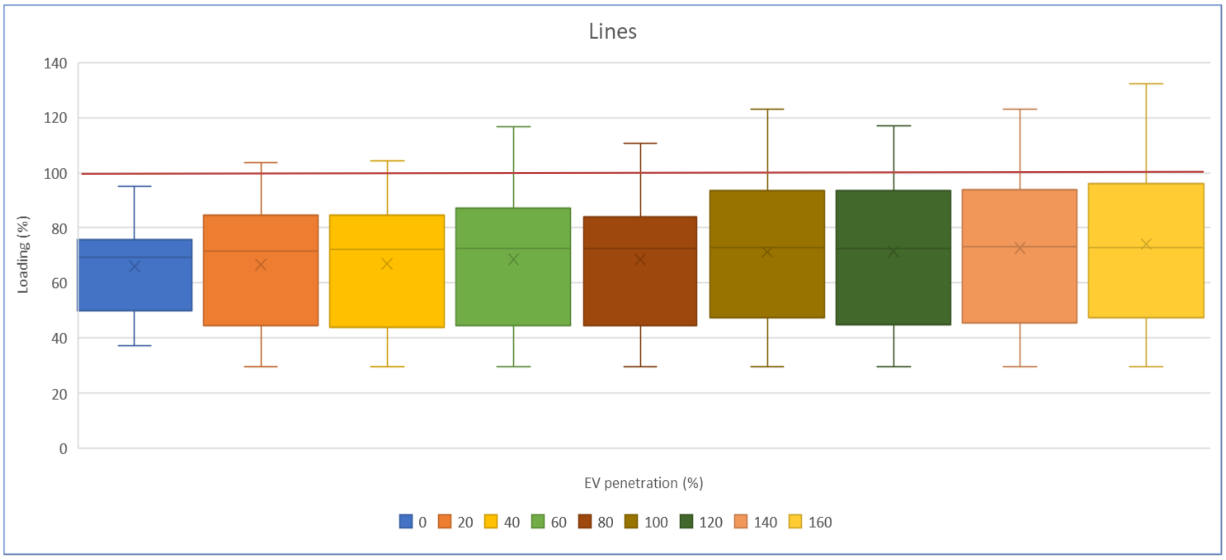


Figure 23: Lines loading during weekends

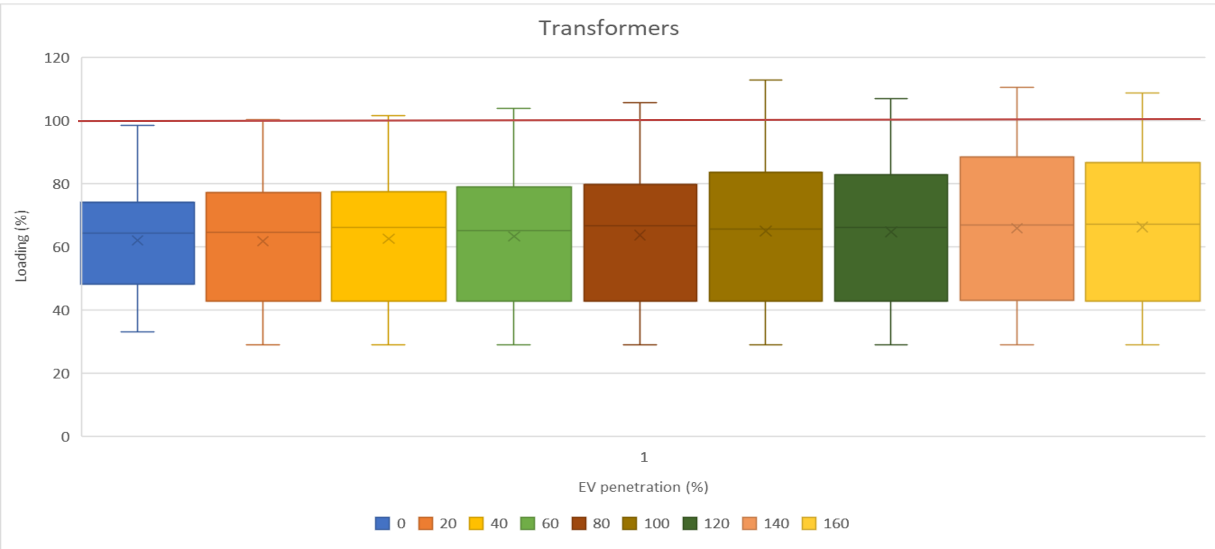
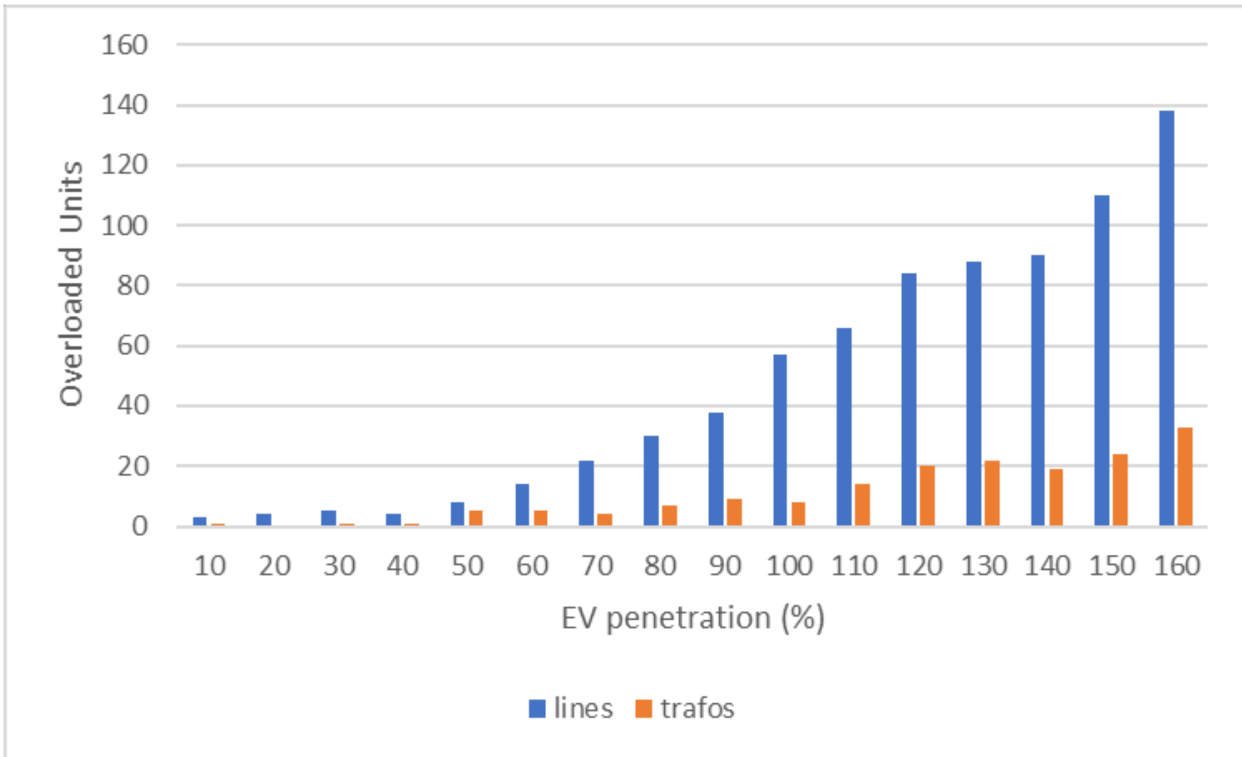


Figure 24: Transformers loading during weekends

Figures 21-24 show the loading percentage of grid elements, specifically referring to lines and transformers. The lines tend to experience greater strain than transformers, largely due to the larger number of lines compared to transformers, there are 5126 lines compared to 209 transformers. As the figures demonstrate, in high EV penetration scenarios, the maximum overloading value of lines can escalate to 120%.

From the 20 % EV scenario onwards, there are already lines and transformers reaching their maximum capacity. Interestingly, the figures also reveal that even in the no-EV scenario, certain lines and transformers are nearing their maximum capacity, reaching up to 98%. This indicates that, even without EVs, this network was already dealing with a substantial demand. It is much more interesting to look at the third quartile. At 0% EV penetration, 25% of the lines and transformers are operating at over 70% of their capacity. However, once EV penetration hits 100%, 25% of the lines and transformers are pushed to over 90% of their capacity.

Figure 25 clearly demonstrates the significant impact on overloading that lines experience in comparison to transformers. As previously mentioned, this network was already dealing with substantial demand, resulting in saturation of some instruments in the early stages of EV penetration. However, this represents a very small number and does not truly reflect the impact of EV charging. It is not until the 50% EV penetration scenarios, with already 8 lines and 5 transformers overloaded during weekdays, that the grid begins to struggle. The increase from this point is quite significant, as in the realistic scenario of 100% EV penetration, the number of saturated lines reaches 57, representing more than a 600% increase. The 160% scenario appears unattainable, with 138 saturated lines (a 1625% increase) and more than 30 transformers (a 500% increase). This is only during the weekdays. During the weekends, the maximum value doubles, with 276 saturated lines and nearly 50 transformers. This provides clear evidence of the necessity to improve grid infrastructure to support such a big increase in demand.



