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ΤΜΗΜΑ ΠΛΗΡΟΦΟΡΙΚΗΣ ΚΑΙ ΤΗΛΕΠΙΚΟΙΝΩΝΙΩΝ**

ΠΡΟΓΡΑΜΜΑ ΜΕΤΑΠΤΥΧΙΑΚΩΝ ΣΠΟΥΔΩΝ

ΔΙΔΑΚΤΟΡΙΚΗ ΔΙΑΤΡΙΒΗ

**Εφαρμογές Θεωρίας Βέλτιστης Παύσης στα Δίκτυα
Επικοινωνιών**

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**Applications of Optimal Stopping Theory in
Communication Networks**

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ΔΙΔΑΚΤΟΡΙΚΗ ΔΙΑΤΡΙΒΗ

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ΠΕΡΙΛΗΨΗ

Η παρούσα διατριβή επικεντρώνεται στη μελέτη μίας κατηγορίας ασύρματων δικτύων όπου η φόρτιση των κόμβων πραγματοποιείται με ασύρματο τρόπο μέσω ενός σταθμού βάσης που λειτουργεί ως πηγή ενέργειας. Εξοπλίζοντας τον κάθε αισθητήρα-κόμβο με τα κατάλληλα κυκλώματα μπορούμε να παρέχουμε αποτελεσματικά μια σταθερή πηγή τροφοδοσίας με έναν τρόπο οικονομικό και εύκολα εφαρμόσιμο. Προφανώς όπως σε κάθε ασύρματη μετάδοση, υπάρχουν παράγοντες που μπορούν να υποβαθμίσουν τη διαδικασία φόρτισης, όπως η ποιότητα του καναλιού μετάδοσης, η απόσταση του αισθητήρα από την πηγή ενέργειας και τα πιθανά φυσικά ή τεχνητά εμπόδια μεταξύ πομπού-δέκτη.

Στα ακόλουθα κεφάλαια επικεντρωνόμαστε σε προβλήματα που αφορούν τη διαδικασία φόρτισης και την επίδραση της μεθόδου αυτής στην ποιότητα λειτουργίας του δικτύου, όταν αυτό χρησιμοποιείται για την ανίχνευση κρίσιμων συμβάντων ή για την παρακολούθηση περιβαλλοντικών παραμέτρων.

Στο τρίτο κεφάλαιο μοντελοποιούμε την διαδικασία φόρτισης θεωρώντας ότι ο σταθμός βάσης εκπέμπει στην millimeter wave περιοχή συχνοτήτων όπου για τους σταθμούς βάσης 5ης γενιάς κυμαίνεται μεταξύ 24GHz και 40GHz. Η χρήση του συγκεκριμένου φάσματος μας δίνει αρκετά πλεονεκτήματα μιας και η κατευθυντικότητα του σήματος βελτιστοποιεί την διαδικασία φόρτισης. Στο ίδιο κεφάλαιο προτείνουμε ένα νέο πρωτόκολλο επικοινωνίας κατά το οποίο όταν ο λοβός ακτινοβολίας στρέφεται προς έναν αισθητήρα, ο αισθητήρας πρώτα φορτίζει για συγκεκριμένη χρονική περίοδο και στην συνέχεια επικοινωνεί με το σταθμό βάσης είτε για να αποστείλει κάποιες βασικές μετρήσεις ή για να ενημερώσει στην περίπτωση ενός συμβάντος.

Το πρώτο πρόβλημα που εξετάζουμε και παρουσιάζεται στο 4ο κεφάλαιο σχετίζεται με τη βελτιστοποίηση της διαδικασίας φόρτισης από την πλευρά του σταθμού βάσης στην περίπτωση αργών μεταβολών του καναλιού και σπάνιων κρίσιμων συμβάντων. Στην περίπτωση αυτή, ο σταθμός βάσης μπορεί να εξάγει αξιόπιστες εκτιμήσεις για το επίπεδο φόρτισης των κόμβων, μέσω μηνυμάτων αναφοράς από τους κόμβους, και λειτουργώντας προδραστικά να προσαρμόσει τον τρόπο φόρτισης. Βασιζόμενοι στις πληροφορίες που λαμβάνει ο σταθμός βάσης για το επίπεδο φόρτισης του κάθε αισθητήρα προτείνουμε δύο αλγόριθμους που καθορίζουν πώς θα κινείται ο λοβός ακτινοβολίας μεταξύ των περιοχών. Τα αποτελέσματα αποδεικνύουν ότι και οι δύο αλγόριθμοι υπερτερούν σε σύγκριση με τις συνήθεις διαδικασίες(κυκλική, τυχαία).

Το πρόβλημα που εξετάζουμε στην συνέχεια και παρουσιάζεται στο 5ο κεφάλαιο, επικεντρώνεται σε ένα δίκτυο αισθητήρων που παρακολουθεί μία περιοχή για πιθανά συμβάντα παρουσία υψηλού θορύβου μετρήσεων. Συγκεκριμένα, οι αισθητήρες θα πρέπει αυτόνομα να αναγνωρίζουν ένα συμβάν, όπως αυτό εκφράζεται ως αλλαγή στην κατανομή μίας μετρήσιμης παραμέτρου, και να μεταδίδουν τις σχετικές πληροφορίες στο σταθμό βάσης. Όμως, σε θορυβώδη περιβάλλοντα, αυξάνεται ο ρυθμός των ψευδών συναγερμών με αποτέλεσμα οι κόμβοι εσφαλμένα να μεταδίδουν συχνότερα προς το σταθμό βάσης και να

εξαντλούν τα ενεργειακά τους αποθέματα. Προσεγγίζουμε το πρόβλημα ως ένα πρόβλημα βέλτιστης παύσης όπου για να ξεπεράσουμε την επίδραση των υψηλών επιπέδων θορύβου στις μετρήσεις επιβάλουμε πριν τον αλγόριθμο ανίχνευσης μια φάση εξομάλυνσης της κατανομής της μετρήσιμης παραμέτρου. Προτείνουμε δύο μεθόδους εξομάλυνσης μια κλασσική τεχνική βασιζόμενη σε AR φίλτρα και μια νέα η οποία βασίζεται σε Beta Particle φίλτρα. Η αποτελεσματικότητα του κάθε φίλτρου στο σχήμα ανίχνευσης αναλύθηκε μέσω προσομοιώσεων.

Τέλος στο 6ο κεφάλαιο εξετάζουμε την περίπτωση που το δίκτυο χρησιμοποιείται για την περιοδική αποστολή μετρήσεων από μια περιοχή ενδιαφέροντος. Στόχος μας είναι να αναδείξουμε τις ιδιαιτερότητες ενός τέτοιου δικτύου και παράλληλα να προτείνουμε μια διαδικασία προγραμματισμού της αποστολής δεδομένων από τον κάθε αισθητήρα, λαμβάνοντας υπόψιν το επίπεδο φόρτισης του. Ο λόγος είναι ότι τα δίκτυα αισθητήρων που φορτίζονται ασύρματα, κάτω από συγκεκριμένες συνθήκες όπως η θέση του αισθητήρα η ποιότητα του καναλιού, αδυνατούν να στείλουν επιτυχώς τις μετρήσεις τους. Συνεπώς η λύση που προτείνουμε βασίζεται στην θεωρία των Markov διαδικασιών απόφασης και η λογική είναι ότι επιτρέπουμε αυτόνομα στον αισθητήρα να επιλέξει αν θα μεταδώσει άμεσα ή θα περιμένει την επόμενη περίοδο ώστε να είναι επαρκώς φορτισμένος.

ΘΕΜΑΤΙΚΗ ΠΕΡΙΟΧΗ: Θεματική Περιοχή

ΛΕΞΕΙΣ ΚΛΕΙΔΙΑ: Δίκτυα επικοινωνίας με ασύρματη μεταφορά ενέργειας, mmWave δίκτυα αισθητήρων, θεωρία βέλτιστης παύσης, διαδικασίες Markov

ABSTRACT

This thesis studies a class of wireless networks where charging is carried out wirelessly through one base station acting as an energy source. Equipping each sensor with the appropriate circuitry enables us to effectively provide a stable power source in a cost-effective and easily implementable manner. However, like any wireless transmission, some factors can degrade the charging process, such as the quality of the transmission channel, the distance of the sensor from the power source, and possibly physical or technical obstacles between the transmitter and receiver.

Therefore, in the following chapters, we focus on problems related to the charging process and to what extent the specific charging method affects the quality of its operation, both as a network for detecting critical events and as a network for monitoring environmental parameters.

In the third chapter, we model the charging process considering that the base station transmits in the millimeter wave frequency band, where 5th-generation base stations expect to operate. The millimeter band ranges between 24GHz and 40GHz. This specific spectrum gives us several advantages since the directionality of the signal optimizes the charging process. In the same chapter, we propose a new communication protocol. Based on the proposed protocol when the antenna directs the radiation beam at the sector where the sensor is located. The sensor first charges for a certain period and then communicates with the base station to send some basic measurements or to raise the alarm in case of an event.

Therefore, the first problem that we consider and presented in the 4th chapter focuses on optimizing the charging process from the side of the base station in case we have a slow variation of the transmission channel and rare critical events. In this case, the base station can derive reliable estimates of the charging level of the nodes through report messages from the nodes and proactively adjust the charging mode. Based on the base station's information about each sensor's charge level, we proposed two algorithms that determine how the radiation beam moves between the sectors. The results prove that both algorithms outperform the classic procedures (round robin, random).

The problem we next introduce and present in Chapter 5 focuses on a network of sensors monitoring an area for potential events in the presence of high measurement noise. In particular, the sensors should autonomously recognize an event, expressed as a change in the distribution of a measurable parameter, and transmit the relevant information to the base station. However, in noisy environments, false alarms increase, causing nodes to erroneously transmit more frequently to the base station and exhaust their energy reserves.

We approach the problem as an optimal stopping problem. To overcome the effect of high noise levels on the environment measurements, we imposed, before the detection algorithm, a smoothing phase of the distribution of the measured parameter. We proposed

two smoothing methods: a classical technique based on AR filters and a new one based on Beta Particle filters. The effectiveness of each filter in the detection scheme was analyzed through simulations.

Finally, in the 6th chapter, we examine the case where the network periodically sends measurements from an area of interest. Our goal is to highlight the features of such a network and propose a scheduling process for sending data from each sensor, considering its charge level. The reason for this is that wireless power sensor networks cannot effectively deliver their measurements when specific conditions exist, such as a far sensor position or poor channel quality. Therefore, the proposed solution is based on the Markov decision processes theory. The logic is that we allow the sensor autonomously to choose whether to transmit immediately or wait for the next period to be sufficiently charged.

SUBJECT AREA: Subject Area

KEYWORDS: Wireless powered communication network (WPCN), energy beamforming, mmWave sensor network, optimal stopping, Particle filters, Markov decision process (MDP)

ΣΥΝΟΠΤΙΚΗ ΠΑΡΟΥΣΙΑΣΗ ΤΗΣ ΔΙΔΑΚΤΟΡΙΚΗΣ ΔΙΑΤΡΙΒΗΣ

Τα τελευταία χρόνια, τα ασύρματα δίκτυα αισθητήρων χρησιμοποιούνται με επιτυχία σε πολλαπλούς τομείς της ανθρώπινης δραστηριότητας παρέχοντας πολλές νέες δυνατότητες. Νέες εφαρμογές και προϊόντα απαιτούν όλο και συχνότερα τη συνεργασία με ασύρματα δίκτυα αισθητήρων με σκοπό την επίλυση προβλημάτων που σχετίζονται με τη καθημερινότητά μας, την προσωπική υγεία, την προστασία του περιβάλλοντος και την ασφάλεια.

Ωστόσο, καθώς τα δίκτυα νέας γενιάς επεκτείνονται, το μέγεθος και η πολυπλοκότητα των δικτύων μεγαλώνουν με αποτέλεσμα πιο σύνθετα προβλήματα και ανάγκες να αναδεικνύονται συνεχώς, δημιουργώντας νέα πεδία έρευνας.

Αν θέλαμε να επισημάνουμε τις σημαντικότερες προκλήσεις στις οποίες τα ασύρματα δίκτυα νέας γενιάς καλούνται να ανταποκριθούν, είναι ο συνεχώς αυξανόμενος αριθμός αισθητήρων που τον απαρτίζουν και η ενεργειακή απόδοση του δικτύου. Συγκεκριμένα, η ραγδαία αύξηση του διαδίκτυου των πραγμάτων (Internet of things) δημιουργεί δίκτυα με δυσανάλογα μεγάλο αριθμό αισθητήρων και διαφορετικές απαιτήσεις. Αυτό οδηγεί αναπόφευκτα στο επανασχεδιασμό του τρόπου επικοινωνίας, τη συνεργασία μεταξύ των αισθητήρων και την χρήση νέων συχνοτήτων. Από την άλλη πλευρά, ένα δίκτυο για να είναι λειτουργικό θα πρέπει να εξασφαλίζει το απαιτούμενο επίπεδο ενεργειακής κάλυψης. Η ενεργειακή απόδοση του δικτύου είναι μια από τις πιο κρίσιμες παραμέτρους που αξιολογούν την απόδοση ενός δικτύου. Ο βαθμός φόρτισης και η δυνατότητα δυναμικής αλλαγής των επιπέδων ενέργειας σύμφωνα με τις απαιτήσεις των εφαρμογών απαιτούν νέες προσεγγίσεις στο πρόβλημα. Η αναλογία ποιότητας υπηρεσιών και ενεργειακής απόδοσης παραμένει ζωτικής σημασίας καθώς συνδέει άμεσα τις εφαρμογές δικτύου με το ενεργειακό αποτύπωμα καθ' αυτού του δικτύου.

Η παρούσα διατριβή εστιάζει σε μια κατηγορία δικτύων αισθητήρων όπου πρώτον η φόρτιση γίνεται ασύρματα χρησιμοποιώντας τεχνολογίες ασύρματης μεταφοράς ενέργειας, και δεύτερον οι συχνότητες που χρησιμοποιούνται τόσο για την φόρτιση όσο και για την επικοινωνία είναι στη ζώνη mmWave.

Οι αισθητήρες είναι εξοπλισμένοι με τα κατάλληλα κυκλώματα ώστε ασύρματα να φορτίζουν από μία ή περισσότερες πηγές ενέργειας. Αυτό δίνει στο δίκτυο ένα μεγάλο πλεονέκτημα διότι μειώνει σημαντικά το κόστος εγκατάστασης και λειτουργίας μιας και δεν απαιτείται ο αισθητήρας να είναι συνδεδεμένος είτε σε μια σταθερή παροχή ενέργειας ή σε μια εναλλακτική πηγή ενέργειας ευαίσθητη στις περιβαλλοντικές αλλαγές.

