National Technical University of Athens
Department of Electrical and Computer Engineering
Division of Communication, Electronic and Information Engineering

PhD THESIS

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ATHENS

March 2019

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Abstract

Modern energy policies drive the electricity market towards a liberalized framework. As a result, concepts from other commodity markets are becoming increasingly relevant in the context of the electricity market. However, there are certain specialties that characterize electricity. Such a specialty is the requirement of constant balance between supply and demand; otherwise the stability of the underlying physical grid is compromised. The traditional approach has been to only control the supply, so that it follows the demand at all times. However, high penetration of non-dispatchable renewable energy sources and load electrification (e.g. electric vehicles) have highlighted the need to also utilize the elasticity that there is at the demand side, by applying Demand Side Management (DSM). The main objective of DSM is to achieve an aggregated consumption pattern that is efficient in terms of energy cost reduction, welfare maximization and/or satisfaction of network constraints. This is generally envisaged by encouraging electricity use at low-peak times.

In this dissertation, we model a set of smart devices at the side of residential electricity consumers and a home energy management system that is able to make decisions about home electricity consumption by taking into account the user's preferences, the dynamic electricity pricing signals as well as the operational constraints of devices. We envisage an electricity service provider that is responsible for incentivizing users to shape their consumption patterns in line with the needs of the electricity system. We study and develop techniques for two general use cases of DSM: online algorithms for real-time consumption curtailment and offline algorithms for day-ahead load scheduling. We considered an intelligent agent at the user's home energy management system able to make strategic decisions. In this setting we formulated a game where each agent tries to optimize its own objective. We formulated the problem of designing online auction mechanisms that are able to bring the system to a Nash equilibrium. Also, the final allocation needs to exhibit attractive properties in terms of the key performance indicators set by the state-of-the-art literature. In order to achieve these goals we drew on concepts of algorithmic game theory and mechanism design.

Specifically, for the real-time demand response case, we designed two online auction schemes for two specific business models. The first is based on Ausubel's clinching auction and achieves the majority of the standard requirements of mechanism design theory. Namely the proposed scheme, achieves economic efficiency, incentive compatibility (in the sense of making it a dominant strategy for each user to act truthfully according to his/her preferences and leaving no room for cheating), scalability, privacy-preservation and individual rationality in contrast to studies in the current literature that achieve only a subset of the aforementioned properties. Furthermore, it is shown to maximize the service provider's profits among all efficient allocations. The second business model refers to cases such as energy cooperatives where the issue of fairness of the allocation is important. We designed a novel mechanism that significantly improves fairness in comparison to the state-of-the-art.

For the day-ahead load scheduling case, we designed and evaluated a novel DSM scheme that addresses several issues that were not jointly addressed before. Specifically, the proposed DSM scheme preserves the economic efficiency, individual rationality and budget-balance properties. It is also able to satisfy coupling, system-wide constraints. The proposed scheme is theoretically proven to always bring the system to the Nash equilibrium. Finally, we studied the problem of jointly considering a day-ahead load scheduling and a real-time DSM scheme that balances unexpected deviations from the agreed schedule. We proposed a differentiated pricing based on a spread, and studied its effect on the users' strategies.

Keywords : **Smart Grid, Demand Response, Game Theory, Mechanism Design**

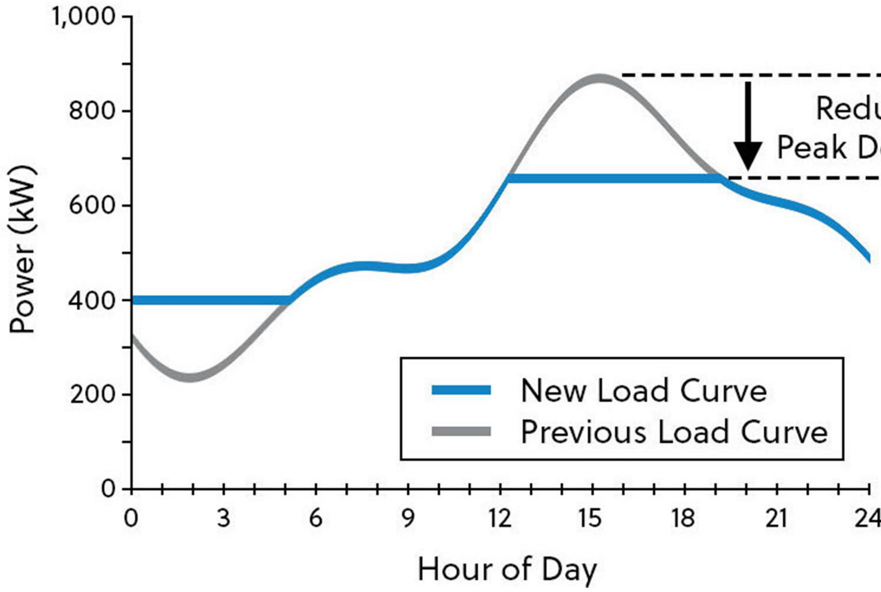
Summary in Greek language

Μέχρι τη δεκαετία του '80, τα συστήματα ηλεκτρικής ενέργειας θεωρούνταν φυσικά μονοπώλια και οργανώθηκαν ως κρατικές ή ως κρατικά ρυθμιζόμενες επιχειρήσεις. Οι κυριότερες κατευθύνσεις που δίνει η ΕΕ κατευθύνονται προς την αύξηση της διείσδυσης των ανανεώσιμων πηγών ενέργειας και την προώθηση της ελευθέρωσης της αγοράς ενέργειας [DIRE09]. Μια σημαντική συνέπεια αυτών των εξελίξεων είναι ότι η ηλεκτρική ενέργεια θεωρείται πλέον προϊόν και αγοραπωλείται αναλόγως, πράγμα που σημαίνει ότι οι λειτουργίες και οι αρχές από τις ελεύθερες αγορές και την οικονομική θεωρία καθίστανται δόκιμες και στην εμπορία ηλεκτρικής ενέργειας. Ωστόσο, οι αγορές ηλεκτρικής ενέργειας και οι μηχανισμοί διαπραγμάτευσης πρέπει να διερευνηθούν και να σχεδιαστούν έτσι ώστε να είναι προσαρμοσμένες στις συγκεκριμένες ιδιαιτερότητες της ηλεκτρικής ενέργειας. Το πιο σημαντικό είναι ότι όλες οι συναλλαγές ηλεκτρικής ενέργειας πρέπει να υλοποιηθούν σε ένα ηλεκτρικό δίκτυο. Αυτό σημαίνει ότι οι περιορισμοί και οι ιδιότητες του δικτύου πρέπει να λαμβάνονται υπόψη προκειμένου να διασφαλιστεί κατά πόσο είναι υλοποιήσιμο το αποτελεσμα της αγοράς καθώς και η σταθερότητα του δικτύου και η ασφάλεια της παροχής ηλεκτρικής ενέργειας.

Μια θεμελιώδης ιδιαιτερότητα του ηλεκτρικού δικτύου είναι ότι η διανομή πραγματοποιείται αυτοστιγμεί, και η παραγωγή πρέπει να είναι ίση με την κατανάλωση ανά πάσα στιγμή (πράγμα το οποίο σχετίζεται με την ευστάθεια του δικτύου). Η παραδοσιακή προσέγγιση για τη διατήρηση αυτής της ισορροπίας είναι ότι η παραγωγή ελέγχεται ώστε να ακολουθεί τη (μη ελεγχόμενη) ζήτηση. Ωστόσο, η διείσδυση των ΑΠΕ φέρνει ολοένα και περισσότερο μη ελέγξιμη παραγωγή στην πλευρά της προσφοράς, ενώ οι μονάδες παραγωγής με γρήγορη απόκριση θεωρούνται δαπανηρές τόσο από οικονομική άποψη όσο και από τις εκπομπές διοξιδείου του άνθρακα. Αυτές οι εξελίξεις οδήγησαν στη συζήτηση σχετικά με τη χρησιμοποίηση των δυνατοτήτων ευελιξίας στην πλευρά της ζήτησης, προκειμένου να καταστεί αποτελεσματικότερη η λειτουργία του δικτύου. Η ιδέα της αξιοποίησης της ευελιξίας της ζήτησης ηλεκτρικής ενέργειας αναφέρεται γενικά ως Διαχείριση Ζήτησης (ΔΖ) - Demand Response (DR).

Τεχνικές διαχείρισης ζήτησης

Η γενική ιδέα της διαχείρισης ζήτησης είναι να δοθούν κίνητρα στους χρήστες να διαμορφώσουν την κατανάλωση ηλεκτρικής ενέργειας ανάλογα με το τι είναι πιο αποδοτικό από την πλευρά του δικτύου ηλεκτρικής ενέργειας. Αυτό σε γενικές γραμμές νοείται ως μετακίνηση φορτίων από τις ώρες αιχμής σε ώρες χαμηλής ζήτησης. Ο λόγος είναι ότι η κατανάλωση ηλεκτρικού ρεύματος τείνει να φτάνει στο ζενίθ κατά τις απογευματινές ώρες. Αυτό καθιστά αναποτελεσματική την εξυπηρέτηση της ζήτησης από άποψη κόστους, διότι πρέπει να καλούνται μονάδες παραγωγής ταχείας απόκρισης, ώστε να καλυφθεί η αιχμή της ζήτησης και οι μονάδες αυτές όμως έχουν ακριβό οριακό κόστος παραγωγής. Χρησιμοποιώντας την παρακάτω εικόνα ως παράδειγμα, για την ίδια συνολική κατανάλωση ενέργειας, είναι πιο αποδοτικά οικονομικά η επίτευξη μιας πιο επίπεδης, ομοιόμορφα κατανεμημένης καμπύλης (μπλε) και όχι μιας καμπύλης με κορυφές και κοιλάδες (γκρι).



Σχήμα: Παράδειγμα τυπικής καμπύλης κατανάλωσης ηλεκτρικής ενέργειας κατά τη διάρκεια μιας ημέρας

Έχουν προταθεί διαφορετικές προσεγγίσεις για την εξόρυξη της ευελιξίας της κατανάλωσης ενέργειας, όπως:

α) Συμβάσεις που παρέχουν στον διαχειριστή του δικτύου τον άμεσο έλεγχο του ηλεκτρικού φορτίου

Η περίπτωση αυτή βρίσκει εφαρμογή κυρίως σε βιομηχανικούς ή εμπορικούς καταναλωτές. Ο καταναλωτής έχει συνάψει σύμβαση με την εταιρεία κοινής ωφελείας, η οποία επιτρέπει στην τελευταία να μειώσει μέρος της ενεργειακής κατανάλωσης του πρώτου σε πραγματικό χρόνο.

β) Σχήματα ενημέρωσης / εκπαίδευσης

Αυτή η προσέγγιση αναφέρεται στην εκπαίδευση των καταναλωτών (κυρίως κατοικιών) σε θέματα σχετικά με την ενεργειακή απόδοση που αποσκοπούν στην μεταβολή της ενεργειακής συμπεριφοράς και στην οικολογική κατανάλωση.

γ) Σχήματα ανταπόδοσης και εικονικά παίγνια

Οι τεχνικές αυτές βασίζονται στις έννοιες της συμπεριφορικής οικονομίας, και σκοπό έχουν να παρακινήσουν τους καταναλωτές να τροποποιήσουν τα πρότυπα κατανάλωσης ενέργειας μέσω της χρήσης συστημάτων ανταμοιβής και συστημάτων συλλογής πόντων.

δ) Διαχείριση Ζήτησης βάσει τιμής

Αυτή η προσέγγιση σχετίζεται με τη θεωρία της οικονομίας (economics) και της χρησιμότητας (utility theory). Ο καταναλωτής θεωρείται ως ένας ορθολογικός παίκτης που αποκομίζει μια συγκεκριμένη αξία / χρησιμότητα από την κατανάλωση ενέργειας του. Έτσι, ο καταναλωτής θα προχωρήσει εθελοντικά στην τροποποίηση του προτύπου κατανάλωσής του ως απόκριση σε μια χρηματική αποζημίωση.

Σε αυτή τη διατριβή επικεντρωνόμαστε στην τελευταία κατηγορία, η οποία βασίζεται στη ΔΖ βάσει τιμολογιακής πολιτικής, όπου οι χρήστες θεωρούνται ότι διαμορφώνουν την ενεργειακή τους κατανάλωση με βάση την τιμή της ενέργειας σε πραγματικό χρόνο. Αυτή η προσέγγιση παρακινεί τη μελέτη των μηχανισμών αγοράς ηλεκτρικής ενέργειας που παρέχουν προηγμένες δυνατότητες και ιδιότητες προσαρμοσμένες στις ιδιαιτερότητες κάθε περίπτωσης.

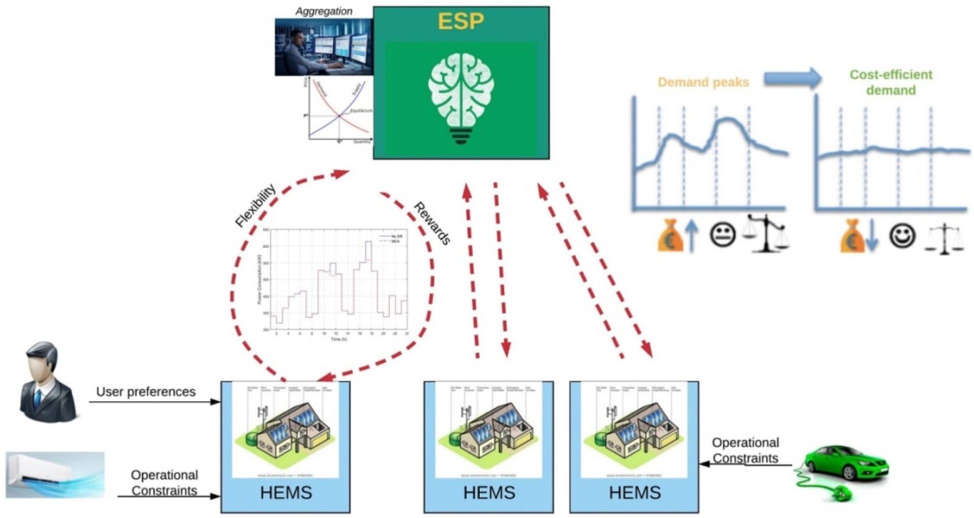
Σε αυτή τη διατριβή, εξετάζουμε ένα περιβάλλον όπου κάθε καταναλωτής ηλεκτρικής ενέργειας διαθέτει μια σειρά έξυπνων συσκευών, οι οποίες είναι συσκευές που υποστηρίζουν την προγραμματισμένη και ελεγχόμενη κατανάλωση ηλεκτρικής ενέργειας καθώς και τις δυνατότητες επικοινωνίας στο πλαίσιο του διαδικτύου των πραγμάτων (internet of things). Επίσης, υποθέτουμε ένα λογισμικού στην πλευρά του κάθε χρήστη, ένα σύστημα διαχείρισης ενέργειας οικίας (HEMS), το οποίο είναι σε θέση να λαμβάνει:

α) τις προτιμήσεις του χρήστη για την κατανάλωση ηλεκτρικής ενέργειας μέσω διεπαφής χρήστη

β) τους ενεργειακούς περιορισμούς των έξυπνων συσκευών

γ) δυναμικά σήματα τιμολόγησης ηλεκτρικής ενέργειας

και να λαμβάνει αποφάσεις εκ μέρους του χρήστη σχετικά με τον προγραμματισμό της κατανάλωσης ηλεκτρικής ενέργειας για κάθε έξυπνη συσκευή. Τέλος, υποθέτουμε ένα δίκτυο επικοινωνιών που είναι χτισμένο επιπλέον του δικτύου ενέργειας και διευκολύνει την ανταλλαγή μηνυμάτων μεταξύ των χρηστών με το σύστημα διαχείρισης ενέργειας και μια συντονιστική οντότητα, την οποία αναφέρουμε ως τον πάροχο υπηρεσιών ηλεκτρικής ενέργειας (ESP). Το παρακάτω σχήμα δείχνει την αρχιτεκτονική του συστήματος.



Σχήμα: Αρχιτεκτονική του συστήματος

Σε αυτή τη διατριβή, κάθε χρήστης (καταναλωτής) θεωρείται ένας ορθολογικός, στρατηγικός παίκτης που επιλέγει τις ενέργειές του με σκοπό τη βελτιστοποίηση του δικού του στόχου (μεγιστοποίηση του κέρδους / ικανοποίησής του). Σε αγορές που περιέχουν μεγάλο αριθμό συμμετεχόντων, οι ενέργειες ενός μεμονωμένου χρήστη είναι ουσιαστικά ασήμαντες, δηλαδή η ενεργειακή συμπεριφορά ενός μεμονωμένου χρήστη είναι αμελητέες, επειδή δεν έχουν σημαντικό αντίκτυπο στις ιδιότητες του συστήματος. Στο πλαίσιο αυτό, αυτή η προσέγγιση θεωρεί ένα μοντέλο όπου οι αποφάσεις ενός μεμονωμένου χρήστη δεν μπορούν να επηρεάσουν τις τιμές της αγοράς. Αυτή η παραδοχή ονομάζεται ευρέως "price-taking" και λέμε ότι ο χρήστης έχει θεωρηθεί ως “price-taker”.

Ωστόσο, στην παρούσα διατριβή έχουμε χαλαρώσει αυτήν την υπόθεση και ο μεμονωμένος χρήστης θεωρείται ως ένας "price-anticipator", δηλαδή ο χρήστης γνωρίζει τον μηχανισμό της αγοράς και συμπεριφέρεται στρατηγικά με σκοπό τη μεγιστοποίηση της δικής του ανταμοιβής. Αυτή η ρύθμιση φέρνει τα ζητήματα που εξετάζονται στην παρούσα διατριβή στη σφαίρα της θεωρίας παιγνίων. Έτσι, θα χρησιμοποιήσουμε κυρίως θεωρητικές και αλγοριθμικές τεχνικές από τη θεωρία παιγνίων προκειμένου να αναλύσουμε τα μοντέλα που θα εξετάσουμε.

Ο συντονισμός της ζήτησης, προκειμένου να καταστεί αποτελεσματικότερο το δίκτυο ηλεκτρικής ενέργειας, αποτελεί κοινωνικό στόχο. Ωστόσο, ο στόχος κάθε μεμονωμένου χρήστη μπορεί να μην ευθυγραμμίζεται πάντα με τον κοινωνικό στόχο. Σε ένα τέτοιο περιβάλλον και για να σχεδιάσουμε μηχανισμούς αγοράς που παρουσιάζουν επιθυμητές ιδιότητες, θα βασιστούμε σε μεγάλο βαθμό σε έννοιες ενός συγκεκριμένου ρεύματος της θεωρίας παιγνίων που ονομάζεται Σχεδιασμός Μηχανισμών.

Η μαθηματική βελτιστοποίηση είναι το εργαλείο για τη βελτιστοποίηση μιας αντικειμενικής συνάρτησης σε μια σειρά από μεταβλητές απόφασης. Μερικές φορές όμως, αυτές οι μεταβλητές δεν ελέγχονται από τον σχεδιαστή του συστήματος. Αντιθέτως, τις ελέγχουν ανεξάρτητοι πράκτορες, που ο καθένας προσπαθεί να βελτιστοποιήσει το δικό του στόχο, ο οποίος μπορεί να μην είναι σε συμφωνία με τον στόχο του σχεδιαστή. Η θεωρία παιγνίων είναι το πεδίο που μελετά μαθηματικά μοντέλα που μελετούν στρατηγικές ανταγωνιστικών ή συνεργατικών, ορθολογικών παικτών και τη διαδραστική συμπεριφορά αυτών. Ο Σχεδιασμός Μηχανισμών είναι ουσιαστικά ένα εργαλείο για το σχεδιασμό κανόνων για συστήματα με στρατηγικούς συμμετέχοντες που κατέχουν ιδιωτικές πληροφορίες, έτσι ώστε το σύστημα να έχει καλές εγγυήσεις απόδοσης (παρόλο που ο σχεδιαστής δεν ελέγχει άμεσα τις μεταβλητές απόφασης). Παραδείγματα μηχανισμών από την καθημερινή ζωή περιλαμβάνουν προβλήματα δρομολόγησης δικτύων (οδικών δικτύων ή δικτύων υπολογιστών) καθώς και δημοπρασίες οποιουδήποτε είδους.

Αλλά τι κάνει έναν συγκεκριμένο μηχανισμό καλύτερο από έναν άλλο; Υπάρχουν ορισμένες γενικώς επιθυμητές ιδιότητες για έναν δεδομένο μηχανισμό:

1) Ισχυρές εγγυήσεις κινήτρων: οι κανόνες είναι τέτοιοι ώστε να μπορούμε να υπολογίσουμε την κυρίαρχη στρατηγική κάθε συμμετέχοντος, πράγμα που ουσιαστικά σημαίνει ότι, αν υποθέσουμε ορθολογικούς συμμετέχοντες, μπορούμε να προβλέψουμε αποτελεσματικά το αποτέλεσμα παρόλο που δεν είμαστε εκείνοι που λαμβάνουν τις αποφάσεις,

2) Ισχυρές εγγυήσεις απόδοσης: οι κανόνες είναι τέτοιοι ώστε οι αποφάσεις των στρατηγικών συμμετεχόντων να βελτιστοποιούν το στόχο του σχεδιαστή,

3) Εγγυήσεις σύγκλισης: οι κανόνες είναι τέτοιοι ώστε οι διαδραστικές συμπεριφορές των συμμετεχόντων να μπορούν να φτάσουν σε ισορροπία σε αποδεκτό χρόνο,

και ενδεχομένως μια σειρά πρόσθετων επιθυμητών ιδιοτήτων, ανάλογα με το δοθέν επιχειρηματικό μοντέλο. Παραδείγματα περιλαμβάνουν εγγυήσεις για: τα έσοδα ορισμένων συμμετεχόντων (π.χ. οι επενδυτές), η ατομική ορθολογικότητα (individual rationality) (δηλαδή, ότι κάθε συμμετέχων συμμετέχει εθελοντικά καθώς έχει μόνο όφελος από τη συμμετοχή του και ποτέ ζημία), εγγυήσεις δικαιοσύνης, προστασία των προσωπικών δεδομένων κ.λ.π. Η σχεδίαση Μηχανισμών έτσι ώστε να παρουσιάζουν συγκεκριμένες ιδιότητες προσαρμοσμένες κάθε φορά στο δοθέν επιχειρηματικό μοντέλο είναι ένα ανοιχτό και σημαντικό ερευνητικό θέμα.

Στο πλαίσιο του έξυπνου δικτύου, οι παραγωγοί, οι φορείς εκμετάλλευσης, οι έμποροι και οι ρυθμιστικές αρχές είναι όλοι συμμετέχοντες με διαφορετικούς στόχους σε ένα σύστημα όπου η απόφαση του ενός επηρεάζει την απόφαση του άλλου. Στο κείμενο που ακολουθεί θα καθορίσουμε κάποιες περιπτώσεις χρήσης (use cases) που εξετάζονται σε αυτή τη διατριβή και τις προκλήσεις τους. Θα περιγράψουμε επίσης τις επιθυμητές ιδιότητες του μηχανισμού ειδικά για τις περιπτώσεις χρήσης που εξετάζονται και θα εξαγάγουμε τους βασικούς δείκτες απόδοσης (KPIs). Τέλος, θα παρουσιάσουμε τις τελευταίες μελέτες για αυτές τις περιπτώσεις χρήσης.

Απαιτήσεις και βασικοί δείκτες απόδοσης

Η παραδοσιακή προσέγγιση στην εμπορία ηλεκτρικής ενέργειας από πλευράς ζήτησης είναι εκείνη στην οποία οι χρήστες χρεώνονται με μια σταθερή τιμή ανά μονάδα κατανάλωσης ενέργειας. Οι τιμές χονδρικής, ωστόσο, υπόκεινται στους κανόνες προσφοράς και ζήτησης της αγοράς ηλεκτρικής ενέργειας. Ειδικότερα, οι παραγωγοί δηλώνουν το οριακό κόστος παραγωγής τους στο διαχειριστή της αγοράς και η τιμή για όλους του συμμετέχοντες καθορίζεται από τον τελευταίο (οριακό) παραγωγό που θα χρειαστεί να κληθεί να λειτουργήσει. Ειδικά στις αγορές με μεγάλη διείσδυση ΑΠΕ, οι τιμές της χονδρικής αγοράς μπορεί να είναι αρκετά ασταθείς, δεδομένου ότι η παραγωγή από ΑΠΕ δεν μπορεί να ρυθμιστεί καθώς εξαρτάται από τις καιρικές συνθήκες.

Στην παραδοσιακή προσέγγιση που περιγράφεται παραπάνω, η πλευρά της ζήτησης δεν λαμβάνει υπόψη τις τιμές της χονδρικής αγοράς και γενικότερα το κόστος ενέργειας σε πραγματικό χρόνο. Αυτό έχει προκαλέσει μια εκτενή συζήτηση μεταξύ τόσο της ακαδημαϊκής κοινότητας όσο και της βιομηχανίας σχετικά με τις πολιτικές λιανικής τιμολόγησης που θα αντικατοπτρίζουν τις τιμές χονδρικής αγοράς στις πληρωμές των τελικών χρηστών. Έχουν προταθεί διάφοροι μηχανισμοί για την επίτευξη αυτού του στόχου, καθένας από τους οποίους επικεντρώνεται σε μια διαφορετική πτυχή του προβλήματος. Ειδικότερα, οι σύχρονοι μηχανισμοί αγοράς ηλεκτρικής ενέργειας μπορούν να αξιολογηθούν με βάση έξι δείκτες:

1. Βελτιστοποίηση / αποτελεσματικότητα: Το συνολικό κέρδος όλων των συμμετεχόντων στην αγορά.

2. Εγγυήσεις κινήτρων / προστασία από στρατηγική συμπεριφορά: Η ανθεκτικότητα του συστήματος σε χρήστες που επωφελούνται από τη δήλωση ψευδών προτιμήσεων. Με άλλα λόγια, λέμε ότι ένας μηχανισμός είναι ανθεκτικός σε στρατηγική συμπεριφορά, όταν οι χρήστες δεν μπορούν να επωφεληθούν από την εξαπάτησή του.

3. Προστασία προσωπικών δεδομένων: Η ποσότητα πληροφοριών που απαιτείται από τον χρήστη.

4. Σύγκλιση / δυνατότητα κλιμάκωσης: Η ταχύτητα σύγκλισης της εφαρμογής του μηχανισμού και η δυνατότητα κλιμάκωσής του (εφαρμογή σε μεγάλο αριθμό χρηστών).

5. Δικαιοσύνη: Η πολιτική για την κατανομή του ενεργειακού κόστους στους καταναλωτές ενέργειας.

6. Εξισορροπημένο κόστος συναλλαγών (budget-balance): Όταν το συνολικό ποσό των χρηματικών συναλλαγών από όλους τους συμμετέχοντες στην αγορά (συμπεριλαμβανομένων των καταναλωτών στην πλευρά της ζήτησης και όλων των συμμετεχόντων στην πλευρά της προσφοράς είναι ισορροπημένο. Με άλλα λόγια, ο σχεδιαστής μηχανισμού δεν χρειάζεται να επιχορηγήσει το εμπόριο, ούτε να εξάγει πλεόνασμα από αυτό.

Τέλος σημειώνουμε ότι ανάλογα με κάθε συγκεκριμένη περίπτωση χρήσης, επιπλέον ιδιότητες του μηχανισμού ενδέχεται να είναι σημαντικές (π.χ. δυνατότητα ικανοποίησης περιορισμών, απλότητα για τους χρήστες να κατανοήσουν τον μηχανισμό κ.λπ.). Στην επόμενη υποενότητα αναλύουμε κάθε KPI με περισσότερες λεπτομέρειες και παρουσιάζουμε τον τρόπο με τον οποίο αντιμετωπίζεται στην πρόσφατη βιβλιογραφία της ΔΖ.

Βιβλιογραφία

Η βέλτιστη αξιοποίηση / αποδοτικότητα έχει μεγάλη σημασία, ιδίως για τους φορείς χάραξης πολιτικής και τους φορείς ρύθμισης της αγοράς. Αναφέρεται στην εξάλειψη των αποτυχιών αγοράς. Όταν υπάρχουν μέρη και στις δύο πλευρές της αγοράς που θα συμφωνούσαν στο εμπόριο σε μια δεδομένη τιμή, αλλά το εμπόριο δεν συμβαίνει για κάποιο λόγο, λέμε ότι υπάρχει μια αποτυχία αγοράς. Οι επίπεδες τιμές λιανικής καθώς και οι στατικές χρονικά διαφοροποιημένες τιμές δημιουργούν αποτυχίες αγοράς, δεδομένου ότι το πραγματικό κόστος και οι τιμές της αγοράς είναι ουσιαστικά αόρατες στην πλευρά της ζήτησης. Έτσι, η τιμολόγηση σε πραγματικό χρόνο (real time pricing) ήταν η πρώτη κατεύθυνση προς την οποία κινήθηκε η ακαδημαϊκή βιβλιογραφία που σχετίζεται με προηγμένα και αυτοματοποιημένα συστήματα ΔΖ. Συγκεκριμένα, η μελέτη [LI10] πρότεινε έναν βέλτιστο μηχανισμό αγοράς (υπό ορισμένες υποθέσεις σχετικά με τις προτιμήσεις των χρηστών και την καταναλωτική συμπεριφορά). Υπό τον περιορισμό ότι η η προσφορά και η ζήτηση πρέπει να ισούνται σε κάθε χρονική στιγμή, διαμορφώθηκε η Lagrangian συνάρτηση του προβλήματος και οι πολλαπλασιαστές Lagrange για το dual πρόβλημα ερμηνεύτηκαν ως τιμές λιανικής αγοράς. Ένας επαναληπτικός αλγόριθμος συγκλίνει στις βέλτιστες τιμές. Ωστόσο, οι υπόλοιποι δείκτες KPI δεν εξετάστηκαν.

Οι εγγυήσεις κινήτρων αναφέρονται στο θέμα της πιθανής εξαπάτησης του μηχανισμού. Πιο συγκεκριμένα, οι μελέτες [LI10], [SAMA10], [GATZ10] υποθέτουν ότι οι χρήστες είναι price-takers (το φορτίο του ατόμου είναι πολύ μικρό σε σύγκριση με το χαρτοφυλάκιο του Aggregator και συνεπώς η συμπεριφορά του πρώτου δεν επηρεάζει τις τιμές). Παρ 'όλα αυτά, υπάρχουν αρκετές περιπτώσεις στις οποίες αυτή η υπόθεση είναι αδόκιμη και αδικαιολόγητη, συμπεριλαμβανομένων των περιπτώσεων όπου έχουμε:

i) μεγάλους βιομηχανικούς καταναλωτές,

ii) χρήστες που συμμετέχουν στο μηχανισμό σε μια συγκεκριμένη γεωγραφική περιοχή όπου εμφανίζονται προβλήματα συμφόρησης,

iii) μικρο-δίκτυα που σχηματίζονται σε τοπικό επίπεδο

Ως αποτέλεσμα, οι χρήστες αναμένεται να συμπεριφέρονται στρατηγικά και η στρατηγική συμπεριφορά μπορεί να θέσει σε κίνδυνο την αποτελεσματικότητα του μηχανισμού. Στη μελέτη [SAMA12], το ζήτημα της στρατηγικής συμπεριφοράς αντιμετωπίστηκε προτείνοντας εναν Vickrey-Clarke-Groves (VCG) για τη λιανική εμπορία ηλεκτρικής ενέργειας. Ο μηχανισμός VCG θεωρείται ευρέως ο ακρογωνιαίος λίθος του Σχεδιασμού Μηχανισμών, καθώς είναι αποδεδειγμένα ο μοναδικός βέλτιστος μηχανισμός (1ο KPI) ενώ ταυτόχρονα παρέχει την ισχυρότερη δυνατή εγγύηση κινήτρων (2ο KPI) [SHOH09]. Ωστόσο, ο μηχανισμός VCG παρουσιάζει σοβαρά μειονεκτήματα σε σχεδόν όλους τους υπόλοιπους δείκτες. Το πιο σημαντικό είναι οτι απαιτεί από τους χρήστες να δηλώσουν όλη τη συνάρτηση των προτιμήσεών τους για κάθε συσκευή τους στον πάροχο υπηρεσιών. Το γεγονός αυτό καθιστά αδύνατη την πρακτική εφαρμογή του, λόγω τόσο της ιδιωτικότητας όσο και των ζητημάτων κωδικοποίησης των προτιμήσεων του χρήστη. Τα ζητήματα κωδικοποίησης αναφέρονται στο ζήτημα που θέλει τους χρήστες να εκφράσουν τις προτιμήσεις τους σε αναλυτικές μαθηματικές συναρτήσεις, ώστε να δοθεί η δυνατότητα στον πάροχο υπηρεσιών να λύσει ένα πρόβλημα βελτιστοποίησης.

Όσον αφορά την προστασία των προσωπικών δεδομένων του χρήστη, στη μελέτη [BAHA14] παρουσιάζεται ένας κατανεμημένος μηχανισμός όπου προτείνεται ένα πρωτόκολλο επικοινωνίας για τη διαδικασία ΔΖ, για την υλοποίηση των ανταλλαγών μηνυμάτων χωρίς να αποκαλύπτονται οι τοπικές πληροφορίες του χρήστη. Ωστόσο, υπάρχουν αρκετές ισχυρές υποθέσεις σχετικά με τις προτιμήσεις του χρήστη. Συγκεκριμένα, οι χρήστες θεωρούνται ότι ενδιαφέρονται μόνο για την ολοκλήρωση μιας συγκεκριμένης εργασίας μέσα σε ένα συγκεκριμένο χρονικό διάστημα και η ολοκλήρωση της εργασίας έχει μοντελοποιηθεί ως περιορισμός, πράγμα που σημαίνει ότι η εργασία θα πραγματοποιηθεί ανεξάρτητα από το κόστος.

Η παραπάνω συζήτηση επικεντρώνεται κυρίως στις περιπτώσεις σχετικά μικρών κοινοτήτων χρηστών. Μια διαφορετική κατεύθυνση έρευνας μελετά το ζήτημα χρήση της δυνατότητας κλίμακωσης (scalability). Τα προβλήματα είναι κυρίως η κλιμάκωση της εφαρμογής του μηχανισμού καθώς και η δικαιοσύνη σε επίπεδο μεμονωμένων χρηστών. Μια μαθηματική προσέγγιση για το πρόβλημα της κλιμάκωσης προτείνεται στη μελέτη [MHAN16], όπου δύο τεχνικές εξομάλυνσης εφαρμόζονται στην αντικειμενική συνάρτηση του προβλήματος βελτιστοποίησης προκειμένου να διευκολυνθεί η γρήγορη σύγκλιση. Μια διαφορετική προσέγγιση προτείνεται στη μελέτη [STEP15] όπου ομάδες χρηστών με παρόμοια χαρακτηριστικά, ομαδοποιούνται και θεωρούνται ότι συμμετέχουν συγκντρωτικά ως μονάδα. Παρόλο που η προσέγγιση αυτή μπορεί να χάσει σε σχέση με το βέλτιστο, μειώνει ωστόσο δραστικά τον χρόνο σύγκλισης.

Ένας διαφορετικός στόχος εξετάζεται στη μελέτη [BAHA13], όπου η προτεραιότητα δίδεται στη δίκαιη μεταχείριση και όχι στην αποδοτικότητα. Συγκεκριμένα, η μελέτη καταδεικνύει ότι υπάρχει ένα trade-off μεταξύ αυτών των δύο KPIs. Η τιμή Shapley [SHAP53] από τη συνεργατική θεωρία παιγνίων χρησιμοποιείται για να οριστει ένας δείκτης δικαιοσύνης και ο μηχανισμός έχει σχεδιαστεί έτσι ώστε να μεγιστοποιηθεί η δικαιοσύνη των τελικών τιμών.

Τέλος, η ιδιότητα του budget-balance συζητείται στη μελέτη [MA14], όπου οι συγγραφείς προτείνουν έναν μηχανισμό AGV (Arrow-d'Aspremont-Gerard-Varet) για τον συντονισμό της κατανάλωσης των χρηστών. Ωστόσο, οι μηχανισμοί AGV εξακολουθούν να είναι ένας μηχανισμός άμεσης αποκάλυψης όπως ο VCG (οι χρήστες πρέπει να δηλώσουν το σύνολο των προτιμήσεών τους), πράγμα που σημαίνει ότι υποφέρει επίσης από προβλήματα ιδιωτικότητας και κωδικοποίησης.

Πρέπει να σημειωθεί ότι οι έξι δείκτες KPI που περιγράφηκαν, αν και πολύ σημαντικοί, είναι αρκετά γενικοί και ενδέχεται να μην επαρκούν σε όλες τις περιπτώσεις. Οι μηχανισμοί πρέπει να λαμβάνουν υπόψη τις ειδικές απαιτήσεις κάθε περίπτωσης και τη σημασία κάθε απαίτησης. Για να είμαστε πιο συγκεκριμένοι, παρουσιάζουμε τα δύο ακόλουθα παραδείγματα.

Μπορεί να χρειαστεί να ικανοποιηθούν περιορισμοί σε επίπεδο συστήματος. Στο πλαίσιο μιας ενεργειακής κοινότητας, αυτού του είδους οι περιορισμοί απαιτούν ένα ορισμένο βαθμό συντονισμού μεταξύ των χρηστών. Η μελέτη [DENG14] παρουσιάζει μια μαθηματική τεχνική βασισμένη στους πολλαπλασιαστές Lagrange, όπου οι πολλαπλασιαστές ενημερώνονται δυναμικά και κατανεμημένα ώστε να χρησιμεύουν ως σήματα συντονισμού.

Ένα άλλο παράδειγμα ειδικών απαιτήσεων αφορά την απλότητα του μηχανισμού (εύκολη υιοθέτηση από τους χρήστες). Οι μελέτες που παρουσιάστηκαν παραπάνω παρέχουν ορισμένες ισχυρές θεωρητικές εγγυήσεις υπό ορισμένες υποθέσεις. Μια κεντρική παραδοχή είναι ο ορθολογισμός της συμπεριφοράς του τελικού χρήστη. Ωστόσο, στην πράξη και ειδικά όσον αφορά τη συμμετοχή των οικιακών χρηστών, δεν μπορούμε να περιμένουμε από τους χρήστες να συμπεριφέρονται πάντα ορθολογικά μέσα σε περίπλοκους μηχανισμούς που δεν καταλαβαίνουν. Έτσι, μια σχετική απαίτηση αφορά την απλότητα του μηχανισμού. Μια μελέτη για την απλότητα, παρουσιάζεται στο [BITA17], προσαρμοσμένη στην τιμολόγηση για φόρτιση ηλεκτρικών αυτοκινήτων. Ειδικότερα, η ταχύτερη φόρτιση χρεώνεται ακριβότερα. Ο χρήστης λαμβάνει έναν κατάλογο τιμών από τον οποίο μπορεί να επιλέξει, όπου η κάθε τιμή αντιστοιχή σε ένα συγκεκριμένο αναμενόμενο χρόνο ολοκλήρωσης της φόρτισης.