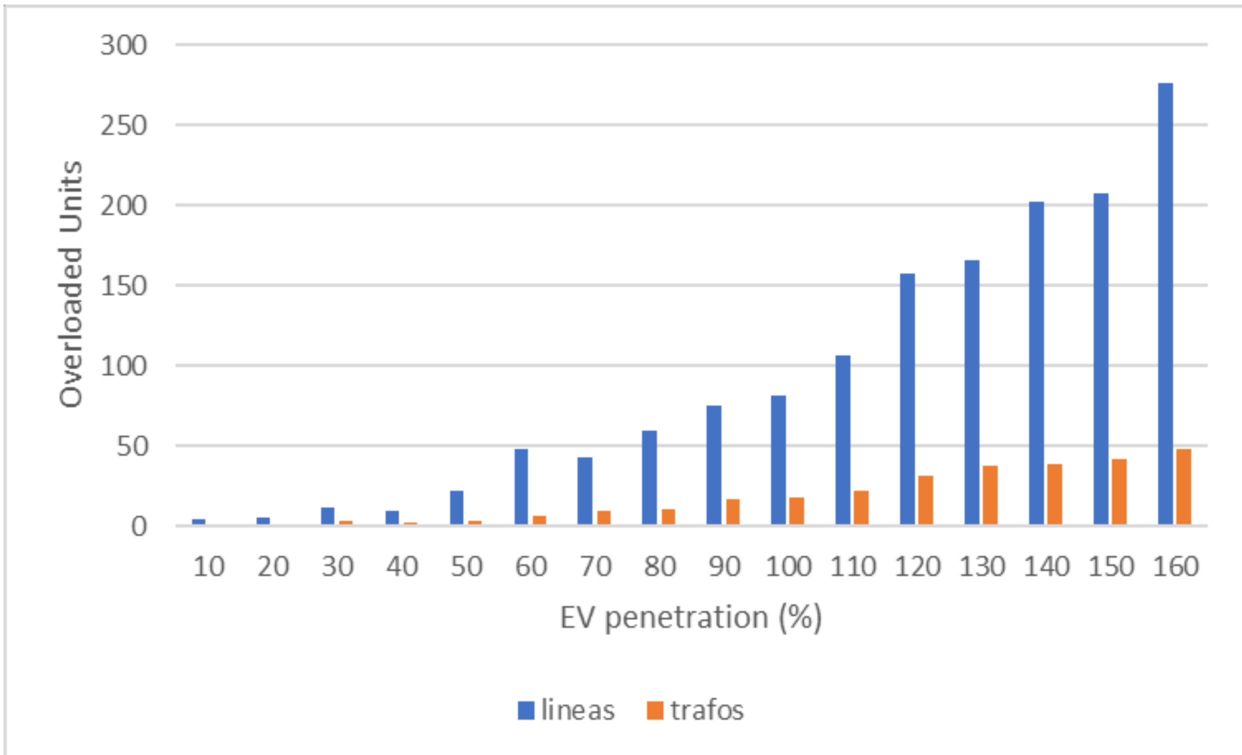


Figure 25: Number of Lines and transformers units overloaded for weekdays (up) and weekends(down)

In addition to branch congestions, voltage limit violations are also studied as they may also pose significant problems whenever there is a high increase in demand. Radial grids represent a substantial economic investment, as all buses are connected to a principal bus, which requires fewer lines to create and is easier to maintain. However, this cost efficiency is balanced by a decrease in reliability; if a problem occurs in a high up bus, the subsequent buses also experience the issue. Furthermore, the quality of energy distribution is inferior in radial grids, as energy losses due to transmission can result in lower voltages for buses farther away from the principal one.

This project grid is not entirely radial, one of the lines makes a loop making it less inclined to having voltage problems as we can see in figure 26. However, this is also due to the fact that this grid is situated in an urban environment, where feeders are closely located to each other, resulting in lower voltage drops. Additionally, this grid is equipped with voltage regulators.

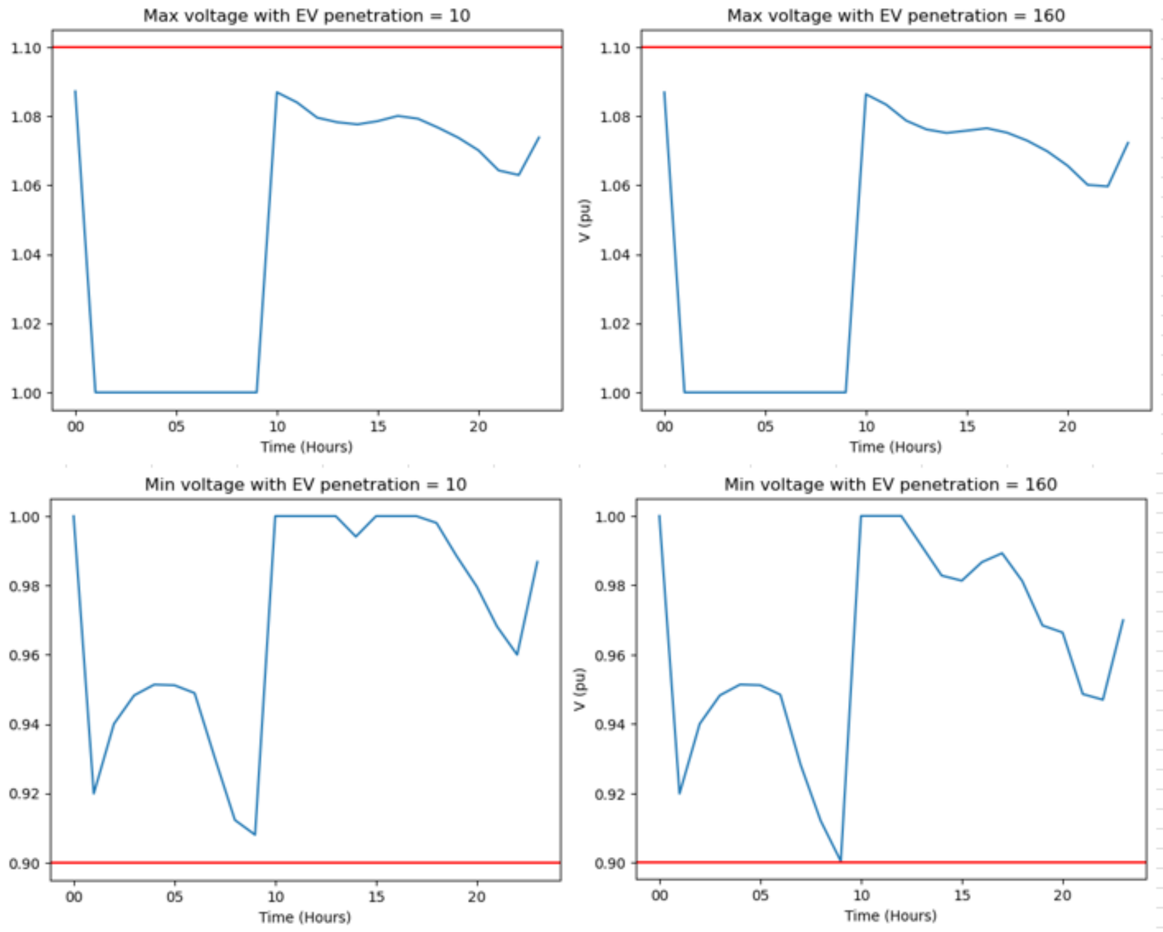


Figure 26: Voltage maximum and minimum values depending on the hour of day for two EV penetrations during weekdays: 10 (left), 160 (right)

The evening peak demand is represented in both scenarios by a drop in voltage for both levels of EV penetration. In the 10% penetration scenario, the peak reaches a value of 0.96 per unit (pu), and in the 160% penetration scenario, it reaches a value of 0.94 pu. Both values fall within the acceptable voltage range (1.1-0.9 pu), and the overall shape of the graph remains largely unchanged, despite the significant increase in demand. This confirms that because of the grid shape, voltages are not the best indicators for grid failure and the most restrictive issues are the line's capacities.

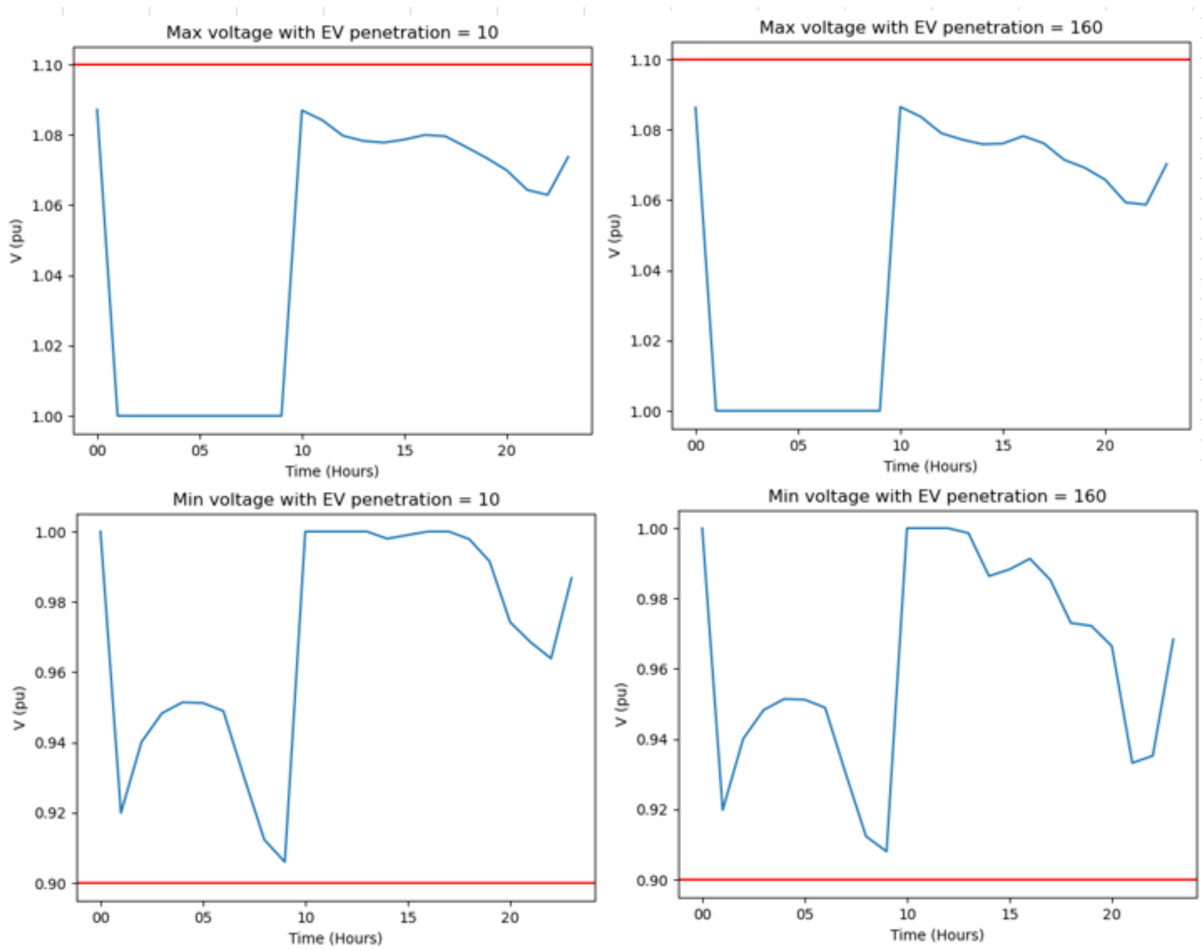


Figure 27: Voltage maximum and minimum values depending on the hour of day for two EV penetrations during weekends: 10 (left), 160 (right)