Επιπλέον, η χρήση των mmWave συχνοτήτων προσδίδει δύο σημαντικά πλεονεκτήματα. Το πρώτο είναι ότι εξαιτίας της κατευθυντικότητας και με τη χρήση κατάλληλων κεραιών, καθίσταται η διαδικασία φόρτισης γρηγορότερη και αποτελεσματικότερη. Το δεύτερο είναι ότι για την επικοινωνία τα δίκτυα αισθητήρων μπορούν να χρησιμοποιήσουν το υφιστάμενο δίκτυο 5ης γενιάς μιας και η mmWave ζώνη συχνοτήτων είναι αναπόσπαστο μέρος του. Συνεπώς, ενσωματώνοντας το δίκτυο αισθητήρων στο υφιστάμενο δίκτυο 5ης γενιάς κάνει

πιο εύκολη τη διαχείρισή του ακόμη και σε δίκτυα που ο αριθμός των αισθητήρων είναι σημαντικά μεγάλος.

Ένα δίκτυο αισθητήρων που φορτίζει ασύρματα πέρα από τα πλεονεκτήματα που αναφέραμε φέρνει και αρκετές προκλήσεις. Το δίκτυο θα πρέπει κάθε στιγμή να είναι κατάλληλα φορτισμένο ώστε να μπορεί να εξυπηρετήσει την εκάστοτε υποστηριζόμενη εφαρμογή. Οι αισθητήρες θα πρέπει να έχουν την απαραίτητη "ευφυΐα" ώστε να μπορούν να προσαρμόζονται στο περιβάλλον και να μπορούν να λαμβάνουν αποφάσεις όπου αυτό απαιτείται. Και τέλος θα πρέπει να μπορούν να λειτουργούν συνεργατικά αυξάνοντας την απόδοση του δικτύου.

Για το σύνολο των προβλημάτων που εξετάζονται στην παρούσα εργασία θεωρούμε ένα mmWave Wireless powered δίκτυο όπου οι αισθητήρες είναι τυχαία τοποθετημένοι σε μια κυκλική περιοχή. Οι αισθητήρες φορτίζονται ασύρματα από ένα σταθμό βάσης τοποθετημένο στο κέντρο της περιοχής. Θεωρούμε ότι ο σταθμός βάσης χρησιμοποιεί μια ομοιόμορφη γραμμική διάταξη κεραιών, και η κεραία στρέφει την δέσμη ακτινοβολίας κυκλικά ή τυχαία μεταξύ των τομέων που ορίζονται στην κυκλική περιοχή. Τέλος, το κανάλι μεταξύ του σταθμού και ενός αισθητήρα μοντελοποιείται ως fast-fading κανάλι Rayleigh, και είναι ανεξάρτητο για κάθε αισθητήρα.

Ο σταθμός βάσης πέρα από την φόρτιση των αισθητήρων είναι υπεύθυνος για την επικοινωνία και τον συντονισμό τους. Συνεπώς, ο καταμερισμός του χρόνου φόρτισης και του χρόνου για επικοινωνία είναι σημαντικός και επηρεάζει την απόδοση του δικτύου.

Το πρωτόκολλο επικοινωνίας που προτείνεται στη βιβλιογραφία θεωρεί ότι ο χρόνος παραμονής του λοβού ακτινοβολίας σε κάθε τομέα είναι σταθερός και κατανέμεται σε ένα ποσοστό για φόρτιση και σε ένα ποσοστό για επικοινωνία. Η δομή του πρωτοκόλλου αν και μας παρέχει την απαραίτητη λειτουργικότητα δεν έχει την ευελιξία που απαιτείται ώστε να μπορέσουμε να εξυπηρετήσουμε νέες λειτουργικότητες. Η παρούσα εργασία προτείνει ένα νέο πρωτόκολλο επικοινωνίας κατά το οποίο όταν η κεραία στρέφεται προς έναν αισθητήρα, ο αισθητήρας πρώτα φορτίζει για συγκεκριμένη χρονική περίοδο και στην συνέχεια επικοινωνεί με το σταθμό βάσης είτε για να αποστείλει κάποιες βασικές μετρήσεις ή για να ενημερώσει στην περίπτωση ενός συμβάντος μεταδίδοντας με όλη την αποθηκευμένη ενέργεια του αισθητήρα. Η κύρια διαφοροποίηση είναι ότι πέρα από τις δύο βασικές περιόδους φόρτισης και επικοινωνίας με το σταθμό βάσης, προστίθεται και μια χρονική περίοδος (reporting) που μπορεί να χρησιμοποιηθεί για διάφορες εφαρμογές όπως για παράδειγμα την επικοινωνία με γειτονικούς αισθητήρες ή την αποστολή σύντομων πληροφοριών στο σταθμό. Κατά την περίοδο αυτήν ο αισθητήρας μεταδίδει χρησιμοποιώντας ένα μικρό ποσοστό της αποθηκευμένης του ενέργειας.

Για την περίοδο φόρτισης, θεωρώντας ένα μη γραμμικό μοντέλο φόρτισης, προσδιορίζουμε τα επίπεδα ενέργειας φόρτισης σε σχέση με το κανάλι και την ταχύτητα φόρτισης του αισθητήρα. Επιπρόσθετα, υπολογίζουμε τη μέση τιμή φόρτισης ανά περίοδο τόσο για διάφορες θέσεις του αισθητήρα όσο και για τα διαφορετικά κανάλια μετάδοσης παρουσιάζοντας την εξάρτηση που έχει ο αισθητήρας από τη θέση του στον τομέα και τη δυνατότητα φόρτισης.

Για την προτεινόμενη περίοδο αναφοράς (reporting) όσο και για την περίοδο μετάδοσης

η κρίσιμη παράμετρος που καθορίζει την αποτελεσματικότητα του δικτύου είναι η εκτίμηση της πιθανότητας επιτυχούς αποστολής της διαθέσιμης πληροφορίας προς το σταθμό βάσης. Με βάση τον τρόπο που η κεραία στρέφει την δέσμη ακτινοβολίας (κυκλικά ή τυχαία) μεταξύ των τομέων υπολογίζεται η πιθανότητα επιτυχούς μετάδοσης και η εξάρτησή της από το μοντέλο φόρτισης. Παρέχουμε με αυτόν τον τρόπο τα κατάλληλα εργαλεία ανάλυσης για τον αποτελεσματικό σχεδιασμό του δικτύου ανάλογα με τις εκάστοτε απαιτήσεις.

Τα δίκτυα αισθητήρων έχουν χρησιμοποιηθεί και αναλυθεί εκτενώς για την ανίχνευση σφαλμάτων. Για την κατηγορία των δικτύων που εξετάζουμε στην παρούσα εργασία έχουν αναδειχθεί νέα προβλήματα που μέχρι στιγμής δεν έχουν αναλυθεί από την υπάρχουσα βιβλιογραφία. Η φόρτιση όπως προαναφέραμε είναι σημαντική παράμετρος που επηρεάζει ουσιαστικά την αποτελεσματικότητα επιτυχούς ανίχνευσης και επικοινωνίας ενός γεγονότος. Συνεπώς, η μέθοδος με την οποία ο σταθμός βάσης φορτίζει το δίκτυο και συγκεκριμένα ο τρόπος που κάθε φορά στρέφει την κεραία του σε έναν τομέα εξασφαλίζει τόσο την διατήρηση ενός ενεργειακού επιπέδου φόρτισης του δικτύου, όσο και την άμεση και επιτυχή επικοινωνία με τους αισθητήρες που βρίσκονται στην περιοχή που δημιουργείται ένα γεγονός.

Η παρούσα διατριβή προτείνει δύο νέες στρατηγικές φόρτισης των αισθητήρων σε σχέση με τις κλασσικές μεθόδους. Εφαρμόζοντας το πρωτόκολλο που αναφέραμε παραπάνω και συγκεκριμένα χρησιμοποιώντας την περίοδο αναφοράς για την αποστολή της ενεργειακής κατάστασης του αισθητήρα, ο σταθμός βάσης λαμβάνει γνώση της ενεργειακής κατάστασης συνολικά του δικτύου. Αυτό δίνει στο σταθμό βάσης την δυνατότητα για επιλογή εναλλακτικών και πιο αποδοτικών στρατηγικών φόρτισης μέσω του αλγορίθμου που επιλέγει κατά πού θα πρέπει να στρέψει η κεραία τη δέσμη ακτινοβολίας.

Η μετάδοση στη mmWave ζώνη συχνοτήτων λόγω της κατευθυντικότητας είναι ευαίσθητη σε φυσικά εμπόδια που δεν επιτρέπουν στον αισθητήρα να φορτιστεί ικανοποιητικά. Για το λόγο αυτό, ως λύση εξετάζουμε την τεχνική flooding για την παράδοση μηνυμάτων αναφοράς. Δηλαδή, προσθέτοντας την δυνατότητα σε κάθε αισθητήρα να μπορεί να λαμβάνει τις αναφορές των γειτονικών αισθητήρων και να λειτουργεί ως αναμεταδότης, αποδεικνύουμε ότι μπορούμε να αυξήσουμε την αξιοπιστία του συστήματος και να ελαχιστοποιήσουμε την καθυστέρηση παράδοσης.

Προτείνονται και αξιολογούνται δύο στρατηγικές σε σχέση με τις κλασσικές μεθόδους όπου μια κεραία στρέφει τη δέσμη ακτινοβολίας (κυκλική και τυχαία) μεταξύ των τομέων. Η πρώτη στρατηγική που προτείνεται στην παρούσα εργασία οδηγεί το σταθμό βάσης να εξυπηρετεί τον κάθε τομέα με διαφορετική συχνότητα, με κριτήριο των αριθμό αναφορών που λαμβάνει. Αυτό μας εξασφαλίζει ενεργειακή επάρκεια του δικτύου χωρίς να αμελούνται παράλληλα τομείς από τους οποίους λαμβάνουμε μικρό αριθμό αναφορών. Αντιθέτως μάλιστα ο αλγόριθμός έχει δυνατότητα να τους εντοπίσει και να τους ενισχύσει εγγυώμενος ένα γρήγορο δίκτυο ανίχνευσης πιθανών γεγονότων. Ο προτεινόμενος αλγόριθμος στηρίζεται σε ένα κριτήριο βελτιστοποίησης που εξισορροπεί δύο κρίσιμες παραμέτρους. Πρώτον, τον αριθμό των αναφορών που λαμβάνει ο σταθμός βάσης από το δίκτυο, δηλαδή μια τιμή που εκφράζει το επίπεδο φόρτισής του και που οδηγεί τον σταθμό βάσης να κατευθύνει την δέσμη του στους τομείς όπου λαμβάνει υψηλό αριθμό αναφορών. Με αυτό τον τρόπο επιτυγχάνει υψηλά επίπεδα φόρτισης, με την πιθανότητα ανίχνευσης και επιτυχούς μετάδο-

σης του γεγονότος να αυξάνονται. Η δεύτερη παράμετρος είναι η χρονική διάρκεια που δεν έχει εξυπηρετηθεί ο εκάστοτε τομέας από την κεραία. Αυτό μας εξασφαλίζει ότι η κεραία θα κατευθυνθεί και σε τομείς με χαμηλό αριθμό αναφορών με στόχο την επαρκή τους φόρτιση. Με αυτό τον τρόπο το δίκτυο σε περίπτωση ενός συμβάντος στους τομείς αυτούς θα μπορεί να μεταδώσει το γεγονός στο σταθμό βάσης με μικρή καθυστέρηση.

Η δεύτερη στρατηγική βασίζεται σε μια κατηγορία προβλημάτων της θεωρίας βέλτιστης παύσης, τα προβλήματα multi-armed bandit. Εν συντομία, ένα χαρακτηριστικό παράδειγμα αυτής της κατηγορίας προβλημάτων που μας εισάγει στις βασικές έννοιες της θεωρίας είναι το πρόβλημα κατά το οποίο ένας παίκτης επισκέπτεται ένα καζίνο και πρέπει να αποφασίσει πόσες φορές θα παίξει και με ποια ακολουθία, μια σειρά από κουλοχέρηδες ώστε να μεγιστοποιήσει τα κέρδη του. Εάν ο παίκτης γνώριζε την κατανομή κερδοφορίας του κάθε μηχανήματος, θα συνέχιζε να παίζει αυτό με την υψηλότερη κερδοφορία. Το ενδιαφέρον είναι στην περίπτωση που δεν γνωρίζει τις κατανομές των μηχανών αλλά καλείται να τις εκτιμήσει καθώς παίζει παρακολουθώντας το αποτελέσματα κάθε επιλογής του. Συνεπώς θα πρέπει μετά από κάθε επιλογή και αξιολογώντας το αποτέλεσμα να αποφασίσει αν θα συνεχίσει με το μηχάνημα που έως τώρα λαμβάνει την μεγαλύτερη ανταμοιβή «exploitation» είτε να επιλέξει κάποια άλλη μηχανή «exploration» για να μάθει περισσότερα για την κερδοφορία της. Ο δεύτερος αλγόριθμος δανείζεται ιδέες από τη λύση του multi-armed bandit προβλήματος και συγκεκριμένα του αλγόριθμου ανώτερου ορίου εμπιστοσύνης (UCB1). Θεωρώντας το ίδιο κριτήριο βελτιστοποίησης όπως και στην πρώτη στρατηγική οι δύο επιλογές που καλείται να επιλέξει ο σταθμός βάσης κάθε φορά που πρέπει να στρέψει προς έναν τομέα τη δέσμη του είναι είτε να παραμείνει στους τομείς που λαμβάνει τις περισσότερες αναφορές («exploitation» σε αντιστοιχία με τα κέρδη του παραδείγματος), είτε να επιλέξει τομείς με μικρό αριθμό αναφορών που πιθανόν θα του προσφέρουν επιπλέον πληροφορίες ή την ενημέρωση για ένα γεγονός. Τα αποτελέσματα των προσομοιώσεων αποδεικνύουν ότι και οι δύο στρατηγικές υπερνικούν τις κλασσικές μεθόδους, αυξάνοντας το επίπεδο φόρτισης του δικτύου, αυξάνοντας την πιθανότητα επιτυχούς μετάδοσης και μειώνοντας το χρόνο μετάδοσης ενός γεγονότος.

Το δεύτερο πρόβλημα που εξετάζει η παρούσα διατριβή εστιάζει στις τρεις βασικές λειτουργίες του αισθητήρα: την φόρτιση, την μετάδοση δεδομένων και την επιτυχή ανίχνευση ενός συμβάντος. Ο αισθητήρας λαμβάνει μετρήσεις από το περιβάλλον και προσπαθεί να ανιχνεύσει μια πιθανή αλλαγή στην κατανομή της παρακολουθούμενης παραμέτρου. Σε περίπτωση συμβάντος, ο αισθητήρας θα πρέπει άμεσα να μεταδώσει ό,τι διαθέσιμη πληροφορία έχει συλλέξει προς το σταθμό βάσης με όση διαθέσιμη ενέργεια διαθέτει. Καθώς οι μετρήσεις που συλλέγει ο αισθητήρας μπορεί να είναι θορυβώδεις λόγω της φύσης του φαινομένου που παρακολουθείται ή της ποιότητας του ίδιου του αισθητήρα, η διαδικασία ανίχνευσης μπορεί να οδηγήσει σε εξαιρετικά μεγάλο αριθμό ψευδών συναγε-
μών.