Υπάρχουν δύο περιπτώσεις γενικής χρήσης μοντέλων ΔΖ: μοντέλα που χρησιμοποιούν απόκριση σε πραγματικό χρόνο και μοντέλα που επιτυγχάνουν προγραμματισμό της κατανάλωσης από την προηγούμενη μέρα (day-ahead). Στην πρώτη περίπτωση, οι χρήστες καλούνται να τροποποιήσουν την κατανάλωσή τους σε πραγματικό χρόνο, έτσι ώστε να ανταποκρίνονται σε αναπάντεχες ανάγκες του δικτύου. Παραδείγματα περιλαμβάνουν βραχυπρόθεσμη πρόβλεψη συμφόρησης δικτύου ή αποτυχίας κάποιας μονάδας παραγωγής. Από την άλλη πλευρά, κατά τον day-ahead προγραμματισμό, η κατανάλωση ηλεκτρικής ενέργειας προγραμματίζεται για έναν δεδομένο ορίζοντα προγραμματισμού και διαμορφώνονται τα προφίλ κατανάλωσης ενέργειας των χρηστών.

Για παράδειγμα, στη μελέτη [GATZ13] προτείνεται ένας απλός μηχανισμός καθορισμού των τιμών για ΔΖ σε πραγματικό χρόνο με σκοπό τη μείωση του φορτίου. Αυτό θα μπορούσε να διευκολύνει τους χρήστες να συσχετίζουν την καταναλωτική τους συμπεριφορά με οικονομικά οφέλη.

Αντίθετα, στη μελέτη [RAD10], ο προτεινόμενος μηχανισμός εξάγει μια κατανομή φορτίων για ένα συγκεκριμένο χρονικό ορίζοντα προγραμματισμού, που θυμίζει το γνωστό αλγοριθμικό πρόβλημα του προγραμματισμού των εργασιών στις μηχανές. Ωστόσο, ειδικά για αυτήν την περίπτωση οι χρήστες ενδέχεται να συμφωνήσουν σε μια συγκεκριμένη καμπύλη κατανάλωσης για την επόμενη ημέρα, αλλά στην πραγματικότητα να την παραβιάσουν κατά τη διάρκεια της ημέρας.

Ένα χαρακτηριστικό παράδειγμα είναι το ζήτημα του bid-parking. Το bid-parking αναφέρεται στο φαινόμενο όπου ένας χρήστης προγραμματίζει ένα ψευδώς μεγάλο φορτίο σε μια δεδομένη στιγμή στο μέλλον, έτσι ώστε η τιμή για εκίνη την ώρα να αυξηθεί. Αυτό οδηγεί τους άλλους χρήστες να προγραμματίσουν τα δικά τους φορτία μακριά από εκείνη την ώρα και ενδεχομένως σε προγεννέστερες ώρες. Έτσι, όταν φθάσει η εν λόγω ώρα, ο αρχικός χρήστης μειώνει το προγραμματισμένο φορτίο στο πραγματικό του φορτίο και επωφελείται από μια μειωμένη τιμή, λόγω του γεγονότος ότι οι άλλοι χρήστες έχουν μεταφέρει (και ήδη εξυπηρετήσει) τα φορτία τους σε προηγούμενες χρονικές στιγμές. Μια πρόταση για την αντιμετώπιση του φαινομένου bid-parking, γίνεται στη μελέτη [CHAP17]. Σε αυτή τη μελέτη προτάθηκε μια clock-proxy δημοπρασία που ασχολείται με το ζήτημα των στρατηγικών χρηστών που θα μπορούσαν να εφαρμόσουν μια τέτοια στρατηγική.

Ως συμπέρασμα από την παραπάνω συζήτηση παρατηρούμε ότι έχουν προταθεί διάφορα μοντέλα για την ενσωμάτωση των μηχανισμών της αγοράς στη λιανική αγορά ηλεκτρικής ενέργειας. Ωστόσο, εξακολουθούν να υπάρχουν δύο σημαντικές ερευνητικές κατευθύνσεις που παραμένουν σχετικά ανεξερεύνητες. Η πρώτη αφορά τον σχεδιασμό μηχανισμών που εξετάζουν από κοινού πάνω από ένα ή δύο από τους προαναφερόμενους KPI και επιτυγχάνουν ένα ελκυστικό συνδυασμό μεταξύ πολλών ή όλων αυτών. Το δεύτερο αφορά μηχανισμούς σχεδιασμού που παρουσιάζουν συγκεκριμένες ιδιότητες προσαρμοσμένες σε κάθε συγκεκριμένη περίπτωση. Παρακάτω παρουσιάζουμε κάποια ζητήματα που δεν εξετάζονται στις μέχρι τώρα μελέτες και αναφέρουμε τη συμβολή αυτής της διατριβής.

Συνεισφορές και διάρθρωση της παρούσας εργασίας

Η συζήτηση για τη βιβλιογραφία στη ΔΖ αποκάλυψε ανοικτά ερευνητικά θέματα, μερικά από τα οποία θα συζητηθούν διεξοδικά στο κείμενο. Σύμφωνα με την κατηγοριοποίηση του προηγούμενου εδαφίου, ταξινομούμε τις συνεισφορές μας σε δύο τομείς: Αλγόριθμους για ΔΖ σε πραγματικό χρόνο και Αλγόριθμους για day-ahead χρονοπρογραμματισμό φορτίων.

Σχετικά με τη ΔΖ σε πραγματικό χρόνο, το πρώτο σημαντικό ζήτημα είναι η απουσία μελέτης που να εξετάζει ταυτόχρονα και τα τέσσερα πρώτα KPIs. Αυτό το ζήτημα είναι πολύ σημαντικό, ειδικά επειδή πολλές μελέτες μελετούν το πρώτο KPI χωρίς να λαμβάνουν υπόψιν το δεύτερο. Ωστόσο, παραλείποντας να αντιμετωπίσει κανείς το δεύτερο KPI, μπορεί εύκολα να θέσει σε κίνδυνο την απόδοση του μηχανισμού και στο πρώτο KPI. Στην παρούσα διατριβή εξετάζονται σε βάθος τα θέματα αυτά και προτείνεται ένας μηχανισμός που αντιμετωπίζει αυτά τα προβλήματα.

Το δεύτερο σημαντικό ζήτημα σχετικά με τη ΔΖ σε πραγματικό χρόνο είναι τα KPIs που σχετίζονται με δικαιοσύνη (fairness) και budget-balance. Από τη μία πλευρά, οι λίγες μελέτες που μελέτησαν τη δικαιοσύνη κάνουν μάλλον ισχυρές υποθέσεις σχετικά με το μοντέλο των χρηστών. Από την άλλη πλευρά, οι μηχανισμοί που θέτουν ως προτεραιότητα την αποδοτικότητα (efficiency), δηλαδή VCG, AGV και άλλοι, δεν είναι budget-balanced. Η σημασία αυτών των δύο ιδιοτήτων συζητείται λεπτομερώς και προτείνεται ένας νέος αλγόριθμος τιμολόγησης για την αντιμετώπιση αυτών των ζητημάτων.

Ακόμα, στο δεύτερο μέρος της διατριβής, ασχολούμαστε με την περίπτωση day-ahead χρονοπρογραμματισμού φορτίων, όπου η μεγάλη πλειοψηφία των σχετικών μελετών είτε υιοθετεί την "price-taker" υπόθεση, είτε κάνει ισχυρές υποθέσεις στα μοντέλα των χρηστών. Στην παρούσα διατριβή αναλύουμε το ζήτημα και συζητούμε επίσης την ειδική περίπτωση όπου απαιτείται η ικανοποίηση περιορισμών. Παρουσιάζεται μια αρχιτεκτονική ΔΖ όπου χαλαρώνονται οι παραπάνω υποθέσεις στο μοντέλο. Ο προτεινόμενος μηχανισμός εγγυάται τη σύγκλιση προς την ισορροπία Nash. Επιπλέον, οι περιορισμοί διασφαλίζονται ότι πληρούνται κατά την τελική κατανομή, ενώ ο μηχανισμός διατηρεί επίσης την ιδιότητα budget-balance.

Τέλος, εξετάζεται επίσης το ζήτημα του bid-parking. Η ρύθμιση που θεωρούμε παρακινεί σε ανάπτυξη peer to peer αγορών ενέργειας, οι οποίες αποτελούν πεδίο εκτεταμένης συζήτησης στα σύγχρονα συστήματα ηλεκτρικής ενέργειας. Διεξάγουμε ανάλυση σχετικά με την αξία των peer to peer αγορών, ενώ οι προσομοιώσεις επιβεβαιώνουν ότι η συσχέτιση των προφίλ ζήτησης διαφορετικών χρηστών παίζει σημαντικό ρόλο.

Λέξεις Κλειδιά : **Έξυπνα Δίκτυα Ενέργειας, Διαχείριση Ζήτησης, Θεωρία Παιγνίων, Σχεδιασμός Μηχανισμών**

Γλωσσάριο αντιστοιχίας τεχνικών όρων

Budget-Balance	Οικονομική Ισορροπία
Constraints	Περιορισμοί
Day-Ahead market	Αγορά προηγούμενης ημέρας
Demand Side Management	Διαχείριση Ζήτησης
Home Energy Management System	Σύστημα διαχείρισης ενέργειας οικίας
Fairness	Δικαιοσύνη
Incentive Compatibility	Συμβατότητα Κινήτρων
Price-taker	Δέκτης τιμών
Privacy	Ιδιωτικότητα
Scalability	Δυνατότητα Κλιμάκωσης

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Chapter 1

INTRODUCTION

1.1 Modern Power Systems and Demand Side Management

1.1.1 Introduction, Evolution and Challenges

Until the 1980s, electricity systems were considered natural monopolies and were organized under cost-of-service regulation. The major directions favored by the EU are headed towards increasing penetration of Renewable Energy Sources (RES) and promoting the liberalization of the energy market (directive 200/72/EC [DIRE09]). A major consequence of these developments is that electricity is envisaged as a commodity and traded accordingly, which means that functionalities and principles from markets and economics are becoming relevant in electricity trading as well. However, electricity markets and trading mechanisms need to be researched and designed, so that they are tailored to the specific specialties of electricity. Most importantly, all electricity trading is made on top of an electricity grid. This means that the network constraints and properties must be taken into account in order to ensure the feasibility of the market outcome, the network stability and the security of supply.

A fundamental specialty of electricity as a commodity is that delivery is made instantly and supply must equal demand at all times (which relates to the network's stability). The traditional approach to maintaining this balance is that generation is controlled to follow the intermittent demand. However, RES penetration is increasingly introducing non-dispatchable generation in the supply side, while fast-responsive generation units are considered costly both in financial terms and in CO2 emissions. These developments have triggered the discussion of utilizing flexibility capabilities on the demand side, in order to make network operation more efficient. The idea of leveraging the flexibility of electricity demand is generally referred to as Demand Response (DR) or Demand Side Management (DSM).

1.1.2 Demand Response techniques

The general idea of Demand Response is to incentivize users to shape their electricity consumption according to what is more efficient in terms of the electricity network. This is generally envisaged as moving loads from peak-demand times to low-demand times. The reason is that electricity consumption tends to form a peak during evening hours. This makes it inefficient for the network to serve, because fast-response, higher cost generation units need to be called in order to cover for the peak demand. Using the following figure as an example, for the same total energy consumption, it is more efficient to achieve a more flat, uniformly distributed curve (blue) rather than a curve with peaks and valleys (grey).

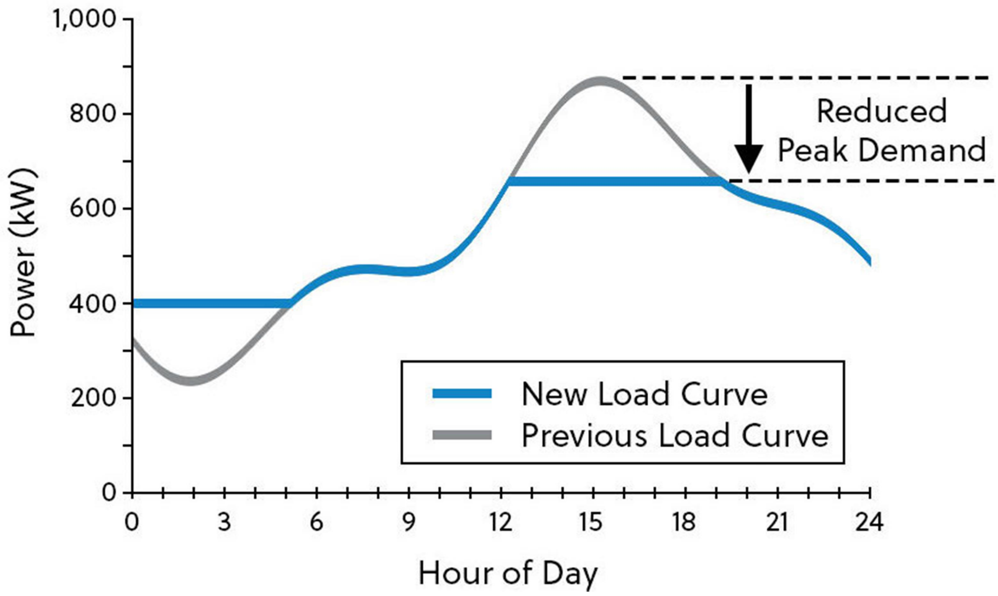


Figure 1.1.f1. Example of a typical electricity consumption curve in a day

There have been proposed different approaches for extracting the flexibility of energy consumption, including:

a) Contracts that facilitate direct load control

   This case is mainly applicable to industrial or commercial consumers. The consumer has a contract with the utility company, which allows the latter to curtail part of the former's energy consumption in real time.

b) Behavioral/motivational/educational schemes

   This approach refers to educating consumers (mainly residential) towards energy efficiency, behavioral change and environmentally friendly consuming behavior.

c) Reward schemes and gamefication

   These techniques draw on the concepts of behavioral economics, in order to motivate consumers to modify their energy consumption patterns through the use of point systems and reward schemes

d) Price-based demand response

   This approach relates to economics and utility theory. The consumer is envisaged as a rational agent that derives a particular value/utility from his/her energy consumption. Thus, the consumer would voluntarily proceed to the modification of his/her consumption pattern in response to a monetary compensation.

In this thesis we focus on the last category, which is price-based DR, where users are considered to shape their consumption patterns in response to monetary incentives. This approach motivates the study of market mechanisms that implement electricity trading featuring advanced capabilities and properties tailored to the specialties of each particular use case.

1.1.3 System Architecture

In this dissertation, we envisage a setting where each electricity consumer possesses a number of smart devices which are devices that support schedulable and controllable electricity consumption as well as communication capabilities in the context of the internet of things. Also, we assume a software component at each user's side, a home energy management system (HEMS), which is able to receive

a) the user's preferences on electricity consumption through a user interface

b) the smart devices' operational constraints

c) dynamic electricity pricing signals

and make decisions on behalf of the user concerning the scheduling of the electricity consumption for each smart device. Finally, we assume a communication network built on top of the power network that facilitates message exchange between the users' home energy management system and a coordinating entity, to which we refer as the Electricity Service Provider (ESP). The following figure demonstrates the system's architecture.

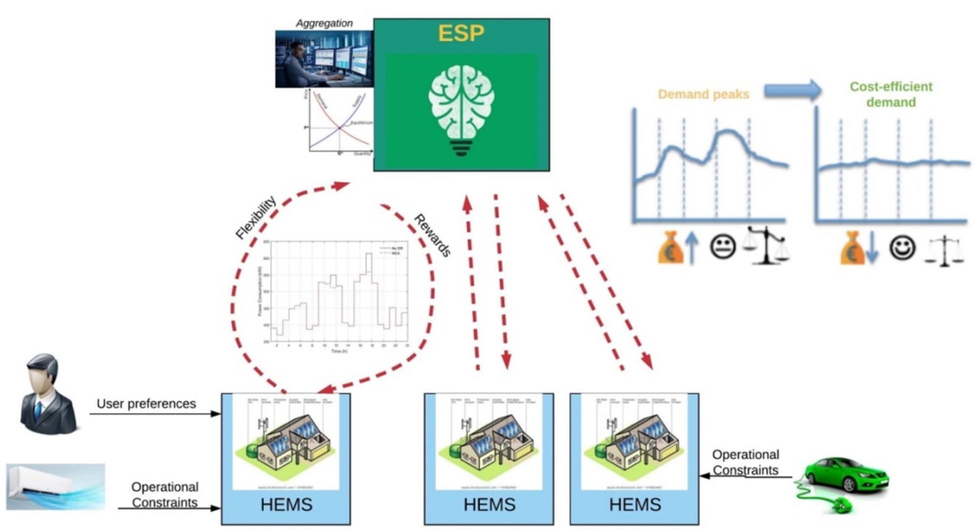


Figure 1.1.f2. System Architecture

1.1.4 Strategic users

In this thesis, each user (consumer) is considered to be a rational, strategic player who chooses his/her actions with the purpose of optimizing his/her own objective (maximizing his/her payoff/utility). When dealing with markets that contain a large number of participants, an individual user's actions are virtually insignificant i.e. a sole user's market actions (taken alone) are negligible since they do not have a significant impact on the system's properties. In our context, this approach considers a model where an individual user's decisions cannot affect the market's prices. This assumption is widely called "price-taking", and we say that the user is modeled as a price-taker.

Nevertheless, in the present thesis we have relaxed this assumption and the individual user is considered to be a "price-anticipator" i.e. the user is aware of the market mechanism and behaves strategically with the purpose of maximizing his/her own payoff. This setting brings the issues considered in this thesis in the realm of game theory and we will mainly leverage game-theoretic concepts, in order to analyze the use case that we will consider.

Coordinating the demand, so as to make the electricity network operate more efficiently constitutes a social objective. However, each individual user's objective may or may not be aligned with the social objective. In such an environment and in order to design market mechanisms that exhibit desired properties, we will largely draw on concepts of a particular stream of game theory called mechanism design.

1.2 Mechanism Design Preliminaries

Mathematical optimization is the tool for optimizing an objective over a number of decision variables. Sometimes though, these decision variables are not under the control of the system designer. Rather, they are in control of independent agents, each one trying to optimize its own objective, which may or may not be in line with the designer's objective (or with the social objective for that matter). Game theory is the field that studies mathematical models that involve competing or cooperative, rational agents and their interactive behavior. Mechanism design is essentially the tool for designing rules for systems with strategic participants holding private information, such that the system has good performance guarantees (even though the designer does not directly control the decision variables). Examples of mechanisms from everyday life include routing problems of (transportation or computer) networks as well as auctions of any kind.

So, what makes a particular mechanism better than another? There are a number of generally desired properties that a mechanism ideally exhibits:

1) Strong incentive guarantees: the rules are such that we can reason about each participant's dominant strategy, which essentially means that, assuming rational participants, we can effectively predict the outcome even though we are not the ones making the decisions.

2) Strong performance guarantees: the rules are such that the decisions of the strategic participants optimize the designer's objective.

3) Tractability guarantees: the rules are such that the participant's interactive behaviors can reach an equilibrium in acceptable time.

and possibly a number of additional desired properties, depending on the particular business model. Examples include guarantees on: some participant's revenue (e.g. the investor's), individual rationality (that is that every participant is better off participating rather than not participating), fairness guarantees, privacy preserving, communication overhead etc. Designing mechanisms that exhibit specific properties tailored to each specific business model is an open and important research topic.

In the context of the Smart Grid, producers, consumers operators, traders and regulators are all participants with different objectives in a system where the decision of one affects the decision of another. In the following subsection we will define the use cases considered in this thesis and their challenges. We will also describe the mechanism's desired properties specifically for the use cases considered, and extract the key performance indicators (KPIs). Finally, we will present the state-of-the-art approaches in these use cases before proceeding to the mathematical formulations and the proposed solutions.

1.3 Mechanism Design for Demand Side Management

1.3.1 Requirements and Key Performance Indicators

The traditional approach to demand-side electricity trading is the one where users are charged with a fixed per-unit price. The wholesale prices on the other hand, are subject to the producers' bids. In particular, producers bid their marginal cost of production in the wholesale market where the marginal producer defines the per-unit payment of all participating producers. Especially in markets with high RES penetration, the wholesale market prices can be quite volatile, since RES production is non-dispatchable and depends on weather conditions.

In the traditional approach described above, the demand side is oblivious of the wholesale market prices and more generally of real-time energy costs. This has provoked an extensive discussion among both the academia and the industry on retail policies that will reflect the wholesale market prices to the end-users payments. There have been proposed several mechanisms to achieve this goal, each one focusing on a different aspect of the problem. In particular, market mechanisms for electricity retail can be generally evaluated by six KPIs

1. **Optimality/efficiency**: The aggregated payoff of all market participants. This is formally defined in economics as the Social Welfare.
2. **Incentive Guarantees/Strategy proof**: The resilience of the system to users who benefit from declaring false preferences. In other words, we say that a mechanism is Incentive Compatible when users cannot benefit from cheating.
3. **Privacy protecting**: The quantity of information that is required from the user.
4. **Convergence/scalability**: The speed of convergence of the mechanism's implementation and its scalability with respect to the number of users.
5. **Fairness**: The policy towards the distribution of the energy costs to energy consumers
6. **Budget-Balanced**: When the total sum of monetary transactions from all market participants (including consumers in the demand side and all participants on the supply side i.e. producers, retailers, operators etc) is balanced. In other words, the mechanism designer does not need to subsidize the trade, nor extracts a surplus from it.

Finally we note that depending on each particular use case, other positive/negative outcomes of the mechanism might be relevant (e.g. controllability in order to satisfy system-wide constraints, simplicity for users to understand the mechanism, etc.). In the next subsection we analyze each KPI in more detail and present how it is treated in the recent DSM literature.

1.3.2 Related work

Optimality/efficiency in terms of Social Welfare is of great importance, especially for policy makers and market operators. It refers to eliminating market inefficiencies. When there are parties on both sides of the market that would agree to trade at a given price, but the trade does not happen for any reason, we say that a market inefficiency occurs. Flat retail prices as well as static time-differentiated prices create market inefficiencies since the real-time costs and prices of the market are essentially invisible to the demand side. Thus, real-time pricing was also the first to be considered in the academic literature for advanced and automated DSM schemes. In particular, [LI10] proposed a market mechanism where the social welfare was optimized (under certain assumptions on user preferences and consumption behavior including the price-taking assumption). Under the constraint that demand must equal supply at all times, the Lagrangian function was formulated and the Lagrange multipliers for the dual problem were interpreted as the retail market prices. An iterative algorithm converges to the prices that maximize the social welfare, assuming that the end-user appliances registered to the market mechanism are automatic in the sense that they can modify their consumption in response to price signals, given the user's programmable set of preferences. However, the rest of the KPIs were not considered.

Incentive Guarantees/Strategy proof refers to the issue of cheating the mechanism. More specifically, the studies in [LI10], [SAMA10], [GATZ10] assume that users are price-takers (an individual user's load is very small compared to the Aggregator's portfolio and thus its behavior does not affect the prices). Nevertheless there are several use cases in which the assumption of price-taking behavior is rather strong and unjustified, including but not limited to:

i) large industrial consumers,

ii) users that participate in DSM in a particular geographic location where congestion problems occur,

iii) islanded micro grids formed at neighborhood level

As a result, users are better expected to behave strategically and strategic behavior may compromise the mechanism's efficiency. In [SAMA12], the issue of strategic behavior was tackled by proposing a Vickrey-Clarke-Groves (VCG) approach for retail electricity trading. The VCG mechanism is widely considered as the cornerstone of mechanism design as it is provably the unique mechanism that achieves the optimal social welfare (1st KPI) while also provides the strongest incentive guarantee (2nd KPI) which is Dominant-Strategy-Incentive-Compatibility (DSIC) [SHOH09]. However, the VCG mechanism comes with serious disadvantages in almost all the rest of the KPIs. Most importantly, it requires from the users to declare their whole set of consumption preferences for each of their appliances to the service provider. This fact is clearly a deal-breaker in practice because of both privacy as well as representation issues. Representation issues refer to the request from the users to capture their preferences in closed form mathematical functions, so as to make it possible for the service provider to solve a large and most probably intractable optimization problem.

Regarding user's privacy protection, a distributed mechanism is proposed in [BAHA14], where a communication protocol was proposed for the DSM procedure, to implement the message exchanges without revealing the user's local information. However, there is a number of strong assumptions regarding user's preferences. More specifically, users are considered to only be interested in completing a certain task within a certain time interval and the task's completion is modeled as a hard constraint, which means that the task will be performed no matter the cost.

The above discussion mainly focuses on the use cases of relatively small communities of users, where user incentives and strategies come into play. A different research direction is studying the use case of large scale aggregation. The problems there are mainly the scalability of the mechanism implementation as well as the fairness at the individual user's level. A mathematical approach towards a solution for the scalability problem is proposed in [MHAN16], where smoothing techniques are applied to the objective function of the optimization problem in order to facilitate fast convergence. A different approach is taken in [STEP15] where groups of users with similar characteristics are considered as an aggregated participation. While this approach might create minor inefficiencies, it drastically reduces the convergence time.

A different objective is considered in [BAHA13], where the social welfare efficiency is partially relaxed for the sake of fairness. In particular, the study demonstrates that there is a trade-off between these two KPIs. The Shapley value [SHAP53] from cooperative game theory is leveraged to define a fairness index and the mechanism is accordingly designed, so as to maximize fairness.

Finally, the budget-balanced property is discussed in [MA14], where the authors propose an AGV (Arrow-d'Aspremont-Gerard-Varet) mechanism is proposed to coordinate load scheduling while keeping the system incentive compatible and budget-balanced. However, AGV mechanisms is still a direct-revelation mechanism like VCG (users are required to declare their whole set of preferences), which means that it also suffers from privacy and representation problems.

It should be noted, that the six KPIs described, although very important, are quite general and might not be enough in all use cases. Mechanisms should take into account the specific requirements of each use case and the importance of each requirement. The special properties required in each use case, are categorized under the "umbrella" term of mechanism externalities. For the cause of being more specific, we present the two following examples.

System-wide constraints on users consumptions might need to be satisfied. In the context of an energy community, this kind of constraints requires a certain amount of coordination among users. The study in [DENG14] presents a mathematical technique based on Lagrange multipliers, where the multipliers are dynamically and in a distributed fashion updated so as to serve as coordination signals. However, the study is not oriented in coordination among users, but rather in keeping an individual user's daily load fixed i.e. apply only temporal rescheduling and not load shedding.

Another example of special requirement relates to the mechanism's simplicity (easy user adoption). The studies presented above provide some strong theoretical guarantees under certain assumptions. A central assumption is the rationality of the end user behavior. However, in practice and especially when it comes to residential user participation, we cannot expect the users to always behave rationally within complicated mechanisms that they don't understand. Thus, a relevant requirement relates to the mechanism's plain simplicity. A study towards simplicity, is presented in [BITA17], tailored to EV charging. In particular, faster EV charging comes with a higher price. However, the proposed PM opts for simplicity and the user is provided with a list of prices to choose from, each one with its own expected time of job completion.

1.3.3 Real-time Demand Response and Period-Ahead Scheduling

In the previous section we provided a description of how each KPI is treated in the recent research literature. A first categorization of the DSM studies follows directly by recognizing the KPIs considered in each study.

In this section we further categorize the state of the art studies with respect to the DR use case that they consider. More specifically, there are two general use cases that relate to the temporality of the DR model: real-time DR and Period-Ahead demand scheduling. In real-time DR, the users are asked to modify their consumption in real-time, so as to meet sudden network needs. Examples include a short-term forecast of network congestion or RES failure. On the other hand, in Period-Ahead scheduling, electricity consumption is scheduled for a given scheduling horizon and the users' energy consumption profiles are shaped.

For example in [GATZ13], a plain and simple flat-pricing mechanism is proposed with the niche of applying DSM with real-time reward for load curtailment on top of the flat-pricing scheme. This might make it easier for users to relate their consumption behavior to financial benefits or at the very least give user the opportunity to not participate in the mechanism if they don't feel they understand it.

On the contrary, in [RAD10], the proposed mechanism outputs an allocation of loads for a given scheduling horizon ahead, reminiscent of the well-known algorithmic problem of scheduling jobs to machines. Especially for this case, there is an issue of keeping the users accountable to the allocation in which they agreed ahead of time. In other words, the users might agree on a certain consumption pattern for the following day, but actually violate it through the day.

A characteristic example is the issue of bid-parking. Bid-parking refers to the phenomenon where a user schedules a falsely large load at a given time in the future, so that the price at that time rises. This drives other users to schedule their own loads away from that time and possibly at earlier times. So, upon delivery time, the focal user reduces the scheduled load to the actual amount and benefits from a reduced price due to other users' having rescheduled (and already served) their loads to earlier times. A case for counteracting bid-parking strategies, is made in [CHAP17]. In this study, a clock-proxy auction was proposed that tackles the issue of strategic users who might apply such a strategy.

As a conclusion to the above discussion, we observe that there have been proposed very elegant models towards the integration of market mechanisms in the retail electricity market. However, there still two major research directions that remain relatively unexplored. The first refers to the design of mechanisms that jointly consider more than one or two of the KPIs presented above and achieve an attractive trade-off among many or all of them. The second refers to designing mechanisms that exhibit specific properties tailored to each specific use case and business model. The following subsection discusses issues not addressed in the state of the art studies and states the contributions of this dissertation.

1.3.4 Contributions and Structure of this Thesis

The discussion on the DR literature revealed open research topics, some of which will be thoroughly discussed in the rest of this text. In accordance with the categorization of the previous subsection, we categorize our contributions in two fields: real-time DR and period-ahead scheduling games.

The first major issue in real-time DR is the absence of a DR mechanism that simultaneously considers the first four KPIs (Efficiency, Incentive Compatibility, Privacy Protection and Scalability). This issue is very important, especially because many studies consider the first KPI without the second. However, failing to address the second KPI, can readily compromise the mechanism's performance also in the first KPI. Section 2.1 discusses these issues in depth and proposes an indirect mechanism that addresses these problems.

The second major issue in real-time DR is the widely overlooked KPIs of Fairness and Budget-Balance. On the one hand, the few studies that studied Fairness make rather strong assumptions regarding the user model. On the other hand, the protagonist mechanisms with efficiency and/or incentive guarantees (namely VCG, AGV and others) are inherently not budget-balanced. The importance of these two properties is discussed in detail in section 2.2 and a novel pricing scheme is proposed to address these issues.

In Section 3 we take on the period-ahead scheduling use case where the vast majority of the relevant studies either adopts the price-taking assumption or imposes strong assumptions on user models. In section 3.1 we analyze the issue and also discuss the special use case of satisfying system-wide constraints which is quite challenging from a technical perspective. A DSM architecture is presented where the above assumptions on usr model are relaxed. The proposed mechanism is guaranteed to converge to the Nash Equilibrium. Moreover, the constraints are guaranteed to be satisfied at the final allocation, while the mechanism also preserves the budget-balance property.

Finally, the issue of violations on the period-ahead schedules is discussed in section 3.2. A spread policy is considered and analyzed. The setting that we consider motivates the development of transactive energy markets which is a field of extensive discussion in modern electricity systems. We conduct an analysis on the value of transactive trade, while simulations confirm that the correlation of the different users' demand profiles is of great importance.

Chapter 2

REAL-TIME DEMAND RESPONSE

2.1 Truthful, practical and privacy-aware demand response via an optimal and distributed mechanism

Serving the energy demand in peak demand times might be quite expensive for the grid operator, because of the need to constantly maintain costly energy reserves. Also, in regions with high penetration of Renewable Energy Sources (RES), adjusting the demand to meet the intermittent generation can enhance the efficiency and economic viability of the system. As a result, the idea of offering monetary incentives (rewards) to consumers in order to decrease their consumption at peak demand times is getting a great deal of attention both from the research community and the Industry. More specifically, when there is a need for reducing energy consumption in real-time, an ad-hoc market is created where the operator offers to buy consumption reduction from the users. Users participate in such a DR event by offering their consumption flexibility in exchange for monetary compensation.

In the modern smart grid, each user (consumer) has a smart meter that measures his/her consumption at all times. The grid operator can assess the aggregated consumption of users at a particular part of the grid in real-time. Users are interested in their own payoff, which results from the reward they receive and the discomfort they experience from reducing their energy consumption. On the other hand, the operator is interested in the reduction of the aggregated consumption at peak times. Assuming strategic user behavior, the above setting turns into a game, since each user's payoff is dependent on the actions of other users. In more detail, discomfort could be modeled through a local function, so that it is expressed in monetary terms. However, users are usually not capable of capturing their preferences in a closed form mathematical function and even if they were, they are reluctant to reveal their preferences. Rather, it is more natural for the users to simply take actions (e.g. turn appliances on/off, or adjust power consumption) in response to price signals.

An intermediate entity is assumed to resolve the formulated game and clear the ad-hoc flexibility market described above. We refer to this entity as the Electricity Service Provider (ESP). The ESP is assumed to be an independent entity with the objective of coordinating the flexibility trading in the most efficient way. Formally, in economics, the "most efficient way" is characterized by the concept of maximizing the social welfare, defined as the aggregated payoff of all market participants. However, the users' local functions (related to their flexibility/comfort levels and consumption habits) are private to each user. This makes the task of the ESP quite challenging, especially when we consider users who act strategically and might misrepresent their local function if that makes them better-off.

In this section, we propose a DR architecture through which ESPs will be able to optimally resolve the aforementioned game. In particular, we draw on concepts of mechanism design theory in order to define an iterative, auction-based mechanism, consisting of an *allocation rule* and a *payment rule*. The *allocation rule* refers to the way that the ESP decides upon how much consumption reduction will be allocated to each user according to the feedback obtained through the auction process. The *payment rule* refers to the way the ESP decides upon the reward of each user for his/her allocation, provided that the user makes the corresponding contribution. Through the auction procedure, the ESP exchanges messages with the users in the form of queries. A query in our case is a price signal communicated from the ESP to the user, to which the latter responds with his/her preferred action (i.e. consumption reduction) according to this signal. Note that a user may respond untruthfully if he/she finds that to be in his/her interest.

A mechanism is generally evaluated by: i) its performance in terms of social welfare, i.e. efficiency, ii) the tractability of the outcome, and iii) its incentive guarantees. The first two are commonly addressed in the literature and point to the allocation's efficiency and the mechanism's convergence time and consequent scalability. In contrast, the third requirement (that points to truthful participation) is widely overlooked in the DR literature. In the few cases where truthfulness is addressed, it comes with a sacrifice of practical implementation ability and user privacy. In the rest of this section we analyze what the third requirement is about and how it is handled in the state-of-the-art DR studies.

User strategies in games such as the one described above are subject to thorough study and discussion. Mechanism design theory classifies a mechanism's incentive guarantees with respect to how users are expected to act when participating in it. The strongest guarantee is called Dominant Strategy Incentive Compatibility (DSIC). We say that a mechanism is DSIC when it is at each user's best interest to truthfully implement his/her true preferences at any query, regardless of what other users do.

Surprisingly, the vast majority of studies in the DR literature do not provide any guarantees as we will analyze shortly. This drawback is typically rationalized by assuming that an individual user's load is very small compared to the whole system's aggregated load and thus the user can be approximated as a price taker (his/her actions, taken alone, have no effect on the system's dynamics). Under this assumption, each user implements his/her most favorable action (consumption decision), assuming the actions of other users to be constant. This process is repeated until an equilibrium is reached. The users are typically modeled to iteratively implement their best-response every time they are asked a query, i.e., they decide upon their preferred consumption upon receiving a price signal. This strategy updating procedure is called best-response dynamics. As analyzed in [NISS07], such myopic "local rationality" does not necessarily imply "global rationality", i.e., given an iterative mechanism, it is not always to the user's best interest to repeatedly best-respond. Rather, a user might be better-off by submitting false bids through the process.

Best-response dynamics converges to an efficient allocation under the price-taking assumption described above. Nevertheless there are several use cases in which the assumption of price-taking behavior is rather strong and unjustified. For example, a large industrial consumer's actions may have a significant effect on the system. Also, when it comes to DR-events, the users called to participate are often required to be in a particular geographic location where congestion problems arise, in which case the relevant user population is not large. Another example includes islanded micro grids formed at neighborhood level, especially ones with high RES penetration. In such use cases, the number of users in the formulated game is drastically reduced. This means that a single user's actions may no longer be insignificant and a mechanism implemented in best-response strategies fails to capture user incentives. As a result, users are better expected to behave strategically, and strategic behavior may compromise the mechanism's efficiency [JOHA05]. In this chapter we also address the third requirement, defined as the capability of the mechanism to provoke strategic users to act truthfully in accordance with their preferences, which is overlooked in most of the DR literature. Moreover, we do so via an indirect and practical mechanism, which allows for distributed and privacy-preserving implementation, in contrast to the few studies that consider incentive guarantees that do not exhibit these characteristics.

The rest of this chapter is organized as follows. In Section 2.1.1, we present a literature review of DR studies from the perspective of incentive guarantees. In Section 2.1.2, we present the model assumed. In Section 2.1.3, we present the problem formulation. In Section 2.1.4, we present and analyze the proposed auction mechanism and prove that it has the desired properties. In Section 2.1.5, we demonstrate the performance and verify the properties of the proposed system. Finally, in Section 2.1.6 we describe a privacy-preserving communication protocol that can implement the proposed mechanism.

2.1.1. Related Work

In the DR architectures/frameworks that have appeared in the literature, the end user is typically modeled as a selfish player who participates in the mechanism with the purpose of maximizing his/her own payoff. The user's preferences are widely modeled as a convex function (e.g. [SAMA10], [LI10], [GKAT13]) in accordance with microeconomic theory [PERL15]. However, studies differ on the way they model the behavior and the strategy of the users participating in the game. More specifically, there are three levels of behavior modeling, in increasing order of user rationality:

A) "naive", de-facto truthful users, assumed to always truthfully report their preferences

B) locally rational users, assumed to apply a myopic best-response process (maximizing their payoff at each iteration of the mechanism as if it were the last iteration)

C) strategic, globally rational users, who are aware of the mechanism's structure and apply a strategy that maximizes their final payoff (possibly by submitting false responses).

