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Analysis of techno-economic issues associated to electric vehicles grid integration

Maria Juliana Suarez Forero

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THÈSE DE DOCTORAT

DE L'UNIVERSITÉ PSL

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Analysis of techno-economic issues associated to electric vehicles grid integration

Soutenue par

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Résumé

Dans le contexte de la transition énergétique, les secteurs du transport et de l'électricité sont appelés à évoluer pour atteindre l'objectif de neutralité carbone. Le déploiement d'une capacité importante d'Energies Renouvelables (EnR) implique une croissante demande de flexibilité pour le réseau électrique alors que, d'autre part, le déploiement d'un parc important de Voiture Electriques (VE) représente une demande d'électricité plus élevée pendant la phase de recharge qui pourraient approcher et même dépasser les limites physiques des réseaux électriques. Cependant, ensemble, les EnR et la flotte de VE pourraient apporter une solution au lieu de deux problèmes. Grâce à un système de charge intelligent, les VE pourraient absorber la surproduction d'EnR ainsi que limiter la puissance sollicitée pendant les heures de forte consommation. Ce travail présente les principaux enjeux de l'intégration de VE dans le réseau électrique au niveau local et au niveau national. Un modèle d'optimisation du prix de l'électricité est développé ainsi qu'un système de contrôle optimal de la charge intelligente qui est implémenté dans un outil de simulation puis dans un VE réel pour tester la viabilité d'une application. L'impact économique et les facteurs techniques de l'intégration sont analysés.

Mots clés : Voitures électriques, Energies renouvelables, Flexibilité du réseau, Optimisation de la charge, Intégration de voitures électriques au réseau *VGI*.

Abstract

In the context of the energy transition the transport and the power sectors are called to change to reach the carbon neutrality objective. The deployment of an important capacity of *Renewable Energies* (REn) involves an increasing requirement of flexibility for the power grid while, on the other hand, the deployment of an important fleet of *Electric Vehicles* (EV) represents a higher electricity demand during the recharge phase that could approach and even exceed the physical limits of the power grids. Though, together the REn mix and the EV fleet could make a solution instead of two problems. Through a smart charge system EV could absorb the REn overproduction as well as limit the appealed power during high consumption hours. This work presents the main challenges of the integration of EV into the power grid at a local and at a national level. An electricity price optimization model is developed as well as an optimal control system for the smart charge which is implemented in a simulation tool and subsequently in a real EV to test the viability of an application. The economic impact and the technical factors of the integration are analyzed.

Keywords : Electric Vehicles, Renewable Energies, Grid flexibility, Charge optimization, Vehicle Grid Integration.

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Acronymes

AC *Alternating current*

ACEA *Association des constructeurs européens d'automobiles*

ACER *Agency for the Cooperation of Energy Regulation*

AVERE *The European Association for Electromobility*

BEV *Battery Electric Vehicles*

BMS *Battery Management System*

CCFA *Comité des constructeurs français d'automobiles*

CRE *Commission de Régulation de l'Énergie*

DC *Direct current*

DSO *Distribution System Operator*

ENTD *Enquête Nationale de Transports et Déplacements*

EU *European Union*

EV *Electric Vehicles*

GHG *Green House Gas*

ICE *Internal Combustion Engine*

IEA *International Energy Agency*

ISO *Independent System Operator*

LPG *Liquefied petroleum gas*

NCEI *National Centers for Environmental Information*

OECD *Organization for Economic Co-operation and Development*

PCR *Price Coupling of Regions*

PHEV *Plug in Hybrid Electric Vehicle*

PSH *Pumped Storage Hydropower*

PV *Photovoltaics*

REMIT *Regulation on Wholesale Market Integrity and Transparency*

REn *Renewable Energies*

RTE *Réseau de Transport d'Électricité*

SCE *Southern California Edison*

SNBC *Stratégie Nationale Bas-Carbone*

SOC *State Of Charge*

ToU *Time of Use*

TSO *Transmission System Operator*

V2B *Vehicle to Building*

V2G *Vehicle to Grid*

V2H *Vehicle to Home*

V2V *Vehicle to Vehicle*

V2X *Vehicle to Anything*

VGI *Vehicle Grid Integration*

Résumé en Français

1 Chapitre I : Les véhicules électriques et leur intégration aux réseaux

La lutte contre le changement climatique passe par la diffusion de solutions de mobilité alternatives, à taux d'émissions faibles voire nuls. Le déploiement des véhicules électriques (VE) participe à de telles stratégies de réduction des émissions de Gaz à Effet de Serre (GES) provenant des transports, secteur qui représente environ les deux tiers de la demande finale de pétrole dans les pays de l'OCDE. En fonction du mix électrique de chaque pays, les VE peuvent contribuer à des objectifs spécifiques de réduction des émissions. Plusieurs pays dans le monde ont préparé la conversion des voitures particulières du moteur à combustion aux carburants alternatifs. Pour réussir la conversion, plusieurs politiques doivent être adoptées par les gouvernements et un effort collectif doit être concilié.

La flotte de VE est appelée à évoluer car elle est un outil stratégique pour accompagner la transition énergétique du secteur des transports et du système électrique. Ce travail se concentre sur la France et l'Allemagne, qui sont les plus grands marchés de voitures de l'UE. Cependant, au-delà du nombre de VE qui circuleront sur les routes, l'impact sur le réseau électrique sera conditionné par le comportement des conducteurs. Ce n'est pas la demande d'énergie dont l'augmentation annuelle en France est estimée entre 28 TWh et 48 TWh d'ici 2050 d'après les exercices prospectifs du gestionnaire de réseau RTE qui est impacterait le réseau mais bien la puissance instantanée qui pourrait troubler son fonctionnement effectif. La complexité d'une estimation réelle vient du fait que le comportement des conducteurs est soumis à de nombreuses incertitudes.

L'intégration des véhicules au réseau VGI, de l'anglais *Vehicle Grid Integration*, fait référence à l'ensemble des technologies, des services et des politiques qui créent un lien entre les systèmes de transport et d'électricité. Cette intégration ajoute de la valeur aux réseaux électriques et aux

véhicules eux-mêmes. Pour parvenir à la réduction des émissions de carbone du secteur du transport routier, un fort développement des VE en Europe au cours des prochaines décennies est nécessaire. Par conséquent, puisqu'il y aura quelques millions de VE sur les routes, ces derniers pourraient potentiellement apporter un service de flexibilité au réseau électrique grâce à la mise en oeuvre de certaines technologies et politiques à cette fin. Néanmoins, cette intégration peut représenter un défi pour les parties prenantes concernées et sa réussite dépendra d'un travail et d'un développement multidisciplinaires coordonnés au cours des prochaines années.

Le passage de la mobilité thermique vers des systèmes de motorisation électrifiés est subordonné à un grand nombre d'évolutions techniques et économiques. Si les problèmes les plus évidents sont l'autonomie de la batterie et les coûts associés, les conditions d'adoption du VGI ont une importance majeure : par exemple, les quantités d'énergie sollicitées en phase de recharge pourraient produire une condition de stress du système accentuant les pics de consommation locaux ou nationaux. Dans cette recherche, l'objectif est d'avoir une vision globale de ces implications et d'étudier les politiques qui y sont liées. De plus, au niveau individuel, le but est de comprendre les comportements et les motivations des conducteurs pour orienter une future acceptation de ces technologies.

Dans le contexte qui vient d'être décrit, les batteries des VE présentent une valeur potentielle en étant susceptibles de répondre à ces besoins de flexibilité des systèmes électriques intégrant massivement des Energies Renouvelables (EnR) variables. Des parcs de VE pourraient constituer des "centrales virtuelles" dont le pilotage serait décentralisé, à partir d'un signal-pilote, chaque véhicule étant autonome.

L'originalité du positionnement de ce projet de recherche est double, en portant une attention spécifique :

- A l'optimisation de la charge et de la décharge des véhicules sur le réseau selon le progrès technique. Ce progrès relatif aux batteries des VE a conduit à des gains importants en termes de capacité de stockage, de sorte qu'il est possible d'envisager les charges et décharges sur le réseau de manière flexible, sans contraindre significativement l'utilité de l'automobiliste. Ce progrès technique renverra également aux évolutions des algorithmes de pilotage, de la connectivité des VE, ainsi que des smart grids.
- Aux perspectives de gains/pertes du propriétaire du VE, selon les conditions de son in-

sersion dans un dispositif de pilotage de sa recharge. Cette focalisation est cohérente dans un contexte où les constructeurs automobiles (Renault, en l'occurrence) étudient tous les leviers pour la rentabilité des VE, afin d'accélérer la constitution d'un parc massif. Notre objectif sera d'analyser les mécanismes de rétribution/incitation déterminant la constitution et l'allocation du surplus.

La recherche est située dans le cadre européen, plus particulièrement par référence aux cas français et allemand, en raison à la fois de l'importance de ces deux marchés automobiles et de la puissance de leurs constructeurs, que des objectifs élevés en termes d'EnR. Compte tenu de l'ensemble de ces éléments, il est tout à fait plausible que la France et l'Allemagne constitueront dans la décennie 2020 des systèmes électriques parmi les plus avancés au monde pour ce qui est de la VGI et que, par conséquent, la question de l'allocation du surplus que l'on souhaite analyser s'y pose avec acuité.

Ce projet de thèse est structuré en trois axes destinés à analyser :

- Le processus optimal de charge et de décharge, cela en prenant en compte le progrès technique (batteries, algorithmes de VGI, capacité de communication des VE, etc.).
- Les conditions de valorisation des services de VGI dans le cadre d'un système local, dans un réseau intelligent intégrant des moyens de production renouvelables.
- Les conditions de valorisation des services de VGI dans le cadre d'un système national, en fonction des prix de marché de gros.

2 Chapitre II : Le VGI dans un réseau local appliqué au cas de Porto Santo

Notre objectif est d'étudier les conséquences d'une décarbonation combinée du système électrique et du secteur des transports sur un territoire isolé. On étudie les émissions globales de carbone et le coût de production d'électricité lorsque on considère l'augmentation de l'offre des EnR et un nombre croissant de VE avec VGI. On utilise des outils d'optimisation et de simulation pour évaluer plusieurs scénarios de développements des EnR et VE. On montre que lorsque les EnR représentent un pourcentage important de l'alimentation électrique annuelle, le coût de l'électricité diminue avec une part croissante de VE dans le parc automobile total jusqu'à un certain point. Une part supérieure de VE n'est plus utile pour le stockage de l'électricité et la réduction des émissions globales de CO_2 . Des résultats similaires sont donnés et discutés pour

différents mix de puissance.

Dans ce chapitre, on étudie l'interaction entre VE et EnR sur le mix électrique dans un contexte d'émissions élevées de CO_2 provenant à la fois des moteurs de voitures et des centrales électriques thermiques. Notre recherche contribue à analyser la problématique avec deux méthodes différentes (simulation et modélisation) et est composée de trois dimensions : une taille de batterie virtuelle (composée de l'agrégation de plusieurs batteries des VE), la part des EnR et le partage entre les deux technologies intermittentes, photovoltaïque (PV) et éolien. Cette approche permet de situer un grand nombre de scénarios possibles dans les années à venir. Les résultats sont présentés en les rapportant à la population (en termes d'habitants) dans le but de permettre une comparaison avec n'importe quel territoire de tailles et de caractéristiques différentes.

On applique l'étude sur Porto Santo, une petite île dont la production électrique provient essentiellement d'une grande centrale thermique et ayant un parc automobile majoritairement composé de voitures à essence, pour laquelle il existe un objectif environnemental de forte réduction des émissions de GES. On analyse l'adoption d'un système de stockage supportant le réseau électrique. Cela amène à une analyse plus approfondie en termes de flottes de VE différentes, puisqu'une même capacité peut être obtenue à travers différentes configurations de nombre de VE et de capacité partagée pour le VGI. Différentes implications techniques en sont tirées.

Dans ce chapitre, on se concentre sur la relation entre le développement des EnR et le développement des VE pour décarboner le secteur de l'électricité et des transports. De plus, On souligne qu'il existe une part optimale de VE en fonction de la part des EnR qui minimise le coût total de production d'électricité.

Le principal résultat est que grâce à l'installation de stockage, il est possible d'atteindre un mix énergétique 100% renouvelable.

La transition vers cet objectif peut être longue et des étapes intermédiaires sont nécessaires. Chaque étape de la transition est un élément clé du chemin, et des décisions doivent être prises en tenant compte des impacts à long terme. Dans ce chapitre, on présente les effets de mener la transition principalement avec PV ou principalement avec l'énergie éolienne. Dans tous les cas, on constate que le stockage est nécessaire et devient utile lorsque la production totale des EnR est supérieure à 40%. En dessous de cette valeur, il n'est pas nécessaire d'avoir une instal-

lation de stockage puisque l'électricité est majoritairement consommée au moment où elle est produite. A l'inverse, pour atteindre les plus hauts niveaux de pénétration des EnR dans le mix énergétique, un stockage d'énergie est impératif. Sans un tel système, une centrale thermique serait une solution alternative utilisant des biocarburants.

On souligne que le coût total de production d'électricité a une forme en **U** lorsque l'on considère une part croissante de VE. D'après les différents scénarios analysés, le stockage des VE privilégie les investissements PV au détriment des investissements éoliens, diminue ensuite l'exigence d'utilisation d'un biocarburant et enfin diminue le prix de l'électricité par rapport à un scénario sans installation de stockage de 4 centimes d'euro par kWh. Cela représente près de 400€ par VE par an.

On a constaté qu'il existe un stockage optimal pour chaque niveau d'EnR sur le mix total. Au-delà de ce point optimal, l'utilisation de chaque batterie et les économies associées diminuent. Cependant, les résultats montrent que le VGI es compatible avec les caractéristiques d'un VE. Chaque VE utiliserait entre 2.2 MWh et 8.6 MWh selon la pénétration des EnR qui correspond respectivement à 150 ou 350 cycles. Une capacité de l'ordre de 16 kWh par VE serait nécessaire pour atteindre un mix 100% EnR et les puissances sollicitées sont très faibles, de 2 kW pour la reinjection à 5 kW pour la charge intelligente.

Les VE peuvent avoir une contribution significative à décarboner le système électrique. Or, pour favoriser l'adoption d'une charge intelligente il faut que les propriétaires trouvent l'intérêt économique et donc, il faut que le coût de la technologie et du déploiement du système soit inférieur au revenus possibles. Cela dépend de la durabilité et du vieillissement de la batterie.

3 Chapitre III : Le VGI dans un réseau national appliqué à la France et l'Allemagne

Les secteurs du transport et de la production d'électricité représentent respectivement 23% et 40% des émissions mondiales de CO_2 liées à l'énergie. Le transport routier, y compris les voitures, les motos et les bus, émettent 16% des émissions de CO_2 . En ce qui concerne le secteur de l'électricité, les centrales au charbon sont les principaux émetteurs, responsables de 29% des émissions de CO_2 . L'Union Européenne (UE), soucieuse et inquiète du changement climatique, prévoit d'atteindre la neutralité carbone d'ici 2050.

L'UE a proposé des objectifs spécifiques pour le déploiement des EnR par le biais de la directive sur les énergies renouvelables. La mise à jour du paquet législatif concerné a été publiée par la Commission Européenne le 14 juillet 2021. À de cette date, elle a annoncé son nouveau projet pour atténuer les effets du changement climatique *Fit for 55* et fixé l'objectif ambitieux de réduire de 55% les émissions de GES d'ici 2030 (par rapport aux niveaux de 1990). L'un des objectifs est de produire 40% de la demande finale d'électricité à partir de ressources renouvelables d'ici 2030. Concernant le secteur des transports, une décarbonation continue des véhicules particuliers est également mise en place. Ainsi, la Commission Européenne envisage d'interdire la vente de voitures neuves thermiques d'ici 2035, ce qui signifie que même les ventes de voitures hybrides devraient être interdites, laissant 100% du marché des véhicules particuliers aux systèmes de carburant alternatifs.

Considérant que le développement des EnR crée une exigence de flexibilité pour le fonctionnement du réseau, l'intégration de VE dans le système électrique est double dans les objectifs de décarbonation : atteindre l'objectif d'obtenir une mobilité plus propre et contribuer à l'adéquation et à la fiabilité du mix électrique obtenu avec plus d'énergie renouvelable.

Le VGI fait référence à l'ensemble des technologies, services et politiques qui créent un lien entre le transport avec ses VE et les systèmes électriques. Cette combinaison entre transport et EnR est importante car avec une adoption massive de VE et sans contrôle de la recharge, le réseau électrique est exposé aux risques de pannes intermittentes alors qu'il ne serait pas en mesure de fournir la puissance instantanée requise. Un système de charge intelligent semble donc nécessaire.

Néanmoins, une bonne intégration avec un système de recharge intelligent nécessite une synergie entre les parties concernées, notamment les opérateurs de réseau, les gouvernements, les constructeurs automobiles et les propriétaires de voitures. Par ailleurs une bonne compréhension des principaux facteurs du système de recharge est nécessaire (par exemple, la puissance des différents chargeurs ou les comportements de charge). Une analyse technique de ces composants est au coeur de ce chapitre.

Différentes organisations estiment qu'il y aura quelques millions de VE sur les routes dans un futur proche. L'adoption d'un parc de VE important entraîne une nouvelle demande électrique lors des phases de recharge. Cette recherche s'appuie sur un algorithme décentralisé développé

par Pierre Nicolas, de la Direction de la Recherche de Renault. Il répond aux préoccupations futures d'un parc de VE et améliore la dynamique actuelle du mix électrique. Le concept a été amélioré et structuré au cours des trois années de thèse à travers plusieurs tests, analyses et discussions. L'idée générale est de créer une batterie virtuelle composée de la somme d'une partie de chaque batterie des VE. Cette capacité cumulée est gérée de manière optimale, directement par chaque VE sans agrégateur. Il pourrait prendre en charge le système d'alimentation en masse pour combler les creux de la demande grâce à la charge intelligente et pour réduire les pics de demande via la reinjection d'électricité.

Dans ce chapitre, on présente le développement et l'implémentation de l'algorithme composé d'un ensemble d'équations qui répondent à un système de contrôle optimal. L'optimisation prend en compte différentes échelles de temps : saisonnière, hebdomadaire et journalière dans le but de prendre en compte les variations du système électrique liées aux conditions météorologiques régionales et aux comportements de la demande d'électricité. L'algorithme reçoit la demande résiduelle comme signal d'entrée. Il est calculé comme la demande totale d'électricité en soustrayant la production d'électricité fatale. L'algorithme comporte deux étapes : avec une première commande, on estime le niveau de charge de la batterie (SOC) qui devrait être atteint par la batterie dans un certain temps et la deuxième commande est un facteur proportionnel qui régule la quantité de puissance appelée à chaque pas de temps.

Ensuite, on présente l'implémentation de l'algorithme de charge intelligente dans un simulateur. Cet outil est capable de reproduire la dynamique de charge d'une flotte importante de VE. Pour la simulation on utilise des données réelles d'une enquête statistique nationale en France avec un pré-traitement. Avec ces données et à l'aide d'un code Matlab, on estime la consommation d'électricité de la flotte et, par conséquent, les besoins réels en alimentation électrique pour chaque jour d'une semaine de travail type. L'objectif du simulateur est de comprendre les paramètres qui pourraient avoir un impact significatif lors de l'intégration d'un parc de VE particuliers dans le réseau électrique en tenant compte des différents comportements des propriétaires de voitures. On considère que la production des centrales conventionnelles et les flux internationaux sont fixes. Ce choix est fait car on trouve une relation étroite entre la demande résiduelle avec les prix du marché de l'électricité ainsi qu'une relation étroite entre la demande résiduelle et les émissions de CO_2 .

La simulation d'une flotte de véhicules réels appliquant un algorithme de recharge intelligent est un outil puissant pour comprendre les principaux défis de la mobilité électrique et on pense

qu'il pourrait être utile à plusieurs parties prenantes : opérateurs de réseau, gouvernements, constructeurs automobiles et universitaires. Par exemple, grâce à la simulation, il est possible d'estimer l'impact de différentes proportions entre la puissance des chargeurs, l'impact d'utiliser ou non les VE comme transport de travail ou de considérer le fait de préparer un long trajet pour le lendemain. On attend des résultats techniques et économiques innovants et intéressants.

Dans l'algorithme il y a deux signaux de commande. Le premier signal fonctionne comme un modulateur d'énergie qui capte les moments les plus appropriés sur une période d'une semaine pour charger les VE. La batterie virtuelle atteint un SOC supérieur ou inférieur selon l'état du réseau électrique par rapport aux $\pm 3,5$ jours. Par exemple, les jours où la demande est faible ou bien où la production d'EnR est élevée, le SOC cible est plus important. Le deuxième signal fonctionne comme un modulateur de puissance dans une période d'une demi-journée. Cette valeur de référence permet de combler les creux du jour pour tenter d'approcher la nouvelle demande résiduelle (la demande résiduelle actuelle plus la demande provenant des VE) vers une courbe plus lisse estimée à travers une valeur moyenne mobile sur une semaine. En appliquant cette valeur de référence, la puissance de charge est maximale aux moments où les creux sont plus profonds.

Ensuite, on a implémenté cet algorithme de charge intelligent dans l'outil de simulation. En variant les multiples paramètres on a trouvé que :

- Avec une pénétration plus élevée des EnR, la flexibilité à court terme est d'avantage marquée et moins prévisible. Les ajustements doivent être surveillés de près.
- La charge des VE est un outil de flexibilité qui doit être programmée différemment selon les saisons.

En hiver par exemple, dans un système électrique comme le modèle allemand, la charge des VE doit être prioritaire pendant les nuits où les courants d'air élevés produisent une faible demande résiduelle.

Alors qu'en été, la production PV produit une demande résiduelle plus faible pendant la journée et donc, la charge des VE est plus utile pendant ces heures de la journée.

- Pour atteindre un haut niveau de charge intelligente qui répond aux différentes variations

possibles du réseau électrique, il est nécessaire de disposer d'une infrastructure de recharge robuste.

- L'infrastructure de recharge idéale est une infrastructure hautement déployée avec de faibles puissances. Une charge à haute puissance n'apporte pas de flexibilité au réseau électrique, à l'inverse, elle pourrait créer des pics indésirables.
- La capacité des batteries a un effet important sur le système de charge intelligente. On a observé que même des petites batteries (20 kWh) peuvent contribuer à apporter de la flexibilité au réseau électrique mais dans une fenêtre quotidienne. Une charge optimale d'une semaine est moins faisable avec ces batteries.
- L'acceptation par les propriétaires des VE d'un système de recharge intelligent est fondamentale. Une meilleure acceptabilité est une capacité disponible plus importante pour apporter de la flexibilité au réseau électrique.

4 Chapitre IV : L'impact du VGI sur le marché de gros de l'électricité

Atteindre les objectifs de l'UE nécessite d'accélérer les investissements dans les énergies éolienne et PV à un rythme élevé qui permettrait aux EnR de représenter en Europe 35% de l'approvisionnement en électricité d'ici 2030, et même des taux autour ou au-dessus de 50% dans des pays tels que l'Allemagne. D'ici 2050, 80% de l'approvisionnement en électricité devrait être produit à partir de sources renouvelables.

Cependant, l'alimentation électrique à partir de ces ressources est intermittente et un déploiement massif nécessitera de nouvelles technologies de flexibilité pour assurer l'équilibre entre la demande et l'offre d'électricité. Jusqu'à présent, les centrales thermiques, les centrales hydrauliques avec pompage (STEP) et la gestion de la demande sont les principales méthodes utilisées pour établir l'équilibre offre/demande. Ces capacités risquent cependant d'approcher leurs limites dans un système à forte variabilité. Dans ce contexte, les VE pourraient bien devenir une ressource capable d'apporter de la flexibilité. L'analyse de leur interaction avec le système électrique à travers le concept du VGI est le fondement de cette recherche.

La production d'électricité à partir des EnR joue un rôle important dans l'établissement

des prix du marché. En tant qu'instrument essentiel pour les gouvernements pour atteindre les objectifs de réduction des émissions de CO_2 , les EnR ont une place prioritaire dans la vente de leur production dans le système du *merit order* avec des mécanismes de rémunération spéciaux tels que *feed-in tariff* puis *feed-in premium*. Le coût marginal à court terme des centrales des EnR est quasi nul : de ce fait, les enchères sur le marché peuvent avoir des valeurs négatives, jusqu'à un prix inférieur en valeur absolue au montant de la subvention, et il existe toujours une rémunération positive pour ces énergies. De plus, il existe un seuil planché de production en deçà duquel les centrales thermiques ne peuvent pas descendre. Par conséquent, les producteurs disposant de centrales thermiques doivent parfois proposer leur production à des valeurs négatives pendant les heures creuses et à des valeurs positives pendant les heures de pointe. Les limitations techniques à une montée en puissance lente de la production jusqu'à un certain niveau les obligent à fixer un prix garantissant que le marché achètera leur production quotidienne. Des prix négatifs peuvent apparaître en raison de certaines règles particulières en Europe : étant donné qu'il existe une priorité pour les EnR, leur excédent d'approvisionnement doit être utilisé. De plus, en raison de la montée en puissance des unités thermiques, il devrait être moins coûteux de maintenir un niveau minimum de production plutôt que de les réduire pendant les heures creuses. Ainsi, lorsqu'il y a un excès d'offre des EnR, un prix négatif peut apparaître. Inversement, lorsque la production des EnR est faible, la consommation est élevée et les importations sont à leur capacité maximale, le prix de marché est fixé par les centrales thermiques les plus chères même à des valeurs supérieures à leurs coûts marginaux, les prix de pénurie. Les deux situations deviennent plus récurrentes alors que de fortes capacités des EnR sont déployées. Récemment, en raison de la crise énergétique depuis fin 2021, les prix de l'électricité ont atteint des valeurs historiquement élevées. À cette époque, le monde a connu l'accumulation de plusieurs circonstances : la reprise économique après la crise pandémique qui a entraîné la plus forte croissance de la demande d'électricité, l'augmentation des prix dans le système d'échange de quotas d'émission de l'UE, des hivers froids, des centrales nucléaires arrêtées à cause du besoin d'entretien et des tensions géopolitiques (principalement la guerre en Ukraine mais aussi l'arrêt des importations de charbon d'Australie vers la Chine par exemple). Ces prix reflètent la dépendance aux énergies fossiles de plusieurs nations qui traversent actuellement un choc économique. Les crises énergétique et économique et le changement climatique ont révélé la nécessité (et l'importance) de l'indépendance énergétique.

On évalue les conséquences d'une augmentation du parc de VE sur le système électrique en considérant une implémentation optimisée de VGI. Cette analyse est réalisée dans le contexte européen des perspectives politiques de décarbonation. On développe des outils de modélisation

pour étudier les interactions entre la charge et la décharge des VE et le système électrique. On l'applique ensuite à l'Allemagne qui se caractérise par une large part de production des EnR (40.1% en 2019) et un parc de voitures particulières très important (47.7M en 2019). Le processus optimisé de VGI est basé sur un algorithme d'écrêtage des pics et de remplissage des creux qui tient compte du comportement des conducteurs.

Une simulation est appliquée pour une flotte importante de VE en utilisant des données historiques de demande sur un an. On évalue l'impact de la modification de la courbe de charge sur le prix de gros de l'électricité, on estime le surplus des producteurs et les émissions de CO_2 du système électrique.

L'analyse des résultats obtenus permet de confirmer l'intérêt de relier les VE particuliers au réseau électrique via un système intelligent pour répondre aux exigences de flexibilité émergentes. La charge optimale d'une flotte de VE pourrait réduire les pics de demande qui conduisent le système à des situations stressantes : de ce fait, un algorithme de VGI permet de limiter la volatilité apportée par l'intégration des EnR et par conséquent, améliore l'adéquation et la fiabilité du système ce qui pourrait améliorer le surplus du producteur du secteur de l'électricité. Le VGI limite le risque d'investissement dans le secteur de l'électricité en réduisant la volatilité des prix. Lors de l'ajout de capacité de flexibilité, le système aurait besoin de moins d'investissements dans de nouvelles capacités de production. Parce que le développement des EnR a été soutenu à l'origine par des subventions, qui restent importantes jusqu'à présent, le surplus le plus élevé devrait apparaître grâce à la flexibilité apportée par la flotte de VE.

L'effet *merit order* sur les marchés de l'électricité, qui déplace la courbe vers la droite ou vers la gauche en fonction de la production d'électricité des EnR, pourrait reculer. La flexibilité des réseaux électriques allemand et français repose actuellement sur le nucléaire et l'hydraulique, qui sont des unités non fossiles. Une batterie virtuelle capable d'absorber cette production (au lieu de la limiter) conduit à un marché plus stable et équitable.

On souligne l'intérêt d'optimiser la charge d'une flotte de VE suivant un signal de demande résiduelle qui capte intrinsèquement les prix et les émissions de CO_2 tout en garantissant la performance du système. On souligne que les VE ont un impact significatif sur le marché de l'électricité. Néanmoins, l'effet de bouclage n'est pas pris en compte lorsque l'optimisation se fait par un signal de prix dans la revue de la littérature. Cependant, on a montré que la charge des VE est capable de modifier les prix du marché.

Chapitre 1

Electric Vehicles and their integration into the power grid

1 The research context

The earth's temperature has risen by 0.08° per decade since 1880. Though, the rate of warming has more than doubled since 1981 reaching 0.18° per decade (Figure 1.1). The increase in global average surface temperature that has occurred since the pre-industrial era (1880-1900) might seem small, but it means a significant increase in accumulated heat. That extra heat is driving regional and seasonal temperature extremes, reducing snow cover and sea ice, intensifying heavy rainfall, and changing habitat ranges for plants and animals. Multiple independent research groups across the world perform their own analysis of the surface temperature data, and they all show a similar upward trend¹. However warming has not been uniform across the planet, the upward trend in the globally averaged temperature shows that more areas are warming than cooling.

The amount of future warming Earth will experience depends on how much carbon dioxide and other *Green House Gas* (GHG) we emit in coming decades. Today, our activities, burning fossil fuels and clearing forests, add about 11 billion metric tons of carbon to the atmosphere each year. Because that is more carbon than natural processes can remove, atmospheric carbon dioxide increases each year. Figure 1.2 presents five possible scenarios :

- No climate policies : projected future emissions if no climate policies were implemented ; this would result in an estimated 4.1°C to 4.8°C warming by 2100 (relative to pre-industrial

1. <https://www.climate.gov/news-features/understanding-climate/climate-change-global-temperature>

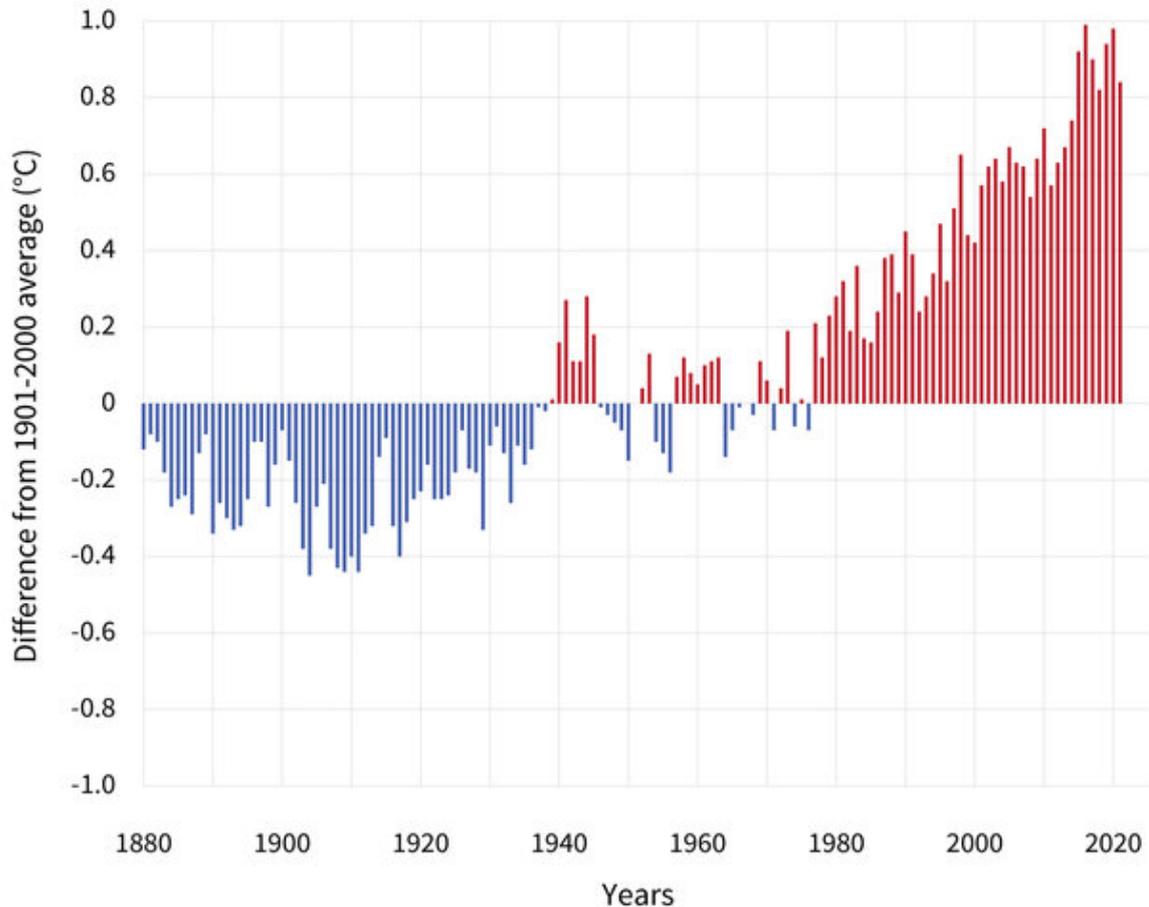


FIGURE 1.1 – Yearly surface temperature.

Unit : °C.

Source : www.climate.gov based on data from the [NCEI](https://www.ncei.noaa.gov/).

temperatures).

- Current climate policies : projected warming of 2.8°C to 3.2°C by 2100 based on current implemented climate policies.
- National pledges : if all countries achieve their current targets/pledges set within the Paris climate agreement, it is estimated average warming by 2100 will be 2.5°C to 2.8°C. This will go well beyond the overall target of the Paris Agreement to keep warming well below 2°C.
- 2°C consistent : there are a range of emissions pathways that would be compatible with limiting average warming to 2°C by 2100. This would require a significant increase in ambition of the current pledges within the Paris Agreement.

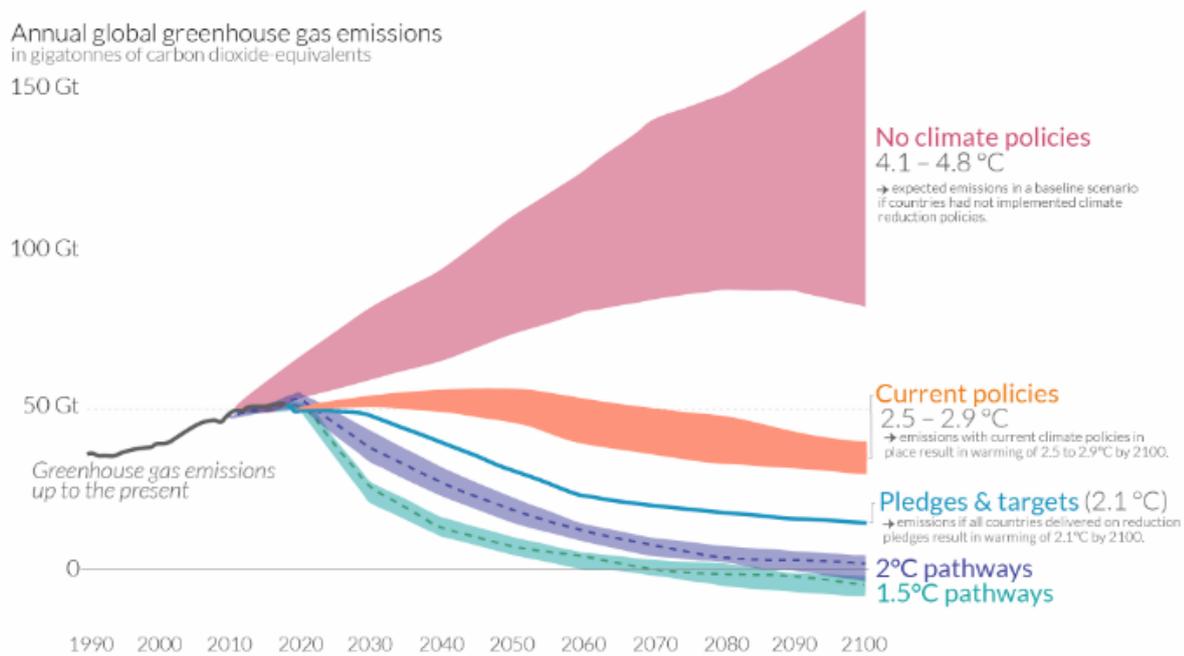


FIGURE 1.2 – Global *Green House Gas* emissions and warming scenarios.

Unit : Gton CO_2 equivalent.

Source : <https://ourworldindata.org/future-emissions>.

- 1.5°C consistent : there are a range of emissions pathways that would be compatible with limiting average warming to 1.5°C by 2100. However, all would require a very urgent and rapid reduction in global GHG.

1.1 The energy transition

The struggle against climate change includes the diffusion of alternative mobility solutions, with low or even zero emission rates. The deployment of *Electric Vehicles* (EV) participate in such strategies for reducing GHG emissions coming from transport, a sector representing around two thirds of final petroleum demand in the *Organization for Economic Co-operation and Development* (OECD) countries. Depending on the electricity mix of each country, EV might contribute to specific targets for reducing emissions. In terms of decreasing GHG emissions, the *International Energy Agency* (IEA) considered that EV should represent at least 40% of new passenger cars in the world by 2040 for reaching Paris Agreement ambitions [IEA, 2018] [IEA, 2022]. In France, to achieve the carbon neutrality by 2050 and after adjustment of the *Stratégie Nationale Bas-Carbone* (SNBC), the government announced that 100% of new cars sales should be EV or hydrogen cars by 2040. Like France, many countries all around the world have prepared the passenger cars conversion (Figure 1.3).

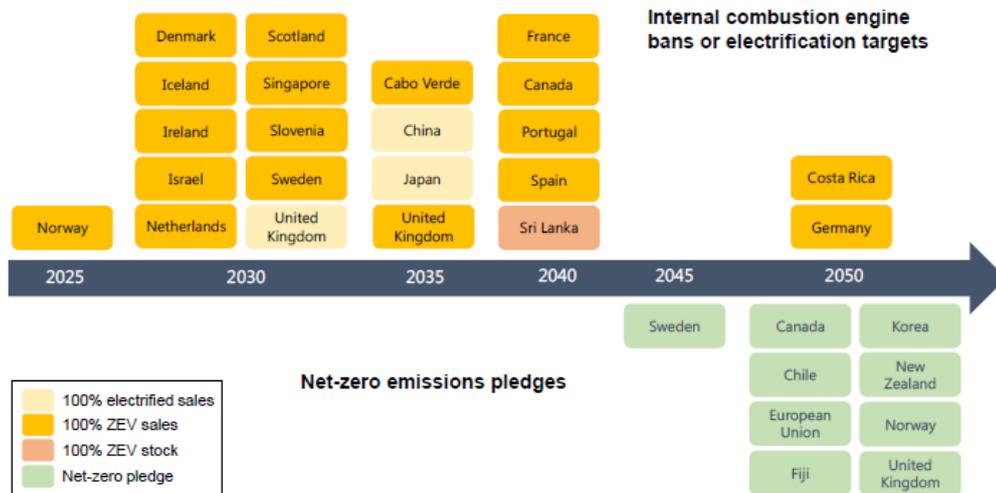


FIGURE 1.3 – Different countries path through the conversion of particular cars from *Internal Combustion Engine* to EV.

Source : IEA.

1.1.1 EV adoption forecasts and promoting policies

To succeed the conversion from *Internal Combustion Engine* (ICE) to EV several policies have been adopted by governments. The existing policies are already becoming a factor that influences EV purchase. We present the EV adoption strategies for France and Germany which are the two main European markets.

In France, the government has implemented specific tools to help its population to make the transition towards cleaner vehicles² :

- The first one is a "conversion grant" that pays for changing from a more pollutant vehicle to less emitters thermal cars, hybrid cars, EV and even motorcycles or bikes. This bonus can reach up to 3,000 € for the purchase of ICE cars releasing less than 137g CO_2/km (if the car has more than 6 months, otherwise 127g CO_2/km) or 5,000 € for hybrids and EV. Since 2018 more than 800,000 conversion bonus have been allocated.
- The second mechanism is the "ecologic bonus". It allocates up to 6,000 € for the purchase of an EV and 1,000 € for the purchase of a *Plug in Hybrid Electric Vehicle* (PHEV). The

2. <https://www.ecologie.gouv.fr/prime-conversion-bonus-ecologique-toutes-aides-en-faveur-lacquisition-vehicules-propres>

amount is fixed depending on the car model and it exists as well for the purchase of electric or hydrogen trucks and buses. In these cases, it can be up to 50,000 €.