Θεωρώντας ότι όλοι οι αισθητήρες αντιμετωπίζουν κάθε συναγε-
μώ ως αληθινό συμβάν, προσπαθούν να μεταδώσουν άμεσα ό,τι διαθέσιμη πληροφορία έχουν συλλέξει για το γεγονός στο σταθμό βάσης. Αυτό έχει ως αποτέλεσμα ο αισθητήρας να εξαντλεί συχνά τα ενεργειακά του αποθέματα και να μην μπορεί να επιτύχει επαρκή φόρτιση μειώνοντας σημαντικά την πιθανότητα επιτυχούς αποστολής της διαθέσιμης πληροφορίας στην περι-

πτώση ενός πραγματικού γεγονότος.

Η παρούσα εργασία προσεγγίζει το πρόβλημα ως ένα πρόβλημα βέλτιστης παύσης που προσδιορίζει την βέλτιστη χρονική στιγμή που ο αισθητήρας θα αποφασίσει να μεταδώσει ότι υφίσταται κάποιο γεγονός. Τρεις είναι οι κύριοι παράγοντες που επηρεάζουν την απόφαση. Η πιθανότητα ψευδούς συναγερμού, η μέση καθυστέρηση στη μετάδοση και η πιθανότητα επιτυχημένης μετάδοσης. Για παράδειγμα, για να μεγιστοποιήσουμε την πιθανότητα μιας επιτυχημένης μετάδοσης, θα πρέπει ο αισθητήρας να αναβάλει την μετάδοση έως ότου φορτιστεί επαρκώς ώστε να είναι σε θέση να μεταδώσει ακόμη και αν οι συνθήκες του καναλιού είναι κακές ή ο αισθητήρας βρίσκεται στα όρια του τομέα. Από την άλλη πλευρά όσο ο αισθητήρας αναβάλει την μετάδοση έχει ως επίπτωση την αύξηση της καθυστέρησης στην μετάδοση της κρίσιμης πληροφορίας προς τον σταθμό βάσης. Επιπρόσθετα, έχοντας θεωρήσει στο πρόβλημα που εξετάζουμε ότι οι αισθητήρες δεν έχουν την δυνατότητα να αναμεταδώσουν πληροφορία από γειτονικούς κόμβους, η πιθανότητα επιτυχούς μετάδοσης είναι άμεσα συνδεδεμένη με το επίπεδο φόρτισης του αισθητήρα. Ο αισθητήρας λαμβάνοντας συνεχόμενες μετρήσεις από το περιβάλλον εκτιμά κάθε χρονική στιγμή την κατανομή της παραμέτρου. Ο αισθητήρας αντιλαμβάνεται ως συμβάν οποιαδήποτε αλλαγή ξεπερνά ένα συγκεκριμένο κατώφλι. Θεωρώντας την ύπαρξη υψηλού θορύβου στο περιβάλλον όπου ο αισθητήρας καλείται να λειτουργήσει, το κατώφλι αυτό διασχίζεται αρκετά συχνά, οδηγώντας τον αισθητήρα σε εσφαλμένες μεταδόσεις και συνεπώς σε χαμηλά επίπεδα φόρτισης.

Για να ξεπεραστεί το πρόβλημα, στη παρούσα εργασία προτείνουμε την προσθήκη ενός επιπλέον βήματος που στοχεύει στην εξομάλυνση της κατανομής πριν ο αισθητήρας αποφασίσει αν η κατανομή έχει ξεπεράσει το κατώφλι που έχουμε ορίσει. Δύο μέθοδοι παρουσιάζονται: α) η κλασσική μέθοδος με χρήση AR φίλτρου και β) μια καινοτόμος μέθοδος η οποία βασίζεται στην θεωρία των Beta Particle φίλτρων. Όλες οι τεχνικές αναλύθηκαν και αξιολογήθηκαν μέσω προσομοιώσεων αναδεικνύοντας τα πλεονεκτήματα και την αποτελεσματικότητά τους.

Η τελευταία εφαρμογή που εξετάζεται στην παρούσα εργασία είναι ένα δίκτυο που χρησιμοποιείται για την περιοδική αποστολή μετρήσεων από μια περιοχή ενδιαφέροντος. Στόχος μας είναι να αναδείξουμε τις ιδιαιτερότητες ενός τέτοιου δικτύου και παράλληλα να προτείνουμε μια διαδικασία προγραμματισμού της αποστολής δεδομένων από τον κάθε αισθητήρα, λαμβάνοντας υπόψιν το επίπεδο φόρτισής του. Ο λόγος είναι ότι οι αισθητήρες που φορτίζονται ασύρματα μέσα σε αυτό το δίκτυο, κάτω από συγκεκριμένες συνθήκες, όπως η θέση και η ποιότητα του καναλιού, αδυνατούν να στείλουν επιτυχώς τις μετρήσεις τους. Για το συγκεκριμένο πρόβλημα, η λύση που προτείνουμε βασίζεται στη θεωρία των διαδικασιών απόφασης Markov και είναι να επιτρέπουμε αυτόνομα στον αισθητήρα να επιλέξει αν θα μεταδώσει άμεσα ή θα περιμένει την επόμενη περίοδο ώστε να είναι επαρκώς φορτισμένος. Για να περιγράψουμε το κέρδος του καναλιού θεωρούμε ένα μοντέλο καναλιού Markov πεπερασμένων καταστάσεων. Η κάθε κατάσταση μοντελοποιεί το λαμβανόμενο SNR και θεωρώντας ένα κανάλι αργών διαλείψεων, επιτρέπουμε μεταβάσεις μόνο μεταξύ γειτονικών καταστάσεων.

Για να ορίσουμε την αλυσίδα αποφάσεων του αισθητήρα, θεωρούμε μια 2-D αλυσίδα Markov, με πρώτη διάσταση την αποθηκευμένη ενέργεια του αισθητήρα πριν από την

απόφαση και ως δεύτερη διάσταση την ενέργεια που συλλέγεται κατά την τρέχουσα χρονική περίοδο. Στη συνέχεια, υπολογίζουμε τις πιθανότητες είτε ο αισθητήρας να συνεχίσει τη φόρτιση ή να μεταδώσει. Ο στόχος είναι να βρεθεί η βέλτιστη πολιτική που μεγιστοποιεί μια ανταμοιβή η οποία θα λαμβάνει υπόψιν τον μέσο αριθμό επιτυχών μεταδόσεων. Επιπρόσθετα, εισάγουμε στη πολιτική μας μια παράμετρο που σκοπό έχει να ρυθμίζει την καθυστέρηση των ενεργειών με βάση την εφαρμογή που εξυπηρετεί το δίκτυο. Εάν η τιμή της παραμέτρου είναι μικρή, τότε δίνεται μικρή έμφαση στις μελλοντικές ανταμοιβές και η ενέργεια γίνεται όσο το δυνατόν νωρίτερα. Από την άλλη, μια μεγάλη τιμή αναβάλλει τις ενέργειες αυξάνοντας την επιτυχή αποστολή των μετρήσεων. Για να βρούμε τη βέλτιστη πολιτική, χρησιμοποιούμε τον γνωστό αλγόριθμό Value iteration και μέσω προσομοιώσεων αναδεικνύουμε τα πλεονεκτήματα της μεθόδου.

Από την διατριβή αυτήν προκύπτουν επιπλέον περιοχές έρευνας και προβλήματα για περαιτέρω μελέτη. Εξοπλίζοντας με νέες λειτουργικότητες τους αισθητήρες που προωθούν την συνεργατικότητα μεταξύ των αισθητήρων, η απόδοση του δικτύου θα μπορούσε να ενισχυθεί περαιτέρω. Σε συνέχεια του προβλήματος επιτυχούς ανίχνευσης σε περιβάλλον υψηλού θορύβου η προσθήκη της συνεργασίας και της διαλειτουργικότητας μεταξύ των αισθητήρων, αυξάνει την "ευφυΐα" του δικτύου και του δίνει τη δυνατότητα να λειτουργήσει και σε χαμηλότερα επίπεδα φόρτισης. Παράλληλα συνθέτοντας από διαφορετικούς αισθητήρες πληροφορίες θα μπορεί το δίκτυο με μεγαλύτερη αξιοπιστία να αποφασίζει για την εγκυρότητα ενός γεγονότος.

Από την πλευρά του σταθμού βάσης, αξιοποιώντας περαιτέρω τον προτεινόμενο μηχανισμό αναφοράς, μπορούμε να τον χρησιμοποιήσουμε και για άλλες κρίσιμες λειτουργίες πέραν της απλής ενημέρωσης των επίπεδων φόρτισης των αισθητήρων. Για παράδειγμα, ενδείξεις πρώιμων συμβάντων θα μπορούσαν να κοινοποιούνται στο σταθμό βάσης, χρησιμοποιώντας τον προτεινόμενο μηχανισμό αναφοράς. Στην περίπτωση αυτή, ο σταθμός βάσης θα μπορούσε προσωρινά να σταματήσει να φορτίζει και να λαμβάνει πληροφορία από τους υπόλοιπους τομείς και να κατευθύνει τη δέσμη της προς την περιοχή ενδιαφέροντος.

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LIST OF PUBLICATIONS

- [1] Michael Koutsoumpos, Evangelos Zervas, Efstathios Hadjiefthymiades, and Lazaros Merakos. Monitoring for rare events in a wireless powered communication mmwave sensor network. *Sensors*, 20(12):3341, 2020.
- [2] Michael Koutsoumpos, Evangelos Zervas, Efstathios Hadjiefthymiades, and Lazaros Merakos. A comprehensive study of event detection in wpcn networks with noisy measurements. *Sensors*, 22(6):2163, 2022.
- [3] Michael Koutsoumpos, Evangelos Zervas, Efstathios Hadjiefthymiades, and Lazaros Merakos. An mdp approach to transmission scheduling in wpcn networks. In *Proceedings of the 26th Pan-Hellenic Conference on Informatics*, pages 169–174, 2022.

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PREFACE

This dissertation is submitted for the degree of Doctor of Philosophy at the National and Kapodistrian University of Athens, Greece. The research described herein was conducted under the guidance and supervision of Professor Lazaros Merakos in the Department of Informatics and Telecommunications, National and Kapodistrian University of Athens, Greece.

Part of work has been presented in a series of international conferences and journal articles, as detailed in the section titled “List of Publications”. This work is at the best of my knowledge original, except where acknowledgments and references are made to previous works. Hereby I declare that this doctoral dissertation, my original investigation and achievement, has not been submitted for any other academic degree, diploma or other qualification at any other university.

Michael Koutsoumpos

January 2023

1. INTRODUCTION

1.1 Wireless Sensor Networks

Future technologies are expected to be fully integrated with the physical environment, providing advanced perceptive capabilities and potentially powered only by the environment. Sensor technology advancements are already successfully applied by various industry sectors. They are used to detect light, heat, position, movement, chemical presence, and other phenomena. Wireless sensor networks, much more than today's personal computers, will undoubtedly become a vital part of our lives soon.

A wireless sensor network refers to a topology of energy-independent nodes used to monitor physical quantities (temperature, pressure, humidity, motion, image, and sound). A typical wireless sensor node comprises sensing, computing, communication, and power components. The sensor location may or may not be predefined. This property gives the sensor network the ability to deploy and expand to areas without having complete knowledge of the deployment environment, such as harness environments.

The way the sensors communicate is another feature of sensor networks. Wirelessly, the nodes transmit their processed or unprocessed data to a base station using a communication protocol. The base station serves as a connection point between the sensors and the backbone network, collecting and processing data from the sensors. Consequently, relative decisions can be made locally by the sensor node (for example, detecting a change in the monitored environment) or centrally by the base station in more complicated scenarios.

1.1.1 Applications of wireless sensor network

In recent years, Wireless Sensor Networks have been successfully applied in various domains. New applications and products adopt wireless sensor technologies, attempting to solve daily problems associated with our urban living, personal health, environmental protection, and safety.

Traffic congestion is an issue that all modern cities face. The failure of current traffic light systems to manage the flow of vehicles at junctions adds to the congestion problem. Most existing systems use a fixed time control to set traffic lighting plans [6]. The difficulty with this sort of control is that it doesn't always favor the flow of most vehicles. Moreover, it is incapable of recognizing when accidents cause traffic gridlock. Wireless sensor networks are used in modern transport systems to collect traffic data and make decisions regarding the traffic plan, such as green light duration. Sensors are set up at various points on the road to keep track of the number and speed of vehicles in each lane of an intersection.

The next-generation healthcare system is another potential WSN application field that will benefit society considerably [17]. There's no doubt that WSN and IoT technologies are revolutionizing healthcare by allowing doctors, patients, and medical devices to communicate in new ways. Patients' healthcare indicators are tracked in real-time using wearable de-

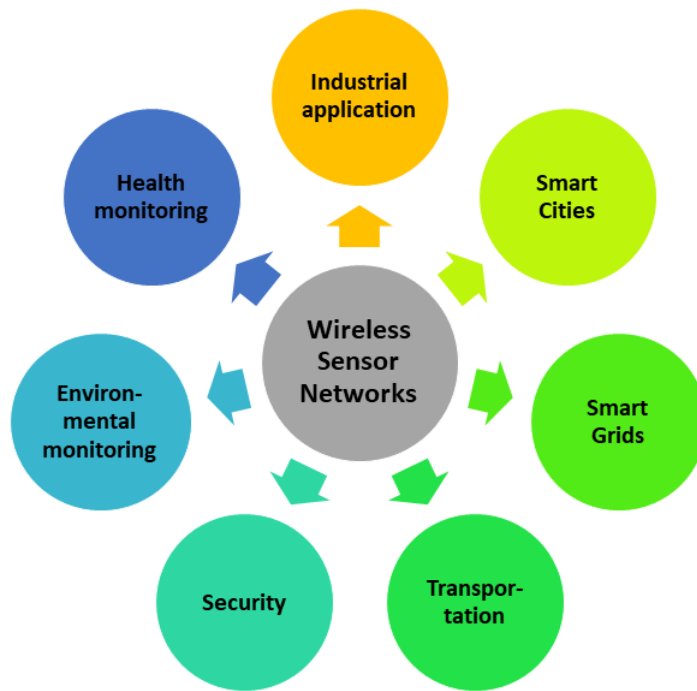


Figure 1.1: Applications of Wireless Sensor Networks.

vices, such as activity trackers, heart rate and blood pressure monitoring sensors. Based on their measurements, they offer patients individualized suggestions on how to improve their medical state. Moreover, potentially life-threatening conditions are recognized early. Sensors also provide doctors with up-to-date information about the patient's health status at the hospital. In turn, doctors can assess therapy effectiveness, learn more about the illness and track its progression.