Several studies either assume naive users of category A ([ALTH15], [TUSH15], [WANG17], [ZHAO13], [AHMA15], [ERDI15], [STER18]) or assume no user preferences and perform central optimization for the scheduling problem (e.g. [BASI17], [TANG14]).

The majority of DR works assume "price-taking users" which translates to category B, i.e., locally rational users. Static-pricing approaches (e.g. [NGUY14]), as well as typical dual decomposition approaches (including [SAMA10], [LI10], [GATZ13] and [QIAN13], [MOHS10], [MHAN16], [SLI16], [JACQ17], [BITA17]), assume users of category B. Under the price-taking assumption, the solution concept is that of a competitive equilibrium. A market-clearing pricing approach brings the system to competitive equilibrium via an iterative best-response process, and the final allocation maximizes the social welfare. However, as described above, in many use cases (such as emerging local energy communities [MAKR18], [MAMO18] islanded micro-grids, etc) the price-taking assumption no longer holds and the efficiency of these mechanisms is compromised [JOHA05]. In mechanism design terms, the mechanisms of the first two categories are not *incentive compatible*, because a strategic user can benefit by manipulating his/her responses.

Few works consider user incentives. When considering strategic users (of category C), the mechanism designer is confronted with a trade-off: the Vickrey-Clarke-Groves (VCG) mechanism is the unique welfare maximizing mechanism implemented in dominant (and not best-response) strategies, meaning that either a VCG-based approach is taken [SAMA12], [NEKO15] or welfare maximization is compromised [YAAG15], [MA14], [CHAP17], [TSAO16], [STER18].

The main problem with the VCG approaches is that they require users to reveal their whole set of preferences to the ESP, while the latter makes all the calculations and decides the allocation and the rewards. This is clearly impractical, since real users generally can't express their preferences in closed-form mathematical functions and even when they can, they are not happy to compromise their privacy by sharing their whole set of preferences with the ESP. In this chapter, we opt for a VCG-like approach, so as to achieve social welfare maximization, but we omit the direct-revelation approach of the typical VCG mechanism. Instead, we design an iterative auction mechanism based on Ausubel's clinching auction, in which users are only required to make decisions regarding their consumption in the presence of price signals. By adopting this approach, we implement the efficient VCG outcome but also allow for a distributed implementation and a privacy-preserving communication protocol.

Summarizing the above, our proposed DR architecture: i) is suitable for a distributed implementation (unlike [SAMA12], [NEKO15]), ii) achieves the VCG outcome and does not sacrifice efficiency (unlike [YAAG15], [MA14]), and iii) is incentive compatible (unlike studies that assume users of categories A and B).

2.1.2 System Model

We consider a flexibility market comprised of an ESP and a set $N \triangleq \{1,2,\dots,n\}$ of n self-interested consumers, hereinafter referred to as users. We also consider a discrete representation of time, where continuous time is divided into timeslots $t \in T$ of equal duration s, where set $T \triangleq \{1,2,\dots,m\}$ represents the scheduling horizon. Each user possesses a number of controllable appliances, with each appliance bearing an energy demand. Since demands of different appliances are assumed independent and are not coupled, we can consider one appliance per user for ease of presentation and without loss of generality. We denote by the set of appliances.

User & appliance modeling

An appliance requires an amount of energy for operation. For example, if an appliance's operating power is 1Watt, and $s = 1$ hour, then the energy that the appliance consumes in one timeslot of operation is $1Wh$. This energy consumption is measurable in real-time and can be shed if the user wishes. In particular, we consider controllable loads, meaning that the user can modify consumption upon request, in exchange for monetary compensation. Such a request for consumption modification is called a DR-event. Upon a DR-event asking for reduction of the real-time consumption in timeslot t, user i can respond by reducing his/her consumption by a quantity q_i^t, assumed to be positive ($q_i^t \geq 0$), without loss of generality.

Also, q_i^t is characterized by its feasible set Q_i (defined by a set of constraints on q_i^t) and the discomfort function $d_i(q_i^t)$ of user i. The discomfort function is private to each user and expresses the minimum compensation in monetary units ($) that a user requires, in order to reduce his/her consumption by the corresponding amount. The discomfort as a function of q_i^t can take various forms, depending on the appliance. We make the following assumptions on the form of function $d_i(q_i^t)$:

Assumption 2.1.1. Zero consumption reduction, brings zero discomfort to the user:

$$d_i(0) = 0$$

Assumption 2.1.2. The discomfort function is non-decreasing in q_i^t:

$$q_{iA}^t \geq q_{iB}^t \;\Leftrightarrow\; d_i(q_{iA}^t) \geq d_i(q_{iB}^t)$$

Assumption 2.1.2 says that consuming more does not make the user less comfortable.

Assumption 2.1.3: The discomfort function is upward sloping, meaning that additional increase of q_i^t brings increasing discomfort to the user:

$$q_{iA}^t \geq q_{iB}^t \;\Leftrightarrow\; d_i(q_{iA}^t + \varepsilon) - d_i(q_{iB}^t + \varepsilon) \geq d_i(q_{iA}^t) - d_i(q_{iB}^t), \qquad \forall \varepsilon, q_{iA}^t, q_{iB}^t > 0.$$

In order to incentivize users to reduce their consumption, the ESP offers a reward $r_i(q_i^t)$. A user's utility is defined as the difference between his/her discomfort for the consumption reduction realized and the reward he/she received for this reduction is

$$U_i = \sum_{t \in T} [r_i(q_i^t) - d_i(q_i^t)] \tag{2.1.1}$$

In order to offer the rewards $r_i(q_i^t)$, the ESP draws on the reward offered by the operator who requests the reduction as described in the following subsection.

DR-event and the ESP

Let L^t denote the aggregated consumption of all users in N, as seen by the operator, within a certain time interval t. Upon a DR-event, the operator (e.g. the DSO that operates the smart grid) asks for a reduction of the users' aggregated consumption during a certain time interval and offers monetary incentives to the ESP towards its realization. Let D^t denote the reduction in the aggregated consumption at t. The incentive (reward) is implemented as a per-unit compensation for the electricity units of reduced consumption. The cost of serving the aggregated energy consumption is typically modeled with quadratic functions ([SAMA10], [LI10], [GATZ13], [QIAN13], [MOHS10], [MHAN16], [SLI16], [JACQ17], [BITA17] as explained in [KOTH03]. In this chapter, we adopt the same approach and in direct analogy we assume that the compensation that is offered to the ESP by the operator, can be modeled as a concave function of D^t. For the purpose of being specific, we adopt here a polynomial function $R^t(D^t)$ of a specific form

$$R^t(D^t) = a \cdot D^t - b \cdot (D^t)^2, \;\; D^t \in [0, L^t] \tag{2.1.2}$$

where a, b are positive parameters with $a \geq 2bL^t$. The proposed DR architecture is open to any other choice of $R^t(D^t)$, provided it is a concave function. Thus, we assume that upon a DR-event, the operator offers a marginal per-unit reward

$$\lambda = \frac{d\left(R^t(D^t)\right)}{d(D^t)} \tag{2.1.3}$$

for a consumption reduction of D^t units.

The ESP is responsible for aggregating the users' participation in the DR-event, coordinating their actions, and dividing the compensation profits (rewards) among the users. We assume a communication network, built on top of the electricity grid, through which the ESP can monitor each user's consumption and exchange messages with the users.

2.1.3 Problem Formulation

With respect to the system described above, we would like to facilitate the allocation of consumption reduction among the users so as to maximize social welfare. Social welfare is defined as the difference between the revenues $R^t(D^t)$ that the ESP receives from the operator for the consumption curtailment D^t and the sum of the discomfort that this curtailment causes to its users. This problem can be formulated from Eqs. (2.1.4) and (2.1.4a) below:

$$\mathbf{max}_{q_i^t \in \mathrm{Q}_i, i \in N} \{R^t(D^t) - \sum_{i \in N}[d_i(q_i^t)]\} \tag{2.1.4}$$

$$s.t.\ D^t = \sum_{i \in N} q_i^t \tag{2.1.4a}$$

The problem defined by Eqs. (2.1.4) and (2.1.4a) is a convex optimization problem and could be solved efficiently if the local functions $d_i(q_i^t)$ were known (or truthfully disclosed). However, $d_i(q_i^t)$ of each user is not known and thus, problem (2.1.4) is typically solved via dual decomposition in the DR literature. This approach, however, is not incentive compatible as we will analyze shortly. In particular, the final allocation of the dual decomposition approach is identical to that obtained through the ascending English auction (see algorithm 2 of [SAMA10]), which halts when supply equals demand. More specifically, in the system model described and in case of an English auction, the ESP would iteratively increase a per-unit reward λ asking the users their consumption reduction $q_i^t(\lambda)$ at each per-unit reward λ (auction query). At each iteration, each user *i* responds with his/her preferred $q_i^t(\lambda)$. A truthful (locally optimal) response by user i, denoted as $\widetilde{q_i^t}(\lambda)$, is one that maximizes i's utility for reward λ. This is mathematically formulated as the solution to maximization problem (2.1.5):

$$\widetilde{q_i^t}(\lambda) = \mathrm{argmax}_{q_i^t \in \mathrm{Q}_i, i \in N} \{\lambda \cdot q_i^t - d_i(q_i^t)\} \tag{2.1.5}$$

Clearly, $\widetilde{q_i^t}(\lambda)$ is non-decreasing in λ, since $q_i^t \geq 0$. The auction terminates when λ reaches a value for which $\sum_{i \in N} q_i^t(\lambda) = D^t(\lambda)$. The final price is commonly called the market-clearing price and it is denoted here as λ_{mc}. The allocation at λ_{mc} is efficient if the users truthfully report their q_i^t at each ESP query. However, truthful report may not be the best strategy for every user. To illustrate this, we present the following example:

Illustrative example

Consider two users and a given timeslot t. User 1 operates a load with power consumption 10 kW while user 2 operates a 50 kW load. Now suppose they participate in a DR event and their discomfort function is $d_i(q_i^t) = \omega_i \cdot (q_i^t)^2$, $i \in \{1,2\}$, where their true flexibility parameters are $\omega_1 = \omega_2 = 0.1$. The reward function is $R^t(\Delta L^t) = 5 \cdot (\Delta L^t)$. Should they act according to their true discomfort function parameters, their utilities (given from Eq. (1)) at equilibrium would be $U_1 = U_2 = 4.875$ units. In case User 2 acts untruthfully according to $\omega_2^{fake} = 0.2$, his utility at equilibrium will be $U_2 = 7$. Therefore, the best strategy of User 2 is to be untruthful. ■

The previous *example* demonstrates how the market-clearing approach builds on the assumption that users behave myopically, by truthfully maximizing their utility at each iteration. However, a DR-event will involve smart players (e.g. industrial consumers, aggregators) and it will not take long before users realize that they can benefit from engineering untruthful responses. The problem is that if we relax the truthfulness assumption and consider strategic users, market-clearing methods (e.g., the English auction presented above) no longer result in efficient allocations. For this reason it is very important to design a mechanism that is not only efficient but also incentive compatible.

In order to facilitate the description of the proposed mechanism, we first present the Vickrey-Clarke-Groves (VCG) mechanism, which is the unique mechanism that makes it a dominant strategy (DSIC as analyzed in the introduction) for each user, to act truthfully, i.e. in accordance with his/her real discomfort function [KRIS02]. Let N_{-i}, denote the set of users, excluding user i. The VCG payment rule is the so called "Clarke pivot rule", which calculates a reward r_i equal to i's "externality". In other words, it rewards each user i with an amount equal to the difference that i's presence makes in the social welfare of other users $j \in N_{-i}$:

$$r_i(q_i^t) = R^t\left(\sum_{j\in N_{-i}} q_j^t\right) - \sum_{j\in N_{-i}} d_j\left(q_j^t\right) - R^t\left(\sum_{j\in N_{-i}} \widehat{q_j^t}\right) + \sum_{j\in N_{-i}} d_j\left(\widehat{q_j^t}\right) \qquad (2.1.6)$$

where q_j^t denotes the vector allocated to user j when problem (2.1.4) is solved with user i included in the system, and $\widehat{q_j^t}$ denotes the vector allocated to user j when the same problem is solved without user i's participation.

In the direct VCG mechanism, users are asked to declare their local functions $d_i(q_i^t)$ to the ESP. Because of the Clarke pivot rule, it is a dominant strategy for each user to make a truthful declaration [KRIS02]. Thus, the efficient allocation that corresponds to the social welfare maximization problem can be calculated at the ESP side. In order to calculate the VCG rewards from Eq. (2.1.6), problem (2.1.4) is solved $|N| + 1$ times (one time with each user in N absent to calculate the payments, plus one time with all users present to calculate the allocation). The major drawback of the direct VCG mechanism is the requirement that the users disclose their discomfort functions $d_i(q_i^t)$ to the ESP. This raises important issues such as a) Lack of privacy in case where users are reluctant to reveal local information (their discomfort function) and b) Difficulty in implementation in cases where users are unable to express their preferences (i.e., their discomfort function) in a closed form function.

In the next subsection, we propose a modification of Ausubel's Clinching auction [AUSU04], which allows for a distributed implementation of VCG as described in section VII, designed to tackle these issues. In particular, we opt for an iterative auction that:

i) facilitates user bids via auction queries, thus making the proposed architecture more easily implementable in practice

ii) engages users in the market and allocates consumption reduction gradually along the way, so that price discovery is facilitated on the users' side

iii) protects user's privacy via a properly designed communication protocol.

2.1.4. Ausubel's Clinching Auction for DR-event participation

The Clinching Auction (CA) is a well-known ascending price auction (similar in fashion to English Auction) that halts when demand equals supply. However, in contrast to most auctions (including the English auction), allocation and rewards are not cleared exclusively at the final iteration. Rather, the goods (consumption reduction in our context) are progressively allocated as the auction proceeds and payments are also progressively built, while the auction design guarantees that the final allocation and payments coincide with the ones obtained through VCG. Thus, both allocation efficiency and incentive compatibility are achieved, while the aforementioned privacy and implementation drawbacks of the direct-VCG mechanism are effectively addressed.

In order for the CA to work in our setting, we need to reverse the price trajectory. In the proposed Modified Clinching Auction (MCA), the ESP begins with a per-unit reward $\lambda = \lambda_{max}$ which gradually decreases at each iteration. By Eq. (2.1.3), reward λ_{max} is $\frac{dR^t(0)}{d\Delta L^t} = a$, which, as analyzed in section 2.1.3, is the highest value possible given that R^t is concave. Users respond by bidding their preferred consumption reduction $\widetilde{q_i^t}(\lambda)$ for each λ. We represent the user's response at λ as the solution to the user utility maximization problem (which is formally defined in Eq. (2.1.5) of the previous section).

The user's objective function is concave in q_i^t, since $\lambda \cdot q_i^t$ is linearly increasing and $d_i(q_i^t)$ is convex by *Assumption 2.1.3*. Also, the solution $\widetilde{q_i^t}$ is increasing in λ, which means that the user's response $\widetilde{q_i^t}$ gradually decreases as λ decreases. Note that in the extreme and trivial case where $\lambda_{max} \cdot \sum_{i \in N}\left(\widetilde{q_i^t}(\lambda_{max})\right) \leq R^t(D^t)$ the users would shut down everything and proportionally share the reward $R^t(D^t)$.

In MCA, the initial price is λ_{max} and in each iteration k the price λ^k is reduced by a small positive number ε. The size of ε adjusts the discretization level of MCA. For the decreasing reward auction that we propose, we relax constraint (2.1.4a) to the inequality

$$D^t \geq \sum_{i \in N} q_i^t \tag{2.1.7}$$

Consider an arbitrary iteration k of the MCA and let $D^t(\lambda^k)$ denote the operator's desired reduction for per-unit reward λ^k. The central idea of the MCA is the following: if there is a set $N^{\not j} \subset N$ for which we have

$$D^t(\lambda^k) - \sum_{j \in N^{\not j}} \left(\widetilde{q_j^t}(\lambda^k) \right) > 0 \tag{2.1.8}$$

then we allocate a reduction equal to $\zeta_i^k = D^t(\lambda^k) - \sum_{j \in N^{\not j}} \left(\widetilde{q_j^t}(\lambda^k) \right)$ to each user $i \notin N^{\not j}$ at a per-unit reward λ^k. We then say that user i "clinched" ζ_i^k units. The MCA auction terminates when set $N^{\not j}$ that satisfies condition (2.1.8) and set N, are equal, that is, constraint (2.1.7) is satisfied. After that, it allocates the remaining $D^t(\lambda^{k-1})$ proportionally to the users that bid in the second-to-last iteration.

The critical advantage of the Clinching auction is that it allocates different amounts of units at different rewards, and the units that a user clinches do not depend on his/her own bid but only on the other users' bids. The algorithm that implements MCA is presented in Table 2.1.t1.

Table 2.1.t1. The MCA algorithm

1. Initialize $\lambda^0 = \lambda_{max}$, $q_i^t(\lambda_{max})$, $D^t(\lambda_{max})$, $k = 0$
2. **while** $D^t(\lambda^k) < \sum_{i \in N} \left(\widetilde{q_i^t}(\lambda^k) \right)$
3. **if** there exists $N^{\not j}$: $\sum_{j \in N^{\not j}} \left(\widetilde{q_j^t}(\lambda^k) \right) < D^t(\lambda^k)$
4. clinch units $\zeta_i^k = D^t(\lambda^k) - \sum_{j \in N^{\not j}} \left(\widetilde{q_j^t}(\lambda^k) \right)$ for all $i \notin N^{\not j}$ at per-unit reward λ^k
5. **else**
6. set $\lambda^{k+1} = \lambda^k - \varepsilon$ and $k = k + 1$
7. ask each user a reduction query for λ^k and collect the responses $q_i^t(\lambda^k)$

8. ask the operator for the desired total reduction $D^t(\lambda^k)$ at per-unit-reward λ^k

9. **End while**

10. Clinch units

$$\zeta_i^k = \left(q_i^t(\lambda^{k-1}) - \sum_{\eta=0}^{k-1} \zeta_i^\eta\right) \cdot \frac{D^t(\lambda^{k-1})}{\sum_{i\in N} q_i^t(\lambda^{k-1})}$$

at per-unit reward (λ^{k-1}), for each $i \in N$

We are now in a position to prove the optimality of MCA in terms of social welfare performance:

Theorem 2.1.1: The social welfare loss at the final allocation of MCA is within $(\varepsilon^2 + \lambda_{max} \cdot \varepsilon)/2b$ of the maximum possible.

Proof: The value of λ at which $D^t = \sum_{i\in N}\left(\widetilde{q_i^t}\right)$ is defined as λ_{mc}, which gives

$$D^t(\lambda_{mc}) = \sum_{i\in N}\left(\widetilde{q_i^t}(\lambda_{mc})\right) \tag{2.1.9}$$

Let $\mathcal{k}$ denote the number of iterations until the auction halts, that is,

$$\mathcal{k} = \left\lceil \frac{\lambda_{max} - \lambda_{mc}}{\varepsilon} \right\rceil \tag{2.1.10}$$

where $\lceil\cdot\rceil$, denotes the rounding to the nearest integer above. We have

$$\left\lceil \frac{\lambda_{max} - \lambda_{mc}}{\varepsilon} \right\rceil \leq \mathcal{k} \leq 1 + \left\lceil \frac{\lambda_{max} - \lambda_{mc}}{\varepsilon} \right\rceil \tag{2.1.11}$$

After the last clinchings (line 10 of the algorithm) we have efficiently allocated $D^t\left(\lambda^{\mathcal{k}-1}\right)$ reduction units to the users. The remaining $D^t(\lambda_{mc}) - D^t\left(\lambda^{\mathcal{k}-1}\right)$ are not allocated and this causes the loss of welfare (W_{loss}) that is depicted as the grey area in Figure 2.1.f1, where the red line represents $D^t(\lambda)$ and the blue line represents $\sum_{i\in N} \widetilde{q_i^t}(\lambda)$.

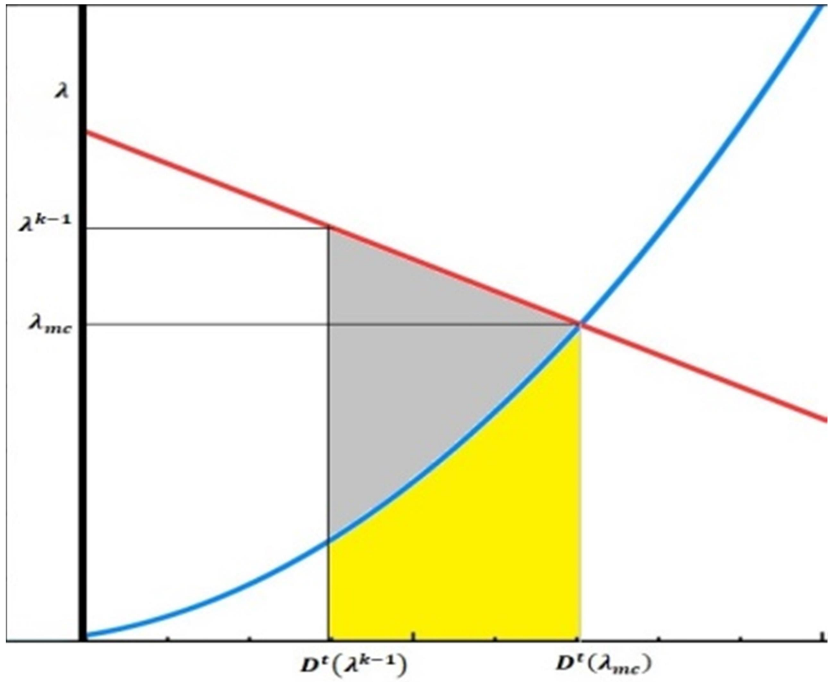


Figure 2.1.f1. $\boldsymbol{D^t}(\boldsymbol{\lambda})$ and $\sum_{i\in N}\left(\widetilde{q_i^t}(\boldsymbol{\lambda^k})\right)$ as a function of $\boldsymbol{\lambda}$

Since we remain agnostic of the closed form of $\sum_{i\in N}\left(\widetilde{q_i^t}(\lambda^k)\right)$, we assume the worst case and calculate an upper bound on the sum of the grey plus the yellow area of **Figure 2.1.f1**:

$$W_{loss} \le \lambda_{mc}\left(D^t(\lambda_{mc}) - D^t\left(\lambda^{k-1}\right)\right) + \frac{1}{2}(\lambda^{k-1} - \lambda_{mc})\left(D^t(\lambda_{mc}) - D^t\left(\lambda^{k-1}\right)\right)$$

By substituting $D^t(\lambda) = \frac{a-\lambda}{2b}$ from Eq. (2.1.3), we get

$$W_{loss} \le \frac{\lambda_{mc}\left(\lambda^{k-1}-\lambda_{mc}\right)}{4b} + \frac{\lambda^{k-1}\left(\lambda^{k-1}-\lambda_{mc}\right)}{4b} \le \frac{\left(\lambda^{k-1}\right)^2-(\lambda_{mc})^2}{4b}$$

By further substituting $\lambda^{k-1} = \lambda_{max} - \varepsilon(k-1)$ and also substituting k from inequalities (2.1.11), using the left inequality when k appears with a minus sign and the right inequality when it appears with a plus sign, we finally obtain

$$W_{loss} \le \frac{\varepsilon^2 + \lambda_{max} \cdot \varepsilon}{2b}$$

completing the proof. ∎

In practice, for the relevant use cases of price-anticipating users (described in the introduction), the computational complexity of the MCA is small, which allows for a very small choice of ε. To emphasize this, it is useful to state the following corollary to Theorem 2.1.1:

Corollary 2.1.1: for $\varepsilon \ll 1$ the welfare loss grows linearly with ε.

Because the MCA includes a price-sensitive response also at the operator's side, we have to verify that the properties of efficiency and incentive compatibility still hold. This is proved in the following Propositions.

Proposition 2.1.1: Truthful bidding is a dominant strategy in MCA.

Proof: Fix an iteration k and suppose that i bids $q_{i,false}^t(\lambda^k) \neq \widetilde{q_i^t}(\lambda^k)$ in that iteration. From step 4 of MCA, we see that ζ_i^k does not depend on q_i^t but only on the other users' bids $q_j^t, j \neq i$. Thus, user i's bid can affect i's allocation only by changing the λ at which the termination condition holds. This means that a false bid $q_{i,false}^t(\lambda^k)$ will make a difference to i, only if k is the last iteration. However, by definition of $\widetilde{q_i^t}(\lambda^k)$ (see Eq. (2.1.5)), any bid $q_{i,false}^t(\lambda^k) \neq \widetilde{q_i^t}(\lambda^k)$ brings strictly lower utility to user i at any iteration k. Thus, truthful bidding brings the highest utility to user i. ■

Furthermore, the following properties of the VCG mechanism hold also for the MCA:

Proposition 2.1.2: MCA is *individually rational*, weakly *budget-balanced*, and achieves the maximum revenue for the ESP among all efficient mechanisms.

Proof: The MCA auction is welfare maximizing (by Theorem 2.1.1*,* for ε small enough) and DSIC (by Proposition 2.1.1). However, the class of VCG mechanisms is the unique class that simultaneously achieves these two properties [SHOH09]. Thus, MCA terminates with the VCG allocation and payments, and it inherits the property of *individual rationality.* For the weak budget balance property, it suffices to show that our setting exhibits the no single-agent effect [SHOH09]. An environment exhibits no single-agent effect if the aggregated utility of $n-1$ users doesn't improve by adding a n^{th} user to the system. This property holds in single-sided auctions with monotonous preferences [SHOH09], since dropping a user only reduces the competition for the remaining users, thus making them better-off.

Moreover by [KRIS02], the VCG mechanism maximizes the auctioneer's utility, which means that the ESP buys flexibility units from the users at the lowest possible price (among all efficient and individually rational mechanisms). ■

2.1.5. Performance Demonstration

In this section, we use simulations to demonstrate the advantages of the MCA and verify its properties. As a benchmark for comparison, we use the typical market-clearing pricing where all users receive a per-unit reward of λ_{mc}. Over a time horizon of 24 timeslots, we simulated two DR events, in timeslots 11 and 17 where there was a peak in the aggregated consumption. Parameters a and b of the reward function were set to $a = 3$ and $b = 0.02$ for both timeslots.

We used a simple model for the user's discomfort function:

$$d_i(q_i^t) = \omega_i^t \cdot (q_i^t)^2,$$

where parameter ω_i^t expresses the user's inelasticity in timeslot t. In order to obtain results for a wide range of parameters ω_i^t, we pick ω_i^t from a random uniform distribution in $[0.5 \cdot \omega_f,\ 1.5 \cdot \omega_f]$ for $t = 11$ and in $[0.05 \cdot \omega_f,\ 1.5 \cdot \omega_f]$ for $t = 17$, where parameter ω_f will vary in our experiments. We set the step $\varepsilon = 10^{-5}$ in the MCA algorithm (Table 2.1.t1). Figure 2.1.f2 depicts the aggregated consumption along all 24 timeslots for $\omega_f = 1$, which shows the reductions in consumption corresponding to the DR events.

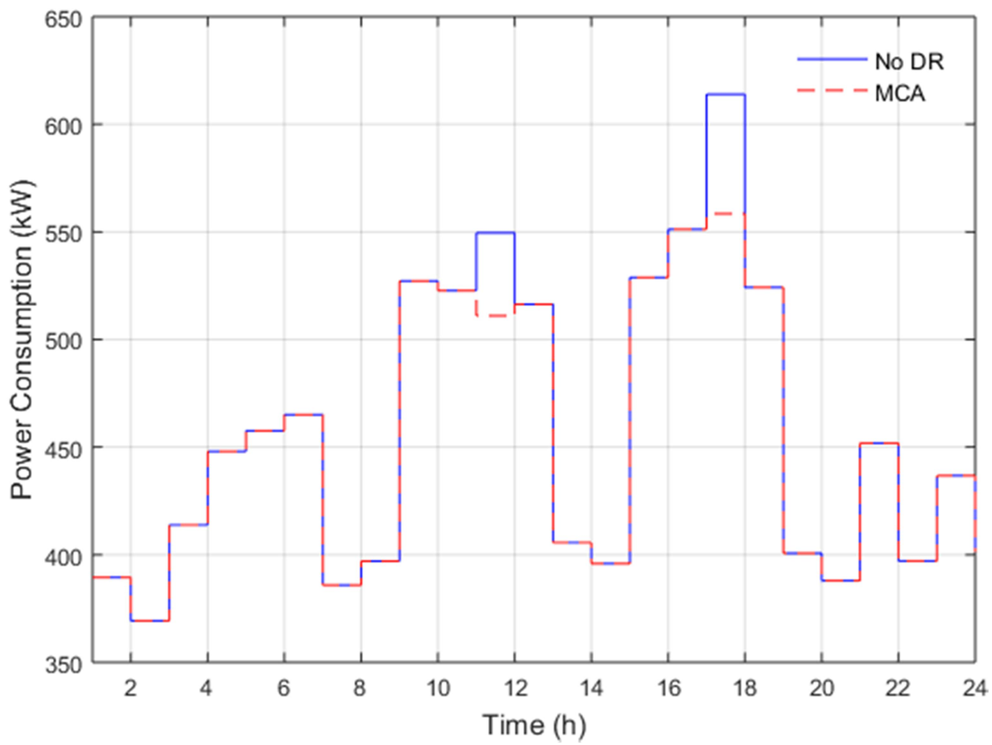


Figure 2.1.f2. Aggregated consumption as a function of time with and without DR events in timeslots 11 and 17

In order to verify the truthfulness property and that a user can only lose by not being truthful, we assume that one user acts untruthfully by manipulating his/her ω_i for timeslot 17, while all other users act truthfully. The untruthful user is indexed by ch (for cheater). The cheater's utility U_{ch} is maximized for a certain choice of ω_{ch}, denoted as $\omega_{ch}^{fake,*}$. Figure 2.1.f3 shows U_{ch} as a function of ω_{ch} (for $\omega_f = 5$).

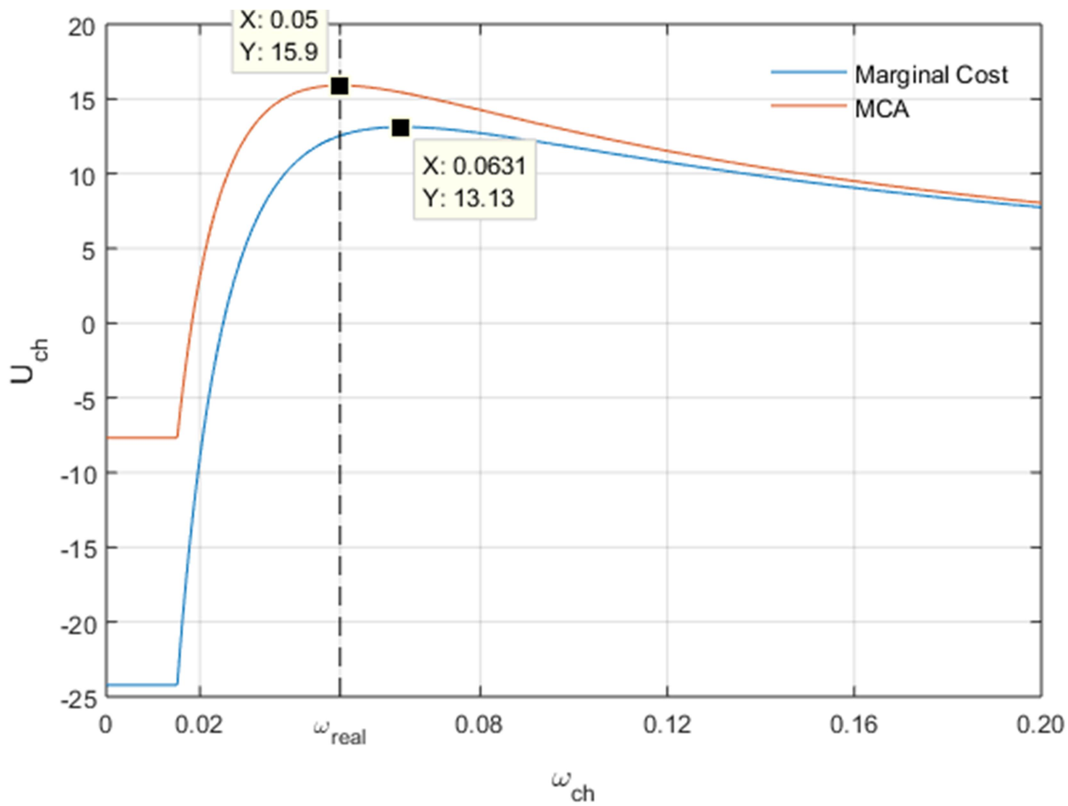


Figure 2.1.f3. Focal user's utility as a function of his/her choice of $\boldsymbol{\omega}$

The black vertical line represents the focal user's actual (real) ω, denoted as ω_{real}. For the MCA, the user's optimal choice of ω coincides with his/her real ω, that is $\omega_{ch}^{fake,*} = \omega_{real}$, thus verifying Proposition 2.1.1.

Next, we investigated the effect that cheating has on the ESP's profits, denoted by $\Pi^{truthful}$ for the case where users act truthfully and by Π^{cheat} for the case where they act according to what brings them the highest utility. Figure 2.1.f4 shows that the ratio $\Pi^{cheat}/\Pi^{truthful}$ is maximized and is equal to 1 for the MCA, verifying our theoretical results. We also observe that the ESP's profit loss due to untruthfulness rises with ω_f (i.e. when users are less elastic), indicating that our scheme's truthfulness property becomes more important in markets where participants are not particularly flexible.

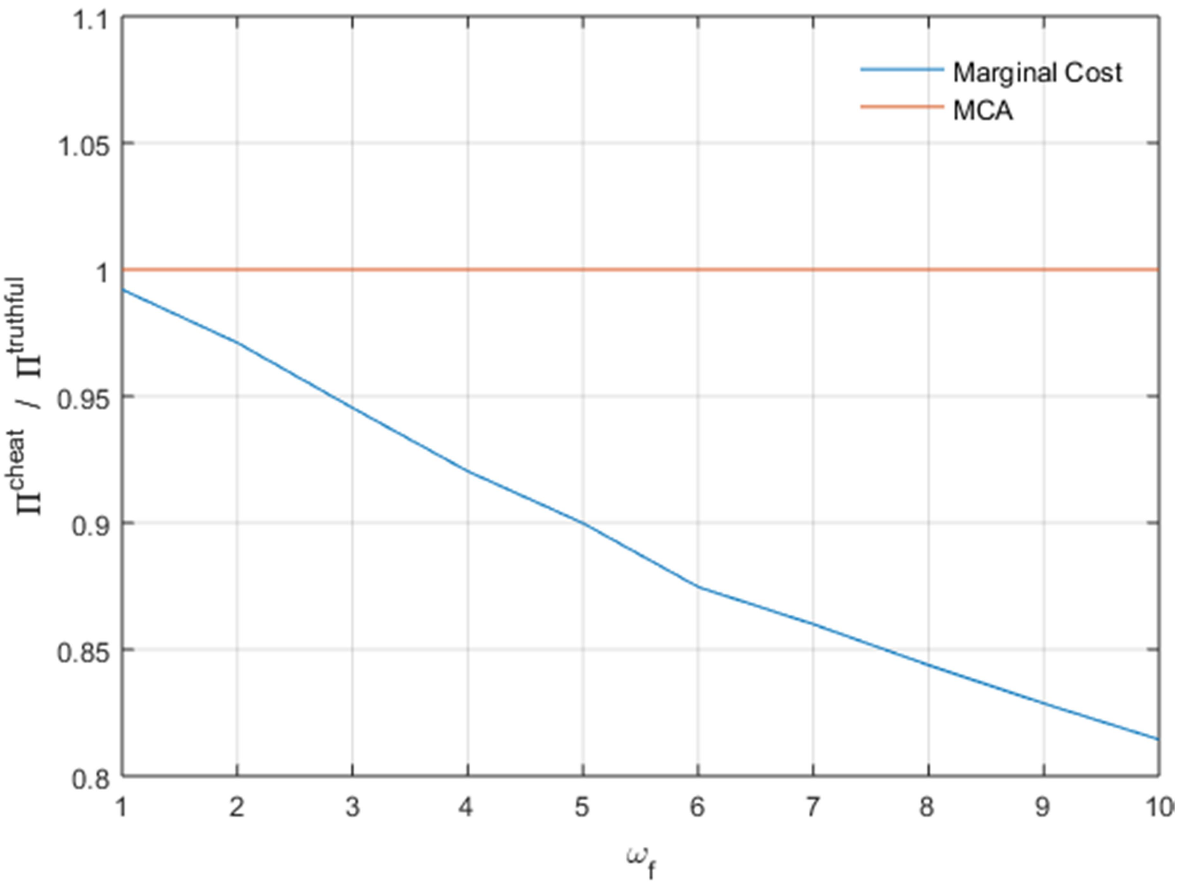


Figure 2.1.f4. Ratio $\frac{\Pi^{cheat}}{\Pi^{truthful}}$ as a function of ω_f

Finally, we simulated the DR-event for timeslot 17 for different values of ε, measuring the proportional welfare loss

$$W_{loss} = \frac{W_{opt} - W_{MCA}}{W_{opt}}$$

where W_{opt} is the optimal welfare and W_{MCA} is the welfare achieved by the MCA. The simulation results in Figure 2.1.f5 verify Corollary 2.1.1, which states that for small values of ε the upper bound on the welfare loss grows linearly with ε.