- To help families with low incomes, the French government facilitates a loan to rent a cleaner car. The vehicle eligibility conditions are the same as for the conversion bonus and the refund is guaranteed at 50% by a social finance group.
- Concerning the recharge points spread, France has created a tax credit that allows to grant 75% and up to 300 € of the installation costs. All taxpayers can benefit, once for its main residence and once for its secondary residence³. Population can use this mechanism even if they are tenants, owners or free occupants of the lodging.

For its part, the German government has established a set of incentives to promote the use of **EV** and the development of the whole **EV** environment (e.g. batteries and components industry, or associated services such as the *Vehicle Grid Integration (VGI)*)^{4 5}.

- By 2018, a bonus of 4,000 € was ongoing for the purchase of a new **EV** and 3,000 € for the purchase of **PHEV**. The carmakers had an equal contribution for each car. During the COVID-19 pandemic, the German government implemented the "innovation premium" which was the increase of the state share of the environmental bonus. For an **EV** which price is under 40,000 €, the ecological bonus reaches up to 9,000 € (6,750 € for **PHEV**). For **EV** which price is between 40,000 € and 65,000 €, the bonus reaches up to 7,500 € (5,625 € for **PHEV**). During the summer 2021, Germany announced the extension of the mechanism until 2025.
- **EV** are exempted of the vehicle tax until 2025. Then, the tax will be completely abolished by 2030.
- 2.5 billion € are committed to investments in charging points and battery cell production. All petrol stations in Germany will be compelled to supply recharge service.

3. <https://www.service-public.fr/particuliers/vosdroits/F35578>

4. <https://www.bmwk.de/Redaktion/EN/Dossier/electric-mobility.html>

5. <https://www.electrive.com/2020/06/04/germany-doubles-ev-subsidies-no-more-diesel-support/>

2 The *Electric Vehicles*

2.1 The **EV** world market

The **EV** fleet is called to evolve since it is a strategic tool to back up the energy transition from the transport sector and the power system. But the way and the speed of its evolution is not certain and depends on different factors such as the price and the battery ranges of available **EV** models in the market or the accessibility to recharge points, among others. According to the **IEA** [IEA, 2022] France and Germany are the largest **EV** markets in *European Union* (**EU**). In France, this market is dominated by the *Battery Electric Vehicles* (**BEV**) while in Germany it is distributed by half between **BEV** and **PHEV**. The *Comité des constructeurs français d'automobiles* (**CCFA**) reported that in France, the highest market variation reached up to 144% in the first quarter of 2020 while in Germany the variation was of 125% with respect to the same quarter of the previous year. In the **EU** the market quarter variations have oscillated between 37% and more than 111% in the period from 2016 to 2021 and the total **BEV** sales grew from 1.1% in 2019 to 3.6% in 2020 [Conway, 2021]. Today there is in place the Zero and Low Emission Vehicle credits mechanism. It allows to average CO_2 emissions from **ICE** with the zero emissions from **EV** fleet sold by carmakers. From 2030, in application of the **EU** package of proposals, this mechanism will be removed, forcing the automotive industry to reinforce their strategies to expand their **EV** market.

2.1.1 Drivers' behavior for using **EV**

Different customers and **EV** segmentation are identified in the existing literature expecting to understand the factors that would lead the spread of this market. These studies are deemed to orientate public policies through the identification of socio-demographic and psychological influential factors as well as purchase behaviors [Nosi, 2014]. For example, Kubiczek [Kubiczek, 2021] identifies the class, the size, the performance and the quality of **EV** as some of the main factors that could direct the choice of purchasers in one European country. The study conducted by Saleem [Saleem, 2018] reveals that 50% of automotive industry customers have "eco-social tendencies" when choosing a personal car in South Asia. Incomes, education, gender and city of residence were the main segments differentiation. For its part, Nayum [Nayum, 2022] explains how the main pro-environment actions, such as the purchase of an **EV**, are guided by personal norms and compensatory beliefs while McLeay [McLeay, 2018] concludes that to encourage the adoption of **EV**, it is necessary to limit the perceived risks associated to finances, psychology, society and time. These few examples show the large range of fields that are discussed in the

existing literature concerning the **EV** adoption and exposes the sources of uncertainty about the number of **EV** and the time horizon to have a significant fleet on the roads.

In France, *The European Association for Electromobility* (**AVERE**) has published in January 2022 its latest report about the perception of **EV**⁶. Among the key results we find that :

- More than 80% of the population is willing to change mobility related practices to struggle the climate change and to improve the air quality.
- The traveled distance has not significantly changed in the last ten years, even taking into account the spread of teleworking since the pandemic. 76% of the population travels less than 50 km per day and the average distance is 29 km.
- A high battery range, a purchase price equivalent to **ICE** cars and the facility to recharge are the key factors to shift to **EV**.
- 1 out of 3 French people have today access to a charge point, at work, at home or at a public place.

Beyond the number of **EV** that will circulate on the roads, the impact on the power grid will be conditioned by drivers' behavior. The electromobility report by *Réseau de Transport d'Electricité* (**RTE**) [RTE, 2019] presents five scenarios with different rates of **EV** deployment by 2035. The annual energy demand increase linked to the **EV** integration is estimated between 28 TWh and 48 TWh which would not impact drastically the grid while it is the instantaneous appealed power which could trouble the effective operation of the grid [RTE, 2019].

The drivers' behavior is submitted to plenty of uncertain factors and it is estimated or assumed in different ways in the literature. For example, Bo [Li, 2022] aims at estimating the **EV** charging behavior in China. They process information collected through the U.S. national household travel survey about one day trips. The survey provides information about the path such as locations, distances, departure and arrival times and information about drivers attributes such as age, gender and work status. Next, they build an **EV** routine applying Markov-chains

6. <https://www.aver-france.org/lavere-france-et-mobivia-revelent-les-resultats-du-barometre-les-francais-et-la-mobilite-electrique-realise-par-ipsos/>

and Monte-Carlo method to estimate a charging load profile.

2.2 The *Vehicle Grid Integration*

The *VGI* refers to the set of technologies, services and policies that create a link between transport and power systems. To achieve the reduction of carbon emissions from the road transport sector, there will be a strong development of *EV* in Europe during the next decades. Consequently, since there will be a few millions of *EV* on the roads, they could potentially bring a service of flexibility to the power grid through the implementation of some enabling technologies and policies.

Nevertheless, this integration can represent a challenge for the concerned parties and its success will depend on a coordinated multidisciplinary work and development during the coming years. The main involved stakeholders are electricity producers and suppliers, *Transmission System Operator (TSO)*, *Distribution System Operator (DSO)*, regulators, flexibility and demand response operators, governments and car manufacturers. They must evaluate issues at different levels, going from drivers' behavior (for example when they will be invited to share their batteries' capacity for supporting the grid) to the expansion and the adaptation of the recharge grid. To approach all these subjects and considering all stakeholders, a robust economic model must be settled.

The optimization of the *VGI* has already been subject of abundant literature, from both technological and economic point of views - starting from the pioneering work of Kempton [Kempton, 1997] who introduced the concept of *Vehicle to Grid (V2G)* - and following a wide variety of angles such as the integration of *REn*, the minimization of recharging costs through electricity tariffs, or even the adjustment of voltage and frequency [Codani, 2015]. To implement all (or some) of these *VGI* services over the coming years, it is necessary to find a compromise between the needs of the networks and those of car drivers. For example, beyond the smart charging, *VGI* could offer a large variety of services to the network, by exploiting the possibility to restore the electricity available in the batteries of *EV*. These services are possible because, used to perform commuting, particular *EV* are usually idle more than 90% of the time (just like thermal vehicles), which makes them potentially available if they are connected to the electricity grid.

The integration of *EV* adds value to power grids and to the vehicles themselves. The question that emerges from this argument, and that has been the subject of several publications, seeks for

the best way to take advantage of this added value. According to Fitzgerald and Langton [Fitzgerald, 2015; Langton, 2013], this value could come from thirteen different services associated with three stakeholders : **the wholesale market**, the link with the **DSO** and the interaction with car owners. Mwasilu [Mwasilu, 2014] presents a compilation of researches about possible sources of income, which are mainly classified into four categories : minimization of operating costs, maximization of profit for the service rendered to the **DSO**, minimization of electricity generation costs for **TSO** and minimization of recharging costs for car drivers. In the reviewed literature, we find the value of **VGI** through the participation in grid services, investment deferral, improved efficiency and reliability of service and savings on costs of purchase and operation of **EV**. Furthermore, we consider that there is an immaterial and non-monetized added value of **VGI** that comes from the moral duty of contributing to decarbonize and preserve the planet.

Thompson [Thompson, 2019] presents in a concrete way the potential of remuneration of several *Vehicle to Anything* (**V2X**)⁷ services in the United States, Canada, Australia, and United Kingdom. His results show that incoming value ranges vary widely from one country to another with the same service. He also shows a correlation between a possible remuneration and local circumstances in the place where the storage capacity is located, for example following the market conditions and the regulations in force. This remuneration will be maximized through participation in several services simultaneously. However, most of the work in the literature is focused on a single service and therefore, a single source of income not exploiting the full potential of **VGI**.

Creating value to **VGI** through the participation of a virtual battery, composed by the aggregation of several batteries of **EV**, in the primary reserve service⁸ has been proposed through different models in the works of Han, Wu, Petit and Arias [Han, 2011; Wu, 2012; Petit, 2013; Bañol Arias, 2020]. Codani [Codani, 2015] presents in his results a range of revenues per vehicle and per year for participation in frequency regulation subject to an auction system that varies according to the power levels to which **EV** are connected. The income obtained with a bidirectional system (**V2G**) is much higher than that of a single way system. The main argument for proposing the participation in frequency regulation, as Kempton [Kempton, 2005] indicates, is that a battery can have a very fast response at a low cost compared to a traditional power plant providing the same service. In Chapter 4, we propose a different **VGI** valuing service, not in the

7. V2X refers to Vehicle to Everything and includes all the possible services of **EV** such as *Vehicle to Grid*, *Vehicle to Building*, *Vehicle to Vehicle* or *Vehicle to Home*.

8. It is an automatic device for frequency regulation with a response time between 15 and 30 seconds. All the primary reserve must be able to trigger off for a frequency deviation of 200 mHz. France must have a capacity of around 540 MW for this regulation. All countries participate in the primary reserve regardless of whether the imbalance comes from its own territory or elsewhere.

balancing market (largely studied) but in the day-ahead market.

An available capacity from *EV* should therefore be submitted to the *Regulation on Wholesale Market Integrity and Transparency* (REMIT) carried out by the *Agency for the Cooperation of Energy Regulation* (ACER) in a way that *capacity hoarding*⁹ or *layering*¹⁰ could not take place [CRE, 2018].

The work of Mwasilu [Mwasilu, 2014] gathers the literature concerning the coordination strategies between *EV* and *REn*. He classified the interests of charging schemes into three categories : *costs*, for research about the minimization of total production and operating costs and the maximization of revenues for the concerned stakeholders (including the recharging costs minimization for *EV* owners), *efficiency*, for research focused on optimizing the use, operation and management of *REn*, typically by charging the batteries when there are surpluses and by restoring energy when there are production shortages, and finally, *emissions*, for research on the positive impact of the use of batteries to meet the objectives of reduction of *CO*₂ emissions.

California is one of the world regions with the biggest *EV* spread. It reports 50% of sales and of the total *EV* fleet in the United States with annual increases of nearly 30% [International Council on Clean Transportation, 2018], laying down new constraints to the transportation and distribution systems and to the market, which must evolve to meet these new requirements. This situation has led the three system operators in this state to conduct smart charging experiments. In the work of Gopal [Gopal, 2018] we find some interesting examples. Pacific Gas & Electric (PG&E) in partnership with BMW offered a flexibility service using a percentage of *EV* batteries capacity and a complementary stationary system. The average *EV* participation was 20% going up to 50% in few cases where the flexibility was required during favorable charging hours according to *Time of Use* (ToU) tariffs. The *Southern California Edison* (SCE) for its part conducted experiments to assess the behaviors of motorists who charge at work and the different residential smart charging technologies to determine the needs of a future driving program.

Transition from *ICE* mobility towards electrified motorization systems is subordinated to a large number of technical and economic evolutions. If the main issues are the battery autonomy and the associated costs, conditions for adopting *VGI* have a major importance because of, for example, appealed energy quantities in recharge phase could produce a system stress condition

9. Acquisition of all or part of the available transport capacity without using it or without using it efficiently

10. Issue by a market participant of a large order or several orders on one side of the order book, in order to carry out one or more transactions on the other order book side

accentuating local or national consumption pics. In our research we look for having a global view of these implications, we identify stakeholders with their own interests and study related policies. Moreover, we understand drivers behaviors and motivations for directing a future acceptance of these technologies.

The **V2G** belongs to the group of services known as **V2X** that represents the use of the **EV** batteries to derive additional value during time of non-use. The **V2G** refers specifically to the services brought to the power grid. It presents the largest revenue potential with direct access to wholesale energy and ancillary services markets [Thompson, 2019]. Geske [Geske, 2018] provides the main barriers for **EV** owners participating in **V2G**.

3 Research questions

In this context, the originality of the positioning of this PhD thesis is twofold, paying specific attention to :

- The optimization of the charging and discharging of vehicles on the network according to technical parameters. The progress related to **EV** batteries has led to significant gains in terms of storage capacity (an evolution which should continue), so that it is possible to consider the charges and discharges on the network in a flexible way, without significantly constrain the utility of a vehicle for drivers. A smart charge algorithm is studied and it is intended to be used for calculating the impacts of smart charging and of **V2G** on the future French and German **EV** fleets.
- The prospect of gains and losses for the **EV** owners (whether it is a household, a company or a community within the framework of the management of a fleet), according to structured possible scenarios and the conditions of its participation in a controlled system of recharge. This focus is consistent in a context where car manufacturers are studying all profitability leverage of **EV**, in order to accelerate the launch of a massive fleet.

It is necessary to differentiate and analyze two issues that emerge with the development of electric mobility in the context of the global energy transition which leads the territories to develop cleaner forms of energy. First, with the massive deployment of **REn**, electricity networks are subject to the need of flexibility in order to respond to the intermittency and the high variability of these resources. Storage systems are becoming a key and essential factor for achieving the established objectives since they will make it possible to absorb sudden peaks in production and

to reinject the stored energy during consumption peaks. Second, we analyze the issues related to **EV** charging. While the installed capacity of electricity production in France is expected to be largely sufficient to cover the charging needs of a large fleet of **EV** in terms of energy, a certain level of charging management seems necessary to manage peaks in daily consumption, mainly in winter. The research is focused on national grids for France and Germany and in a local grid.

Thus, we define the research questions which follow :

- How could **VGI** development assist the massive adoption of **EV** during a key period through the energy transition with ambitious objectives of **REn** deployment ?
- Which benefits could bring up **VGI** from a technical and an economic point of view for stakeholders? (in a local island context and at a national level in France and Germany)

To answer these questions we have developed several modeling frameworks and we apply them first to an island case (Porto Santo) and then in France and Germany over the three next chapters. This leads us to answer to sub-questions that we present below :

- How would result the implementation of a recharge algorithm in a large expected **EV** fleet ?
- How to avoid possible stress on power systems with the introduction of a new significant electricity demand owed to charging several **EV** during peak demand periods ?
- How could **VGI** impact electricity markets ?
- What are the appropriate methods for encouraging stakeholders to adopt **VGI** ?

In Chapter 2 we aim at investigating the consequences of a combined decarbonation of the power system and the transportation sector in an isolated territory. We study the global carbon emissions and the power generation costs when we consider increasing **REn** supply and a growing number of **EV** with **VGI**. We use optimization and simulation tools to assess several scenarios of **REn** and **EV** developments. We show that when **REn** stand for a high level of **REn** generation over the annual power supply, the electricity cost decreases with an increasing share of **EV** in the total fleet of cars until reaching an optimal point. An upper share of **EV** is no more useful for

electricity storage and global CO_2 emissions reduction. Similar results are given and discussed for different power mix.

In Chapter 3 we present the solution of an optimal control model applied as a smart charge algorithm for an EV fleet. Then, we implement this smart charge algorithm in a simulation tool developed to analyze the impact of the adoption of an important EV fleet when varying several technical parameters. We highlight the possible positive impact of the EV charge modulation.

In Chapter 4 we present an empirical methodology and analysis of the integration impact of an significant fleet of EV on electricity markets. From our results in Chapter 3 we conclude that this integration will raise the electricity demand and what is more important, will produce a significant change in residual demand. Nowadays, this residual demand sets the dynamics of the *day-ahead* market prices. Our hypothesis is that if EV modify residual demand, they will modify market prices as well. We present a comparative of charge prices when applying our smart charge algorithm and when letting the natural charge.

Chapitre 2

The *Vehicle Grid Integration* in a local network : case study of Porto Santo

1 Introduction

The development and the deployment of storage systems depend on several criteria such as the cost, the performance or the availability [Cristofari, 2010]. For example, some territories do not have the adequate conditions to use water resources as storage system and some others, particularly isolated territories, do not have interconnections with other power grids. Different sources of flexibility, aligned with the energy transition objectives, might be evaluated and integrated in these power systems.

Transition from ICE mobility towards electrified motorization systems is subordinated to a large number of technical and economic breakthroughs. While the most evident challenges in the adoption of EV are related to the battery autonomy and the associated cost, other issues need to be also addressed; for example, the energy demand from EV during recharging phase, could produce stress into the system accentuating local or national consumption peaks [Dubarry, 2017; Redondo-Iglesias, 2019; Uddin, 2018]. These concerns lead to the VGI concept presented in Chapter 1, which refers to the set of technologies, services and policies that create a link between transport and power systems. The concept allows the creation of value when using the residual energy stored in EV batteries for offering different energy services. Some of the services that have been studied are for domestic usage (*Vehicle to Home* (V2H)), collective usage (*Vehicle to Building* (V2B)) or for using directly into the power system (*Vehicle to Grid* (V2G)). For the purpose of this research we focus on the use of the electricity storage capacity for supporting the bulk power system. We show that the EV interaction with a national or a

local power system constitutes an opportunity to reduce **GHG** emissions from transportation and to smoothen variations coming from the **REn** integration.

In this chapter, we study the interaction between **EV** and **REn** on the electricity mix in a context of high CO_2 emissions from both car engines and thermal power units. Our research contributes to analyze the issue with two different methods (simulating and modeling) and is composed of three dimensions : a virtual battery size (composed of the aggregation of several **EV** batteries), the share of **REn** and the split between the two intermittent **REn** technologies **PV** and wind. This approach allows to situate a large amount of possible scenarios in the coming years. In addition, we show results in terms of inhabitants with the aim of enabling a comparison with any territory of different sizes and characteristics.

We focus our study in Porto Santo, a small island which is nowadays characterized by a large thermal power unit and a larger number of gasoline cars and for which there is an environmental objective of strong reduction of **GHG** emissions. We analyze the adoption of a storage system that constitutes an entire capacity (MWh supporting the power grid). This carry us to a further analysis in terms of different **EV** fleets, since one same capacity might be obtained through different configurations of number of **EV** and shared capacity for **VGI**. Different technical implications are drawn from this.

2 Literature review

Intermittent sources of electricity generation, mainly wind and **PV**, will be widely deployed into the power systems in order to meet energy transition objectives. Nevertheless, with a significant penetration of **REn** in the energy mix (greater than 15% according to [Kempton, 2005] and 20% according to the results of [Villavicencio, 2017]), the management of fluctuations becomes a problem for the grid. This is a major issue and the high variability of these resources is reflected in economic and technical failures of the power system. The challenge for the **TSO** is to find the balance between the targets of **REn** penetration in the electricity mix and the flexibility needs which are increasing at the same time.

The variability of **PV** and wind resources for generating electricity must be considered in different time horizons, till in seasonal and daily periods we find different characteristics that impact the dimensioning of the power system. The capacity factor, that is the measure of the real generation with respect to the installed capacity, is estimated at levels between 15% and

25% for PV and between 25% and 35% for wind turbines. These capacity factors have an important economic impact on investment decisions in a system expecting a massive adoption of these technologies [Bothwell, 2017]. This is why, the reliability of power grids must be ensured not only through an appropriated operation (in a short term) but through an appropriated expansion planning (in a long term) [Koritano, 2021]. For this reason, the main contribution of storage systems is based on its flexibility, which brings the capacity to resource adequacy and reliability to the power grids [Ani, 2016]. This asset is specially important and useful in the transition through more REn electricity mix [Gay, 2018].

Because of their flexibility, *Pumped Storage Hydropower* (PSH) plants can be quickly dispatched with high ramp rates to meet peak demands when power grids have already mobilized the cheaper resources for generating electricity. Their contribution to the power system adequacy and reliability is quantified by Perez-Diaz [Pérez-Díaz, 2016], who estimates a reduction in electricity generation costs between 2.5% and 11% through the use of PSH plants in an isolated system that generates electricity with wind power and that compensates variations with a thermal power plant. This flexibility, characteristic of PSH plants, leads us to compare the technology with another storage system, which, until now, has not been used in large scale for power systems. It is the EV batteries, that with an aggregated capacity could bring flexibility to the power system in a similar way that PSH plants. Nevertheless, important differences must be remarked before emphasizing the potential contribution of EV to the power grid. The first one is the investment system. The building time of a PSH plant is estimated at 7 or 10 years and its capital cost is very high [Koritano, 2021]. Once the system is operable, the management of the power plant is easy, cheap and flexible. Whereas that for a virtual battery, composed by the aggregation of several EV, the investment cost is distributed in each participating EV and the size of the virtual battery can be expanded progressively while the EV fleet expands. Its contribution can begin even with a small EV fleet at a first moment. In contrast, the management is less simple because there will be an influence of drivers behavior in terms of plug-in to the grid and in terms of the electricity consumption for supplying the required energy for transportation.

Liu [Liu, 2015] gathers the literature that concerns the coordination between EV and REn. He classifies the researchers' interests into three categories : *costs*, for research around the minimization of total production and operating costs and the maximization of revenues for the concerned actors (including the minimization of the cost of recharging for EV owners), *efficiency*, for research focused on optimizing the use, operation and management of REn, typically by charging the batteries when there are surpluses and by restoring energy when there are pro-

duction deficits, and finally, *emissions*, for research on the positive impact of the use of batteries to meet the objectives of reduction of CO_2 emissions. From these three categories, research on VGI includes efforts for smartly link EV into the power grid through different approaches such as bidirectional communication devices, or simpler, through charge strategies adopted by car owners responding to an outstanding signal [Ferro, 2018 ; Shaaban, 2017].

It is possible to manage the EV recharge as function of the power system conditions of a national or a local mesh [Cortés, 2019 ; Sachan, 2018 ; Ahmadian, 2018]. Shifting charge would lag power appeal as a signal response (i.e. electricity tariff, CO_2 emissions) for avoiding to resort to carbonate and expensive electricity, as well as to absorb fatal electricity from wind and PV resources [Clairand, 2017 ; Chiao-Ting Li, 2012 ; Saber, 2011]. Beyond charge management, VGI could offer a variety of services to power grid since it is possible to restore the electricity from EV batteries. This is possible because EV are idle 90% of the time just as ICE vehicles, being available to be connected to the power grid. This availability will depend widely of car owners acceptability and behaviors who will respond to incentives (economic, environmental, etc) and to a proper communication about agreement conditions with the system operators (TSO/DSO) or an aggregator about the EV battery usage [Gopal, 2018 ; Geske, 2018 ; Noel, 2019 ; Li, 2017].

In this context, EV batteries represent a potential value for being capable to respond to the flexibility requirements of power systems integrating massively intermittent REn. EV fleets could constitute a "virtual power plant" whose management could be handled by an aggregator or in a decentralized way, letting absolute autonomy to each vehicle attending to a pilotage signal [Masoum, 2013]. In any case, VGI could contribute to peak shaving for national or local grids when shifting charge out of high consumption periods during the day [Blasius, 2018], to synchronize power reserve available for facing a sudden demand increase or the unexpected halt of a power unit, to frequency regulation and to voltage regulation. The optimal operation of EV for these services has been subject of a wide literature from a technological point of view as well as from an economic point of view (starting from the work of Kempton [Kempton, 1997] in the 90's). Different dynamic programming approaches for the VGI are proposed by Cortes and Sioshansi [Cortés, 2019 ; Sioshansi, 2014], taking into account stochastic patterns of REn supply.

Some examples of the approaches in the literature are REn integration, charge costs minimization following electricity prices, incomes maximization by participating in grid services or improvement of CO_2 reduction strategies. The common point is that VGI adds value to power grids and EV themselves, which leads to interrogate about what is the best way to benefit from

this value. The income sources can be found in different ways : participation to grid services, grids deferral, improvement in adequacy and reliability or decrease of operational and investment costs on EV. Tangible or manifested differently in the literature, we find the value of VGI with participation in grid services, investment deferral, improved efficiency and reliability of service and savings on costs of purchase and operation of EV. According to a report about the German energy transition [Energiewende, 2019], EV represent lower carbon emissions with respect to ICE still when taking into account the whole lifecycle analysis. Although, the power consumed to operate EV is the most impacting factor in their carbon footprint and therefore, enhancing the electricity used to charge EV batteries will make them a cleaner mobility solution. Furthermore, we consider that there is an immaterial and non monetized added value of VGI that comes from the moral duty of contributing to decarbonize and preserve the planet. Indeed, remuneration might rely in drawn energy from batteries, its usury or its availability. Each kind of service could have higher or lower profits, but an heterogeneous monetary evaluation is required because of the sensibility of results to the geographic zone (its energy mix, topology and specific market rules) [Thompson, 2019].

Studies about energetic independence and REn expansion are introduced to different isolated territories that historically have depended on fossil resources for power generation. Results show how in different scenarios it will be possible to achieve the objective of getting these territories 100% renewable in the coming decades, harnessing storage resources and satisfying the equilibrium demand/supply at every moment of the year [Babonneau, 2019; Gay, 2018; Cristofari, 2010]. These studies are carried out following a limited number of hypotheses about the storage availability and the REn shares. Babonneau [Babonneau, 2019], for example, evaluates 5 different scenarios using three different EV shares (12%, 25% and 100% over the total fleet of the territory) while the REn share is a result of the optimization under fixed model parameters. A report from Artelys [Chiche, 2016], sets one only hypotheses about the number of EV for optimizing the investments in the power mix. And both references optimize their models looking for a mix 100% REn. The work of Villavicencio [Villavicencio, 2017] and [Van Stiphout, 2015], optimizes the capacity of different storage technologies, defined as a variable in their models, and estimate the value that they will have on the transition towards a REn power mix. We found in this literature, an analysis that is mainly from the power system point of view, but that do not consider a progressive evolution of a storage system. we did not find an establishment of the relationship between the proportions of intermittent REn installed capacities and the availability of a storage system for different REn shares.

We consider that reaching the state of the assumptions done in one hypotheses of specific scenarios might be an unlikely event. Our research aims to estimate a large number of possible scenarios in terms of available storage, proportions of intermittent **REn** installed capacities and the different **REn** shares (which are expected to be reached in a progressive way). The three parameters could evolve at different rates depending on the policies adopted by the governments.

Some literature has been reviewed about the power system and the integration of **REn** in Porto Santo. Delgado [Delgado, 2011] analyzes, for example, the impact of the intermittency of **REn** in the bulk power system taking into account the island weather conditions (variations of irradiation with clouds and heavy gusts of wind) through an electrical simulation. Storage requirements for becoming a 100% renewable island are analyzed in the work of Duic [Dui, 2004] which concludes that because of wind conditions in the island *only up to 45% of electricity demand could be delivered from 6 MW of wind turbines*. They use fuel cells as storage system for different kind of configurations between **PV** and wind power units. More recently, Torabi [Torabi, 2018] studies the requirements in storage and demand side management for going towards a more renewable energy mix while harnessing as much as possible these resources, namely without curtailment.

In this chapter, we focus on the relationship between the development of **REn** and the development of **EV** to decarbonize electricity and transportation sectors. Furthermore, we point out that there is an optimal share of **EV** depending on **REn** share which minimizes the total power generation cost. This comes from **VGI** and **REn** electricity storage during the off peak hours.

3 Materials and methodology

Our case study is based on Porto Santo, a Portuguese island in Madeira archipelago. The regional authorities of Porto Santo develop a strategy on **EV** with intelligent and reversible recharge. Porto Santo's surface is $42.17km^2$ and it is located on the Atlantic Ocean west of Morocco. Nowadays, the electricity supply comes mainly from thermal power units. At the same time, there are around 3,000 passenger cars with a petrol engine for a population of 5,500 inhabitants. Consequently, there is a project of a *Fossil Free Island* responding to objectives of energy transition and looking for energy independence. This aims at switching **ICE** to **EV** and to develop **REn** for the power supply.

TABLE 2.1 – Electricity demand in Porto Santo in 2017.
 Unit : MW.
 Source : EEM

Month	Mean	Std. Deviation	Observations
January	3.15	0.39	744
February	3.07	0.33	672
March	3.13	0.32	744
April	3.44	0.33	720
May	3.92	0.33	720
June	4.6	0.47	720
July	4.96	0.5	744
August	5.45	0.65	744
September	4.87	0.51	720
October	4.22	0.48	744
November	3.48	0.35	720
December	3.27	0.39	744
Total	3.97	0.91	8760

The electricity demand which is around 3.97 MW has some strong daily and seasonal variations from 2.2 MW to 7.2 MW. The consumption is driven by two different patterns : without tourism (normal season) and with tourism (summer season). The normal season stands from January to June and September to December (302 days in 2017) whilst it is growing during the summer season from July to the beginning of September (63 days in 2017) as pointed out in Figure 2.1b. The average demand is 5.2 MW during the summer season whilst it stands to 3.7 MW during the normal season. Moreover, the variations of this demand are higher during the summer season as pointed out by the higher standard deviations (Table 2.1). These large variations of the electricity demand can be also appreciated through the screening curve (Figure 2.2) : a high peak of the demand (greater than 5,783 MW which correspond to the mean value + 2 standard deviations) is observed over 289 hours. This represents an important challenge for the electricity company. Furthermore, a particular attention has to be paid to avoid the EV batteries charge during this time.

The power supply comes from a thermal power unit with a capacity of 17.3 MW (using diesel oil), PV units and wind turbines with a capacity of respectively 2.62 MW and 1.11 MW. Nowadays, 85% of the annual production is supplied by the thermal power plant and the remaining 15% is supplied by REn power units. The isolated territory (neither electricity imports nor exports) looks for becoming 100% REn while keeping the adequacy, ensuring the demand/supply equilibrium at every moment all along the year. The statistical of the REn supply (PV and wind turbines) and the electricity demand point out some very different patterns.

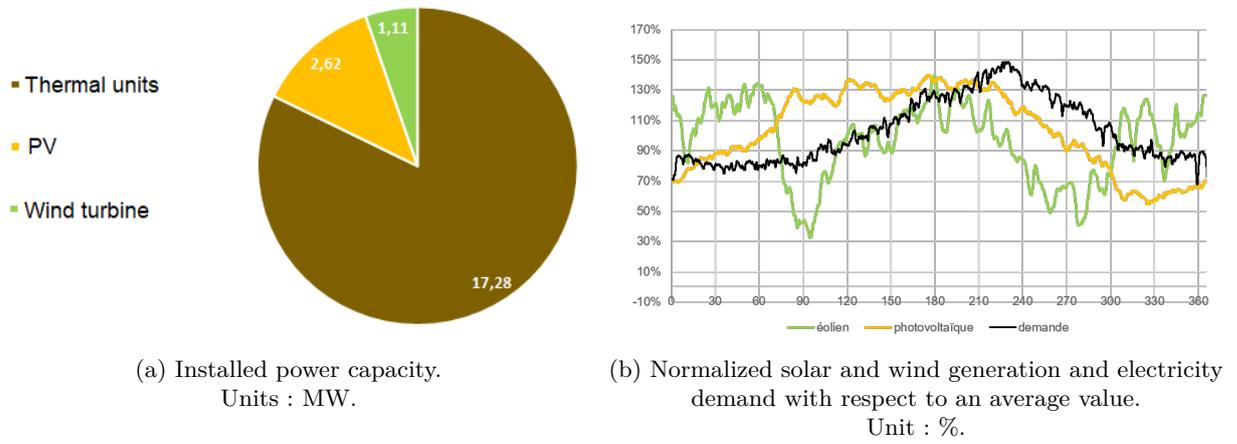


FIGURE 2.1 – Porto Santo’s power system and weather characteristics.
Source : Authors with data from EEM.

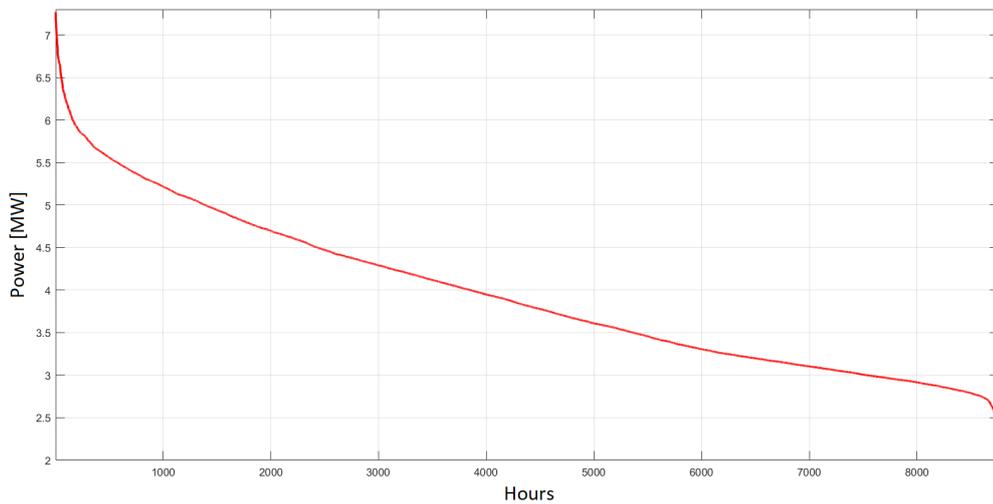


FIGURE 2.2 – Electricity screening curve.
Unit : MW.
Source : authors with data from EEM.

TABLE 2.2 – Hourly REn supply and Electricity demand.

Unit : MW.

Source : authors with data from EEM.

Hour	PV		Wind		Demand	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
0	0	0	0.146	0.157	3.745	0.665
1	0	0	0.140	0.158	3.619	0.654
2	0	0	0.140	0.156	3.540	0.634
3	0	0	0.135	0.151	3.523	0.648
4	0	0	0.133	0.151	3.546	0.656
5	0	0	0.141	0.159	3.582	0.663
6	0.001	0.004	0.138	0.159	3.613	0.644
7	0.064	0.075	0.142	0.165	3.785	0.729
8	0.297	0.218	0.146	0.162	3.925	0.912
9	0.624	0.333	0.158	0.164	4.008	0.951
10	0.896	0.401	0.159	0.160	4.035	0.932
11	1.080	0.439	0.163	0.154	4.059	0.927
12	1.196	0.446	0.168	0.152	4.021	0.942
13	1.217	0.445	0.170	0.149	3.985	0.960
14	1.122	0.427	0.170	0.150	3.912	0.918
15	0.958	0.394	0.170	0.152	3.852	0.908
16	0.701	0.319	0.170	0.163	3.872	0.926
17	0.372	0.233	0.163	0.162	3.997	0.998
18	0.105	0.098	0.156	0.161	4.338	0.986
19	0.011	0.019	0.154	0.163	4.675	0.919
20	0	0	0.150	0.162	4.780	0.928
21	0	0	0.149	0.162	4.574	0.879
22	0	0	0.146	0.157	4.290	0.824
23	0	0	0.147	0.156	3.991	0.717

However, when we compare the hourly REn power generation and the demand (Table 2.2) the wind turbines have some quite mean hourly values but with some large fluctuations. Conversely, the PV supply has a maximum at 12 p.m. which match with the demand for the lunch time but doesnt correspond to the evening peak starting at 18 :00. Thus, if REn supply is encouraged, this requires some flexibility on the demand side (EV batteries charging) and storage facilities. Nevertheless, we will see that extreme events involves some backup power generation units.

Besides the simplification of a non-interconnected territory, the optimization model on an island has different interests since it allows to reduce certain constraints which could not be simplified in more complex and linked systems such as the European grid. In regards to the energy transition, this work aims to optimize the different possible configurations of energy mix analyzing the contribution of a storage system provided by EV. In a first instance, using data

from Porto Santo TSO (Empresa de Eletricidade da Madeira) with information about the daily electricity generation and consumption during one year in hourly steps, a Matlab simulation is run for analyzing storage requirements and the different energy mix that could be expected in a transition through a REn island including V2G facilities. This is a first and important approach. Nevertheless, simulations only take into account a technical energetic analysis without including an economic approach. Therefore, we also develop an economic optimization model for the power system considering EV adoption and introducing VGI facilities. The model allows to account for and modify different parameters which could have an impact on different scenarios and to analyze the evolution of the system through the progressive change of these parameters.

The integration of EV batteries in an island is of special interest because of the fragility of isolated territories, less capable to respond to unexpected technical situations such as voltage drops, failures in the system or even extreme weather conditions. More reliability is required by means of *reserves to secure the operation of the system*, as pointed out by Diaz [Díaz, 2015], a review that reflects the convenience of VGI for allowing a better deployment of REn and for reaching the fuel independence of these territories.

3.1 Simulation of REn supply with and without EV batteries storage

An optimal EV charge system provides REn savings. These savings depend on the electricity demand, the solar and wind power installed capacities, the EV batteries available capacities, and the remuneration of the electricity storage. Because the load curve point out the maximum demand during the evening peak, the development of the solar PV with a peak at 12 p.m. gives an interesting opportunity for EV batteries to store electricity.

We simulate a total fixed installed capacity where we set different spreads for wind and PV shares. Configurations vary between equivalent proportions, a more important wind capacity and a more important PV capacity. Using historical data we calculate in an hourly basis if REn production is higher, equal or lower than demand. If REn production is higher, we consider it is an overproduction hour and if REn production is lower, we consider it is a scarcity hour. Next, we make a daily balance calculating the difference between these overproductions and scarcities for each day of one year. For doing so, two distinct scenarios are simulated : one without a storage system and one with a storage system. If REn production is higher than demand during the day i) for the scenario without storage, we supply the whole demand with this production and the overproduction is lost ii) for the scenario with storage, we stock this overproduction

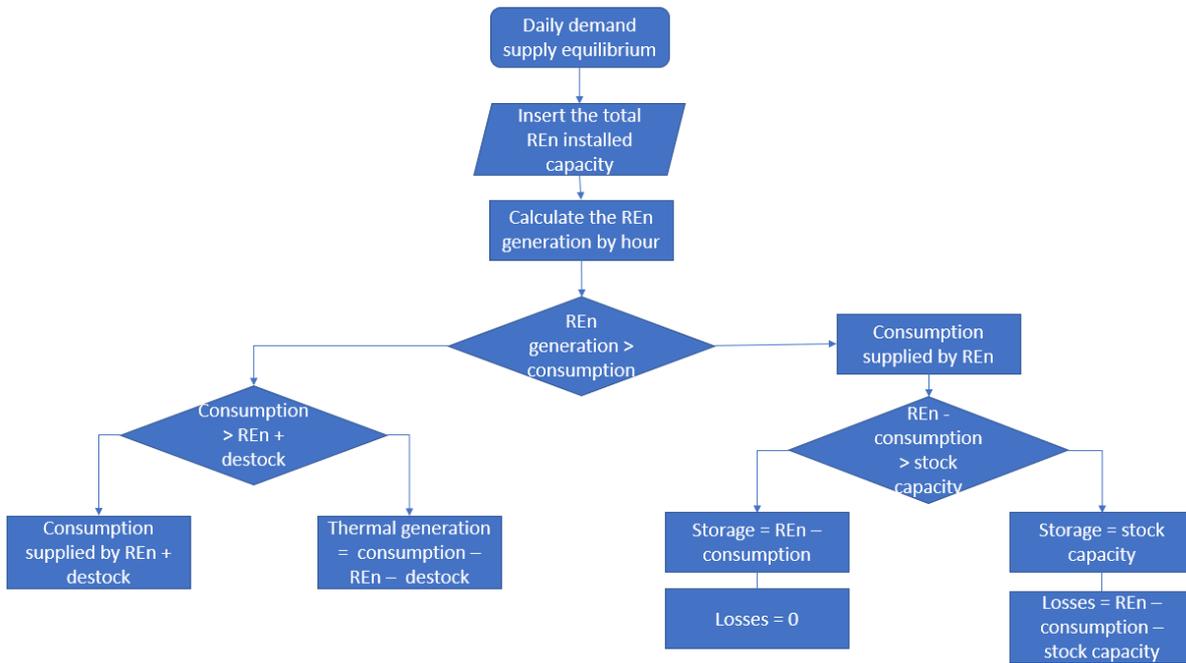


FIGURE 2.3 – Flowchart for estimating the behavior of the power system in an hourly basis. Source : authors.

until the maximal storage capacity. If demand is higher than REn production during the day i) for the scenario without storage, the thermal power plant supplies the required difference. ii) for the scenario with storage, if during the day there was REn overproduction, we supply as much as possible with the EV batteries facility and just the remaining demand is supplied by the thermal power plant. In this case we expect the storage capacity to reduce thermal power plant production while harnessing REn generation.

For the simulation, we estimate the hourly behavior of the power mix according to the flowchart described in Figure 2.3. It has been developed with Matlab.