Bridges, buildings, and other civil engineering structures/infrastructure are essential for our society's safe and effective operation. To effectively monitor and analyze civil engineering structures is crucial. Wireless sensor networks can successfully monitor and evaluate civil engineering constructions, providing city-states with a low-cost solution to increase public safety. This type of system keeps track of a structure by collecting data from sensors, recognizing defects, and evaluating the information to determine the structural condition. Additionally, various structural features (such as bending and fracture) may require monitoring from several sensors. A wireless sensor network can easily support such a dense network of sensors, providing a low-cost real-time monitoring solution [64].

In the modern world, agriculture faces many challenges, such as the exponential increase in food demand because of population growth, water, and air pollution, greenhouse gas emissions, and global warming. All the abovementioned problems bring us closer and closer to the danger of lack of resources and highlight the urgent need for creative and long-term solutions based on innovative technology, such as wireless sensor networks [1]. A wireless sensor network expands across the field and gathers real-time data from the soil

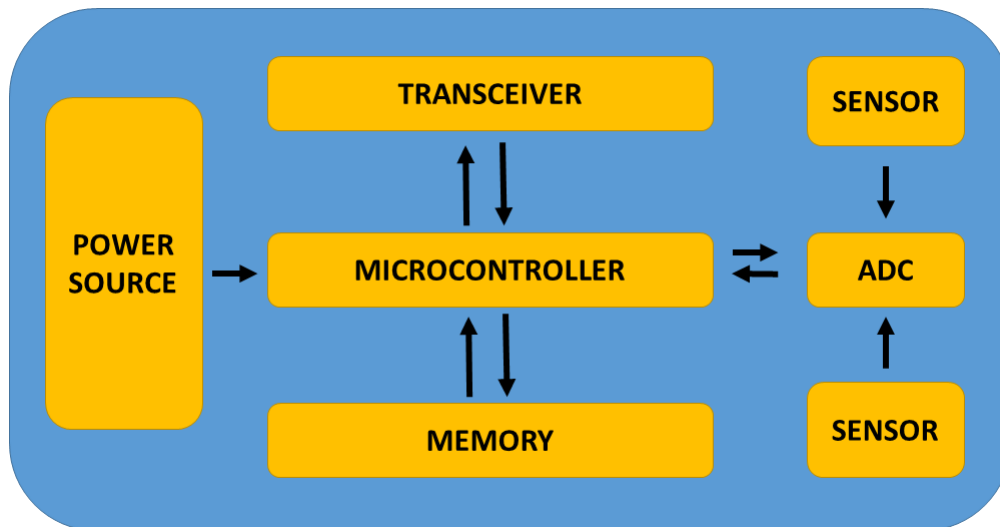


Figure 1.2: Structure of a wireless sensor network.

and environment. Soil moisture, temperature, humidity, and crop conditions are indicative monitor parameters that the system can be relied on for improved farming decisions and protection against hazardous phenomena.

1.1.2 Structure of a wireless sensor network

A sensor node is composed of an RF transceiver for communication, a microprocessor (CPU), random access memory (RAM) for data processing (optional can also carry permanent data storage), and a small battery that provides it with limited energy autonomy. The node is equipped with the appropriate sensors for data collection (temperature, humidity, object detection). It includes an ADC (Analogue to Digital) conversion unit that transforms data gathered by the sensors from the analog to the digital domain for further processing by the node processor before delivering it to the sink node through the wireless network.

Optionally, a node can have a GPS unit that helps locate the node within the network development area and map its exact location. Moreover, a node can utilize a module unit that allows it to recharge its battery using an alternate kind of energy (photovoltaic cells).

Each node consists of the following essential components:

1. Micro-controller: The microcontroller is the most fundamental component since it is necessary for system synchronization and task execution. The devices process, send and receive data based on the microcontroller. In certain circumstances, general-purpose microprocessors such as FPGA, DSP, and ASIC are used instead of microcontrollers, although they are not ideal when the system requires low energy, low cost, ease of programming, and collaboration with the system's peripherals.
2. Memory (external memory): Most often, the use of flash is selected in combination

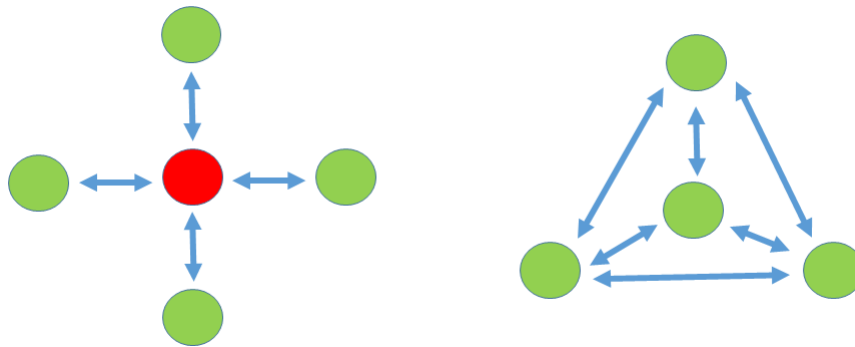


Figure 1.3: Star topology (left), Mesh topology (right).

with the processor's built-in memory. The reason is that in this way we achieve low energy consumption.

3. Transceiver: Transceivers are the building components for communication between nodes or the base station. Radiofrequency (RF), optical communication (laser), and infrared (IR) are the most common communication technologies used. The most prominent is RF since the other two confront challenges such as eye contact, suitable environmental conditions, and a lack of broadcast capability.
4. Power source: The most critical challenge in wireless sensor networks is energy conservation and power supply. Each node element necessitates the use of energy from batteries or other renewable sources (solar panels). The highest percentage of energy consumption is due to communication tasks with either the neighboring nodes or the base station. Usually, the energy consumption for processing tasks is considered negligible.

1.1.3 Topology of a wireless sensor node

Sources and sinks are essential components of wireless sensor networks. Sources gather data by examining their surroundings, whereas sinks are the destination nodes of the collected data and information. How the sources interact with each other and the sinks determines the topology of each network. The most common topologies are:

Star network

A star network is composed of a single base station(sink) located at the center of the monitor area. Sink sends/receives messages to/from all nodes located in its communication area. The simplicity of the scheme and the ability to keep node power consumption to a minimum are two advantages of this type of topology.

Low-latency communication between the distant node and the base station is also possible due to the direct link between the node and the base station.

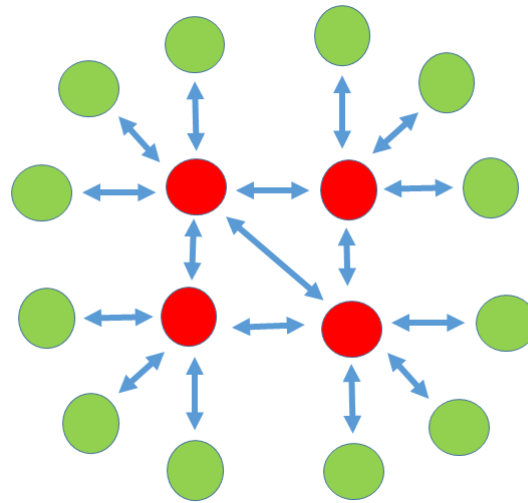


Figure 1.4: Hybrid topology.

Mesh network

A mesh network allows data to be sent from one node to another within its radio broadcast radius. If a node needs to forward a message to a distant node located out of its radio communications range, it must use an intermediary node to transfer the message to the intended node.

This network topology provides redundancy and scalability. If a single node used to forward a message fails, the source node can still communicate with all the other neighbor nodes to efficiently transmit the message to the intended destination. Moreover, the mesh topology gives the network operator the ability to efficiently and cost-effectively expand the monitor area by simply adding more nodes to the system.

A disadvantage of the mesh topology is the power consumption for nodes that implement multi-hop communications compared to the star topology. Moreover, as the number of communication hops to a destination increases, so does the delay in delivering the message.

Hybrid star

A hybrid of the star and mesh networks provides a resilient and adaptable communications network while keeping the power consumption of the wireless sensor nodes to a minimum. The sensor nodes with the lowest power energy are not allowed to relay messages in this network design. This ensures that power usage is kept to a minimum.

Nodes with high energy capacity, on the other hand, possess multi-hop capabilities, which allow them to relay messages from low-power nodes to other network nodes. Multi-hop nodes are usually more powerful and, if feasible, are connected to the electricity network.

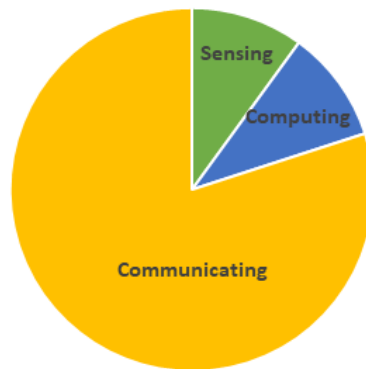


Figure 1.5: Energy consumption in wireless sensor network.

1.1.4 Energy consumption in wireless sensor network

Since batteries are often the only power source of sensor nodes, energy consumption is the most crucial aspect in determining the lifespan of a sensor network. Energy optimization includes approaches for both decreasing energy usage and prolonging the network's life as much as possible. The algorithms should assure the optimal use of energy overall, both as a system and individually for each node.

Sensing Energy Consumption

A sensing unit measures physical parameters in the sensory environment and transforms them into digital signals. The processing unit then processes these signals. The sensing unit consumes energy for physical signal sampling and analog to digital conversion.

The level of consumption is related to the characteristics of the parameter we want to observe. Intermittent sensing, for example, uses less energy than continuous monitoring; hence, if the monitor parameter allows for periodic sampling, intermittent sensing can be used as a power-saving method. However, it's worth noticing that sensing energy represents only a small fraction of the total power consumption in a WSN.

Computing Energy Consumption

A microcontroller unit (MCU) with memory serves as the processing unit. Its job is to process data from the sensor unit, to make decisions, and to ensure that the sensor node runs smoothly. Specifically, a micro-operating system is installed on the computing unit to control and manage the sensing, processing, and communication components.

Energy consumption is related to the operating voltage and frequency of the sensor. Energy-saving strategies aim to optimally adjust the aforementioned parameters while maintaining microcontroller performance. However, similar to sensing energy consumption, computing consumption represents only a small fraction of the total power consumption in a WSN.

Communicating Energy Consumption

A short-range RF circuit that handles data transmission and reception is the essential component of a sensor node's communication unit. The frequency of the communication task and the transmission distance are the main parameters that affect energy consumption by the communication unit.

Two major energy-saving approaches include reducing transmission distances and assigning processing activities to the sensor. To shorten the transmission range between nodes, we employ multi-hop routing rather than single-hop. Additionally, local data processing may reduce the amount of data to be transferred thus saving a considerable amount of energy. As a result, minimizing the quantity of data transferred between sensors and dividing a long transmission distance into multiple short ones are critical components of optimizing communication energy.

1.2 Wireless Power Sensor Networks

Wireless power sensor systems are composed of sensors whose integrated batteries recharge wirelessly using microwave wireless power transfer (WPT) technology.

Therefore, wireless charging methods provide us the flexibility to disconnect the sensor operation from all its limitations and dependencies that fall under the exclusive use of classic batteries. This allows us to operate the sensor at a higher energy consumption level (as an example for transmission) and achieve a longer battery life [50],[36]

Wireless charging in a sensor network has significant advantages over renewable energy source solutions. First, the network is powered constantly by a power source usually situated at the system's center. Secondly, the sensor network is not significantly affected by environmental conditions.

The main energy-harvesting techniques are magnetic induction and radio-frequency-based wireless power transfer (WPT). The former can be used effectively only on a few centimeters of transmission ranges, and it is today used in various devices, including mobile phone charging pads and medical implants. On the other hand, Radiofrequency (RF) WPT supports relatively long transmission ranges, suitable for IoT devices, such as wireless power sensors located in dense areas.

1.2.1 Wireless power transfer

We can divide WPT into three major categories

- Inductive coupling
- magnetic resonant coupling
- RF-enabled WET

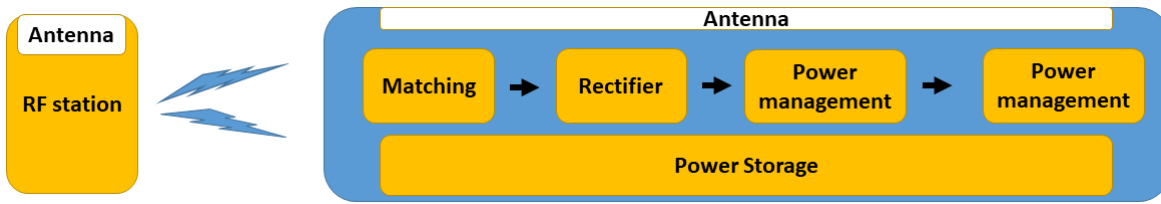


Figure 1.6: Energy harvesting system.

Inductive and magnetic resonant coupling is near-field wireless charging technologies [69],[9] compared to RF-enabled WET [43].

Inductive coupling is the transmission of energy from one coil to another caused by mutual inductance between the two coils. It occurs when an alternating current in the transmitter coil creates a magnetic field across the receiver coil. The generated magnetic field causes a voltage generation in the receiver coil, which we can use to power electronics. This approach is particularly efficient when the transmitter and receiver coils are close to each other.

Compared to inductive coupling, magnetic resonant coupling can efficiently transfer energy from one coil to another over longer distances (a few meters) by tuning the two coils at the same resonant frequency.

Due to the radiative nature of electromagnetic waves, RF-enabled WPT can function across larger distances. The main elements of an RF energy harvesting system are

- antenna: RF signal collection
- matching circuit: Ensure maximum RF power
- rectifier: RF to DC converter
- DC power: Energy storage

RF energy harvesting sources can be classified into two categories [45]:

- Ambient RF sources
- Dedicated RF sources

Ambient RF sources are energy sources available in the environment from other telecommunication sources like WiFi access points and mobile stations. The main characteristic is that they are sources not dedicated to energy transfer [52],[18].

On the other hand, Dedicated RF sources are designed exclusively for on-demand RF energy transmission. Therefore, they are better suited to applications with QoS limitations due to their high power density and programmable behavior.