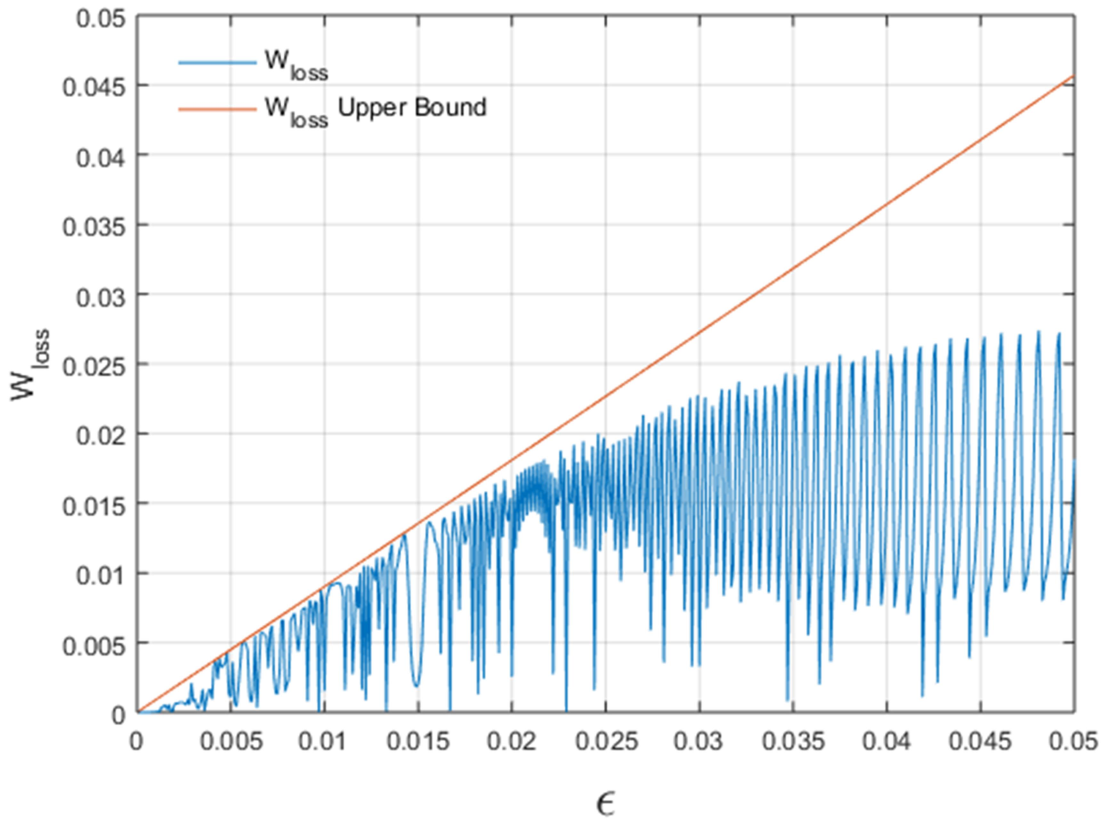


Figure 2.1.f5. Proportional welfare loss of MCA as a function of the price step ε

2.1.6 Privacy-preserving distributed implementation

A major drawback of the direct VCG mechanism is that it requires each user to know and disclose his/her discomfort function to a central entity, e.g., the ESP. The MCA auction implements the VCG allocation and payments via an indirect mechanism. In this way users are only required to respond to ESP queries, instead of being required to communicate their discomfort function. This allows a distributed implementation of an efficient and truthful DR architecture. In what follows we present a distributed communication protocol that preserves privacy while simultaneously ensuring an efficient allocation.

The proposed DR architecture exploits [ZYSK15] in order to execute MCA in a distributed fashion. In this way, the ESP does not have to learn the answers to the queries, which are instead acquired only by users in N in a distributed fashion. Thus, the proposed DR architecture acts as a substrate that offers a service over which participating users cooperate in order to protect their personal data (i.e. their discomfort functions $d_i(\cdot)$) from the ESP. In order to achieve this, [ZYSK15] uses the scheme proposed by Kademlia [MAYM02] in which each node (i.e., end user/energy consumer) is identified by a number (nodeID) in a specific virtual space. The nodeIDs do not serve only as identification, but they are also used by the Kademlia algorithm to store and locate values/data hashes (i.e., the answers to the ESP queries). This process is realized through a peer to peer routing service (implemented in the network application layer) that Kademlia offers. Towards this end, participating nodes create and dynamically maintain routing tables in a bottom up organized way. In fact, the nodeID provides a direct map to these data hashes by storing information on where to obtain them. The proposed algorithm is executed in three steps:

1. *Data insertion*: At each iteration k of the algorithm, each user (node) i stores its bid $\widetilde{q_i^t}(\lambda_k)$ in another random node w through the use of the aforementioned [MAYM02] system. It is highlighted that w is different for each i and k (as it is derived from the output of the hash function that Kademlia uses), and in this way collusion of two users (which is a requirement that [BAHA14] sets), or even collusion of a relatively small number of users to acquire data, will fail.

2. *Calculation of* $\zeta_i^k(\lambda_k)$: Kademlia organizes the participating nodes in a tree like structure. The proposed system exploits this structure in order to calculate the sum $\sum_{i\in N} \widetilde{q_i^t}(\lambda^k)$. To do so in a distributed way, node j waits until all nodes with lower nodeID from it, inform j on possible data values they have to send to j. This process continues recursively until the node with the highest id acquires the desirable data and then it calculates the sum. At this point, this node also receives $D^t(\lambda^k)$ from the ESP and checks the termination condition. If it doesn't hold, the node proceeds by broadcasting $\sum_{i\in N} \widetilde{q_i^t}(\lambda^k)$ and $D^t(\lambda^k)$ to all nodes through the use of Kademlia tree [MAYM02]. Thus, each node j calculates $\zeta_i^k(\lambda^k)$ by subtracting the $\widetilde{q_i^t}(\lambda^k)$ value that is stored in it (which is not its own $\widetilde{q_j^t}(\lambda^k)$ value, and it doesn't know whose it is).

3. *Final allocation and payments calculation*: at the next iteration $k+1$, a different instance of Kademlia tree is created, so that $\zeta_i^{k+1}(\lambda^{k+1})$ is stored at a new node g, other than j. Thus, even in the case that a node is malicious, data privacy is not compromised. The tuple $A_i = \{\sum_{m=1}^{k} \zeta_i^m(\lambda^m), \sum_{m=1}^{k}[\zeta_i^m(\lambda^m)\cdot\lambda^m]\}$, which contains the allocation and payments of user i up until iteration k, is passed from user j to g. At the final iteration, the tuples A_i are communicated to the ESP. Note that the ESP receives only the final allocation and payments for each user, i.e., only the sum of $\zeta_i^k(\lambda^k)$ and not all the intermediate values $\zeta_i^m(\lambda^m)$. This means that the ESP (and any other node for that matter) does not have the data to construct the entire local discomfort function $d_i(\cdot)$ of user i.

Note that the analysis above assumes that the service provider is honest-but-curious. By this we mean that the ESP is curious to know the discomfort functions of end users, but is also honest and will never attack the system in order to acquire them. In case of malicious ESP (i.e. with no hesitations to break the law), more strict privacy assumptions are needed, but this case is outside the scope of the present work.

2.2 Personalized real time pricing for efficient and fair demand response in energy cooperatives

The electricity market is moving from a market where energy is produced in a centralized fashion from traditional and often environmentally harmful sources to a liberalized/competitive and possibly distributed market that exploits renewable energy sources (RES) [REGUL]. A major challenge in this new environment is the alignment between the varying and to large extent unpredictable energy supply (e.g. RES) and the ad-hoc energy demand of the end users. In addition, innovative concepts such as flexibility markets, energy poverty and energy efficiency are continuously emerging in the energy sector. Towards this goal, the research community focuses on the development of pricing mechanisms, which are able to affect the energy consumption by enabling a dynamic and sophisticated interaction between the pricing of energy (incentives) and the way end users consume it (scheduling). Studies under this premise develop algorithms that belong to the generic family of demand side management (DSM) algorithms. This is a promising approach that aims to affect energy consumption and create an additional tool in the optimization and the stability of energy systems.

As analyzed in [GATZ13] residential participation in DSM is commonly envisaged via aggregated participation because of implementation and scalability issues.

Along with these technical and socio-economic changes, there is a rise of innovative business models for aggregating the DSM participation of a set of users. In particular, collective DSM participation can be undertaken by a non-profit organization representing the interests of its portfolio of users [RESCOOP], a public (regulated) entity or a private company. In this section, we assume that the aggregating entity only passes the energy costs to the consumers without extracting profit [CHAP17]. This use case represents the cases where:

1) the private aggregating company operates in a highly competitive environment.
2) the profit margins of the private aggregating company are regulated
3) users form a cooperative organization to represent their interests
4) the aggregating company is a public and non-profit entity.

Throughout this section, we will refer to the aggregating entity with electricity service provider (ESP) and cover all four use cases.

In [MAKR18], we try to facilitate the easy, rich and deep communication between energy efficiency stakeholders and end users, allowing them to discover each other, educate themselves so as to understand the difficulties and challenges each one faces, interact and trade with each other.

Under this perspective, we focus on the development of pricing mechanisms that give to the end users the opportunity to derive direct financial benefits from the actions they undertake regarding their energy consumption. In more detail, through community pricing [STER18] or personalized pricing mechanisms that we developed, we avoid the well-known problem of the tragedy of the commons [MANI13]. This is a phenomenon, where users do not change their behavior (energy consumption in this case) due to the low impact that this change would have on their bill. In contrast, a personalized pricing mechanism is able to treat different users in different ways, according to their flexibility, and thus achieve a specific behavioral change efficiently.

More specifically, in this section we refer to “system efficiency” as the maximization of Social Welfare, which is defined as the aggregated users’ welfare (AUW) and relates to the difference between the users’ satisfaction from electricity consumption and the users’ bills.

The challenge lies in the fact that each user’s satisfaction function is private and not known to the ESP, while users are generally considered as selfish, which means that each one opts for maximizing her own welfare, which is not necessarily aligned with the system’s objective.

Moreover, for the use cases of the ESP that we consider, it is very important that a DSM algorithm also exhibits two positive externalities apart from efficiency. Those are:

1) Reduction of the system’s cost, which relates to systems with: higher energy efficiency, more stable and sustainable networks, lower capital expenditure in overprovisioned grid facilities, lower CO2 emissions etc.
2) Fair allocation of the system’s resources among the users. This is particularly important for the business cases considered, because all users will remain under the ESP, only if they know that they get a fair percentage of the benefits that they have incurred in the first place. In our case, we want to allocate the system’s energy savings to the users that provoke those savings.

In such an environment, it is the job of the ESP to set the rules of energy trading in a smart way, such that: the system possesses the budget-balance property; selfish users’ actions bring the system to an equilibrium; and their deliberate choices bring the system to an outcome with desirable properties namely high users’ welfare (KPI-2.2.1), low system’s cost (KPI-2.2.2), fairness (KPI-2.2.3).

Designing such rules is studied by a special sector of game theory, called ‘mechanism design’. The desirable properties above constitute the mechanism’s key performance indicators (KPIs) and they are generally adopted widely in the literature.

A brief overview of energy pricing models for DSM started with the enhancement of the traditional flat electricity tariff (fixed price per consumed unit of energy and identical at all time instances) with inclining block rates (IBRs) [MOHS10], [PALE11]. In IBR, the price of each unit depends on the total amount of energy a customer consumes. IBR was the first simple solution to incentivize energy curtailments, usually during a large time interval. A more sophisticated approach is time-of-use (ToU) pricing where prices are predetermined based on prediction of the relationship between aggregate production and consumption. However, TOU is insensitive to the users' response to the prices and often creates reverse peaks. Finally, real time pricing (RTP) mechanisms create the price per energy unit depending on the total cost of energy production and the total consumption.

2.2.1 Related Work

Liberalized electricity markets, smart grids and high penetration of RES led to the development of novel markets whose objective is the harmonization between production and demand (i.e. flexibility markets). This necessitates the development of novel pricing schemes able to allow ESPs to exploit flexibility in the energy consumption curves of their consumers.

The general idea described above has been approached in different ways in the literature, including ex-post [MHAN16] & ex-ante pricing methods [LI10], [SAMA10], [SAMA12], [CHAI14], [QIAN13], [SOLI14], [RAD10], [MA14], [DENG14], [BAHA13], [BAHA14], [VUPP11], [YAAG15]. Many pricing mechanisms [GATZ13], [LI10], [SAMA10], [SAMA12], [CHAI14] opt for system efficiency (KPI-2.2.1), but at a risk of either running a deficit or extracting a large surplus from the users as explained in [CHAP17] and are not compatible with the emerging environments described. In particular, the authors in [LI10] [SAMA10], achieve an efficient allocation, but the system does not possess the budget-balance property described in the introduction. Moreover, users are considered to be price-takers, that is, they do not consider the effect that their choices have on the price. In [SAMA12], the users are considered as price-anticipators and the efficient Vickrey-Clarke-Groves (VCG) mechanism is applied, which is inherently not budget-balanced and additionally requires a simple and well-defined form of the user's utility function in order to remain tractable.

Another class of DSM algorithms [CHAP17], [MOHS10], [QIAN13], [SOLI14], [RAD10], [MA14], [DENG14] have been designed to guide the users' behavior towards more desirable demand profiles. This class of algorithms possesses the budget-balance property. In particular, in [MOHS10], [SOLI14], [RAD10], [DENG14], the authors opt for minimizing the system's cost (KPI-2.2.2), under the constraint that each load will be fully satisfied within its defined interval. The efficiency of the system is defined as the minimization of system's cost. In this class of studies, the users' dissatisfaction from deviation from their desired consumption profile is not modeled. In [CHAP17], [MA14], where budget-balanced mechanisms are also proposed, the model does not capture load curtailments, but only load shifting. Moreover, none of the above works considers the property of fairness.

Finally, a third class of studies [BAHA13], [BAHA14], [VUPP11], [YAAG15], opts for enhancing the system's fairness (KPI-2.2.3). In particular, the authors in [BAHA13] propose a pricing model based on the principle that each user should be billed according to her contribution to the system's cost. The Shapley value from cooperative game theory is used to express this contribution. The same authors in their later work [BAHA14] argue that the model of [BAHA13] sacrifices efficiency to achieve fairness. In [BAHA14] the trade-off between fairness and cost minimization in the design of pricing mechanisms is assessed. However, the users are assumed to distribute evenly their load throughout the eligible timeslots and the user's satisfaction is again disregarded.

Thus, through the study of the literature, one can confirm that the generally desired KPIs in the design of a pricing mechanism are the ones that we presented in the previous section and adopt in this section's context.

As analyzed in the previous paragraphs, the models proposed so far in the literature cope only with one or two of the above KPIs. To the best of our knowledge, there is no prior work that directly assesses the issue of designing a pricing mechanism that achieves an attractive trade-off among all three of the above KPIs. Our approach for the design of such a pricing mechanism is to adopt the concept of personalized–real time pricing (P-RTP).

Motivated from the above, the major contributions of this section are:

1) A P-RTP algorithm that reduces the energy cost without sacrificing at all the aggregated users' welfare. Moreover, the proposed scheme achieves a fair allocation of the energy cost savings among the users.
2) An analysis on the proposed algorithm's convergence properties.
3) A comparison of the proposed P-RTP with the existing RTP mechanisms that testifies its superiority according to the aforementioned perspectives.
4) An analysis on the findings with useful guidelines towards the design of pricing mechanisms in open and competitive markets.

2.2.2 System Model & Problem Formulation

In this section, we describe prerequisites that will facilitate the presentation of our pricing mechanism and existing widely accepted models (i.e. user model, energy cost model) that will act as the test bed in order to objectively evaluate and compare the proposed pricing mechanism.

We consider a set (community) $N = \{1, 2, \dots, n\}$ of n energy consumers (users). Each user is equipped with a smart meter, tracking his/her consumption at all time instances and an energy management system that schedules his/her consumption. We consider a finite time horizon, which is divided into h time slots $H = \{1, 2, \dots, h\}$ of equal duration. An ESP, in coordination with the distribution system operator (DSO), installs the necessary equipment to each user and is responsible for the possible failures and upgrades. Various parties, such as Utilities and DSOs, may act as ESPs, depending on the legislation of each country. A communication network lies on top of the electric grid and all parties are able to exchange messages with each other.

The consumption of user i in timeslot t is denoted as x_i^t, where $t \in H$ and $i \in N$. The comfort of user i at a time-slot t is expressed by a utility function $u_i^t(x_i^t, \omega_i^t)$, where ω_i^t is an appropriate elasticity parameter. The utility function expresses, in monetary units, how much user i values the consumption x_i^t at time t. To better characterize the properties of the utility function, the DSM literature draws on two concepts from microeconomics [MAS95]. The first concept is that of diminishing returns, which, in our context, means that:

1) The more a user consumes, the more utility he/she gains $(u_i^t(x_i^t, \omega_i^t)$ is increasing with $x_i^t)$.
2) The more a user consumes, the less the added utility $(u_i^t(x_i^t, \omega_i^t)$ is concave).

The second concept relates to demand elasticity, defined as the rate of change of the utility function with respect to small changes in the consumption quantity. This is expressed through parameter ω_i^t, where low values of ω_i^t correspond to elastic demand (very responsive to price), whereas higher values of ω_i^t correspond to inelastic demand (less responsive to price). The dependence of ω_i^t on i and t captures the fact that different users, at different times, value consumption differently.

In what follows, we will sometimes use the shorthand notation $\dot{u}_i^t$, with the dot notating that it is a function. In the evaluation of the results, we show that the performance of the proposed mechanism is not affected by the particular choice of $\dot{u}_i^t$ as long as it is based on the two concepts presented above.

By the concavity of $\dot{u}_i^t$, it is clear that there is a saturation point beyond which utility no longer increases with x_i^t. This is regarded as the user's maximum desired consumption and is denoted it as $\widetilde{x_i^t}$. The respective $u_i^t\left(\widetilde{x_i^t}, \omega_i^t\right)$ is denoted as $\widetilde{u_i^t}$. In this section, we assume that the user's $\widetilde{x_i^t}$ is known to the ESP (e.g. through statistical data and machine learning) but the particular form of the user's utility function as well as the user's elasticity parameter ω_i^t, remain private . The model can also be extended to model the comfort derived from the consumption of each electric appliance, in which case the total comfort of the user would be the sum of concave functions for the different appliances that the user possesses, and would again be concave. For the scope of the current work and without loss of generality (as in [GATZ13], [MOHS10], [SAMA10], [SAMA12], [BAHA13], [BAHA14], we assume only one continuous, dispatchable and positive load $x_i^t > 0$ for user i, representing the sum of the consumptions of all his/her electric appliances.

The supply side is usually modeled either as a game (e.g. a market that admits to a Nash equilibrium [CHAI13], [CLI17]) or (more simplistically) as a cost function that approximately relates the aggregate demand with the cost of the energy supplied. In this work, we adopt the latter approach, in which the system's cost (denoted as G_N^t) depends on the total load $\sum_{i \in N} x_i^t$ of the users in set N at timeslot $t \in H$ through an increasing convex function:

$$G_N^t = G(\sum_{i \in N} x_i^t) \tag{2.2.1}$$

The cost function is commonly approximated by a quadratic cost function in the literature:

$$G_N^t = c(\sum_{i \in N} x_i^t)^2 \tag{2.2.2}$$

where c is a cost parameter. Equation (2.2.2) represents the cost for the ESP to buy an amount of energy equal to the total demand. As described in the introduction, the system needs to be budget-balanced (the sum of the bills of the participating users needs to be equal with the total system's cost). The aforementioned function offers a fair test-bed in order to evaluate and compare pricing mechanisms and for this reason it is widely accepted.

The objective at each timeslot t is to find the users' consumptions $\hat{x}_i^t$, $\forall\, i \in N$ that maximize the system's efficiency (maximize the user comfort and minimize the energy cost):

$$\max_{\iota \in N} \; \{ \sum_{i \in N} [\dot{u}_i^t] - G_N^t \} \tag{2.2.3}$$

$$\text{s.t.} \quad \sum_{i \in N} [p_i^t x_i^t] = G_N^t \tag{2.2.4}$$

Constraint (2.2.4) expresses the budget-balanced (non-profit) property. We present a model that deals only with load curtailments, implying a memoryless system. This means that the scheduling problem can be solved for the time horizon H, by solving for each timeslot independently. In order to solve (2.2.3), it is required from all users in N to disclose their comfort functions to the ESP and also accept a direct ESP control over their loads. Since these requirements are not generally met in practice, the research community focuses on iterative pricing mechanisms that converge to equilibrium (set of prices) that satisfy the KPIs analyzed in the introduction. Considering (2.2.4), the prices set by the ESP, are meant to efficiently distribute the energy cost to the users and thus inherently depend on G_N^t.

At the user's side, we consider selfish users that choose their x_i^t, so as to maximize their own welfare under the ESP's pricing:

$$x_i^t = \text{argmax}_{x_i^t} \; \{ \, u_i^t - p^t x_i^t \, \} \tag{2.2.5}$$

Equation (2.2.5) implies a price-taking user. This models a user that either is very small compared to the aggregated system's consumption and therefore his/her choice of x_i^t does not affect the price p^t or does not understand/consider the effect of his/her choice of x_i^t at price p^t. In that case, (2.2.3) can be solved via dual decomposition, where the ESP applies an efficient algorithm for finding the optimal set of prices by exchanging messages with each user (as presented in [SAMA10]). In contrast, we consider price-anticipating users, who further consider the effect of their x_i^t on the price. Thus, user's problem (2.2.5), is converted into:

$$x_i^t = \text{argmax}_{x_i^t} \; \{ u_i^t - \, p^t(x_i^t, \boldsymbol{x}_{-i}^t) \, x_i^t \, \} \tag{2.2.6}$$

where the expression to be maximized is referred to as the user's welfare. Moreover, vector $\boldsymbol{x}_{-i}^t$ denotes the consumptions of users other than i. This, latter co-relation essentially motivates a game Γ where game participants are users $i \in N$; a user's strategy is his/her choice of x_i^t; a user's payoff is his/her welfare.

Notice that the VCG mechanism is proved to converge to the unique allocation $\hat{x}_i^t$ that optimizes (2.2.3). However, constraint (2.2.4) excludes VCG from consideration, as argued in the related work.

Moreover, efficient allocations in general, require disclosure of the users' utility functions to the ESP. Such an assumption would make the model convenient for analytical analysis. It is however a strong assumption and it doesn't properly capture the intricacies of household energy usage, while also raising privacy as well as representation issues. In contrast, we chose to remain agnostic to the particular form of the user's utility function. Because of this latter property, the efficiency of equilibria cannot be justified for the general case. Nonetheless, we focus on designing a pricing mechanism, such that:

1) Game Γ converges to a Nash equilibrium (NE).
2) The system at equilibrium, achieves an attractive trade-off among efficiency, low-cost and fairness.

2.2.3 The state of the art approach

We start the description of our personalized pricing mechanism by first presenting the existing RTP approach.

For timeslot $t \in H$, at the ESP-level, the users' scheduled energy consumptions x_i^t are taken as input and the price p^t of timeslot *t* (electricity per unit price, which under RTP is common for all users *i*) is calculated according to:

$$p^t = \frac{G_N^t}{\sum_{i \in N} x_i^t} \tag{2.2.7}$$

Equation (2.2.7) leads to a user's bill which is proportional to the user's consumption $\left(\frac{x_i^t}{\sum_{i \in N} x_i^t} G_N^t\right)$, which ensures that the system is budget-balanced (the users' bills equals the total energy cost).

At user-level, users sequentially choose their x_i^t from (2.2.6). During this calculation, $\boldsymbol{x}_{-i}^t$ is considered fixed. Notice that although, user i might be agnostic of $p^t(x_i^t, \boldsymbol{x}_{-i}^t)$, he/she can however detect the pricing trend by exchanging messages with the ESP. More specifically, by trying different x_i^t and receiving the respective p^t, the user can detect $p^t(x_i^t, \boldsymbol{x}_{-i}^t)$,by applying some polynomial fitting algorithm. This approach allows for a distributed implementation, which is in line with state of the art requirements [BAHA14], [LIU17], [STEP15].

After a limited number of sequential iterations (calculations) of each user's updated x_i^t, the system converges to the equilibrium price where no user wishes to further modify his/her x_i^t. A user's final x_i^t at equilibrium is denoted as $\hat{x}_i^{t,RTP}$, $\forall\, i \in N$. The procedure is described in Algorithm 2.2.1 (where *k* denotes the algorithm's iterations):

Algorithm 2.2.1 RTP

Initialization:

Set *k*=1, $x_i^{t,k} = \widetilde{x_i^t}, \forall\, i \in N$ and $p^t = \frac{G_N^t}{\sum_{i \in N} x_i^t}$

Repeat

for each $i \in N$

repeat

Calculate p^t from (7)

Calculate $x_i^{t,k+1}$ by solving (5)

until convergence

end for

Calculate divergence $\Delta = \max\{|x_i^{t,k+1} - x_i^{t,k}|\}$

Set $k = k+1$

until $\Delta < \varepsilon$ (desired accuracy)

End

2.2.4 Personalized Real-Time Pricing approach

In this section we propose the concept of P-RTP, meaning that the price will no longer be a scalar p^t (same for all users $i \in N$) but each user will receive a different price p_i^t.

From the class of all possible P-RTP mechanisms, we formulate a particular mechanism that is designed to perform well, in the three KPIs that described. The proposed mechanism allocates lower prices to those users who consume a lower percentage of their desired consumption ($\widetilde{x_i^t}$), compared to users who consume a higher percentage of their desired consumption. In particular, for a user i and a timeslot t we allocate the price p_i^t according to the degree to which the user curtails his consumption. Elastic users receive lower prices and inelastic users receive higher prices. It is highlighted that P-RTP assumes the knowledge of the desired energy consumption ($\widetilde{x_i^t}$). In case that we allow for a user to declare a fake (larger) desired consumption, P-RTP would favor him. Thus, this pricing mechanism is suitable for automated environments (through ICT systems) where user do not manually declare their consumption. On the other hand the exploitation of the desired energy consumption leads to very effective pricing mechanisms. In this section, we present a pricing model for the use case of automated environments.

In order to achieve prices with a discount proportional to the percentage of curtailments, we set:

$$(p_i^t - \widetilde{p^t}) \,/\, \widetilde{p^t} = (x_i^t - \widetilde{x_i^t}) \,/\, \widetilde{x_i^t} \tag{2.2.8}$$

where $\widetilde{p^t}$ is introduced in order to tune the prices, so that constraint (2.2.4) holds. Let us denote as γ_i^t the percentage of the curtailment of user i at time instant t:

$$\gamma_i^t = (x_i^t - \widetilde{x_i^t}) \,/\, \widetilde{x_i^t} \tag{2.2.9}$$

Thus, (2.2.8) through the use of (2.2.9) becomes:

$$p_i^t = \widetilde{p^t}(1 + \gamma_i^t) \tag{2.2.10}$$

Now through the use of (2.2.4) we have:

$$\widetilde{p^t} = \frac{G_N^t}{\sum_{i \in N}[x_i^t(1+\gamma_i^t)]} \tag{2.2.11}$$

If we now combine (2.2.10) and (2.2.11) we have:

$$p_i^t = (1+\gamma_i^t)G_N^t / \sum_{i\in N}[x_i^t(1+\gamma_i^t)] \qquad (2.2.12)$$

In the proposed mechanism, we iteratively solve (2.2.6) and calculate the prices from (2.2.12). The process is described in Algorithm 2.2.2.

Algorithm 2.2.2 P-RTP

Initialization: set k=1, $x_i^{t,k} = \widetilde{x_i^t}, \forall\, i \in N$

Repeat

  for each $i \in N$

    repeat

      Calculate p_i^t from (12)

      Calculate $x_i^{t,k+1}$ by solving (6)

    until convergence

  end for

 Calculate divergence $\Delta = \max\{|x_i^{t,k+1} - x_i^{t,k}|\}$

 Set $k = k$+1

until $\Delta < \varepsilon$ (desired accuracy)

End

Theorem 2.2.1: Algorithm 2.2.2 converges to a NE after a finite number of iterations via best response dynamics.

Proof: the strategy for the proof of the convergence of P-RTP is to find a function that is bounded from above and increases in every iteration of P-RTP. We consider the AUW according to (2.2.13).

$$AUW = \sum_{i\in N}(\dot{u}_i^t - p_i^t x_i^t) \qquad (2.2.13)$$

AUW is bounded from above (the theoretical maximum is in the case in which every user consumes all the energy that (s)he needs and the price is zero). It remains now to prove that AUW increases in every iteration of P-RTP. Note that we cannot study the monotonicity of AUW by exploiting its derivative, because no assumption is made on the differentiability of $\dot{u}_i^t$.

Consider an arbitrary instance of game Γ where it is user i's turn. User i's state is x_i^t and the state of users' other than i is fixed. We denote the latter as $\boldsymbol{x}_j^t$, where $j \in N, j \neq i$.. Holding $\boldsymbol{x}_j^t$ fixed, suppose i deviates to $\widehat{x_i^t}$. The calculation of the change in AUW breaks down in the calculation of the welfare of user i (2.2.6) and the welfare of users in set j. According to (2.2.13) and the recent notation in order to prove that AUW increases in every iteration of P-RTP it must be proven that:

$$U\left(\widehat{x_i^t}\right) - \widehat{x_i^t} p_i^t\left(\widehat{x_i^t}, \boldsymbol{x}_j^t\right) + \sum_{j \neq i} U\left(x_j^t\right) - \sum_{j \neq i} x_j^t p_j^t\left(\widehat{x_i^t}, \boldsymbol{x}_j^t\right) > U(x_i^t) - x_i^t p_i^t\left(x_i^t, \boldsymbol{x}_j^t\right) + \sum_{j \neq i} U\left(x_j^t\right) - \sum_{j \neq i} x_j^t p_j^t\left(x_i^t, \boldsymbol{x}_j^t\right) \tag{2.2.14}$$

Best response dynamics means that each user at any instance selects a strategy that maximizes her/his own welfare. So, since user i deviates, it holds by definition:

$$U\left(\widehat{x_i^t}\right) - \widehat{x_i^t} p_i^t\left(\widehat{x_i^t}, \boldsymbol{x}_j^t\right) > U(x_i^t) - x_i^t p_i^t\left(x_i^t, \boldsymbol{x}_j^t\right) \tag{2.2.15}$$

From (2.2.13) and (2.2.14), it suffices to prove that:

$$\sum_{j \neq i} x_j^t p_j^t\left(x_i^t, \boldsymbol{x}_j^t\right) > \sum_{j \neq i} x_j^t p_j^t\left(\widehat{x_i^t}, \boldsymbol{x}_j^t\right) \tag{2.2.16}$$

We present here the case for $\widehat{x_i^t} > x_i^t$. The exact same proof holds symmetrically for $\widehat{x_i^t} < x_i^t$. Since we have $\widehat{x_i^t} > x_i^t$ without harm of generality:

$$G_N^t\left(\sum_{j \neq i} x_j^t + \widehat{x_i^t}\right) > G_N^t\left(\sum_{j \neq i} x_j^t + x_i^t\right) \tag{2.2.17}$$

which means that the system cost has increased by:

$$\Delta G = G_N^t\left(\sum_{j \neq i} x_j^t + \widehat{x_i^t}\right) - G_N^t\left(\sum_{j \neq i} x_j^t + x_i^t\right) \tag{2.2.18}$$

In addition the bill of user *i* has increased by:

$$\Delta B_i = \widehat{x_i^t} p\left(\widehat{x_i^t}, \boldsymbol{x}_j^t\right) - x_i^t p\left(x_i^t, \boldsymbol{x}_j^t\right) \tag{2.2.19}$$

We will study now the relation between ΔB_i and ΔG. In case it is $\Delta B_i > \Delta G$ it means that user i pays more than the cost difference that she/he creates and thus the new bills of other users are lower in the new state which means that (2.2.16) holds. In more formality, because of the budget-balance property of P-RTP, it is:

$$\Delta B_i + \Delta\left(\sum_{j \neq i} B_j\right) = \Delta G \tag{2.2.20}$$

which means that (2.2.15) holds for:

$$\Delta B_i - \Delta G > 0 \tag{2.2.21}$$

By replacing (2.2.12) in (2.2.21) it is:

$$\Delta B_i - \Delta G = \frac{\widehat{x_i^t}(1+\gamma_i^t)G_N^t\left(\sum_{j\neq i} x_j^t + \widehat{x_i^t}\right)}{\sum_{i\in N}\left[\widehat{x_i^t}(1+\gamma_i^t)\right]} - \frac{x_i^t(1+\gamma_i^t)G_N^t\left(\sum_{j\neq i} x_j^t + x_i^t\right)}{\sum_{i\in N}\left[x_i^t(1+\gamma_i^t)\right]} - G_N^t\left(\sum_{j\neq i} x_j^t + \widehat{x_i^t}\right) + G_N^t\left(\sum_{j\neq i} x_j^t + x_i^t\right) \qquad (2.2.22)$$

After replacing γ_i^t from (2.2.9) and doing some calculus, we have:

$$\Delta B_i - \Delta G = G_N^t\left(\sum_{j\neq i} x_j^t + \widehat{x_i^t}\right)\left(\frac{\widehat{x_i^t}^2}{\widetilde{x_i^t}\left(\sum_{j\neq i}\frac{\left(x_j^t\right)^2}{\widetilde{x_j^t}} + \frac{\left(\widehat{x_i^t}\right)^2}{\widetilde{x_i^t}}\right)} - 1\right) - G_N^t\left(\sum_{j\neq i} x_j^t + x_i^t\right)\left(\frac{{x_i^t}^2}{\widetilde{x_i^t}\left(\sum_{j\neq i}\frac{\left(x_j^t\right)^2}{\widetilde{x_j^t}} + \frac{\left(x_i^t\right)^2}{\widetilde{x_i^t}}\right)} - 1\right) \qquad (2.2.23)$$

Observe that (2.2.23) can be written in the form $\Delta B_i - \Delta G = \Phi(\widehat{x_i^t}) - \Phi(x_i^t)$ with:

$$\Phi(z) = G_N^t\left(\sum_{j\neq i} x_j^t + z\right)\left(\frac{z^2}{\widetilde{x_i^t}\left(\sum_{j\neq i}\left(\frac{\left(x_j^t\right)^2}{\widetilde{x_j^t}}\right) + \frac{z^2}{\widetilde{x_i^t}}\right)} - 1\right) \qquad (2.2.24)$$

Since it is $\widehat{x_i^t} > x_i^t$, it suffices to show that

$$\frac{\mathrm{d}\Phi(z)}{\mathrm{d}z} > 0 \qquad (2.2.25)$$

After replacing (2.2.2) and (2.2.23) in (2.2.24) and differentiating we have:

$$\frac{2\sum_{j\neq i}\left(\frac{\left(x_j^t\right)^2}{\widetilde{x_j^t}}\right)c\left(z+\sum_{j\neq i} x_j^t\right)\left(\left(\sum_{j\neq i} x_j^t\right)z - \left(\sum_{j\neq i}\left(\frac{\left(x_j^t\right)^2}{\widetilde{x_j^t}}\right)\right)\widetilde{x_i^t}\right)}{\left(\mathbf{z^2} + \left(\sum_{j\neq i}\left(\frac{\left(x_j^t\right)^2}{\widetilde{x_j^t}}\right)\right)\widetilde{x_i^t}\right)^{\mathbf{2}}} > 0 \qquad (2.2.26)$$

which reduces to

$$z > \frac{\left[\sum_{j\neq i}\left(\frac{\left(x_j^t\right)^2}{\widetilde{x_j^t}}\right)\right]\widetilde{x_i^t}}{\sum_{j\neq i} x_j^t} \qquad (2.2.27)$$

Observe that $\frac{x_j^t}{\widetilde{x_j^t}} < 1$ (since the denominator is by definition the upper limit of the nominator). We have that:

$$\frac{\left(\sum_{j\neq i}\left(\frac{\left(x_j^t\right)^2}{\widetilde{x_j^t}}\right)\right)\widetilde{x_i^t}}{\sum_{j\neq i}x_j^t} = \frac{\sum_{j\neq i}\left(\frac{x_j^t}{\widetilde{x_j^t}}\cdot x_j^t\right)\widetilde{x_i^t}}{\sum_{j\neq i}x_j^t} < \widetilde{x_i^t} \tag{2.2.28}$$

Thus, because of (2.2.28) there is a feasible region of $x_i^t \in \left[\frac{\left(\sum_{j\neq i}\left(\frac{\left(x_j^t\right)^2}{\widetilde{x_j^t}}\right)\right)\cdot\widetilde{x_i^t}}{\left(\sum_{j\neq i}x_j^t\right)}, \widetilde{x_i^t}\right]$, for which condition (2.2.16) holds.

2.2.5 Performance Evaluation and Comparisons

In this section we present simulation results to demonstrate the proposed P-RTP mechanism's performance in the KPIs sought. In order to have a benchmark for comparisons, we compare with the simple RTP mechanism (Algorithm 2.2.1). The evaluation considers scenarios under a variety of assumptions for the values of the parameters in the two models.

In order to evaluate mechanisms, the research community usually models end users as follows: a concave and increasing function of x_i^t and ω_i^t with a constant maximum value after a saturation point, has been widely adopted:

$$u_i^t(x_i^t, \omega_i^t) = \begin{cases} \widetilde{u_i^t} - \omega_i^t\left(x_i^t - \widetilde{x_i^t}\right)^2 & 0 < x_i^t < \widetilde{x_i^t} \\ \widetilde{u_i^t} & x_i^t \geq \widetilde{x_i^t} \end{cases} \tag{2.2.29}$$

The utility function's general form is assumed to be the same for all i and t. In what follows, we present simulations for a representative set of 100 users. Moreover, the optimization problem can be solved for each timeslot independently. Thus, without loss of generality, we run the simulation for one timeslot ($h = 1$) and present the results. Parameter $\widetilde{u_i^t}$ expresses the user's maximum utility (i.e.utility at $x_i^t \geq \widetilde{x_i^t}$) and was set to $\widetilde{u_i^t} = \omega_i^t\left(\widetilde{x_i^t}\right)^2$. Unless stated otherwise, parameter c was set to $c = 0.02$. The flexibility parameter ω_i^t for each user i was selected randomly in the interval [0.1, 5]. These choices are in line with the literature [LI10], [SAMA10], [SAMA12], [CHAI14].