3.2 Optimization model

We want to demonstrate that EV batteries can be used to store power supply excess from REn production and to restore this energy during the peak hours demand, harnessing EV storage capacity without degrading the main service of a car, the one of transporting. We develop an optimization model of the power system including VGI. The optimization model takes into account the power system characteristics, the EV electricity demand, the driving conditions and includes the uncertainty that raises from intermittency of REn through probability distributions. We model a storage system supporting the power grid service that is expected to allow

the expansion of intermittent **REn** resources.

The model results in an optimized energy mix considering the initial installed capacities, power plants availability, CO_2 emissions and investment costs of power units as well as **EV** fleet characteristics : quantity, batteries capacity, shared capacity for **V2G**, average traveled distance, availability and energy consumption. We describe below the model equations whose variables and parameters description are presented in Tables 2.3 and 2.4. The indices are given in Table 2.5.

The objective function minimizes the total cost denoted by \mathbf{Z} in equation 2.1 that includes investment for new installed capacities or capital costs (CAPEX) and operational costs (OPEX). We assume CAPEX are constant. For the OPEX, a carbon tax is included and further in the model the avoided CO_2 emissions by means of the use of **EV** instead of conventional **ICE** are also calculated.

$$\begin{aligned}
 \mathbf{Z} = & \underbrace{\sum_{i_{REn}} FC_{i_{REn}} \cdot NC_{i_{REn}}}_{\text{fixed costs}} + \underbrace{\sum_i \sum_p \sum_a FE_i \cdot C_{CO_2} \cdot \rho_a \cdot P_{i,p,a}}_{\text{carbon tax}} \\
 & + \underbrace{\sum_p \sum_a C_{comb} \cdot \rho_a \cdot P_{TH,p,a}}_{\text{fuel cost}} + \underbrace{\sum_p \sum_a C_{\Phi^{out}} \cdot \rho_a \cdot \Phi_{p,a}^{out}}_{\text{storage cost}} \quad (2.1)
 \end{aligned}$$

As a constraint, the balance equation guaranties, through thermal and **REn** generation plus stocking out **EV** batteries, the system adequacy at each time step for different stochastic scenarios of wind production.

$$\sum_i P_{i,p,a} + \Phi_{p,a}^{out} \geq Dn_{p,a} + g_{E_p} + \Phi_{p,a}^{in} \quad (2.2)$$

At first, the model was validated through the configuration of current parameters with the current installed capacities and usual consumption in the island. The expected mix of 85% thermal production and 15% **REn**, that represents the power system nowadays, was well reflected. The results were subjected to a root-mean-square error calculation (RMSE) for verification.

A carbon tax is applied for CO_2 emissions coming from thermal power plants while **REn** units are considered as 0 CO_2 emissions units. The **REn** share is a model parameter that determines

the part of REn over the total annual electricity generation. For fixing the REn share, we use the following constraint :

$$\sum_i \sum_p \sum_a P_{iREn,p,a} \geq \theta_{REn} \cdot \sum_p \sum_a Dn_{p,a} \quad (2.3)$$

The storage process is described through a system of binary variables that decides the flux of energy inside and outside the EV batteries respecting the constraints of capacity. The available capacity for V2G is just a percentage of each one of the batteries so that a minimal capacity for driving requirements is always reserved. Each binary variable represents the availability of the virtual battery composed of all EV in the island at each time step.

$$\Phi_{p,a}^{in} \leq I1_{ch,p,a} \cdot Cap_{bat} \quad (2.4)$$

$$\Phi_{p,a}^{out} \leq I2_{dch,p,a} \cdot Cap_{bat} \quad (2.5)$$

$$I1_{ch,p,a} + I2_{dch,p,a} \leq 1 \quad (2.6)$$

As optimization is solved in a three days period, we create a circularity condition in the model for setting the state of charge S of the virtual battery at the beginning of the period to the level of the S at the end of the period. Next we estimate the state of the battery depending on the storage behavior :

$$S_{t0,a} = S_{T,a} \quad (2.7)$$

$$S_{t,a} = S_{t-1,a} + \Phi_{p,a}^{in} - \Phi_{p,a}^{out} \quad (2.8)$$

TABLE 2.3 – Optimization model parameters

Parameter	Units	Description
CI_i	[MW]	Initial capacity
$\alpha_{i,p}$	[%]	Power plants availability
FE_i	[$kgCO_2/MWh$]	Power plants CO_2 emissions
FE_v	[$kgCO_2/km$]	Thermal cars CO_2 emissions
CCO_2	[€/kg]	CO_2 price
C_{comb}	[€/MWh]	Fuel price
$FC_{i_{EnR}}$	[€/MW]	Fixed costs
ρ_a	[%]	Random probability
D_p	[MWh]	Demand per time slot
$Dn_{p,a}$	[MWh]	Net demand per time slot and random
Q_{EV}	-	Evs quantity
C_{EV}	kWh	EVs capacity
γ_{EV}	[%]	V2G availability
G_{EV}	[kWh/km]	EVs consumption
F_{EV}	[km/j]	Daily traveled distance
Cap_{bat}	[MWh]	Total EVs battery capacity
θ_{EnR}	[%]	REs share
$C_{\Phi_{out}}$	[€/MWh]	Stock out price

TABLE 2.4 – Optimization model variables

Variable	Units	Description
Z	[€]	Total production costs
$P_{i,p,a}$	[MWh]	Delivered energy per power plant per time slot
NC_i	[MW]	New installed capacity per power plant
C_f	[MW]	Final capacity per power plant
g_{EV_p}	[MWh]	EVs charge demand per time slot
E_{CO_2}	[tCO_2]	Total CO_2 emissions
$\Phi_{p,a}^{in}$	[MWh]	Stored energy in EVs batteries
$\Phi_{p,a}^{out}$	[MWh]	Restored energy by EVs batteries
$S_{t,a}$	[MWh]	Batteries state at instant
$I1_{ch_{p,a}}$	(0,1)	Decision variable for charging
$I2_{dch_{p,a}}$	(0,1)	Decision variable for discharging

TABLE 2.5 – Indices of variables and parameters

pp	$\in P$	Time slots
tt	$\in P$	Time instants
i	$\in I$	Power plants
i_{REn}	$\in I_{REs} \subset I$	Renewable power plants
a	$\in A$	Random

4 Results and discussion

4.1 Analysis of simulation

As example, we show results for a simulation with 15 MW of installed capacity where 75% corresponds to PV and 25% corresponds to wind power. In the first scenario (Figure 2.4a), with no storage capacity we find that energy losses are higher when PV is predominant in the REn mix for the same total installed capacity. This might occur because the peak demand hours do not coincide with the peak of sunny hours in the day. Around noon the PV production is maximal while demand is relatively low. With this configuration we calculate losses at a level of 5 GWh over the year, a considerable value with respect to the total electricity demand. When wind is the dominant REn resource we find less losses but more appeal to thermal power plant because its availability is less predictable than PV. In the second scenario (Figure 2.4b), as expected, losses are lower and REn resources increment their contribution to electricity supply. With a storage system of 3.9 kWh per person (21.3 MW in the island), we increase the use of REn from 42% to 55% and reduce the use of the thermal power plant by 24%. In this case we calculate annual losses reach barely 0.7 GWh over the year.

Subsequently, according to these results and looking for analyzing relations between storage and installed capacity requirements in Porto Santo, we applied the bisection method to our simulation to get a swept from 5% to 95% of total REn share as well as a swept on wind/PV proportions from 0% wind - 100% PV to 100% wind - 0% PV. We use data over one year for calculations. As result, we get the total REn installed capacity and the mean storage capacity per day to reach the REn share with the different wind and PV distributions (Figure 2.5). We present results in units per person to enable comparison within different territories. We observe that a storage system becomes interesting for the power grid from a REn share around 40%; below this threshold there are not considerable REn overproductions.

This energetic analysis can be brought up to see the influence of the mix distribution between PV and wind power on the storage capacity requirements. For having a considerable high REn share on the total production, a system with a dominant PV installed power needs much more storage capacity -given the constraint to provide electricity during the hours without sun irradiation- but with a smaller installed capacity needed -because during the daily hours the irradiation presence is rather constant-. Whereas, with a dominant percentage of wind power it is harder to predict the moments of the day with airstreams and it is possible to have several days with a very low wind turbine electricity generation. In this case it would be necessary to

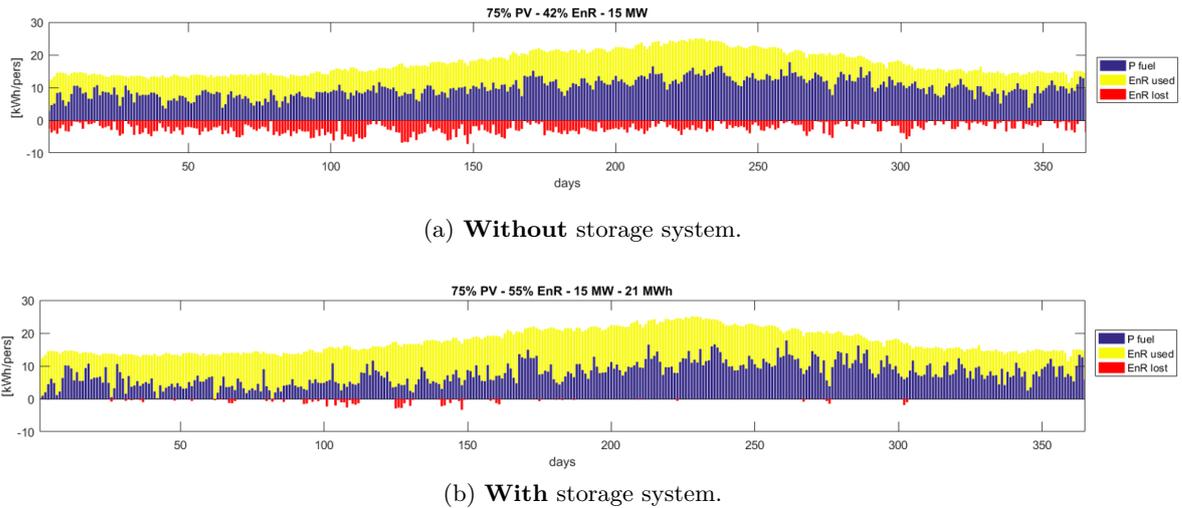


FIGURE 2.4 – Example of the daily electricity production during one year with 15MW of RE installed capacity with a distribution of 75% PV and 25% wind power.

Unit : kWh/inhabitant.

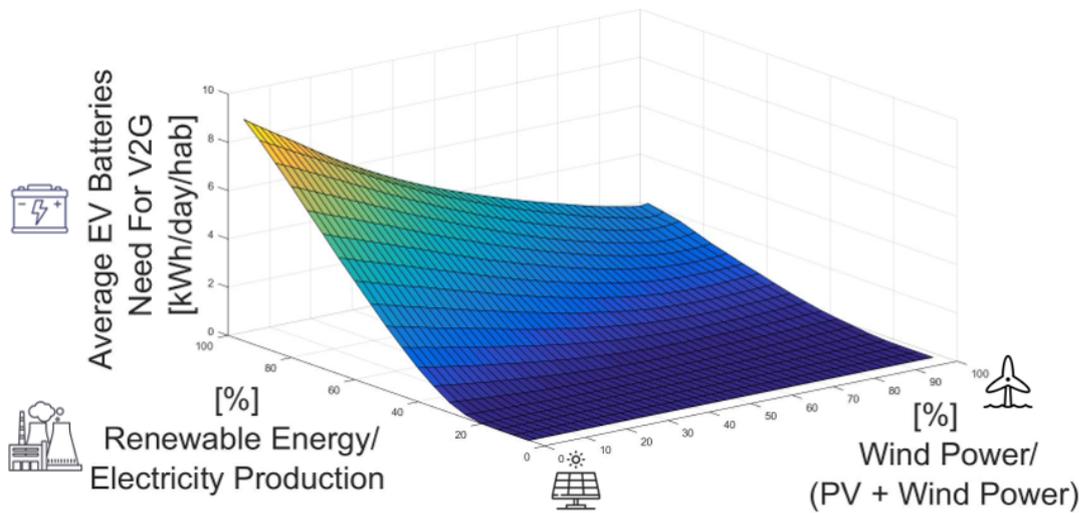
Source : authors.

have a higher installed capacity with a smaller storage capacity.

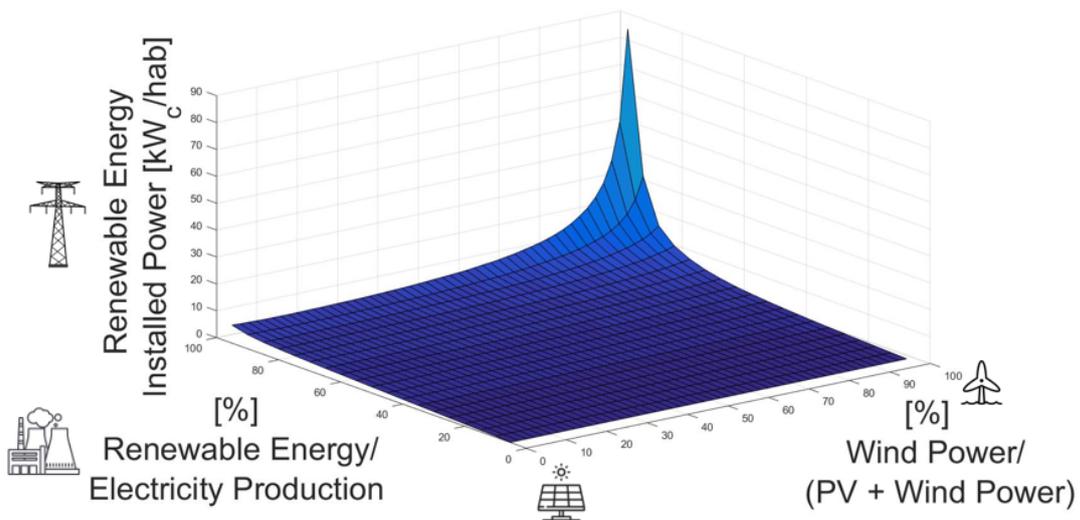
The analysis of the storage needs associated with the development of RE reveals high levels when there is a significant share of renewable resources in the electricity mix (in particular above 90% of PV). For very high values (close to 100%), the storage needs are even greater and correspond to higher costs, difficult to bear from an economic point of view. Other solutions based on thermal units with biofuels could be considered. It is therefore necessary to optimize storage capacities according to the level of RE penetration. This is the purpose of the next section.

4.2 Analysis of the optimization model

The representation of Porto Santo power supply is done through three types of power units (already described above) : a thermal power plant which has the possibility to be used with fuel oil or biofuel, a wind farm and PV. From descriptive statistics we determined that annual demand could be split in two homogeneous different periods : a normal season (NS) of 302 days for months from September to June and a summer season (SS) of 63 days including days of July, August and September when demand increases significantly because of the presence of tourists. In both seasons there are not significant variations in demand between the different days within one week because there is no industry and the main activity comes from the tertiary sector. In these periods we observe a difference of PV production which is significantly more important during summer months as mentioned before. The average electricity consumption and PV



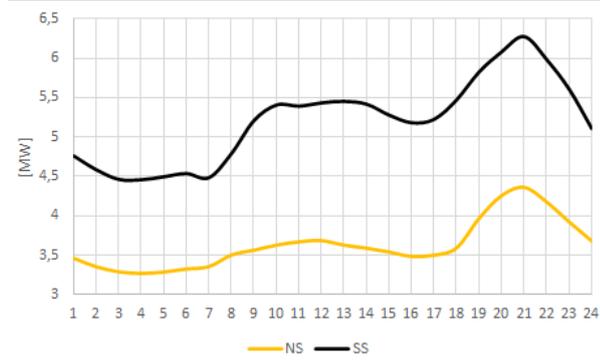
(a) Total REn installed capacity.
Unit : kWh/inh.



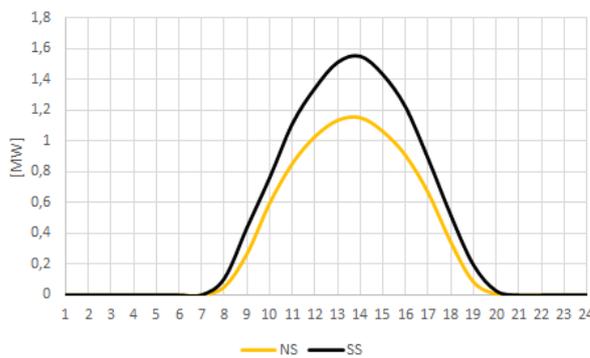
(b) Required storage capacity.
Unit : kW/inh.

FIGURE 2.5 – Swept of REn share and a swept of different configurations of PV and wind power.

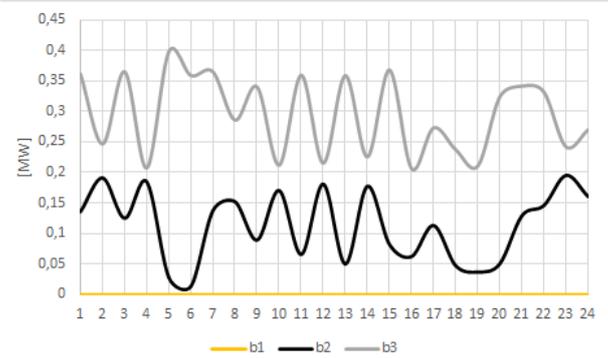
Source : authors.



(a) Hourly load curve.



(b) Photovoltaics generation.



(c) Wind turbine electricity generation.

FIGURE 2.6 – Parameters of electricity generation from **REn** by hour used for the optimization model for normal season (NS) and summer season (SS).

Unit : MW.

Source : authors with data from EEM.

production, which are parameters of the model, are calculated for each season by hourly time steps as shown in Figures 2.6a and 2.6b . For modeling wind power generation we calculate three possible airstream scenarios and its occurrence probabilities. For considering the **REn** variations, including when **TSO** should manage several days without wind, a mixed integer programming model is solved for three consecutive days with repetitive demand and with all possible wind conditions. Combining Figure 2.6c profiles results in 27 possible cases (3^3) that represent wind turbine production in an hourly step.

It is not necessary to have large capacity batteries to supply the required energy for regular trips and, nevertheless, **EV** have large enough capacity batteries that could be exploited for supporting **REn** integration in the isolated territory while bringing benefits to drivers. For parameterizing the model, we set 16 km of average daily trips in Porto Santo. This represents an average consumption of 2.56 kWh/day at a rate of 0.16 kWh/km from an **EV** battery. The virtual battery capacity is calculated from three parameters : the individual battery capacity,

the EV fleet and the available percentage for VGI. The resulting capacity might be obtained from different configurations, giving flexibility to our analysis. For example, we could get a 12.5 MWh virtual battery from 500 EV that decide to share the 50% of its 50 kWh capacity for the VGI as well as from 1000 EV that decide to share 25% of its 50 kWh capacity. In comparable terms of inhabitants, it would be 2.18 kWh of storage per person. We assume that the virtual battery capacity is available for the power grid at every moment. Regarding the other parameters, the applied carbon tax is 23.61€/ton¹ and the investment costs are obtained from the report [Haeusler, 2020] about the REn costs in continental Europe. Results might be sensible to these parameters but, to the best of our knowledge, there is no specific information about investment costs of REn in oversea islands.

The optimization model is applied for a variable size of EV fleet from 0% to 100% of the total current cars fleet with incremental steps of 100 EV (3.33% of the fleet) and for a REn share percentage varying from 10% to 100% with incremental steps of 10%. This analysis allows us to see the relation between REn generation and EV storage usage for VGI in Porto Santo when taking into account economic parameters and minimizing the total annual electricity production cost. Hourly production from each one of the power plants, storage (in and out) and batteries recharge (for driving usual requirement) is analyzed for each season (normal and summer) and for each probabilistic scenario. Results are presented in mathematical expectation for simplification of the analysis.

Below a 40% REn share, we don't find a significant influence of the storage system over the total electricity production costs. Over this threshold, when increasing the storage capacity, we find a reduction of total costs, and we observe that the reduction is more important when the REn share becomes more important too. One of the main results of our study is that the total costs have a U shape. Initially, the introduction of EV allows electricity storage with the VGI. The increase in the number of cars makes it possible to store more energy and we arrive at a balance between storage facility and average level of surplus of REn. Beyond that, the EV storage extra-capacity is unnecessary on average and the demand of electricity for cars is increasing : this increases the cost of electricity generation. *It means that we minimize the total costs with a specific storage capacity for each REn share* (Figure 2.7). The optimal point shifts to the right when we increase the REn share. From this minimal point, there is not interest for the power grid to add more storage capacity and the curve increases softly because of the additional demand for recharging EV for their typical trips.

1. <https://expresso.pt/economia/2020-02-14-Taxa-de-carbono-quase-duplica-nos-combustiveis>

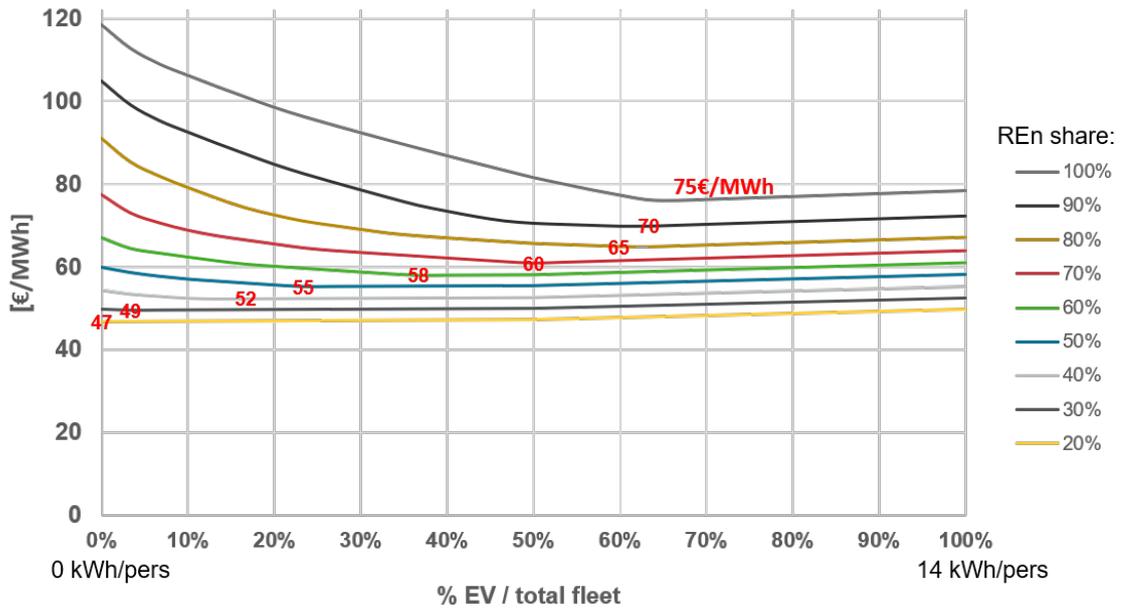


FIGURE 2.7 – For different **REn** shares and different **EV** fleets (including running costs and investment costs) from the optimization model. Average cost per MWh.

Unit : €/MWh.

Source : authors.

From the total costs function \mathbf{Z} , we calculated the savings for the power grid when a storage system is available and we assumed that this value is the profit of **EV** owners who let their battery for the **V2G** service. Figure 2.8 shows that savings lay between some tens of euros to some hundreds of euros. The maximal benefit per **EV** is reached at the optimum since from this point, the same profit would be distributed between more **EV** owners, each one participating in **V2G** with a smaller capacity.

Figure 2.9 shows the use of the batteries as a function of the **REn** share and the **EV** fleet. In Figure 2.9a we observe the annual electricity supplied for **V2G** by the whole **EV** fleet. For each **REn** share, the appeal to **EV** batteries increases in a mostly linear trend until an asymptotic point corresponding to the previously described optimum value. After reaching this maximal point, the appealed energy remains constant. From Figure 2.9b, as it is expected from the prior results, we observe that when increasing the **EV** fleet, the daily **V2G** contribution of each one of these **EV** decreases. For high **REn** shares and small **EV** fleets (less than 10%), we find that the power grid appeals the whole capacity of each **EV** more than once a day, confirming the interest of the storage system for the power operation.

A technical outcome is drawn from the model and it is presented in Figure 2.10. It is the

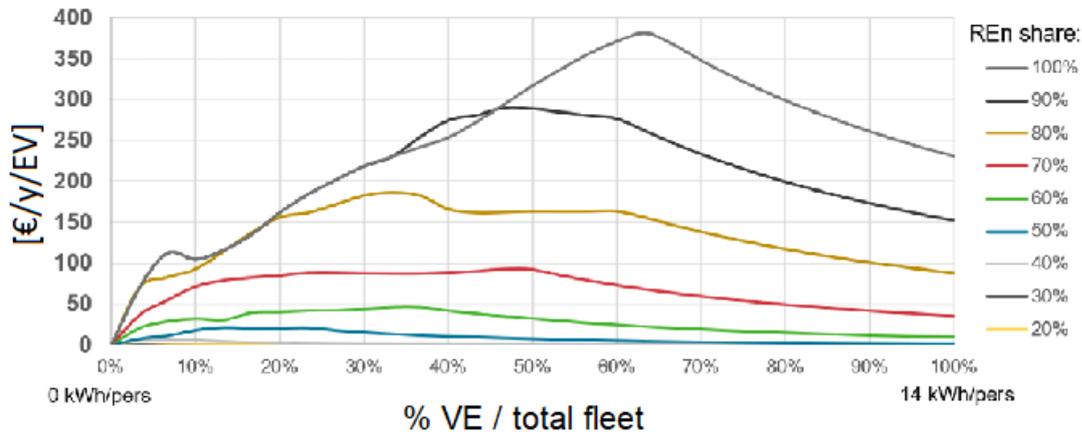


FIGURE 2.8 – Saving for the power system for different **REn** shares and different **EV** fleets (including running costs and investment costs) from the optimization model.

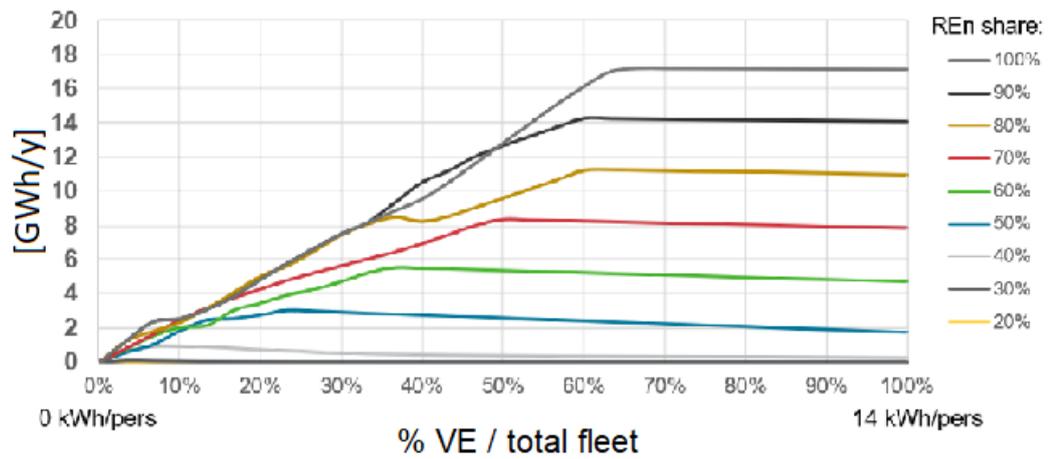
Unit : €/y/EV.

Source : authors.

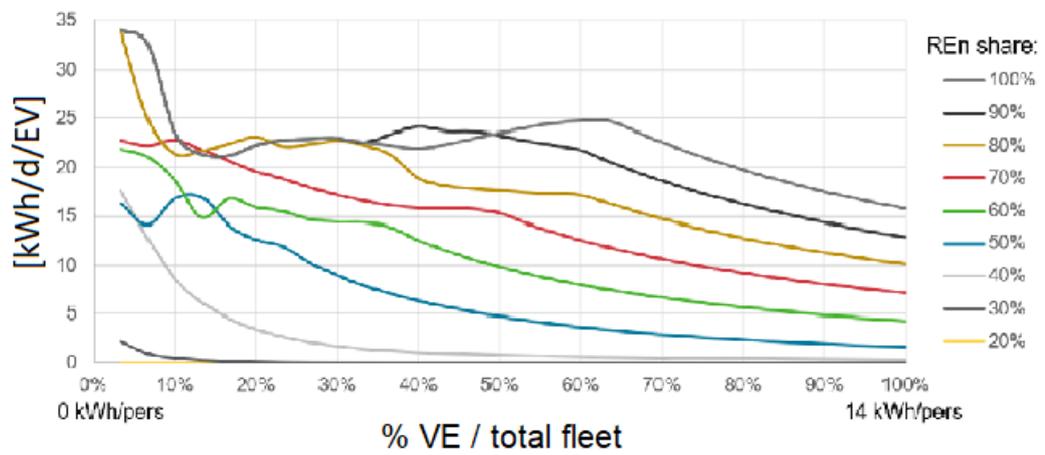
charge and discharge powers, which are relevant factors in the adoption of **V2G**. We observe that power values are low, reaching a maximal value of 4.5 kW when the **REn** share is high and the **EV** fleet is small. There is no need for high power devices in the integration of **EV** to the power grid.

Figure 2.11 shows some of the results of the annual electricity production by each one of the power units for different **REn** shares depending on the **EV** fleet. We can see the evolution of the usage of the storage system that becomes more important for high **REn** shares. One of the main outcomes is that, the model does not reach the highest **REn** shares with exclusively intermittent **REn**. In a scenario without storage system, with 80% of **REn** share, it is necessary to use the thermal power plant with biofuel. This requirement of biofuel for reaching the highest shares of **REn** decreases and it is even avoided when a storage system comes to support the power grid. Another important outcome is that in the absence of a storage system or, if the storage capacity is lower than the optimal storage capacity, the economic optimum is reached investing mainly in wind power, while, when the storage capacity is higher than the optimal storage capacity, the investment is concentrated on **PV**. These two important results are also explained through Figure 2.12 that presents the decompositions of the total costs for 70% and 100% **REn** shares, for different **EV** fleets.

In Figure 2.13 we present the power grid behavior in time, in hourly steps during three days for 70% and 100% **REn** shares respectively. They include the charging moments required for



(a) V2G annual supply.
Unit : GWh/y.



(b) V2G daily supply.
Unit : kWh/d/EV

FIGURE 2.9 – Results from optimization model.
Source : authors.

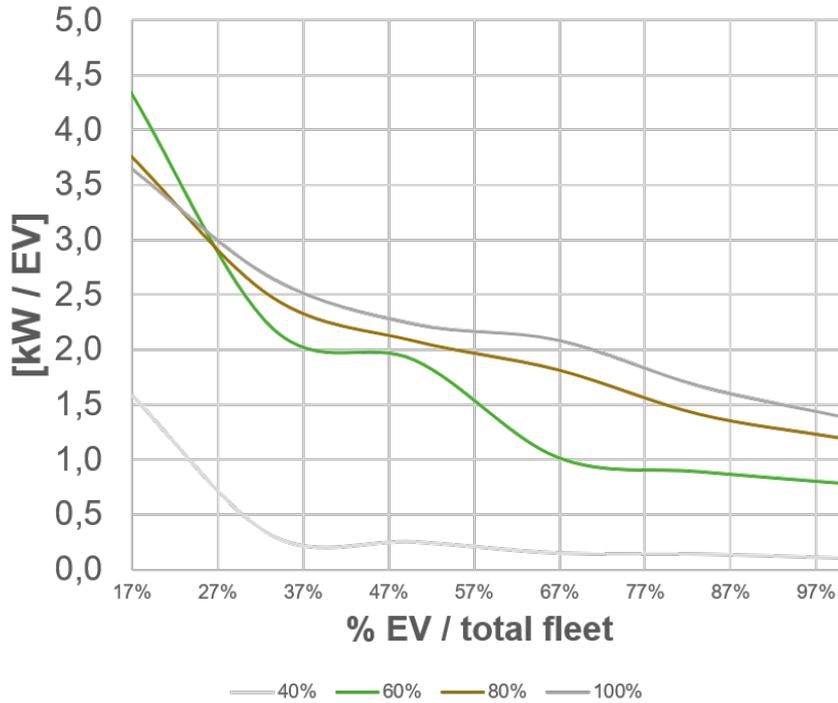


FIGURE 2.10 – Maximal discharge power for different REn shares and different EV fleets.
 Unit : kW/EV.
 Source : authors.

TABLE 2.6 – Results of CO₂ emissions for some of the REn shares and EV fleets.
 Unit : tonnes of CO₂ per year.
 Source : authors.

	20%	50%	90%	100%
500	21814	14341,6	4378,4	1887,6
1500	21636,6	13947,58	3695,56	1132,56
2500	21459,2	13553,57	3012,73	377,52

regular trips. We find all the characteristics we have described in this section about the power grid behavior when a storage system is available.

The total CO₂ emissions correspond to those of the thermal power plant and the ICE cars fleet. We consider zero emissions from REn power plants. For the calculations we use an emission parameter for the thermal power plant of 777 kgCO₂/MWh and an emission parameter for the ICE cars of 0.13 kgCO₂/km. Some of the results are presented in Table 2.6. We observe an important impact of the storage system for assisting the neutrality carbon targets.

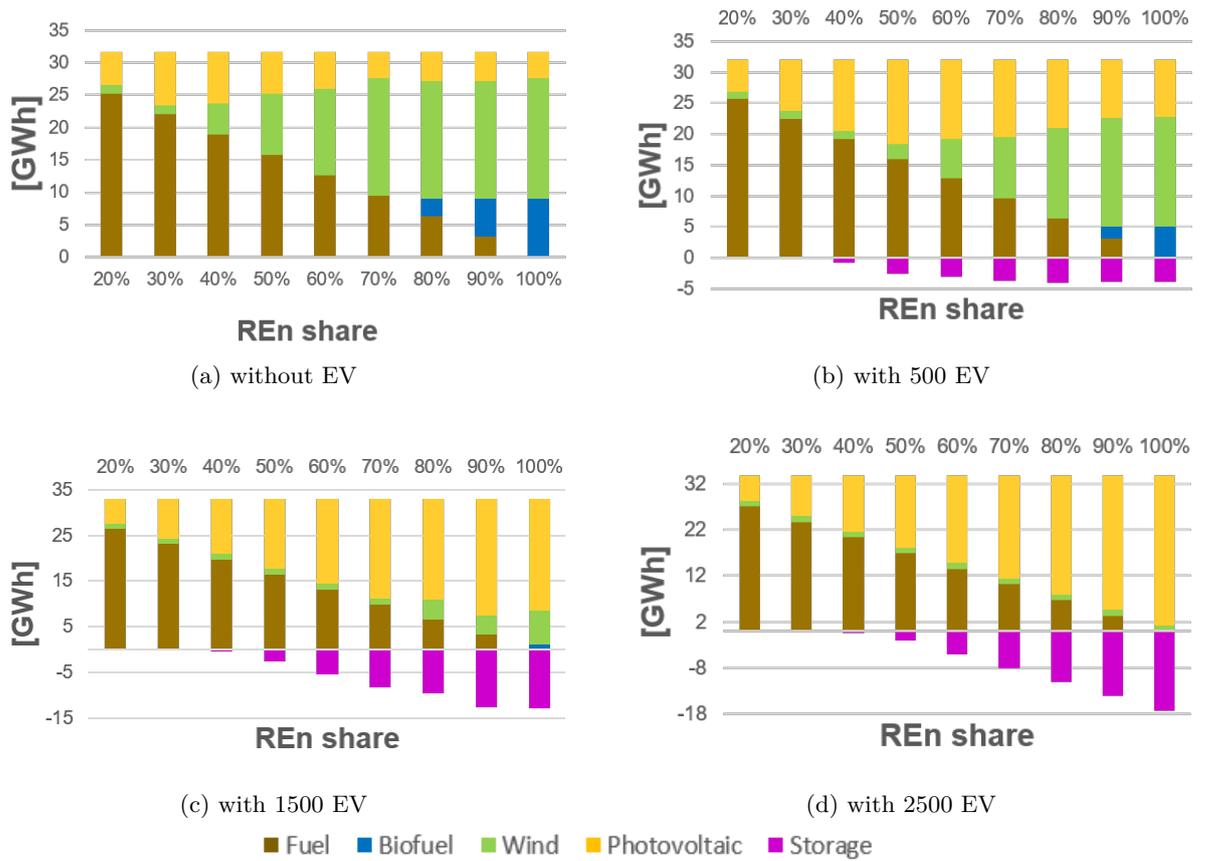


FIGURE 2.11 – Annual electricity production by type of power plant for different REEn shares.
Units : GWh.
Source : authors.

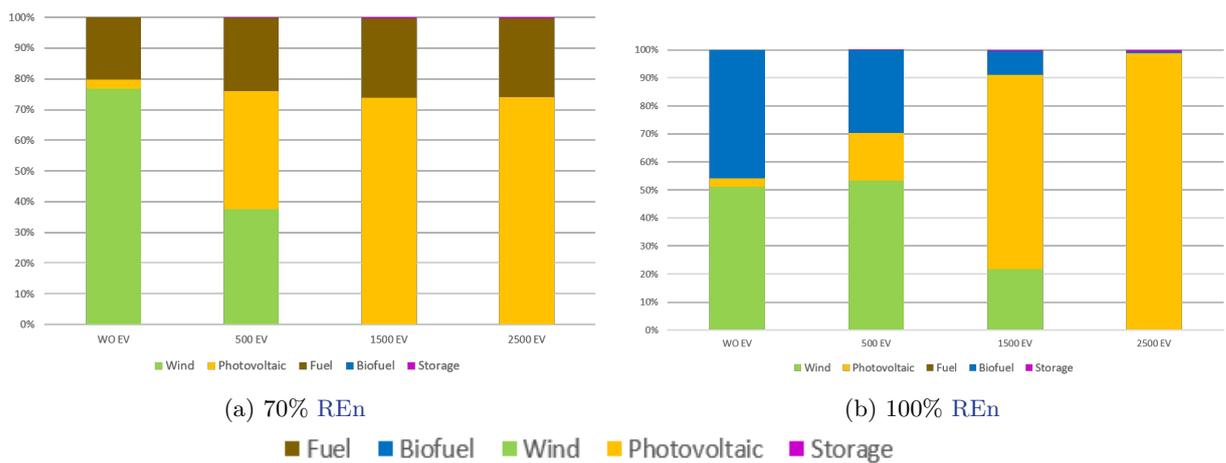


FIGURE 2.12 – Annual total costs decomposition.
Unit : %.
Source : authors.

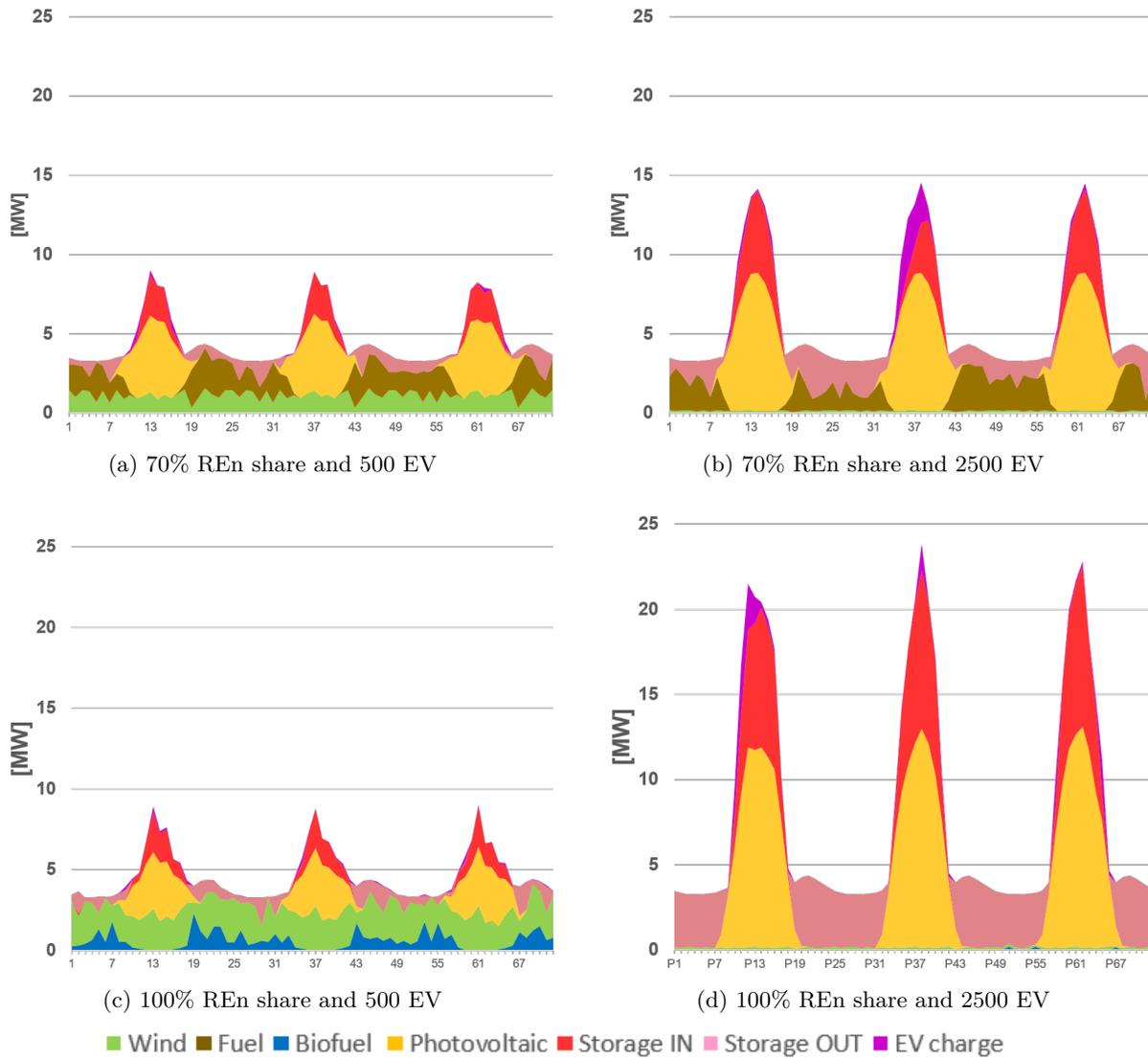


FIGURE 2.13 – Power system behavior in one hour time step during 3 days (72 hours).