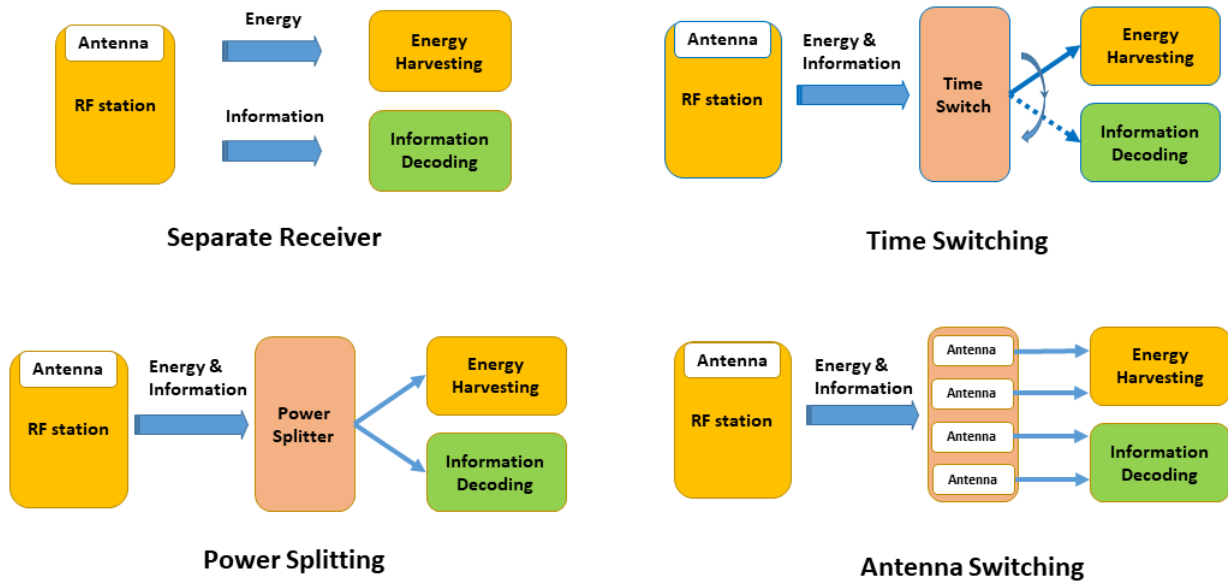


Figure 1.7: SWIPT Architectures.

1.2.2 Simultaneous Wireless Information and Power Transfer

SWIPT is a novel technique based on the existing WPT methods that enable the simultaneous wireless transmission of information and power. However, the SWIPT approach uses the same RF signal for energy harvesting (EH) and information decoding (ID) instead of using different frequencies to transfer energy and information. There are four main architectures for SWIPT enabled receivers:

- Separate Receiver (SR)
- Time Switching (TS)
- Power Splitting (PS)
- Antenna Switching (AS)

Separate Receiver (SR) The receiver has two distinct antenna elements one for information transfer and the other for energy harvesting. The receiver is capable to communicate with a transmitter equipped with multiple antennas. [28],[60],[80].

These two separate antennas operate in different communication channels allowing the system to operate concurrently for energy harvesting and information transfer.

Time Switching (TS) The Time Switching method uses the same antenna for EH and information reception. The receiver is composed of an RF energy harvester, an information decoder, and a switch to periodically switch the antenna system from the EH mode to IT mode [83],[26],[16],[20],[42].

A Time Switching receiver thus requires time synchronization between the sensor and the base station. Moreover, the system's performance depends on the applied information/energy scheduling algorithms due to channel uncertainty.

Power Splitting Receiver The Power Splitting receiver separates the received signal into two streams of different power levels. The proportion between the two power levels is fixed and determined by channel parameters and system requirements. Streams are delivered simultaneously to an information decoder and an energy harvester for ID and EH [48],[47],[82],[82].

Antenna Switching Receiver The antenna switching (AS) approach dynamically changes each antenna element between decoding and rectification. A subset of antennas performs information decoding on the receiver, and the remaining antennas work for energy harvesting [28], [80], [35]. Compared to time-switching and power-splitting, antenna switching is more straightforward and desirable for practical SWIPT architectural designs.

1.3 Millimeter-Wave 5G Networks & IOT

1.3.1 Millimeter-Wave 5G

One of the most promising technologies of the fifth-generation (5G) mobile broadband network is the Internet of Things (IoT). The Internet of Things (IoT) intends to connect all electrical devices used in everyday life to the Internet. Users will be able to remotely operate these devices and automate their functionality based on their demands by using a mix of mobile applications and cloud infrastructure [59].

3GPP and ITU have proposed standards for the interconnection of massive devices that we expect to operate at low cost, low energy, low latency, and high availability.

5G mobile network services are classified into three categories:

- e-MBB: Enhanced mobile broadband
- m-MTC: Massive machine-type communications
- u-RLLC: Ultra-reliable and low-latency communications

mmWave communication technologies can dramatically enhance and improve all the services described above. Moreover, mmWave, as a critical part of fifth-generation networks, can accommodate all desired services and applications that Internet of Things technology promises to bring.

Enhanced mobile broadband

eMBB aims to achieve throughput speeds up to 10Gbps in fixed terminals or up to 1 Gbps in mobile terminals moving at high speed. In addition, we expect that the accumulated traffic will be proportional to these speeds and will be served efficiently by the network.

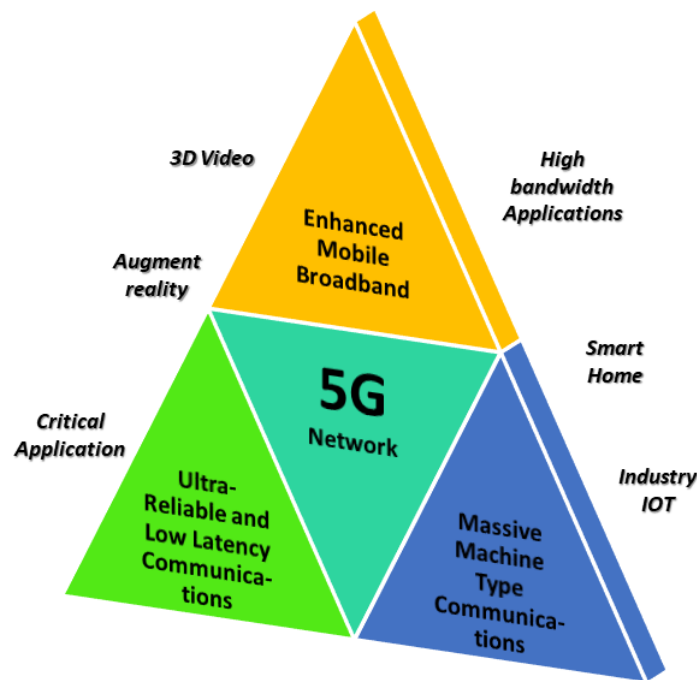


Figure 1.8: 5G mobile network services.

mmWave is a proven radio access communication technology that can achieve high data rates [51]. This is possible by deploying mmWave technology in parallel with massive multiple input, multiple output antennas.

Another important aspect is how the network can handle the increased traffic from the access network to the core network. Even though most of today's traffic pass through an extensive fiber network, there are cases where fiber deployment is not feasible. mmWave technology can be used as a backhaul communication solution to provide fiber-like data speeds. On the other hand, a mobile mm-wave system requires low latency and fast connectivity to provide reliable services. This brings new challenges to the network architecture since the user must be able to move continuously inside a multiple base station network without facing any disruption to the service.

In order to reduce the outage probability during user mobility and maintain uninterrupted service continuity, 5G standardized bodies propose the integration of edge computing and cloud infrastructure into the existing scheme [61]. Edge computing and cloud services can provide additional tools like joint scheduling schemes between nodes, radio signal management, and efficient communication and computation resource allocation. These functionalities help the network to overcome problems related to user mobility scenarios where nodes must cooperate to achieve the required quality of experience metrics [77].

Finally, a significant disadvantage of mmWave technology is that steerable and directive beams make the system vulnerable to transmission interference from neighboring mmWave transmitters. Existing works propose advanced interference management schemes to increase system reliability.

Massive machine-type communications

mMTC-based applications are settings in which low-power, low-data-volume devices interconnect on a large scale. An essential characteristic of that type of network is that not all of these massive numbers of devices will be in active mode continuously. The communication time, duration, and amount of data will largely depend on the device's service type at a given time. As a result, the network must simultaneously serve many devices in various modes, such as idle, transmit, and receive.

It is expected that 5G networks will overcome existing limitations of a current cellular network, like its inefficiency in serving a large number of devices that transmit various packet sizes (e.g., short, long, burst packets).

Ultra-reliable and low-latency communications

uRLLC aims to deliver user and device information with high reliability and low latency. These requirements are essential in applications requiring high network reliability and low latency. For example, quick response is crucial in applications related to health care or the detection of environmental hazardous phenomena. In 5G networks, we expect latency variation between 1 ms to multiple milliseconds [15].

As mentioned before, mmWave is proven capable of achieving high data rates. Moreover, it can also support low latency communication when the node is in the base station line of sight. In reality, a low-latency connection is not always possible for two major reasons. First, the terminal cannot communicate directly with the base station (for example, a building obstacle) and receives the signal through reflections and diffractions. Second, the transmission channel changes over time due to environmental changes or random moving obstacles between the transmitter and the receiver.

The aforementioned problems, negatively impact the mmWave communication reliability and latency. Thus, a need arises for essential network services to be pushed closer to edge devices to minimize latency. Moreover, by transforming the network this way, we can exploit new techniques like a scheme of multilink communications via multiple radio access links. We will consider the case of user mobility to demonstrate the method's benefits. User mobility in an ultra-dense architecture will undergo frequent handovers that impact the service's latency and continuity. However, if the user terminal can connect to multiple base stations simultaneously with the appropriate cooperation algorithm between base stations, the service continuity is feasible.

1.3.2 Internet of Things

The Internet of Things (IoT) represents a network of physical objects equipped with sensors, software, and other capabilities to communicate with other devices and systems over the Internet. Recent technology advances have made IoT functional in many actual use case scenarios. Some of the recent achievements which are essential to mention are:

- Low-cost sensor technology. Manufacturers can produce IoT technology solutions

at low cost due to the high market supply and demand for sensors.

- **Connectivity.** Enabling internet protocols on the sensor communication building block allows the sensors to connect directly to the cloud.
- **Cloud platforms.** Cloud platforms allow applications easy to access the sensors elements and manage them.
- **Machine learning and analytics.** The sensors transmit various data information, which the cloud collects and stores. Therefore in the cloud, there is a vast amount of data that, through the use of machine learning and analytics techniques, can give much helpful information to the user.
- **Artificial intelligence (AI).** Natural-language processing applications like Amazon Alexa are available to several IoT devices.

Application Categories There are two main categories of applications relating to all the exciting opportunities provided by IoT.

Category One

Category one refers to applications that exploit the interconnection of a massive number of unique identified devices. IoT provides all the available tools to automate the communication between machine-to-machine (M2M) or between machines and the physical world. Use cases of that category are:

- Asset tracking
- Resource allocation
- Automation and decision optimization.

Category Two

Category two refers to applications that exploit all the available information stored in the IoT cloud. In this category, data mining is crucial to provide helpful information and insights for the users or the industry. The analyzed information helps insurance and marketing companies to provide personalized information to their customers.

Building Blocks of the IoT

Sensing Nodes

Depending on the applications, there might be a variety of sensing nodes. Examples are an intelligent camera system for image recognition, water or gas smart meters, and RFID readers recognizing the presence of an object or person. Each node has a unique ID and can be managed remotely via IOT cloud infrastructure.

Layers of Embedded Processing Nodes

The IoT highly depends on the embedded processing provided by MCUs. In an IoT environment, computer processing is located in integrated MCU devices near the sensor nodes or as part of the sensor node. Today MCUs can offer a variety of computing processing capabilities required for many IoT applications.

Advantages that make MCUs ideal for use in the IoT are:

- Energy efficiency
- Interoperability with various IOT software platforms
- Different levels of performance and a variety of I/O interfaces
- Cost-effectiveness
- Quality and reliability
- Security

Wired and Wireless Communication

The communication node's purpose is to communicate information collected by sensing nodes and processed by local embedded processing nodes to the IoT Cloud. Today's wireless landscape provides a variety of communications technologies to the IoT landscape. Bluetooth Low Energy, ZigBee, Low-power WiFi, and Narrowband LTE are some examples of communication protocols already used for IoT applications.

Requirements for communication nodes are almost the same as for embedded processing nodes:

- Cost-effectiveness
- Low power
- Quality and reliability
- Security

Cloud computing

Cloud collect, process, and store the available data transmitted from the sensor nodes. Even though some decisions or execution of simple automation tasks can be made locally from the sensor nodes, based on their MCUs, that is not possible when we take more complicated actions. In an IoT environment where a decision must be made collectively, considering information from many nodes, cloud processing capability allows us to control and operate complicated tasks effectively.

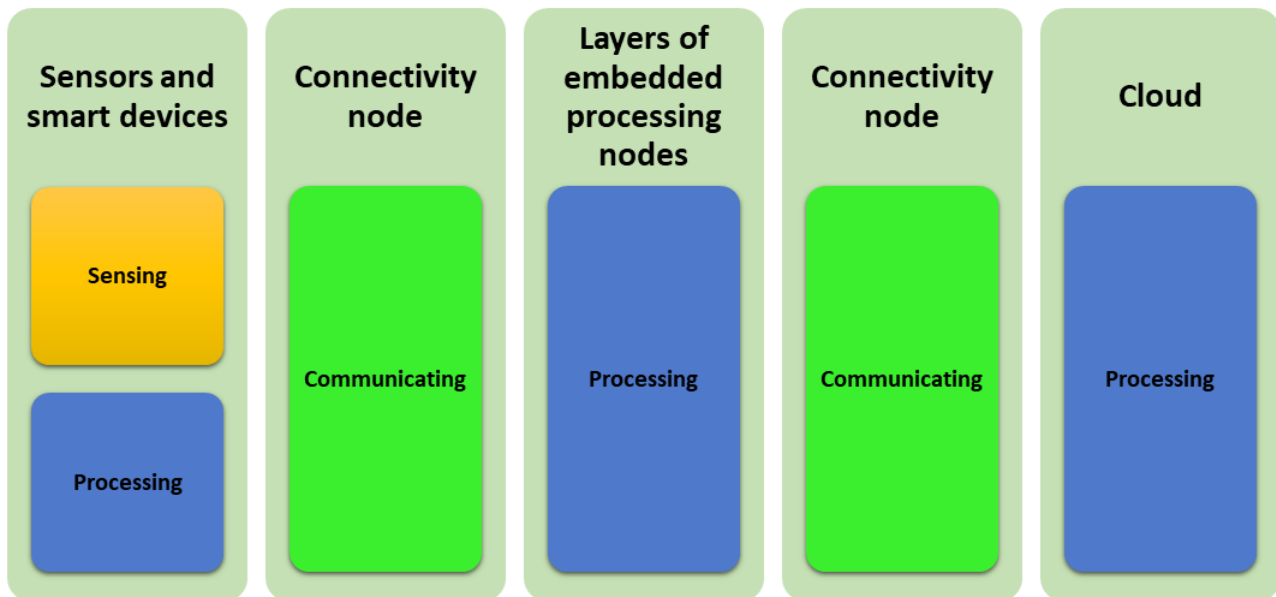


Figure 1.9: Functional view of internet of things technologies.