In correspondence with the three KPIs, we define four index metrics for the evaluation:

1) Aggregated users' welfare (AUW) is a straightforward index for system efficiency (KPI-2.2.1).

$$AUW = \sum_{\boldsymbol{i\in N}}(\dot{u}_i^t - p_i^t\, x_i^t) \tag{2.2.30}$$

2) The allocation's cost G is also a straightforward index metric of system cost KPI-2.2.2.

$$G = c\left(\sum_{\boldsymbol{i}\in\boldsymbol{N}}[x_i^t]\right)^2 \tag{2.2.31}$$

We evaluate P-RTP and simple RTP with respect to these two KPIs for different values of c and ω_i^t in order to show that the performance of our mechanism does not depend on the parameters of the system. KPI-2.2.1 and KPI-2.2.2 are generally mutually-conflicting; for example, a low system's cost can lead to lower users' welfare (because of lower consumption) unless we reward the users with lower prices to compensate for the users' welfare. We define behavioral reciprocity (BR) as a metric that captures this trade-off:

3) Behavioral Reciprocity BR_i of user i is the degree of correlation between the behavioral change of *i* and the reward that *i* gets for it:

$$BR_i = \frac{D_i^A}{D_i^R} \quad \forall\, i \in N \tag{2.2.32}$$

where

$$D_i^A = \left(\widetilde{x_i^t} - x_i^t\right)\frac{G\left(\sum_{i=1}^N \widetilde{x_i^t}\right) - G\left(\sum_{i=1}^N x_i^t\right)}{\sum_{i=1}^N \widetilde{x_i^t} - \sum_{i=1}^N x_i^t} \tag{2.2.33}$$

represents the discount achieved, i.e. the system cost reduction, for which user i is responsible and:

$$D_i^R = \widetilde{x_i^t}\,\frac{G\left(\sum_{i=1}^N \widetilde{x_i^t}\right)}{\sum_{i=1}^N \widetilde{x_i^t}} - x_i^t p_i^t \tag{2.2.34}$$

represents the discount received, i.e. the difference between the user's bill with the original system's state ($x_i^t = \widetilde{x_i^t}$) and the actual user's bill (after applying RTP or P-RTP). Values of BR_i close to 1 indicate a better trade-off between *AUW* and *G*, and thus a more fair pricing mechanism.

4) User i welfare deviation (UWD_i) is defined to capture the degree of the deviation of user *i* from the average user's welfare:

$$UWD_i = \frac{\left[\left(u_i^t - p_i^t\, x_i^t\right) - \frac{AUW}{n}\right]}{\frac{AUW}{n}} \quad \forall\, i \in N \tag{2.2.35}$$

Its scope is to depict that a mechanism's performance, does not come with the expense of treating a subset of users unfairly. A low *UWD* means that there are no users with very high welfare and users with very low welfare (which means that they will leave the ESP in case of competition or they will be very unhappy in case of monopoly). Thus, the objective here is to keep *UWD* low.

Having defined the metrics of interest, we now proceed to the presentation of the results obtained. In all figures we normalize the metric by dividing with the highest metric value. Figure 2.2.f1 compares the energy costs (G) with RTP and P-RTP pricing under various values of parameter c.

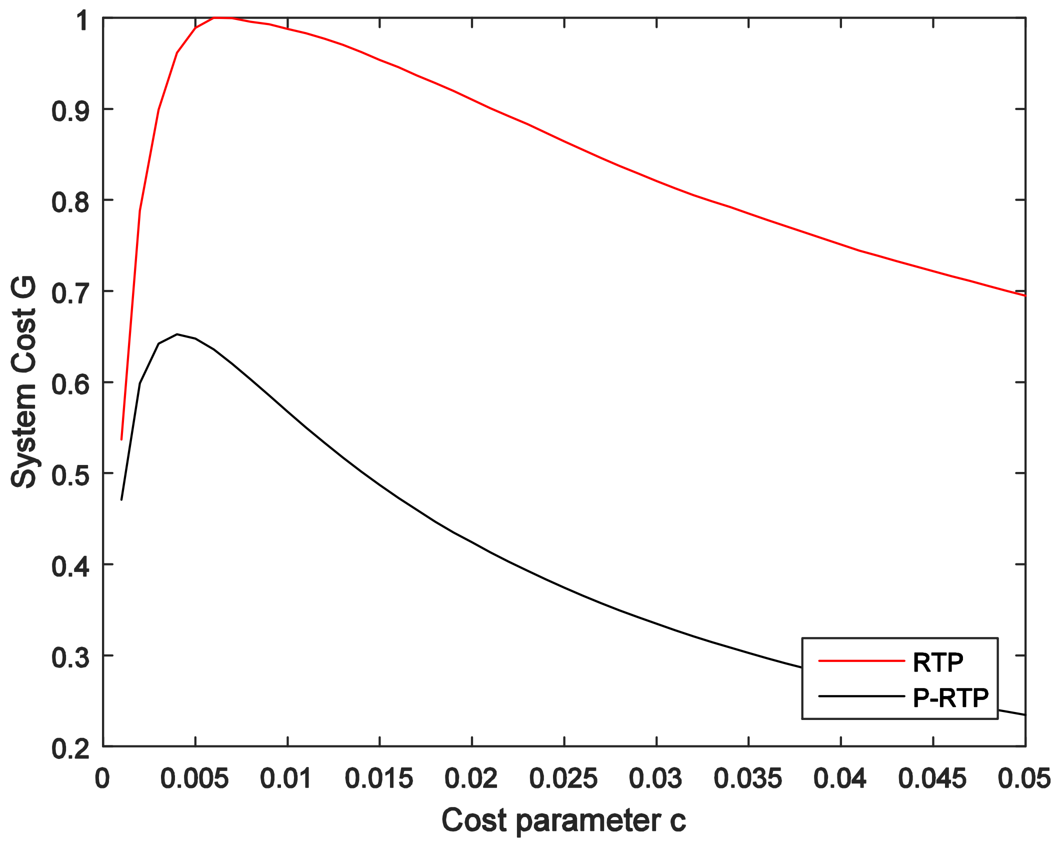


Figure 2.2.f1 Energy costs G as a function of cost parameter c

As is obvious from Figure 2.2.f1, the proposed P-RTP reduces the cost of energy for every value of c, thus showing that P-RTP indeed manages to achieve a lower system cost, regardless of the cost function we use. This is because P-RTP leads to smaller load level than RTP. In order to show that the results are not affected by the elasticity parameter we use, we multiply ω_i^t by a factor (omega factor) ω_f in $[0.1, 3]$. According to these, Figure 2.2.f2 compares the energy costs (G) with RTP and P-RTP pricing as a function of ω_f. From Figure 2.2.f2 we observe that P-RTP always brings a reduction in the energy cost. Thus, its performance is consistent and significant for any choice of the flexibility parameter for the participating users.

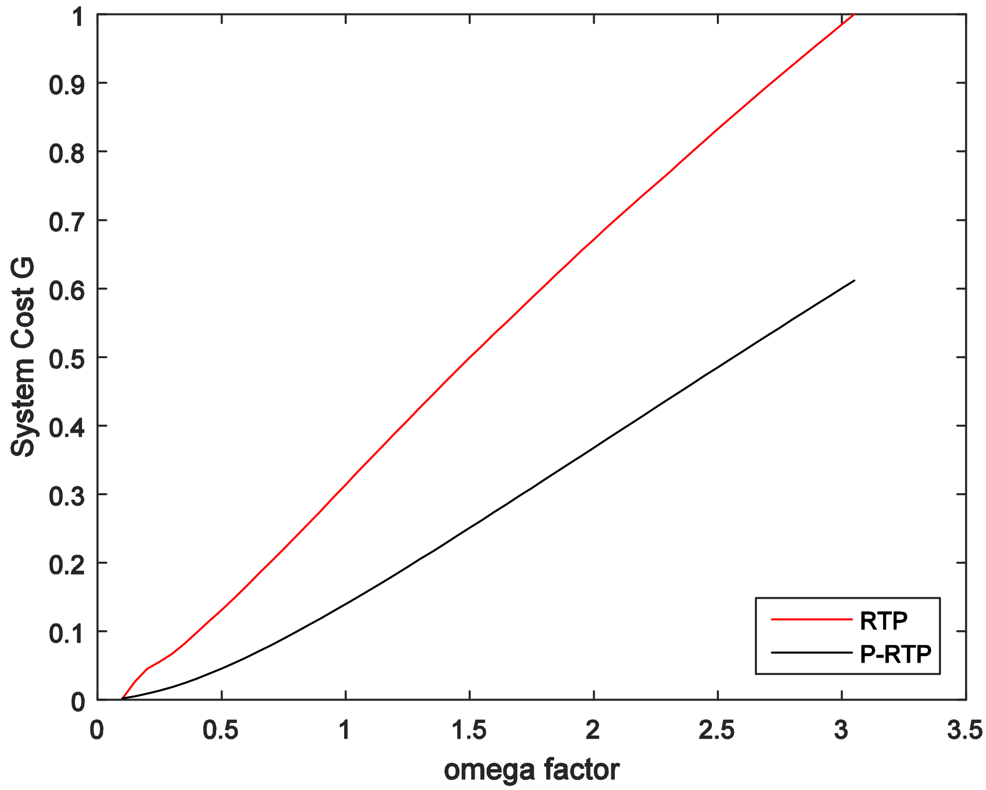


Figure 2.2.f2 Energy costs (G) of P-RTP and RTP as a function of omega factor (ω_f)

The reason behind the reduction of the energy costs is clarified through Fig. 3, where we present the cumulative distribution function (CDF) of the BR_i metric exhibited by the users i in N. The dotted vertical lines represent the average UWD of all users. As is depicted in Figure 2.2.f3, under P-RTP, users obtain benefits (discounts received) according to their behavioral change (discount achieved). In more detail, we observe that P-RTP not only offers a better trade-off between AUW and G (the average BR for P-RTP is closer to 1 than the average BR for RTP) but also results into a much narrower distribution of users around the average. This means that the behavioral change that the users offer is better and more fairly reciprocated. In other words, with the proposed P-RTP, inflexible users do not benefit from the actions of flexible users. This implies that, with P-RTP, flexible users have stronger motives to adapt their behavior, as they know that they will benefit from such an adaptation, while non adaptive users will not receive benefits.

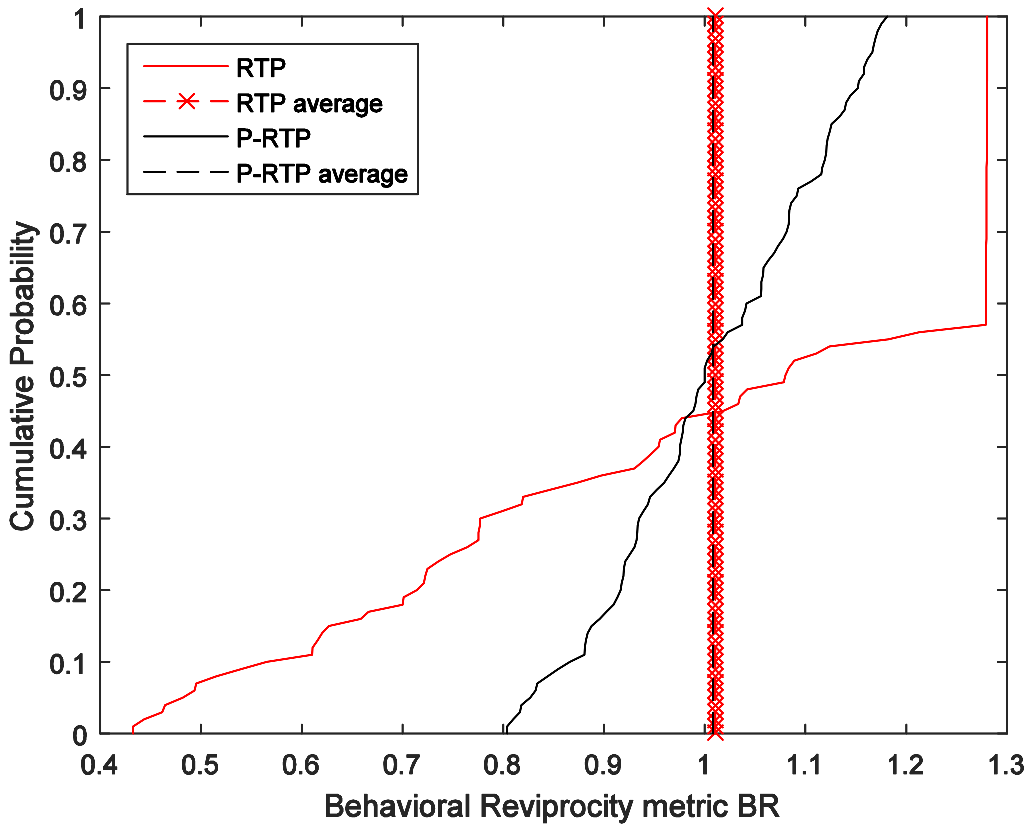


Figure 2.2.f3 CDF of metric BR_i among participating users under RTP and P-RTP pricing

The following figures show that the reduction in the energy cost is achieved without sacrificing at all the user's welfare. In more detail, Figures 2.2.f4 and 2.2.f5 present metric AUW, for the RTP and the P-RTP mechanism, as a function of c and ω_f respectively.

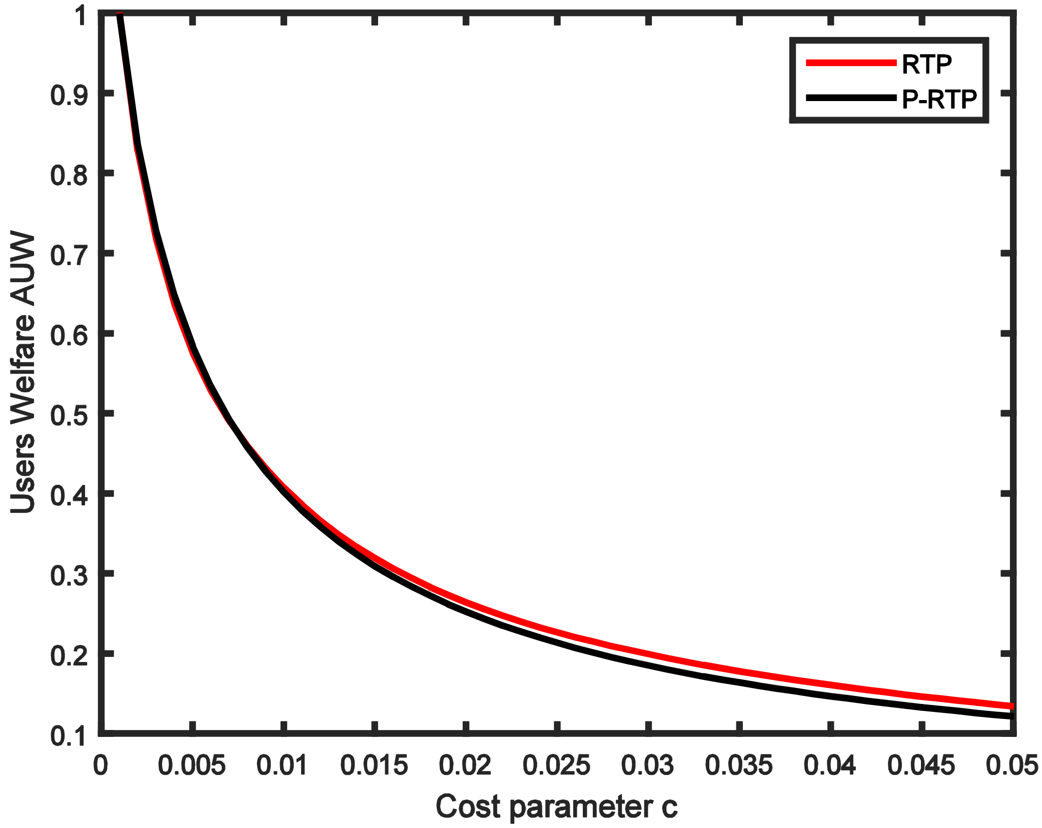


Figure 2.2.f4 Aggregated users' welfare *AUW* under P-RTP and RTP as a function of cost parameter *c*

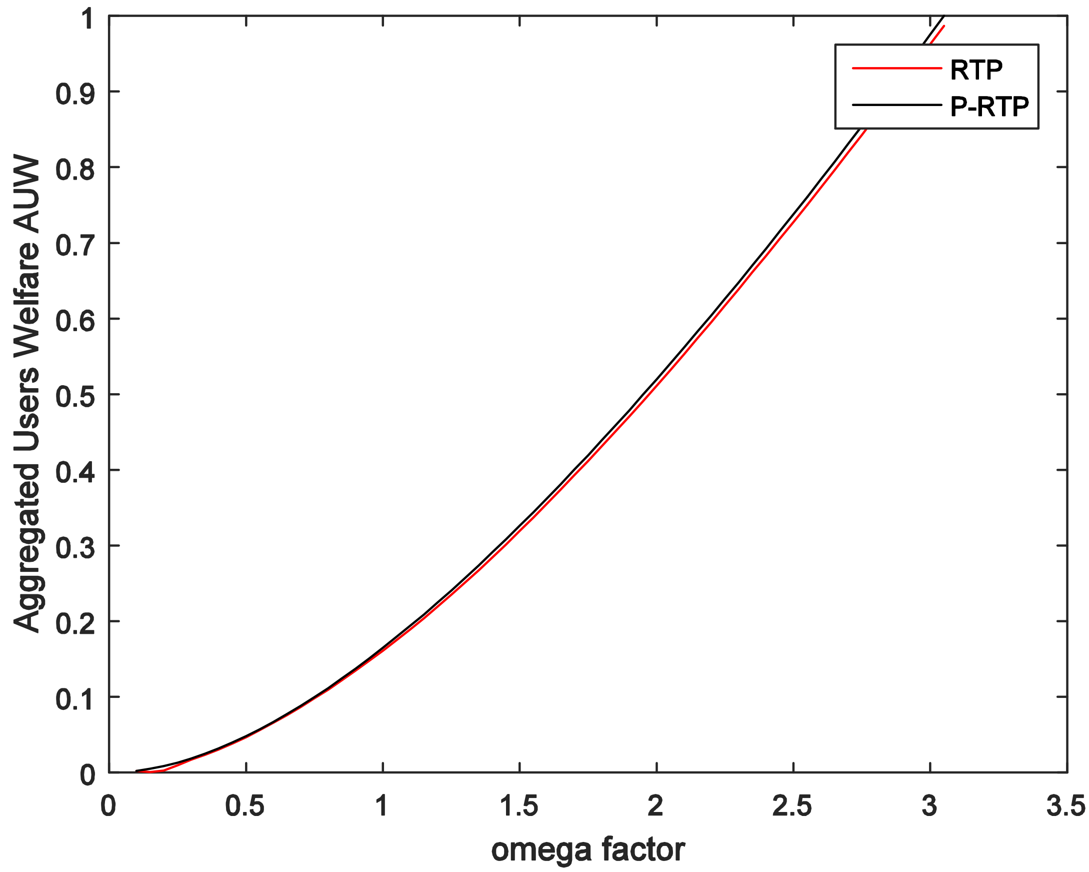


Figure 2.2.f5 Aggregated users' welfare AUW under P-RTP and RTP as a function of the omega factor (ω_f)

By comparing Figures 2.2.f1 and 2.2.f4, one can see that, the system's cost has been reduced and the system's fairness has been enhanced, without loss on users' aggregated welfare, that is without sacrificing efficiency. This is rationalized by the fact that P-RTP allocates financial savings to the users that provoke the cost reduction and not to the inflexible ones. In comparison with the simple RTP model, this leads to an increase in the flexible users welfare and a decrease in the inflexible users' welfare, thus the total AUW remains the same.

Though the AUW metric is no better with RTP, we also want to make sure that this benefit does not come with a sacrifice of welfare from a particular subset of users. In Figure 2.2.f6, we present the CDF for UWD_i. The dotted vertical lines represent the average UWD of all users in the set N. The averages coincide with each other while the distribution with P-RTP is insignificantly narrower.

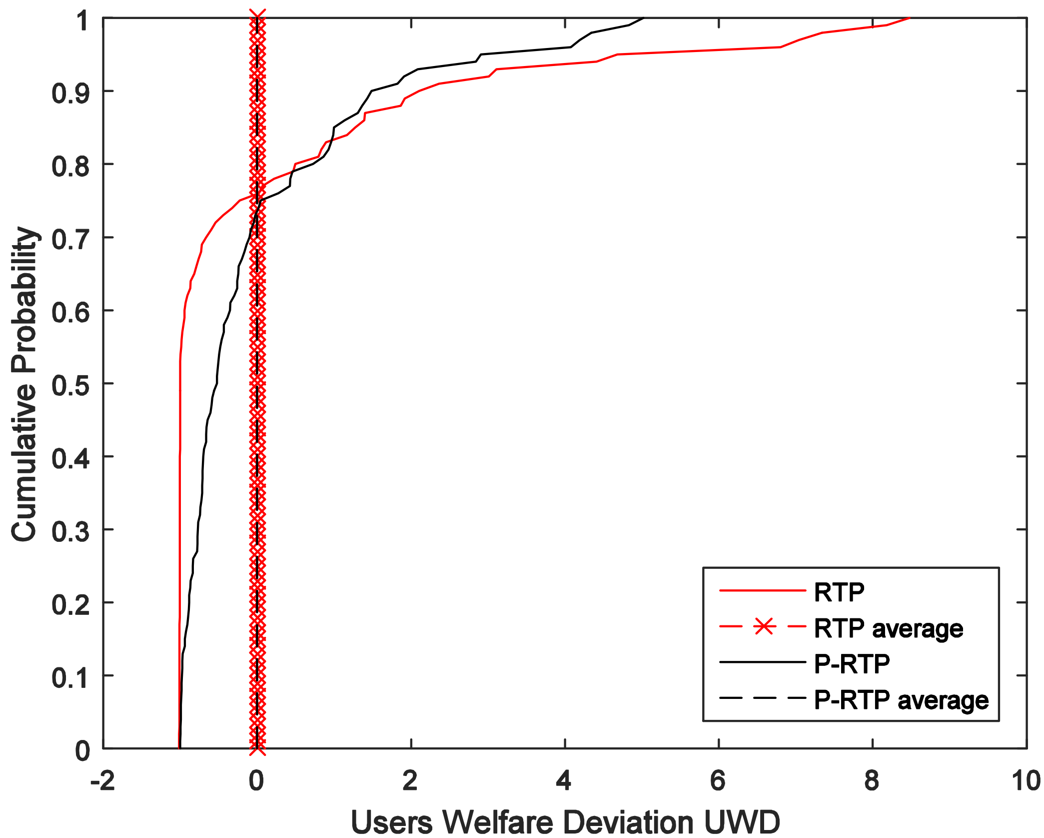


Figure 2.2.f6 CDF of metric UWD in P-RTP and RTP

2.3 Conclusions and Future Work

In this chapter, we took on the case of providing real-time demand response services. We proposed two schemes, each suitable for a particular business model. In the first subsection, we showcased the inefficiency of previous state-of-the-art approaches, which either do not consider user incentives, or adopt a direct-revelation approach, respectively leading to either lack of truthfulness and consequent inefficiency, or to lack of privacy and scalability. To overcome these shortcomings, we presented a novel iterative auction mechanism based on Ausubel's clinching auction, that implements the truthful and efficient VCG outcome but also allows for a distributed implementation and a privacy-preserving communication protocol. Our theoretical and simulation results verified that the proposed scheme combines the desired properties with very good performance and small overhead. Future work can further extend user rationality to also anticipate future DR-events based on local information and learning techniques.

In the second subsection, we considered a business model of a budget-balanced aggregating entity serving as ESP for its registered users. We proposed a P-RTP mechanism and evaluated its performance against that of the classic RTP mechanism in terms, of the most well established KPIs derived in the literature. In order to focus on the merits of the main idea, we kept the system model simple so as not to harm the generality of the results. Future research can extend the results to more advanced system models that include: a) the possibility of load shifting in addition to load curtailment; b) RES and energy storage systems (ESS).

In addition, the user's utility function and the way the user makes decisions is still an open area for research. Distinct models for different devices could be considered and applied under the P-RTP paradigm. Moreover, in electricity markets, different pricing mechanisms (P-RTP, RTP, flat-price, etc) are to be offered to real users as an option, making the co-existence of different pricing mechanisms for different users in a given market an interesting problem. Finally, the new prospects of electricity pricing offered by P-RTP will impact, if adopted, the sizing (investment cost) of RES and ESSs. We believe that the integration of RES and ESS sizing with P-RTP mechanism design may give rise to new capabilities for self-sufficient micro-grids and advanced demand side management.

Chapter 3

PERIOD-AHEAD PRICING AND LOAD SCHEDULING

In this chapter we turn our attention to problems of the Period-Ahead scheduling use case. In this use case we consider a scheduling horizon ahead, and take on the problem of designing efficient mechanisms that achieve an efficient scheduling of the users' profiles. In particular, section 3.1 presents a near optimal mechanism for satisfying coupling constraints in an environment where users act strategically. Section 3.2 studies the problem of committing to the agreed schedule in delivery time.

3.1 Near-optimal demand side management in electricity markets with coupling constraints

Residential participation in DSM is commonly envisaged via aggregated participation because of implementation and scalability issues. An Electricity Service Provider (ESP) is considered for the role of aggregating and coordinating the users' actions. Applying direct control over the end-users' loads is not an attractive option since it comes with massive consumer dissatisfaction and arbitrary load prioritization, which leads to loss of social welfare. Along with the trend of liberalization of the electricity market, principles of economics that are already applied in most markets are now becoming more relevant to the electricity market as well. Thus, the state of the art approach to DSM is to motivate electricity consumers towards economically efficient consumption patterns by providing monetary incentives. That is, consumers are expected to modify their consumption patterns voluntarily in response to pricing signals.

Nevertheless, each user is typically trying to optimize his/her own objective, which may or may not be in line with the social objective. A particular stream of game theory called mechanism design is essentially the tool for designing rules (namely, an allocation rule through which end users determine their consumption pattern, and a billing rule through which their bills are determined) for systems with strategic participants holding private information, such that the system at equilibrium has good performance guarantees.

Modern ESPs in the era of the smart grid have to embed DSM in their business models. A DSM architecture includes the mechanism (allocation rule and billing rule) through which the DSM participants (namely, the users and the ESP) interact as well as the local algorithm through which each participant decided his/her actions. Through a carefully designed DSM architecture, we can hopefully bring the system to an efficient state, even though the designer does not directly control the decision variables. According to our requirement analysis [SED6.1], a DSM architecture has to fulfill three properties, described in the following subsections.

A. Welfare Maximization

The first property is the maximization of the welfare (i.e. the aggregated users' utility). The utility of a user/energy consumer is defined as the difference between: i) a metric (noted here as valuation function) that quantifies how much the user valuates/appreciates a specific energy consumption profile/pattern and ii) the bill that the user has to pay for it.

Maximizing the welfare through mechanism design can be relatively easy or really challenging, depending on the assumptions made about the actual users' behavior and preferences. Making strong assumptions on the form of user's preferences makes the system conducive to theoretically strong results but the validity of these assumptions is often questionable [CHAP13]. Also, a common assumption regarding the user's behavior refers to the user being modeled as a price-taker, which means not considering the effect of his/her own decisions on the electricity price. While this might be relevant for large systems, in emerging energy communities and decentralized systems this assumption no longer holds and the user might be a price-anticipator. The latter user model only makes things more complicated when it comes to welfare maximization and it is avoided in most of the literature (see [SAMA12] and references therein). In contrast, in the present section users are price anticipators.

Finally, the aggregated users' utility alone is not enough. A typically desired property is the property of individual rationality. A mechanism is called individually rational if each and every user benefits from participating in it. In other words, at equilibrium, each user is better-off participating in the DSM, rather than not participating.

B. Budget-balance

We consider a benevolent ESP that acts on behalf of the users and not against them. The ESP is not a profit maximizing entity but a representative of the users and their interests. Budget-balance refers to the fact that the mechanism is not required to subsidize the DSM participation nor does it extract a surplus from the users, but only divides the system's energy cost among users. Indicative use cases of this business model are: i) the case of energy cooperatives [RESCOOP], ii) public companies [ECOPOWER] around public authorities acting as ESPs, iii) private monopolistic companies with regulated profit margins, iv) virtual associations of users [VIMSEN] v) islanded energy communities and vi) any other use case in which the ESP's primary interest is the welfare of the users in its portfolio.

C. Constraint Satisfaction

The third property is the coordination of the aggregated users' consumption in order to satisfy system-wide constraints. Such constraints indicatively aim to

Case a) keep the aggregated consumption below a certain threshold at all times or

Case b) keep the system's overall cost within certain margins.

The necessity of satisfying such constraints is met in many use cases in modern smart grids which include:

1) Enhancing the self-sufficiency of the community

2) Keeping islanded microgrids economically viable [STAD16]

3) Mitigate suppliers' exercise of market power by taking coordinated action to reduce the demand in the face of such situations [BORE00]

4) Meeting the physical network's constraints by implementing the DSO's orders

5) Enhancing the community's participation in flexibility markets [USEF], [DNV]

6) Reducing CO2 emissions and respecting modern legal frameworks towards energy cost reduction [DIREC12]

7) Enhancing RES penetration by adapting demand to the intermittent generation [POLICY]

From a technical point of view, satisfying a system-wide constraint can be a challenge. In particular, constraint satisfaction typically depends on the aggregated consumption profile of end users. This couples the system's decision variables that are controlled by different users, which brings a fair amount of complications in the underlying n-person game [LI14]. The proposed DSM architecture can be used for both cases a) and b) of constraints described above. In this section, we present a theoretical analysis for case a), which is the most difficult of the two but in the evaluation section we present simulations for both cases.

Further requirements might apply depending on the context and the particular business model of the system. Designing a DSM architecture that exhibits specific properties tailored to each specific business model is an open research topic.

Summarizing the above, the contribution of this section is the design of a DSM architecture that is able to meet system-wide constraints (e.g. energy cost reduction) and at the same time achieve users' welfare very close to optimal. The proposed scheme also preserves both the budget-balance and the individual rationality properties.

3.1.1 Related Work

In the DSM context described above, we set three main requirements for the proposed mechanism. We need a DSM architecture that: a) achieves close to optimal users' welfare, b) preserves the *budget-balance* property, and c) provides the ESP with the ability to control the overall consumption cost (satisfaction of a system constraint).

The welfare-maximizing requirement is highly dependent on user modeling. That is, a theoretically optimal allocation can be achieved, only under certain assumptions on the users' preferences representation. DSM studies can be categorized into three main branches with respect to how they model user preferences.

The first branch includes many works (e.g. [MHAN16], [TUSH15], [XCHEN13], [SOLI14], [BAHR14], [MA14], [BAHA17], [ZHAO13], [SAMA13], [RAD10], [BAHA13]) that consider users who exhibit no preference towards the consumption pattern, as long as their whole load is satisfied within a defined time interval. In simple words, users set constraints on their consumption but there are no preferences among the time intervals as long as the consumption constraints are met.

The second branch of the literature (e.g. [GATZ13], [YAAG15], [WANG17], [QIAN13], [LI10], [MOHS10], [SAMA10] and [DENG14]), considers user preferences and price sensitive consumption patterns. The study in [YAAG15], approaches the solution with a regret-based algorithm, [QIAN13] with Simulated Annealing, and the rest of the works typically formulate a convex optimization problem and reach the optimal solution by solving its dual problem. During this process, the ESP and the users solve their local problems and exchange messages. Under the assumption of price-taking users, the final allocation is welfare-maximizing.

In the third branch (e.g. [SAMA12], [NEKO15]) this assumption has been relaxed and users are considered as price-anticipators, that is, they consider the effect of their actions on the prices. In this case, the dual approach no longer achieves welfare maximization, as analyzed in [JOHA07, chapter 21]. So, the studies in this third branch opt for a Vickrey-Clarke-Groves (VCG) mechanism. However, the practical applicability of the VCG mechanism is highly debated because it is a direct mechanism (requires users to reveal their preferences to the ESP), which raises not only privacy but also representation issues (see [CHAP17] for a more detailed analysis).

From the above three user model research branches, only the first one preserves the *budget-balance* property. The convex optimization approach typically ends up with the market-clearing prices and extracts a big surplus from the users, especially when the latter are price-takers. Also, the VCG mechanism is inherently not *budget-balanced*.

Finally, constraint satisfaction complicates things when it comes to indirect mechanisms. This is because typical market-clearing approaches are often not suitable for constraint satisfaction, especially when the constraints couple the optimization variables. Thus, the works that induce some kind of controllability, either relax the welfare-maximization requirement [ALTH15], or the user preferences modeling [XCHEN13], or adopt a central optimization approach [ERDI17], [TANG14] with a consequent assumption of direct control on user loads. Also, dual optimization approaches can apply some control on the consumption patterns by manipulating the prices, but that comes at the expense of high user dissatisfaction.

In this work we present a DSM architecture for price-anticipating users that: i) achieves near optimal welfare (reaches 91%-99% of the optimal value), ii) is theoretically proven to preserve the *budget balance* and the *individual rationality* properties, iii) provides the ESP with controllability over the overall system's cost (which is a coupling and quadratic constraint). To the best of our knowledge, this is the first work to satisfy all three of the requirements described above.

3.1.2 System Model

We consider an electricity market comprised of an Electricity Service Provider (ESP) and a set $N \triangleq \{1,2,\dots,n\}$ of self-interested consumers, hereinafter referred to as users. We also consider a discrete representation of time, where continuous time is divided into timeslots $t \in H$, of equal duration s, where $H \triangleq \{1,2,\dots,m\}$ represents the scheduling horizon. A user possesses a number of controllable appliances where each appliance bears an energy demand. We consider each appliance as one user, for ease of presentation and without loss of generality. Thus, we will use the terms "user" and "appliance" interchangeably throughout.

User & Appliance modeling

An appliance i requires an amount of energy for operation. For example, if an appliance's operating power is 1W, and $s = 1h$, then the energy that the appliance consumes in one timeslot of operation is $1Wh$. This energy consumption is controllable via a decision variable x_i^t, which denotes the amount of energy consumed by appliance $i \in N$, at timeslot $t \in H$. Throughout this section we assume $x_i^t \geq 0$. Each appliance i is characterized by

i) a feasible consumption set, defined by a set of constraints on x_i^t, which is presented below and

ii) a valuation function of the energy that i consumes throughout H.

The aforementioned set of constraints includes upper and lower consumption bounds, restrictions on consumption timeslots and a coupling constraint. More specifically, appliance i cannot consume more than an upper bound $\overline{x_i}$, that is,

$$0 \leq x_i^t \leq \overline{x_i} \tag{3.1.1}$$

An appliance i also bears a set of timeslots $h_i \subseteq H$, in which its operation is feasible (e.g., an electric vehicle can be plugged in only at timeslots during which its owner is home):

$$x_i^t = 0, \quad t \notin h_i \tag{3.1.2}$$

We denote an appliance's feasible consumption profile, as a vector $\boldsymbol{x_i} = \{x_i^1, x_i^2, \dots, x_i^m\} \in \mathcal{X}_i$, where x_i^t satisfies (3.1.1), (3.1.2) and $\mathcal{X}_i \subseteq \mathbb{R}^m$ denotes the feasible set for i's consumption profile:

$$\mathcal{X}_i \triangleq \{\boldsymbol{x_i} \mid x_i^t \text{ such that (3.1.1), (3.1.2) hold}\}, i \in N \tag{3.1.3}$$

Finally, the $n \times m$ matrix containing all users' consumptions at all timeslots is denoted as $X = \{\boldsymbol{x_1}, \boldsymbol{x_2}, \dots, \boldsymbol{x_n}\} \in \mathcal{X}$ where $\mathcal{X} = \{\mathcal{X}_i\}_{i \in N}$ denotes the Cartesian product of the $\mathcal{X}_i$'s.

The valuation function is expressed in monetary units ($), and it is private (the user does not share it with the ESP or other users). It is generally a function of $\boldsymbol{x_i}$ and expresses the maximum amount of money that a user is willing to pay for the operation profile $\boldsymbol{x_i}$. The valuation function $v_i(\boldsymbol{x_i})$ can take various forms, depending on the appliance. Let $\boldsymbol{0}^m$ denote the *m*-vector with all of its elements equal to zero. We adopt some common assumptions based on microeconomics theory on the form of $v_i(\boldsymbol{x_i})$:

Assumption 3.1.1: Zero consumption brings zero value to the user:

$$v_i(\boldsymbol{0}^m) = 0 \tag{3.1.4a}$$

Assumption 3.1.2: Consuming more does not make the user less happy. That is, for two arbitrary vectors $\boldsymbol{x_{iA}}$, $\boldsymbol{x_{iB}}$, we have:

$$v_i(\boldsymbol{x_{iA}}) \le v_i(\boldsymbol{x_{iA}} + \boldsymbol{x_{iB}}), \quad \forall\, \boldsymbol{x_{iA}}, \boldsymbol{x_{iB}} \tag{3.1.4b}$$

Assumption 3.1.3: (concavity) for two arbitrary vectors $\boldsymbol{x_{iA}}$, $\boldsymbol{x_{iB}}$ and for any scalar $0 < a < 1$:

$$a v_i(\boldsymbol{x_{iA}}) + (1-a) v_i(\boldsymbol{x_{iB}}) \le v_i(a \cdot \boldsymbol{x_{iA}} + (1-a) \cdot \boldsymbol{x_{iB}}) \tag{3.1.4c}$$

Finally, the user's utility is defined as the difference between the user's valuation for his/her consumption profile and the bill he/she has to pay for it:

$$U_i(\boldsymbol{x_i}) = v_i(\boldsymbol{x_i}) - b_i(\boldsymbol{x_i}) \tag{3.1.5}$$

System Cost & Electricity Billing

The ESP is responsible for purchasing energy from the grid and delivering it to the users. We assume that the ESP faces a per-timeslot cost that is a strictly increasing function $C^t(\cdot)$ of the aggregated consumption $\sum_{i \in N} x_i^t$. In particular, quadratic or piecewise linear functions are widely used in the literature, to model the generation cost of marginal units. We present the case for quadratic cost:

$$C^t\left(\sum_{i \in N} x_i^t\right) = c \cdot \left(\sum_{i \in N} x_i^t\right)^2 \tag{3.1.6}$$

As explained in the introduction, we consider a use case where the ESP needs to be able to control the system's cost so as to keep it below a certain threshold C_{ref}. Moreover, we consider a benevolent ESP that acts on behalf of the users and not against them. We assume that, for the scheduling horizon, the ESP collects the financial cost C which is:

$$C = \sum_{t \in H} C^t \left(\sum_{i \in N} x_i^t\right) \tag{3.1.7}$$

by applying a billing rule $b(\boldsymbol{x_i})$ to each user. We state some requirements for $b(\boldsymbol{x_i})$:

Requirement 1: The sum of the users' bills should add up to the system's cost:

$$\sum_{i \in N} b(\boldsymbol{x_i}) = C^t \left(\sum_{i \in N} x_i^t\right) \tag{3.1.8}$$

Eq. (3.1.8) captures the *budget balance* property analyzed in the introduction.

Requirement 2: At equilibrium, each user should have weakly positive utility.

This is equivalent to stating that each user should be better-off participating in the mechanism rather than not participating. This is equivalent to the *individual rationality* property.

ESP-user interaction & implementation

We assume a communication network, built on top of the power grid, allowing the ESP and the users to exchange messages. In particular, in order for an indirect mechanism to be implemented, we assume that the users can respond to demand queries. That is, the ESP provides the user with the necessary billing data and the user is expected to respond with his/her demand, that is, with the desired consumption vector $\boldsymbol{x_i}$ that maximizes the user's utility $U_i(\boldsymbol{x_i})$ given from Eq. (3.1.5).