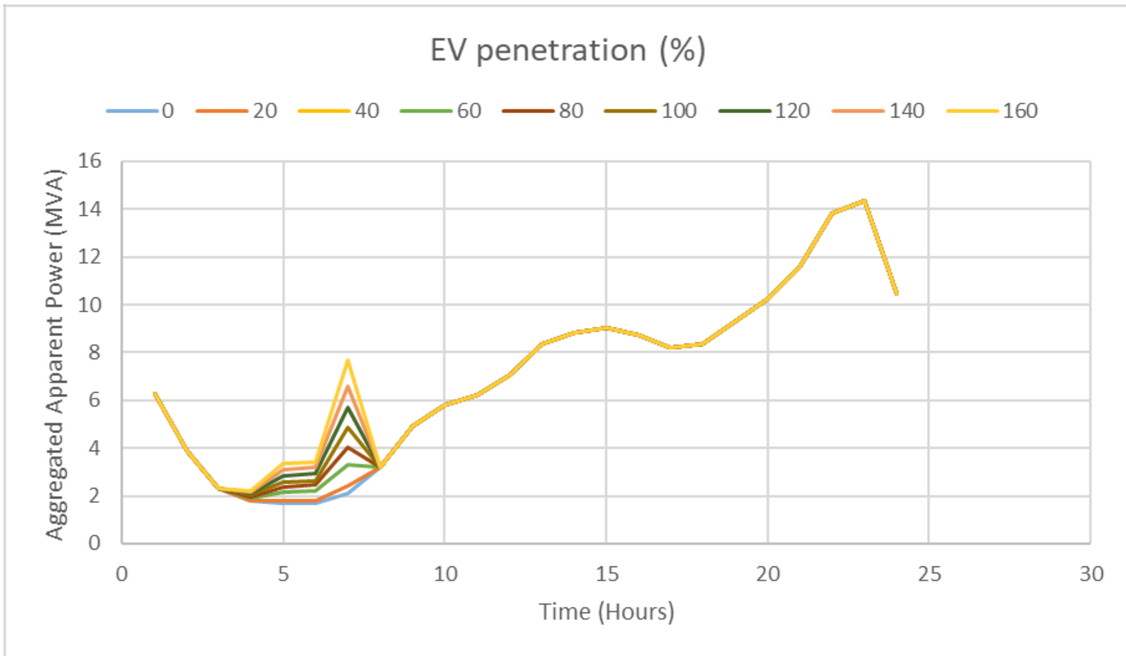
Weekends also presents for both EV penetrations the same shape as Figure 27 shows.

In conclusion, this type of uncontrolled charging puts considerable strain on the grid, particularly on assets such as lines and transformers, from penetration levels of 50%. If smart charging strategies were not implemented, all of these elements would need to be replaced, essentially requiring a complete overhaul of the grid. Such a rapid undertaking would necessitate an extremely fast replacement of elements, which poses a significant challenge given the 'lead time' between planning and execution of these projects, something that the grid might not be able to manage.

5.2 TOU STRATEGY

The first solution to try to prevent grid failure is changing charging times from peak hours to off peak hours. This is done by introducing a time of use pricing which incentivises customers to charge at that time with low electricity prices.

In this strategy, charging times are now concentrated between 1:00 and 7:00 as stipulated by the Time of Use (TOU) pricing. There is no longer an evening peak, and the demand remains stable at 14 MVA for both weekdays and weekends, as shown in Figure 28. However, a new peak now emerges during the 'off-peak period'. At 0% EV penetration, the demand was around 2 MVA, but in the realistic scenarios, the demand now reaches 5 MVA, representing a 150% increase. In the most demanding scenario, this demand escalates to over 8 MVA, a 300% increase, during the weekends. Compared to the uncontrolled charging strategy, the demand reaches smaller values under this TOU pricing scheme. However, the rate of increase is significantly more aggressive. The impact of this shift on lines and transformers will be explored next.



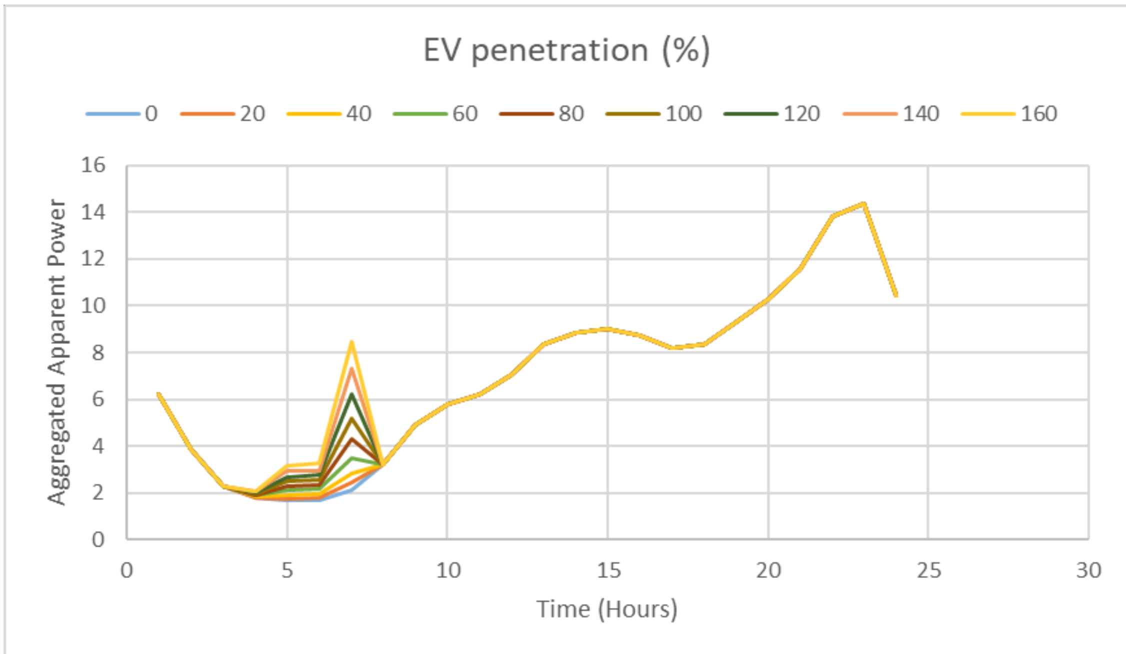


Figure 28: Aggregated Apparent Power depending on the hour during the weekdays (up) and weekends (down)

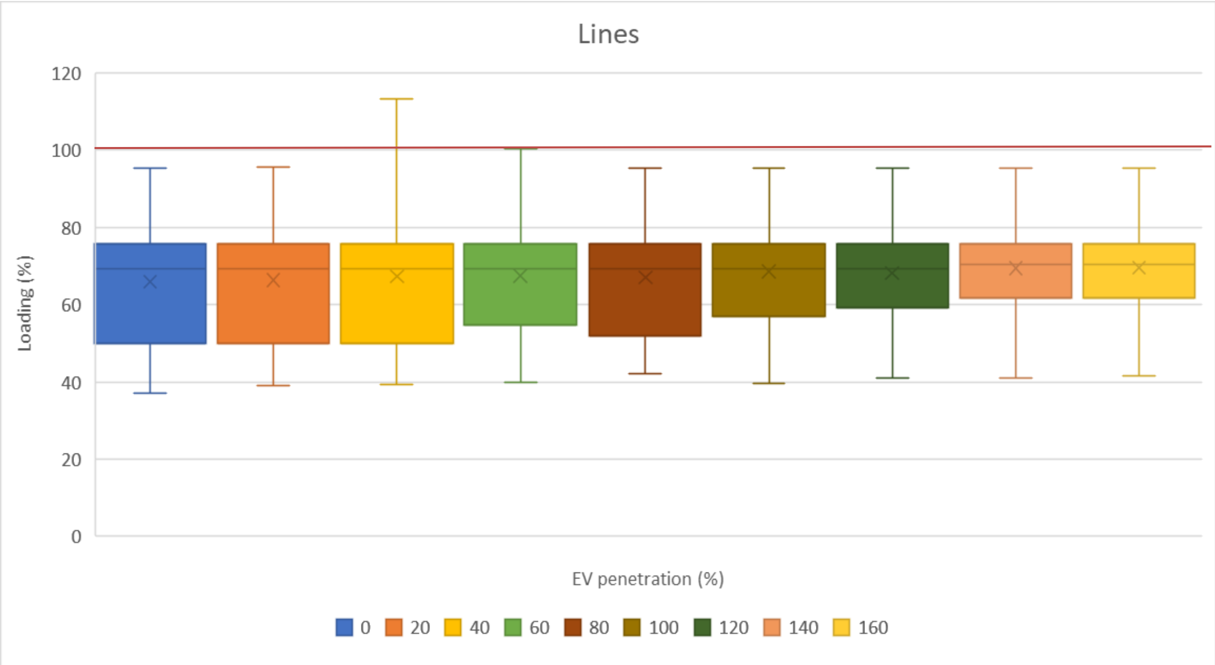
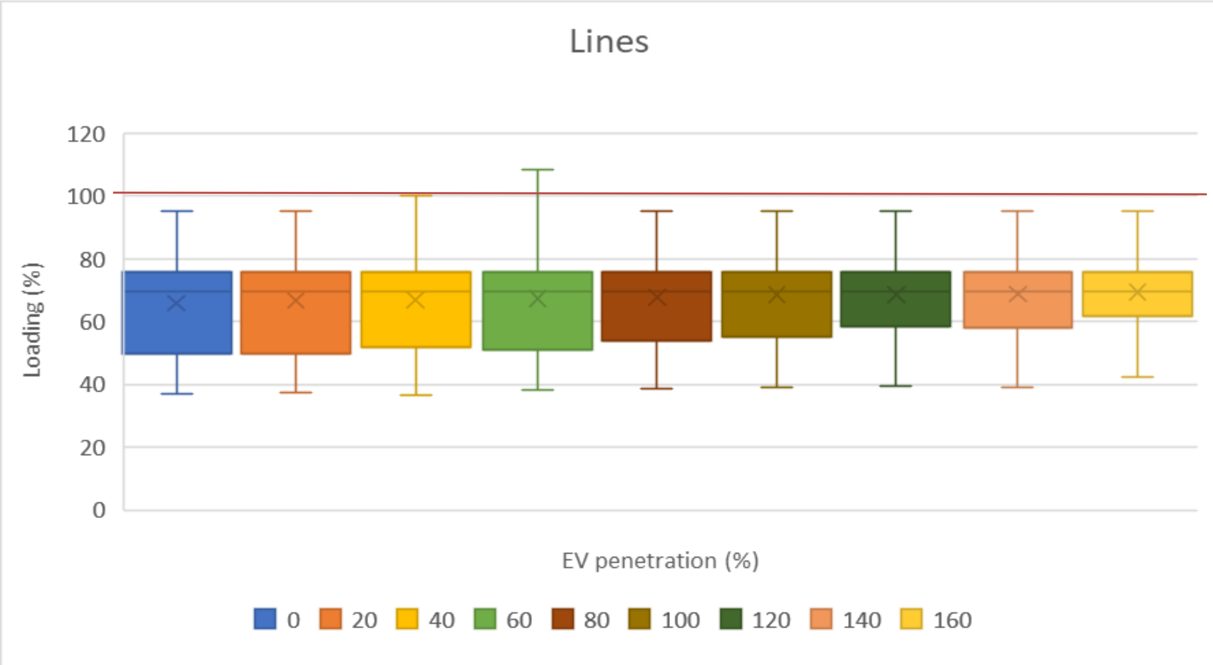