1.4 Wirelessly Powered Sensor Networks challenges

Wireless power sensor networks have received much attention and advancement in recent years. However, as new generation networks expand, the size and complexity of these networks grow. As a result, more complex problems and needs for research in this domain emerge, necessitating new advanced solutions in an ever-changing world. Below, we provide some new challenges crucial for wireless power sensor network evolution at this point.

Increased number of Sensors

To date, research focuses only on methods to efficiently charge a small number of sensors wirelessly. However, the explosion of the Internet of Things demands optimal efficiency in a network with a disproportionately large number of sensors. As a result new issues arise, such as how energy will be divided equitably across the sensors. This necessitates modifications in RF circuit design and the development of efficient charging techniques [11].

Multi-Hop WPSNs

In a network where the number of sensors is large, there are scenarios where each of the sensors must communicate with neighbor nodes. Then, sensors cooperatively forward the information to the base station. This consists a wireless multi-hop communication power network. Multi-hop communication works efficiently in traditional wireless sensor networks supporting many known applications. However, in the case of a wireless power sensors network, the charging aspect parallel to the transmission requires new techniques and algorithms [2].

Energy-Efficient WPSNs

The energy efficiency of the network is one of the critical parameters when evaluating the performance of the network. The necessary charge rate and the ability to dynamically change energy levels according to the requirements of the applications demand new approaches to the problem. The ratio of quality of service and energy efficiency remains crucial as it directly connects network applications with the energy footprint of the network itself [40],[39],[74]. Next, we discuss the benefits of using mm-wave technology for the WPSN.

1.4.1 Millimeter-Wave Communication

Fifth-generation (5G) cellular networks give a new strong foundation for establishing and upgrading wireless power sensor network infrastructure [7].

The use of millimeter-wave (mmWave) and massive multiple-input multiple-output (MIMO) new radio antenna technologies provide new opportunities and advantages. More specifically, all these technologies allow the network to deploy base stations (BSs) in such a way that they can form efficient and scalable ultra-dense networks. As a result, both available transmission capacity and coverage area per square meter improve.

New challenges and opportunities arise combining wireless power transfer and mmWaves [54]. The use of mm-wave technology significantly increases communication bandwidth. On the other hand, short wavelength communications suffer from considerable propagation losses and are vulnerable to obstacles [38].

1.5 CONTRIBUTIONS OF THIS THESIS

This thesis focuses on a type of sensor network in which charging is performed wirelessly through the use of wireless energy transfer technologies. In addition, both the charging and transmission frequencies are in the mmWave spectrum. These characteristics provide a significant benefit to the network. First, it dramatically decreases installation and operation expenses because the sensor does not need to be attached to a fixed power supply or an alternate power source responsive to environmental changes. Moreover, the use of mmWave frequencies makes the charging process faster and more efficient because of the directionality of the signal.

Beyond the benefits we listed, a sensor network that wirelessly charges brings several challenges. The network must be sufficiently charged to operate, be adaptable, work cooperatively, and be intelligent to make decisions where this is required.

The standard communication protocol proposed by the literature considers that the time the antenna stays in each sector is constant and distributed with a percentage for charging and communication. Although the protocol structure provides us with the necessary functionality, it must have the flexibility required to serve new functionalities.

Therefore, the thesis proposes a new communication protocol. It introduces a new period for reporting in addition to the two primary periods of charging and communication with the base station, which can be exploited for various applications, such as communication with neighbors' sensors or sending short information to the station. During this period, the sensor transmits using a small percentage of its stored energy. Therefore, we calculate the average harvest energy for different locations and transmission channels for the charging period, showing the sensor's dependence on its location and ability to charge quickly.

For the proposed reporting period and transmission period, we present how we can use as a metric the probability of successfully transmitting the available information to the base station to determine the effectiveness of the network. That provides us with an effective analysis tool for network planning. Therefore, based on how the antenna shifts the radiation beam (circularly or randomly) between the sectors, we calculate the probability of successful transmission.

Fault detection in wireless sensor networks is a well-studied academic topic. However, wirelessly powered sensor network advancements have given rise to new challenges that existing literature has not yet studied. As we mentioned above, the charging process is an important parameter that essentially affects the effectiveness of successful detection and communication of an event. Therefore, the process by which the base station charges the network, precisely the way it points its antenna to a sector each time, assures that the network is sufficiently charged to detect and inform in case of a critical event. This thesis proposes two new strategies for charging the sensors concerning the classical methods. By applying the proposed protocol and specifically by using the reporting period for sending the energy status of the sensor, the base station acquires knowledge of the overall energy status of the network. This allows the base station to choose alternative and more efficient charging strategies.

Furthermore, due to directivity, the mmWave frequency band is sensitive to physical obstacles that do not allow the sensor to charge efficiently. For this reason, we introduce a flooding technique to transmit the report messages. That is, by adding the ability for each sensor to receive reports from the neighboring sensors and act as a relay, we can increase the system's reliability and minimize the delivery delay.

Two strategies are proposed and evaluated concerning the classical methods that an antenna directs the radiation beam (circular and random) between the domains. The first strategy we propose in this paper directs the base station to serve each sector with a different frequency based on the number of reports it receives. That ensures the energy sufficiency of the network without neglecting sectors that receive a small number of reports; on the contrary, the algorithm can identify and strengthen them, guaranteeing a fast detection network of possible events. Therefore, the proposed algorithm is based on an optimization criterion that balances two critical parameters. The first parameter is the number of reports that the base station receives from the network, a value that expresses the energy status of the network. That leads the base station to direct its beam to areas where it receives high reports to achieve high charging levels and increase the probability of detection and successful event transmission.

The second parameter is the time period from the last time the antenna steers each sector. That ensures that sectors with low reporting will be served accordingly, ensuring that the network will transmit the event to the base station with little delay in case of an event.

The second strategy is based on a class of optimal stopping problems called multi-armed bandit problems. A typical example of this class of problems that introduces us to the basic concepts is the problem where a player enters a casino. It has to decide a) how many times to play, b) in what sequence a series of slots to maximize his winnings. If the player knew the payoff distribution of each machine, he would continue to draw the one with the highest payoff. However, the interest is when he does not know the distributions of the machines, and he must estimate them as he plays. After each choice, he must assess the outcome and decide to continue with the machine that has received the highest "exploitation" payout up to this point or to select another "exploration" machine to learn more about its profitability. The second algorithm borrows ideas from a class of multi-armed bandit problems, namely the upper confidence bound algorithm (UCB1). Considering the same optimization criterion as in the first strategy, two are the options that the base station has to choose each time it has to direct its beam to a sector. First, either to remain "exploitation" in the sectors that receive the most reports (corresponding to the profits of the example). Or, to choose areas with a few reports that are likely to provide additional information or information about an event (exploration). The simulation results prove that both strategies outperform the classical methods, increasing the network energy level and successfully transmitting an event with low delay.

The second problem addressed in this thesis focuses on the sensor's three essential functions: charging, data transmission, and successful detection of an event. The sensor takes measurements from the environment and tries to detect a possible change in the distribution of the monitored parameter. In case of an event, the sensor should immediately transmit the information it has collected to the base station with all the available energy.

As the measurements collected by the sensor may be noisy due to the nature of the phenomenon being monitored or the quality of the sensor itself, the detection process may result in an extremely high number of false alarms. Assuming that all sensors treat each alarm as an actual event, they try to immediately transmit whatever information they have collected about the event to the base station. This results in the sensor often exhausting its energy reserves and significantly reducing the probability of successfully sending the available information in the case of an actual event. This work approaches the problem as an optimal stopping problem that determines the moment the sensor must decide to transmit the existence of an event. Three main factors influence the decision: the false alarm probability, the average transmission delay, and the probability of successful transmission.

For example, to maximize the probability of a successful transmission, the sensor should delay transmission until sufficiently charged, ensuring successful transmission even if the channel conditions are poor or the sensor is at the domain's boundary. On the other hand, as long as the sensor postpones the transmission, it increases the delay in transmitting critical information to the base station. Additionally, assuming that the sensors cannot relay information from neighboring nodes, the probability of successful transmission is

directly linked to the sensor's storage energy level. The sensor, by taking measurements from the environment, continuously estimates the distribution of the parameter of interest. In addition, the sensor perceives any change that exceeds a certain threshold as an event.

Considering the high noise in the environment where the sensor is called to function, this threshold is often exceeded, driving the sensor to low charging levels. Therefore, the paper proposes adding an extra step to smooth the distribution before the sensor decides whether the distribution has exceeded the threshold we set. Two methods are present, a) the classic method using an AR filter and b) an innovative one based on the theory of Beta Particle filters. All techniques were analyzed and evaluated through simulations proving the advantages of the proposed methods.

Finally, we considered a network that periodically sends measurements from an area of interest. Our goal is to highlight the particularities of such a network and, simultaneously, propose a scheduling process for sending data from each sensor based on its charging level. The reason is that sensors in that type of network, under certain conditions, such as sensor location and channel quality, cannot successfully send their measurements. Therefore the solution we propose is based on the theory of Markov decision processes, allowing the sensor autonomously choose whether to transmit immediately or wait for the next period to be sufficiently charged.

To describe the channel gain, we considered a Finite State Markov Channel model whereby dividing the value range into a finite number of intervals, say using 2db steps, creates a finite state model for the fading channel. Additionally, considering a slow-fading channel, we only allow transitions between neighboring states.

To define the sensor decision chain, we first consider a 2-D Markov chain, with the first dimension the stored energy of the sensor before the decision and the second dimension the energy collected during the current period. Additionally, we calculate the probabilities of a sensor continuing to charge and transmit

The objective is to find the optimal policy to maximize a reward that considers the average number of successful transmissions. We introduce a parameter that aims to adjust the delay of actions based on the application serving the network. If the parameter's value is small, there is little emphasis on future rewards, and the action is made as early as possible. On the other hand, a large value postpones the actions by increasing the successfulness of sending measurements. We use the well-known Value iteration algorithm to find the optimal policy, and through simulations, we prove the method's advantages.

Additional areas and problems for further study emerge from this thesis. Additional functionalities in the sensors that promote cooperation could further enhance network performance. Following the problem of successful detection in a high-noise environment, the addition of cooperation between sensors increases the network's intelligence and enables it to operate at lower power levels. While on the other hand, synthesizing information from different sensors makes the network decisions more reliable.

From the base station perspective, exploiting the proposed reporting mechanism, we can devise more advanced functions than the basic functionality of informing the base station

of the sensor charge level. For example, indications of early events could be communicated to the base station using the proposed reporting mechanism. In this case, the base station could temporarily stop charging and receiving information from the remaining sectors and direct its beam to the area of interest.

1.6 Thesis organization

The first chapter briefly presents wireless sensor networks' essential characteristics and applications. Then, we highlight the characteristics that differentiate WPSNs from classical sensor networks. In addition, 5th-generation networks and the Internet of Things are mentioned. Finally, we present the challenges WPSNs face as part of the new generation networks. In the same chapter, we present this work's contribution and its structure. The second chapter presents the relevant references on which this thesis was based and related works. The third chapter describes the system model and the proposed charging and communication protocol. In addition, an extensive analysis of both the charging and communication process is carried out, defining the performance criteria of the network. Chapters 4 to 6 define the optimization problems that this work highlighted, the proposed algorithms, and, finally, the simulations' results. Chapter 7 describes the conclusions and new research areas arising from this work. The appendices present the proofs to determine the probability of successful reporting and the fundamental traits of the theories underlying this thesis, including the Markov Decision Process, Particle Filtering, and Multi-Armed Bandit.

2. BACKGROUND AND RELATED WORK

Recently, energy harvesting (EH) technologies have been proposed [10, 27, 5] as a solution to extend battery lifetime. In [10], authors propose a practical multi-antenna WPSN protocol that includes an adaptive energy beamforming scheme and a duty cycle control algorithm. Testbed experiments show that the proposed beamforming algorithm achieves higher receive power efficiency than the random beamforming scheme when six transmit antennas are used. They also show that the RF energy transfer efficiency is linearly affected by the number of antennas when the energy beamforming is applied.

In [27], a summary of recent developments in wireless power transfer is provided, along with several exciting applications highlighting potential future developments. Furthermore, the authors present an energy scheduling scheme in a wireless power device-to-device relay network, where they defined an optimization problem for energy scheduling and a two-stage directional water-filling algorithm. Results show the relationship and the importance of scheduling in a wireless power transfer scheme.

The problem of idle listening, which necessitates additional power consumption for wireless Internet of Things (IoT) transmission, is considered in [5]. The authors provide a detailed classification of the research efforts and recent breakthroughs in RF wake-up radio technology and RF energy transfer and harvesting techniques.

Several recent publications in wireless power transfer in the millimeter wave band show that the directivity of the transmit power signal can increase charging performance. On the other hand, studies show that many parameters must be considered, such as environmental changes and antenna design, so that an access point can charge many sensors wirelessly.

The work in [30] focused on the performance of WPT in mmWave massive multiple-input-multiple-output (MIMO) systems. Based on a channel model that considers characteristics such as path loss, small-scale fading, and the effects of rain show that the amount of energy that sensors harvest increases linearly with the number of antennas at the access point. Additionally, on the performance of SWIPT schemes for mm-wave communication systems, the authors of [49] evaluate the performance assuming two different wireless channel models. A well-known model, namely Two Wave with Diffused Power and a generalization named Fluctuating Two Ray. Simulations provide insight into how the choice of wireless channel model affects system design.

Moreover, in [76], the authors studied the required number of RF chains to achieve a fully digital beamforming performance based on a hybrid analog/digital beamforming with a limited number of RF chains. Finally, the work in [13] considered a SWIPT scheme in massive MIMO-NOMA systems to achieve the optimal trade-off between spectrum and energy efficiency. The authors propose an algorithm based on user grouping, hybrid precoding, power allocation, and power splitting techniques. Results show that applying the proposed algorithm can increase the system's performance.

The work in [79] studied the performance of SWIPT with 5G frequencies at 3.5 and 28

GHz. It proposed an architecture that increases the throughput of cell-edge users and improves the energy-harvesting efficiency of cell-center users. The paper also provides actual measurements from urban roads and corridors in a U-type building for the two different frequencies. Based on these measurements, the authors construct a more accurate channel model for 3.5 GHz and 28 GHz.

The feasibility of a wireless power sensor network powered by a mmWave MIMO antenna is presented in [21, 54]. The authors elaborate on the benefits in terms of energy harvesting efficiency. Optimal section selection algorithms are introduced and analyzed to maximize the power coverage of the network.