Since an efficient allocation involves a certain degree of coordination among users, it may take a number of message exchanges between the ESP and each user to converge to equilibrium. For this reason, we expect the user to respond to each demand query in a reasonable amount of time. A commonly accepted response time in computer science is a time that is, in the worst case, polynomial in bits of precision required. For the latter property to hold, the billing rule should be simple enough. A sufficient condition that fulfills this property is captured in a third requirement, which is:

Requirement 3: The user's bill $b(\boldsymbol{x_i})$, is convex in $\boldsymbol{x_i}$.

To justify the sufficiency of *Requirement 3,* recall the definition of the user's utility from Eq. (3.1.5). The first term is concave by *Assumption 3.* A convex $b(\boldsymbol{x_i})$ makes the user's utility $U_i(\boldsymbol{x_i})$ concave in $\boldsymbol{x_i}$. Thus, the user's response to a demand query becomes a convex optimization problem, which is tractable.

3.1.3 Problem Formulation

In this section, we formalize the problem to be solved, which is maximizing the aggregated users' utility (Eq. 3.1.9):

$$\max_{\boldsymbol{x_i}\in\mathcal{X}_i, i\in N} \sum_{i\in N}\big(v_i(\boldsymbol{x_i}) - b(\boldsymbol{x_i})\big) \tag{3.1.9}$$

while keeping the system's cost below a predefined threshold C_{ref}. By using Eq. (3.1.8) in Eq. (3.1.9) we have:

$$\max_{\boldsymbol{x_i}\in\mathcal{X}_i, i\in N}\{\sum_{\boldsymbol{i}\in\boldsymbol{N}}[v_i(\boldsymbol{x_i})] - \sum_{t\in H}[C^t(\sum_{i\in N} x_i^t)]\} \tag{3.1.10}$$

$$s.t.\ \sum_{t\in H}[C^t(\sum_{i\in N} x_i^t)] \le C_{ref}, \tag{3.1.10a}$$

Constraint (3.1.10a) couples the variables x_i^t across both $i \in N$ and $t \in T$. We will demonstrate that this is a standard convex optimization problem where a concave function is maximized over a convex set $\mathcal{X} \subseteq \mathbb{R}^{n\times m}$ that is defined by the inequality constraints (3.1.1), (3.1.10a) and the equality constraint (3.1.2).

Lemma 3.1.1: The problem defined by Eq. (3.1.10) under constraints (3.1.1), (3.1.2) and (3.1.10a) is a convex optimization problem. In particular:

i) The objective function $f(X) = \sum_{\boldsymbol{i}\in\boldsymbol{N}}[v_i(\boldsymbol{x_i})] - \sum_{t\in H}[C^t(\sum_{i\in N} x_i^t)]$ is concave in $X \in \mathcal{X}$.

ii) Inequality constraint functions (3.1.1), (3.1.10a) are convex in $X \in \mathcal{X}$

iii) Equality constraint functions (3.1.2) are affine in $X \in \mathcal{X}$

Proof:

i) Since $\sum_{i\in N}[v_i(\boldsymbol{x_i})]$ is a sum of concave functions in subspaces of $\mathcal{X}$, it is concave in $\mathcal{X}$. Let $\mathbf{1}_n$ be the all-ones n-dimensional vector and $\mathbf{1}_{n\times n}$ the all-ones $n \times n$ dimensional matrix. Let also $\boldsymbol{x^t} \triangleq (x_1^t, x_2^t, \dots, x_n^t)^T$ be the vector containing all the users' consumptions in timeslot t. Then

$$C^t\left(\sum_{i\in N} x_i^t\right) = c \cdot ((\mathbf{1}_n)^T \ \cdot x^t)^2 = c \cdot (x^t)^T \mathbf{1}_{n\times n} x^t$$

is convex because it is a quadratic function and $\mathbf{1}_{n\times n}$ is positive semi-definite. Therefore,

$$-\sum_{t\in H}[C^t(\sum_{i\in N} x_i^t)]$$

is concave in $\mathcal{X}$, as a sum of concave functions in subspaces of $\mathcal{X}$ and (i) is true because f is a sum of concave functions.

ii) Constraint (3.1.1) is trivially convex and (3.1.10a) is also convex as shown in the second term of f.

iii) Constraint (3.1.2) is trivially affine, for all $i \in N$, in a subspace of $\mathcal{X}$, and so it is also affine in $\mathcal{X}$. ■

Thus, problem (3.1.10) is convex and has a global optimal solution. If valuations $v_i(\boldsymbol{x_i}) \triangleq v_i(x_i^t; t \in H)$ were known, it could be solved through the use of an interior point method. However, $v_i(\boldsymbol{x_i})$ is private. Moreover, we assume strategic users who opt for maximizing their own utility, that is,

$$\boldsymbol{x_i} = \underset{\boldsymbol{x_i} \in \mathcal{X}_i}{\operatorname{argmax}} \{v_i(\boldsymbol{x_i}) - b(\boldsymbol{x_i})\} \tag{3.1.11}$$

The latter objective is not necessarily aligned with the social objective and depends on the billing rule $b(\boldsymbol{x_i})$. Since the cost function couples the users' variables $\boldsymbol{x_i}$, $i \in N$, a user's utility depends not only on her/his own profile but also on the other users' consumption choices. This latter fact brings problem (3.1.10) in the realm of game theory. In order to bring the system to an equilibrium that optimizes (3.1.10), we will draw on the concepts of mechanism design.

We consider a game-theoretic framework, where the ESP announces the billing rule and users iteratively select their preferred allocations, thus formulating the following game Γ.

Definition of game Γ:

- *Players:* users in N
- *Strategies:* each user selects her/his $\boldsymbol{x_i}$, according to (3.1.11)
- *Payoffs:* a user's payoff is his/her utility as defined in (3.1.5)

Since problem (3.1.10) naturally prioritizes users with higher valuation for energy allocation, we need to prevent users from faking a high $v_i(\boldsymbol{x_i})$. This is the role of the billing rule. The Vickrey-Clarke-Groves (VCG) mechanism has been proven to be the unique welfare-maximizing mechanism that makes it a dominant strategy for each user, to truthfully declare his/her local valuation. Unfortunately, VCG-like mechanisms are not useful here since they violate the *budget-balance* property (*Requirement* 2) and also come with a number of other problems as explained in the introduction. In what follows, we opt for designing a DSM architecture which includes:

a) an indirect and *individually rational* mechanism, including a *budget-balanced* billing rule, implemented in best-response strategies. Although we have to relax the welfare-maximization property, we are actually able to reach a near-optimal solution.

b) an algorithm at the ESP side, which iteratively decides a parameter of the billing rule, thus providing the ESP with online controllability over the system's cost, so that constraint (10a) is satisfied at equilibrium.

3.1.4 Proposed DSM Architecture

In this section, we present the proposed DSM architecture that fulfills the aforementioned requirements. The presentation is complemented with the presentation of the theorems that prove analytically that the requirements we have set are fulfilled. In more detail, we developed a DSM architecture such that:

a) game Γ admits to a Nash Equilibrium (NE)

b) users' actions converge to NE via best-response dynamics

c) the DSM mechanism provides the ESP with controllability over the system's cost, which means that the ESP brings the system to an equilibrium that respects constraint (3.1.10a), in case that it is possible.

d) the allocation at equilibrium is as close as possible to the optimal value of problem (3.1.10).

A. The billing rule

Best-response dynamics means that, at each iteration, each user chooses his/her strategy assuming the strategies $\boldsymbol{x_{-i}}$ of other users to be constant. Thus, from a user's perspective, at a certain iteration, his/her bill only depends on his/her own choice of $\boldsymbol{x_i}$. The following equation presents the proposed billing rule:

$$b(\boldsymbol{x_i}) = \sum_{t\in H}\left[x_i^t \cdot \frac{C^t\left(\sum_{j\in N} x_j^t\right)}{\sum_{j\in N} x_j^t}\right] + \gamma \cdot \left[\sum_{t\in H}\left[x_i^t \cdot \sum_{j\neq i}\left(x_j^t\right)\right] - \frac{\sum_{j\in N}\left[\sum_{t\in H}\left(x_j^t \cdot \sum_{k\neq j} x_k^t\right)\right]}{n}\right] \tag{3.1.12}$$

The first term of the sum is identical to existing billing rules. The second term has the purpose to reward/penalize flexibility/inflexibility (ability of user i to modify energy consumption profile). The value of γ is iteratively updated by the ESP. The rationale of Eq. (3.1.12) is that it penalizes users for synchronizing their loads with others and uses the penalties for rewarding users who counter-balance the aggregated consumption by consuming their load at off-peak timeslots. With respect to the billing rule, we state the following lemma:

Lemma 3.1.2: For constant values of $\boldsymbol{x_{-i}}$, the bill $b(\boldsymbol{x_i})$, given by Eq. (3.1.12), is strictly convex in $\boldsymbol{x_i}$**.**

Proof:

We denote by $\mathcal{H}^b$ the Hessian matrix of function $b(\boldsymbol{x_i})$, defined in Eq. (3.1.12). We have to show that $\mathcal{H}$ is positive definite. By substituting Eq. (3.1.6) in Eq. (3.1.12), we have

$$b(\boldsymbol{x_i}) = \sum_{t\in H}\left[x_i^t \cdot c \cdot \left(\sum_{j\in N} x_j^t\right)\right] + \gamma \cdot \left[\sum_{t\in H}\left[x_i^t \cdot \sum_{j\neq i}\left(x_j^t\right)\right] - \frac{1}{n} \cdot \sum_{j\in N}\left[\sum_{t\in H}\left(x_j^t \cdot \sum_{k\neq j} x_k^t\right)\right]\right]$$

$$= \sum_{t\in H}\left[x_i^t \cdot c \cdot \left(\sum_{j\in N} x_j^t\right)\right] + \gamma \cdot \left[\frac{n-1}{n} \cdot \sum_{t\in H}\left[x_i^t \cdot \sum_{j\neq i}\left(x_j^t\right)\right] - \frac{1}{n} \cdot \sum_{j\neq i}\left[\sum_{t\in H}\left(x_j^t \cdot \sum_{k\neq j} x_k^t\right)\right]\right]$$

By taking the derivatives:

$$\frac{\partial b(\boldsymbol{x_i})}{\partial x_i^{t_1}} = c\sum_{j\in N} x_j^{t_1} + c x_i^{t_1} + \gamma\left[\frac{n-1}{n}\sum_{j\neq i}\left(x_j^{t_1}\right) - \frac{1}{n}\sum_{j\neq i} x_j^{t_1}\right]$$

and

$$\mathcal{H}_{t_1 t_2}^b = \frac{\partial^2 b(\boldsymbol{x_i})}{\partial x_i^{t_2} \partial x_i^{t_1}} = \begin{cases} 2c, t_1 = t_2 \\ 0, t_1 \neq t_2 \end{cases}$$

Thus, $\mathcal{H}^b = diag(2c)$ is positive definite. ■

The user communicates his/her demand profile $\boldsymbol{x_i}$ to the ESP and receives the respective bill $b(\boldsymbol{x_i})$. Since problem (3.1.11) is convex (by *Lemma 3.1.1* and *Assumption 3.1.3*) the user can apply a gradient projection method to compute his/her best response. Next, we analyze the properties of game Γ:

Theorem 3.1.1: A Nash Equilibrium for game Γ exists and is unique. Furthermore, best-response dynamics converges to the Nash Equilibrium strategy vector.

Proof:

a) The user's payoff is his/her utility given by eq. (3.1.5). The first term is concave in $\boldsymbol{x_i}$ by *Assumption 3.1.3*. The second term is strictly convex in $\boldsymbol{x_i}$ by *Lemma 3.1.1*. Hence, for $x_i^t \geq 0$, $U_i(\boldsymbol{x_i})$ is strictly concave in $\boldsymbol{x_i}$. Since this holds for every user, we have that Γ is a strictly concave n-person game. Thus, by [ROSE65, th.1], we have that a NE exists.

b) By [MOND96], it suffices to show that Γ is an exact potential game with a concave potential function. Indeed, consider the function:

$$\wp(X) = \sum_{i\in N} v_i(\boldsymbol{x_i}) - \sum_{t\in H}\left\{\frac{c}{2} \cdot \left[\left(\sum_{i\in N} x_i^t\right)^2 + \sum_{i\in N}[(x_i^t)^2]\right] + \frac{\gamma(n-2)}{2n} \cdot \sum_{i\in N}\left(x_i^t \cdot \sum_{j\neq i}\left(x_j^t\right)\right)\right\}$$

Function $\wp(X)$ has the property of potential:

$$\nabla_{\boldsymbol{x_i}}\wp(X) = \nabla_{\boldsymbol{x_i}} U_i(\boldsymbol{x_i}), \qquad \forall i \in N$$

Moreover, $\sum_{i\in N} v_i(\boldsymbol{x_i})$ is concave in X (concave in $\boldsymbol{x_i}$ by *Assumption 3.1.3* and zero in $\boldsymbol{x_j}, \forall j \neq i$). Thus, it suffices to prove that the term

$$\wp_2 = -\sum_{t\in H}\left\{\frac{c}{2}\cdot\left[\left(\sum_{i\in N} x_i^t\right)^2 + \sum_{i\in N}[(x_i^t)^2]\right] + \frac{\gamma(n-2)}{2n}\cdot\sum_{i\in N}\left[x_i^t\cdot\sum_{j\neq i}(x_j^t)\right]\right\}$$

is also concave, or equivalently that $-\wp_2$ is convex.

It is $\nabla_{\boldsymbol{x_i}}(-\wp_2) = \nabla_{\boldsymbol{x_i}} b_i(\boldsymbol{x_i})$ which yields

$$\nabla_{\boldsymbol{x_i}}^2(-\wp_2) = \nabla_{\boldsymbol{x_i}}^2 b_i(\boldsymbol{x_i}) = \mathcal{H}_i^b$$

which by Lemma 3.1.1 is positive definite. Hence, $\wp_2$ is also concave in X, since its Hessian

$$\mathcal{H}^{\wp_2} = \nabla_X^2\wp_2 = blkdiag(\{\mathcal{H}_i^b\}_{i=1}^n)$$

is a block diagonal positive definite matrix. Hence $\wp$ is concave in $X = (\boldsymbol{x_1}, \dots, \boldsymbol{x_i}, \dots, \boldsymbol{x_n})$ as a sum of concave functions in X.

c) Since the potential function is concave and players maximize, it directly follows that best-response dynamics converges to the unique NE. ■

The second term of the sum in (3.1.12) introduces a price-discrimination component among users with different levels of flexibility. The ESP can control the magnitude of this discrimination by adjusting parameter γ, as will be analyzed in subsection *B.* of this section. Thus, by increasing γ, users are increasingly incentivized to modify their consumption patterns. Note that γ does not increase the bills in general but only controls the way that the system's cost is shared among users. This provides an intuition on the way (3.1.12) keeps the system *budget balanced*, and is proved formally below.

Theorem 3.1.2: The billing rule $b(\boldsymbol{x_i})$, given by Eq. (3.1.12), satisfies the *budget balance* property.

Proof:

It suffices to show that

$$\sum_{i\in N} b(\boldsymbol{x_i}) = \sum_{t\in H}\left[C^t\left(\sum_{i\in N} x_i^t\right)\right]$$

By substituting $b(\boldsymbol{x_i})$ from Eq. (3.1.12), we have

$$\sum_{i\in N} b(\boldsymbol{x_i}) = \sum_{i\in N}\left\{\sum_{t\in H}\left[\frac{x_i^t}{\sum_{j\in N}[x_j^t]}\cdot C^t\left(\sum_{j\in N} x_j^t\right)\right] + \gamma \cdot\left[\sum_{t\in H}\left[x_i^t\cdot\sum_{j\neq i}(x_j^t)\right] - \frac{\sum_{j\in N}\left[\sum_{t\in H}\left(x_j^t\cdot\sum_{k\neq j} x_k^t\right)\right]}{n}\right]\right\}$$

$$= \sum_{t\in T}\sum_{i\in N}\left[\frac{x_i^t}{\sum_{j\in N}\left[x_j^t\right]}\cdot C^t\left(\sum_{j\in N}x_j^t\right)\right] + \gamma\sum_{i\in N}\sum_{t\in H}\left[x_i^t\cdot\sum_{j\neq i}\left(x_j^t\right)\right] - \gamma \cdot\sum_{i\in N}\left[\frac{\sum_{j\in N}\left[\sum_{t\in H}\left(x_j^t\cdot\sum_{k\neq j}x_k^t\right)\right]}{n}\right]$$

$$= \sum_{t\in T}\left[C^t\left(\sum_{i\in N}x_i^t\right)\right] + \gamma\cdot\left[\sum_{i\in N}\sum_{t\in H}\left(x_i^t\cdot\sum_{j\neq i}\left(x_j^t\right)\right) - \sum_{j\in N}\sum_{t\in H}\left(x_j^t\cdot\sum_{k\neq j}\left(x_k^t\right)\right)\right]$$

$$= \sum_{t\in T}\left[C^t\left(\sum_{i\in N}x_i^t\right)\right]$$

which completes the proof. ■

Furthermore, for the proposed billing rule given by Eq. (3.1.12), we also verify *Requirement 2.*

Theorem 3.1.3: Game Γ, in equilibrium, satisfies the *individual rationality* property.

Proof:

The root vector $\boldsymbol{x_i^{root}} \triangleq \{x_i^{t,root}\}, t \in H$, for which $b(\boldsymbol{x_i^{root}}) = 0$, is derived by solving from Eq. (3.1.12):

$$x_i^{t,root} = \frac{1}{2cn}\left[-\sum_{j\neq i}\left(x_j^t\right)\cdot\left(n(c+1)-\gamma-1\right) \pm \sqrt{\left[\sum_{j\neq i}\left(x_j^t\right)\cdot\left(n(c+1)-\gamma-1\right)\right]^2 + 4c\gamma n}\right]$$

Setting $\sum_{j\neq i}x_j^t\cdot(n(c+1)-\gamma-1) = \alpha$ and $4c\gamma n = \beta$, we get

$$x_i^{t,root} = \frac{1}{2cn}\left[-\alpha \pm \sqrt{\alpha^2+\beta}\right]$$

which means that there is always exactly one $x_i^{t,root} \geq 0$. By *Assumptions* 3.1.1 and 3.1.2, we have $v_i(x_i^{t,root}) \geq 0$. Thus, from Eq. (3.1.5) we get that $U_i(\boldsymbol{x_i^{root}}) \geq 0$. This means that each user's utility is weakly positive, which completes the proof. ■

B. The ESP's algorithm for constraint satisfaction

While the users are concerned with maximizing their utility, the ESP is responsible for satisfying constraint (3.1.10a). As discussed earlier, the ESP controls the system's cost via parameter γ. A low value of γ would lead to high energy cost, while a large value of

γ would have a negative impact on the welfare. Thus, the proposed DSM architecture also needs an algorithm for the ESP to identify the appropriate choice of γ, which brings the system to an allocation that respects constraint (3.1.10a) with the least possible sacrifice on the users' utility. Since the ESP is agnostic of the users' valuation functions, determining the appropriate γ calls for a global optimization approach. We opt for a Simulated Annealing (SA) method for determining γ. The entire DSM procedure is depicted in Table 3.1.t1.

Table 3.1.t1 The proposed DSM procedure

1	set $x_i^t = \overline{x_i}$, $\forall i \in N, k = 0, T_0, \gamma_0, \Delta_0$
2	**Repeat**
3	**Repeat**
4	for $i \in N$
5	i calculates best-response $\boldsymbol{x_i}(\gamma_k)$ from (3.1.11)
6	**until** Nash Equilibrium
7	ESP calculates cost at NE (C_k)
8	$\Delta_k = \left(C_k - C_{ref}\right)^2 - \left(C_{k-1} - C_{ref}\right)^2$
9	$k = k + 1$
10	$T_k = T_0 \cdot 0.95^k$
11	ESP determines next γ_k as a function of $T_k, \Delta_{k-1}, \gamma_{k-1}$
12	**Until** $\frac{\sum_{k-500}^{k} \Delta_k}{500} \leq \varepsilon$

Parameter T_k is the so called "temperature" of the SA algorithm. In line 11, the SA algorithm determines the next value of γ_k based on a probabilistic calculation, which is not presented here due to space limitations.

3.1.5 Performance Evaluation

In this section, we demonstrate the performance of the proposed architecture. In our simulation setup, we consider 24 hourly intervals $H = \{1,2, \dots, 24\}$ and $n = 50$ users. For each user i, the upper bound $\overline{x_i^t}$ on consumption is chosen randomly from the set $\{1.5, 4, 5.5, 7.5\}$. The feasible set h_i is modeled as a continuous set of timeslots starting at timeslot t_i^s and ending at timeslot t_i^f. Parameter t_i^s was picked from a random uniform distribution. In order to model the afternoon peak demand, for half the users, parameter t_i^s was picked in the interval $[1, 17]$ and for the other half in the interval $[18, 21]$. Parameter t_i^f was modeled as $t_i^f = \min((t_i^s + d_i), 24)$, where d_i was chosen randomly in the set $\{3,4,5,6,7\}$. Finally, parameter c of the cost function was set to $c = 0.02$.

We tested the proposed architecture for three different user models (valuation functions) that satisfy assumptions 1-3: Model A is taken from [GATZ13] and [SAMA10], model B from [SAMA12] and [LI10] and model C from [MOHS10]. Parameter ω relates to the user's inelasticity/inflexibility.

User model A: $$v_i(\boldsymbol{x_i}) = v_{max,i}^t - \omega_i \cdot \left(\overline{x_i^t} - x_i^t\right)^2$$

where $v_{max,i}^t = \omega_i \cdot \left(\overline{x_i^t}\right)^2$. This model captures the use case where a user's valuation function is temporally decoupled. Parameter ω_i was randomly selected in the interval [1, 2].

User model B: $$v_i(\boldsymbol{x_i}) = \begin{cases} v_i^{max} - \omega_i \cdot (E_i - \sum_{t=1}^{H} x_i^t)^2, & \sum_{t=1}^{H} x_i^t < E_i \\ v_i^{max}, & \sum_{t=1}^{H} x_i^t \geq E_i \end{cases}$$

where E_i is the user's desired energy to complete a task, randomly chosen from $\{4.5, 16, 22, 30\}$. This model captures the use case where the user is interested only in his/her total consumption at the end of the day and not at the particular timeslots of consumption, i.e. shiftable loads. Parameter ω_i was randomly selected in the interval [0.25, 1.25], while we have set $v_i^{max} = \omega_i \cdot (E_i)^2$.

User model C:

$$
v_i(\boldsymbol{x_i}) = \begin{cases} v_i^{max} - \omega_i \cdot \left(E_i - \sum_{t=1}^{H} x_i^t\right)^2 - \sum_{t=t_i^{des}+1}^{t_i^f} \left(\delta_i^{t-t_i^{des}} \cdot x_i^t\right), \\ \qquad \text{for } \sum_{t=1}^{H} x_i^t < E_i \\ v_i^{max} - \sum_{t=t_i^{des}+1}^{t_i^f} \left(\delta_i^{t-t_i^{des}} \cdot x_i^t\right), \\ \qquad \text{for } \sum_{t=1}^{H} x_i^t \geq E_i \end{cases}
$$

where the last term expresses the user's discomfort from postponing consumption to later timeslots: δ is an elasticity/flexibility parameter randomly selected in the interval [1, 1.2] and $t_i^{des} = t_i^s + E_i / \overline{x_i^t}$ is the desired timeslot for task completion. Naturally, it is $t_i^{des} < t_i^f$. Parameter ω_i was randomly selected in the range [0.25, 1.25].

For Figure 3.1.f1 we used user model B. Figure 3.1.f1 shows the aggregated consumption of the users throughout the time horizon H, in the cases of a) no DSM, b) DSM with $C_{ref} = 800\$$ and c) DSM with $C_{ref} = 600\$$.

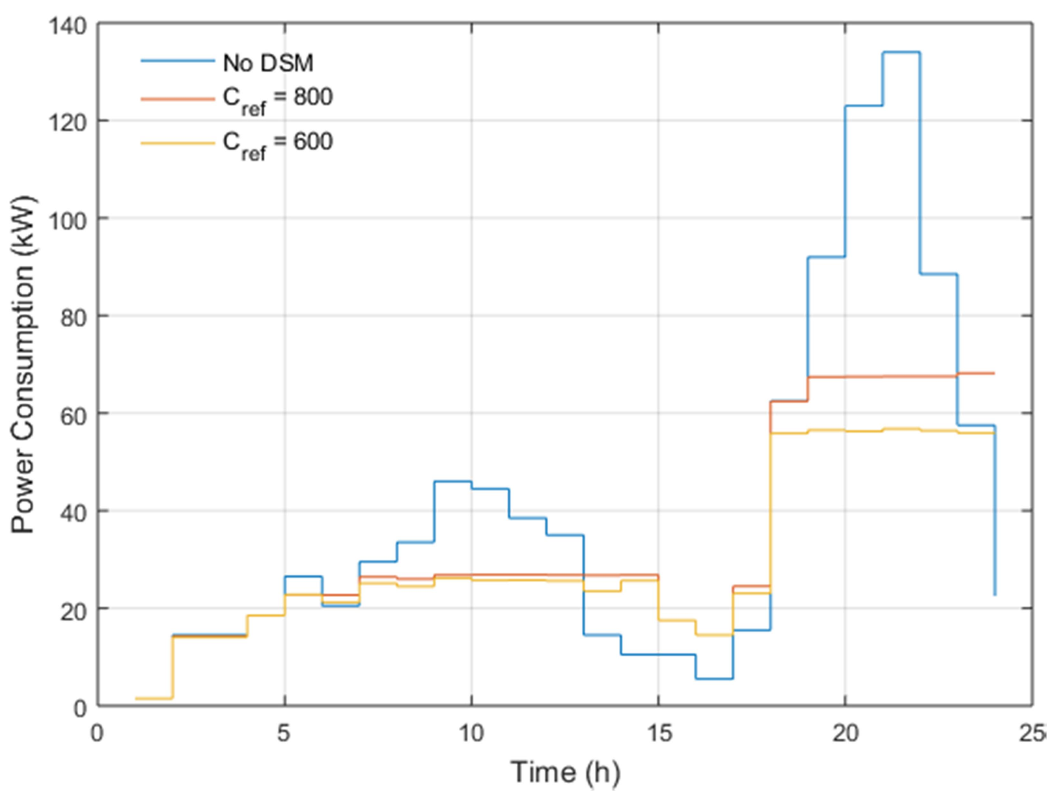
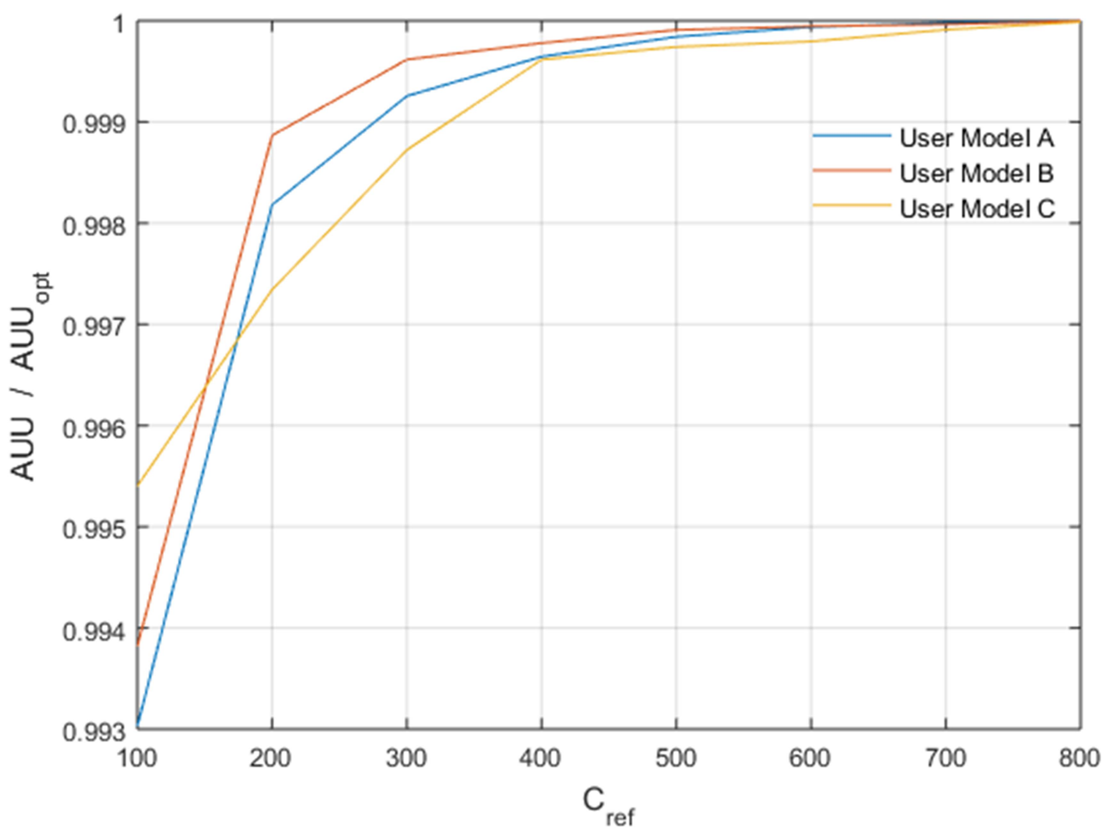


Figure 3.1.f1 Aggregated Users' Energy Consumption Curve – Cost Constraint

In Figures 3.1.f2 and 3.1.f3 we evaluate the performance of our scheme for all three user models, in terms of the Aggregated Users' Utility (AUU) which is defined as $AUU = \sum_{i \in N} U_i$. In particular, we depict the ratio of the AUU achieved with the proposed system over the AUU of the central (optimal) solution which would be reached if the users' valuations were known (AUU_{opt}). Figure 3.1.f2 depicts our scheme's performance as a function of the constraint on the system cost, whereas in Figure 3.1.f3 we depict the use case where the constraint is not posed on the system's cost but on the aggregated consumption at each timeslot. That is, there is a cap Y_{max} such that $\sum_{i \in N} x_i^t \leq Y_{max}$, $\forall t \in H$.



c) Figure 3.1.f2 Ratio between AUU and optimal AUU as a function of C_{ref}

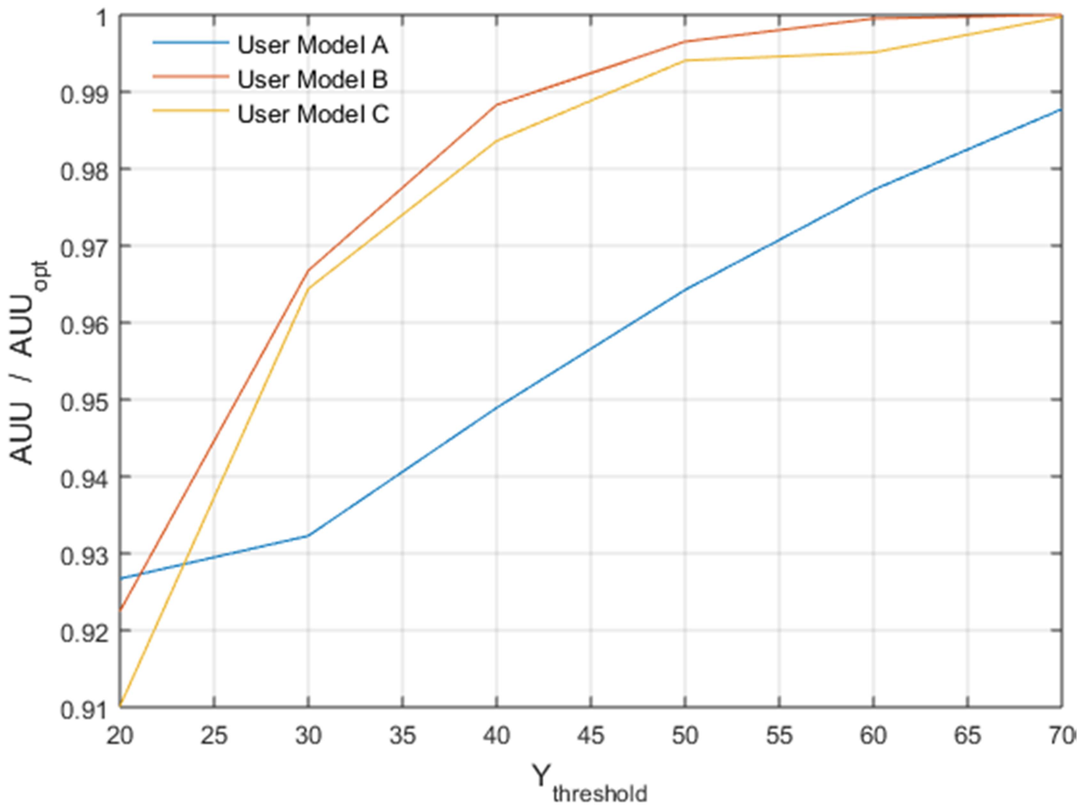


Figure 3.1.f3 Ratio between AUU and optimal AUU as a function of Y_{max}

We observe that the AUU achieved by the proposed system reaches up to 97%-99% that of the optimal solution. In extreme cases (for excessively low cap Y_{max}), AUU is still within 90% of the optimal solution.

A user's bill is affected by his/her inelasticity parameter ω. In particular, b_i/b_{sup} expresses the ratio of i's bill to his/her bill for the supremum ω_i, denoted as b_{sup}. In Figure 3.1.f4 we show how the ratio b_i/b_{sup} is affected by i's inelasticity ω_i (User Model B and $C_{ref} = 600$). The user's bill is increasing with respect to his/her inelasticity parameter.

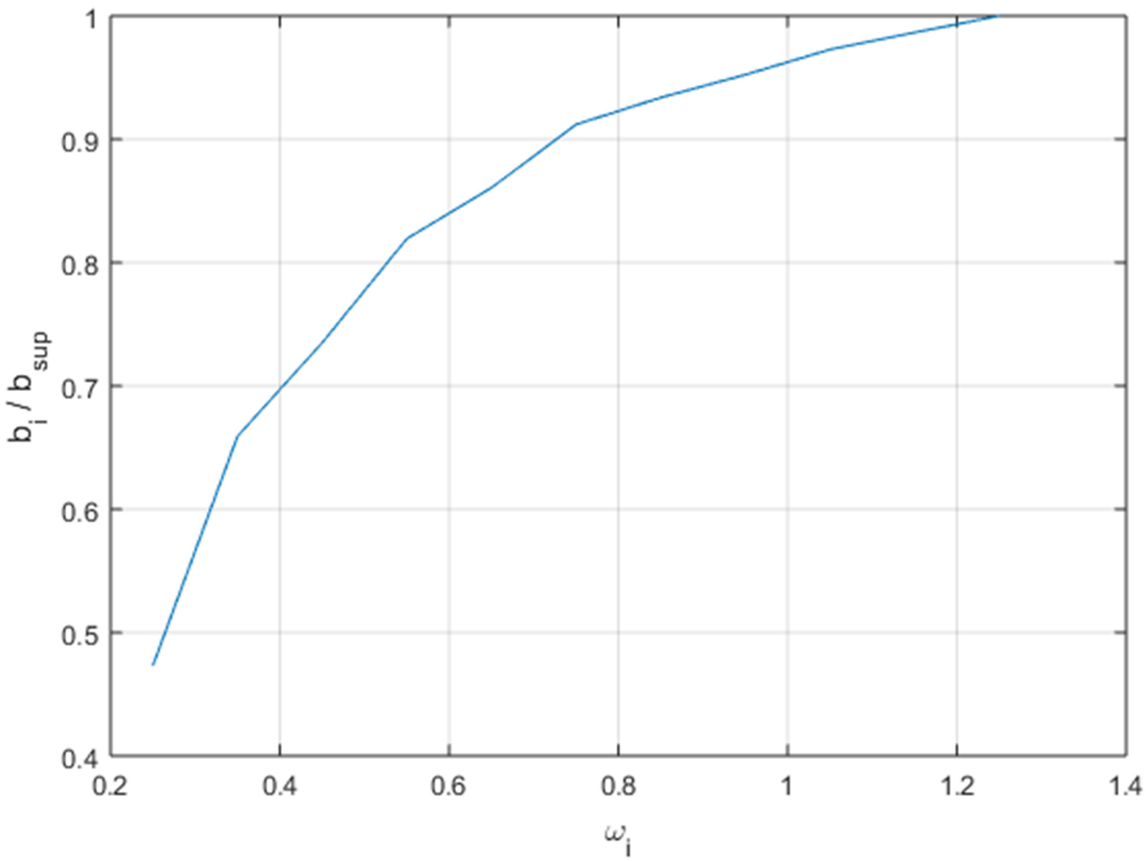


Figure 3.1.f4 Ratio between b_i and b_{sup} as a function of ω_i

3.2 Penalizing Volatility and motivating transactive Energy Markets: the Value of Aggregation, Flexibility, and Correlation

As RES are being developed and used ever more extensively, a large degree of volatility and unpredictability is added to the grid, necessitating a radical revision of the traditional Grid and of the Market Model. Volatility constitutes a negative externality caused by certain (especially RES) market participants but affecting all participants, and in order to minimize it, the ones causing it should be appropriately penalized. Holding those who cause market volatility financially responsible for it, is increasingly important as the penetration of RES producers increases. With current market rules, producers or consumers with high volatility get a free ride, and the rest of the market pays the price for it.

Distributed generation of electricity has been the principal trigger for developing the concept of the Smart Grid. Currently, RES are less (economically) competitive than traditional fossil fuel sources, while also causing extra costs to the system [STRA16], partly due to their unpredictability, making it very challenging to satisfy demands for both cleaner and cheaper energy. This challenge has opened up new domains of research, including the development of new business models to facilitate the incorporation of more RES in the grid [MOL09], by internalizing both positive (e.g. environmental and location benefits) bit also negative (e.g. volatility) externalities. As a result of the changes in the Electricity Market, medium and small energy prosumers (i.e. producers and consumers at the same time) are emerging at the center of interest in the new liberalized energy market. Extensive recent and ongoing research focuses on DR techniques [PALE11] as well as on integrating DR in the economic and optimization models [FEU14]. A great deal of work also focuses on managing distributed RES in local electricity markets [AMP14], [ILIC12], [MENN09], [HVE06].