Figure 29: Lines and transformers loading depending on the EV penetration using TOU during weekdays



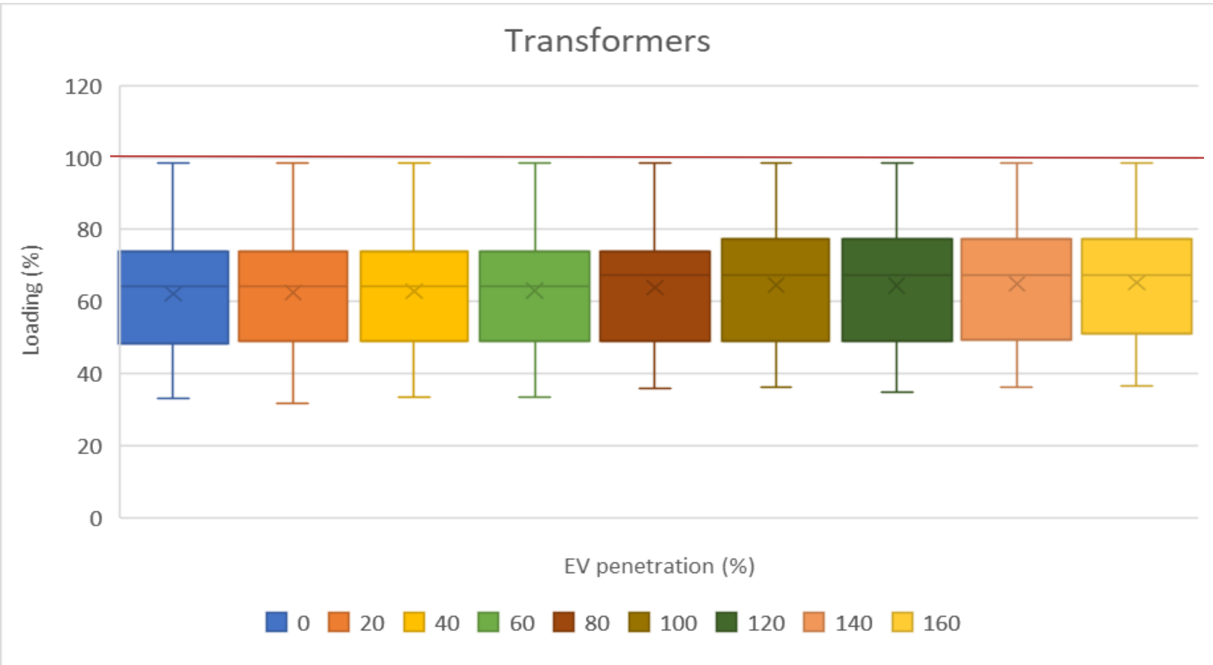


Figure 30: Lines and transformers loading depending on the EV penetration using TOU during weekends

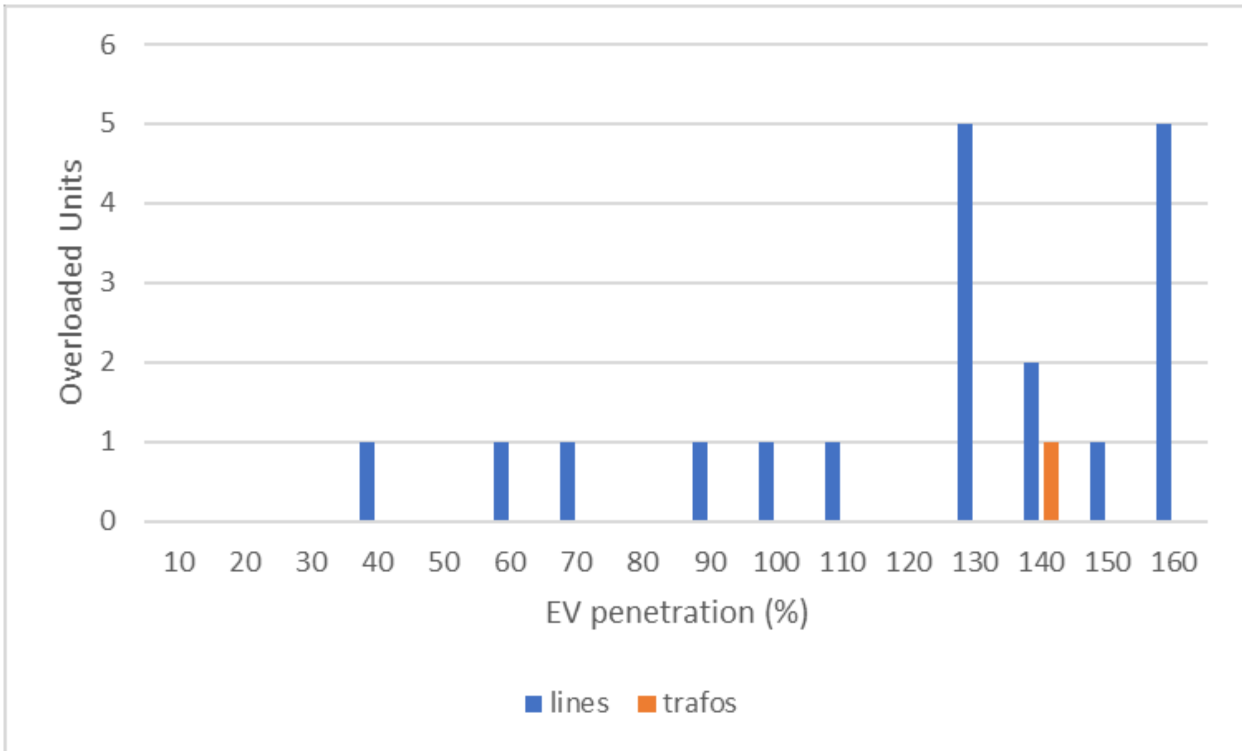
Under this strategy, both lines and transformers rarely exceed 100% overloading. For lines, it only happens at 40% EV penetration during weekdays and 60% during weekends. For transformers, it only happens once at 140% EV penetration during weekdays. This represents a significant improvement compared to the uncontrolled charging strategy, where almost all penetration levels led to at least one asset overloading.

Moreover, if we look at the third quartile, in all penetration levels, 25% of the lines and transformers experience an overloading higher than 70%, compared to the previous 90% seen with the uncontrolled strategy. So there is still available capacity in the assets that could be used.

However, the lower limit (first quartile) appears to have worsened, increasing in the worst-case scenario from nearly 50% with uncontrolled charging to 60% in the case of lines. This is logical, as the minimum value was associated with off-peak times. Now that charging occurs during these periods, the assets must deal with more demand than before. Still, this peak does not seem to be causing many overloading problems.

Figure 31 clearly illustrates the reduction in asset overloading under this strategy. As previously mentioned, there is only one transformer that saturates throughout the entire analysis of this strategy. It is not until the EV penetration reaches 120%, which is beyond the realistic scenario for Spain, that more than one line begins to saturate, with a total of 4 lines overloading on weekends and the overloading starting at 130% EV penetration for weekdays.

The worst-case scenario under this strategy would occur at an EV penetration of 150% on weekends, with a total of 10 lines saturating. This represents a significant reduction of 96% in asset overloading compared to the worst-case scenario under the uncontrolled strategy, which saw 276 lines become saturated.



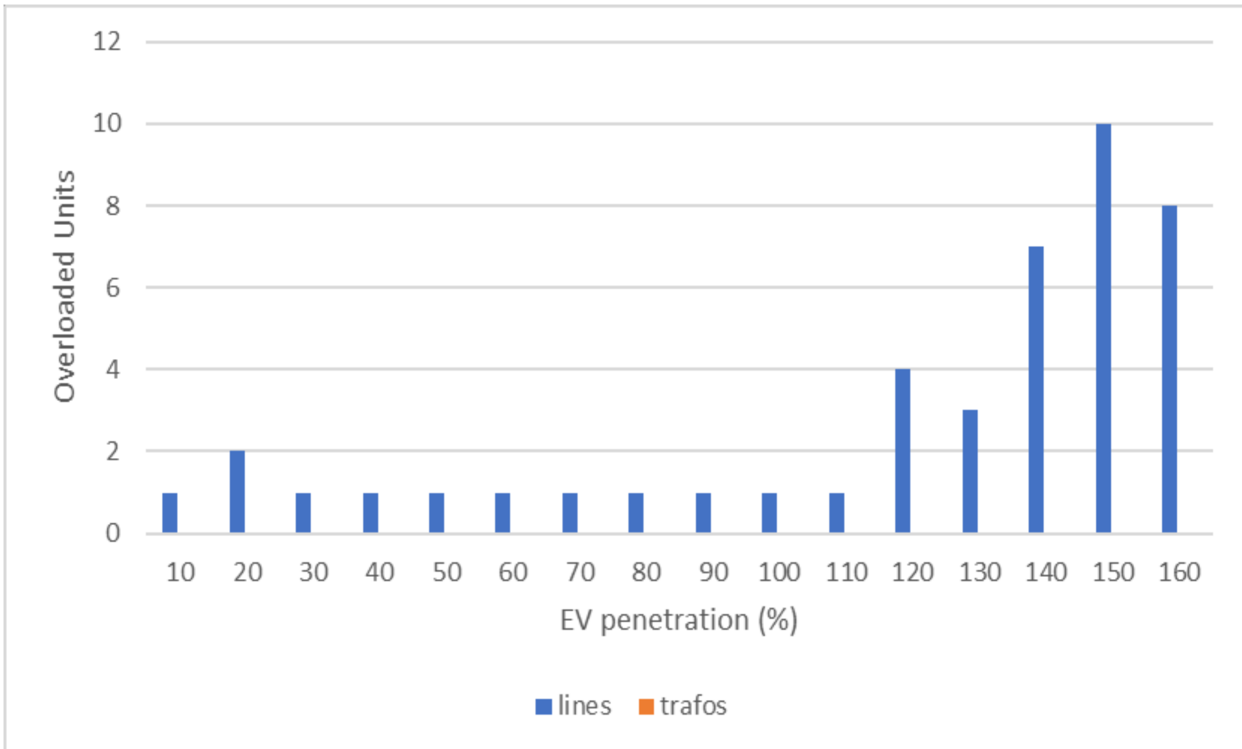


Figure 31:Number of lines and transformers saturated depending on the EV penetration using a TOU on weekdays (up) and weekends (down)

In the case of voltage results under this strategy, there is a noticeable difference, as Figure 32 shows. The shapes of the voltage curves for the 10% scenario and the 160% scenario are not identical in this case. There is a prominent voltage peak at 06:00, evident in both the maximum and minimum voltage graphs. This peak corresponds with the demand surge caused by the Time-of-Use (TOU) strategy.