Unit : MW.

Source : authors.

5 Conclusion

Through simulation and modelization tools we assess the impact of the integration of an **EV** fleet in an isolated territory. The first and probably the main outcome is that through the storage facility it is possible to reach an energy mix 100% renewable.

The transition towards this objective can be long and intermediate steps are necessary. Each stage of the transition is a key part of the path and decisions need to be taken considering the long term impacts. In this chapter we present the effects of leading the transition mainly with **PV** or mainly with wind power. In any case, we observe that the storage facility is required and becomes useful when the total **REn** production is higher than 40%. Under this value, it is not necessary to have a storage facility since the electricity is mainly consumed at the time it is produced. Conversely, to reach the highest levels of **REn** penetration in the energy mix, a storage facility is mandatory. Without it, a thermal power plant would be the alternative solution using biofuels.

We point out that the total electricity production cost has a U shape when we consider an increasing share of **EV**. For our empirical analysis, we have worked on Porto Santo island (Madeira archipelago). This island is characterized by a current large share of electricity from a thermal power plant (85%) and an important number of passenger cars with an objective of net zero emissions for the next decades.

From the different scenarios we have analyzed, the **EV** storage prioritizes the **PV** investments in detriment of the wind power investments, lowers the requirement of the use of a biofuel and lowers the electricity price, with respect to a scenario without storage facility, by 4 cents of euro by kWh. This represents close to 400€ by **EV** by year.

We found that there is an optimal storage for each level of **REn** over the total mix. Beyond this optimal point, the use of each battery decreases as well as the economies for each **EV**. Though, the results show a compatible use of the battery for the **VGI** with respect to an **EV** characteristics. Each **EV** would use between 2.2 MWh and 8.6 MWh depending on the **REn** penetration that correspond to 150 or 350 cycles respectively. A capacity of around 16 kWh by **EV** would be necessary to reach a 100% **REn** mix and the appealed powers are very low, from 2 kW for the **V2G** to 5 kW for the smart charge.

EV can have a significant contribution to decarbonate the power system. Though, to pro-

mote the adoption of a smart charge it is necessary for the EV owners to find the economic interest and therefore, it is necessary that the cost of the technology and of the deployment of the system, be lower than the possible revenues. This depends on the durability and the battery aging.

Chapitre 3

The *Vehicle Grid Integration* in a national network : emphasis on France and Germany

1 Introduction

Transportation and electricity generation sectors account for respectively 23% and 40% of the global energy related CO_2 emissions according to the *International Energy Agency* (IEA)¹. Road transport, including cars, motorcycles and buses, realize 16% of CO_2 emissions by their own. Regarding the power sector, coal power plants are the main emitters, responsible of 29% of CO_2 emissions. *European Union* (EU), concerned and worried about climate change, expects to reach carbon neutrality by 2050.

EU proposed specific targets for the *Renewable Energies* deployment through the Renewable Energy Directive. The update of the concerning legislation package was released by the European Commission on July 14th 2021. From this date, it announced its new project to mitigate the climate change *Fit for 55*², and set the ambitious target of reducing 55% of the GHG emissions by 2030 (compared to 1990 levels). One of the objectives is to produce 40% of the final electricity demand from renewable resources by 2030. Concerning the transport sector, a continuous evolution of particular vehicles was established as well. In this current legislation, the European Commission considers to ban the sales of new ICE cars by 2035, meaning that even hybrid cars must be set apart from the roads, letting 100% of the particular vehicles market to alternative fuel systems.

1. <https://www.iea.org/data-and-statistics/charts/global-energy-related-co2-emissions-by-sector>
2. https://ec.europa.eu/commission/presscorner/detail/en/IP_21_3541

Considering that the development of **REn** creates a flexibility requirement for the grid operation, the integration of **EV** in the power system is two-fold in the decarbonization goals : to reach the objective of getting a cleaner mobility and to assist adequacy and reliability in more renewable electricity mixes.

The *Vehicle Grid Integration* refers to the set of technologies, services and policies that create a link between transport with its **EV** and the power systems. This combination between transport and **REn** supply is key because with a massive adoption of **EV** and with no control over the recharge, the power grid risks intermittent failures when it would not be able to supply the required instantaneous power. A smart charge system seems necessary.

Nevertheless, a proper integration with a smart charging system requires synergy between the related parties including grid operators, governments, car makers and car owners as well as a good understanding of the main factors of the recharge system that could impact the power grid and that therefore are essential for the **VGI** (e.g. the different chargers power or the charge behaviors). A technical analysis of these components is the core of this chapter.

Different organizations estimate that there will be some millions of **EV** on the roads in a close future. The adoption of a significant **EV** fleet entails a new electric load during the recharge phases. Our research is based on a decentralized algorithm developed by Pierre Nicolas, from the Research Direction of Renault. It responds to the future concerns of an **EV** fleet and that improves the current electricity mix dynamics. The concept was improved and structured during the three years of PhD through several tests, analyses and discussions. The general idea is to create a virtual battery composed by the sum of a part of each **EV** battery. This cumulated capacity is managed in an optimal way, directly by each **EV** without aggregator. It could support the bulk power system for filling demand valleys through the smart charging and for shaving demand peaks through **V2G**.

In this chapter we present the development and implementation of the **VGI** algorithm composed by a set of equations that respond to an optimal control system. The optimization considers different time scales : seasonal, weekly and daily with the aim of taking into account the variations on the power system that are linked to regional weather conditions and electricity demand behaviors. The algorithm receives the residual demand as input signal. It is calculated as the total electricity demand subtracting the fatal electricity production³. The algorithm has two

3. This is the electricity produced from **REn** that is not controllable and if it is not injected to the power grid, it is lost

stages : with a first command we estimate the *State Of Charge* (SOC) that should be reached by the battery in an horizon time and the second command is a proportional factor that regulates the amount of the appealed power at each time step.

Next, we present the implementation of the smart charging algorithm in a VGI simulator. This tool is able to reproduce the charging dynamics of an important EV fleet. For the simulation we use actual data from a national statistical survey in France with a pre-treatment brought by Pierre Nicolas. With this data and using a Matlab code we estimate the driving consumption of the fleet and therefore, the actual electricity supply requirements for each day of a typical laboring week. The aim of the simulator is to understand the parameters that could have a significant impact during the integration of a particular light duty EV fleet in the power grid considering different car owners behaviors. We consider that conventional power plants generation and international flows are fixed. This choice is made since we find a close relationship between residual demand with electricity market prices as well as a close relationship between residual demand and CO_2 emissions. Some of the parameters of the simulator are the chargers power and their availability, the charging thresholds (the SOC at which a car owner plugs its EV), etc.

The simulation of an existing vehicle fleet applying a smart charging algorithm is a powerful tool to understand the main EV challenges and we believe it might be useful for several stakeholders : grid operators, governments, car makers and academics. For example, through the simulation it is possible to estimate the impact of different proportions between chargers power, the impact of using or not the EV as work transport or consider the fact of preparing a long trip for the next day. We expect to have innovative and interesting technical and economic outcomes.

2 The context of the EV charge

The VGI is a system composed by several systems. It involves many variable features and framework characteristics that depend each one, on different actors and on different factors (technical, social, economic, etc.). This is why, the integration of EV during the upcoming years needs to be thought in a structural way. For example, to succeed a charge, a charging station or an electrical outlet with a proper cable should be accessible. This accessibility depends on the location of the EV. If a charging point is available, the following factors that condition the recharge are the charging price at the charging point and the SOC of the battery at the moment, if there is a real need to charge or not. Besides, the charging price depends on lo-

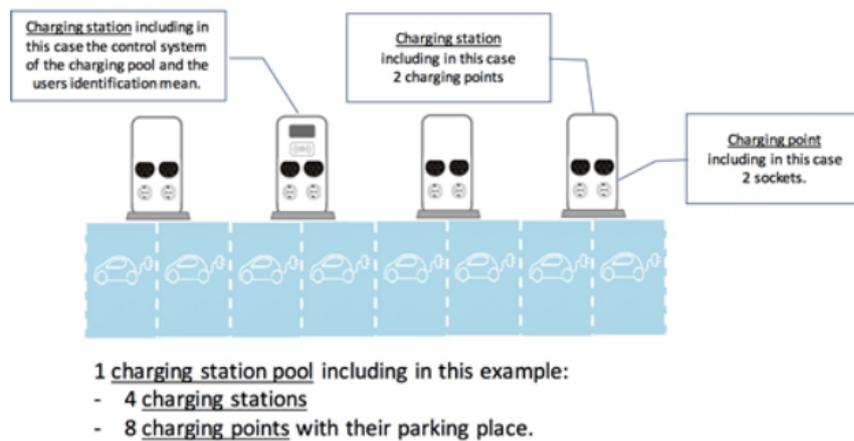


FIGURE 3.1 – Illustration of the components of the recharging infrastructure.
 Source : AFIREV.

cal or national policies if it is a public station or on the economic model of private suppliers otherwise. And so on. In addition to the above-mentioned, many other elements shape an individual charge behavior. The sum of these individual EV behaviors shapes a global behavior that will influence DSO, governments and car makers decisions. In this context, we approach the VGI from a perspective of three main elements : the EV presented in Section 2 of Chapter 1, the charging infrastructure presented in this chapter and the power grid presented in Chapter 4 .

2.1 Recharging infrastructure

The European Association for Electromobility (AVERE) aims at supporting and accelerating the transition to zero emission mobility. To do so, it expects to accelerate the goal of 100% zero-emissions new cars by 2030, to reinforce CO_2 emissions standards, to scale up the EU battery industry, to promote the use of renewable fuels and to create the optimal conditions for a reinforced charging infrastructure. This last one, the accessibility to recharge points, is one of the main concerns since it could represent a barrier to the deployment of EV.

Some key definitions to develop the subject are presented hereby⁴ and their relationship is represented in Figure 3.1 :

- Charging infrastructure : this is the whole system including electrical circuits, charging stations and management systems.

4. <https://afirev.fr/en/4751/>

- Charging station pool : it is the association of a charging station with a parking space.
- Charging station : it is the gathering of some charging points incorporating communication, metering and payment devices.
- Charging point : it is an interface able to recharge a single electric vehicle at a time, associated with a parking space. It includes at least one socket for plug, and/or one cable attached with connector for EV.

In France, the deployment of the charging infrastructure in the parking zones is regulated by the decree n° 2016-968 from July 13th 2016. The companies have the duty to install a minimal number of charging points depending on the total number of parking places and on the type of building. It goes from 5% of the total parking places in commercial buildings and cinemas with a minimum of 1 charging point when there are less than 40 places, to 20% in the tertiary and industrial sectors when there are more than 40 parking places.

Given the fast evolution of the EV market and the ambitious targets for the upcoming years in terms of the electrification of the total particular vehicles, such a number of charging points in public places would not be enough. It seems hard to imagine that each parking place could become a charging point and that each parking lot could become a charging station pool. Even though, there is a close example that shows the way the EV recharge infrastructure in public parking could follow. It is the case of the *block heater poles* used to heat car engines in regions with very cold winters such as in Canada, Russia and Scandinavia. Carparks are fitted with electrical outlets to power the block heaters as shown in Figure 3.2. The deployment of low power chargers is feasible and could be a simple and low cost solution to supply flexibility to the power grid. Nevertheless, the identification of the EV and the question around the pricing for such a system remains a barrier.

The EV roaming is the service that looks for easing the integration of the two main parties involved in the batteries recharge on public places : the charging spot operators and the e-mobility service providers. The former operates charging stations and supplies electricity charging service to vehicles connected to them while the latter produces services to an EV user according to the contract signed with him. Their relationship is illustrated in Figure 3.3. For example, the EV roaming allows to geolocalize the charging points, to know its availability, to book, to authorize and to pay a charge. The roaming should facilitate the EV recharge without



FIGURE 3.2 – Example of block heaters in a parking lot.

Source : CVT News

<https://regina.ctvnews.ca/saskpower-giving-away-50-000-block-heater-timers-1.730150>.

the requirement of having a subscription with different operators⁵. Though, there is still a long way to integrate all stakeholders in a practical and efficient economic model. Today, it is based on the benefits of each one of these enterprise and this is why there is still the requirement of a variety of subscription cards resulting sometimes in a complicated access to public chargers. Moreover, payments by credit card are not available in most of the charging points, though, it is the case for public parking. There are two main reasons i) each transaction represents a cost that operators can not pay and ii) it is necessary to have a good network coverage to succeed bank authorizations but in certain zones where charging points are located, this access remains limited. The spread of this method of payment should become more popular in the upcoming years and it would raise one of the barriers of the EV adoption.

In France, since 2015, the French Association for Roaming of EV Charging Services (AFI-REV) has been created by some of the main actors of the electromobility. Today, the association is composed of 30 members gathering charging spot operators, services suppliers for EV users, roaming services suppliers and representative actors of the elctromobility. Companies of the energy sector (Engie, Total EV charge, Vinci Energies), automotive industry (PSA, Renault) and research institutes (Vedecom) are some of the current members. As for Germany, country is part of the European project *evRoaming4EU* in collaboration with Denmark, Austria and the Netherlands whose ultimate goal is to allow any EV driver to charge at any charging station in the EU.

5. <https://afirev.fr/en/what-is-roaming-of-ev-charging-services/>

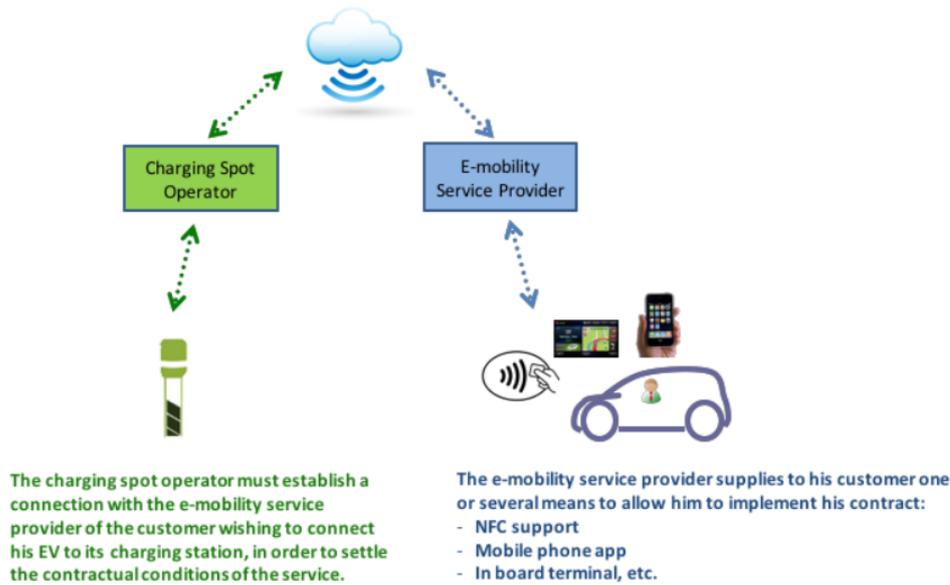


FIGURE 3.3 – Schematic explanation of the roaming of EV charging services.
Source : AFIREV.

Regarding the research about charging infrastructure, Almutairi [Almutairi, 2022] proposes an interesting classification : the first group is the one for the problems focused on a local management, for example those works estimating the number of charging points for a charging station pool and their practical location and those works compiling analyses of limitations and governance issues. The second one involves researches in a larger magnitude like those estimating and assessing the deployment of the recharge infrastructure in a region or even in a country. In all these works, as well as in governments speeches, the electromobility is presented as such an essential factor for reaching the energy transition goals. Nevertheless, besides the obvious advantages in terms of air quality, noise and its potential support to the massive adoption of **REn**, there are significant negative effects, mainly in terms of stability for the power grid, harmonics, phase and voltage unbalance and overloading [Das, 2020 ; Ashfaq, 2021 ; Jog, 2021]. This is from a technical point of view. However, to assist a massive **EV** adoption it is necessary to respond to the social barriers presented in Section 2.1.1 of Chapter 1 as well.

2.2 The recharge power

In the work of Ashfaq [Ashfaq, 2021] there is a first global classification of conductive charging systems into *On-board* and *Off-board* chargers. On-board chargers are low power and they work with *Alternating current* (AC) while Off-board chargers have high power levels and work with *Direct current* (DC). On-board chargers have a rectifier (to convert the input AC voltage

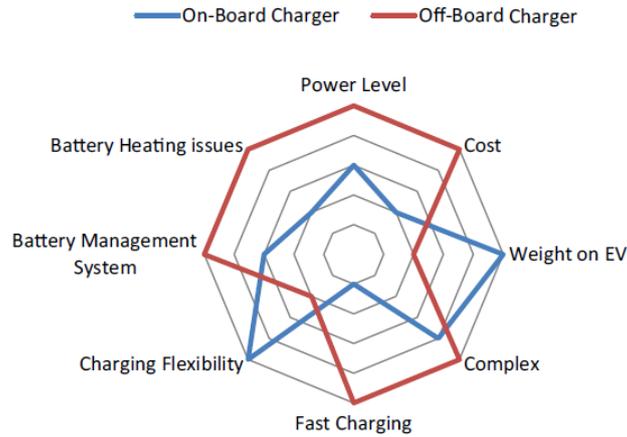


FIGURE 3.4 – Comparison between On-board and Off-board chargers.
Source : [Ashfaq, 2021].

TABLE 3.1 – AC charge powers

	Power [kW]	Current [A]
Standard outlet	1.8	8
	2.3	10
Reinforced outlet	3.2	14
	3.7	16
Wallbox	7.4	32
	11	3x16
	22	3x32

to DC) and battery regulation (to maintain the output DC voltage to a constant) inside the EV while in the case of off-board chargers these two components are outside the EV [Ahmad, 2018]. A comparative analysis is presented in Figure 3.4 [Habib, 2018 ; Ashfaq, 2021 ; Moradewicz, 2019]. We want to emphasize on a single outcome of this analysis. It is not feasible nor interesting, to pretend to use the EV fleet such a flexibility resource when using high power fast charging for two main reasons : the power peaks would be hard to control and the time of charge is too short.

The Table 3.1 presents different AC charge powers. Car manufacturers have designed wires with limited intensity to avoid overheating. This is why in the standard outlets that we find anywhere the charge power is between 1.8 kW and 2.3 kW at 8 or 10 A. For the next level, Legrand has designed the *Green'up* outlet which, through a mechanical system reaches a higher power of 3.2 kW at 14 A. Finally, the wallbox are the devices designed for the EV charge at higher powers reaching a maximal value of 22 kW with a three-phase charge.

2.3 The future of the power grid and the flexibility concern

Today, the power system secures the demand supply with a mix that includes different kind of technologies and resources. On the one hand, there are the conventional power plants that include nuclear, thermal and hydro power. They are all controllable with more flexibility for the thermal and hydro power plants and less flexibility for nuclear power plants. On the other hand, there are the REn power plants, mainly *Photovoltaics (PV)* and wind generators, which are not controllable neither flexible. Their electricity is injected with priority to the grid. Thus, the power system needs to adjust the supply from conventional power plants to guarantee the equilibrium demand/supply. To reach the goals of carbon neutrality fixed by the European policies, this power system is called to evolve in the upcoming years. REn will increase their part in the energy mix while thermal pollutant power plants will go out gradually.

Between this range of power plants there are two ways to produce electricity without releasing GHG emissions : through REn and through nuclear power plants. The use of the latter has been debated for several years because of the fear produced from many unfortunate events including Chernobyl and Fukushima. This is why countries like Germany have decided to go out of this source of energy and have favoured the use of coal, fuel and gas power plants. These energetic resources come to Europe mainly from Saudi Arabia, Kazakhstan, Russia, Nigeria, Algeria, Norway and the Netherlands. The consequences of the decision of dispense of nuclear power while keeping the dependence on fossil fuels coming from these countries are adverse in the current geopolitical context from an economic and environmental point of view. This dependency on energetic resources has shown to be a major weak point and concern for the energy transition since the energy crisis of late 2021 and even more since the beginning of war in Ukraine in February 2022. Electricity prices have increased in disproportional measures, the most pollutant power plants are appealed as a last resort and what is worst, the risk of shortage for the next months is at stake.

The power appealed from the flexible power plants is called the residual demand and it depends on two factors : the REn production and the electricity consumption. It can be simply estimated as the total demand minus the fatal production (this subject is developed in detail in Chapter 4).

The flexibility of a power system is its capacity of adaptation to variations coming from demand and supply. These flexibility requirements follow different time scale trends. As demand and supply may be different in winter with respect to summer, the magnitude of flexibility re-

quirements is different as well. Even from one year to another for a same season, flexibility needs may change since weather conditions have significant changes. Figure 3.5 shows residual demand for France and Germany for the two consecutive years 2019 and 2020. These curves respond to the energy mix and the consumption of each country. In France, because of the widespread electric heating, electricity demand is significantly higher in winter than in summer months and therefore, residual demand is higher in this period of the year ; while in Germany, it is the large REn installed capacity that shapes the residual demand all along the year. In France, following the trend of the average value, there are short time variations which amplitude remains around 20 GW in summer months and around 30 GW in winter months. In Germany, the short time variations have more amplitude going from 40 GW to 60 GW independently of the season. In an evolving energy mix, new flexibility sources will be required to absorb the strong variations on residual demand entailed by REn. A short-time adjustment on electricity demand is an option to bring this flexibility and this is where EV may play an important role.

When observing the power grid operation in France, there are repetitive patterns at different time scales. There is the *duck curve* with two bumps during the day, indicating that electricity consumption is higher during some hours (peak hours) and it is lower during a period of the day and during the nights (there are two valley periods per day). In the same way, with a larger regard, it is observed that the magnitude of the duck curve is lower during the weekends with respect to week days. This may be explained because economic activity is significantly reduced during the weekend. In an even larger regard, there are seasonal trends during the year. In winter, mainly because of heating, electricity demand is higher than during summer months.

From the demand side, European policies promoting the massive adoption of EV could have an effect on the residual demand curve. Without modulation, EV could add an important electricity demand during peak hours. As REn generation is not in phase with these peak hours, in the expected scenario where conventional power plants generation will decrease (specially thermal power plants which bring flexibility today), the system will risk more of shortage and failure. Under this concern, governments look for practical solutions. For example, UK proposes a law to switch off home and work chargers during peak hours and to make them work no more than 9 hours a day⁶. Like this measure but less constraining, a flexibility system brought by smart EV charge would allow to shift and to adapt the electricity demand to the periods of low demand and high REn generation.

6. <https://insideevs.com/news/537120/ev-chargers-switched-off-uk/>

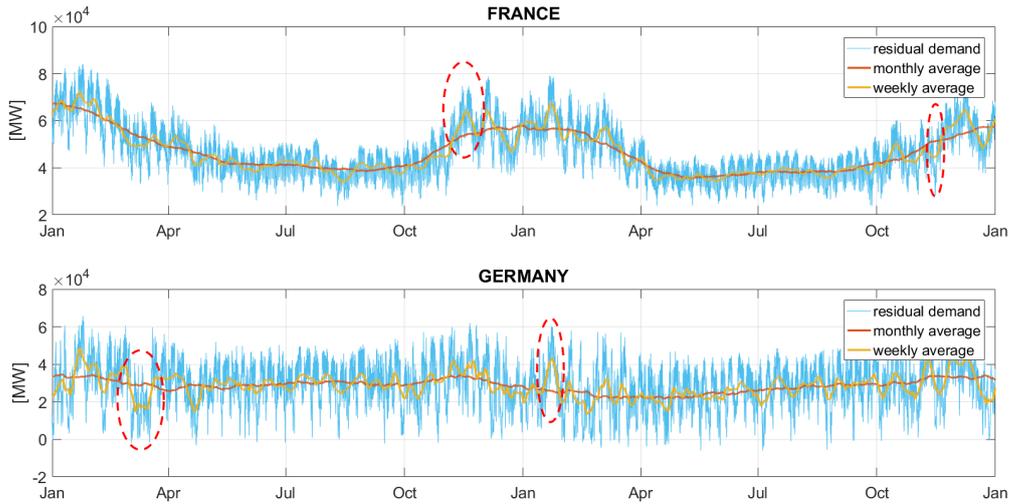


FIGURE 3.5 – Normalized electricity demand for two consecutive years 2019-2020 and its moving average over one month.
Unit : MW.
Source : data from ENTSO-E.

Figure 3.6 illustrates the changes in the French residual demand, and therefore in flexibility requirements, for a random week in spring when increasing the PV and wind generators installed capacities by respectively 2 and 3 times the current capacity. The patterns remain the same, the curve shifts down and especially, valleys become deeper, which is mainly the effect of more PV during sunny hours. There are strong variations from one day to another. For example in the night from Monday to Tuesday the valley is higher (less deep) than the rest of the week. When we increase the REn installed capacity the night valley does not change significantly, while the daily valley becomes much deeper (it passes from 80% to 55%). This could be explained by a sunny day and a night without wind. In such situation, from the power grid perspective, the EV charge would be more interesting during the day valley than during the night valley. Conversely, on Wednesday during the entire day and in the night from Wednesday to Thursday there is a strong variation on residual demand when increasing the REn installed capacity. The day valley as well as the night valley become deeper and both valleys are interesting from the grid perspective to recharge EV. Following the sense of this example, the EV fleet could reduce the deep valleys that could entail problems to the power grid.

To contribute to the flexibility of the power grid it is mandatory to closely follow the equilibrium demand/supply (this means in short time periods). Weather phenomena like anticyclones and depressions influence the electricity production as well as weather conditions as cold snaps or heatwaves influence the electricity demand. These conditions are susceptible to change in a

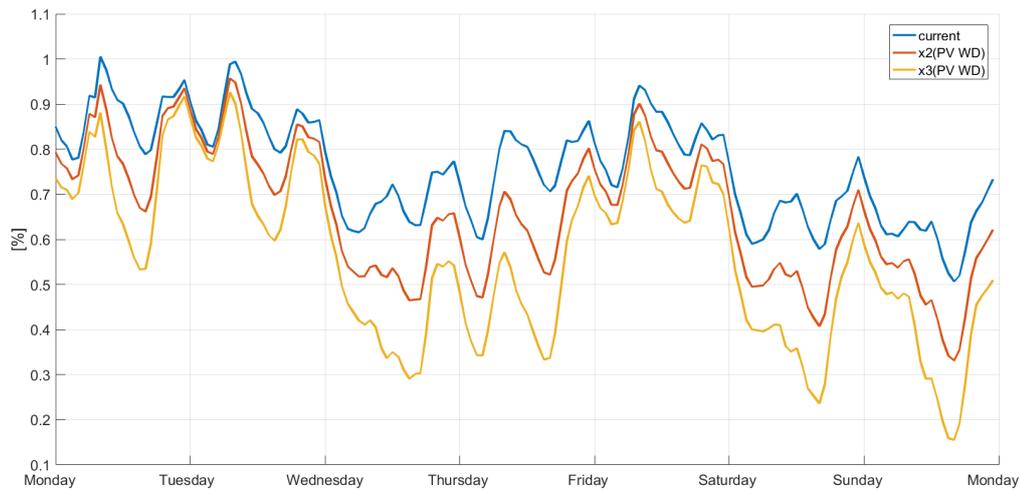


FIGURE 3.6 – Residual demand in France normalized with respect to the average value, for one week in spring. The blue curve is the original one. The red one is the resulting curve of doubling the PV and wind installed capacities and the orange curve is the resulting curve of tripling these capacities.

Unit : MW.

Source : authors.

few days period and this is why a monthly (or a longer time period) average signal such as the one in the red lines of Figure 3.5 should not be the reference for programming a flexibility system. We can observe into the circles that the monthly trend may be inaccurate to capture the residual demand behavior. The yellow lines are the moving weekly average (± 3.5 days). They follow in a more accurate way the residual demand behavior and they are a better estimation of the flexibility requirements. Because of the uncertainty of a long future weather condition, the French TSO, forecasts the electricity demand using the 7 past days consumption and the 9 days forward weather forecast⁷.

From these observations and facts and for the aim of this work, we estimate that a window of 7 days (± 3.5) corresponds to the household's cyclicity and constitutes an appropriate timing to program the flexibility that the particular EV fleet could bring to the power grid through VGI.

3 The optimization model

Among the objectives of optimization of the EV charge there is the REn integration in the electricity mix [Chiao-Ting Li, 2012], the CO₂ emissions reduction [Saber, 2011 ; Hajimiragha,

7. <https://www.services-rte.com/fr/visualisez-les-donnees-publiees-par-rte/previsions-de-consommation.html>

2011], the recharge costs minimization [Shaaban, 2017; Sachan, 2018], the battery life preservation [Fernández, 2013] and the power grid services provision including the grid congestion management [Staudt, 2018] (which might be at a local or a national level and that we describe in detail in Chapter 4). In between these grid services, EV could contribute to ancillary services such as frequency regulation and voltage control, to investment deferment and to smooth demand curve through pic shaving and valley filling. With this broad range of objectives and services it is inherent to think in a broad range of involved actors : the power system agents, governments, automotive industry, particular EV fleets, etc. The share of participation of each one of these actors is still not well defined and it will depend on future policies. This general layout allows to see the complexity and the interest of the subject at the same time.

One of the upper levels outcome in the literature review is the management of the charge by means of two different ways : a decentralized one, where a single EV optimizes its charge by its own, following a signal or a given criteria [Gan, 2013; Ma, 2010; Moschella, 2021], and an aggregated one, where several EV are managed at the same time as a whole, following a signal or a criteria as well, which is sent and commanded only by an external agent [Rocchetta, 2015; Clairand, 2017]. Cortes [Cortés, 2019] points out that optimization problems are solved faster in centralized algorithms than in decentralized methods, while the advantage of these last ones is the few quantity of personal information (such as location) that needs to be communicated.

Independently from the kind of management, VGI control systems modelize and take into account the power system conditions and the EV owners behaviors. Both are uncertainty sources in models, therefore statistical data [Rocchetta, 2015; Sachan, 2018; Li, 2022] or fixed hypothesis [Shaaban, 2017] are used to describe the REn production and the EV fleet behavior (e.g. departure and arrival times, trip distances, etc. and charging behaviors such as the well known range anxiety⁸ or contrariwise, a frequently deep discharge behavior). We consider that technical and economics characteristics of batteries (kind of technology, capacity, lifetime) and of charging points (maximal power, supply price, availability) are key factors to analyze the suitability of a smart charging adoption. This information should be included, in stochastic or deterministic methodologies, to modelize and simulate optimal charge/discharge schedules while guaranteeing to meet all travel needs.

8. It is the fear of driving an electric vehicle and running out of power, without being able to find a charging station on time to replenish the battery

3.1 The different charge strategies

The time and speed of recharging an **EV** fleet are major factors that can impact power grids on a local and national scale. The natural charge⁹, without any type of control, could challenge the balance of one of these systems during peak hours of electricity demand. A massive adoption of **EV** entails the arrival of a new significant electricity demand and therefore imposes a challenge for all the concerned players : electricity producers and suppliers, **TSO**, **DSO**, flexibility and demand response operators, regulators, car manufacturers, start-ups offering management solutions or the operation of charging stations, among others [RTE, 2019].

The possible negative effects of **EV** integration can be mitigated by shifting charge periods through different ways : incentives for owners with differentiated tariffs over time, direct control of charging (smart charging) in a single or bidirectional exchange between **EV** and networks (**V2G**) or more recently, like the example of UK presented in Section 2.3, through stringent regulations forbidding the **EV** charge during some hours of the day. Adapting the typical use of **EV** with new operation strategies for its batteries could simplify the massive adoption of electrified transport and accelerate the benefits on air quality and the reduction of **GHG** emissions [Langton, 2013]. The idea of these strategies is to find the best time to charge **EV** [Richardson, 2013]. This remains a large concept that, as indicated at the beginning of the section, could take into account a price signal, the network saturation, an electricity overproduction or CO_2 emissions, among others.

The implementation of charging strategies could find several obstacles, not just technically but also because of the complexity of **EV** owners behavior. As mentioned by Oliver [Oliver, 2017], in the perspective of a possible business between an aggregator and drivers for applying **VGI**, it is necessary to evaluate the possible barriers that could lead **EV** owners not to accept the service (a claim that can be extended to decentralized strategies as well). For example, these obstacles could be a lack of communication on the justification of the service and on the respect of private life with the exchanges of data or the concern about a possible loss of availability and control over their vehicle.

We hereby present the two main ways to optimize the charge that are analyzed and even implemented in some countries : the *Time of Use (ToU)* with a price effect and the smart charging algorithms.

9. The definition and characteristics of natural charge will be detailed further in this chapter.

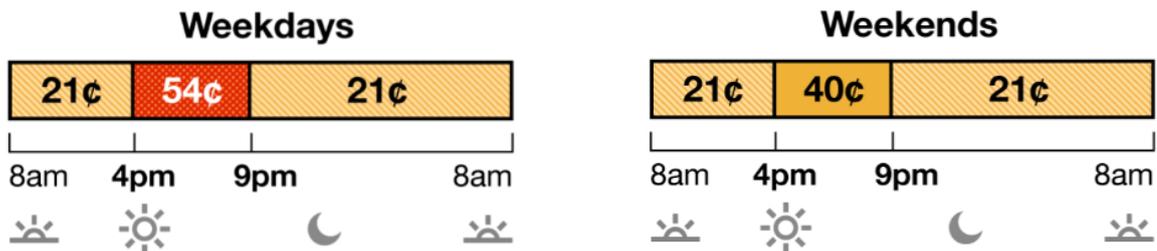
3.1.1 *Time of Use*

The *Time of Use* is a strategy used by electricity suppliers seeking to encourage users to shift their electricity demand towards the hours of least demand on power networks through lower prices. This is done by means of differentiated tariffs by time slots. Pricing can be *fixed* with two or three different periods a day, each one with a price that depends on the average electricity demand, with highest prices for peak hours and lower prices for valley hours. Another pricing method is *dynamic*, with prices that change constantly depending on spot market electricity prices in real time. For example, Jacopo [Torriti, 2012] analyzed data from more than one thousand smart meters in North Italy. His results evidence a higher average electricity consumption and lower payments for users adopting *ToU*. A peak shaving was evidenced in the morning while the afternoon peak was roughly divided into two peaks.

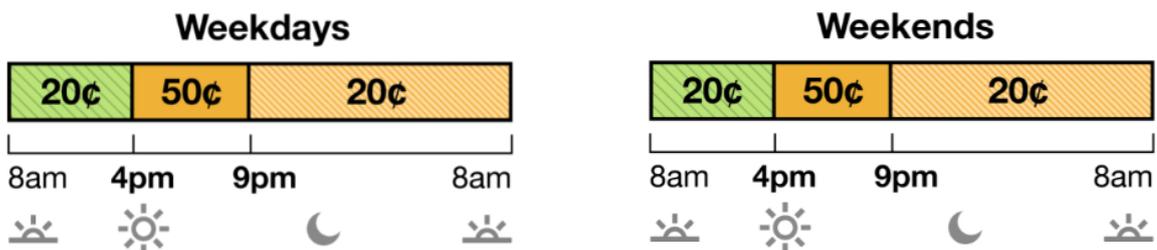
Some researchers have studied the implementation of the fixed *ToU* strategy on *EV* to minimize the recharge cost and their impact on power grids [Shao, 2010; Chen, 2022]. The implementation of *ToU* tariffs for *EV* charge in the case of fixed prices seems easy since the start and end time of recharge can be programmed on the charger or on the *EV* directly. *EV* owners should just schedule their charge during the low price hours. In the case of dynamic *ToU* the application for *EV* charge is more complex since a communication and an aggregated control systems are necessary to notify the lowest price hours and to send a start/stop charge signal. This is a growing field with still open questions leading to further research. Though, there are already interesting results in the existing literature. Through a marginal price model including ramping constraints, Wesseh [Wesseh, 2022] shows the impact of the flexibility provided by *EV* charge to propose lower *ToU* tariffs during valley hours. Results of Chen [Chen, 2022] indicate a potential reduction of the *EV* charge cost when using *REn* and dynamic pricing. Less favorable results are presented in the work of Pimm [Pimm, 2018] who found that the *ToU* could produce a rebound peak if many *EV* start charging at the beginning of the low price period and concludes that it is not a good strategy for achieving peak shaving and valley filling. Nevertheless, this rebound peak is a well known problem for *DSO* when activating heat pumps during valley hours. To handle, they use a delay between the activation of these devices by sectors of neighborhood under the same power transformer. The same approach could be used for an *EV* fleet charging under a *ToU* directive.

California is the state with the most important *EV* fleet in the USA and according to the last IAE Global EV Outlook [IEA, 2022] they have the largest budget commitment for *EV* at the state level. California is one of the pioneers who has adopted the *ToU* strategy with the aim

of limiting stressful situations on the networks during peak demand hours. They classified the price rates as *peak-on* for hours with more demand and *peak-off* for hours with less demand. Some experiences show that EV owners with a ToU tariff contract respond well to the "price motivation", they mainly charge their EV during lower electricity prices and minimize their total recharge cost. Among the population that adopts ToU tariffs there is a variable response on account of the duration (number of hours) of the low tariff (*peak-off*) in one day as well as the proportion between the *peak-on* and the *peak-off* tariffs. That is, more drivers shift charge towards the *peak-off* tariff time when the relationship between peak-on/peak-off tariffs is 6 :1 compared to the number of drivers who shift the charge when this relationship is 2 :1. However, most EV owners do not subscribe to differentiated price contracts and remain on the standard prices [Gopal, 2018]. In line with these results, the work of Shao [Shao, 2010] concludes the importance of making the right choice of ToU rates and periods. They suggest that a higher *peak-on* tariff would encourage more demand response. Figure 3.7 is an example of the proposed ToU tariffs in California by the *Independent System Operator* (ISO) Southern California Edison designed specifically for EV charge.



(a) In summer, from June to September



(b) In winter, from October to May

FIGURE 3.7 – ToU tariffs proposed by ISO Southern California Edison
Source : <https://www.sce.com/residential/rates/electric-vehicle-plans>

The UK has also used the ToU strategy for several decades now. They were initially looking to shift electricity demand to the moments of the day when production was mainly by coal and nuclear power plants which had a lower production cost. ToU offers have evolved and have been

adapted to the context of the world’s energy transition. As a result, today there are contract offers with three time slots and a 1 :5 ratio between the lowest and the highest tariff. Research remains open to analyze the impact of ToU on EV charge. Other regions of the world, such as Ontario and Australia are examples of ToU adoption [Pimm, 2018].

In France, the electricity bill has two components. A fixed one for the subscribed power and another one for the consumption. For consumption component there are four different pricing options. The first one is a fixed tariff named *Base* and the other three options follow the concept of ToU. 99% of users have subscribed the fixed pricing or the first ToU option. The electricity suppliers who emerged after the market liberalization can offer only the two main pricing options (*Base* and *Heures creuses*) while the historic supplier can propose the *Tempo* option as well¹⁰ :

- **Heures creuses** : it is the same concept of *peak-off* and *peak-on* tariffs used elsewhere in the world. The regional DSO chooses the time slots. The current prices of EDF (the historic French supplier) for this offer are 0.1841€/kWh during pic hours and 0.1470€/kWh during valley hours. This is a ratio of 1 :1.2.
- **Tempo** : the principle of this pricing option is to make electricity much more expensive during the periods of highest consumption by region. There are three types of days : 300 days per year are blue, 43 days are white and 22 are red. Within each type of day there are pic and valley hours and the current prices are indicated in Table 3.2. There is a low ratio between peak hours tariff and valley hours tariff in blue days (1 :1.4) against a higher ratio in red days (1 :4.4).
- **EJP** : This option can not be subscribed anymore by new users, but it is still valid for those who were subscribed before 1998. In here, there are 343 days of the year with a tariff of 0.1283 €/kWh and 22 days with a tariff of 0.9418 €/kWh. This is a ratio 1 :7.3.

The work of Szinai [Szinai, 2020] analyses different EV charge strategies. His results show that ToU is a good strategy to respond to peak impacts on the grid with respect to an unmanaged scenario but that smart charge algorithms represent a better option to reduce the power system costs.

10. <https://prix-elec.com/energie/comprendre/options-tarifaires>

TABLE 3.2 – French historic electricity supplier’s (EDF) current tariffs for Tempo pricing option.
Source : EDF.