The new business and market models need effective information exchange in a distributed context, thus creating new challenges for the Information and Communication Technologies (ICT) field [YAN13]. As ICT is introduced in the energy network, the concept of virtualization of energy resources also becomes feasible. A big energy prosumer is no longer necessarily formed through heavy investing on big prosumption facilities. Multiple small prosumers can organize themselves in bigger associations that participate as a single entity in the market, thus forming a virtual big energy prosumer, called a Virtual Micro Grid Association (VMGA) [MAMO16], [VERG15]. The VMGAs increase the market negotiation power of small prosumers, their combined reliability (and thus their ability to make Service Level Agreements - SLAs) and also decrease complexity and book-keeping for the DSO who needs to deal with a smaller set of players. VMGs form the central idea in the ongoing Virtual Micro Grids for Smart Energy Networks (VIMSEN) project [VIMSEN], the architecture of which is assumed in our present work. In compliance with the VIMSEN architecture, the prosumers will be called VIMSEN Prosumers (VPs). The concepts described above, open up new possibilities in the way electricity is traded. Small market participants become more active through the VIMSEN platform, and are represented by a new actor, the VMG Association. A VMG Association has similarities but also differences from traditional Virtual Power Plants (VPP) and Flexibility Aggregators, as explained in the following section. Thus, electricity trading/delivery cease to be strictly bounded to big beneficiaries. As a result, the electricity market is in need of new policies to embrace the emerging functionalities, address volatility issues and satisfy the new demands.

In the present work, we assume that the VIMSEN architecture, described in Section 3.2.2.1, is used as the marketplace for electricity trading. In this market setting, the MO makes Service Level Agreements (SLA) for the delivery of a certain amount of production or a certain amount of flexibility (consumption reduction) at specific time intervals with VMG Associations, which in turn make SLAs with their constituent individual VPs. Volatile/unpredictable prosumers (or VMG Associations of prosumers) are defined as those that make an SLA with a VMG Association (or with the MO, respectively) but cannot keep it and are forced to violate it. Volatility causes significant costs to market participants, which should be shouldered by those creating it, both for the sake of fairness but also in order to (have incentives) to minimize it. In Section 3.2.2.2 we introduce electricity market procedures based on a spread between buy and sell price in a BRP market, that can be used to penalize volatile participants, including prosumers and VMG Associations of prosumers. This proposed spread-based policy is general and can either be used by the MO to penalize the volatility/undpredictability/SLA non-conformance exhibited by VMG Associations in order to make them behave more responsibly, or be used by a VMG Association in order to make its constituent members do so (or be used in both situations). In the former case, it is a market policy (and may be subject to regulation) used in MO-to-VMG interactions, while in the latter case it is an internal policy of the VMG Association used in VMG-to-VP interactions. For the sake of being specific, we assume in our description the latter case, where the policy is used to penalize SLA violations between a VMGA and its constituent VPs. Starting with Section 3.2.3.1, we take the perspective of the VP. We analyze and compare two different strategies (an Active and a Passive one)), first introduced in [KOK13], for strategic load rescheduling and give the conditions under which each strategy should be used. We also propose a novel, hybrid strategy that combines the benefits of the two approaches and show that it always achieves better profits than Active and Passive. We study the penalty savings obtained by a VP who uses the optimal rescheduling strategy as a function of the proposed per-unit penalty and the VP's flexibility. We also give insights on the effects that the size of the penalty has and the way it can be employed by the VMGA (or the MO) in motivating VPs (or VMG Associations, respectively) to function more or less conservatively, according to the VMG's (or the System Operator's)needs, thus providing important insights regarding the parameters of future pricing policies.

We also study the value of the VPs' flexibility, by quantifying the payback for being flexible and the degree to which it is worth investing in storage facilities or sacrificing the user's comfort in DR operations. The insights obtained can be used as input in storage sizing studies [BAYR11] and training algorithms that try to achieve a tradeoff between user's comfort and user's financial savings. They also help in describing a step-by-step procedure for defining the VP's flexibility based on the user's desires, which can be used as a reference point for developing future policies for exploiting and compensating a prosumer's flexibility.

In Section 3.2.3.2, we take the perspective of the VMGA by studying the value of cooperation between VPs belonging to the same VMG Association. We assess the concept of correlation between the production patterns of the cooperating VPs and study the revenues that the VPs enjoy from their cooperation as a function of the number of the VPs in a coalition and also as a function of their correlation. We show that the revenues gained by a VP are increased through cooperation with others, especially when the cooperating VPs have negatively-correlated forecasting errors. A somewhat surprising result is that there is value in the cooperation even for positively-correlated VPs. The results imply that a production investment is more profitable with respect to flexibility compensations when placed close to negatively correlated prosumers. Future investment subsidy policies can take these insights into account in order to motivate small production units to be developed in areas, where they would be more efficient. In Section 3.2.4, we present the simulation model and the data used, which is then employed in Section 3.2.5, to present performance evaluation results and comparisons between different strategies and cooperation cases. Specifically, we obtain results on the effect different parameters have on appropriately defined Value of Strategy, Value of Flexibility and Value of Cooperation metrics. Finally, in Section 3.2.6, we present our conclusions and the policy implications derived from our study.

3.2.1 Background and Literature Review

A typical wholesale electricity market in European countries is further divided in derivatives markets depending on the time of the trade as presented in Figure 3.2.f1 [RUSK11].

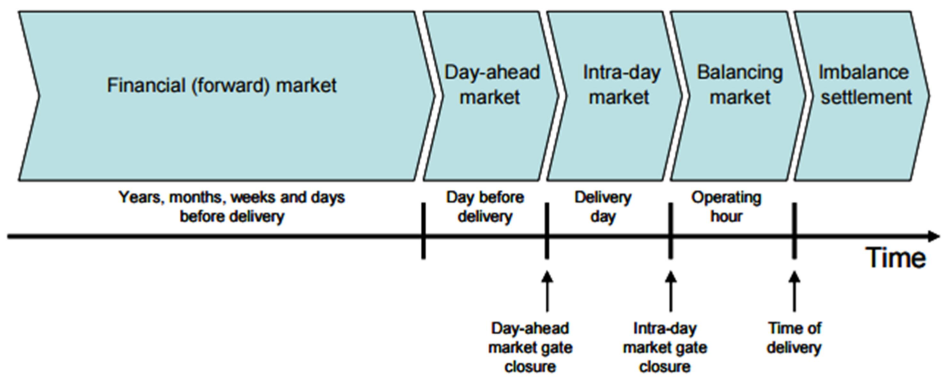


Figure 3.2.f1- Wholesale electricity markets [RUSK11]

While single VPs are quite small market players, VMGAs can actually have the critical size required to participate in the wholesale electricity market. The market participation, decisions and general management of the associated VPs is materialized by through the VMG Association they belong to. The Association deals with the efficient integration of variable RES production and consumption loads' flexibility in the market, which is accomplished via sophisticated management of the resources with the use of ICT tools and algorithms [DAMS15]. Multiple RES production sites can also jointly participate in the market through the concept of a Virtual Power Plant (VPP) [NIKO12], while consumers with DR flexibility can participate in the market through the concept of Aggregators [GATZ13]. The differences between the VPP, the Flexibility Aggregator, and the VMG Association concept proposed in the present section are described in [VERG16] & [DOUL17], and are summarized in the following. A VMG aggregating producers resembles a Virtual Power Plant (VPP), except that the former consists of a *dynamic* group of producers chosen so as to optimize different criteria at a time. A VMG combining consumers resembles a Flexibility Aggregators, with the important difference that a VMG is *not necessarily a profit seeking* market entity as a Flexibility Aggregator is. The VMG concept resembles the software platform of cell phones store markets, which act as distributors of apps developed and do not specify the price of an app or the Point Of Sales (POS), thus serving as an interface between customers and retailers. For example, a VMG's profit does *not* depend on the difference between the price offered to the market and that obtained from its constituent prosumers (in which case it would seek to minimize the latter, acting against them) but on (for example) the contracts made, that is, the number of registered prosumers in the VMG platform. This means a VMG Association's benefits can be *perfectly aligned* with those of its constituent prosumers, which is not the case with the usual concept of Flexibility Aggregators or of VPPs who are profit-seeking entities, with their own interests and strategies. It should be noted that the research problem studied in this section covers all types of aggregators that currently exist in the electricity markets.

Forward trading opens up new possibilities for the market players, offering advantages for both suppliers and consumers. An analysis of the effects of the strategic use of forward trading in electricity markets is presented in [VAZQ12]. A day-ahead market takes place one day before delivery. By taking into account the forecasts for the next day, different parties can trade their expected demand or supply, and subsequently the Market Operator (MO) is able to make a more informed scheduling for the next day when trying to match supply with demand.

Accurate forecasts of the VMGA's prosumption form an important asset for the Association to be able to efficiently bid in the day-ahead market. The MO runs all the supply and demand bids through a clearing process, which ultimately defines the electricity price, in order to match supply with demand. A review of forecasting models for electricity prices is presented in [WER14]. Put simply, the price is set where the (expected) curves for sell and buy quantities meet each other [NORD]. A state of the art market clearing model applied in the Power Matching City project is described in [KOK13]. Based on the output of the process, the Association forms the Service Level Agreement (SLA) with the MO, for the next day, specifying how much energy it will produce/consume at each hour of the following day. The grouping of VPs in the VMGA affects the forecasting accuracy, as analyzed in [SILV14]. Since both RES production (mainly) and the users' electricity consumption are subject to abrupt, real-time changes, presumption deviations from the SLA will always occur. These deviations cause undesired volatility and should be subject to financial penalties that can be imposed in various ways [BITA12], [ZUGN13]. The users can attempt to avoid these charges by rescheduling their prosumption profile using unit commitment techniques, such as DR, making use of the prosumers' DR flexibility [CEC11]. Numerous works, including

[LOG12], [RAD10], [MOHS10], [SAMA10], [QIAN13], have provided optimal solutions to VP scheduling. However, the above studies assume either day-ahead scheduling or real-time scheduling without formerly-agreed SLAs and do not consider compensating for the deviations between a day-ahead SLA and a deviated profile.

Cooperation among prosumers of the same geographical area has been considered in order to tackle a variety of issues, such as power losses' minimization [SAAD11] and market profits maximization [WOO14]. The role of the correlation factor among the prosumption patterns of the cooperating prosumers has been investigated in [TSAO16]. Other studies adopt data-driven approaches, where the cluster of prosumers optimize their bid to the wholesale market and a bi-level optimization problem is formed but without treating the price as a control variable [GALL16]. In the work presented in [FEUE16], different scenarios for DR integration were compared in terms of profit maximization. "Scenario A" of [FEUE16] represents an active approach, whereas "scenario C" represents a passive one.

In our study, we take on the case where there are deviations from the day-ahead agreed SLA, making the demand curves of the prosumers different and also the prices of the balancing market different from the day-ahead prices. We apply load rescheduling in order to reduce exposure to market losses resulting from the different prices and also from the spread that is introduced between buy and sell price. We assume to have forecast/prediction algorithms for energy prosumers' participation in balancing markets and the respective forecasts for the Balancing Market prices. The way those forecasts are derived, as well as their accuracy, is out of the scope of the current work and it is extensively discussed in [WER14], [DIMO16].

We adopt Active and Passive approaches and evaluate them in the case described. A Hybrid strategy is also proposed and is proved to be optimal for any value of the spread parameter used to penalize SLA violations. Our main contributions lie in that we also consider 1) a spread between buy and sell price of electricity, 2) the prosumers correlation (in terms of profiles deviations) when aggregating them in a cluster. We study the effects of the two factors and argue that they should be taken into account when applying demand side management algorithms. Finally, 3) we propose a novel "hybrid" scheduling strategy for near-real-time participation in balancing markets.

3.2.2 Market Participation Framework

3.2.2.1 Architecture, basic VMG Association role and responsibilities

The actors of a typical Smart Grid architecture and the connections among them, as adopted by the VIMSEN project as well as by other research projects, are illustrated in Figure 3.2.f2. The main inter-relations/responsibilities in which the new actors are engaged are identified as follows:

- Each VP is associated with a specific VMGA under contract by an SLA. Sole VPs that are not part of a VMGA are not considered in our framework.
- The VMGA is responsible for the negotiations -on behalf of its own VPs- with other VMGAs and/or Balance Responsible Parties (BRPs), or the biddings to the energy market (technically, through a VIMSEN portal), in order to sell the surplus energy (aggregate energy from prosumers) to BRPs or on the energy market, or to buy energy from the same, while maximizing profits.
- The VMGA can strategically motivate its VPs to apply smart rescheduling in order to improve its market position.
- The Telecom Provider (TP) will be responsible for the reliable, on-time exchange of energy specific messages among VIMSEN actors.
- We assume that the trading above, satisfies any physical constraints, in the sense that the DSO makes sure that the energy can be bought/sold by the actors involved at their specific locations.
- We also assume that the VPs are price-takers, in the sense that they are part of a much bigger system and their own deviations are not directly reflected in the balancing market prices.

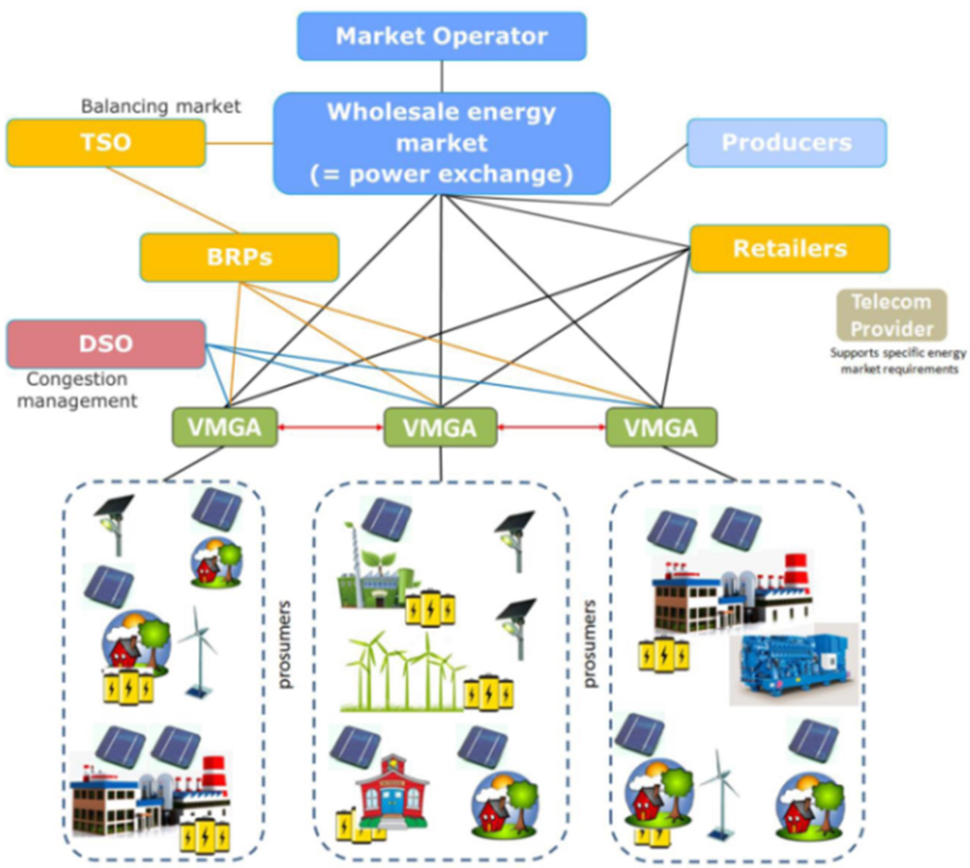


Figure 3.2.f2 - VIMSEN Architecture [LYB14]

3.2.2.2 Market Procedures and Penalty Policy

Day-ahead market

Producers and retailers make their bids (bidding curves) according to their forecasts for the next day. Based on these bids, the MO matches supply with demand and creates a set of hourly prices for the day-ahead market. These are extracted using market clearing techniques (commonly a bidding process with bidding curves) as is already applied from many market operating parties worldwide. The result of market clearing is that the price is higher for peak demand hours and lower for low demand hours. Wholesale suppliers and consumers (or, more generally, sellers and buyers) make contracts to buy/sell electricity for the next day, for a certain control area (that is the VMGA's portfolio). Considering hourly time blocks, the contract defines the quantity of electricity to be bought/sold at each hour of each day at a specific price, which is generally different for each hour. According to its portfolio's forecasted daily electricity needs, the VMGA can adjust its bids to better serve its clients and its own interests. After the day-ahead market gate closure, the SLA is formed. The SLA for a certain day is in the form of a curve representing agreed energy prosumption versus time.

Balancing Market

According to its real-time needs, a VP might need more/less energy than that agreed in the SLA. These SLA violations are the quantities to be traded in the balancing market. The usual procedure is that it participates in the balancing market through bidding. Upon delivery, further deviations that occur, are compensated from the System Operator and charged a-posteriori to the VP (see Imbalance Settlement of Figure 3.2.f1) directly from the MO or via the BRP, depending on the architecture (it differs in some countries). Also, concerning the Balancing Market, the VMGA can undertake the role of the BRP for its own portfolio, or provide services to the corresponding BRP. Within the scope of our present work, we are only interested in the prices at which the VMGA and the VP buys and sells electricity in the Balancing Market, so our study applies to either of the above mentioned use cases.

The prices of the balancing market also differ from one hour to another. Compensating the VPs' imbalances from their SLAs bears additional costs, such as unexpected lines' congestion, need for reserves and need for fast-response, low-efficiency units (e.g. fuel-based) to be utilized. For this reason, it is justified to penalize the VPs who deviate from their SLA. In our model, instead of a fixed penalty, we propose that the penalty is incorporated in the balancing market prices. So, the VP that needs more energy than its SLA has to buy it at a higher per-unit price (balancing market price plus penalty) and a VP which needs to sell more energy, sells it in a lower price (balancing market price minus penalty). This means that there is a *spread* between the price that the VP receives for selling and the price that the VP pays for buying. So, if the market price for a certain hour of the balancing market is *p*, the VP receives two prices:

- (*p* + spread) for selling electricity
- (*p* – spread) for buying electricity

The concept of spread is thought to be used on top of existing balancing markets by applying the spread to the balancing prices.

The effect of the spread on the price of a certain hour is presented in Figure 3.2.f3, where the blue line represents the day-ahead market prices and the red line represents the balancing market prices.

Figure 3.2.f3- Prices after apply of spread

Note that now in the balancing market, the VP receives generally less beneficial prices than in the day-ahead market because of the spread. The choice of the spread parameter is discussed later in this work, but it should be pointed out that it is also subject to regulation. We only study the effect of the spread in the scheduling strategies. A spread policy can be used to penalize violations either in the SLA between a VMG and its constituent VPs, or between the MO and the VMG Associations (in each case, combined with any other penalty policy for the other case of violation), or it can be used as a unified policy in both situations.

Within the framework described, the VP can apply scheduling strategies (like load shifting) that reduce its exposure to violations. By applying the above, a procedure for defining each VP's flexibility and applying the scheduling is described:

1) VMGA receives forecasts for the day-ahead from VPs and communicates bids to the MO.

2) MO defines the day-ahead market prices and clears the day-ahead market. The SLAs are formed.

3) After the day-ahead market gate closure and before the time of delivery, more accurate forecasts show the violations to be expected.
4) The forecasts of the market-clearing prices (balancing market-prices before applying the spread) are created.
5) VMGA decides the spread value depending on statistical data of flexibility and on its own goals (see Theorem 1 of the mathematical model).
6) Based on 4) and 5), VMGA extracts the function for the value of flexibility, which is the cost for a VP subject to the flexibility it is willing to offer.
7) The curve is communicated to each VP and the VP chooses its flexibility according to the user's desires (e.g. if the curve's slope is high, user might be willing to sacrifice comfort for revenue).
8) The scheduling algorithms for the VP are applied, subject to the flexibility value chosen and extract the load shifts to be made.
9) Any deviations left are cleared in the balancing market.

Later, we provide specific insights on the way the spread of step 5 is defined and also the function of step 7 is derived.

3.2.3 Methodology and Problem Formulation

Considering a scheduling horizon h(e.g., h=24 hours), let us denote the VP's prosumption forecast (from the previous day) as an array of 24 elements, each representing the prosumption forecast for a given time unit (e.g hour) of the day ahead:

$$X = (X^1, X^2, \dots, X^h)$$

where X^i expresses the energy that the VP consumes minus the energy it produces in hour i. The variable X^i is expresed in kWhs and can also be negative when the VP produces more energy than it consumes. The actual per hour prosumption (which is generally different from X) is denoted as

$$Y = (Y^1, Y^2, \dots, Y^h)$$

and the difference between the two is the violations array (i.e. VP's SLA violations)

$$V = Y - X \ = (X^1 - Y^1, X^2 - Y^2, \dots, X^h - Y^h)$$

where in the preceding vector subtraction is interpreted componentwise. An entry V^i can be negative if the VP consumes less energy or produces more energy than expected during hour i.

At time close to delivery time, the MO takes into account updated, more accurate, forecasts that become available, and broadcasts to the VMGAs the expected pricing curve for the balancing market (red curve of Figure 3). Mathematically, this would be expressed as a h-element array

$$P = (P^1, P^2, \dots, P^h)$$

where P^i denotes the market price (€ per kWh) at each of the h time intervals (hours). Vector P is extracted by market-clearing processes, according to the aggregated violations. Note that we refer to the balancing market prices. The day-ahead market prices do not concern our study, since we only focus on the trading after the day-ahead market gate closure. The more accurate the forecasts, the more similar P would be to the day-ahead market prices. To embed the implementation of penalties in the prices, a spread factor s is applied to P, as explained in the previous section (adding s to the prices for quantities that are bought and subtracting s from the prices for quantities that are sold) thus creating the Balancing Market Prices (M) as denoted in Eq. (3.2.1). Again, by M, we refer to the expected prices for the balancing market, which may differ from the final ones, if further deviations occur:

$$M = (M^1, M^2, \dots, M^{24})$$

$$\text{where } M^i = \begin{cases} P^i + s, & V^i > 0 \\ P^i - s, & V^i < 0 \end{cases}, \tag{3.2.1}$$

Instead of waiting for the imbalance to happen, the VMGA can turn to its own portfolio VPs and give incentives for load rescheduling, in the form of load shifting or storage in batteries, in order to compensate for the violations before they occur.

3.2.3.1 Load scheduling at the VP layer

The goal of load scheduling is to form a more beneficial prosumption curve $\tilde{Y}$ and consequently violation curve $\tilde{V}$ than the ones expected (i.e., *Y* and *V,* respectively), so at to avoid costly transactions in the Balancing Market. Note that the physical network constraints are not implemented in this study; thus, the output should be evaluated by the System Operator before applied.

Active & Passive Strategies and the spread

The resulting curve can be made to more beneficial using two different Strategies, similarly to those described in [KOK13].

Passive Strategy: Tries to minimize its SLA violations at all times *I,* which we symbolically denote as

$\tilde{V}^i \to 0$, for all i in $[1, h]$

Thus, the passive strategy tries to move loads/production from hours with demand/supply surplus to hours with supply/demand surplus in order to minimize SLA violation (recall that a violation needs to be traded in the balancing market, in a generally non-beneficial price due to the spread). This strategy is referred to as passive, when the VP tries to meet its SLA.

Active Strategy: The VP tries to counteract the overall system's imbalance. Given the application of market clearing processes by MO, a high price for a certain hour means that in this hour, there is extra demand for electricity. This Strategy tries to help the system to counteract its deviations from the aggregated SLAs (and benefit from that) by moving loads/production from the high/low price hours to the low/high ones.

$$\min\{\tilde{V}^i\} \text{ for } i \text{ where } P^i = high$$

$$\max\{\tilde{V}^i\} \text{ for } i \text{ where } P^i = low$$

where the terms high and low are defined by corresponding threshold values that are under our proposed system's control. Note that in the Active Strategy, the scheduling is planned regardless of the VP's own imbalance. Furthermore, let us consider a case where for a certain hour, the VP's SLA violation is opposite to the overall system's imbalance (e.g., has less demand than agreed in the SLA, while the overall system has extra demand than expected). In this case the VP makes profit from his SLA violation, because being opposite to the system's overall imbalance, this violation actually helps the system. This strategy is referred to as active, when the VP tries to counteract the overall system's imbalance, without caring for its own SLA. In a nutshell, the passive strategy's objective is to minimize SLA violations whereas the active strategy's objective is to provoke SLA violations, opposite to the system's imbalance.

The degree of freedom for the VP's load shifting is constrained by the VPs' flexibility. For example, it is not acceptable for a VP's lights to be turned off at night and compensate for this by turning them on during daytime, so it is not a flexible load. However, a washing machine, or a PHEV can provide more flexibility. A VP's flexibility is expressed as a percentage f of flexible loads, such that the VP's prosumption Y^i at hour *i* (after applying load rescheduling for the flexible loads) becomes $\tilde{Y}^i$:

$$(1-f)\cdot Y^i < \tilde{Y}^i < (1+f)\cdot Y^i$$

With the nomenclature cleared, we can express the original optimization problem as the minimization of the VP's 24 hours cost for electricity defined as:

$$\min_{\tilde{Y}^i} VP_{\text{Cost}} = \sum_{i=1}^{24}[M^i\cdot(\tilde{Y}^i - X^i)] = M*(\tilde{Y} - X) \tag{3.2.2a}$$

$$\text{subject to} \qquad \sum_{i=1}^{24}\tilde{Y}^i = \sum_{i=1}^{24}Y^i \tag{3.2.2b}$$

$$(1-f)\cdot Y^i \le \tilde{Y}^i \le (1+f)\cdot Y^i, \tag{3.2.2c}$$

where $*$ denotes vector inner product. That is, by moving flexible loads among hours with different prices, the VP is trying to minimize the overall 24h cost. Equation (3.2.2b) expresses the fact that we do not deal with load shedding, but only with load rescheduling, so that the overall VP's 24h prosumption in the scheduling horizon remains the same.

For spread $s > 0$, the Active Strategy is exposed to non-beneficial decisions (note that Strategies are performed based on vector P and not BMP). This is validated by the fact that s can cause the following effect: Given a case where we have $P^i > P^j$ for a pair of hours i and j, the Active Strategy would make a load shift from i to j. But s can be high enough to cause $BMP^i < BMP^j$, thus rendering the load shift non-beneficial. The higher the value of s, the larger the number of pairs *i,j* for which this may be true, and the higher the cost of the Active Strategy.

With respect to problem (3.2.2) we state the following lemma:

Lemma 3.2.1: Active Strategy is optimal when spread $s = 0$.

Proof: Let us consider a VP with a violations array V and assume that after applying load rescheduling with Active Strategy the violations array becomes $\tilde{V}$. The proof will be done by contradiction. Let us suppose that there is a strategy Z with a violations array $\tilde{Z}$, different from $\tilde{V}$ that achieves lower cost. Since $s = 0$, we have $M^i = P^i$ for every i. Then from Eq. (3.2.2a), we have, regarding the costs of the Strategies, that

$$\sum_{i=1}^{24}[P^i \cdot \tilde{Z}^i] < \sum_{i=1}^{24}[P^i \cdot \tilde{V}^i], \text{ or } P * \tilde{Z} < P * \tilde{V},$$

where $*$ denotes vector inner product. This implies that there is at least one pair of hours a, b for which

$$P^a \cdot \tilde{Z}^a + P^b \cdot \tilde{Z}^b < P^a \cdot \tilde{V}^a + P^b \cdot \tilde{V}^b \tag{3.2.3a}$$

$$\text{with } \tilde{Z}^i = \tilde{V}^i \text{ for every } i \neq a, b \tag{3.2.3b}$$

From (3.2.3a) we have

$$P^a \cdot (\tilde{Z}^a - \tilde{V}^a) + P^b \cdot (\tilde{Z}^b - \tilde{V}^b) < 0, \tag{3.2.3c}$$

and from (3.2.2b) and (3.2.3b) we get

$$\tilde{Z}^a = -\tilde{Z}^b \text{ and } \tilde{V}^a = -\tilde{V}^b \tag{3.2.3d}$$

From (3.2.3c) and (3.2.3d), we have

$$P^a \cdot (\tilde{Z}^a - \tilde{V}^a) - P^b \cdot (\tilde{Z}^a - \tilde{V}^a) < 0,$$

Thus

$$(\tilde{Z}^a - \tilde{V}^a) \cdot (P^a - P^b) < 0,$$

which yields two cases:

1) if $P^a > P^b$, we have $\tilde{Z}^a < \tilde{V}^a$ and $\tilde{Z}^b > \tilde{V}^b$

2) if $P^a < P^b$, we have $\tilde{Z}^a > \tilde{V}^a$ and $\tilde{Z}^b < \tilde{V}^b$

But from the definition of the Active Strategy, in each case Active would transfer as much load as possible:

1) from $\tilde{V}^a$ to $\tilde{V}^b$, i.e. $\min\{\tilde{V}^a\}$ and $\max\{\tilde{V}^b\}$

2) from $\tilde{V}^b$ to $\tilde{V}^a$, i.e. $\min\{\tilde{V}^b\}$ and $\max\{\tilde{V}^a\}$

From (3.2.2c), we have that both $\tilde{V}^i$ and $\tilde{Z}^i$ are bounded by the same margins. So for both cases we have

$$\tilde{V}^a = \tilde{Z}^a \text{ and } \tilde{V}^b = \tilde{Z}^b \tag{3.2.3e}$$

From (3.2.3e) and (3.2.3b), we have that $\tilde{Z}^i = \tilde{V}^i$ for every i , i.e. $\tilde{Z} = \tilde{V}$.

This means that Optimal Strategy and Active Strategy are identical, proving the lemma ■

The optimality of the Active Strategy when $s = 0$, implies the following corollary to Lemma 3.2.1:

Corollary 3.2.1: *for* $s = 0$*, Active Strategy has lower cost than Passive.*

As for the Passive Strategy, we can show the following lemma.

Lemma 3.2.2: Passive Strategy is optimal when spread s is very high.

Proof: Let us consider a VP with a violations array V and assume that after applying load rescheduling with Passive Strategy its violations array becomes $\tilde{V}$. The proof that Passive Strategy is optimal for high enough *s* will be done by contradiction. Let us assume that there is another strategy Z that when applied results in a violations array $\tilde{Z}$, different than $\tilde{V}$, and with lower cost. A very high s means that for every *i,j* with $\tilde{V}^i > 0$ and $\tilde{V}^j < 0$, we have that $M^i > M^j$. As in (3.2.3a), in this case there is at least one pair of hours *a*, *b* for which

$$M^a \cdot \tilde{Z}^a + M^b \cdot \tilde{Z}^b < P^a \cdot \tilde{V}^a + P^b \cdot \tilde{V}^b$$

which in view of Eq.(3.2.1) and (3.2.3d) (that stands also here) becomes

$$(P^a + s) \cdot \tilde{Z}^a - (P^a - s) \cdot \tilde{Z}^a < (P^a + s) \cdot \tilde{V}^a - (P^a - s) \cdot \tilde{V}^a$$

Consequently, $\tilde{Z}^a \cdot (2s) < \tilde{V}^a \cdot 2s$, or $\tilde{Z}^a < \tilde{V}^a$. Then, because of (3.2.3b), we have $\tilde{Z} < \tilde{V}$, which implies that Z is the Passive Strategy since by definition it is the one that minimizes the violations and the violations array. ■

Corollary 3.2.2 (to Lemma 2): When the spread s is high, Passive Strategy has lower cost than Active.

Combining Eq. (3.2.1) with the VP's cost function given by (3.2.2a), we observe that the *VP_Cost* function is strictly increasing with respect to s for any $\tilde{Y}$, with the cost curve's slope given by

$$l = \sum_{i=1}^{h}(\tilde{Y}^i - X^i).$$

Since Passive Strategy attempts to drive $\tilde{Y}^i - X^i$ as close to zero as possible, we have for the derivatives of the *VP_Cost* functions

$$l_{Active} > l_{Passive} \tag{3.2.4}$$

From (3.2.4) and Lemmas 3.2.1 & 3.2.2 we conclude the following theorem.

Theorem 3.2.1: Given the set S of spreads, there is unique $s^* \epsilon S$ for which Active and Passive Strategies' cost is equal.

The preceding Theorem tells us that the VMG Association, when dealing with its constituent VPs, can strategically choose a general s value, in a way that can serve its goals. That is, it can choose a high spread s when it has reasons to want the VPs to try to meet their SLAs (function more "passively") or a low spread s when it wants to give incentives to the VPs to try to counteract the overall system's imbalance (function more "actively"). Thus, the VMGA can utilize s as a control variable for implementing the tradeoff between motivating users towards predictability (passive) or towards flexibility to rescheduling (active).

The Proposed Hybrid Strategy

We propose a Hybrid Strategy as a way to combine the advantages of Active and Passive Strategies. Hybrid Strategy splits problem (3.2.2) in two subproblems, by dividing the set of hours into two groups:

~ Group *A* contains all hour indices *i* for which there exists an hour *z* such that either of the following inequalities holds

$$P^i - s > P^z + s \tag{3.2.5a}$$

$$P^i + s < P^z - s \tag{3.2.5b}$$

~Group B, contains all the remaining hours (in which the price difference among them, is smaller than the spread). The Hybrid Strategy is defined as follows:

Definition of Hybrid Strategy: apply the Active Strategy in Group A, and the Passive Strategy in Group B.

The following theorem can be proven:

Theorem 3.2.2: Hybrid Strategy is optimal for every value s of the spread

Proof: We denote the violations array resulting by the Hybrid strategy as $\tilde{Y}$ and will prove it to be optimal for any value of s. For the sake of contradiction, let us assume that

$\tilde{Y}$ is not optimal and there is an optimal solution $\widetilde{W} \neq \tilde{Y}$. If $\widetilde{W} \neq \tilde{Y}$ then there is at least one pair of hours i, j such that:

$$\widetilde{W}^i - \tilde{Y}^i = e \tag{3.2.6a}$$

$$\widetilde{W}^j - \tilde{Y}^j = -e \tag{3.2.6b}$$

and

$$\widetilde{W}^a = \tilde{Y}^a \text{ for every } a \neq i, j \tag{3.2.6c}$$

where e is a prosumption quantity in kWhs.

We distinguish three cases:

1) Case $i, j \in A$:

Condition (3.2.5) actually implies that Hybrid is based on M and not on P, as it defines the groups by the hour's M^i. From the proof of Lemma 3.2.1, by adding the value of s (in other words, replacing P^i with M^i), it is easily concluded that $\widetilde{W}^a = \tilde{Y}^a$ for every hour $a \in A$. So Hybrid is optimal for Group A. From Eq. (3.2.6c) we have that $\widetilde{W}^a = \tilde{Y}^a$ for every $a \in B$, proving $\widetilde{W} = \tilde{Y}$.

2) Case $i, j \in B$:

Conditions (3.2.5) & (3.2.3) are equivalent and so Lemma 3.2.2 applies as it is, and $\widetilde{W}^a = \tilde{Y}^a$ for every $a \in B$. Similarly to above, from Eq.(3.2.6c) we have that $\widetilde{W}^a = \tilde{Y}^a$ for every $a \in A$, proving $\widetilde{W} = \tilde{Y}$.

3) Case $i \in A, j \in B$:

From Eqs. (3.2.6a) & (3.2.6b) we have $M^i > M^j$. But this is in direct contradiction with (3.2.5a) & (3.2.5b), because if such *i, j* exist they would both be in group A by definition (because they act as an alternative policy *z* for each other). Since *i, j* always belong to the same group, constraint (3.2.2b) can be split in two constraints:

$$\sum_{i \in A} \widetilde{W}^i = K$$

$$\sum_{j \in B} \widetilde{W}^j = L$$

with $K + L = \sum_{i=1}^{24} Y^i$,

where each constraint involves only variables from one of the subvectors $\tilde{Y}^{i \in A}$ and $\tilde{Y}^{i \in B}$. Thus, the problem becomes trivially parallelizable, which means that the decomposed problem (Hybrid approach) is equivalent to the original one, and also from cases 1 and 2 above, we have $\widetilde{W} = \tilde{Y}$. ■

Up till now, we have looked at the Balancing market in the presence of the spread parameter *s,* which is used to penalize VPs that do not meet their SLAs. We proved that the optimal strategies to be followed by a VP for small and large values of the spread are the Active and the Passive strategies, respectively, and then showed that Hybrid is the optimal strategy for any value of the spread. With Theorem 3.2.2 proven, we assume from now on that all VPs apply the Hybrid Strategy in all cases. In accordance with Lemmas 3.2.1 and 3.2.2, Hybrid strategy is expected to approach Active Strategy for $s \to 0$ and approach Passive Strategy as s increases. We will verify this in the simulation results. We can intuitively understand the previous conclusions, by recalling that a low value of s represents favoring users' flexibility, whereas a high value of s represents favoring users' predictability.

The strategies described for an individual VP, when trying to minimize the violations and the corresponding penalties in its SLA with a VMG Association, are also applicable to a VMG Association in order to reschedule the loads of its constituent VPs and minimize the Association's violations and penalties in its SLA with the MO. The only difference is that when the rescheduling is decided collectively, the results are better than when decided distributedly (each user for itself) due to statistical multiplexing, or else the additional degrees of freedom the VMG Association has by aggregating the flexibility of several VPs.

In the following subsection, we look at the *value of flexibility* and how it is increased by combining VPs into VMG Associations. We define the difference between the Independent and the Associations case as the *value of cooperation*. Flexibility Aggregators (as described in the literature) can utilize the same possibility; the difference is that Flexibility Aggregators would do it in order to make profits themselves, while VMG Associations do it to create savings for their users.

Study of Flexibility

In any case, the profits stemming from a prosumer cluster portfolio's flexibility have to be shared among (in the case of VMG Associations) or with (in the case of Flexibility Aggregators) the VPs who provide this flexibility. The flexibility of a VP is defined by parameter f of Eq. (3.2.2c). Thus, what we refer to as *value of flexibility* is the revenues the Association can achieve by using the flexibility of its VPs. By using the knowledge of the flexibility value, the Association can introduce new ways of pricing its clients or even introduce a new energy market product, which can be called "Flexibility Retail Market", to buy flexibility from the VPs.