As was observed with the uncontrolled strategy, voltage levels around this time are typically low. Consequently, an increase in demand causes a more significant voltage drop, pushing the voltage levels beyond the established limits. When this occurs, the grid's transformers are adjusted, changing their tap settings to compensate for the voltage drop, leading to the sudden increase in voltage at that time. This assumption might pose a problem, as not all transformers are automated to respond to unforeseen voltage drops, which could result in violation of voltage limitations.

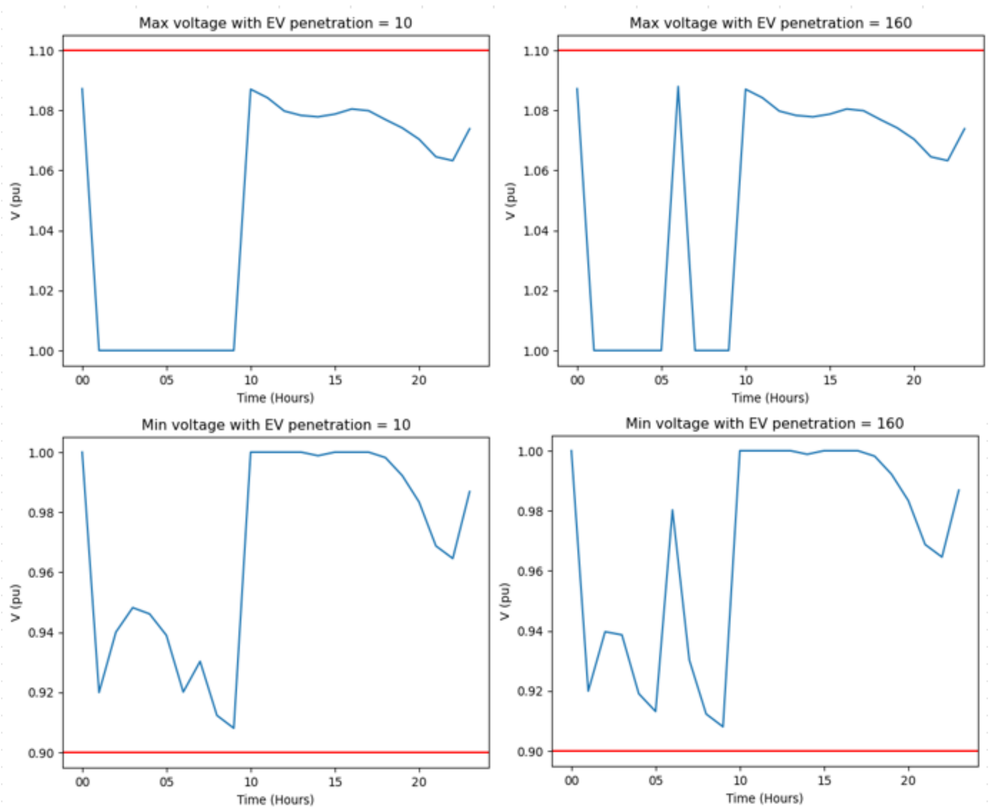


Figure 32: Voltage maximum and minimum values depending on the hour of day for two EV penetrations using TOU during weekdays: 10 (left), 160 (right)

For the realistic scenario the situation is the same:

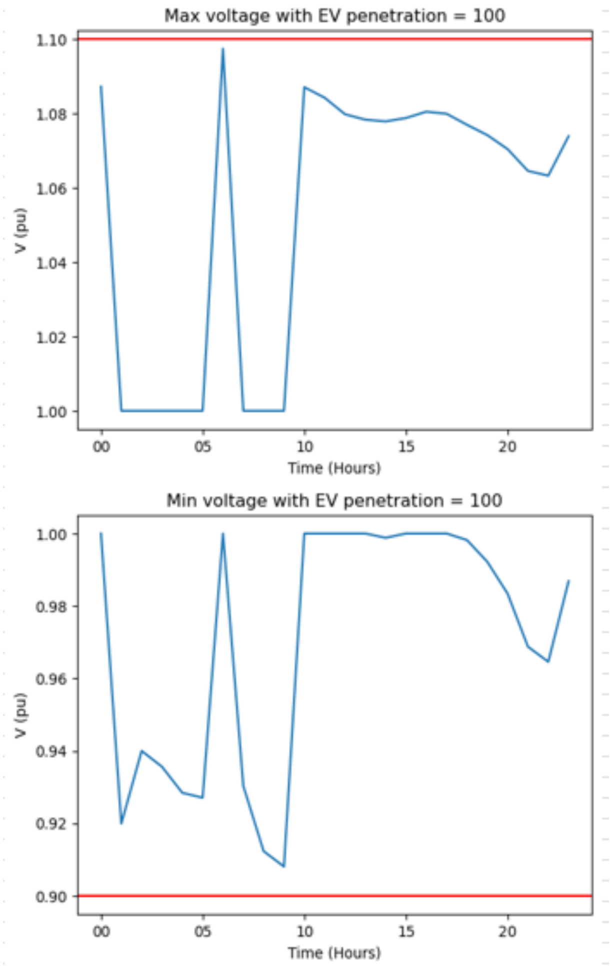


Figure 33:Voltage maximum and minimum values depending on the hour of day for 100 % EV penetration using TOU during weekdays

In conclusion, the implementation of a Time-of-Use (TOU) pricing strategy substantially mitigates the issue of asset overloading, thereby reducing the risk of grid failure. Nevertheless, it is a strategy that does not guarantee a full control over the EV charging demand since it is uncertain how many customers will alter their habits and charge their vehicles during the designated interval. Moreover, there exists the risk of a secondary peak emerging within this interval, which could potentially trigger the same and/or new issues in the grid. Therefore, while the TOU strategy offers significant benefits, these risks and uncertainties highlight the need for further refinement or complementary strategies.

5.3 RATIO TOU

As previously observed, the Time-of-Use (TOU) strategy significantly reduces asset overloading but leaves considerable unused capacity that could potentially be utilized more effectively. Consequently, the goal of this strategy is to explore the limits of TOU by combining it with an uncontrolled charging approach. This hybrid strategy aims to optimize the utilization of grid assets by balancing the distribution of demand between peak and off-peak periods, thus providing a more comprehensive understanding of the network's capacity under combined charging regimes.

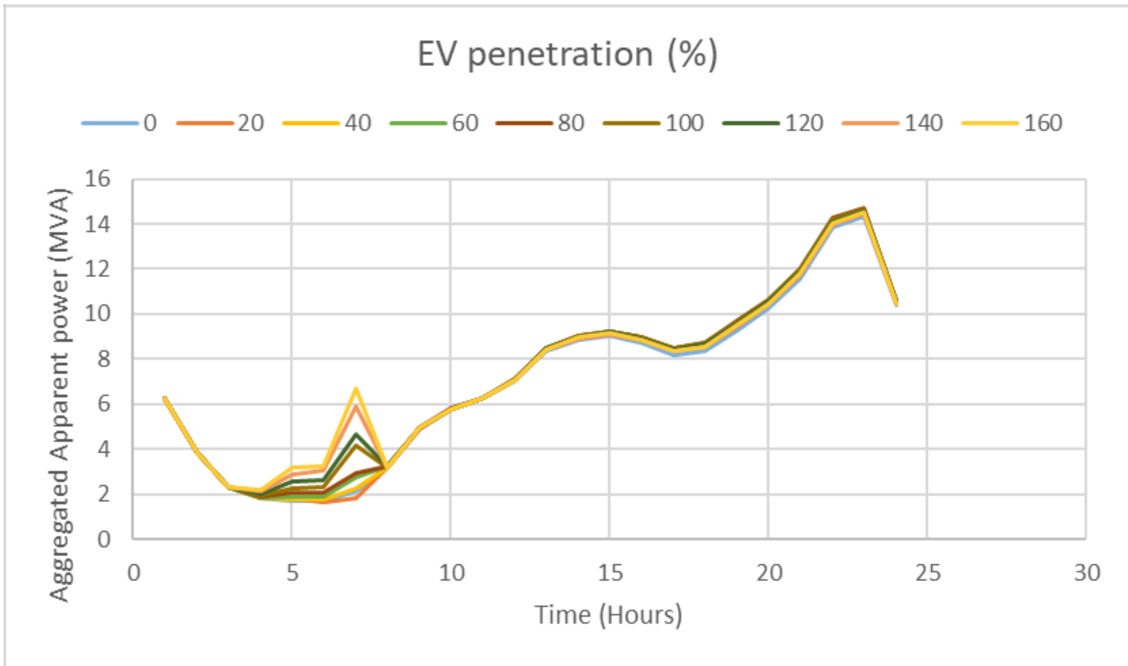
In this strategy, the ratio corresponds to the minimum percentage of individuals who need to adhere to the Time-of-Use (TOU) pricing in order to prevent grid failure. Hence, for all Electric Vehicle (EV) penetration levels, the examined scenario is based on the ratio at which one or two assets begin to show signs of overloading.