	Valley [€/kWh]	Peak [€/kWh]
Blue	0.1112	0.1653
White	0.0862	0.1272
Red	0.1222	0.5486

3.1.2 Charging algorithms

The development of optimization algorithms for the **EV** charge is one of the main subjects concerning the **VGI** research. The global research question is, expecting to reach a defined goal, how to coordinate and control the right moment for appealing the right amount of electricity from the grid and restoring this electricity afterwards in the case of **V2G**. Researches have a wide amount of approaches taking different objectives and methodologies for solving the problem. The works of Yang and Das [Yang, 2015; Das, 2020] summarize and classify the literature around smart charging strategies based on their computational techniques. From analytical charge scheduling to meta-heuristic algorithms are included in their work and they are all represented in Figure 3.8. We consider that another possible way to classify the charging algorithms is between those optimizing the charge in terms of power and those optimizing the charge in terms of time. The advantage of the power modulation for valley filling is that at the deepest time of the valley the power is maximal.

Depending on the formulation of the optimization problem, benefits are attributed to different agents or parties. For example, Kuran [Kuran, 2015] proposes two perspectives of optimization : the first one maximizes the revenues of a parking lot manager and the second one maximizes the number of **EV** fulfilling their recharging requirements (in which case **EV** owners take the advantage). Wu [Wu, 2022] also applies and compares two different optimization strategies : the minimization cost of recharge from the **EV** owner perspective and the minimization of peak loads from the **TSO** perspective. The work of Chiao [Chiao-Ting Li, 2012] analyses the position of the **TSO** as well minimizing the system costs when reducing ancillary services and replacing fossil fuel generation by wind energy while, from the perspective of the **DSO** and with a technical objective, Masoum [Masoum, 2013] minimizes system losses through the regulation of bus voltages.

Several works that present the optimization under the perspective of **EV** owners look for minimizing the charge costs [Shaaban, 2017; Wu, 2022; Clairand, 2017; Saber, 2011]. To do

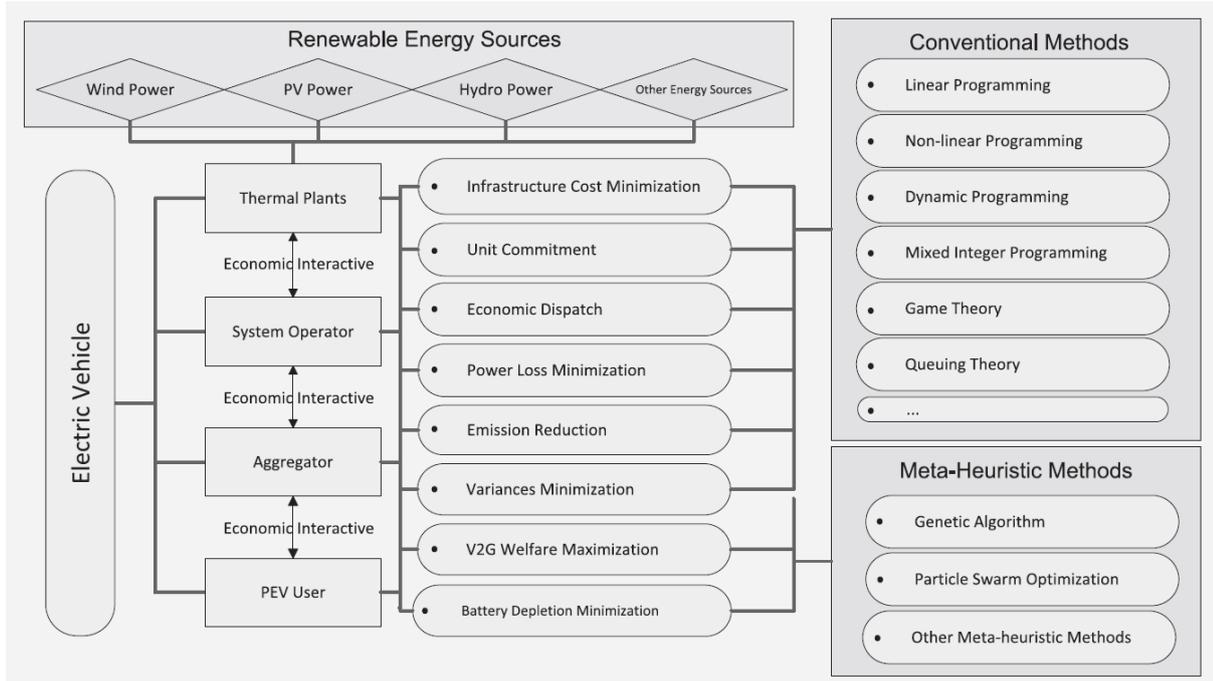


FIGURE 3.8 – Smart charging objectives and methods.
Source : [Yang, 2015].

so, using different approaches and methodologies, the EV charge is programmed as much as possible during low-price periods. To our knowledge, in the existing literature the recharge cost minimization is analyzed as an open loop. It means that researchers do not consider the fact that the aggregation of some millions of EV charging at the same low-price period will create a peak where there was a valley and could entail stability problems for the DSO and TSO. We consider that the capacity of EV is often under estimated¹¹ but we will explain this subject in detail in Chapter 4. If the charge of a significant EV fleet at a current valley period is correctly considered, the valley might disappear together with the corresponding low-price. The methodologies presented in the literature are applicable for minimizing the recharge cost of small fleets but do not for the significant number of EV that are expected in the upcoming years. The negative effects of an open loop charge optimization could lead regulators to impose a close loop optimization system and impose, for example, car manufacturers to communicate a provisional estimation of the appealed power from the EV fleet for the upcoming hours or days. This, with the aim to find the best charge profile in closed loop that would have less impact for the power grid and from this, to create and propose an adequate pricing model. Though, this would be complex and expensive for EV owners and for car manufacturers. This is why the impact of the recharge at local and national levels needs to be carefully considered.

11. For example, 2 millions EV charging at 3.5 kW represent 7 GW which is comparable to the capacity of PSH

Optimization algorithms are subject to parameters that depend on human behaviors and that are difficult to predict. Some researchers use statistical data [Clairand, 2020; Fotouhi, 2019] while some works use other methods such as regression models or machine learning to predict these EV parameters [Singh, 2022; Shahriar, 2021; Chung, 2019]. Whichever EV behavior prediction method, it is important to consider that results strongly depend on the analyzed country or region and that they are not scalable. For example, Clairand [Clairand, 2017] uses estimations from studies about working hours for creating a randomized plug in behavior. For the daily EV consumption the authors use average values of traveled distance applying an efficiency coefficient and they use a constraint to set a target SOC that responds to the analyzed EV fleet requirements. These data originate from Ecuador and its use in analysis for a different region may not be accurate since the departure and arrival time as well as the traveled distance and the energy consumption might not be the same. This is the case of the work of Bo [Li, 2022] who uses a national survey from USA to determine the impact of the EV charge on the Chinese power grid.

Using a different methodology from the one of statistical surveys, some of the authors contributing to this literature propose that EV owners communicate some information for applying a further optimization [Wu, 2012; Alinia, 2019; Darabi, 2011]. It can be their departure time or the desired SOC by the end of the charge through the use of an application or directly in the charger. Though, we think this could be an obstacle for EV owners in the acceptance of smart charging if first, it takes some time to execute the procedure (even if it is just few minutes) and second, it could be a "liberty thief" if they feel constrained to leave at the time they communicated and not whenever they want to if there is an eventual change. Another possible obstacle for the smart charging deployment is the requirement of complex communication systems between the EV fleet and aggregators. Some algorithms need a real time communication as feed back to send the charge control signal for the next time step. The latency could be significant if there is information transmission in both directions (from and to the EV) and if the charge control system uses short time steps. If the communication system needs to be integrated in the EV or in the charger, it is important to consider the incurred costs.

3.2 Methodology : the development of an optimal control model

We look for assessing the impact of the aggregation of an significant EV fleet participating in the VGI. To do so, we use an *optimal control* approach to study the evolution of the energy stored in the virtual battery¹² throughout time. The *optimal control* is a branch of mathematical optimization used to deal with complex dynamical systems composed by large amounts of

12. The virtual battery is composed by the sum of a part of each EV battery and it is the capacity the power grid disposes to apply the VGI.

associated parameters and variables. It aims at bringing the system from an initial state at an initial time to an expected final state at a fixed final time while respecting some constraints. These are the system's *state variables*. Now, the dynamics of the system constitute an optimal performance through the minimization or the maximization of a function controlled by the command signal which is the *control variable* of the system.

If the integration of some millions of EV adds a significant demand to the power grid during peak hours, CO_2 emission might be higher, the risk of failure more significant and economic impacts such as variations on electricity market prices can be more pronounced. Therefore, it is the interest of the DSO to shift the EV charge to valley hours, especially during the weekends, to avoid adding stress to the power grid. An optimal charge dynamic that considers the seasonal trends and the short term variations on the power system, as was described in Section 2.3, is the goal of the algorithm described in this section.

This is a two stages optimal discrete-time control problem : the system will track a control signal by time step $t \in \mathcal{T} := \{1, \dots, T\}$ and will reach a target state at a fixed time T. To capture the different trends of the power grid previously explained, we compute a centered moving average of the input signal over a period of 7 days (± 3.5 days) in time steps t . To our knowledge, in previous reviewed works there is no optimization that considers a whole week probably due to the size of a dynamic programming model based on hourly states. This is new in our method.

Here we decided to use residual demand as input signal and the duration of time steps is one hour. We name the input signal at time t as y_t and its moving average as \bar{y}_t . In this work we use historical data provided by the French TSO. Nevertheless, in a future application of the algorithm, this estimation could be done in real time through the forecasted data for the 3.5 next days and the consolidated data for the 3.5 past days. These data would be provided by the DSO at a regional scale, for example.

However, the track of the optimization of the charge is estimated in shorter periods of half a day. The two time windows of optimization by day are parameterized responding to peaks and valleys of the duck curve as indicated for some days in Figure 3.9. We select the morning and the afternoon peak hours depending on the season because, for example, the afternoon demand peak arrives later during summer and spring seasons since days are longer while the morning peak takes place later during winter and fall seasons. We name these two trigger times as t_d for the diurnal one and as t_w for the nocturnal one into the previously defined set of time \mathcal{T} . Recharge

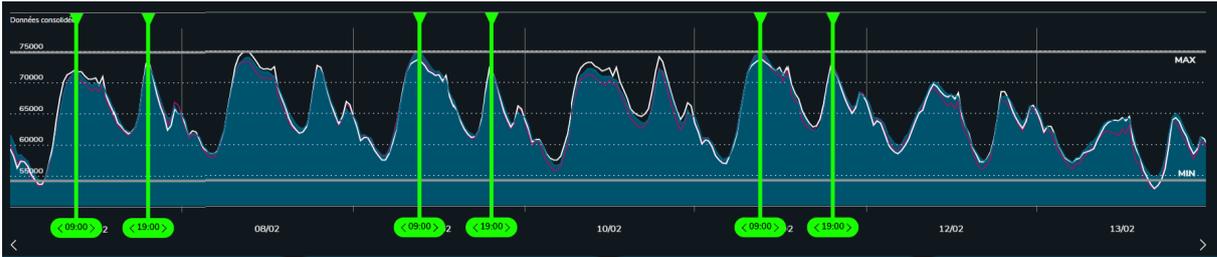


FIGURE 3.9 – Electricity demand for one random week from Monday to Sunday in February 2022. Peak demand hours for three days are indicated by the green vertical lines.

Units : MW.

Source : éCO2mix by RTE.

optimization is done during the valleys between t_d and t_w and between t_w and t_{d+1} . These are the two charging periods. For simplification we name a trigger time, diurnal or nocturnal, as t_{tr} and the next trigger time as t_{tr+1} .

In the first stage of the algorithm we estimate the level of charge that the virtual battery should reach by the end of the charging period (this is at next trigger t_{tr+1} at t_d or t_w depending on the period of the day that is been evaluated). We name this value $\mathcal{E} \in \mathbb{R}$ and it is estimated using the difference between the the moving average and the input signal. This difference is a filter that allows to capture only the variations with respect to a reference value removing the seasonal tendencies. For example, the resulting signal for France and Germany during January 2019 is shown in Figure 3.10.

If the average signal \bar{y}_t is higher than the input signal y_t at time t , this difference is positive and it is an indicator that this is a good moment to charge EV. The residual demand is low with respect to the average value. If the difference is negative, it indicates that residual demand is high and it is not an adequate moment to recharge EV. We use the accumulated value of this difference by time step until the end of the period T to estimate the energy that the power system could supply to EV through smart charging if the sum is positive or absorb from EV through V2G if the sum is negative. We apply two different methods that are evaluated and compared to determine the value of \mathcal{E} :

- In the first one, we estimate the accumulated sum of the difference between the moving average and the input signal by time step from t_{tr} to t_{tr+1} . Each value captures the state of the power grid at the evaluated moment but considering the past and the future states. The resulting value is the one we send as first command to the virtual battery. It is the target SOC that should be reached by t_{tr+1} .

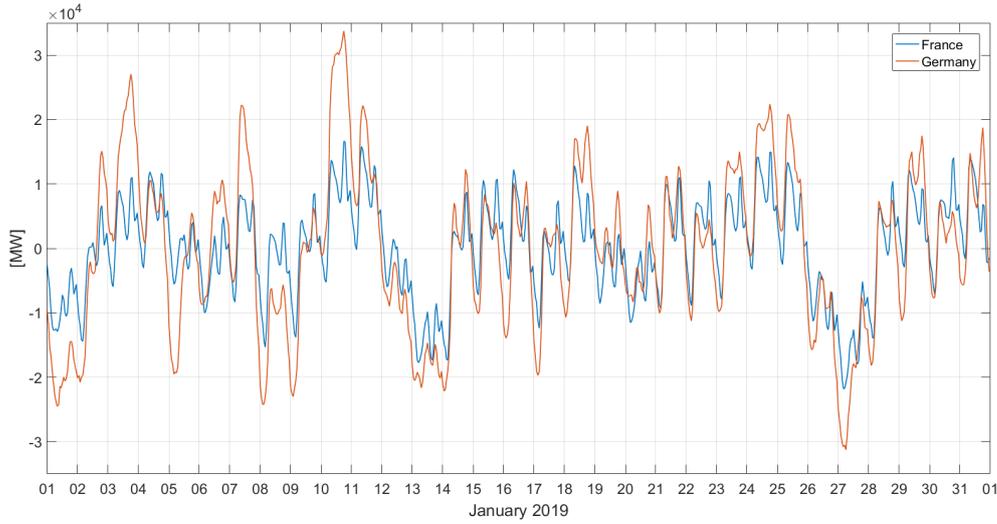


FIGURE 3.10 – Difference between input signal and the average signal. We obtain the short term variations eliminating the seasonal effects.

Units : MW.

Source : authors.

$$\mathcal{E}_T = \mathcal{E}_{T-1} + \sum \bar{y}_t - y_t \mid t = tr + 1 \quad (3.1)$$

- In the second one, we present a simplified target SOC with three possible levels : 60%, 80% and 100%. To determine the target SOC that the virtual battery should reach at t_{tr+1} , instead of keeping the accumulated value, we estimate the mean value of the difference between the moving average and the input signal over the whole time window. We situate this value with respect to two referent values r^+ and r^- . A positive one that indicates that conditions are favorable to charge EV, a negative one that indicates that conditions are less favorable to charge EV and an intermediate one. If the mean value is lower than the negative reference, the command \mathcal{E} received by the virtual battery as target SOC to reach at t_{tr+1} is 60%. If it is higher than the positive reference, the commanded target SOC is 100% and if it is in the middle interval, the commanded target SOC is 80%.

$$m = \frac{\sum_{t_{tr}}^{t_{tr+1}} \bar{y}_t - y_t}{T}$$

$$\mathcal{E}_T = \begin{cases} 0.6 & \text{if } m \leq r^- \\ 0.8 & \text{if } r^- < m \leq r^+ \\ 1 & \text{if } m > r^+ \end{cases} \quad (3.2)$$

In the second stage of the algorithm we estimate the command variable that the system will track by time step. It is a power modulation. To do so, we use the reference signal we have presented all along the previous sections, the moving average over a period of 7 days \bar{y}_t .

When integrating a significant fleet of **EV**, the resultant residual demand corresponds to the current residual demand plus the demand coming from **EV**. We name this state variable z_t .

$$z_t = y_t + P_t \cdot x_t$$

Where $x_t \in [0, 1]$ is the control variable and $P_t \in \mathbb{R}$ is the total **EV** electricity demand, it means the sum of the individual **EV** demand by time step. We denote each **EV** by $n \in \mathcal{N} := \{1, \dots, N\}$.

$$P_t = \sum_1^N p_{n,t}$$

To achieve a smoother new residual demand curve z_t , with lower peaks and filled valleys, we propose a function that reduces the gap between this curve and the reference signal. The objective function is the minimization of \mathcal{J} , the square of the difference between the estimated moving average and the new residual demand.

$$\min \quad \mathcal{J}_{x,y,z,t} = \sum_1^T |\bar{y}_t - z_t|^2 = \sum_1^T |\bar{y}_t - (y_t + P_t)|^2 \quad (3.3)$$

Each EV is characterized by its battery capacity B_n . The state variables are the SOC of the battery of each EV n at time t which are denoted by $s_{n,t} \in \mathcal{S} := \{0, \dots, B_b\}$. The maximal value of the power supplied by the charging point at each time step t when an EV n is plugged is denoted $Q_{n,t} \in \mathbb{R}^+$. For representing the availability of a charging point for an EV n at time t we use a binary variable $u_{n,t} \in \mathcal{U} := \{0, 1\}$. This variable depends on the location of the EV and on the availability of chargers. The initial and the final states of the variables and the dynamic equation linking the state and the control variables are :

$$\begin{aligned}
 s_{n,0} &= b & s_{n,T} &= \mathcal{E} \cdot B_n & p_{n,0} &= 0 \\
 s_{n,t} &= s_{n,t-1} + p_{n,t} \cdot u_{n,t} - c_{n,t} \\
 p_{n,t} &= Q_{n,t} \cdot (\mathcal{E}_T - s_{n,t}) \cdot \frac{x_t}{\int_0^t x_t} & \dot{s}_{n,t} &= p_{n,t}
 \end{aligned} \tag{3.4}$$

Through equation 3.4 the EV follows a specific charge law all along the period from t_{tr} to t_{tr+1} guaranteeing the achievement of the SOC estimated through \mathcal{E} .

Demonstration

f is a continuous and integrable function. Let's denote :

$$F(x) = \int_0^x f(u) du$$

Since $F'(x) = f(x)$ we can write :

$$\frac{f(x)}{F(x)} = \frac{d(\log(F(x)))}{dx}$$

The ratios' equality implies the derivatives' equality as well :

$$\log(F) = \log(G) + c$$

We can transform this expression as follows :

$$F = e^c \cdot G = a \cdot G$$

Finally we have that $\forall x$:

$$\int_0^x f(u) - a \cdot g(u) du = 0$$

And therefore :

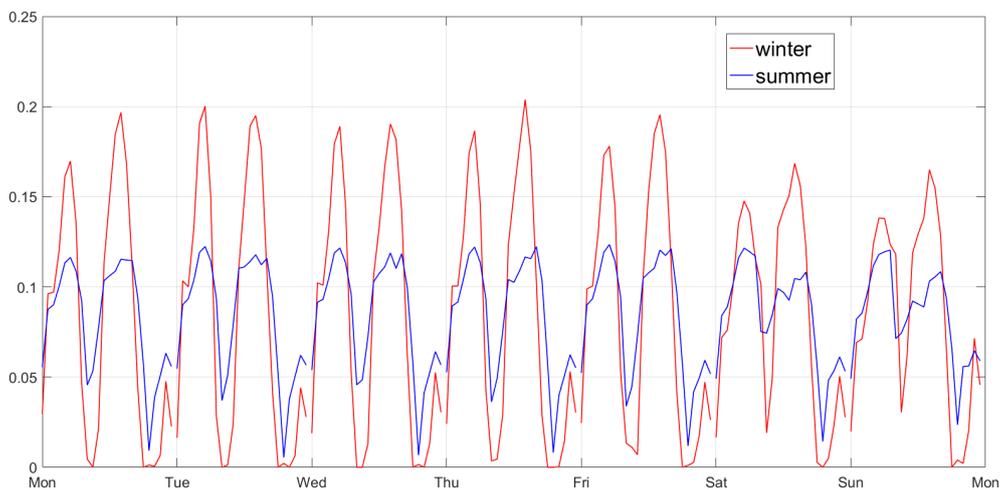
$$f = a \cdot g$$

Two different control variables are estimated depending on the season. One for months from April to September and a different one for the rest of the months of the year. Figure 3.11a (a) presents the resulting signal x_t and (b) presents $\int_0^t x_t$ which is the remaining proportion by charge period used in the calculation of Equation 3.4. The choice of using one only signal for every week of the same season (one for winter and one for summer) instead of estimating one signal based on the forecasts of the next few days, lays in the projection of the application of the algorithm in a real EV fleet. This solution allows to minimize the requirement of a constant communication between an operator (TSO or DSO) and the EV and therefore, the algorithm could be implemented with low software and hardware changes and low cost.

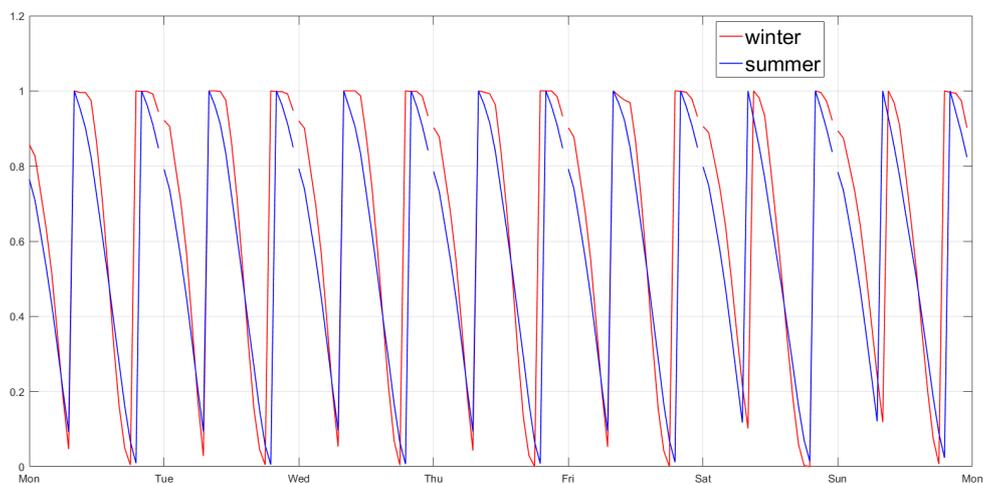
The V2G is modeled using the input signal y_t , a threshold value H_{V2G} and a correction parameter α that allows to shift its average \bar{y}_t in the vertical axis. Both, H_{V2G} and α are inputs in the model. We define the signal ω_t :

$$\omega_t = \min(H_{V2G}, \bar{y}_t + \alpha)$$

The resulting curve for one year is shown in Figure 3.12. The indicator for the DSO or the TSO that the V2G could be usefully applied to the power grid is that the input signal y_t exceeds the $V2G_t$ value. For this, we use the binary function described in Equation 3.5. This function captures the highest demand moments of the week. It is estimated using the average value \bar{y}_t to



(a) Resulting power control signal x_t for winter and summer months



(b) Remaining proportion by charge period $\int_0^t x_t$

FIGURE 3.11 – Reference signal for the optimal charge.

Unit : %.

Source : authors.

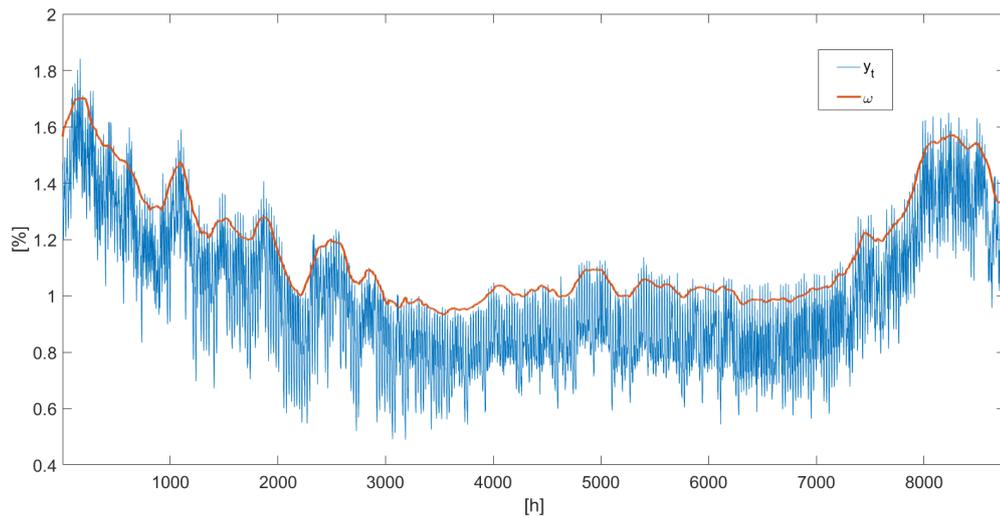


FIGURE 3.12 – Resulting signal to determine the moments of the year to apply the V2G.

Unit : %.

Source : authors.

make possible the application of the V2G all along the year. If a fixed value was used equally during summer and winter months as reference instead of the moving average, the V2G would never be used in summer months.

$$V2G_t = \begin{cases} 1 & \text{if } y_t > \omega_t \\ 0 & \text{if } y_t < \omega_t \end{cases} \quad (3.5)$$

To define the command signal that EV receive for doing the V2G we use a different trigger time t_{tr_V2G} that takes place at a time when there is not a high demand and we estimate the accumulated value of $V2G_t$ in one day (24 hours from the t_{tr_V2G}) :

$$V2G_d = \sum_{t_{tr_V2G}}^{t_{tr_V2G}^{+1}} (y_t - \omega_t) \times V2G_t \quad (3.6)$$

Finally, the power $p_{n,t}$ that each EV n participating in V2G is appealed to restore to the grid by time step t is :

$$p_{n,t}^{V2G} = -Q_{n,t} \times \frac{(y_t - \omega_t) \times V2G_t}{V2G_d} \quad (3.7)$$

4 The simulator

To evaluate the impact of the smart charge algorithm applied to a representative EV fleet we develop a simulation tool. All Matlab codes are included in Annex 3.A. We choose to use the French national survey dating from 2008 : the *Enquête Nationale de Transports et Déplacements* (ENTD). It includes the information of the travels performed during one week of almost ten thousand particular ICE cars from all around the country. Each vehicle has a ponderation value and together, they represent the total passenger cars fleet. The data we retain for each vehicle from the survey is the departure and arrival times (including the information about the day of the week) and the trip's speed and destination. The ENTD has a code for 31 different destinations classified by motivations as personal, purchases, medical, administrative, visits, accompany, hobbies, vacations and professional. We simplified these destinations with a code that indicates if the vehicle is going back home, going to work, going to any kind of store, going to visit someone or if there is another reason for traveling.

At first this information was used to create a "presence schedule" that starts on Monday at 00 :00 and finishes on Sunday at midnight. During the whole week it indicates the location of each car if it is idle or it indicates if it is in the middle of a trip with the respective duration. Table 3.3 shows the retained code to identify the presence places and Figure 3.13 shows an example of the presence schedule for 107 EVs.

With the aim to have consistent values and minimize possible error sources in the simulation

TABLE 3.3 – Presence schedule code.
Source : ENTD.

Code	Indication
0	trip
1	home
2	work
3	store
4	friend / family
5	other



FIGURE 3.13 – An example of the presence schedule of 107 EV during one week (each EV is a vertical colored line). Black cells represent EV is the middle of a trip, gray cells at home, red cells at workplace, blue cells at stores, green cells visiting family or friends and yellow ones represent the rest of possible locations.

Source : authors with data from [ENTD](#).

tool, we set two parameters to estimate the electricity consumption during a trip : the first one is a typical value of the consumption of an EV battery per traveled kilometer $c_{km} = 0.18$ kWh/km that is equivalent to a consumption of 18 kWh per 100 km and the second one is a minimal value of consumption if an EV travels during one hour $c_{1h} = 7$ kWh/h. The battery consumption for each trip of EV is estimated as the maximal value between a) the product of the trip duration, the speed and c_{km} and b) the product of the trip duration and c_{1h} . Next, with a simple summation it is possible to determine the consumption of each EV per day. We consider that an EV that consumes the entire capacity of its battery in one day is an EV that makes a long trip during that day.

We target the application of the smart charge algorithm only in two locations : at home and at work where we consider that EV could bring more flexibility to the grid because of the time cars stay at and because of the low power chargers that are used. From a recent survey about EV owners behavior by ENEDIS¹³, a french DSO, households are the main and privileged recharge location even for those living in collective buildings and 88% of participants never use public charging points.

From the presence schedule we estimate the availability to charge of EV during each hour of the week. Figure 3.14 presents the percentage of the total fleet that are present at home or at work. As is logical, during the nights the presence is more important than during the day while the weekend is the moment of the week with less availability with a minimum of 61% on Saturday which is still an important amount of storage that could be available for the power grid. Two groups are identified among the cars of the ENTND : those who make at least one trip during the week with the workplace as destination and those who never go to the workplace during the week. 46% of the fleet is identified like cars used to go to the workplace, we refer to this group of cars like n_w . We assume that all EV have access to a charge point at home. Though, not all n_w have access to charge at the workplace. This will be detailed in section 4.1.

As we explained in Section 3.2, for the real application of the algorithm it would be possible to use data provided by the DSO from the precedent and the next days. In the simulation we use historical data from 2019 to June 2022.

13. <https://www.enedis.fr/sites/default/files/documents/pdf/enquete-comportementale-possesseurs-de-vehicules-electriques.pdf>

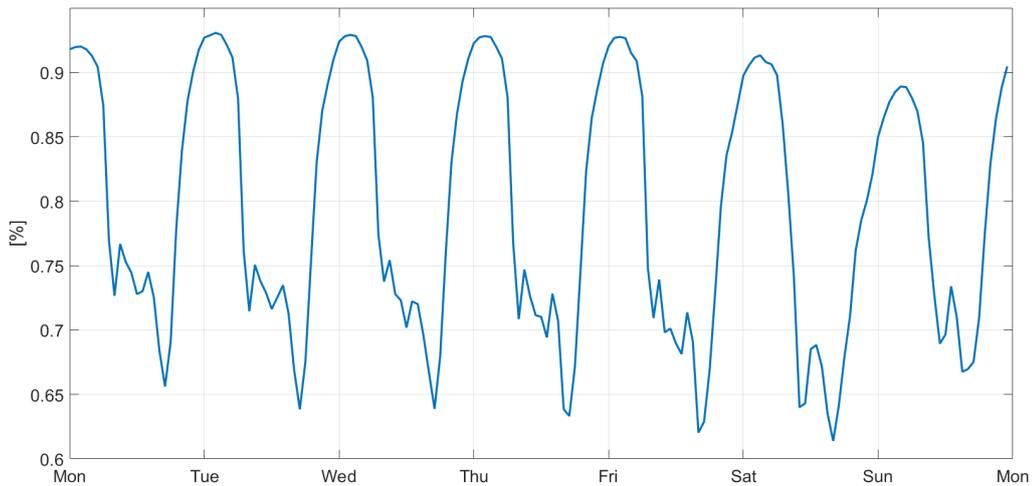


FIGURE 3.14 – Percentage of **EV** present at home or at work for each hour of the week.

Source : authors with data from the French national survey in 2008.

Unit : %.

Source : authors with data from **ENTD**.

4.1 The parameters

- Simulation weeks : is the number of weeks that we want to simulate. The trips are considered the same for all weeks but the **SOC** at the end of each simulated week is taken as the initial value for the next week. Results are presented only for the last simulated week. With this parameter we expect to mitigate the effect of initial values that are set manually.
- Start date : is the first day of the simulation. It is mandatory to provide a date comprised in the historical data.
- Natural or optimal charge : this parameter can take the values 1 or 2. Number 1 is to set the natural charge. This mode simulates the **EV** fleet charging at maximal power since the moment it is plugged in and the target **SOC** is 100% of the battery capacity. Number 2 is the mode for optimal charge where the algorithm is applied.
- **SOC** method : this parameter can take the values 0, 1 or 2. In optimal charge, if the parameter is set at 1, it is the second method that is applied (the one by steps of 60%, 80% or 100% presented in Equation 3.2). If the parameter is 2, it indicates that the algorithm applies the first presented method for estimating the target **SOC** (Equation 3.1).

- Advised charge acceptance : this parameter is a percentage of the fleet that would accept to charge under an instruction coming from DSO. It is aleatory attributed.
- Work plug availability : Not all EV used to go to work have the possibility to charge at the workplace. This parameter allows to set the proportion of EV in n_w having access to a recharge point at their workplace.
- V2G acceptance : this is the proportion of EV disposing a bidirectional device and accepting to participate in the V2G. For EV in n_w the condition to participate in V2G is to have access to a recharge point at their workplace.
- Battery capacity : it is possible to set two different battery capacities for two proportions of the EV fleet. This capacity is defined in kWh.
- Minimal charge SOC : is a threshold of the SOC of the battery. Under this value the smart charging algorithm is not applied and the EV charges at maximal power. Once the battery attains this value, the EV follows the algorithm instructions. Through this parameter we guarantee a minimal capacity to make a trip.
- Minimal plug SOC : this is a threshold to plug the EV to the power grid.
- Minimal V2G SOC : this is the minimal battery level to make the EV participate in the V2G.
- Charge/discharge power : it is possible to parameterize two different power values for the charge that are uniformly attributed to charging points at workplaces and homes and a different value might be parameterized for the discharge in the case of V2G.

4.2 The plug-in EV owners behavior

We create a variable to describe the plug in behavior. It indicates the availability of the EV n to be charged at time t . We name this variable as $g_n(t) \in \mathcal{G} := \{0, 1\}$ and it depends on the verification of the accessibility to a charging point $u_n(t) = 1$ (even if there is a charging point available, we consider that the vehicle is not necessarily plugged in), on the SOC $s_n(t)$ and on the drivers' rational. We consider that EV owners prioritize the charge at night since they want

to feel free to use their car at any moment during the day if needed. This behavior is modified through the parameter *Advised charge acceptance* where they would accept to charge the **EV** during the best condition times (for example at noon if there is a lot of photovoltaic production) following an instruction coming from the **DSO**. We also consider that n_w owners having access to a charging point at their workplace prioritize the charge at work. This is because in many cases the charge is free at workplaces, it is easier to access for example for people living in co-property buildings or because charging points have the best locations in the parking lot. Now we describe the plug behavior we have simulated :

- If the **EV** is not used to go to work or if it is used to go to work but there is not a charging point at the workplace and it is not at home, the **EV** is not plugged $g_n(t) = 0$.
- If the **EV** is used to go to work with access to a charging point and it is at home, it plugs only if its **SOC** is lower than the *Minimal SOC* or during the weekend if there is a long trip planned.
- If it is an **EV** participating in **V2G** it is plugged ($g_n(t) = 1$) while it is at home.

The following items are applied at workplace for **EV** having access to a charging point or at home for the rest of the fleet :

- If there is a long trip planned during the upcoming hours
- If the **EV** owner does not accept the *Advised charge* and its **SOC** is lower than the parameterized *Minimal plug SOC*
- If the *Advised charge* is accepted, the **EV** plugs depending on the signal sent by the **DSO** twice a day (one signal for each charge period from t_{tr} to t_{tr+1}). This signal depends itself on the power grid conditions. There are three possible states settled as was explained in Equation 3.2 : favorable days with a significant **REn** production and/or a low electricity demand that the **DSO** would identify as **GREEN days**, the target **SOC** \mathcal{E} is 100% and the **EV** would be plugged at 60% of its battery capacity. Unfavorable days with low **REn** production and/or high electricity demand that the **DSO** would identify as **RED days**, the target **SOC** \mathcal{E} is 60% and **EV** owners would wait longer before plugging the **EV**, set

at 40% of the battery capacity. Finally, a mid-term condition with average values of **REn** production and electricity demand that the **DSO** would identify as **ORANGE days**, the target **SOC** \mathcal{E} is 80% and the *Minimal plug SOC* is set at 50% of the battery capacity. A higher *Minimal plug SOC* during *green* and *orange* days means that **EV** owners would plug their car before reaching the parameterized *Minimal plug SOC* value and that they could benefit from the favorable meteorologic conditions to charge.

4.3 The *Vehicle to Grid*

EV participating in **V2G** restore some of the electricity stored in their batteries when the power grid has a high demand with respect to an average value following the command presented in Section 3.2. We simulate that there is just a little capacity of the battery used in the **V2G** with the view to impacting as less as possible the battery life cycle. As a condition for restoring some electricity to the power grid, the battery needs to be charged at least at the value set by the parameter *minimal V2G SOC* and it is the remaining percentage of the capacity that provides the service following the control signal.

The **EV** participating in **V2G** are selected through an uniform distribution depending on the parameter *V2G acceptance*. The service is exclusively provided when **EV** are at home and by **EV** that are not used to go to work or that have access to a charging point at workplace. The maximal power that an **EV** can restore to the grid is the parameter *Discharge power*.

4.4 The Power delivery for **EV**

For each **EV** n we simulate the power by time step t of one hour during the whole week.

- If the vehicle is not plugged following the conditions presented in Section 4.2 the power is 0.
- If the **EV** participates in **V2G**, the command signal indicates $V2G_t = 1$ and the vehicle satisfies the conditions indicated in the previous Section, the power is the estimated $-p_{n,t}$.
- If the **EV** is plugged, the **SOC** is lower than the battery capacity and the parameter *Natural charge* is activated, the power is the maximal value $Q_{n,t}$ that has been attributed depending on the location (home or workplace).
- If the parameter *Optimal charge* is activated but the **SOC** is lower than the *Minimal charge SOC*, the **EV** charges at maximal power until it reaches the minimal **SOC** necessary to

follow the optimal charge signal.

- If there are less than 3 remaining hours before the next trigger time t_{tr} and the vehicle was not charging ($p_{n,t-1} = 0$), the power is 0. With this we prevent a peak load on the power grid since the algorithm would try to charge at maximal power to reach the target SOC \mathcal{E} by the time of the t_{tr} .
- If the EV is in *Optimal charge* mode and satisfies the conditions to follow the command signal, the power is $p_{n,t}$ estimated in Equation 3.4. If ever this calculation is higher than the maximal available power, the power is the maximal value.

5 Results

Our simulator has several parameters that can be set to recreate multiple possible scenarios. Though, for the aim of this manuscript if we try to combine all parameters, the number of results would be exponential. We have chosen the parameters we think can give the most interesting and relevant results. We found that they are not the same for France and for Germany, so we present results separately.

5.1 Simulations for France

Some parameters remain unchanged for all the simulations we present hereafter for France :

- The target SOC method is the continuous one presented in Equation 3.1.
- Half of the EV fleet has a battery capacity of 50 kWh and the other half has 20 kWh.
- 70% of home chargers are 3 kW with the remaining 30% at 7 kW while 70% of work chargers are 7 kW with the remaining 30% at 3 kW.
- The V2G power is 7 kW.

The first simulation we want to present is to show the effect of the natural charge against an optimal charge. For this example we recreate a scenario with the same energy mix as today in France and we consider that there is only 10% of the total particular cars ($\sim 32M$) that

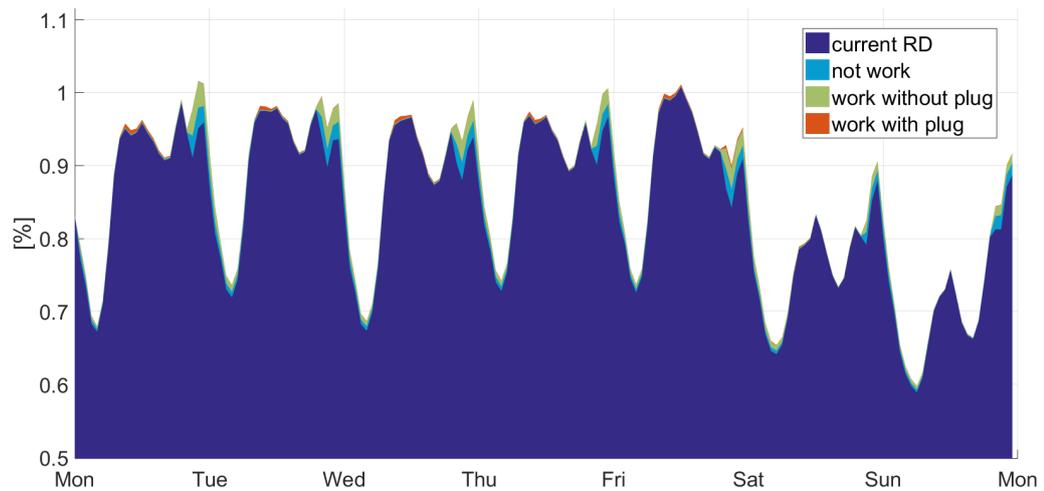
are EV. The natural charge follows the same plug behavior as the optimal one but the power charge is maximal until reaching the total EV battery capacity. The work plug availability is 15%.