Assuming $s = s^*$, (i.e., the spread at which Active and Passive Strategies' cost is equal, we want to study the way the Cost of the VP changes with f. From problem (3.2.2) we have that the Cost of the VP is

$$\sum_{i=1}^{24}[M^i \cdot \tilde{V}^i] = M * \tilde{V}$$

where $\tilde{V}^i = \tilde{Y}^i - X^i$ is the violation remaining after the optimal Hybrid strategy is applied. For the hours i in which the Active Strategy is applied, we have

$$\tilde{V}_A^i = V^i - f \cdot Y^i$$

whereas for the hours i where the Passive Strategy is applied, we have

$$\tilde{V^i}_P = \begin{cases} V^i - f \cdot Y^i, & V^i > f \cdot Y^i \\ 0, & V^i < f \cdot Y^i \end{cases}$$

This is because Passive stops adding or subtracting loads from hour i once $\tilde{V}^i = 0$ (i.e., once the violation at time *i* has been minimized), while Active continues subtracting load from hour *i* trying to reverse the violation, as long as more flexibility is available. So, when f increases $\tilde{V^i}_P$ also decreases (but not linearly) up to certain point where $\tilde{V^i}_P = 0$, beyond which it does not decrease anymore. So, although the function's derivatives cannot be expressed in closed analytical form (because $\tilde{V^i}_P$ is not differentiable at point $V^i = f \cdot Y^i$), it is quite clear that:

Statement 3.2.1: The cost of the VP is a strictly decreasing, non-linear and convex function of f.

The validity of Statement 1 will also be confirmed through the simulation results. By the non-linearity and convexity of the cost function, one can see that sacrificing comfort to achieve very high values of flexibility is rewarded with diminishing returns, i.e, some revenue is obtained but not necessarily as high as the discomfort level caused. On the other hand, from Eq. (3.2.2a) we have that the cost and consequently the value of flexibility is also dependent on the value of s.

3.2.3.2 VP cooperation and rescheduling at the VMG layer

In this section, we assess the advantages that can be obtained through the cooperation of multiple VPs that are aggregated in *coalitions*, or clusters, namely the VMG Associations. We also study the profits of cooperation in the case of positive, zero, and negative correlation among the violation patterns of the VPs forming a cluster, giving insights on the criteria that should be used to cluster VPs. In particular, we show that VPs whose violation patterns are negatively correlated can gain important benefits from their cooperation, but the benefits of cooperation also extend, even though reduced, to VPs that are uncorrelated or even positively correlated.

VMGA communicates the balancing market pricing pattern to the VPs and the scheduling algorithms run in each VP. In the cooperative case, the VPs communicate to the VMGA their violations , the VMGA applies the cooperative scheduling algorithms (that now run in the Association's side) and the outputs are communicated back to the VPs.

Denoting the final violations array of a VP A and a VP B as $\tilde{V}_A$ and $\tilde{V}_B$, respectively, the total cost of the VPs' violations when acting individually (non-cooperatively) would be

$$Cost^{\,non-coop} = VP\_Cost_A + VP\_Cost_B = \sum_{i=1}^{h} M_A^i \cdot \tilde{V}_A^i + \sum_{i=1}^{h} M_B^i \cdot \tilde{V}_B^i$$

whereas the cost of the violations of a cluster made up of VP A and B (cooperating) would be

$$Cost^{\,coop} = VP\_Cost_{A\cup B} = \sum_{i=1}^{h} M_{AB}^i \cdot \left(\tilde{V}_A^i + \tilde{V}_B^i\right).$$

Note that $Cost^{\,coop}$ is not equivalent to $Cost^{\,non-coop}$, because for those hours i that $\tilde{V}_A^i \cdot \tilde{V}_B^i < 0$, we have $M_A^i \neq M_B^i$ (see Eq.(3.2.1)). In other words, when A and B combine in a cluster they may reduce or overhaul some of the SLA violations (penalized through the spread s).

For all hours i for which we have $\tilde{V}_A^i \cdot \tilde{V}_B^i > 0$, we have

$$Cost^{\,non-coop}\,(i) = Cost^{\,coop}\,(i), \text{ for } i \text{ s.t. } \tilde{V}_A^i \cdot \tilde{V}_B^i > 0 \tag{3.2.7a}$$

Let us consider now an hour i where A and B have opposite violations, that is,

$$\tilde{V}_A^i \cdot \tilde{V}_B^i < 0 \tag{3.2.7b}$$

For the individual case we then have

$$M_A^i \cdot \tilde{V}_A^i + M_B^i \cdot \tilde{V}_B^i = (P^i + s) \cdot \tilde{V}_A^i + (P^i - s) \cdot \tilde{V}_B^i = P^i \cdot (\tilde{V}_A^i + \tilde{V}_B^i) + s \cdot (\tilde{V}_A^i - \tilde{V}_B^i) \tag{3.2.7c}$$

whereas for the cooperative case we have

$$M_{AB}^i \cdot \left(\tilde{V}_A^i + \tilde{V}_B^i\right) = (P^i + s)(\tilde{V}_A^i + \tilde{V}_B^i) = P^i \cdot (\tilde{V}_A^i + \tilde{V}_B^i) + s \cdot (\tilde{V}_A^i + \tilde{V}_B^i) \tag{3.2.7d}$$

From Eqs.(3.2.7c) & Eq.(3.2.7d) and (3.2.7b) we conclude that

$$M_A^i \cdot \tilde{V}_A^i + M_B^i \cdot \tilde{V}_B^i \geq M_{AB}^i \cdot \left(\tilde{V}_A^i + \tilde{V}_B^i\right) \tag{3.2.7e}$$

From (3.2.7e) & Eq.(3.2.7a), we have for the overall cost of the non-cooperative and the cooperative case:

$$\sum_{i=1}^{24}\left[M_A^i \cdot \tilde{V}_A^i\right] + \sum_{i=1}^{24}\left[M_B^i \cdot \tilde{V}_B^i\right] \geq \sum_{i=1}^{24}\left[M_{AB}^i \cdot \left(\tilde{V}_A^i + \tilde{V}_B^i\right)\right] \tag{3.2.7f}$$

Equation (3.2.7f) expresses that the cost of two VPs' violations is higher than or equal to that of a virtual united VP (cluster) that participates in the market as one entity and thus there is a profit from their cooperation. An important parameter that affects the amount of this profit is the number of hours i for which (3.2.7b) stands. This is related to the criteria that are used to select the particular VPs that should be grouped together into clusters for energy exchange.

Useful in making the clustering decisions for VPs is the concept of *VPs' correlation*. A VP A will be said to be *positively correlated* to a VP B when their violations patterns are affected (by the weather and other conditions) probabilistically in the same way, or mathematically, if their violation vectors defined as $\tilde{V}_A$ and $\tilde{V}_B$, have strictly positive cross-correlation:

$$E(\tilde{V}_A * \tilde{V}_B) > 0$$

where * denotes the inner product between vectors and $E(\,)$ denotes the expected value. An example of positively correlated VPs would be a set of solar parks located in nearby geographical areas, where an unexpected loss of sunshine would affect all the VP production patterns in the same way. Similarly, VP A will be said to be negatively correlated to VP B when an increase/decrease in the production of A is connected with a corresponding decrease/increase in the production of B, that is,

$$E(\tilde{V}_A * \tilde{V}_B) < 0.$$

VP A will be said to be uncorrelated to VP B, when their production sources are independently affected, that is,

$$E(\tilde{V}_A * \tilde{V}_B) = E(\tilde{V}_A) * E(\tilde{V}_B) = 0,$$

where we have assumed that $E(\tilde{V}_A) = E(\tilde{V}_B) = 0$, as is the case for unbiased estimators (forecasters).

In the performance results, we examine the cases where a cluster is composed of:

a) maximally positively correlated VPs,

b) uncorrelated VPs and

c) pairs of negatively correlated VPs.

Our results will show that the profit of cooperation is low but positive for positive correlated VPs, higher for uncorrelated VPs, and is the highest for negatively correlated VPs.

3.2.4 Model and data used for simulation

3.2.4.1 Simulation model

In our simulation experiments, a VP is modeled as a set of 4 parameters, $VP = (S, B, DF, f)$, where $S = (S^1, S^2, \dots, S^{24})$ is a 24-element array denoting the amounts of energy (kWhs) that the VP agrees to sell (in its SLA) throughout the next day with a sampling time of one hour. Also, $B = (B^1, B^2, \dots, B^{24})$ is a 24-element array denoting the amounts of energy (kWhs) that the VP agrees to buy (in its SLA) throughout the next day with a sampling time of one hour. For demonstration purposes, we chose a 24h scheduling horizon, in order to obtain the results throughout a whole day. It should be noted though, that balancing market prices are generally unpredictable and the larger the scheduling horizon the more the results will deviate from the actual optimal. Nevertheless this issue can be tackled by iteratively running the scheduling algorithm in real-time during the day. The implementation of the real-time version is left for a future study.

We define the prosumption array as $X = B - S$. We also define a violation vector V as the difference between the vector Y containing the actual hourly prosumption values and the vector X containing the forecasted prosumption pattern, that is, $V = (v^1, v^2, \dots, v^{24}) = X - Y$. The entry v^i is assumed to be a random variable that is uniformly distributed in $[\text{-DF}, \text{DF}]$; parameter DF is referred to as the Deviation Factor, indicating the margins ($\pm DF$) according to which the VP is expected to deviate from the SLA, and is expressed in kWh per hour. The Flexibility Factor f is a float variable, indicating the amount of energy prosumption shifting that the VP can accomplish. It is expressed as a scalar between 0 and 1 or corresponding % value (0 corresponds to no flexibility, and 1 or 100% corresponds to all loads and/or supply units being flexible). Note that prosumption shifting can be accomplished either by shifting loads and/or by shifting energy supply (e.g. using scheduling for controllable units or storage capacity for RES).

The VP communicates its deviation vector V to the VMGA. At the Association level, a set of market-clearing prices is created for each hour of a certain day and is represented by vector:

$$P = (P^1, P^2, \dots, P^{24})$$

is a 24-element array denoting the market price (€ per kWh) at each of the 24 time intervals (hours) before the spread is applied. Taking into account the spread s, we obtain the Balancing Market Prices by Eq. (3.2.1) and assign them to vector M.

Vector M is communicated by the Association to the VP. By now, the VP can calculate the expected daily $Cost$ with no scheduling techniques applied, to use it as a reference for the strategies evaluation:

$$VP\_Cost(\varnothing) = \sum_{i=1}^{24} [V^i \cdot M^i],$$

where the ⌀ (null) in the parenthesis signifies the cost when no rescheduling strategy is applied. The VP applies load shifting strategy L in {Active, Passive, Hybrid}, subject to its flexibility factor f, thus changing its initial violation vector V to a new violation vector denoted as $V(L)$. The cost of the applied strategy is calculated as

$VP\_Cost(L) = \sum_{i=1}^{24}[V(L)^i \cdot M^i]$, for any strategy L in {Active, Passive, Hybrid}.

The percentage savings realized by strategy L is given as

Value of Strategy L (VOS(L)) % $= (VP\_Cost(\varnothing) - VP\_Cost(L)) \cdot 100 \,/\, VP\_Cost(\varnothing)$,

our metric of merit for evaluating the performance of the strategy (Active, Passive, or Hybrid) applied.

3.2.4.2 VPs Cooperation

A use case of cooperation was implemented for n VPs in direct representation of the mathematical model and the daily energy cost per VP was calculated resulting in two cases: the average daily cost per VP when they do not cooperate, denoted as $Cost^{\,non-coop}$, and the average daily cost per VP when they cooperate in a cluster, denoted as $Cost^{\,coop}$. For the calculation of $Cost^{\,coop}$, we formed and used the $24 \cdot n$ violations matrix V_n, with n being the number of cooperating VPs and elements $V_n^{a,i}$ representing the violation of VP a at hour i:

$$Cost^{\,non-coop} = \frac{\sum_{a=1}^{n}(VP\_Cost^a)}{n}$$

$$Cost^{\,coop} = \frac{\sum_{i=1}^{24}\left[\left(\sum_{a=1}^{n} V^{a,i}\right) \cdot M^i\right]}{n}$$

The difference between these values gives the daily monetary profit that each VP gains on average through cooperation and the corresponding % gain is defined as:

Value of Cooperation (VOC) % $= (Cost^{non-coop} - Cost^{coop}) \cdot 100 \,/\, Cost^{non-coop}$

3.2.4.3 Data Used in Simulations

The implementation was made in Python environment. For the pricing and the prosumption data, we used sets of values extracted from the VIMSEN Decision Support System (DSS), which provides open source data for production, consumption and pricing derived from Hellenic Electricity Distribution Network Operator, regarding 100 RES producers (of different kinds), 150 consumers (industrial, commercial, residential) and 50 very small prosumers in Greece during 2015. Many of them are located in the same LV/MV substation, making it feasible to apply the proposed aggregation strategies. Because variable v^i of the violation vector V of the model is a random variable, the simulation was run for a large number of iterations to extract the average value for all the results.

Strategies evaluation and study of spread

As school buildings constitute an important prosumer type in Greece whose data is recorded in VIMSEN's DSS, for the prosumption data we consider a typical school at a typical day in Athens. For the results presented in section 6.1 regarding the strategies' evaluation and the choice of spread, we assume *DF*=1.5 kW, $f = 25\%$ and an average presumption array

$$X = [1.54, 2.12, 2.05, 1.52, 1.42, 1.42, 1.47, 0.89, 0.87, 1.16, 0.76, 0.91, 0.72, 1.13, 3.51,$$
$$3.45, 3.74, 4.26, 4.37, 3.31, 1.58, 1.71, 1.73, 1.60]$$

The pricing data is given by the vector:

$$P = [3.75, 3.66, 3.66, 3.70, 3.66, 3.54, 3.70, 5.03, 6.27, 6.5, 7.43, 7.47, 7.21, 6.80, 6.41,$$
$$5.78, 6, 6, 5.5, 3.9, 2.9, 3.7, 3.95, 5.5].$$

Set of prosumers, cooperation and correlation

For the results presented regarding the value of the cooperation among the VPs as well as the effect of their correlation, we used both real and simulated data. The real data was extracted from [VIMGIT] for a set of different prosumers all for March 21st 2015, 24 hours. For the simulated data experiments, 100 synthetic profiles were created by random uniform distributions of prosumption with a median value of 3 kWh and a standard deviation of 3. In both cases, we again assumed $f = 25\%$ and $DF = 1.5$.

3.2.5 Simulation Results and Discussion

In this section, we evaluate the strategies described and also the cooperation framework defined. In particular, in section 3.2.5.1, we evaluate the Value of Strategy for the Active, passive and Hybrid strategies, and study the effect of the spread parameter s. In section 3.2.5.2, we analyze the Value of Flexibility of the VPs, as a function of parameter f. The savings that can be obtained through cooperation, that is the $\text{Value of Cooperation}\,\%$ metric, are investigated in section 3.2.5.3 along with the role played by correlation factor.

3.2.5.1 Policies' evaluation and study of spread

Through simulation, we evaluate the Value of Strategy L (% savings) gained with each strategy L in $\{$Active, Passive, or Hybrid$\}$ for different values of s. The results obtained are depicted in Figure 3.2.f4. We present the results beginning from s = 1, because in lower spreads the curves scale are higher and the results would not be as clear for the reader.

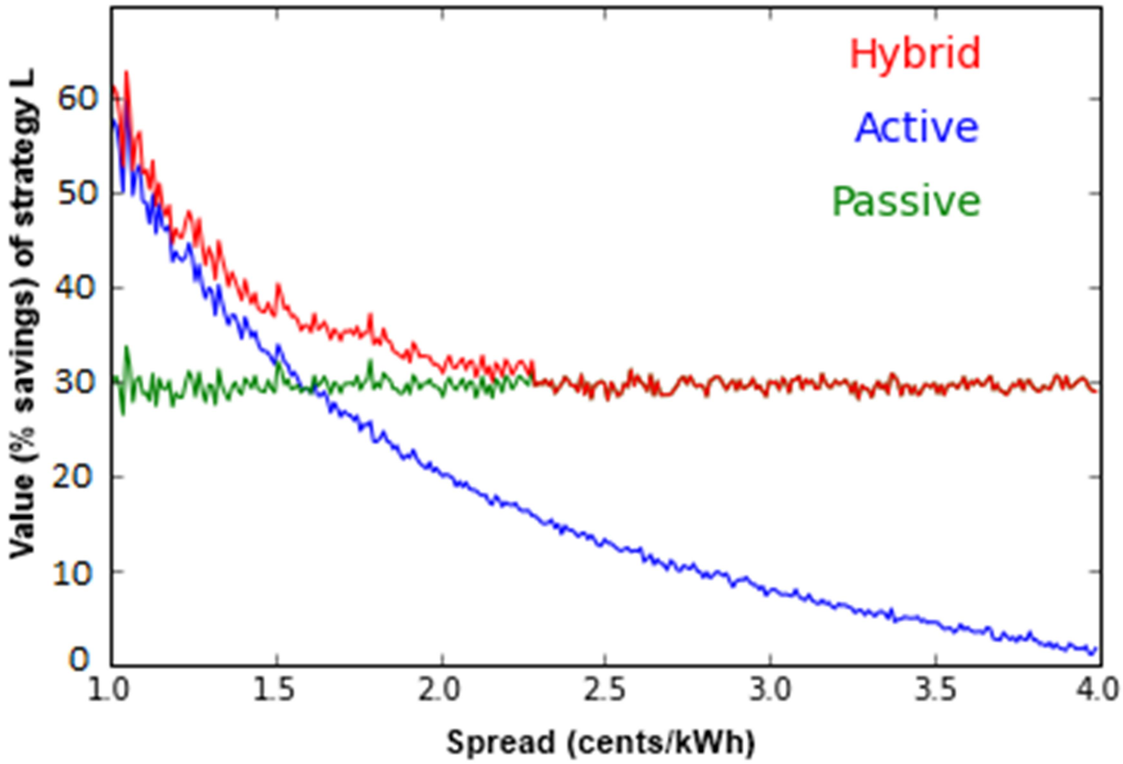


Figure 3.2.f4- Value (% savings) of Strategy L = Active, Passive, or Hybrid as a function of spread s

The results in Figure 3.2.f4 are in completely aligned with Lemmas 3.2.1 and 3.2.2, and Theorems 3.2.1 and 3.2.2, as follows:

- The performance of the Active strategy approaches that of the Hybrid strategy for small values of s, as expected by Lemma 3.2.1. Its Value of Strategy metric (% savings) is monotonically decreasing with s as expected, since a higher spread trims the price difference between a high-value and a low-value element of P.
- The value (% savings) of Passive strategy is not affected by the spread s, as expected, since by definition the Passive strategy tries to meet the VP's SLA agreement, regardless of the s value. For a high spread, Passive strategy becomes optimal, as expected by Lemma 3.2.2.
- After a certain spread value, the Active strategy becomes less beneficial than the Passive. There is a unique s value in which the two strategies are equally beneficial (Theorem 3.2.1).
- The lower the s, the more "actively" the Hybrid strategy behaves and the higher the s, the more "passively" the Hybrid strategy behaves.

- The Hybrid strategy (optimal for every s, from Theorem 3.2.2) outperforms the other two strategies examined, yielding significant savings ranging from 30-60% for the parameter values examined.

3.2.5.2 The Value of Flexibility

The model used in the previous section to evaluate the rescheduling strategies, considered a single VP having a given flexibility factor f. In this subsection, we investigate the degree to which a VMG Association's profits are affected by its portfolio's flexibility. The simulation experiments assumed fixed spread equal to s^* and flexibility parameter f varying from 0 up to 100%. Figure 3.2.f5 depicts the Value of Flexibility (% savings) metric as a function of f. We observe that the Value of Flexibility (savings) function under the Hybrid strategy is indeed strictly increasing, not linear and concave, confirming Statement 3.2.1. As expected, the Hybrid strategy achieves the best % savings over all strategies and for all values of f, reaching savings of about 75% for high flexibility, in the experiments conducted.

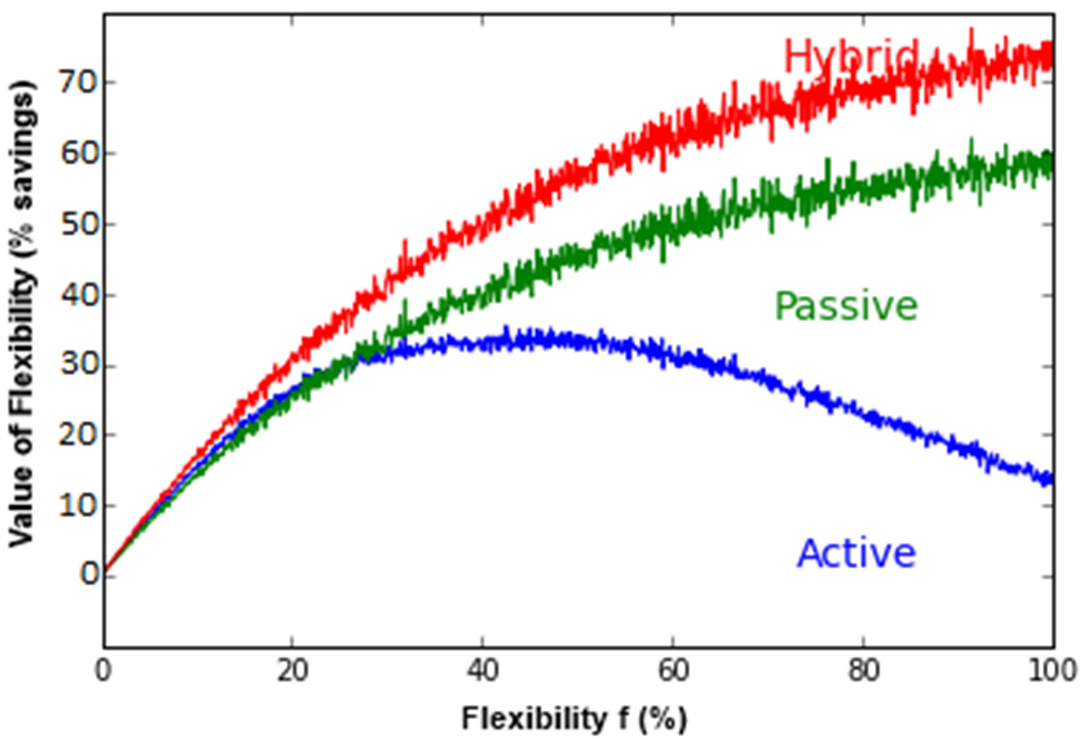


Figure 3.2.5- Value of Flexibility (% savings) as a function of flexibility parameter f

Note that the Active strategy becomes less profitable when more than 25% flexibility is available. This is because the simulation was run for $s = s^*$, with s^* extracted in the results for $f = 25\%$ (the intersection point in Figure 3.2.f4 gives $s^* = 1.6$). But what is more important at this point is that Hybrid strategy is verified to be the most profitable strategy for every value of f and for every value of s. So, from now on we assume that all VPs apply the Hybrid strategy in all cases.

Simulation experiments were carried out for a range of values of f (0-100 %) and values of s (1-4 cents/kWh) and a 3D curve was extracted, showing the way the Value of Flexibility (VOF) metric depends on these two factors (Figure 3.2.f6). Such a curve is extracted by the Association after step 4 of the procedure described for defining each VP's flexibility. Thus, even in a use case where the value of s is not constant but is adapted by the MO, the Association can also adapt the value (savings) function of flexibility by applying the real-time s value to Figure 3.2.f6 and extract the respective 2D curve.

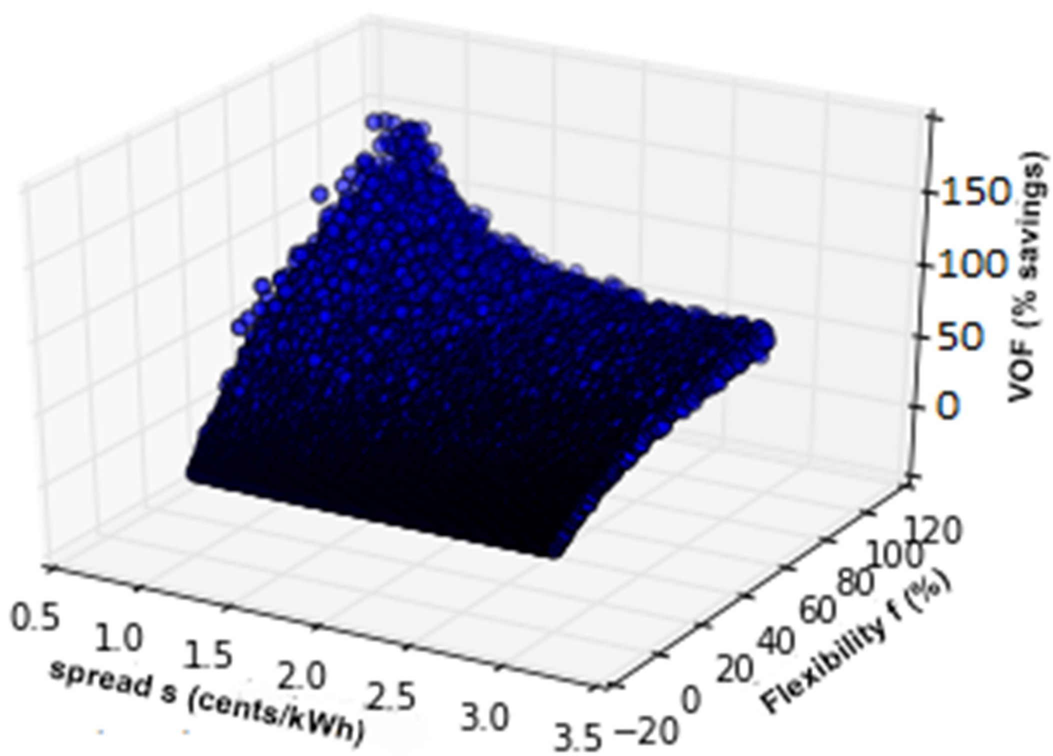


Figure 3.2.f6 - Value of flexibility (% savings) as a function of the spread s and flexibility parameter f (Hybrid Strategy is applied)

3.2.5.3 Evaluation of the value of Cooperation

In this set of experiments, we evaluated the Value of Cooperation metric as a function of the number n of cooperating VPs under the negatively-, positively- and un-correlated VP cases. For the simulation we used the same profile and deviation distribution data with sections 3.2.5.1 and 3.2.5.2. The results are plotted on the same graph in Figure 3.2.f7 for the three correlation cases, and for 1 to n=20 cooperating VPs. The simulation algorithm aggregates the prosumers' profiles and applies the Hybrid strategy.

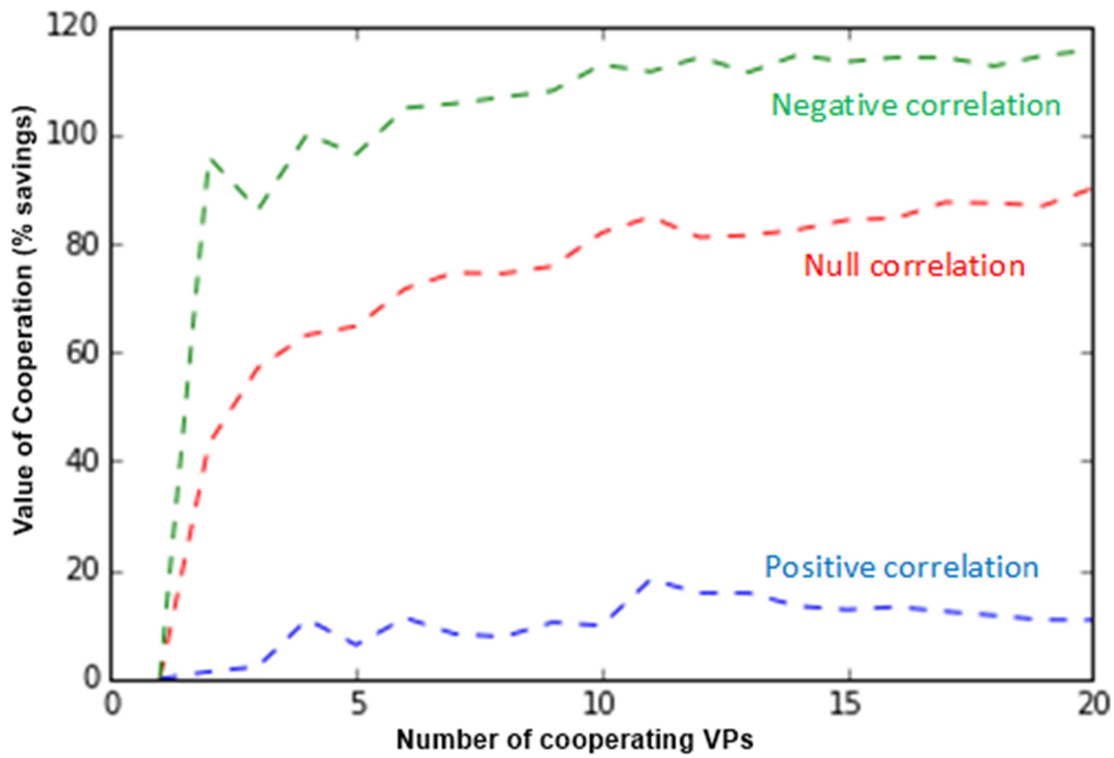


Figure 3.2.f7- Value of Cooperation (% savings) as a function of the number n of cooperating VPs

Figure 3.2.f7 confirms Eq. (3.2.7f), stating that the savings due to cooperation over the non-cooperative case are always positive (even for positively-correlated VPs!). It also shows that negatively correlated VPs exhibit savings of the order of 100%, as expected, since they are able to cancel out each other's violations when cooperating. The Value of Cooperation is significantly smaller in the case of independent VPs (of the order of 40% when n=2), but it increases rapidly with n, and approaches that of negatively-correlated VPs when n is large. Hence, a higher number of cooperating VPs results to a higher profit per VP when the VPs are independent. When the VPs are positively or negatively-correlated, the incorporation of a very large number of VPs in the cluster has diminishing returns, in the sense that it yields little savings beyond a certain point. Forming larger coalitions, however, is highly beneficial when the VPs are independent.

To demonstrate these conclusions more clearly, we run additional simulations for a set of synthetic (simulated as opposed to real) prosumption data and a larger number of cooperating VPs (n=100). The results are shown in Figure 3.2f8. We observe that the curve obtained with the real data is actually no different than that obtained with synthetic data.

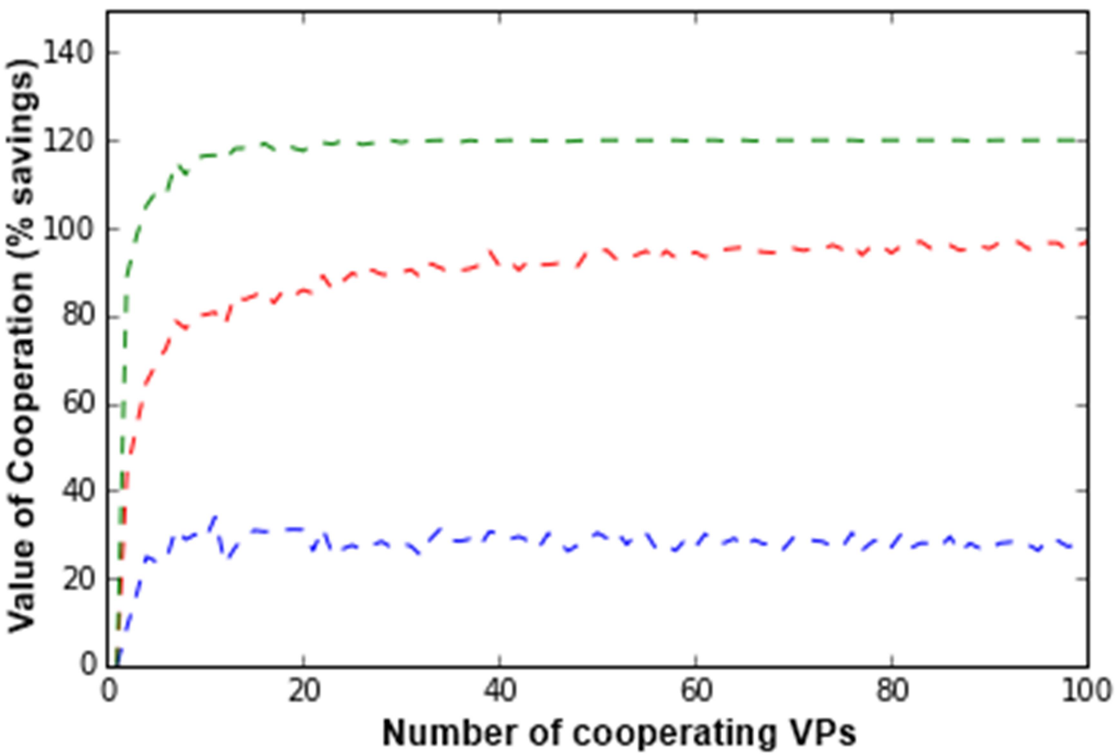


Figure 3.2.f8- Value of Cooperation (% savings) as a function of the number of cooperating VPs with simulated data

Chapter 4

CONCLUSIONS, FUTURE WORK, POLICY IMPLICATIONS

In this dissertation, we considered a set of smart devices at the side of residential electricity consumers and a home energy management system that is able to make decisions about home electricity consumption by taking into account the user's preferences, the dynamic electricity pricing signals as well as the operational constraints of devices. We took on the problem of incentivizing users to shape their consumption patterns in line with the needs of the electricity system. In this setting we formulated a game where each agent tries to optimize its own objective. We formulated the problem of designing online auction mechanisms that are able to bring the system to a Nash equilibrium. In order to achieve these goals we drew on concepts of algorithmic game theory and mechanism design.

We studied and develop techniques for two general use cases of DSM: online algorithms for real-time consumption curtailment and offline algorithms for day-ahead load scheduling. For the real-time demand response case, we designed two online auction schemes for two specific business models.

In the first one, we considered a setting of strategic, intelligent users and an ESP seeking to incentivize them in order to curtail part of their consumption in response to a DR-event. We showcased the inefficiency of previous state-of-the-art approaches, which either do not consider user incentives, or adopt a direct-revelation approach, respectively leading to either lack of truthfulness and consequent inefficiency, or to lack of privacy and scalability. To overcome these shortcomings, we presented a novel iterative auction mechanism based on Ausubel's clinching auction, that implements the truthful and efficient VCG outcome but also allows for a distributed implementation and a privacy-preserving communication protocol. Our theoretical and simulation results verified that the proposed scheme combines the desired properties with very good performance and small overhead. Future work can further extend user rationality to also anticipate future DR-events based on local information and learning techniques.

The second business model refers to cases such as energy cooperatives where the issue of fairness of the allocation is important. We considered a model of a budget-balanced aggregating entity serving as ESP for its registered users. We proposed a P-RTP mechanism and evaluated its performance against that of the classic RTP mechanism in terms, of the most well established KPIs derived in the literature. In order to focus on the merits of the main idea, we kept the system model simple so as not to harm the generality of the results. Future research can extend the results to more advanced system models that include: a) the possibility of load shifting in addition to load curtailment; b) RES and energy storage systems (ESS). In addition, the user's utility function and the way the user makes decisions is still an open area for research. Distinct models for different devices could be considered and applied under the P-RTP paradigm. Moreover, in electricity markets, different pricing mechanisms (P-RTP, RTP, flat-price, etc) are to be offered to real users as an option, making the co-existence of different pricing mechanisms for different users in a given market an interesting problem. Finally, the new prospects of electricity pricing offered by P-RTP will impact, if adopted, the sizing (investment cost) of RES and ESSs. We believe that the integration of RES and ESS sizing with P-RTP mechanism design may give rise to new capabilities for self-sufficient micro-grids and advanced demand side management.

For the day-ahead load scheduling case, we designed and evaluated a novel DSM scheme that addresses several issues that were not jointly addressed before. We focused on modern energy pricing models and argued that they do not fairly reward demand responsive users, who are more willing than others to adopt energy efficient schedules. Thus, existing pricing models are not designed to trigger behavioral changes as they do not provide energy consumers with attractive incentives in the form of fair compensation. Motivated by this observation, we developed a hybrid billing mechanism that disposes an adjustable level of rewarding users by offering them financial incentives to modify their consumption schedules. The proposed DSM scheme preserves the economic efficiency, individual rationality and budget-balance properties. It is also able to satisfy coupling, system-wide constraints. The proposed scheme is theoretically proven to always bring the system to the Nash equilibrium. Our algorithm can be a valuable tool in the hands of an ESP in order for the latter to employ innovative business models and respective revenue streams mainly by selling DSM units in various types of flexibility markets. It aims at motivating its customers to exploit their shiftable and curtailable devices in order to reduce the cost of conventional energy usage. Our evaluation uses a standard state of the art scheme as a benchmark and we show that the proposed scheme manages to prompt energy behavioral changes of users much more efficiently than the state of the art. Future studies, can study the impact of our results in: islanded microgrids, energy communities and innovative business models for ESPs towards the latters' participation in the emerging flexibility markets.

Finally, we studied the problem of jointly considering a day-ahead load scheduling and a real-time DSM scheme that balances unexpected deviations from the agreed schedule. An energy market model (day-ahead and balancing market) was described that is aligned with the emerging liberalized electricity market expected to prevail within the next years. Given the day-ahead market agreements, we considered an approach where a market beneficiary violating its schedule is exposed to a dynamic per-unit penalty (the so called spread) through trading its violations in the balancing market, instead of incurring a fixed SLA violation penalty. Three different strategies (Active and Passive and Hybrid) for load shifting towards reducing market losses were described, simulated and compared. The Active strategy was proven to outperform the Passive one for spread values below a specific point. A Hybrid strategy, combining the advantages of the two, was also proposed and shown both theoretically and experimentally to perform better for any value of the flexibility and the spread. The spread parameter can be strategically chosen by the market operator to give incentives towards the desired energy prosumers' behavior. Our study can provide insights to policy makers for taking into account the expected users' behavior when defining the penalty policy. Applying the Hybrid strategy, we extracted a curve of revenue improvements as a function of flexibility and observed that they are linked in a monotonically increasing and convex way. We also presented a 3D graph showing the improvements obtained for different values for the flexibility and the spread.

Future research can use this study as an input: (i) for algorithms that define a user's flexibility versus discomfort tradeoff, modeling and accounting for the user's customized preferences, and (ii) policies regarding the consumers' compensation for providing flexibility. The benefits of cooperation were also demonstrated and studied for the case of multiple users forming clusters. The benefits of cooperation are higher when the cooperating users have negatively-correlated violation patterns, but they can also become significant for users with independent patterns, by increasing the number of participants. Our results can provide insights to investors and help subsidy policy makers in motivating investments of the most suitable kind in terms of DR flexibility efficiency in each geographical area. Future research directions include studying the degree to which cooperating users can increase their negotiating power towards becoming significant and active players in the energy market, by implementing a real-time receding horizon version of our algorithms to compensate for inaccurate forecasts, also taking into account physical network constraints.

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