Logically, with lower EV penetrations, the need to shift charging from peak to off-peak hours is lesser, as the peak demand itself is lower. Figure 35 appears more similar to Figure 28 than to Figures 19-20, as expected. This is because, with the uncontrolled strategy, significant grid congestions start to appear from 50% EV penetration, requiring then a high percentage of people using the TOU pricing. This means that, from 50% to 160% EV penetration, a large part of the charging would be concentrated during TOU hours.

There is indeed a peak in power demand during the TOU pricing interval. However, the maximum value of the aggregated power during weekdays is lower in this case than for the TOU-only strategy. The value is 6.7 MVA, while in the other case it's 7.7 MVA, representing a decrease of 13%. On weekends, the maximum peak value remains at 8.5 MVA. This difference is because the ratio of people using TOU at 160% EV penetration during weekdays is 90%, whereas on weekends it is 100%. This shows the small but significant increase in demand on weekends.

EV penetration (%)	Ratio weekdays	Ratio weekends
10	30	30
20	40	30
30	40	35
40	50	55
50	50	65
60	50	70
70	60	75
80	60	80
90	70	85
100	70	90
110	80	100
120	80	100
130	90	100
140	90	100
150	90	100
160	90	100

Table 11:TOU adoption ratio depending on the EV penetration



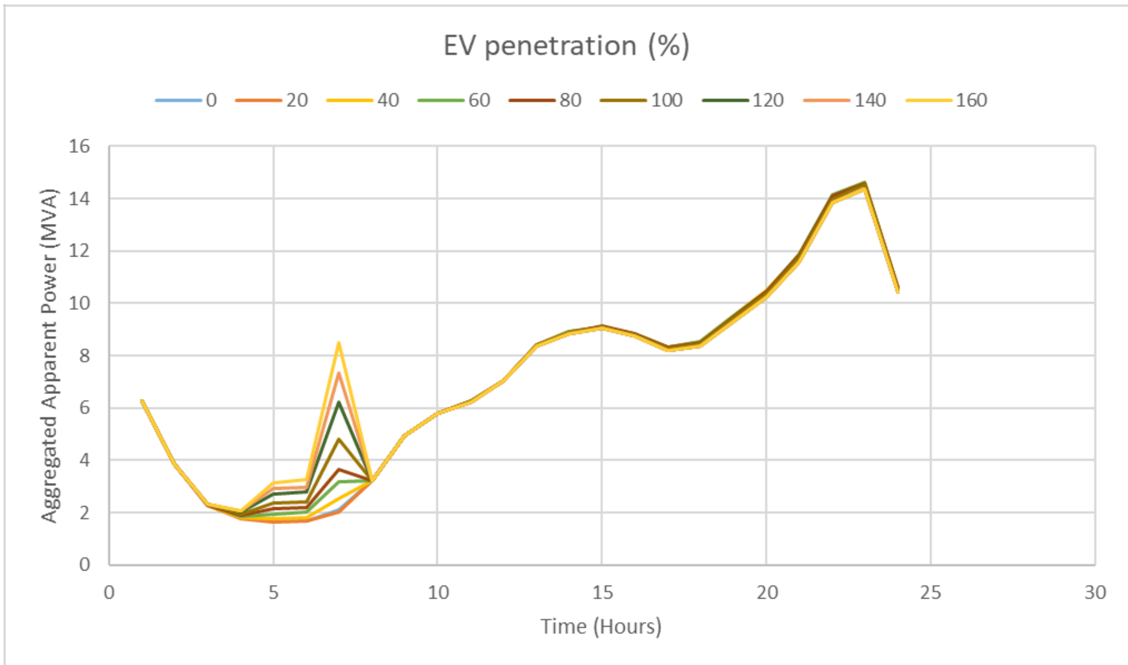
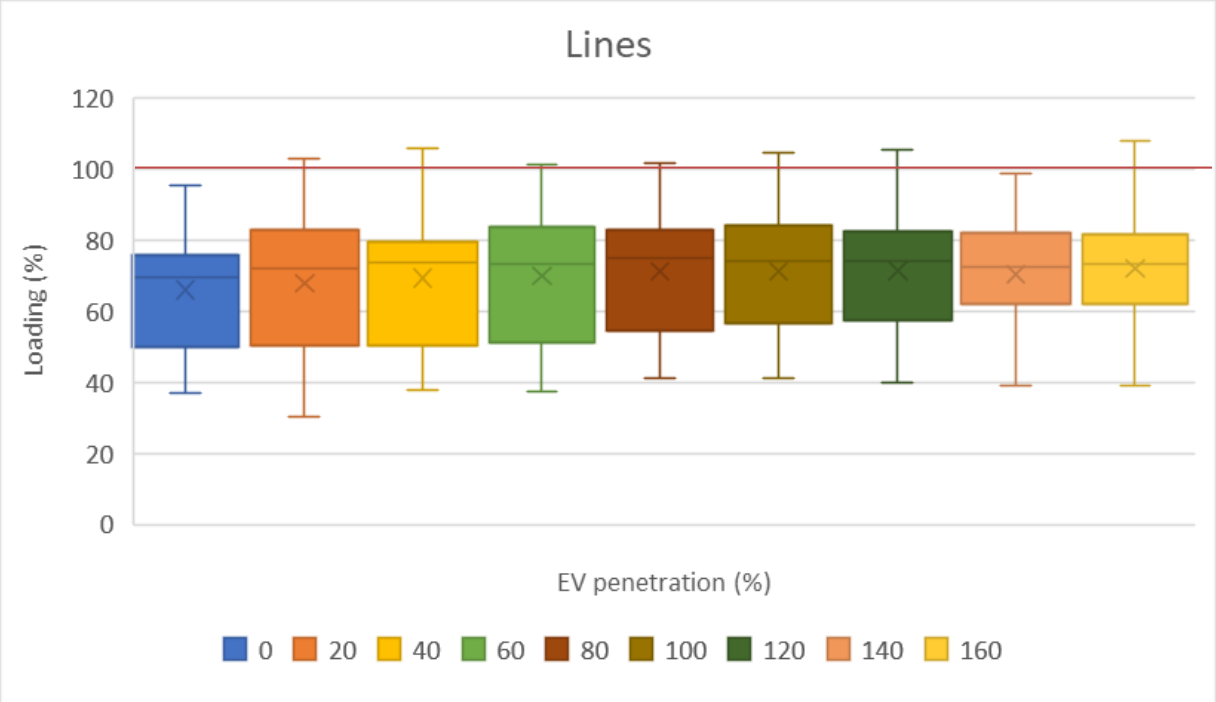


Figure 34:Aggregated Apparent Power depending on the hour using a mix strategy during the weekdays (up) and weekends (down)



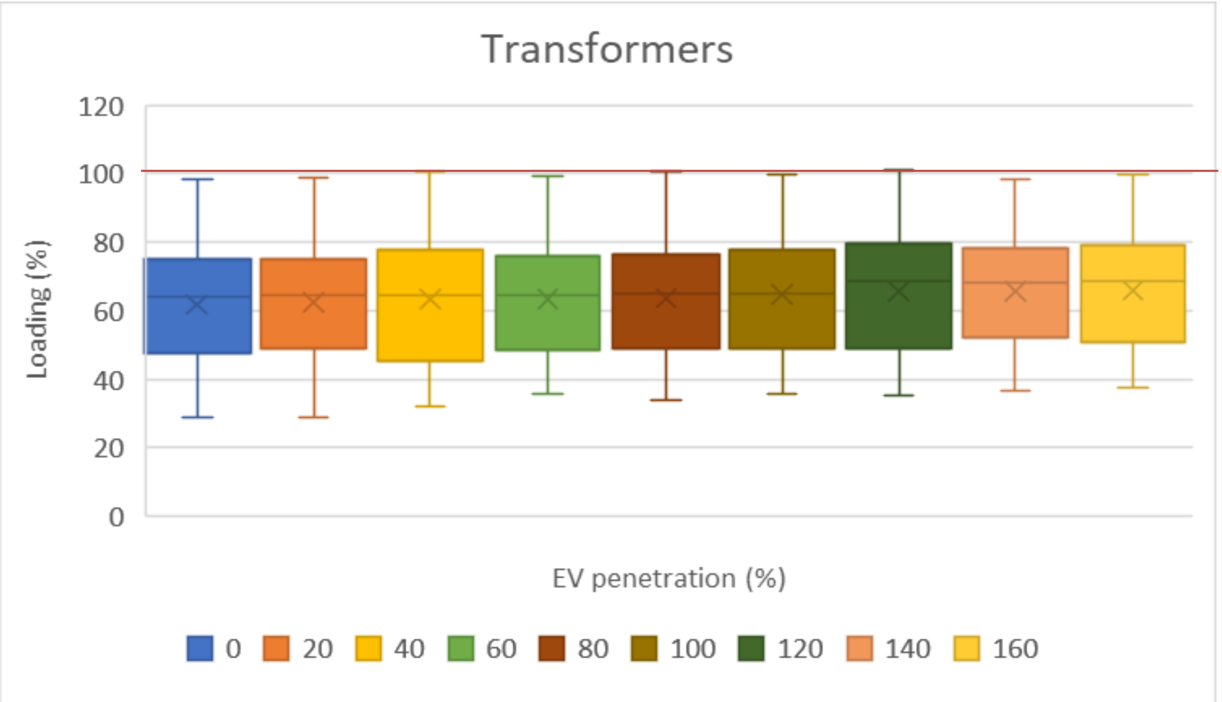


Figure 35:Lines and transformers loading depending on the EV penetration using a mix strategy during weekdays