The work in [21] studies a network inside which multiple devices are wirelessly charged by millimeter wave power beacons. To improve beamforming performance, the authors propose a directional power transfer scheme. During the training phase, each power beacon directs its beam toward the beamforming direction that receives the most power. The aggregated power from the power beacons is harvested by the devices. The proposed scheme is feasible within a dense topology of power beacons and can improve system performance when compared to the random beamforming technique, according to the results.

The work in [54] presents a random beamforming technique to transfer energy to sensors where the antenna steering direction is randomly selected. If the stored energy rises above a set threshold, the sensors use the stored energy to power their uplink transmission. The energy outage and beam outage probability were calculated using analytical expressions. Furthermore, location-aware selection strategies were proposed, where the AP prefers a sector or based on the number of sensors in that area. It has been proven that the proposed schemes outperform the random approach.

Sensing area partitioning and energy coverage are important factors for the reliability and efficiency of the network. Sensor positioning information is crucial to the performance of sensor networks, especially when the sensors are deployed in harsh environments. The authors of [12] presented recent advances in the field of wireless positioning under sensor mobility, highlighting the importance of mobility exploitation, sensor cooperation in terms of processing power, and advanced signal processing techniques.

Reliable positioning in multiple access points and sensors connectivity scenario was considered in [37]. The authors propose a beamforming strategy at the receiver that can establish robust connectivity to overcome the uncertainties of the mmWave channel and the sensitivity to blockages. Results show that a coordinated multipoint reception considerably increases positioning accuracy and the achievable rate. The target tracking problem was considered in [32]. The authors construct a novel mmWave beamforming antenna system showing that it can detect and track multiple targets simultaneously. Performance was tested in an indoor scenario and with multiple targets.

The authors of [23] investigated the energy coverage of a mmWave small-cell network by modeling the network as a homogeneous Poisson point process (HPPP) and applying stochastic geometry. Using the analysis, the authors define the minimum number of base stations required to achieve the desired coverage when the EH power requirement of

sensor nodes is known.

An energy-efficient coverage algorithm was presented in [73], aiming for a balance between coverage rate and energy cost by adjusting the sensing radius of each sensor node. On the another hand, aiming for the energy economy of the sensors, a well-organized sensor network is required to implement energy-efficient routing protocols.

Clustering methods can easily organize the network and reduce energy consumption by controlling intracluster communications. The authors of [71, 72] considered optimal methods to select the cluster sensor head. In [71], authors propose a novel method for clustering that combines machine learning with a well-known method named affinity propagation. The algorithm first searches for the optimal initial cluster centers and then forms the topology around that center. Simulations show that the proposed algorithm outperforms several know clustering methods. In [71, 72] the authors approach the energy efficiency problem of the sensor nodes as a clustering problem where cluster centers play an essential role in cluster energy efficiency and communications. The authors propose an algorithm that considers the communication distance of the sensor from the base station and the cluster center and the minimum stored energy. Results show that the proposed algorithm outperforms existing known algorithms.

The work in [25] considered a system that consists of multiple sensors that are deployed to obtain information about a common parameter of interest. They examined the beam pattern selection and charging power allocation with considerations on the distributed estimation performance of the monitor parameter.

The millimeter-wave (mmWave) and wireless power transfer with the use of large-scale antenna arrays are studied in [65] showing that even though the proposed scheme can achieve significant array gains many security issues arise. The authors focus on the security of the communications in a downlink SWIPT mmWave ultra-dense network, where users wirelessly charge and communicate over the mmWave link in the presence of multiple eavesdroppers. Using stochastic geometry, the analytical expressions of the energy-information coverage probability are obtained for both the power splitting and the time switching policies and also the secrecy probability in the presence of multiple listeners. Moreover, the effective secrecy throughput is calculated, which can be used to measure network energy coverage as well as secure and reliable transmission performance in a unified manner. Results confirm that as transmit power, power/time splitting ratio, code-word transmission rate, and confidential information rate increase, the effective secrecy throughput increases first and then decreases. Finally, the simulation shows that shortening the signal beam width at BSs can minimize information leakage and improve effective secrecy throughput.

The work presented in [29] demonstrates unmanned aerial vehicles (UAVs) use for wireless communications and their integration into the next-generation 5G networks. To support the integration of different UAVs into next-generation wireless communication networks, the authors propose a hierarchical architecture of UAVs with multilayer and distributed functionalities. The scheme explores solutions based on advances in mm-wave communications, energy harvesting, and power transfer technology.

Event detection is one of the most important tasks of sensor networks, with a wide range of applications like intrusion detection, environmental monitoring, fire detection, and outlier detection in sensor networks [19, 31, 58]. Event detection most of the time is expressed as a change in the distribution of a monitored parameter from the sensor network. Observations are assumed to be taken sequentially in time, and the objective is to detect the change as quickly as possible subject to the probability of false alarm. The problem of event detection in a multiple sensors network has been studied in various contexts. One area of interest is how the event is perceived from the sensor network. Works in [66, 67] assume that only one sensor senses the change in the environment and its identity is unknown. Work in [66] focuses on quick anomaly detection for early detection of computer network attacks that change network traffic. Their method is based on Page's cumulative sum (CUSUM). The authors show that the method can be effectively applied to detect denial-of-service attacks, worm-based attacks, port-scanning, and man-in-the-middle attacks. The author in [67] presents the recent advances in change detection theory and how we can apply them to a problem where we have a large-scale network. It also presents the scalability of asymptotic theory in specific problems and the performance based on specific optimality criteria.

An extension in [75] assumes that an unknown subset of affected sensors detects the event at the same time. The authors present an algorithm for monitoring parallel data streams for a change-point event that impacts just a subset of streams. Furthermore, no data stream structure existence is assumed. From the analysis authors provide an analytical expression for the expected detection delay after an event and the average convergence time.

The case where the sensors perceive the change at different times is studied in [55, 22]. In [55], it is assumed a scenario where the event propagates in time, affecting different nodes at different time instances. The event propagation is modeled as a Markov process. The authors provide analytical expressions for the probability of a false alarm in a region where a change in probability occurs and provide an optimization solution to the problem of minimizing the average detection delay subject to a false alarm.

In [22] a scheme is studied where multiple sensors detect an event sequentially and have only one chance to transmit their information to the fusion center. Analysis shows that a simple strategy, where the fusion center reacts when the first sensor communication occurs, is as efficient as other, more complex methods.

The work in [25] considers the performance of the network in terms of energy harvest efficiency and the ability of the sensor network to successfully detect environmental changes. The authors propose a solution that balances the two criteria. The authors in [33] introduce a reporting scheme that allows sensor nodes to inform the AP about their energy levels. Based on these reports, efficient energy-beamforming strategies are devised so that, acting proactively, all sensors are sufficiently charged most of the time and are capable of successfully transmitting their information upon detection of an event.

Another aspect of multiple sensor detection focuses on where the event information from the sensors is located for decision making. For the decentralized version, each sensor,

based on his measurements, decides if a change in the monitored environment consists of an alarm [46, 63]. On the contrary, for the centralized scenario [68], event information is available at several wireless sensors in the network, which transmit their information to a fusion center. The fusion center is responsible to raise an alarm as soon as possible subject to a false alarm rate constraint.

The work in [53] considers the scenario where all sensors communicate their information to a fusion center. The fusion center is responsible for the decision process by monitoring the posterior probability of the received measurements.

Additionally, the fusion center, in order to minimize the energy consumption of the sensors, chooses each time which sensors to keep enabled. Sensors are collocated and events happen at a random time following a geometric distribution. The proposed algorithm accomplishes to detect the intrusion (event) as early as possible using a minimal number of observations subject to a false alarm probability. One disadvantage of the method, as is concluded from the simulation results, is the computational complexity of the algorithm that depends on the number of active sensors.

The authors in [78] propose a two-stage detection process in a sensor network used for fire detection. At first, each sensor based on its measurements monitors for any differences in parameter distribution. By defining a soft threshold and using a modified CUMSUM algorithm to sequentially detect the change, the sensor upon detection sends all the available information to a fusion center. At the second step, the fusion center, based on the measurements received by detecting nodes, applies a hard threshold to raise a fire alarm.

There are two common approaches to solve a change detection problem. Firstly, the minimax method [41], where the objective is to minimize the worst-case delay subject to a lower bound in the meantime between false alarms. Secondly, the Bayesian approach [62], where the time of the change (event) is assumed to be a random variable with known distribution and the goal is to minimize the detection delay subject to the probability of false alarm. Minimax optimal solution minimizes the cost under the worst-case change-time distribution, which is generally unknown. Therefore, we follow the Bayesian approach which uses prior information about the distribution of the change time. This prior distribution can be estimated using historic data. An additional constraint has been incorporated in the optimization process to accommodate the probability of successful information transmission.

3. SYSTEM MODEL AND BASIC ANALYTICAL RESULTS

We present the system model, the energy harvesting mechanism, and fundamental analytical results regarding the probability of successful reception and reporting based on the proposed reporting scheme.

3.1 System Model

The system model, the proposed protocol time format, and the analysis of the energy harvesting process that is used to address the issues mentioned in chapters 4 and 5 are all described in this section.

3.1.1 Network Topology

We consider a mmWave WPCN with sensor nodes scattered randomly in a circular area of radius ρ . Sensor nodes are wirelessly charged by an Access Point (AP) centered at the origin of the monitored area. A uniform linear array of M antennas at the AP is used to switch the radiation beam along S sectors. Switching among sectors can be performed in a circular fashion or randomly. Figure 3.1 depicts the topology of the system. The channel between the AP and a sensor node is modeled as a fast-fading Rayleigh channel, independent for each sensor node.

Basic Time Slot Format

Time is slotted and the duration of each slot, T_S , is taken equal to the residence time of the AP beam to each sector. For the time slot per se we consider two formats. In the simplest one, each slot is comprised of two fields: the harvesting period T_H and the information period T_I , as it is shown in Figure 3.2a.

During the energy harvesting period (T_H), sensors located in the served sector harvest energy and charge their battery. This process is discussed in the next subsection. Upon detection of an event, the node will transmit its identity (ID) and proper information (measurements) regarding the event during the information period (T_I).

To maximize the probability of successful reception of the information message by the AP, the sensor nodes use all their stored energy for transmission. Since, neighboring nodes can simultaneously detect the event, to avoid collisions of multiple transmissions at the AP, an orthogonal multiple access scheme, like FDMA, is adopted. The justification for such a choice is the abundance of bandwidth in the mmWave band and the low rate of information transmission.

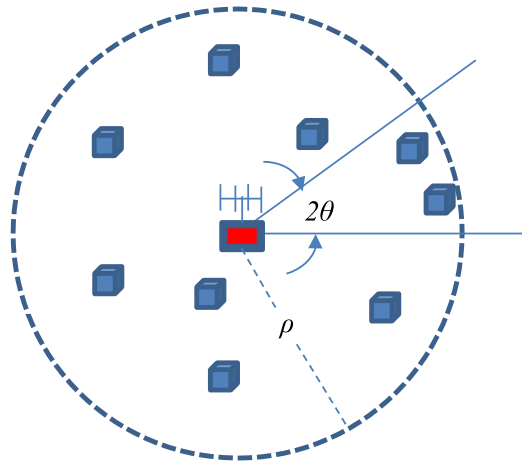


Figure 3.1: Network topology with sensor nodes depicted with boxes.

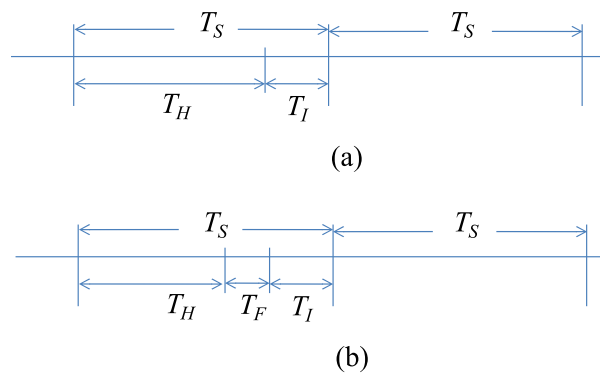


Figure 3.2: System time is slotted with slot duration T_s equal to the residence time of the charging beam to each sector. **(a)** During each slot nodes in the served sector charge for a period T_H and transmit (if necessary) for a period T_I . **(b)** An alternative slot format allows sensor nodes to exchange information for fusion or message relaying using period T_F .

Reporting Time Slot Format

The second time slot format was proposed in [33]. Time is slotted, and each slot (of duration T_s) consists of three fields, the harvesting period T_H , the reporting period T_R , and the information period T_I .

During the energy-harvesting period, sensors located in the served sector harvest energy and charge their battery. If the stored energy level of a sensor exceeds a threshold, $\mathcal{E}_\tau$, the sensor reports its condition to the AP using the surplus energy. Reporting takes place during T_R and gives a chance to the AP to acquire knowledge for the sensors' condition and select alternative beamforming strategies. Two benchmark strategies for energy transfer to nodes are considered in this work: random selection and circular selection of sectors to be energy-beamformed. In both cases, the reporting field may be omitted, leaving more time for energy harvesting and/or information transmission in case of an event. We should mention that reporting does not deplete the stored energy, and nodes that have exceeded the energy threshold $\mathcal{E}_\tau$ reserve this amount of energy for possible information transmission. Upon detection of an event, the node will transmit its ID and proper information regarding the event in the time period T_I . To increase the probability of correct reception by the AP, the sensor node uses all its available power for information transmission. As reporting is unnecessary in this case, a node holding information continues to charge during the interval T_R (instead of transmitting a report) in an effort to maximize its transmission power and, thus, the probability of successful reception of its message.

The information message may not reach the AP for several reasons, such as bad channel condition, blockage of the node, etc. To overcome this problem, we may allow nodes to act as relays. Nodes in the neighbor of the information transmission node intercept the message and retransmit it when their home sector is selected by the AP. This process is repeated and the information message is propagated in an epidemic fashion towards the AP. Although the epidemic dissemination of the information message is not the focus of this work, some simulation results are provided for comparison reasons. To avoid the collision of multiple transmission at the AP, we adopt an orthogonal multiple access scheme, for example, FDMA.