In this case the number of EV is much lower than what is expected for the next decades. Though, we observe that there is already an impact in the power grid. The main outcome of this simulation is that the *natural charge* of the vehicles takes place at peak hours as shown in Figure 3.15a. This entails the appeal of more expensive and pollutant power plants or the risk of failure if these conventional systems are not available any more. Through the application of the algorithm we aim at improving these results. Figure 3.15b shows how the *optimal charge* would shift the demand to valley hours when there is less stress on the power grid.

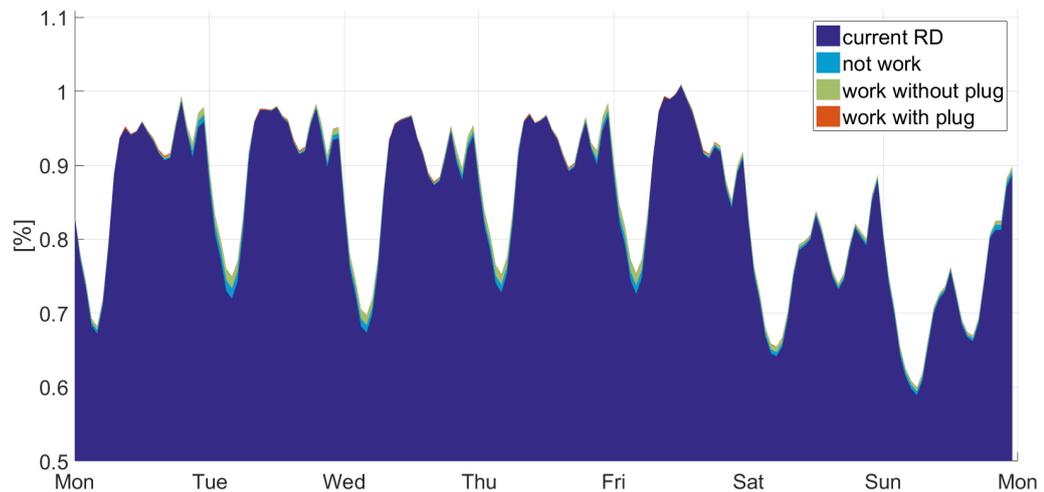
The next simulations are all in optimal charge mode.

We situate this analysis some years later but well before the 2050 horizon. By this time the electricity markets will have probably changed in a radical way and this is out of the scope of our research. In the meantime, an important percentage of the particular cars fleet is supposed to be switched into non pollutant engines. For the following simulations we consider that this goal is reached at least at a level of 70% EV over the total fleet. By the same time the energy mix will be different from what it is today. For this case we use the scenario N03 from the French TSO RTE report [RTE, 2021] where the PV is expected to be 7 times the current capacity and the wind to be 2.5 times the current installed capacity. This is the most basic proposed scenario for 2050 and therefore we consider that it is reachable in a sooner horizon. The most ambitious scenario goes until 21 times the current PV installed capacity and 4 times the current wind power installed capacity without any nuclear. Considering the requirements of flexibility as we explained in Section 2.3, variations would be extremely constraining to the power grid. In both scenarios, the significant capacity of PV creates deep valleys during the days while the wind, with its undefined patterns, can change the shape of the curve at any moment of the day and at any day of the week.

In the first case, shown in Figure 3.16a, we simulate the same low quantity of charging points at work as in the previous simulation (15%). Even if the charge follows an optimal signal, the lack of charging points also produces an impact on peak hours since the batteries charge takes place mainly at home during the nights when residual demand is higher. In the case presented in Figure 3.16b we increased the number of charging points at work to 80%. EV having access to these charging points help decrease the variations of residual demand because they fill the bottom of the valleys produced by PV during the day when they are parked at work places. In



(a) Natural charge



(b) Optimal charge

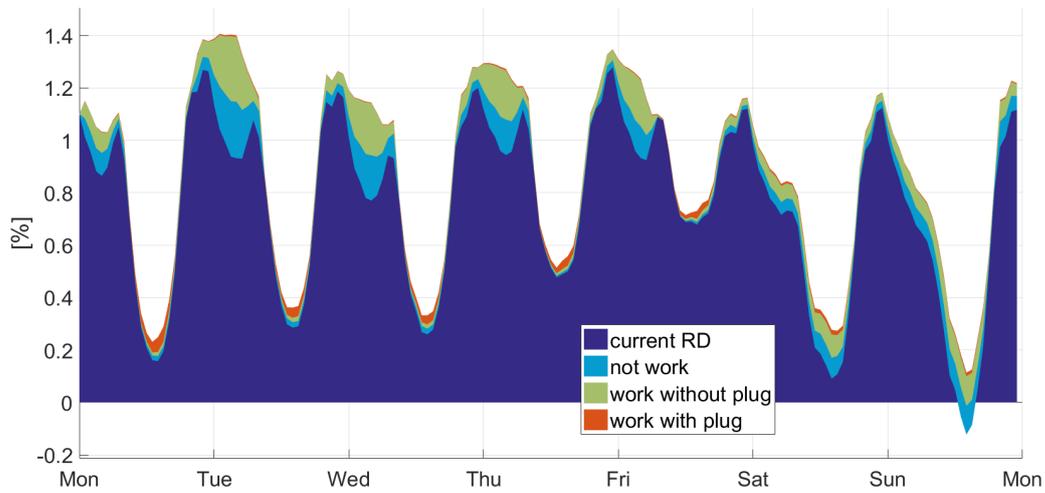
FIGURE 3.15 – Natural and optimal charge comparison for a week of summer in 2019. 10% of EV with the electricity mix as it is today.

Unit : %.

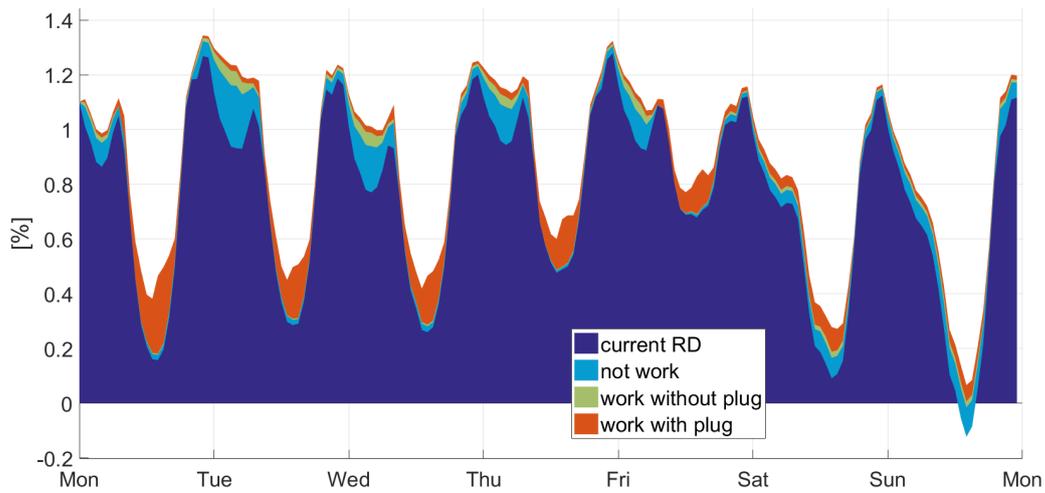
Source : authors.

Figure 3.17a we set at 70% the quantity of EV that would accept to charge their car under an instruction coming from the DSO or the TSO. More of the EV which are not used to go to work accept to plug and charge during the day filling more the valleys produced by PV. Finally, Figure 3.17b shows a simulation with V2G included where the highest peaks of the week are shaved. Figure 3.18 shows the evolution of the residual demand when applying the optimal charge and changing the described parameters. The red line presents the initial case of natural charge and the green one presents the optimal charge with V2G included. Variation from valley hours to

peak hours passes from an amplitude of 189% to 126% with respect to the average value (100%).



(a) With 15% of available charging points at work.

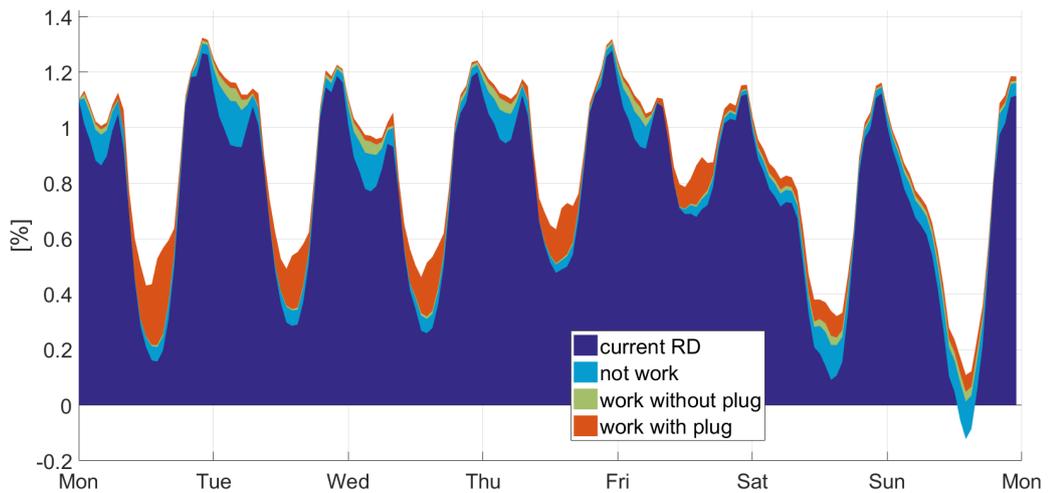


(b) With 80% of available charging points at work.

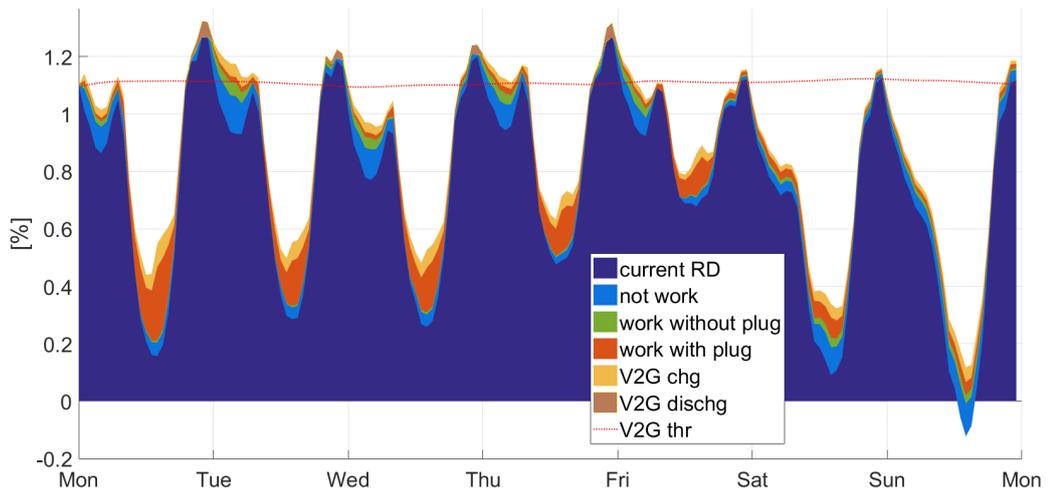
FIGURE 3.16 – Scenarios for France with 7 times the current PV installed capacity, 4 times the wind power and 70% of EV. It is a summer week in 2019.

Unit : %.

Source : authors.



(a) With 70% of advised charge acceptance.



(b) The effect of 20% of the EV fleet participating in V2G for a week in summer.

FIGURE 3.17 – Scenarios for France with 7 times the current PV installed capacity, 4 times the wind power and 70% of EV. It is a summer week in 2019.

Unit : %.

Source : authors.

5.2 Simulation for Germany

The case of Germany is different from the French one because of the advance it has in terms of REn and the small share of nuclear in the electricity production. Their flexibility requirements are already variable and it is much harder to find repetitive patterns during the week. Figure 3.19 shows the residual demand for three different and random weeks during the winter 2021. The deeper valleys are during the nights when there are probably important wind streams while

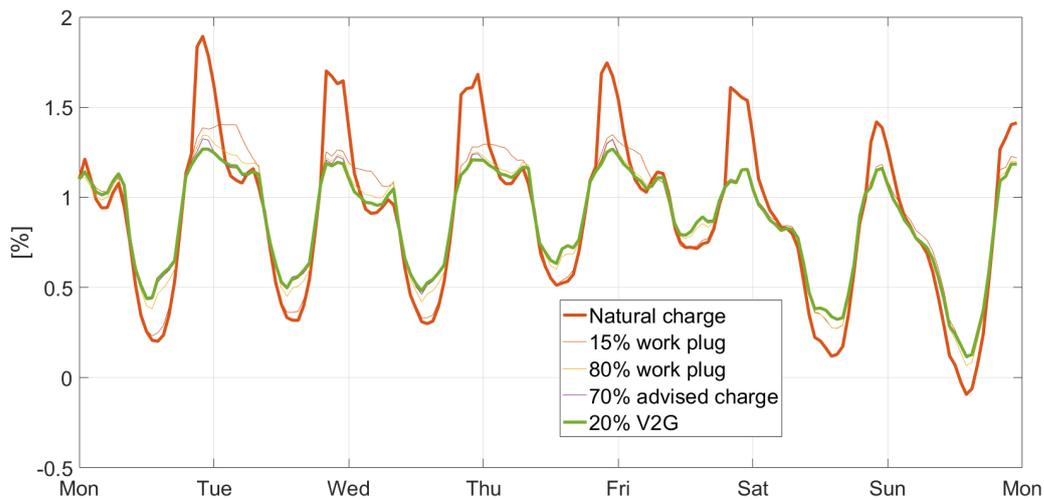


FIGURE 3.18 – Evolution of the residual demand curve from natural charge to optimal charge improving the most impacting parameters until the application of **V2G** for one same week of summer in France. With 7 times the current **PV** installed capacity, 4 times the wind power and 70% of **EV**.
Unit : %.
Source : authors.

the daily valleys are smaller (or even do not exist as for example on Monday for the blue curve) since there is not a significant **PV** production.

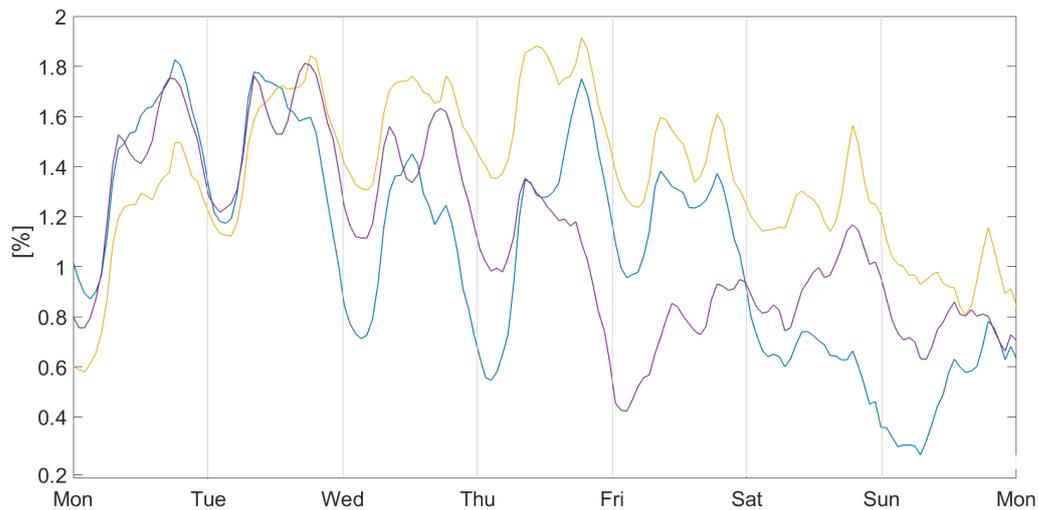


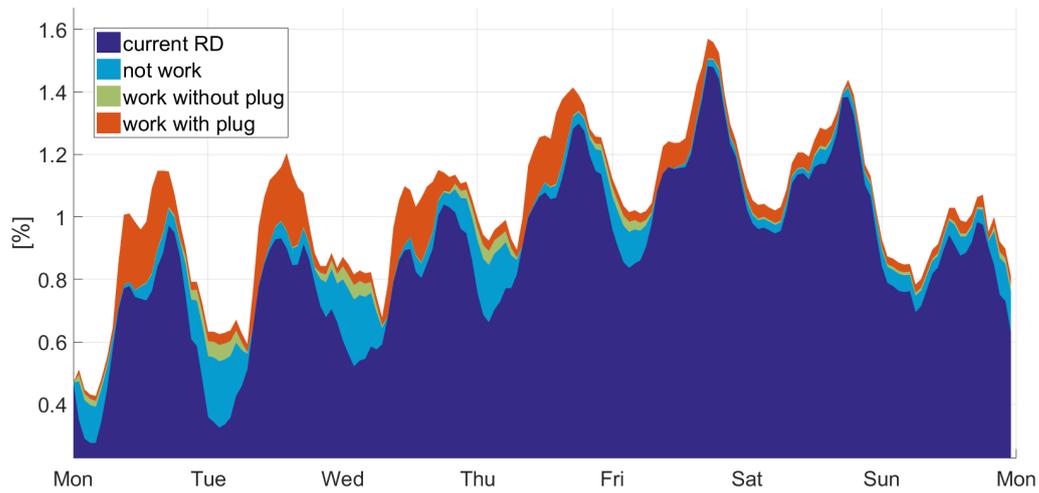
FIGURE 3.19 – Residual demand for three random week of winter 2021 in Germany.
Unit : %.
Source : authors with data from ENTSO-E.

For the German simulations we use the same energy mix as it is today. We want to show the

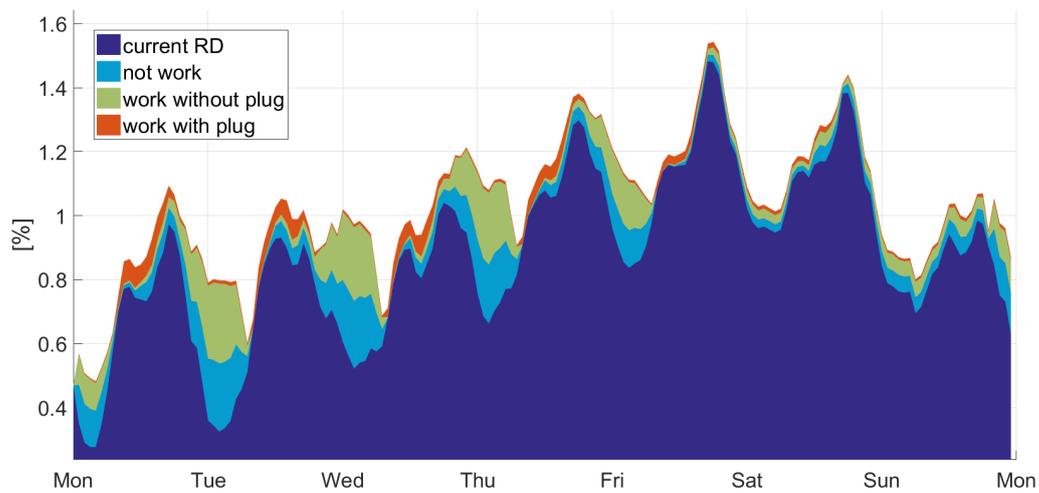
impact **EV** could have since now and therefore, how they could be an even more important tool if the energy mix continues to change towards **REn**.

We keep some of the assumptions from simulations for France. We consider the same share of 50% between the battery capacities of 20 kWh and 50 kWh as well as the share of the charge powers modifying the 7 kW chargers to 11 kW. The total particular cars fleet is 48 million and we simulate 50% is **EV**.

Figure 3.21 presents two different scenarios for Germany analyzed in winter and in summer. In the first one (Figure 3.20a) there is a significant number of **EV** that privileges the recharge at work because they have access to a charging point during the day. Unlike France, in Germany the power grid does not benefit from this daily recharge in winter months since the residual demand is higher and **EV** increase the existing peak. **EV** owners should be incentivised to privilege their charge during the nights as shown in Figure 3.20b where there is only 25% of the **EV** fleet that access to a charging point at work. In summer months (Figures 3.21a and 3.21b) with deeper daily valleys produced by a significant **PV** production, the best results are obtained when the recharge of **EV** at work is combined with the recharge of **EV** that are not used to go to work at night. The resultant residual demand curve is smoother.



(a) With 85% of available charging points at work in winter.

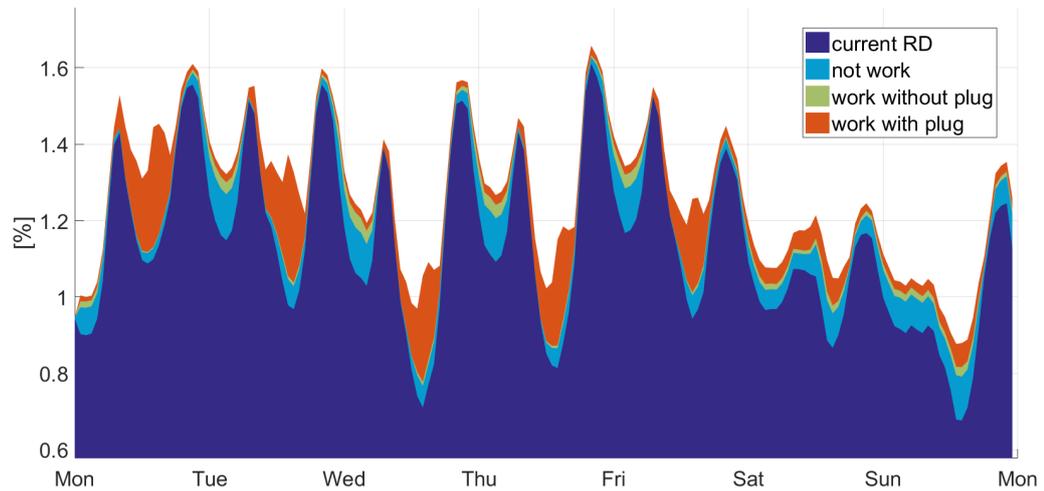


(b) With 25% of available charging points at work in winter.

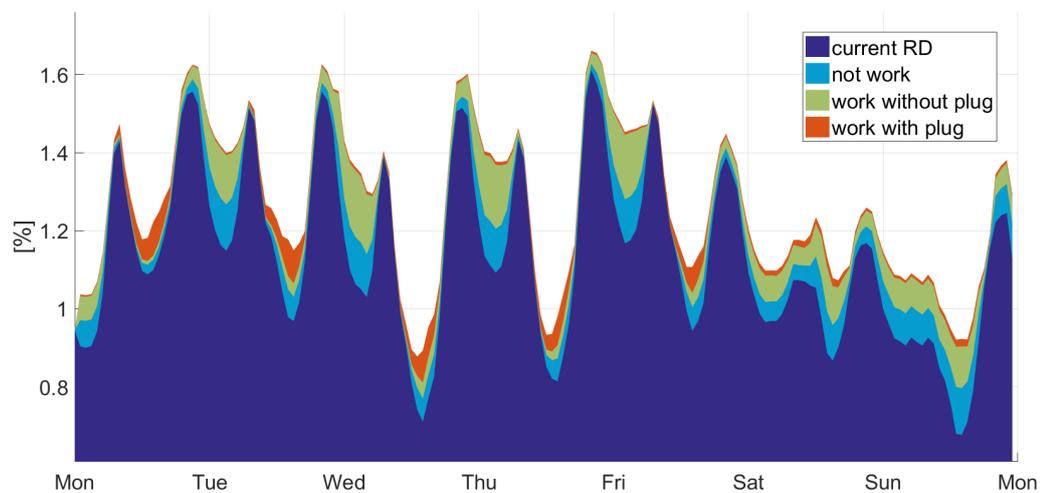
FIGURE 3.20 – Two scenarios of work plug availability for winter in Germany. 50% of EV and the electricity mix as it is today.

Unit : %.

Source : authors.



(a) With 85% of available charging points at work in summer.



(b) With 25% of available charging points at work in summer.

FIGURE 3.21 – Two scenarios of work plug availability for summer in Germany. 50% of EV and the electricity mix as it is today.

Unit : %.

Source : authors.

6 A practical application

Finally, to conclude this chapter we present the practical application of the smart charge system in an actual EV. It was a Renault ZOE with a battery of 52 kWh. Before the implementation we have evaluated the possible ways to integrate the smart charge algorithm we present in Section 3.2 of this chapter. We found three possible solutions :

The first one was to use the charging point to modulate the power output. The second one was to use the *Battery Management System* (BMS) inside the EV. Both solutions are complex and require software and hardware manipulation. This involves an administrative procedure inside the carmakers' hierarchy that could take several years to result in a viable solution. Therefore, our third solution was to use the cloud system that is already used by EV owners to remotely program the charge or some other comfort functions like turning on the heating system before a trip. This solution doesn't require any software neither hardware manipulations and therefore its implementation would be easier than the other two options.

We have used existent Python libraries (aiohttp, to access the EV charge through the user's account. We wrote a code that estimates the value of the target SOC using the Equation 3.8 derived from Equation 3.4. Every five minutes (this could be a different time) we read the value of the EV SOC. If the SOC is higher than the target SOC, we stop the charge. Otherwise, we continue charging.

$$s_{n,t} = \mathcal{E}_T - \int_t^T x_t dt \times \left(\frac{\mathcal{E}_T - s_{n,0}}{\int_{t_0}^T x_t dt} \right) \quad (3.8)$$

Considering the favorable results from the implementation test, we propose a simple and economical solution to implement the smart charge algorithm in an EV fleet using the communication method proposed in Figure 3.22. The time response of the EV when sending a start or stop charge signal is around 50 seconds. This is not a limitation for the application of the algorithm.

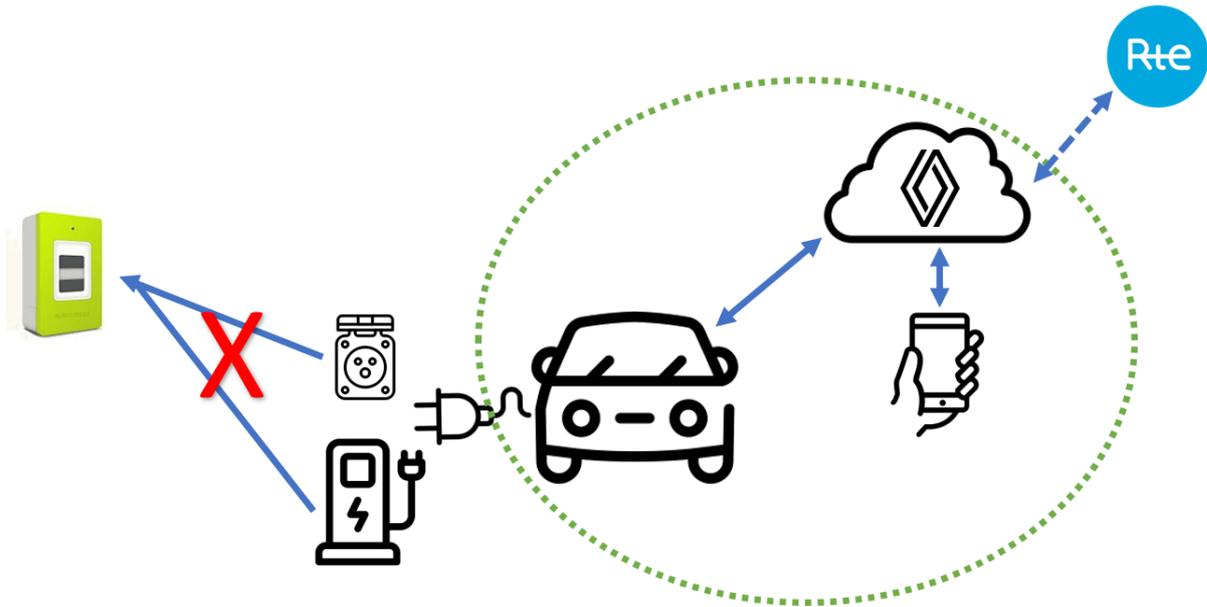


FIGURE 3.22 – Proposed communication diagram between **EV** and the carmaker’s cloud taking public data from **DSO/TSO** about the electricity consumption.

Source : authors.

7 Conclusion

In this chapter We have presented the solution of an optimal control model applied as a smart charge algorithm for an **EV** fleet. The algorithm is composed of two different signals which are estimated using the residual demand as reference value.

The first signal operates as an energy modulator that captures the most appropriated moments over a period of one week to charge **EV**. The virtual battery, composed by the aggregation of the **EV** fleet batteries, reaches a higher or a lower **SOC** depending on the state of the power grid with respect to the ± 3.5 days. For example, the days when demand is low or **REn** production is high, the target **SOC** is higher.

The second signal operates as a power modulator within a period of half a day. This reference value allows to fill the valleys of the day to try to approach the new residual demand (the current residual demand plus the demand coming from **EV**) to a smoother curve estimated through a moving average value over one week. When applying this reference value, the power charge is maximum at the moments when valleys are deeper.

Next, we have implemented this smart charge algorithm in a simulation tool developed to

analyze the impact of the adoption of a significant EV fleet. The simulator has multiple parameters that we have varied and we found out :

- With higher penetration of RE_n the flexibility requirements in short term are more obvious and less predictable. Adjustments need to be closely monitored.
- The EV charge is a flexibility facility that should be programmed differently depending on the season.
- In winter for example, in a power system like the German, the EV charge should be prioritized during the nights when high air streams produce a low residual demand. While in summer, *Photovoltaics* (PV) generation produces a lower residual demand during the day and therefore, the EV charge is more useful during these hours of the day.
- To achieve a high level of smart charge that responds to different possible variation of the power grid, it is necessary to have a robust recharge infrastructure.
- The ideal recharge infrastructure is a highly deployed one with low powers. High power charge doesn't bring flexibility to the power grid, however, it could create undesirable peaks.
- The batteries capacity has an important effect on the smart charge system. We observed that even small batteries (20 kWh) can contribute to bring flexibility to the power grid but in a daily window. A one week optimal charge is less feasible with these batteries but their contribution to do peak shaving could be significant.
- The acceptance from EV owners of a smart charge system is fundamental. A better acceptability is a more important available capacity to bring flexibility to the power grid.

3.A Matlab codes

```

clear
clc
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%INPUT PARAMETERS FOR ALGORITHM %%%%%%%%%%
Country = 1; %1 for Germany 2 for France
%April to september is summer and the rest of the year is winter
if Country == 1
    %Input signal from excel file (data in MW per time step)
    conso = importdata('RD_Germany_19-20-21-22.txt'); %this file has the total load
    minus waste, biomass (and hydro run of river for GE)
    prod_PV = importdata('PV_Germany_19-20-21-22.txt');
    prod_WD = importdata('WD_Germany_19-20-21-22.txt');
    price = importdata('price_Germany_19-20-21-22.txt');

    %High and Low thresholds (1) for winter and (2) for summer
    H_threshold = 130;
    L_threshold = [115 115];

    %Week average correction in MW(1) for winter and (2) for summer
    week_aver_cor(1,:,1) = [0 0.2] ;
    week_aver_cor(1,:,2) = [0.15 0.5] ;

    %Triggers (1) for winter and (2) for summer
    trig_V2G = 4;
    trigger_time(:, :, 1) = [8 17; 8 17; 8 17; 8 17; 8 17; 17 18; 20 21]; %col1:
    trigger (diurnal charge) col2: half day trigger (nocturnal charge)
    trigger_time(:, :, 2) = [9 21; 9 20; 9 20; 9 21; 8 20; 19 21; 19 20]; %col1:
    trigger (diurnal charge) col2: half day trigger (nocturnal charge)

    Total_cars = 48; %in millions
else
    %Input signal from excel file (data in MW per time step)
    conso = importdata('RD_France_19-20-21-22.txt'); %this file has the total load
    minus waste, biomass (and hydro run of river for GE)
    prod_PV = importdata('PV_France_19-20-21-22.txt');
    prod_WD = importdata('WD_France_19-20-21-22.txt');
    price = importdata('price_France_19-20.txt');

    %High and Low thresholds (1) for winter and (2) for summer
    H_threshold = -47;
    L_threshold = [-52 -52];

    %Week average correction in MW (1) for winter and (2) for summer
    week_aver_cor(1,:,1) = [-0.04 -0.04] ;
    week_aver_cor(1,:,2) = [0.15 0.5] ;

    %Triggers (1) for winter and (2) for summer
    trig_V2G = 4;
    trigger_time(:, :, 1) = [8 20; 9 20; 9 20; 8 20; 8 20; 17 18; 19 20]; %col1:
    trigger (diurnal charge) col2: half day trigger (nocturnal charge)
    trigger_time(:, :, 2) = [9 21; 9 21; 9 20; 9 21; 8 20; 19 21; 19 20]; %col1:
    trigger (diurnal charge) col2: half day trigger (nocturnal charge)

```

```
Total_cars = 32; %in millions
end

fact_PV = 1;
fact_WD = 1;
input = conso - fact_PV*prod_PV - fact_WD*prod_WD ; %data in %
av_input = mean(input);
input_perc = input / av_input;
input_step = 1 ; %time step of input data in an hour basis
input_l = length(input); %number of input data
days = input_l / input_step / 24 ; %number of days in the input data
daily_data = input_l / days ;
date_ini = datetime('01-Jan-2019'); %initial date of input data
dates = date_ini + caldays(0:days-1)' ; %array with the whole dates for input data
dates_numb = datenum(dates);
month_numb = month(dates);
week_day = weekday(dates_numb); %sunday = 1
week_day = week_day - 1;

tempo_vector2 = datetime(date_ini:hours:dates(end)+1);
tempo_vector2(end)=[];

for p = 1 : days
    if week_day(p) == 0
        week_day(p) = 7;
    end
end

%V2G threshold is in MW
V2G_threshold = 1.2;
V2G_threshold_cor = 0.35 ;

AV_threshold = [(H_threshold+L_threshold(1))/2, (H_threshold+L_threshold(2))/2];

VGI_optim
Average_distribution
```

```

days_average = 7; %over how many days will be calculated the seasonal average
r = (days_average * 24/input_step)/2;
seas_aver = movmean(input_perc, [r-1,r]);

price_aver = movmean(price, [r-1,r]);

%seasonal trend filtering
Delta_seas = (input_perc - seas_aver) ; %if Delta is >0 it is a good moment to
charge (residual demand is under the average value)

%integral of Delta
CUM_Delta = zeros(input_l,1);
for i = 2 : input_l
    CUM_Delta(i) = (CUM_Delta(i-1) - Delta_seas(i)) * input_step;
end

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%VIRTUAL SOC BATTERY

%capped integral. Delta is an image of expected power distribution,
%integral is image of energy
CUM_Delta_cap = zeros(input_l,1);
CUM_Delta_cap(1) = H_threshold;
for i = 2 : input_l
    d = ceil(i / 24) ;
    if CUM_Delta_cap(i-1) - Delta_seas(i) > H_threshold
        CUM_Delta_cap(i) = CUM_Delta_cap(i-1);
    elseif month_numb(d) > 3 && month_numb(d) < 10 && (CUM_Delta_cap(i-1) -
Delta_seas(i)) < L_threshold(2)
        CUM_Delta_cap(i) = CUM_Delta_cap(i-1);
    elseif (month_numb(d) < 4 || month_numb(d) > 9) && (CUM_Delta_cap(i-1) -
Delta_seas(i)) < L_threshold(1)
        CUM_Delta_cap(i) = CUM_Delta_cap(i-1);
    else
        CUM_Delta_cap(i) = CUM_Delta_cap(i-1) - Delta_seas(i);
    end
end

%target SOC 0-100% in allowed area per time step; including limitation
%under 100% (battery full) and 0% (lower level of allowed area)
Target_SOC = zeros(input_l,1);
for i = 1 : input_l
    d = ceil(i / 24) ;
    if month_numb(d) > 3 && month_numb(d) < 10
        if CUM_Delta_cap(i) - AV_threshold(2) > 0
            Target_SOC(i) = 0.5 + (CUM_Delta_cap(i) - AV_threshold(2)) /
(H_threshold - AV_threshold(2)) / 2 ;
        else
            Target_SOC(i) = 0.5 - (CUM_Delta_cap(i) - AV_threshold(2)) /
(L_threshold(2) - AV_threshold(2)) / 2 ;
        end
    else
        if CUM_Delta_cap(i) - AV_threshold(1) > 0

```

```

        Target_SOC(i) = 0.5 + (CUM_Delta_cap(i) - AV_threshold(1)) / ↵
(H_threshold - AV_threshold(1)) / 2 ;
    else
        Target_SOC(i) = 0.5 - (CUM_Delta_cap(i) - AV_threshold(1)) / ↵
(L_threshold(1) - AV_threshold(1)) / 2 ;
    end
end
end

% columns 1 for trigger (diurnal charge) and columns 2 for half day trigger
% (nocturnal charge)
seas_aver_cor = zeros(input_1,1);
%%% OUTPUT target SOC
Out_Target_SOC = zeros(days,2,2);
opt_day_aver = zeros(days,2);

for d = 1 : days-1

    if month_numb(d) > 3 && month_numb(d) < 10
        win_sum = 2;
    else
        win_sum = 1;
    end

    day = week_day(d);

    if week_day(d) == 7
        nxt_day = 1;
    else
        nxt_day = week_day(d)+1;
    end

    j = (d-1)*daily_data + (trigger_time(day,2,win_sum)+1) ;
    k = d*daily_data + (trigger_time(nxt_day,1,win_sum)+1) ;
    m = (d-1)*daily_data + (trigger_time(day,1,win_sum)+1) ;

    Out_Target_SOC(d,:,2) = [Target_SOC(j),Target_SOC(k)]; %Out target SOC ↵
continuous

    seas_aver_cor(m:j-1)=seas_aver(m:j-1)+week_aver_cor(1,1,win_sum);
    seas_aver_cor(j:k-1)=seas_aver(j:k-1)+week_aver_cor(1,2,win_sum);

    opt_day_aver(d,1) = mean(Delta_seas(m:j-1));
    opt_day_aver(d,2) = mean(Delta_seas(j:k-1));

    threshold1 = mean(opt_day_aver(opt_day_aver > 0));
    threshold1 = mean(threshold1);
    threshold2 = mean(opt_day_aver(opt_day_aver < 0));
    threshold2 = mean(threshold2);

    if opt_day_aver(d,:) < threshold2
        Out_Target_SOC(d,:,1) = 1; %Out target SOC 1 is by steps (60% - 80% - ↵
100%)

```

```
elseif opt_day_aver(d,:) > threshold1
    Out_Target_SOC(d,:,1) = 0.6;
else
    Out_Target_SOC(d,:,1) = 0.8;
end
end

Delta_seas_cor = (seas_aver_cor - input_perc) .* ((seas_aver_cor - input_perc) > 0) ↵
;
```

```

t = 24/input_step ;
profile= zeros(t,7,2); %1 for winter, 2 for summer
counter = zeros(t,7,2);

for i = 1 : input_1
    d = ceil(i/daily_data);
    h = i - (d-1)*daily_data;
    if month_numb(d) > 3 && month_numb(d) < 10
        profile(h,week_day(d),2) = profile(h,week_day(d),2) + Delta_seas_cor(i);
        counter(h,week_day(d),2) = counter(h,week_day(d),2) + 1 ;
    else
        profile(h,week_day(d),1) = profile(h,week_day(d),1) + Delta_seas_cor(i);
        counter(h,week_day(d),1) = counter(h,week_day(d),1) + 1 ;
    end
end

Xt1 = zeros(daily_data,7,2); %not normalized values
Xt = zeros(daily_data,7,2); %normalized values

for i = 1 : daily_data
    for j = 1 : 7
        Xt1(i,j,1) = profile(i,j,1)/counter(i,j,1);
        Xt1(i,j,2) = profile(i,j,2)/counter(i,j,2);
    end
end

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
Sum_Xt = zeros(t,7,2);
Int1_Xt = zeros(t,7,2);
Int_Xt = zeros(t,7,2); %es el porcentaje que va a faltar por cargar al final de la hora
%valeurs au début du pas de temps. A trigger time = 0.
for j = 1:2
    m = sum(Xt1(trigger_time(7,2,j)+1:24,7,j));

    for d = 1:7
        for h = 1:daily_data
            if d == 1 && h == 1
                Sum_Xt(h,d,j) = m + Xt1(h,d,j);
            elseif d ~= 1 && h == 1
                Sum_Xt(h,d,j) = Sum_Xt(24,d-1,j) + Xt1(h,d,j);
            elseif h ~= trigger_time(d,1,j)+2 && h ~= trigger_time(d,2,j)+2
                Sum_Xt(h,d,j) = Sum_Xt(h-1,d,j) + Xt1(h,d,j);
            else
                Sum_Xt(h,d,j) = Xt1(h,d,j);
            end
        end
    end

    for d = 1:7
        for h = 1:daily_data