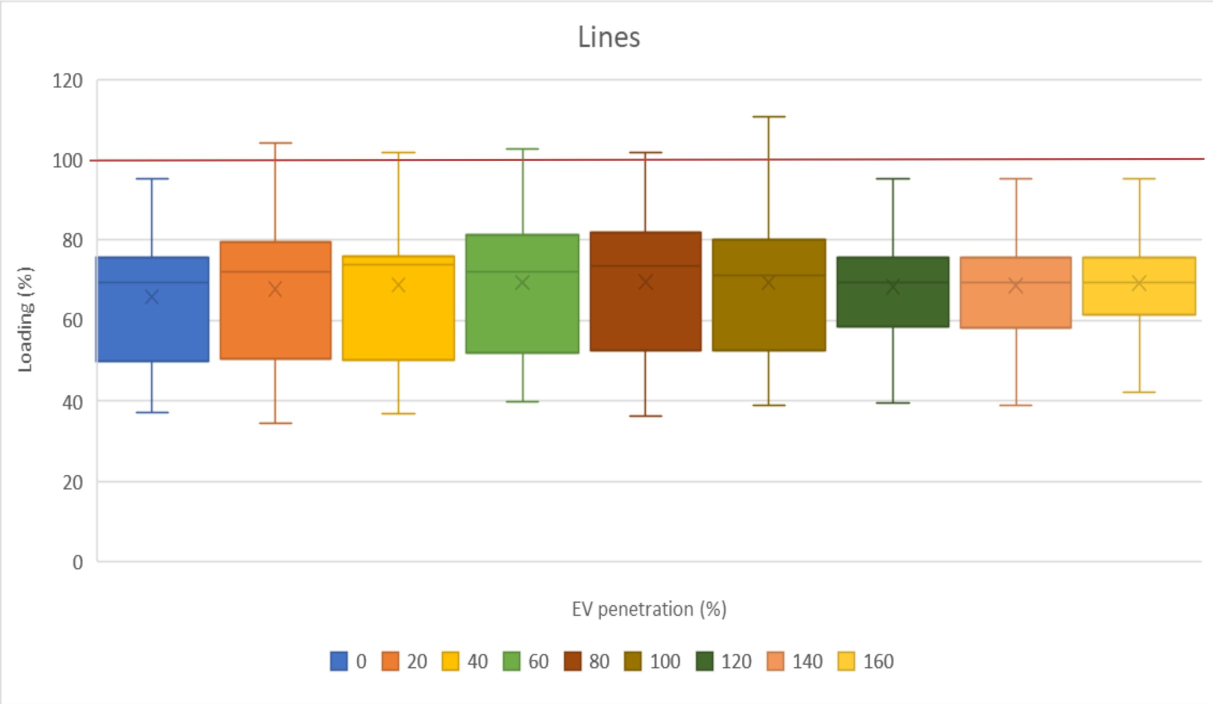


Figure 36: Lines and transformers loading depending on the EV penetration using a mix strategy during weekends

As previously stated, this strategy was designed to search for the TOU ratio limit by stopping whenever 1 or 2 assets were saturated. Hence, it's normal to see in Figures 35-36 the maximum overloading value surpassing 100%.

Comparing this with the TOU strategy, there has been an improvement in capacity usage. Now, examining the third quartile, 25% of the transformers have an overloading higher than 80%. This is better than the 70% of the TOU strategy and also better than the 90% in the uncontrolled strategy, making it a safer value. This mainly happens between the intermediate EV penetrations of 20% - 120%. Before these values, the demand is still too small, and past these values, the demand is too high, so the TOU ratio is also high. This demonstrates the balancing effect this mixed strategy has on asset loading, optimizing their usage without pushing them into overload.

The following charts present the TOU adoption ratio evolution depending on the EV penetration:

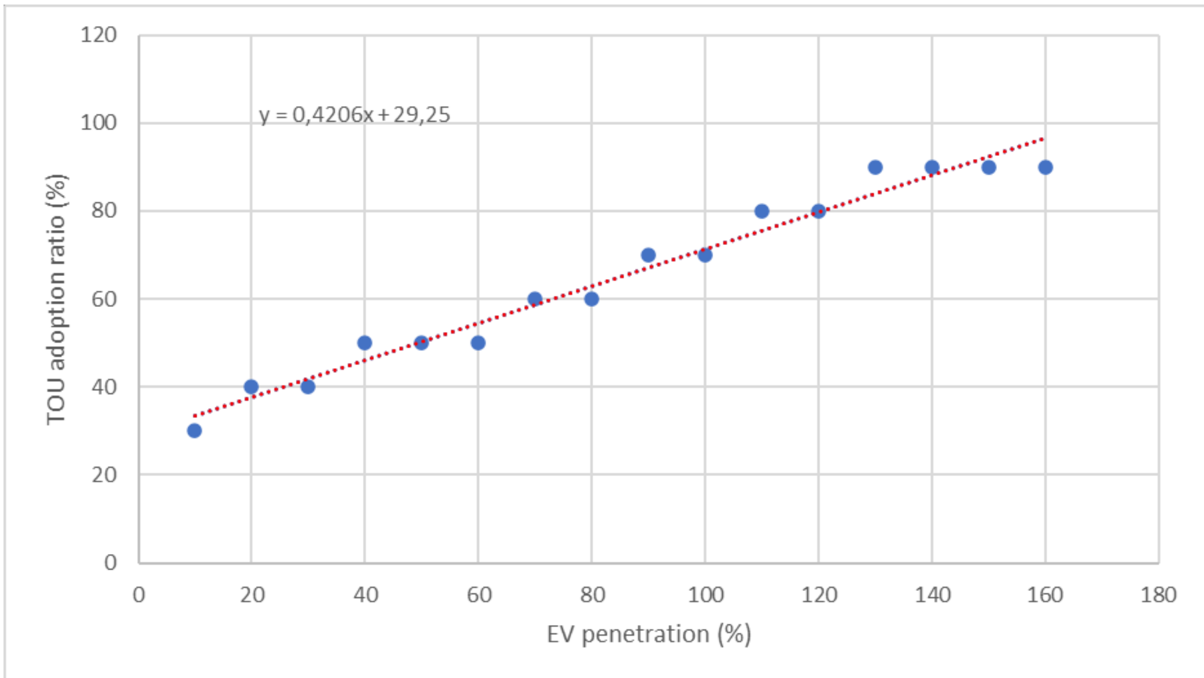


Figure 37: TOU adoption ratio evolution in function of the EV penetration on weekdays with a complete tendency line

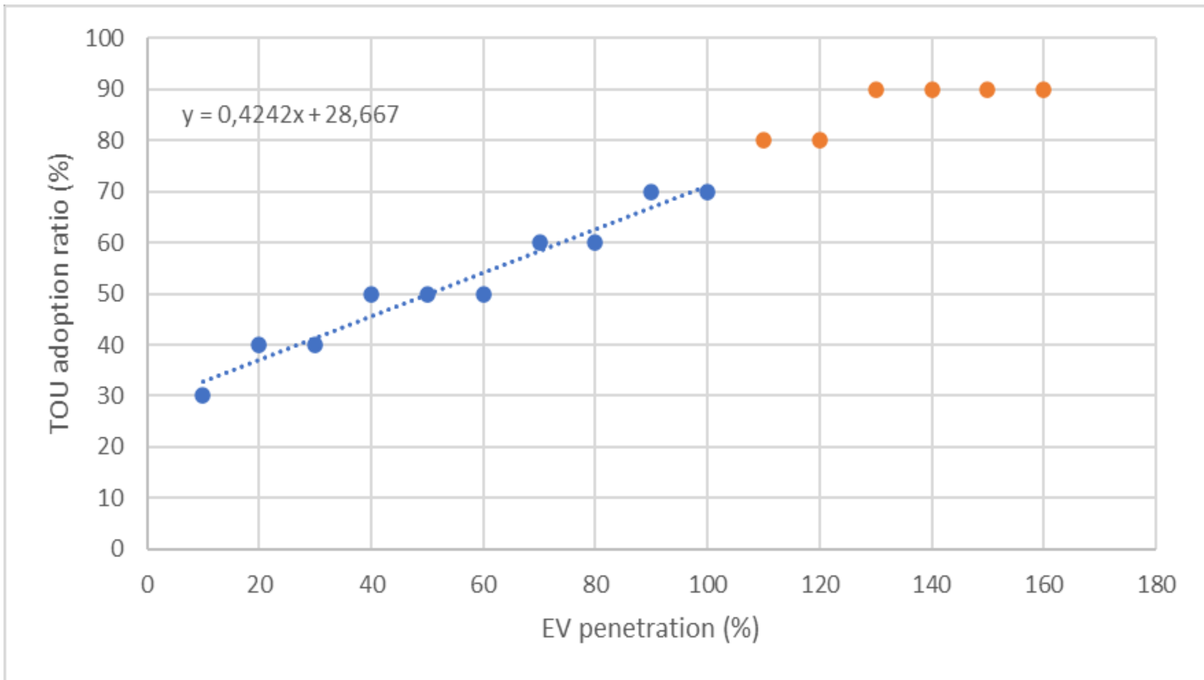


Figure 38:TOU adoption ratio evolution in function of the EV penetration on weekdays with a partial tendency line

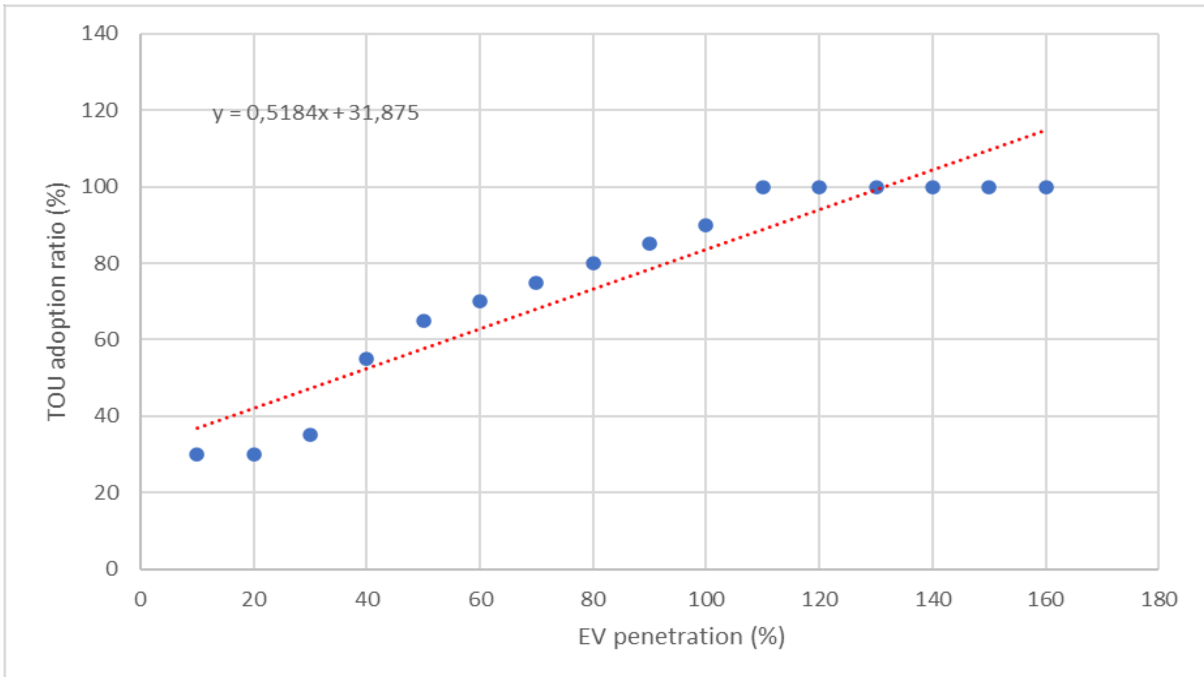


Figure 39: TOU adoption ratio evolution in function of the EV penetration on weekdays with a complete tendency line