```

```

if h <= trigger_time(d,1,j)
    Int1_Xt(h,d,j) = Sum_Xt(trigger_time(d,1,j)+1,d,j) - Sum_Xt(h,d,j) ↵
;
    Int_Xt(h,d,j) = Int1_Xt(h,d,j) / Sum_Xt(trigger_time(d,1,j)+1,d,j);
elseif h == trigger_time(d,1,j)+1
    Int1_Xt(h,d,j) = Sum_Xt(trigger_time(d,2,j)+1,d,j);
    Int_Xt(h,d,j) = Int1_Xt(h,d,j) / Sum_Xt(trigger_time(d,2,j)+1,d,j);
elseif h > trigger_time(d,1,j)+1 && h <= trigger_time(d,2,j)
    Int1_Xt(h,d,j) = Sum_Xt(trigger_time(d,2,j)+1,d,j) - Sum_Xt(h,d,j) ↵
;
    Int_Xt(h,d,j) = Int1_Xt(h,d,j) / Sum_Xt(trigger_time(d,2,j)+1,d,j);
elseif h == trigger_time(d,2,j)+1
    if d == 7
        Int1_Xt(h,d,j) = Sum_Xt(trigger_time(1,1,j)+1,1,j);
        Int_Xt(h,d,j) = Int1_Xt(h,d,j) / Sum_Xt(trigger_time(1,1,j)+1, ↵
1,j);
    else
        Int1_Xt(h,d,j) = Sum_Xt(trigger_time(d+1,1,j)+1,d+1,j);
        Int_Xt(h,d,j) = Int1_Xt(h,d,j) / Sum_Xt(trigger_time(d+1,1,j) ↵
+1,d+1,j);
    end
elseif h > trigger_time(d,2,j)+1 && d == 7
    Int1_Xt(h,d,j) = Sum_Xt(trigger_time(1,1,j)+1,d,j) - Sum_Xt(h,d,j) ↵
;
    Int_Xt(h,d,j) = Int1_Xt(h,d,j) / Sum_Xt(trigger_time(1,1,j)+1,d,j);
else
    Int1_Xt(h,d,j) = Sum_Xt(trigger_time(d+1,1,j)+1,d+1,j) - Sum_Xt(h, ↵
d,j) ;
    Int_Xt(h,d,j) = Int1_Xt(h,d,j) / Sum_Xt(trigger_time(d+1,1,j)+1, ↵
d+1,j);
end
end
end

for d = 1:7
    for h =1:daily_data
        if h <= trigger_time(d,1,j)
            Xt(h,d,j) = Xt1(h,d,j) / Sum_Xt(trigger_time(d,1,j),d,j) ;
        elseif h > trigger_time(d,1,j) && h <= trigger_time(d,2,j)
            Xt(h,d,j) = Xt1(h,d,j) / Sum_Xt(trigger_time(d,2,j),d,j);
        elseif h > trigger_time(d,2,j) && d == 7
            Xt(h,d,j) = Xt1(h,d,j) / Sum_Xt(trigger_time(1,1,j),1,j) ;
        else
            Xt(h,d,j) = Xt1(h,d,j) / Sum_Xt(trigger_time(d+1,1,j),d+1,j);
        end
    end
end
end
end

```

```

#####GENERAL PARAMETERS FOR SIMULATION #####
General_parameters_algo

load location.mat;
load consumption.mat;
load daily_conso.mat;
load input_data;

simul_weeks = 52;
date_start = datetime('07-Jan-2019'); %initial date of input data
SOC_method = 2; %0 for 100%, 1 for steps and 2 for continuous
advice_charge_accept = 0.5; %(0 mandatory if natural charge (nat_opt=1 -->
day_charge_accept=0)
nat_opt = 2 ; %1 for natural charge and 2 for optimal charge
V2G_accept = 0.2; %%
#####PARAMETERS#####
tstep = 1; %output step in hours
time_step = tstep / daily_data; %in days
conso_km = 0.18; % this is 18 kWh/100km energy consumption in 100km
conso_min = 7; %kWh/h minimal energy consumption in 1 hour
#####
Qty_EV = 0.5; %percentage of the total fleet
battery_capacity1 = 50;
battery_capacity2 = 20;
perc_bat_cap1 = 0.5; %percentage of the fleet with the capacity 1 (1-perc_bat_cap1)
is the rest of the fleet with the capacity 2
#####
work_plug_avail = 0.5;
P_chg_1 = 3;
P_chg_2 = 11;
Perc_chg1_home = 0.7; %percentage of chargers with power 1 at home (perc_power2 = 1
- Perc_chg1_home)
Perc_chg1_work = 0.3; %percentage of chargers with power 1 at work (perc_power2 = 1
- Perc_chg1_work)
P_V2G = 7;
#####
EV_ID = unique(T.ID_EV);
EV_qty_ENTD = length(EV_ID);
work = unique(T.ID_EV(T.motif == 9.91,:)); %EV that are used to go to work
unif_dist = rand(EV_qty_ENTD,1);
unif_dist2 = rand(EV_qty_ENTD,1);
%% T2 is the table with 1 row by EV containing all its information
T2 = table();
T2.EV_ID = EV_ID;
T2.bat_capacity = ((unif_dist2 <= perc_bat_cap1) * battery_capacity1) +
((unif_dist2 > perc_bat_cap1) * battery_capacity2);
T2.long_trip = T2.bat_capacity;
T2.SOC_init = 0.5 * T2.bat_capacity;
T2.SOC_min = 0.2 * T2.bat_capacity;
T2.SOC_min_friday = 0.75 * T2.bat_capacity;
T2.SOC_min_red_day = 0.4 * T2.bat_capacity;
T2.SOC_min_orange_day = 0.6 * T2.bat_capacity;
T2.SOC_min_green_day = 0.8 * T2.bat_capacity;

```

```
T2.SOC_min_plug = T2.SOC_min_red_day;
T2.SOC_min_V2G = 0.6 * T2.bat_capacity;
T2.work = ismember(EV_ID,work);
T2.prob_plug_work = rand(EV_qty_ENTD,1) .* T2.work;
T2.prob_V2G = rand(EV_qty_ENTD,1);
T2.prob_plug_advice = unif_dist ;
T2.chg_advice = (T2.prob_plug_advice <= advice_charge_accept);
T2.work_plug = (T2.work & T2.prob_plug_work <= work_plug_avail);
T2.V2G = (T2.prob_V2G <= V2G_accept) & (T2.work_plug | ~T2.work);
T2.home_power = ((unif_dist <= Perc_chg1_home) * P_chg_1) + ((unif_dist > Perc_chg1_home) * P_chg_2);
T2.work_power = (((unif_dist >= (1 - Perc_chg1_work)) * P_chg_1) + ((unif_dist < (1 - Perc_chg1_work)) * P_chg_2)) .* T2.work ;
max_trip = max(daily_conso,[],2);
T2.long_trip = (max_trip >= T2.long_trip);
T2.outside_chg = T2.work.*0;
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
time_vector = (1 : time_step : 8);
l = length(time_vector) - 1;
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
sample_work_plug = sum(T2.work & T2.work_plug & ~T2.V2G);
sample_work_not_plug = sum(T2.work & ~T2.work_plug & ~T2.V2G);
sample_not_work = sum(~T2.work & ~T2.V2G);
sample_V2G = sum(T2.V2G);
% %%%%%%%%% codes execution %%%%%%%%%
V2G
plug_charge_SOC3
Graph
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%% V2G
```

```
sample_V2G = sum(T2.V2G);
```

```
V2G_t = max(seas_aver + V2G_threshold_cor,V2G_threshold);
```

```
Delta_V2G = (input_perc - V2G_t) .* ((input_perc - V2G_t) > 0);
```

```
CUM_V2G = zeros(days,1);
```

```
Out_V2G = zeros(input_l,1);
```

```
for d = 1 : days-1
```

```
    j = (d-1) * daily_data + (trig_V2G + 1 / input_step) ;
```

```
    k = j + daily_data - 1;
```

```
    CUM_V2G(d) = sum(Delta_V2G(j:k));
```

```
end
```

```
V2G_max_avail = (mean(T2.bat_capacity(T2.V2G == true)) - mean(T2.SOC_min_V2G(T2.V2G == true))) * sample_V2G * ((Total_cars * Qty_EV * 1000) / EV_qty_ENTD / av_input) ;
```

```
day_V2G_disch = (CUM_V2G / V2G_max_avail) * (V2G_max_avail > 0);
```

```
for i = 1 : (input_l - daily_data)
```

```
    k = floor(i/24) + 1;
```

```
    if CUM_V2G(k) > 0
```

```
        Out_V2G(i) = day_V2G_disch(k) * Delta_V2G(i) / CUM_V2G(k);
```

```
    end
```

```
end
```

```

SOC = zeros(EV_qty_ENTD,1);
power = zeros(EV_qty_ENTD,1);
SOC(:,1,:) = T2.SOC_init;
plug = zeros(EV_qty_ENTD,1);
time_vector = zeros(1,1);
power_V2G = zeros(EV_qty_ENTD,1);
prev1=zeros(EV_qty_ENTD,1);

time_vector1 = weekday(date_start) -1 ;
if time_vector1 == 0
    time_vector1 = 7;
end
time_vector(1) = time_vector1 + time_step;

for i = 2 : 1
    if round(time_vector(i-1) + time_step,4) > 8
        time_vector(i) = 1; % in days
    else
        time_vector(i) = time_vector(i-1) + time_step ;
    end
end

K = zeros(1,1);
date1 = date_start;

for k = 1 : simul_weeks
    p = find(dates == date1); %start position
    if month_numb(p) > 3 && month_numb(p) < 10
        win_sum = 2;
        work_plug_avail = 0.85;
    else
        win_sum = 1;
        work_plug_avail = 0.25;
    end
    T2.work_plug = (T2.work & T2.probab_plug_work <= work_plug_avail);
    T2.V2G = (T2.probab_V2G <= V2G_accept) & (T2.work_plug | ~T2.work);
    q = p + 6;
    Target_SOC = Out_Target_SOC(p:q, :, :);
    j = (p-1) * daily_data +1;
    signal_V2G = Out_V2G(j:j+1-1);
    threshold_V2G_t = V2G_t(j:j+1-1);
    in2 = input_perc(j:j+1-1);
    for i = 2 : 1
        dh = round(mod(time_vector(i),1),4); %hour in the day
        wd = floor(time_vector(i)); %week day
        if dh == 0 || dh == 1
            wd = wd - 1;
            dh = 1;
        end

        day_start = (trigger_time(wd,1,win_sum)/daily_data) ;
        night_start = (trigger_time(wd,2,win_sum)/daily_data) ;
    end
end

```

```

Pmax = (location(:,i) == 1) .* T2.home_power + (location(:,i) == 2) .* T2.
work_power;

if dh <= day_start
    if wd == 1
        m = 7;
        n = 2;
    else
        m = wd - 1;
        n = 2;
    end
elseif dh > day_start && dh <= night_start
    m = wd;
    n = 1;
else
    m = wd;
    n = 2;
end

if Target_SOC(m,n,1) == 1 %corresponds to green day
    SOC_plug_advice = T2.SOC_min_green_day;
elseif Target_SOC(m,n,1) == 0.8 %corresponds to orange day
    SOC_plug_advice = T2.SOC_min_orange_day;
elseif Target_SOC(m,n,1) == 0.6
    SOC_plug_advice = T2.SOC_min_red_day; %corresponds to red day
end

time2 = round(time_vector,4);
h24 = find(time2 == round(dh + time_vector1,4)); %for positioning over 24 h
if dh == 1
    h24 = 24;
end

if Int_Xt(h24,wd,win_sum) ~= 0
    K(i) = (Xt(h24,wd,win_sum) ./ Int_Xt(h24,wd,win_sum));
else
    K(i) = 0;
end

SOC1 = SOC(:,i-1) + power(:,i-1) - consumption(:,i-1);
%with w we indicate that if the SOC is 0 the EV does a fast charge
%and gets the full battery capacity instantaneously
w = SOC1 < 0 ;
SOC(:,i) = w .* T2.bat_capacity + ~w .* SOC1;

if SOC_method == 0
    smart_chg = ((T2.bat_capacity) - SOC(:,i)) .* K(i) ;
elseif SOC_method == 1
    smart_chg = ((T2.bat_capacity .* Target_SOC(m,n,1)) - SOC(:,i)) .* K
(i) ;
else
    smart_chg = ((0.6*T2.bat_capacity + (T2.bat_capacity - 0.6*T2.
bat_capacity) .* Target_SOC(m,n,2)) - SOC(:,i)) .* K(i) ;

```

```

end

available = location(:,i) == 1 | (location(:,i) == 2 & T2.work_plug);

%%%CASE OF FORCED CHARGE
case1 = available & (SOC(:,i) < T2.SOC_min); %& (SOC(:,i) < T2.
bat_capacity)

%%%SMART CHARGING
x = ~(case1 == true); %true if case1 is false

friday = (wd == 5 & dh > night_start) | (wd == 6 & dh <= day_start);
wknd = friday | (wd == 6 & dh > day_start) | (wd == 7 & dh <= night_start);
%wknd = friday | (wd == 6 & dh > day_start) | wd == 7 ;

if dh > day_start && dh <= night_start
    p1 = find(time2 == round(wd + night_start,4)) + 1;
elseif dh <= day_start
    p1 = find(time2 == round(wd + day_start,4)) + 1;
elseif dh > night_start && wd ~= floor(time_vector(1))-1
    p1 = find(time2 == round(wd + 1 + day_start,4)) + 1;
else
    p1 = find(time2 == round(time_vector1 + day_start,4)) ;
end
if p1 + 11 < 1
    prev1(:,i) = sum(consumption(:,p1:p1+11),2);
else
    prev1(:,i) = sum(consumption(:,p1:1),2) + sum(consumption(1:
day_start*daily_data),2);
end

prevision = SOC(:,i) < (T2.SOC_min + prev1(:,i));

advised_charge = T2.chg_advice & SOC(:,i) < SOC_plug_advice;

plug_home1 = (~T2.work | (T2.work & ~T2.work_plug)) & (prevision |
advised_charge | (~T2.chg_advice & SOC(:,i) < T2.SOC_min_plug & dh >=
night_start));
%plug_home1 = (prevision | advised_charge | (~T2.chg_advice & SOC(:,i) <
T2.SOC_min_plug & dh >= night_start));
plug_home2 = (T2.work & T2.work_plug) & (SOC(:,i) < T2.SOC_min | (wknd &
prevision));
plug_home = plug(:,i-1) == 0 & location(:,i) == 1 & (plug_home1 |
plug_home2);
plug_work = plug(:,i-1) == 0 & (location(:,i) == 2 & T2.work_plug) &
(prevision | (friday & SOC(:,i) < T2.SOC_min_friday) | (~T2.chg_advice & SOC(:,i) <
T2.SOC_min_plug) | advised_charge);

%V2G
plug_V2G = location(:,i) == 1 & T2.V2G & SOC(:,i) > T2.SOC_min_V2G ; %
location(:,i) == 1 &

```

```

    % if plug for smart charging happens 3h before trigger times
    plug_trig = ~(power(:,i-1) == 0 & (plug_home | plug_work) & ((dh * 24/tstep <
>= trigger_time(wd,1,win_sum) - 3 & dh * 24/tstep <= trigger_time(wd,1,win_sum)) | <
(dh * 24/tstep >= trigger_time(wd,2,win_sum) - 3 & dh * 24/tstep <= trigger_time <
(wd,2,win_sum)))));
    plug(:,i) = ((plug_home | plug_work) .* plug_trig) | (available & plug(:,i- <
1) == 1) | plug_V2G ;

    case2 = x & plug(:,i); %the first case of forced charge is false and EV is <
plugged

    % if charge after 1h is lower than the total battery capacity -->
    casela = (SOC(:,i) + Pmax * tstep) <= T2.bat_capacity;
    case2a = smart_chg > Pmax;

    % for the V2G
    y = signal_V2G(i) > 0 & plug_V2G ;%
    z = ~y;
    power_V2G(:,i) = y .* max(-(T2.bat_capacity - T2.SOC_min_V2G) .* signal_V2G <
(i), -P_V2G) ;

    if nat_opt == 1
        %this is for natural charge
        power(:,i) = (case1 .* ((casela .* Pmax) + (~casela .* ((T2. <
bat_capacity - SOC(:,i)) / tstep)))) + (case2 .* ((casela .* Pmax) + (~casela .* <
((T2.bat_capacity - SOC(:,i)) / tstep)))) ;
    else
        %this is for the optimal charge
        power(:,i) = z .* ((case1 .* ((casela .* Pmax) + (~casela .* ((T2. <
bat_capacity - SOC(:,i)) / tstep)))) + (case2 .* ((case2a .* Pmax) + (~case2a .* <
max(0,smart_chg)))) + power_V2G(:,i);
    end
end

SOC(:,1)=SOC(:,1);
date1 = dates(q+1);
T2.outside_chg = T2.outside_chg + w;

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

work_plug_P = power(T2.work & T2.work_plug & ~T2.V2G,:);
delate = find(isnan(work_plug_P(:,1)));
work_plug_P(delate,:)=[];
aver_work_plug = mean(work_plug_P);

work_not_plug_P = power(T2.work & ~T2.work_plug & ~T2.V2G,:);
delate2 = find(isnan(work_not_plug_P(:,1)));
work_not_plug_P(delate2,:)=[];
aver_work_not_plug = mean(work_not_plug_P);

not_work_P = power(~T2.work & ~T2.V2G,:);
delate3 = find(isnan(not_work_P(:,1)));
not_work_P(delate3,:)=[];

```

```
aver_not_work = mean(not_work_P);

V2G_P = power(T2.V2G,:);
delate4 = find(isnan(V2G_P(:,1)));
V2G_P(delate4,:)=[];
aver_V2G = mean(V2G_P);

V2G_chg_P = V2G_P .* (V2G_P > 0);
aver_V2G_chg = mean(V2G_chg_P);
V2G_dischg_P = V2G_P .* (V2G_P < 0);
aver_V2G_dischg = mean(V2G_dischg_P);

fact = Total_cars * Qty_EV * 1000 / EV_qty_ENTD / av_input;
agreg_work_plug = fact * aver_work_plug * sample_work_plug ;
agreg_work_not_plug = fact * aver_work_not_plug * sample_work_not_plug ;
agreg_not_work = fact * aver_not_work * sample_not_work ;
agreg_V2G_chg = fact * aver_V2G_chg * sample_V2G ;
agreg_V2G_dischg = fact * aver_V2G_dischg * sample_V2G ;

Y = [in2 (agreg_not_work)' (agreg_work_not_plug)' (agreg_work_plug)' ↵
(agreg_V2G_chg)' (agreg_V2G_dischg)'];
% Y = [in2 (agreg_not_work)' (agreg_work_not_plug)' (agreg_work_plug)'];
Y = sum(Y,2);
b = 1 * (k-1) +1;
new_RD(b:b+1-1,1) = Y;

end

%power(T2.outside_chg ~= false,:)=0;
```


Chapitre 4

The impact of the *Vehicle Grid Integration* on the spot electricity market

1 Introduction

The growing interest in supplying electricity from **REn** sources and in deploying cleaner mobility systems lays in the low carbon energy transition context all around the world.

Reaching the EU objectives requires to accelerate investments in wind power and **PV** generation units at a rate that could represent in the EU 35% of the electricity supply by 2030, and even rates around or above 50% in countries such as Germany. By 2050, 80% of the electricity supply is expected to be produced from renewable sources [European Commission, 2014a; European Commission, 2014b; European Commission, 2019; European Commission, 2021a].

However, the power supply from these resources is intermittent and a massive deployment will require new flexibility technologies to ensure the equilibrium between electricity demand and supply. So far, thermal power plants, *Pumped Storage Hydropower* (PSH) plants¹ and demand side management are the main used methods for setting the equilibrium demand/supply. These capacities risk to approach their limits in a high variable system, though. In this context, *Electric Vehicles* (EV) may well become a resource able to bring flexibility. The analysis of their interaction with the power system through the *Vehicle Grid Integration* (VGI) concept is the core of this research.

1. Pumped storage hydropower represents 94% of the worldwide storage capacity for electricity according to the International Hydropower Association (IHA) but their construction is not accessible to all kind of territories.

The electricity generation from **REn** plays an important role in the establishment of market prices. As an essential instrument for governments to achieve the objectives of reducing CO_2 emissions, **REn** have had a priority place in the sale of their production in the merit order system² with special remuneration mechanisms such as *feed-in tariff* and then *feed-in premium*. The short term marginal cost of **REn** plants is almost zero, hence, biddings on the market can have negative values, up to a price lower in absolute value than the amount of the grant, and there is still a positive remuneration for these energies. Moreover, there is a minimal production threshold from where thermal power plants cannot go below. Therefore, sometimes producers with thermal power plants must bid their production at negative values during off-peak hours and at positive values during the peak production hours. The technical limitations to slowly ramp-up production up to a certain level force them to set a price that guarantees that the market will buy their daily production. Negative prices could appear due to some particular rules in Europe : because there is a priority for **REn** sources, the excess of **REn** supply should be used. Furthermore, due to ramping capacity of the thermal units, it should be cheaper to maintain a minimum level of production rather than reducing them during off-peak hours. Thus, when there is an excess of **REn** supply, a negative price could appear. Conversely, when production from **REn** is low, consumption is high and imports are at its maximal capacity, market price is fixed by the most expensive thermal power plants even at higher values than their marginal costs, the scarcity prices. Both situations become more recurrent while high **REn** capacities are deployed. Recently, due to the energy crisis since the end 2021, the electricity prices have reached historical high values. By this time, the world experienced the accumulation of several circumstances : the economic recovery after the pandemic crisis that led to the highest electricity demand growth, the increase of prices in the European Union Emissions Trading System, cold winters, nuclear power plants turned off due to a requirement of maintenance and geopolitical tensions (mainly the war in Ukraine but also the halt of imports of coal from Australia to China for example). These prices reflect the dependence on fossil fuels of several nations which are now going through an economic shock. The energy and economic crises and the climate change have revealed the necessity (and the importance) of the energy independence.

In this chapter we present an empirical methodology and analysis of the impact of the integration of an important fleet of **EV** on electricity markets. From our results in Chapter 3 we conclude that this integration will raise the electricity demand and what is more important, will produce a significant change in residual demand. Nowadays, this residual demand sets the

2. All power producers offer the electricity quantity they are able to produce at a specific time of the next day at a price that equals its marginal cost. The lowest cost producers are assigned at first, then the next lowest ones and so on until reaching the last required dispatching unit for supplying demand. All producers are remunerated at the marginal cost of the last dispatched unit.

dynamics of the *day-ahead* market prices. Our hypothesis is that if EV modify residual demand, they will modify market prices as well. We present a comparative of charge prices when applying our smart charge algorithm and when letting the natural charge.

2 Electricity markets

We can identify two time periods in the spot electricity market : a first daily market which takes place every day at noon to prepare the energy flows for the next day (*day-ahead*). This market is carried out through an auction system at a uniform price for each hour of the day, that is, 24 blocks of energy marketed at the same time. The second part of the spot market is the *intra-day* equilibrium market which allows transactions up to few minutes before the delivery time³.

The local markets are supported by the European spot market, coupled through the *Price Coupling of Regions* (PCR) system, which since 2014 has sought the integration of the markets of several countries with interconnection capacities to improve the efficiency of the service and the liquidity of the sector and to promote effective competition. Every day at noon, in the *day-ahead* energy market, each supplier presents a balance program indicating the quantities of energy they wish to buy or sell and at which price, within a threshold of -500€ to 3,000€. Then, the optimization problem is solved within 10 minutes and we obtain, as result, the base prices by region for the *intra-day* market, which contrary to the *day-ahead* market, does not use a uniform price but each transaction is remunerated at a different price. One of the main objectives of integrating these markets is to improve the adoption of RE_n and to reduce the negative prices that are very present in the markets.

The problems associated with negative prices in spot markets are widely developed in the literature. Several authors agree on the incompatibility of the current market structure with an excessive penetration of RE_n, mainly due to the decrease in the flow of money necessary to cover the fixed costs of conventional power plants and with this, the increase in the risk that would not allow investments in these types of technologies [Blazquez, 2018 ; Pikk, 2013]. The problem of negative prices on the market is based on the priority given to RE_n during *off peak* hours without taking into account the needs during the *peak hours* to come (reason why thermal power plants are forced to offer their energy at a negative price). According to this analysis, auctions which reflect actual operational costs without including subsidies would allow fairer

3. From the IAEE podcast *The European integration of the energy spot markets* by Clara Balardy on April 20 2020

remuneration for all the production plants. The capacity mechanisms, already implemented by several markets, are one of the strategies for remunerating power plants which do not produce during many hours a year but which are necessary to guarantee security of supply.

New regulations on REn products aim at making the electricity market fairer. In Germany for example, if the price remains negative for more than 6 consecutive hours, REn producers do not receive a subsidy. France, even if until now has not been strongly impacted by negative prices, with the forecasts of integration of new capacities, will impose the *curtailment*⁴ of wind turbines during negative peaks in market prices and the first 20 hours at a negative price will not be remunerated.

Hereafter we present a brief description of the electricity markets operation.

2.1 Frequency regulation

Equipment constituting electricity systems are designed to operate under a specific frequency range. Going out of these nominal values represents a risk of malfunction or even damage of the materials. Variations in frequency occur when there is an imbalance between production and demand as follows : with a decrease in consumption the machines tend to increase the frequency and with an increase in consumption the frequency decreases. It is an inertial principle. In an interconnected system like the European one, all loads and production plants are synchronized at the same frequency.

Maintaining the demand supply balance (and therefore the frequency balance) requires constant monitoring of production and consumption levels. For this, it is necessary to have mobilizable power reserves that can be operated automatically or manually. There are three categories for frequency regulation reserves : primary reserve, secondary reserve and tertiary reserve.

- Primary reserve : it is an automatic device with a response time between 15 and 30 seconds. All the primary reserve must be able to trigger off for a frequency deviation of 200 mHz. France must have a capacity of around 540 MW for this regulation. All countries participate in the primary reserve regardless of whether the imbalance comes from its own

4. It is the deliberate reduction in output below what could have been produced in order to balance energy supply and demand or due to transmission constraints.

territory or elsewhere.

- Secondary reserve : this is a centralized automatic system, managed by RTE in France. After the first adjustment, a frequency difference could remain and the secondary reserve must be activated in the territory where the imbalance has occurred. The primary reserve is released and becomes back available for a new imbalance. The volume of the reserve is calculated in half hourly steps and in France, this reserve varies between 500 MW and 1180 MW. All producers over 120 MW have the obligation to participate.
- Tertiary reserve or adjustment mechanism : this reserve is manual. It supports the secondary reserve to rebalance demand supply equilibrium and it is classified in two different reserves : contractually guaranteed tertiary reserve, which responds in 15 or 30 minutes, and the unsecured tertiary reserve which responds in several hours.

The reserve services for equilibrium is distributed among all the producers who are able to build it up to guarantee availability in the event of a malfunction of one of the players or the partial disconnection of the network. The primary and secondary reserves are remunerated at the reference spot price of the time step concerned while the tertiary reserve is remunerated on the basis of the price of the offer made by the adjustment actor⁵. In the event of a deficiency in system services, those responsible for reserves must pay a compensation to RTE.

For the primary frequency reserve, France participates in a market in cooperation with Austria, Belgium, the Netherlands, Switzerland, Denmark and Germany, which encourages transparent competition by ensuring the security of supply for each of the participating countries. Auctions are scheduled weekly and take place on Thursdays before the delivery week. Each network operator proposes the offers received in its territory and, through an optimization algorithm, participates in a common *merit-order* system.

The characteristics of this market are : the offers are symmetrical upwards and downwards, the temporary delivery step is one day, the offers can be divisible or indivisible, the minimum capacity and the resolution of the offers is 1 MW and there are import / export limits. While the import and export limits are not reached, a single common marginal price will remunerate the service. If the limits are reached, the price is set by the maximum bids made in the corresponding country. Auctions begin 14 days before the delivery date.

5. <https://www.cre.fr/Electricite/Reseaux-d-electricite/services-systeme-et-mecanisme-d-ajustement>

2.2 Voltage regulation

Similar to frequency, there is an operating range for system voltage. This can be disturbed by variations in consumption levels and by reactive power flows in the networks. Producers have the obligation to participate in the return of nominal values when necessary.

- Primary control : this is an automatic device triggered locally by the power plants that have it.
- Secondary regulation : it is a centralized device which sends a signal to power plants to modify the injection or absorption of reactive power.

2.3 Capacity mechanisms

Capacity mechanisms are contracts established in the medium and long term, with the objective of ensuring the security of electricity supply during winter peaks. These peak periods are between the months of November to March and during the slots of 7 am - 3 pm and 8 am - 8 pm. There are between 10 and 15 peak days per year.

Electricity suppliers, to meet customers demand during peak periods, have the obligation to acquire these capacity guarantees. They can buy them on the spot market or over-the-counter. Producers for their part, through the sale of these guarantees provided by RTE, undertake to produce or to decrease a certain power according to the needs of the network. The minimum capacity to participate is 1 MW.

Capacity mechanisms are designed to induce compliance with a supply level. Trade of capacity certificates begins four years before the delivery year (with several trade sessions) and ends three years later with the adjustment between estimated obligations, acquired obligations and actual obligations.

The prices communicated by the *Commission de Régulation de l'Énergie* (CRE) vary from one year to the next with a strong increasing trend, ranging from 20,000 €/MW in 2016 to 60,000 €/MW in 2020. Intermittent energies also have the possibility of being certified subject to a standard which neutralizes meteorological uncertainty [CRE, 2018].

3 Energy transition context in Europe

3.1 The flexibility needs of the electricity sector

The development of intermittent **REn** involves large fluctuations in power generation, creating peaks and valleys on the demand supply curves. Consequently, there is a flexibility requirement. A large literature on this topic exists both from a technical and an economics point of view. With an increasing implementation of **REn** in the electricity mix, the management of large fluctuations on the power supply becomes a problem for grid operators [Kempton, 2005; Villavicencio, 2017]. This is a major issue since the high variability of these renewable resources is reflected in the failures of the electricity market through negative prices, high price variability or insufficient long-term incentives [Villavicencio, 2017]. According to Percebois [Percebois, 2019], without storage systems, the substitution of conventional power resources by **REn** leads to the called *merit order effect* : this is the decrease of market prices that brings power plants to disrupt because they are not profitable enough. As pointed by Nicolosi [Nicolosi, 2010], in periods of high electricity production fluctuation it has been observed that the wholesale power price changes its usual behavior : when demand is high, market prices exceed variable costs while when demand is low, market prices fall under variable costs.

Other researches approach more technical issues of the **REn** integration. For example, results from the work of Van Stiphout [Van Stiphout, 2015] show that a power system with high **REn** penetration leads to significant losses through curtailment. The estimated losses are of around 18% in a mix with 50% of **REn** installed capacity. The increase of economic and technical problems has conducted most of the EU countries to review and upgrade their financial support schemes [Villavicencio, 2017] such as the complement remuneration or the previously mentioned, *feed-in tariff* and *feed-in premium*, and to evaluate the different flexibility technologies. The challenge for the power system is thereby to find the balance between the targets of **REn** penetration in the electricity mix, and the flexibility needs, which are increasing at the same time.

The flexibility of a power system is its capacity of adaptation to variations coming from demand and production. To do so, thermal power plants ramp -up or -down their production and **PSH** plants fill or empty their reservoirs. Given the interconnections of power systems between neighboring countries, imports and exports are performed as well for dispatching overproduction and for supplying demand when there is a local production shortage. Nevertheless, when these power plants and interconnection grids reach their technical boundaries, the production system does not have how to absorb variations and a tight market situation occurs. **RTE**, the French

TSO observed in the case of France and Germany, that the French nuclear power supply is modulated as a function of German REn production and that this can result in negative prices on the electricity market [RTE, 2019]. Figure 4.1 shows an example of these situations in April 2020, when weather conditions were particularly good while demand was particularly low because of the lockdown. On April 13th 2020 at 3 :00pm the German market price reached -78.15 €/MWh and the French market price was fixed at -75.82 €/MWh. By this time, there was an overproduction of the German power system which was absorbed through the French nuclear power with a modulation of 15 GW under its average generation value⁶. The European market integration is an important target to improve the efficiency of the electricity supply. Some long term factors impacting this market integration are the specific stakeholders' initiatives and the expansion of interconnection capacities, while the short term factors include technical issues producing outages and sudden demand or supply changes (for example a high REn production with a very low demand). The region including French and German bidding zones reached full price convergence in around 48% of the hours in the year 2020 according to the report of the European Commission [European Commission, 2020]. Following the definition of convergence from the work of Keppler [Keppler, 2016], i.e. the situation in which the price difference is lower than 0.1 €/MWh, the integration of more REn capacities will produce more divergence in market prices, which is an evidence of market inefficiency. For example, in Germany, in 2019 there were 211 hours with negative prices averaging -17.27 €/MWh while the precedent year there were 134 hours with negative prices and an average price of -13.73 €/MWh⁷.

3.2 The passenger vehicles

During the last decades, the use of passenger cars has evolved as well as the fuels for powering them. According to the European Commission's report [European Commission, 2021b], in 2018 there were more than 47 million passenger cars registered in Germany and 32 million in France. Both vehicle fleets have remained stable through the last years, therefore, sales correspond mainly to replacement markets. In Germany, 3.6 million of new cars were sold in 2019 and 2.9 million in 2020. In France, 2.2 million of new cars were sold in 2019 and 1.6 million in 2020. While these new cars integrate a country fleet, a part of the existing fleet must go out because cars do not meet current policies criteria anymore. For this purpose, different end-of-life strategies

6. In 2019, Germany exported electricity during 72% of the time and imported electricity during the remaining 28% of the year. Germany exports its electricity mainly to Austria, Poland and Switzerland and imports mainly from France. The order of magnitude of imports and exports is some tens of TWh per year. <https://www.ise.fraunhofer.de/en/press-media/news/2019/Public-net-electricity-generation-in-germany-2019.html>

7. <https://www.districtenergy.org/blogs/district-energy/2020/05/01/germanys-negative-price-rules-bring-negative-conse>

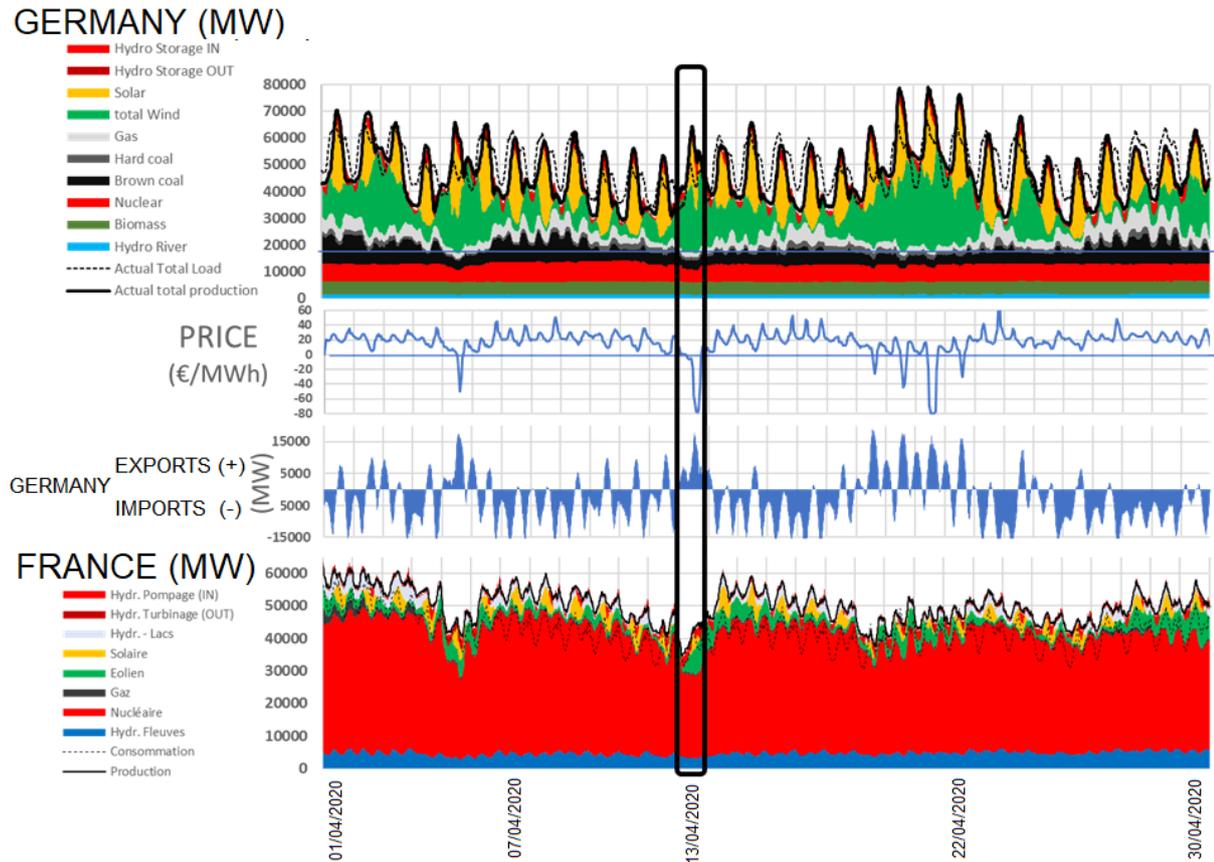


FIGURE 4.1 – French and German electricity generation, German exports and imports and German *day ahead* prices in April 2020. Marker on the 13th of April 2020 at 3pm.

Unit : production [MW], price [€/MWh].

Source : authors with original data from ENTSOE.

are applied in each country, and as a result, around 3 million vehicles are decommissioned every year in Germany while in France the corresponding amount is 1.3 million cars. The evolution of the most important passenger cars fleets in Europe from 2010 to 2019 are presented in Table 4.1.

From 2018 to 2020, in Germany and France, around 60% of new vehicle registrations correspond to petrol powered cars and 32% and 38% respectively, correspond to diesel powered cars. The remaining percentage were registrations of alternative energies vehicles including *Liquefied petroleum gas* (LPG), electric cars and hybrid cars [European Commission, 2021b]. The adoption of new vehicles with alternative fuels has depended on the governments' incentives such as tax reductions, subsidies or benefits on parking and tolls. The year when these incentives have been adopted led to the development of fleets of alternative fuel cars in the different countries [Noel, 2019; Li, 2017]. According to data from the *Comité des constructeurs français d'automobiles* (CCFA) and *Association des constructeurs européens d'automobiles* (ACEA), between 2018 and 2019, there was a rise of 60.9% in sales of EV and rechargeable hybrid cars in Germany while

TABLE 4.1 – Main passenger car fleets in Europe from 2010 to 2019 in millions.
Unit : million cars.
Source : Eurostat.

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Germany	42.3	42.9	43.4	43.8	44.4	45	45.8	46.4	47.1	47.7
Italy	36.7	37.1	37	36.9	37	37.3	37.8	37.9	39	39.5
France	31.6	31.7	32.1	32.8	32.5	32.3	32	32	32	32.4
U.K.	28.4	28.4	28.7	29.6	30.1	30.2	30.8	31.2	31.5	32.5
Spain	22.1	22.2	22.2	22	22	22.3	22.8	23.5	24	24.5
Poland	17.2	18.1	18.7	19.3	20	20.7	21.6	22.5	23.4	24.3

in France it was of 34.6%. In 2020, the sales of these alternative fuel cars increased significantly, achieving a rise of 262.9% in Germany and 202.4% in France with respect to 2019.

A continuous and important evolution of particular vehicles, and of transportation in general, is expected during the coming years. As it was previously mentioned, in the current legislation with the new proposals of *Fit for 55*, the European Commission expects to ban the sales of ICE cars by 2035 and let 100% of the particular vehicles market to alternative fuel systems. To achieve this goal within the expected term, by 2030 particular vehicles are expected to have reduced 55% of their CO_2 emissions.

3.2.1 Charging systems requirement

The adoption of electric mobility implies an increase in electricity demand. The average electricity consumption of a citizen car is around 0.16 kWh/km. Thus, a fleet of 10 million electric city cars traveling 10000 km in one year, would represent 16 TWh of electricity demand. Their recharge might be performed in different ways that depend on drivers' behavior. For example, a massive natural charge behavior (when car drivers plug their EV and start the charge at any-time of the day, without considering the power system condition) could challenge the balance of the system during peak hours of electricity demand, and it will be more or less environment friendly depending on the electricity mix at the moment of the recharge. Thus, time and speed of charge (that depends on the charge power) of an EV fleet are critical factors that can impact power grids balance at local or national scales. The power consumed to operate EV is the most impacting factor in their carbon footprint and therefore, enhancing the electricity used to charge batteries will make them a cleaner mobility solution.

4 Methodology

We propose an empirical analysis of the storage system from EV as a device to help capacity expansion deferral for all kind of power plants (conventional and renewable) and to decrease the total cost of production when progressively REn targets increase. This, by means of a better and more stable remuneration in the *day-ahead* market.

Keppler and Percebois [Percebois, 2019; Keppler, 2016] point out that the integration of more REn capacities will shift the electricity supply curve to the right since the production of these power plants will arrive at the base of the merit order function with their close to zero marginal cost. Figure 4.2 presents both situations producing variability in the electricity market equilibrium. Figure 4.2a corresponds to a typical case with equilibrium price $P1$. In Figure 4.2b we represent the case where an important REn capacity is available; production from nuclear and thermal power plants shifts to the right and the equilibrium price $P2$ decreases. Finally, Figure 4.2c represents the case where renewable capacity is low; production from nuclear and thermal power plants shifts to the left and the equilibrium price $P3$ is higher⁸. We consider that through a smart charging system for EV, a regulation of equilibrium prices might be applied to obtain benefits for the power system and the consumers.

Residual demand can be defined as the electricity supplied by non fatal energy sources. References [Do, 2021; Wagner, 2014; Smolen, 2017] explain the importance and the impact of residual demand in electricity markets. They show that inelastic production from REn leads to a direct relationship between residual demand, supplied by conventional power plants, and market prices, and that this relationship is more direct than the one with the total demand.

In a general perspective, an equilibrium electricity price can be determined through the merit order model [Boiteux, 1956]. Thus, the price is determined by the last cheapest unit available to supply the demand; the marginal cost of the last power unit. Nevertheless, there are several factors that influence the actual market price. The ramp-up and ramp-down conditions of thermal power plants, the maintenance periods or the physical limits of transmission lines are modifiable factors of the actual market prices. This is why we have looked for an indicator that remains independent from these factors to better understand the relationship between the market prices and the residual demand.

8. The green areas correspond to producer's surplus. It is the integral of the zone limited by the horizontal of the equilibrium price and the offer curve.

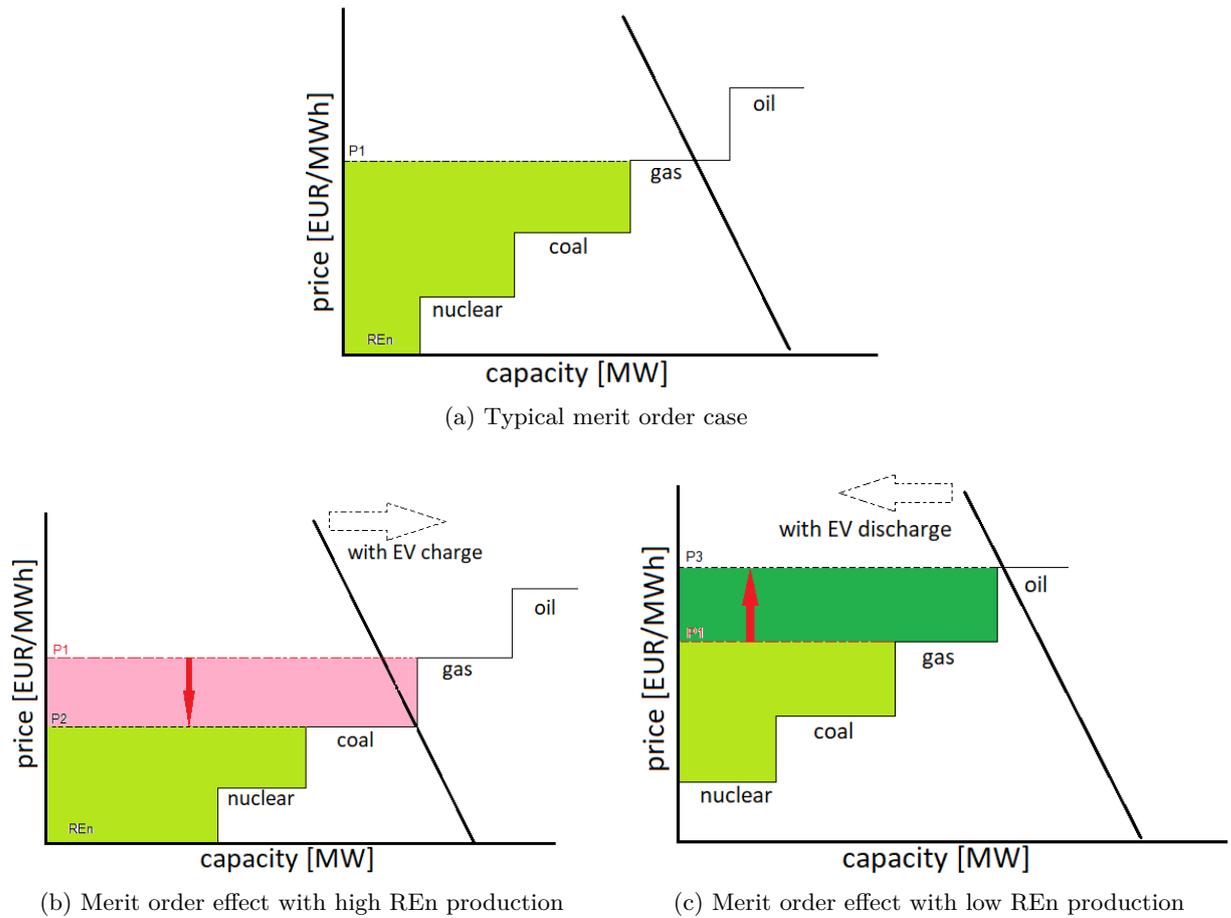


FIGURE 4.2 – The merit order effect.

Units : €/MWh.

Source : authors.

Independently, we have analyzed the years 2019, 2020, 2021 and the first semester of 2022 with hourly data. We estimated the correlation between the prices and the residual demand, in level terms and in variation terms.

The calculations of the variations have been performed to assess the percentage of variations of a given demand (or price) compared to the centered moving average of the same series.

Denoting D_t the residual demand for t , the centered moving average for a week D_t^c is defined by Equation 4.1. There are 168 hours during 7 days, 84 hours before t and 83 hours after t .

$$D_t^c = \frac{1}{168} \sum_{h=1}^{168} D_{t-85+h} \quad (4.1)$$

The percentage of variation D_t^v with respect to the centered moving average is defined by Equation 4.2. On the same way denoting P_t the price and P_t^c the moving average of the price, the percentage of variation is defined by Equation 4.3. Then, we split the demand D_t per percentile D_t^{vp} and we calculate the average variation of price \bar{p}_t^{vp} for each one of them.

$$D_t^v = \frac{D_t}{D_t^c} - 1 \quad (4.2)$$

$$P_t^v = \frac{P_t}{P_t^c} - 1 \quad (4.3)$$

We have summarized the main results in Figure 4.3. This is confirmed by the regression analysis (Annex 4.A). We observe that variations on prices are linearly proportional to variations of residual demand. It is typically the case except during the COVID pandemic. In 2020 the behavior of electricity markets does not respond to the pattern while we keep observing the relationship even during the energy crisis of 2022. Figure 4.4 presents the average values for one week. Both curves have a very close behavior.

Our methodology is based on the three main following elements. For our purpose, (i) we implement the bidirectional (V2G) recharge system algorithm described in Chapter 3 that re-

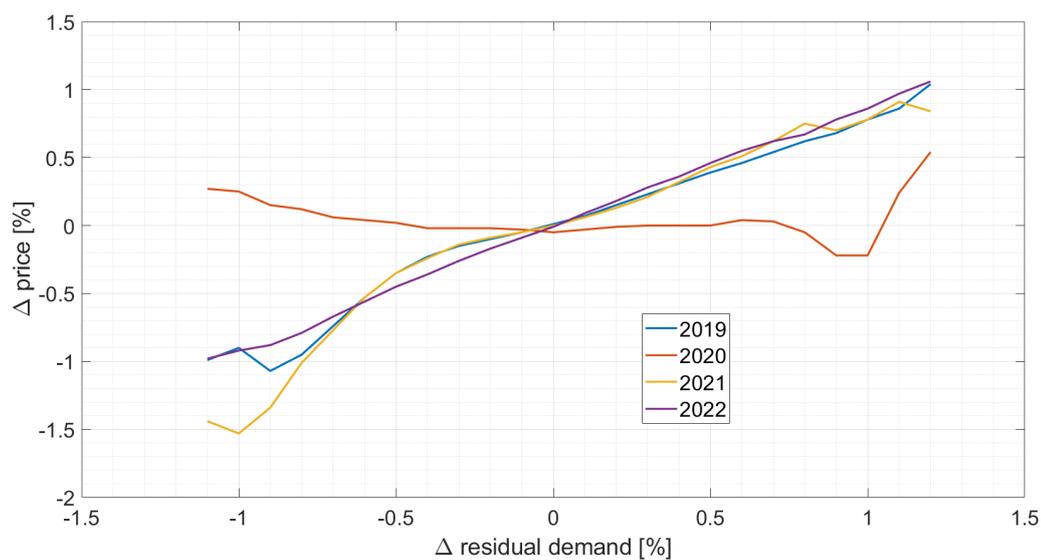


FIGURE 4.3 – Correlation between residual demand and market prices for 2019, 2020, 2021 and 2022.

Units : %.

Source : authors.

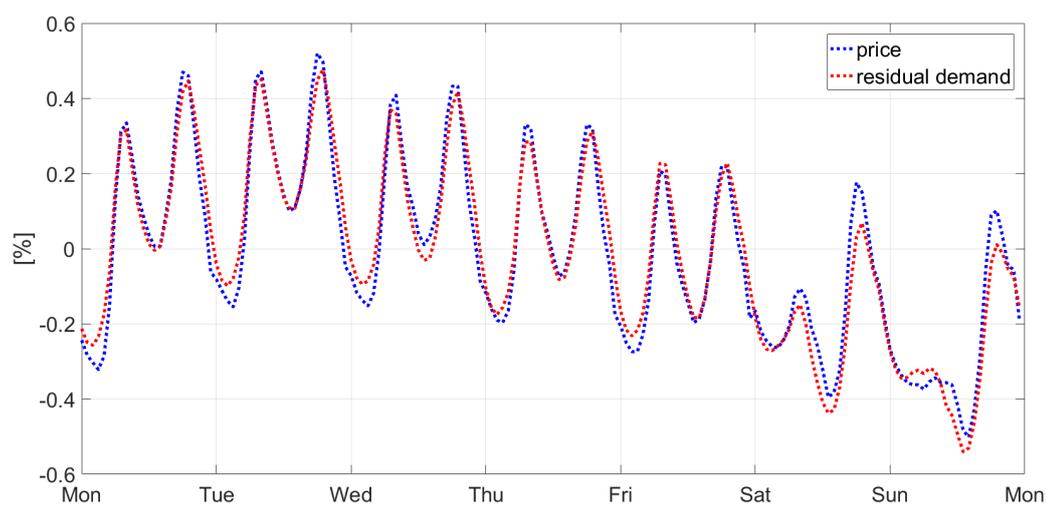


FIGURE 4.4 – Average values of *Delta* price and *Delta* residual demand for an average week.

Units : %.

Source : authors.

sponds to a residual demand signal and we apply it to a national EV fleet (ii) we estimate the electricity supply curve (merit order curve) and finally (iii) using the simulation tool we estimate a new residual demand curve for two different cases : a natural charge and an optimal charge.

At first, we estimate the electricity supply curve through a polynomial regression to empirically model the electricity price system. Using this method, we analyze the different relationships between residual demand with *day-ahead* market prices and residual demand with CO_2 emissions. Next, as a result of the application of the smart charge algorithm we obtain a new residual demand curve which is expected to be less variable than the one the system would perceive in natural charge. Through the polynomial function that describes the market behavior, we estimate the new electricity prices by time step using the value obtained by the equilibrium between electricity demand and supply. We consider three main indicators derived from the simulations :

- The percentage of negative prices (number of periods of one hour during which the market prices are negative). This indicator reflects how the electricity storage capacities of the EV batteries avoid very low prices. It is defined in percentage.
- The producer surplus, typically defined as the surface between the equilibrium price and the supply curve which has been previously estimated with the polynomial regression.
- The CO_2 emissions from the power sector.

4.1 Estimation of the merit order curve using a polynomial regression model

The assessment of the economic impact of the integration of RE_n in the power mix and the massive adoption of EV requires an electricity supply model able to reproduce the power system failures mentioned in Section 3.1. We aim to capture the effects of the high RE_n variability. For this purpose, we use an hourly step time series of the year 2019 with data from ENTSO-E⁹ to calculate the residual demand as follows : from total demand we subtract the fatal production. This is the onshore wind, offshore wind, PV, run-of-river, biomass and waste. We choose to consider biomass, waste and run-of-river as fatal energies after an analysis of their behavior in the production system. These power plants do not have a variable behavior and therefore, represent a constant block in production. Whichever is the demand/supply condition,

9. European Network of Transmission System Operators for Electricity

this electricity is primarily appealed and absorbed by the system as well as the **REn**.

Following the work of Smolen [Smolen, 2017], we estimate the supply curve through a polynomial function that fits the high and low spikes that occur during the stressful conditions.

5 Application for Germany

Germany is an interesting case study because of the important role it has in the two main dimensions of the **VGI** : it is a country that has reached **REn** adoption objectives faster than expected and it has had for long time the most important cars market in Europe, including **EV** market. A nearby impact of the electricity demand coming from **EV** should be attended. For example, if there are 2 million integrated **EV** with a large battery capacity (as is the case of new commercialized **EV**) and they are connected at 3.5 kW, the power grid would dispose of 7,000 MW of flexibility. This capacity is comparable to the one of **PSH** plants in Germany which reach 6,700 MW and it is not negligible compared to the 30,000 MW of flexibility brought by the whole window of imports and exports as it is shown in Fig. 4.1.

We apply the proposed methodology for this country using time series hourly data from 2019 as a reference period. This year, **REn** production was exceptionally high, thus we can approximate a representation of the impact of this research in the close future when the **REn** capacity will be still more important [Benatia, 2020].

5.1 Energy mix context

The structural changes of the energy mix in Germany takes place in the *Energiewende* starting in 2010. In 2011 Germany took over policies concerning nuclear exit and prioritized the shutdown of these power plants over the one of fossil power plants. The country passed from producing 25% of total electricity with 17 reactors to 12% with 6 reactors. The total shutdown of nuclear power plants was expected by the end of 2022. These political decisions entail an electricity balance purely from thermal power plants which include nowadays 84 coal-fired plants that, for its part, were expected to be reduced to 24 plants by 2022 and 8 plants in 2030. These will keep turning until 2038. Afterwards, the system balance was expected to be provided by gas power plants. Though, the current geopolitics situation has unsettled the whole power system condition and the energy independence is nowadays a priority that probably, would make

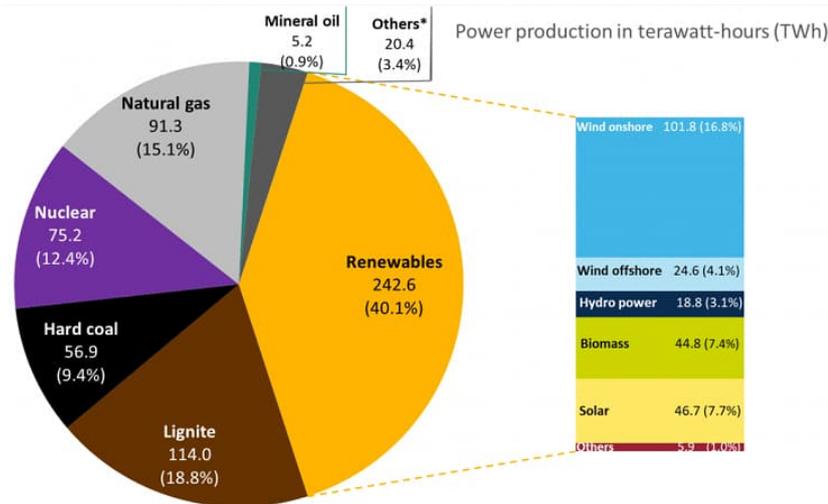


FIGURE 4.5 – German electricity mix in 2019.
Unit : TWh.
Source : BDEW.

reconsider the expected future energy mix.

In 2010, Germany had set the objective of producing 35% of its electricity from **REn** by 2020 in the energy transition trend with the same large daily variations. This objective was exceeded since 2018. The next transition stages aim to produce 50% of electricity from **REn** by 2030, 65% by 2040 and 80% by 2050. Moreover, with the accelerated success of the transition, the country decided to set the objective of 65% of **REn** by 2030¹⁰. By the end of 2019 Germany produced 40% of the total electricity demand from **REn** resources (Fig. 4.5). This renewable production was reached with an installed capacity of 123 GW, while conventional power plants had around 92 GW of installed capacity corresponding to 30 GW of hard coal, 23 GW of lignite, 28 GW of gas, 8 GW of nuclear and 3 GW of oil. With this power capacity mix, in 2019 electricity production was responsible of the emission of 362 gCO_2/kWh and a total of 219 million of tonnes CO_2 in the year.

German electricity mix keeps changing constantly and it will still look differently in the coming years. According to energy political choices what is sure is that production from thermal power plants is still necessary for ensuring the system’s reliability and adequacy when absorbing **REn** variability. New flexibility technologies will be developed but these will take several years to be included and considered as part of the energy mix. However, with such a significant production from **REn**, producers are facing a lack of long term incentives for staying in the market. We consider that thermal power plants subsistence, receiving a fair remuneration, is neither against

10. Data from IEA - www.iea.org/reports/germany-2020

the transition goals nor the decarbonization goals since, on the contrary, without them it would be impossible to reach the equilibrium demand/supply at every time of the year.

5.2 Electricity market

The largest part of the electricity production is commercialized in medium and long term contracts within periods that can vary from several months to several years. The remaining demanded electricity is commercialized on the electricity market. In 2019 Germany had the largest share in the EPEX Spot¹¹ *day-ahead* market with 226 TWh over a total of 604 TWh¹². This means that 63% was purchased in long term contracts and the remaining 37% of the total production passed through the market. For the purpose of this research we assume that the residual demand is the amount of electricity commercialized in the *day-ahead* market which means that we do not consider the existence of the *intra-day* market, which is a limitation of our methodology.

The German power system has a typical behavior as pointed out in Figure 4.6 : because of the significant installed capacity, when residual demand is low, Germany fills its PSH reservoirs at first (which have a capacity of 6,000 MW) and exports to neighboring countries until reaching the maximal physical capacities. There is a relatively constant production from nuclear power plants and then, coal, gas and oil power plants adapt their production to residual demand. When demand is very high, Germany becomes an importer country and makes the possible variations on nuclear production while staying into the safe modulations.

5.3 EV in the German car market

Germany has the largest car market in Europe. The country accounted for 47.71 millions of light duty vehicles by the end of 2019 and has the largest EV fleet in Europe with more than seven hundred thousand electric and hybrid vehicles registered since 2010. EV registrations passed from 108,839 EV in 2019 to 394,943 in 2020. The EV market share achieved more than 13% in 2020. This represents a raise of 262.9% in this market in the last two years.

11. European Power Exchange. It operates the power spot markets for short-term trading in Austria, Belgium, Denmark, Finland, France, Germany, Great Britain, Luxembourg, the Netherlands, Norway, Poland, Sweden and Switzerland

12. New trading record on EPEX Spot in 2019. <https://www.epexspot.com/en/news/new-trading-record-epex-spot-2019> Consulted on 29th November 2021

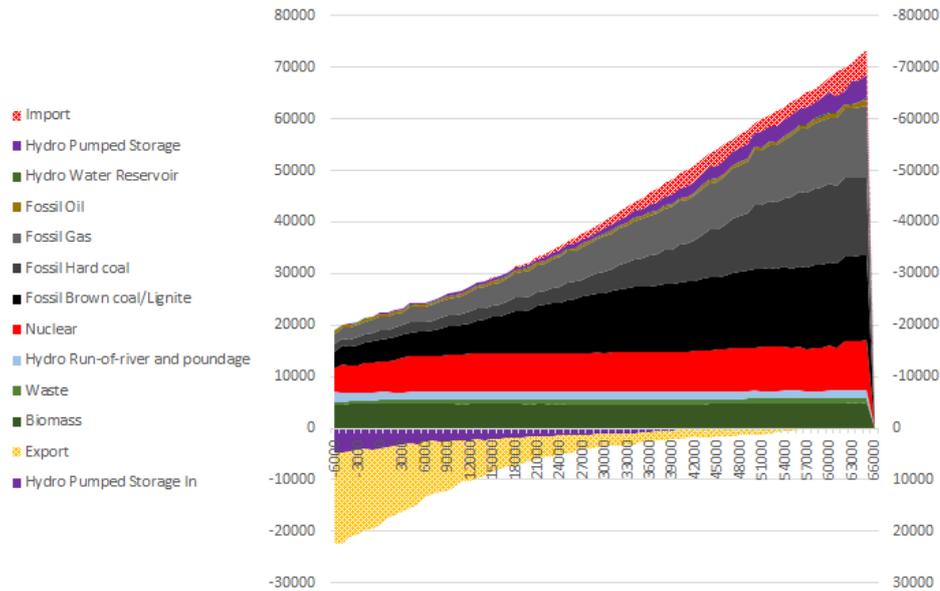


FIGURE 4.6 – Electricity generation by power plant type as function of residual demand.
Unit : MW.

Source : authors with original data from ENTSOE.

Electric mobility is a major issue for the German government who has set the objective of reaching from 7 to 10 millions **EV** by 2030 with 1 million public recharging points. To reach the objective, and as consequence of the COVID crisis, the purchase bonus passed from 6,000 € to 9,000 €. This bonus is offered now for purchasing new **EV** with a price lower than 40,000 € and there is as well a bonus for used **EV** and for plug-in hybrid cars.

About emissions in transport, the sector was responsible of 163 Mton CO_2 in 2019 in Germany¹³.

6 Empirical results

6.1 The application of the smart charge algorithm

The details of the algorithm are presented in Chapter 3.

The objective of the algorithm is to control the charge/discharge power and to modulate the stored energy to make the virtual battery (the aggregation of the batteries participating in **VGI**) follow as close as possible, an average and smooth signal estimated from the residual demand.

Our decentralized algorithm (without aggregator and without any upward communication

13. Data from www.statista.com/statistics/989341/greenhouse-gas-emissions-by-sector-germany/

TABLE 4.2 – Parameters for the simulation of the impact of an EV fleet in natural and in optimal charge.

Parameter	Natural charge	Optimal charge
Part of EV [%]	50	50
EV with V2G [%]	-	20
Advised charge [%]	-	50
Charge powers [kW]	3/11	3/11
Batteries capacity [kWh]	20/50	20/50
Work plug [%]	50	25(winter)/ 85(summer)

from cars) optimizes the charge of the virtual battery through a one week period using a centered moving average value. With this approach we do peak shaving and valley filling considering the variations of the load curve and of REn during the different days of the week. Expected results of the algorithm implementation are :

- Easing REn integration through the compensation of its variability
- Limiting EV impacts on electrical power plants and transmission and distribution grids
- Reducing CO₂ emissions when limiting thermal power plants appeals and optimizing the use of controllable decarbonized power plants
- Limiting electricity price rises for users

For the aim of this chapter we have simulated the whole year 2019 applying the parameters presented in Table 4.2 in natural and in optimal charge. For each hour of the year we obtained a new residual demand representative of the future conditions of the power grid when a significant EV fleet will be adopted.

6.2 The polynomial function

We estimate the polynomial function for German conventional power supply prices using data from 2019. For this purpose we estimate the average values of electricity price by step of 500 MW. The estimated polynomial function of the *day-ahead* price P[elec] as a function of the electricity transaction [elec] is given by the equation (4.4) and presented in Figure 4.7.

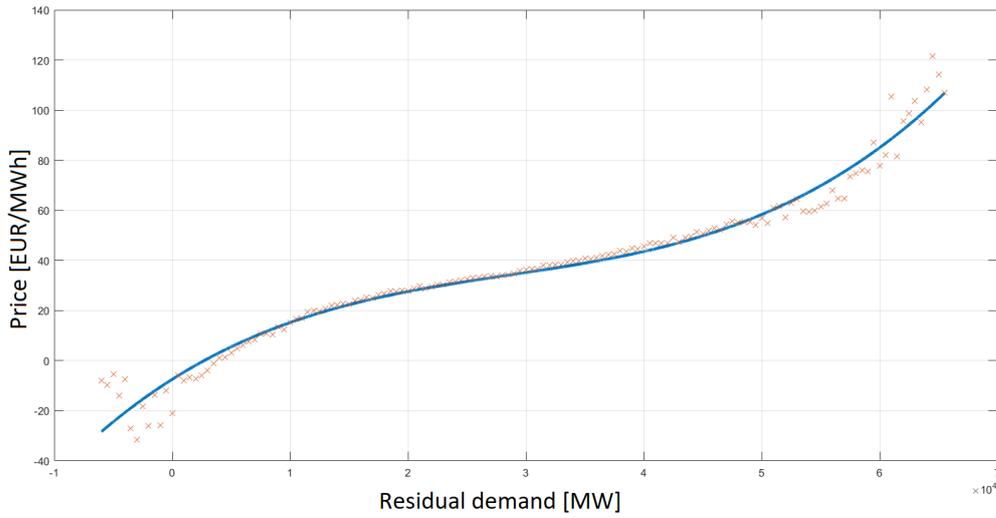


FIGURE 4.7 – Electricity supply curve for conventional power units : polynomial model estimation.

Unit : €/MWh.

Source : authors with original data from ENTSOE.

TABLE 4.3 – Comparative results between natural and optimal charge.

Source : authors.

Parameter	Natural charge	Optimal charge
Average charge price [€/MWh]	57	43
Negative prices [%]	0.79	0.24
Producers surplus [M€]	7434	7568
CO ₂ emissions [kg/MWh]	346	316

$$P[elec] = \begin{matrix} -7.48 & +2.92 \times 10^{-3}[elec] & -7.94 \times 10^{-8}[elec]^2 & +9.26 \times 10^{-13}[elec]^3 \\ (98.02E - 2) & (1.42E - 4) & (5.89E - 09) & (6.46E - 14) \end{matrix}$$

$$R^2 = 0.969$$

$$n = 144$$

(4.4)

Applying the polynomial function in the results of the simulation of the EV charge over one year we obtained the results presented in Table 4.3. We observe a reduction of 25% of the average recharge price as well as a reduction in the average CO₂ emissions. Conversely, the producers' surplus is improved since the power system operation is optimized. Figure 4.8 presents the results for a typical week of the charge profile in natural and in optimal charge modes as well as the respective electricity prices.

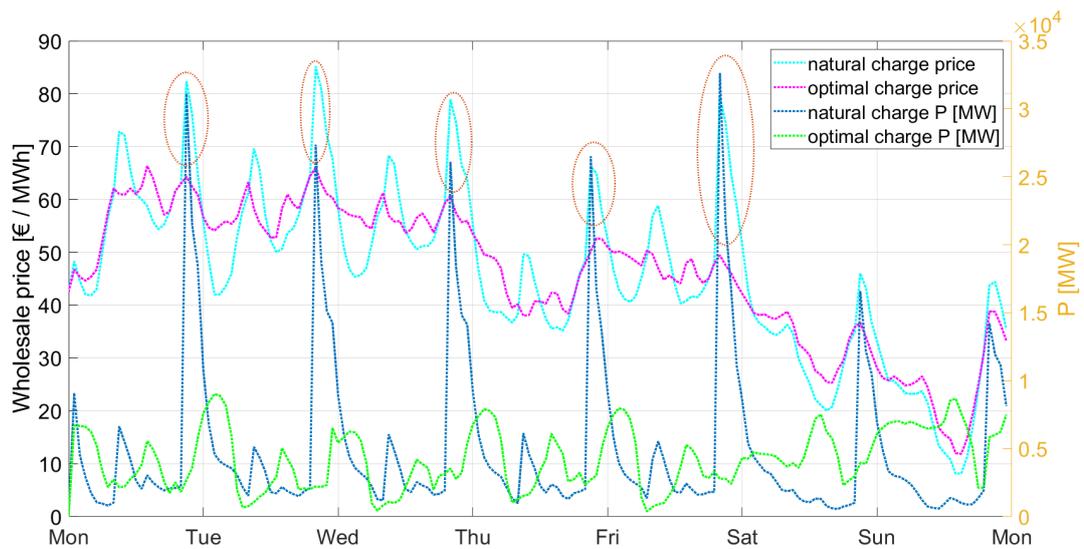


FIGURE 4.8 – Results for a random week of charge powers and electricity prices in natural and in optimal charge.

Left unit : €/MWh. Right unit : MW.
Source : authors.

7 Conclusion

In this chapter, we assess the consequences of an increasing **EV** fleet on the power system considering an optimized **VGI** implementation. This analysis is performed in the European context of decarbonization policy perspectives. We develop modeling tools to study the interactions between **EV** charge and discharge and the power sector. We apply then to Germany which is characterized by a large share of **REn** supply (40.1% in 2019) and a very important passenger car fleet (47.7M in 2019). The optimized process of **VGI** is based on a peak shaving and valley filling algorithm that considers the drivers behavior.

A simulation is applied for a significant fleet of **EV** using historical demand data over one year. We assess the impact of modifying the load curve through smart **EV** charging on the wholesale electricity price, we estimate the producers surplus and the power system CO_2 emissions. We apply this methodology to Germany which has both the biggest personal car fleet and the largest **REn** supply in Europe.

From the results, we confirm the interest of linking passenger **EV** to the bulk power system through a smart system to support the emergent flexibility requirements. The optimal charge of a fleet of **EV** could reduce the demand peaks that lead the system to stressful situations, therefore, a **VGI** algorithm helps limiting the volatility brought up by the integration of **REn** and as

a consequence, improves the system's adequacy and reliability and could improve the producer surplus of the power sector. VGI limits investments risk in the power sector by reducing the price volatility and helps capacity deferral. When adding EV flexibility capacity, the system would need less investments in new generation capacity. Because the development of REn has been originally supported by large subsidies, which remain important until now, highest surplus should appear thanks to the flexibility brought by EV fleet.

The merit order effect on electricity markets, that shifts the curve through the right or through the left depending on the REn electricity generation, could step back. The flexibility of the German and French electricity grids is currently based on nuclear and hydro, which are non fossil fuel units. A virtual battery capable of absorbing this production (instead of limiting it) leads to a more stable and fair market.

We highlight the interest of optimizing an EV fleet charge following a residual demand signal that captures inherently prices and CO_2 emissions while guaranteeing the performance of the system. We point out that EV have a significant impact on the electricity market. Nevertheless, the loop effect is not taken into account when optimization is done through a pricing signal in the revised literature. However, we have shown that EV charge is able to change the market prices.

4.A Polynomial regression Electricity price in Germany

The series statistics on ELEC have been set up from the power generation on the German grid over 8,760 hours. After sorting the data, we defined 144 points (average values for classes of the accumulated distribution curve). Negative values correspond to period during which Germany has net imports. For each observation, we calculate the average values of the electricity market price (Figure 4.9).

Thus, we run a polynomial regression. The degree 3 has been determined with the Mallows Cp criterion.

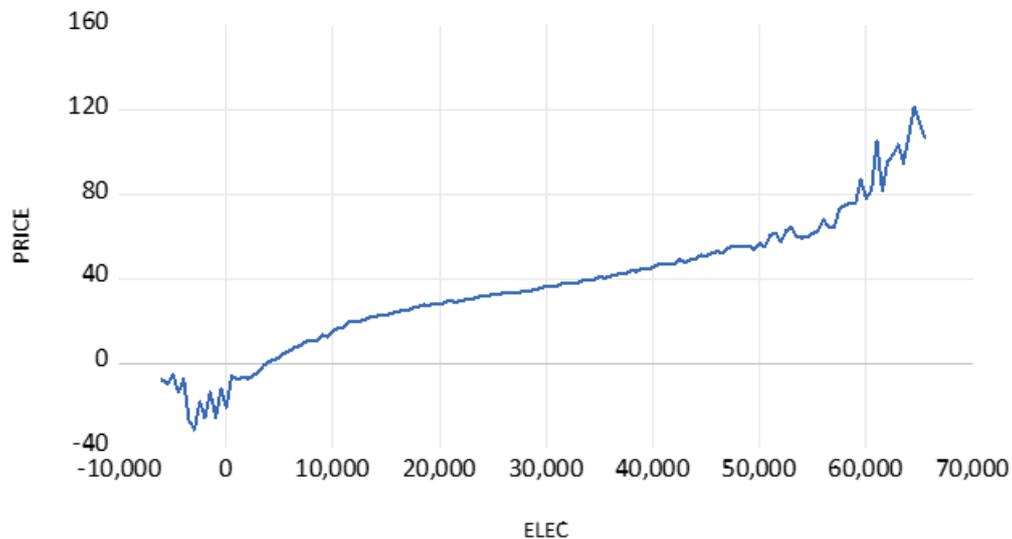


FIGURE 4.9 – German power generation and electricity price.
Unit : elec [MW], price [€/MWh]
Source : authors.

Regression output Dependent Variable : PRICE.

Method: Least Squares
 Sample: 1 144
 Included observations: 144

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-7.488330	0.980285	-7.638930	0.0000
ELEC	0.002971	0.000142	20.94405	0.0000
ELEC^2	-7.94E-08	5.89E-09	-13.49425	0.0000
ELEC^3	9.27E-13	6.46E-14	14.34299	0.0000

R-squared	0.969479	Mean dependent var	36.41813
Adjusted R-squared	0.968825	S.D. dependent var	30.96252
S.E. of regression	5.466884	Akaike info criterion	6.262679
Sum squared resid	4184.155	Schwarz criterion	6.345174
Log likelihood	-446.9129	Hannan-Quinn criter.	6.296201
F-statistic	1482.334	Durbin-Watson stat	0.948952
Prob(F-statistic)	0.000000		

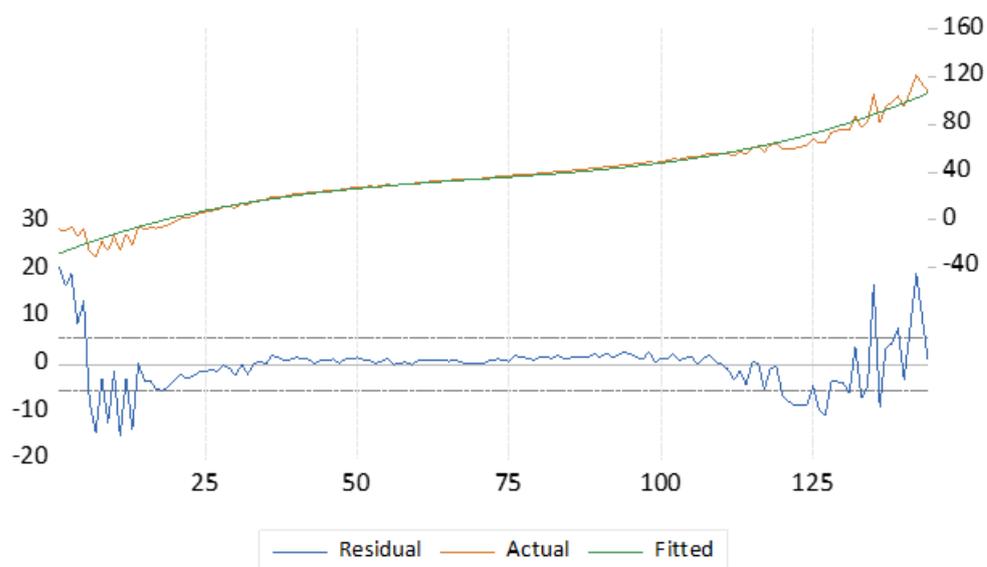


FIGURE 4.10 – Actual, fitted value, residuals

General conclusion

Our thesis on the analysis of techno-economic issues associated to electric *Vehicle Grid Integration* (VGI) takes place in the general objective of decarbonization of both transportation and power generation sectors. As pointed out in the review of literature of each chapter of the thesis, this research topic has provided a lot of papers over the last three decades, based on techno-economic models.

The originality of my research is that it has been supported by the Direction of Research of Renault car manufacturer and that I have been enrolled in the team in charge of the development of simulation tools of VGI. Consequently, the thesis is based on both economic theory and modeling framework associated to VGI and the engineering modeling of *Electric Vehicles* (EV) connection to the grid. This leads us to the main results concerning the VGI at a local level (Chapter 2), the VGI at a national level (Chapter 3) and the impact of the VGI on the spot electricity market (Chapter 4).

First, we analyze the impact of the integration of an EV fleet in an isolated territory using modeling tools that we developed for this purpose. We point out that it is possible to reach an energy mix 100% renewable with storage facility. Nevertheless, the transition towards this objective can be long and intermediate steps are necessary to find the best adequacy between *Renewable Energies* (REn) supply and storage facility. Each stage of the transition is determinant and decisions need to be taken considering the long term impacts. In this chapter we present the effects of leading the transition mainly with PV or mainly with wind power. In any case, we observe that the storage facility is required and becomes useful when the total REn production is higher than 40%. Under this value, it is not necessary to have a storage facility since the electricity is mainly consumed at the time it is produced. Conversely, to reach the highest levels of REn penetration in the energy mix, a storage facility is mandatory. Otherwise, a thermal power plant based on biofuel would be the alternative solution. Furthermore, we point

out that the total electricity production cost has a U shape when we consider an increasing share of **EV**. For our empirical analysis, we have worked on Porto Santo island (Madeira archipelago). We found that there is an optimal storage for each level of **REn** over the total mix. Beyond this optimal point, the use of each battery decreases as well as the economies for each **EV**. Though, the results show a compatible use of the battery for the **VGI** with respect to an **EV** characteristics. Finally, to promote the adoption of a smart charge it is necessary for the **EV** owners to find the economic interest and therefore, it is necessary that the cost of the technology and of the deployment of the system, be lower than the possible revenues.

Next, we have presented the solution of an optimal control model applied as a smart charge algorithm for an **EV** fleet. The optimal control tries to approach the new residual demand (the current residual demand plus the demand coming from **EV**) to a smoother curve estimated through a moving average value over one week. The algorithm uses the residual demand as reference value from where we obtain two different signals. The first one operates as an energy modulator while the second one operates as a power modulator. Different time horizons are taken into account. Next, we have implemented this smart charge algorithm in a simulation tool developed to analyze the impact of the adoption of a significant **EV** fleet. The simulator has multiple parameters and several outcomes were found. First, the adjustments of the **EV** charge need to be closely monitored to follow the **REn** unpredictable behaviors and to respond to seasonal weather variations. Second, a robust recharge infrastructure to ease the **EV** charge access is fundamental and low power chargers are those capable to bring flexibility to the power grid. Third, all batteries capacities can contribute to the **VGI** in different time windows. Small capacities can bring only short term flexibility, which is still useful and necessary. And finally, the acceptability of **EV** owners is another key factor. The availability of the flexibility facility depends on if, whether or not, they agree to participate in the **VGI**.

Finally, we analyze the impact of an increasing **EV** fleet on the power system considering an optimized **VGI** implementation. We develop modeling tools to study the interactions between **EV** charge and discharge and the power sector. We apply to Germany which is characterized by a large share of **REn** supply and a very important passenger car fleet. We assess the impact of modifying the load curve through smart **EV** charging on the wholesale electricity price, we estimate the producers surplus and the power system CO_2 emissions. With our results, we confirm the interest of linking passenger **EV** to the bulk power system through a smart system to support the emergent flexibility requirements. A **VGI** algorithm helps limiting the volatility brought up by the integration of **REn** and as a consequence, improves the system's adequacy and reliability

and could improve the producer surplus of the power sector. **VGI** limits investments risk in the power sector by reducing the price volatility and helps capacity deferral. When adding **EV** flexibility capacity, the system would need less investments in new generation capacity. Through the smart charge system, a virtual battery can absorb production from clean resources (nuclear and hydro) when demand is low instead of limiting it. This leads to a more stable and fair market.

New topics related to **VGI** could be investigated derived from the work presented in this thesis. This concerns how to share the gains associated to **VGI** and the interactions between **VGI** and electricity prices.

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RÉSUMÉ

Dans le contexte de la transition énergétique, les secteurs du transport et de l'électricité sont appelés à évoluer pour atteindre l'objectif de neutralité carbone. Le déploiement d'une capacité importante d'Energies Renouvelables (EnR) implique une croissante demande de flexibilité pour le réseau électrique alors que, d'autre part, le déploiement d'un parc important de Voiture Electriques (VE) représente une demande d'électricité plus élevée pendant la phase de recharge qui pourraient approcher et même dépasser les limites physiques des réseaux électriques. Cependant, ensemble, les EnR et la flotte de VE pourraient apporter une solution au lieu de deux problèmes. Grâce à un système de charge intelligent, les VE pourraient absorber la surproduction d'EnR ainsi que limiter la puissance sollicitée pendant les heures de forte consommation. Ce travail présente les principaux enjeux de l'intégration de VE dans le réseau électrique au niveau local et au niveau national. Un modèle d'optimisation du prix de l'électricité est développé ainsi qu'un système de contrôle optimal de la charge intelligente qui est implémenté dans un outil de simulation puis dans un VE réel pour tester la viabilité d'une application. L'impact économique et les facteurs techniques de l'intégration sont analysés.

MOTS CLÉS

Voitures électriques, Energies renouvelables, Flexibilité du réseau, Optimisation de la charge, Intégration de voitures électriques au réseau *VGI*

ABSTRACT

In the context of the energy transition the transport and the power sectors are called to change to reach the carbon neutrality objective. The deployment of an important capacity of *Renewable Energies* (REn) involves an increasing requirement of flexibility for the power grid while, on the other hand, the deployment of an important fleet of *Electric Vehicles* (EV) represents a higher electricity demand during the recharge phase that could approach and even exceed the physical limits of the power grids. Though, together the REn mix and the EV fleet could make a solution instead of two problems. Through a smart charge system EV could absorb the REn overproduction as well as limit the appealed power during high consumption hours. This work presents the main challenges of the integration of EV into the power grid at a local and at a national level. An electricity price optimization model is developed as well as an optimal control system for the smart charge which is implemented in a simulation tool and subsequently in a real EV to test the viability of an application. The economic impact and the technical factors of the integration are analyzed.

KEYWORDS

Electric Vehicles, Renewable Energies, Grid flexibility, Charge optimization, Vehicle Grid Integration.