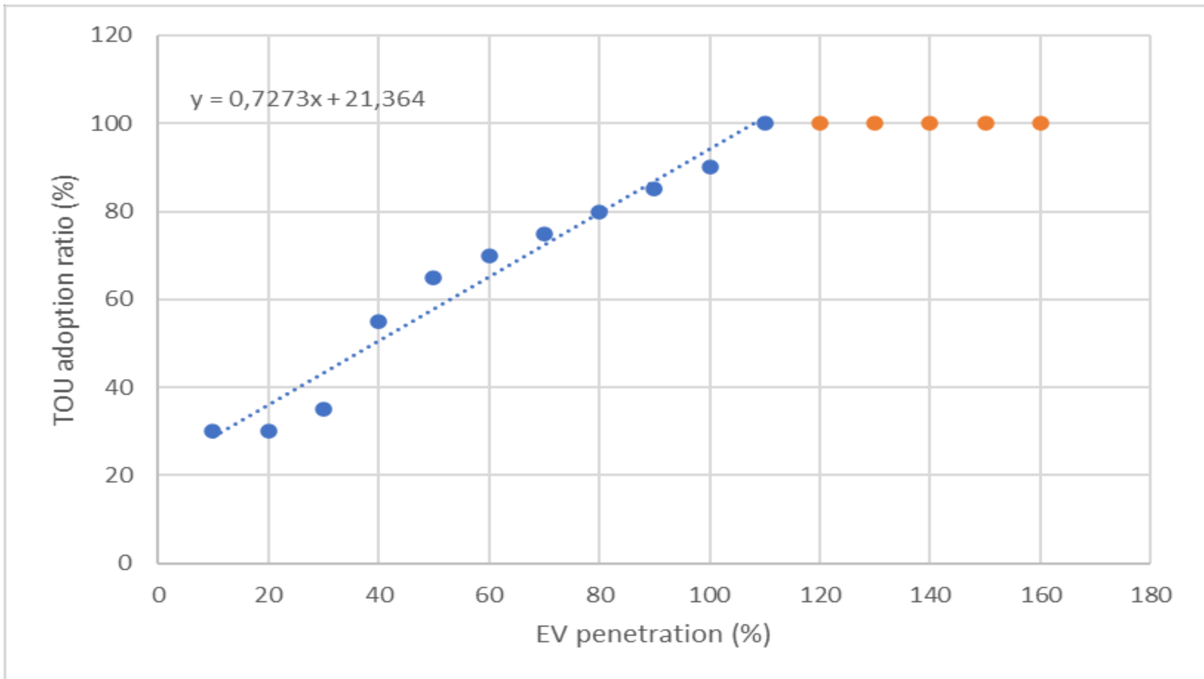


Figure 40:TOU ratio evolution in function of the EV penetration on weekdays with a partial tendency line

As anticipated, this represents an increasing trend which indicates that with more EV penetration, a higher TOU ratio is required. For the weekdays, there are two charts - one displaying the trend line considering all EV penetration levels, and one stopping at the realistic Spanish scenario (100%).

The latter is aimed at emphasizing more on the rising part of the curve since in high demand scenarios, the EV demand can potentially be too high. The ratio varies between 30% - 90%, reaching that value at the 130% scenario. When all the scenarios are taken into account, the trend line follows this equation:

$$y = 0.4206x + 29.25$$

And when only until the realistic scenario:

$$y = 0.4242x + 21.364$$

During weekdays, including these high demand scenarios doesn't greatly alter the trend line. This is due to the fact that they occur at a high penetration and never reach the maximum value of 100%, hence the curve continues to rise. However, for weekends, these are the two equations:

$$y = 0.5184x + 31.875$$

$$y = 0.7273x + 21.364$$

For the weekend scenario, it is essential to consider only the partial trend line. This is because it accurately captures the rapid increase in the Ratio due to the high penetration.

In the voltages case, the voltages still do not change a lot. They are for both situations inside the interval.

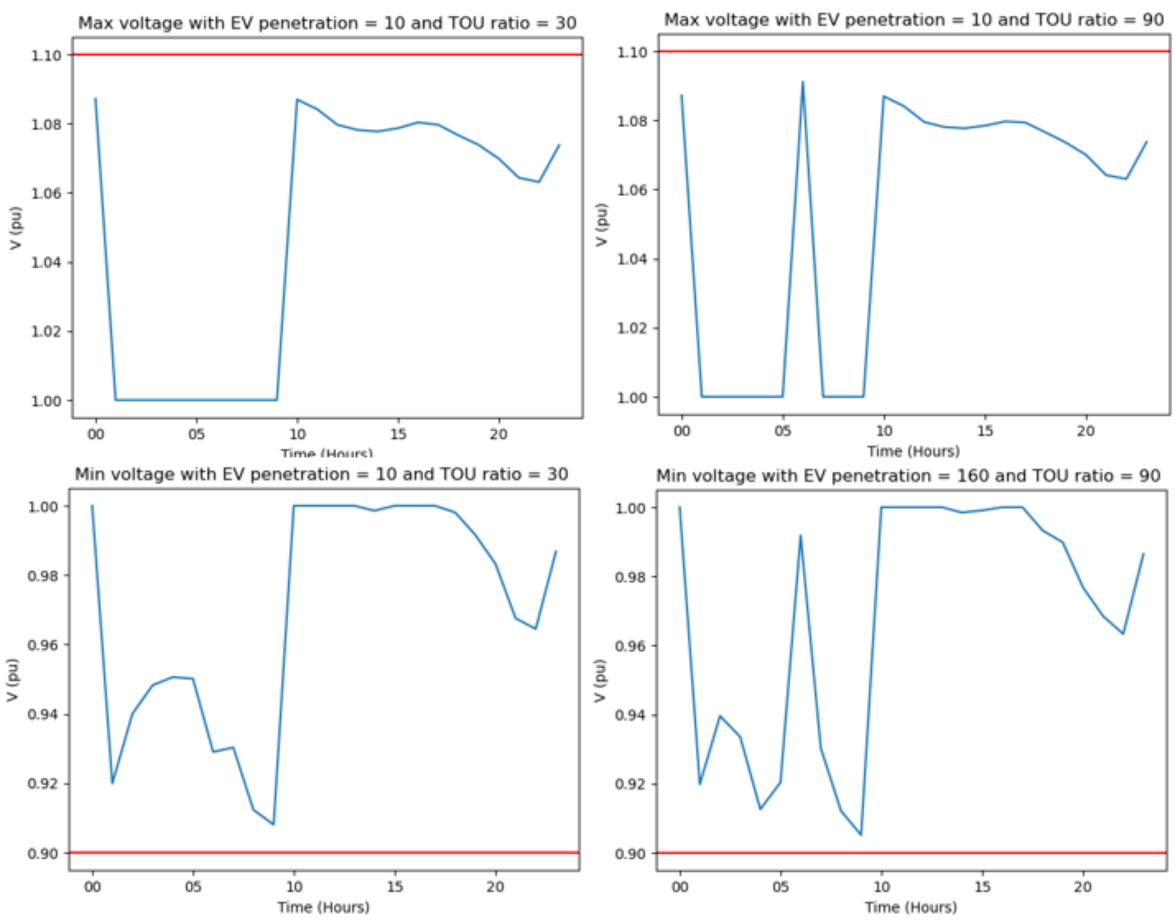


Figure 41: Voltage maximum and minimum values depending on the hour of day for two EV penetrations using a mix strategy during weekdays: 10 (left), 160 (right)

In conclusion, this strategy has successfully enhanced the use of grid capacity for certain penetration levels. However, this was applicable only for a few penetration scenarios since the Time-of-Use (TOU) ratio escalates rapidly with the increase in EV penetration. Thus, while this strategy seems excellent for scenarios with low-level penetration, it doesn't seem adequate to handle a scenario where there is a total shift in the automobile sector towards EVs.

CHAPTER 6. CONCLUSIONS

This project has centered around examining the grid impact of various types of EV charging, such as uncontrolled charging, which implies EVs charge to their full demand during peak hours, Time of Use (TOU), a smart charging technique aimed at shifting charging from peak to off-peak hours (peak shaving), and a mixed strategy that consists of a percentage of EV drivers using TOU while others charge during peak hours.

The analysis was conducted in a large, semi-radial urban grid, comprising both Low Voltage and Mid Voltage parts, with the assumption that the 4905 load buses correspond to consumer households. The presence of voltage regulators and the short distance between feeders make voltage drop analysis a less critical indicator of smart charging strategies' impact on the grid.

The findings revealed that uncontrolled EV charging began to cause grid issues from a 50% EV penetration scenario, with 22 grid elements already overloaded, and reaching nearly 120% loading with a maximum of over 250 overloaded elements in the most demanding scenario at 160% penetration.

Smart charging strategies considerably mitigate element loading on the grid. Implementing a TOU strategy reduces the number of overloaded elements to almost zero, with a maximum of 10 saturated elements appearing only in the most demanding scenarios (160% penetration). However, there are also downsides; first, the grid elements capacity is not fully utilized, with 75% of transformers having a maximum capacity usage of less than 80%, leaving room for additional demand. Second, a new demand peak emerges during the off-peak period, which could potentially trigger more issues than the previous peak associated with uncontrolled charging.

The mixed strategy, a combination of the previous two, also drastically reduces the number of overloaded units and helps in improving element capacity. However, it's mostly effective for low-level EV penetrations, as the need for a higher TOU adoption ratio increases rapidly with EV penetration. Thus, this strategy is suitable for scenarios with low EV demand. In maximum EV penetration scenarios, it presents the same drawbacks as a TOU strategy.

Smart charging strategies significantly reduce the impact of EV charging on the grid, but their uncontrolled nature, due to the unpredictability of people adopting these strategies, makes them short-term solutions, as they introduce other complications.

Future works will focus on refining the models associated with EV demand profiles, as more data becomes available over time. New technologies related to smart charging strategies are being developed, offering the possibility to study deeper the impact of more complex strategies such as V1G and V2G. These works will provide insights into the benefits of increasing complexity with smart charging strategies.

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