3.1.2 Energy Harvesting Phase

The amount of harvested energy by a node depends on the received RF power, denoted by P^{RF} , and the exposure time to radiation. For this work, we adopt the nonlinear model presented in [8], according to which

$$\mathcal{E} = \frac{t\gamma\mathcal{E}_b(1 - \exp(-\zeta_1 P^{\text{RF}}))}{1 + \exp(-\zeta_1(P^{\text{RF}} - \zeta_2))} \quad (3.1)$$

The constants ζ_1, ζ_2 are circuit implementation dependent, $\mathcal{E}_b$ denotes the batteries' maximum energy storage, and the critical parameter $\gamma \in [0, 1]$ models the efficiency of the

charging process. The harvested energy is an increasing function of the received power, $\mathcal{E} = h(P^{\text{RF}})$, and therefore:

$$P\{\mathcal{E} \leq \epsilon\} = P\{P^{\text{RF}} \leq h^{-1}(\epsilon)\} \quad (3.2)$$

Solving Equation (3.1) for P^{RF} , we obtain

$$P^{\text{RF}} = -\frac{1}{\zeta_1} \ln \left(\frac{t\gamma\mathcal{E}_b - \epsilon}{t\gamma\mathcal{E}_b + \epsilon \exp(\zeta_1\zeta_2)} \right) = \eta(t, \epsilon) \quad (3.3)$$

Thus,

$$\mathcal{E} \leq \epsilon \iff P^{\text{RF}} \leq \eta(t, \epsilon) \quad (3.4)$$

For the received power P^{RF} , we use the model in [14]. For a node located at distance r from the AP and at a physical angle ϕ from the direction of the serving beam, the received power is

$$P^{\text{RF}} = \frac{P_0 |g|^2 F_M(\phi)}{1 + r^\alpha} \quad (3.5)$$

where P_0 is the BS transmit power, α is the path loss exponent, and g is the complex channel gain between the sensor node and the AP, modeled as complex Gaussian with zero mean and unit variance, i.e., $g \sim CN(0, 1)$. The function $F_M(\phi)$ represents the Fejér kernel of order M , that is

$$F_M(\phi) = \frac{1}{M} \frac{\sin^2\left(\frac{\pi M \phi'}{2}\right)}{\sin^2\left(\frac{\pi \phi'}{2}\right)}, \phi' = \frac{2d}{\lambda} \sin(\phi) \quad (3.6)$$

where $\phi \in [-\frac{\pi}{2}, \frac{\pi}{2}]$ is the physical angle of departure, ϕ' is the normalized direction, d is the minimum distance between antenna elements and λ is the carrier wavelength. Hereafter, we assume $d = \frac{\lambda}{2}$.

Therefore, for a harvesting period T_H , we obtain

$$\begin{aligned} F_{\mathcal{E}}(\epsilon|r, \phi) = P\{\mathcal{E} \leq \epsilon|r, \phi\} &= P\{P^{\text{RF}} \leq \eta(T_H, \epsilon)\} = P\left\{|g|^2 \leq \frac{\eta(T_H, \epsilon)(1 + r^\alpha)}{P_0 F_M(\phi)}\right\} \\ &= 1 - \exp\left(-\eta(T_H, \epsilon) \frac{1 + r^\alpha}{P_0 F_M(\phi)}\right) \end{aligned} \quad (3.7)$$

where the equality in the second line of equations is due to the fact that $|g|^2$ is exponentially distributed.

The previous relation depends on the node's location (r, ϕ) . By marginalizing over the spatial distribution Φ of distances and angles we estimate the average c.d.f. of $\mathcal{E}$ as

$$\begin{aligned}
F_{\mathcal{E}}(\epsilon) &= 1 - \mathbb{E}_{\phi} \left[\exp \left(-\eta(T_H, \epsilon) \frac{1 + r^a}{P_0 F_M(\phi)} \right) \right] \\
&= 1 - \frac{1}{\theta \rho^2} \int_{-\theta}^{\theta} \int_0^{\rho} \exp \left(-\eta(T_H, \epsilon) \frac{(1 + r^a)}{P_0 F_M(\phi)} \right) r dr d\phi
\end{aligned} \tag{3.8}$$

Moreover, we can modify the previous relation to taking account the blockage effect, that is the nLOS probability of a link. The blockage effect was modeled in [54] and according to this model, the probability that the link between the sensor and the access point is not obstructed is given by $p_{LOS} = \exp(\beta d)$, where β is a non-negative constant that is determined by the blockages' characteristics (e.g. density, length).

Thus, relation Equation (3.8) is modified as follows:

$$\begin{aligned}
F_{\mathcal{E}}(\epsilon) &= 1 - \frac{1}{\theta \rho^2} \int_{-\theta}^{\theta} \int_0^{\rho} \exp \left(-\eta(T_H, \epsilon) \frac{(1 + r^a)}{P_0 F_M(\phi)} - \beta r \right) r dr d\phi \\
&\tag{3.9}
\end{aligned} \tag{3.10}$$

For a given r and ϕ the average harvested energy per time slot can be found by

$$\mathcal{E}_{av,s}(r, \phi) = \int_0^{\infty} (1 - F_{\mathcal{E}}(\epsilon)) d\epsilon = \int_0^{\gamma T_H \mathcal{E}_b} (1 - F_{\mathcal{E}}(\epsilon)) d\epsilon \tag{3.11}$$

Figure 3.3 shows the average harvested energy per slot for the parameter set used in the simulation section (see Table 3.1) and for three different values of the parameter γ . Note that for large distances from the AP, the harvested energy for nodes located at the edge of the beam (dotted lines, $\phi = 12^\circ$) is considerably lower than the energy harvested by nodes located at the axial direction of the beam (solid lines, $\phi = 0^\circ$). If a sensor node is aware of its location, i.e., explicit deployment of nodes, it can anticipate the number of time slots needed to reach a specific energy level and thus act appropriately in a case of an event. For example, for $\gamma = 0.03$ and a node located at the axial direction of the beam, 50 time slots are required at most for the node to become fully charged.

If the location (r, ϕ) of the sensor node is unknown, we have to average over the spatial distribution of distances and angles in the serving sector to estimate the average harvested energy per time slot. In this case

$$\mathcal{E}_{av,s} = \frac{1}{\theta \rho^2} \int_{-\theta}^{\theta} \int_0^{\rho} \int_0^{\gamma T_H \mathcal{E}_b} \exp \left(-\eta(T_H, \epsilon) \frac{(1 + r^a)}{P_0 F_M(\phi)} \right) r dr d\phi d\epsilon \tag{3.12}$$

The average harvested energy per slot, $\mathcal{E}_{av,s}$, is plotted vs. γ in Figure 3.4 for three values of the path loss exponent α . As it is expected, as α increases the amount of energy harvested by a sensor node at each time slot is reduced. The differences are magnified for larger values of the parameter γ .

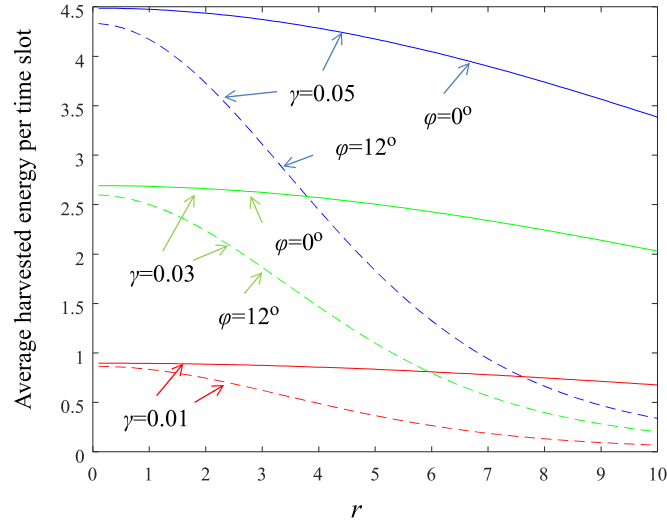


Figure 3.3: Average harvested energy $\mathcal{E}_{av,s}(r, \phi)$ per time slot. Solid lines: $\phi = 0^\circ$, dotted lines: $\phi = 12^\circ$. Blue color corresponds to $\gamma = 0.05$, green color to $\gamma = 0.03$, and red color to $\gamma = 0.01$.

Table 3.1: Parameters used in simulations.

Parameter	Value
$\zeta_1, \zeta_2, \mathcal{E}_b$	1500, 0.0022, 100
ρ, θ, α, M	10 m, $\pi/15$, 2, 8
$P_0, \sigma^2,$	−10 db, −30 db
D_I, W'	1024 bits, 1 KHz

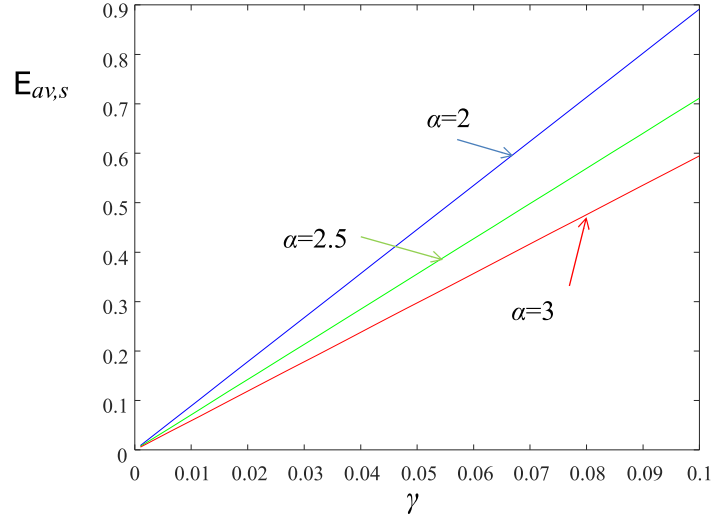


Figure 3.4: Average harvested energy $\mathcal{E}_{av,s}$ vs. γ for various values of the path loss exponent α . Blue color corresponds to $\alpha = 2$, green color to $\alpha = 2.5$, and red color to $\alpha = 3$.

3.1.3 Markov Chain Modeling of Battery Energy Levels

In this section, we model the energy level of a node battery as a finite Markov chain (MC). Each battery is of size $\mathcal{E}_b$ which we discretize in N levels, $\epsilon_i = i\mathcal{E}_b/N$, $i = 0, \dots, N$. The discretization step $\mathcal{E}_s = \mathcal{E}_b/N$ is taken equal to the energy needed by the sensor node to sense the environment and to complete necessary processing tasks during a time slot. The node operation depends on whether the node is located in the served sector or not.

- If the node is outside the served sector, then it senses the environment for a period of $T_H + T_R$, and then it enters the reception mode (for a period T_I) to listen possible information transmissions by neighboring nodes. To accomplish these tasks, the sensor node depletes one energy unit, that is, $\mathcal{E}_s = \mathcal{E}_b/N$;
- If the sensor is located in the sector that the AP is currently pointed to, it harvests energy for a period T_H , and if its battery level $\mathcal{E}_m = m\mathcal{E}_s$ exceeds a threshold $\mathcal{E}_\tau = \tau\mathcal{E}_s$, it uses $(m - \tau)\mathcal{E}_s$ energy units to report its condition to the AP during the period T_R . Then, it enters the reception mode for a period T_I in order to listen possible information transmissions by neighboring nodes. Sensing and listening costs one unit of energy;
- If the sensor node has detected an event in its sensing area, it awaits until the AP steers its beam towards its host sector. Then, it harvests energy for a period $T_H + T_R$ and transmits the relative information, during the period T_I , using all its available energy. In the epidemic information dissemination scenario, neighboring nodes that intercept such a message act as relays and retransmit the message in a

following time slot in an effort to increase redundancy and, thus, the reliability of the system. These nodes deplete all the stored energy and start charging again from zero. The detection of an event signals the end of the analysis horizon, and therefore, it is not included in the modeling process.

From the discussion above, it is clear that by the end of each time slot, the sensor battery energy level assumes one of $\tau + 1$ possible values, $0, \dots, \tau$, with $\tau < N$. Therefore, to model the stored energy process of a sensor node, we use an MC with states S_i , $i = 0, \dots, \tau$, where each transition takes place at the end of each time slot. The probability that a node lies on the served sector or not depends on the beamforming strategy used by the AP. If the AP selects sectors randomly, then

$$q = P\{\text{sector served at time } n\} = \frac{\theta}{\pi}$$

with 2θ the central angle of a sector. If the AP selects the sectors in a circular fashion, then for a typical node

$$q(n) = P\{\text{sector served at time } n\} = \mathbf{I}(\text{mod}(n, S) = 0)$$

where $\mathbf{I}(\cdot)$ denotes the indicator function. This choice leads to a nonhomogeneous MC, thus complicating the analysis. To this end, we use basic principles to derive expressions for the involved probabilities of successful information reception and reporting. Assuming that the CDF of the charging process is known, $F_{\mathcal{E}}(\epsilon) = P\{\mathcal{E} \leq \epsilon\}$ the possible transitions between states S_i , $i = 0, \dots, \tau$ of the MC are as follows:

- Transitions $S_i \rightarrow S_{i-1}$

$$p_{i,i-1} = 1 - q + qP\{\mathcal{E} < \mathcal{E}_s\} = 1 - q + qF_{\mathcal{E}}(\mathcal{E}_s)$$

Note that one unit of energy is consumed for sensing and listening, and therefore, if the sensor node is outside the served sector (with probability $1 - q$) or the sensor node is inside the serving sector (with probability q) and the harvested energy is below $\mathcal{E}_s$, the node will transit to a lower state;

- Transitions $S_0 \rightarrow S_0$

$$p_{0,0} = 1 - q + qP\{\mathcal{E} < 2\mathcal{E}_s\} = 1 - q + qF_{\mathcal{E}}(2\mathcal{E}_s)$$

- Transitions $S_i \rightarrow S_{i+j}$

$$\begin{aligned} p_{i,i+j} &= qP\{(j+1)\mathcal{E}_s \leq \mathcal{E} < (j+2)\mathcal{E}_s\} \\ &= q(F_{\mathcal{E}}((j+2)\mathcal{E}_s) - F_{\mathcal{E}}((j+1)\mathcal{E}_s)), \quad j = 0, \dots, \tau - i - 1 \end{aligned}$$

A transition of this type is possible whenever the sensor node is inside the served sector (with probability q) and the harvested energy is $(j+1)\mathcal{E}_s$ energy units;

- Transitions $S_i \rightarrow S_\tau$

$$p_{i,\tau} = qP\{\mathcal{E} \geq (\tau + 1 - i)\mathcal{E}_s\} = q(1 - F_{\mathcal{E}}((\tau + 1 - i)\mathcal{E}_s))$$

Having in our disposal the transition probability matrix $P = \{p_{i,j}\}$, we find the steady state distribution ψ of the Markov chain. Using the method presented in [34]

$$\psi = (P^T - I + B)^{-1}\mathbf{e} \quad (3.13)$$

with $\mathbf{e} = [1 \dots 1]^T$ and $B_{i,j} = 1, \forall i, j$.

3.2 Basic Analytical Results

3.2.1 Probability of successful reception

Upon detection of an event, the sensing node awaits until the AP switches the beam towards its direction, charges for a period T_H and then transmits during the period T_I .

If after charging the node's battery is at energy level $\mathcal{E}$, the transmission power is

$$P = \frac{\mathcal{E}}{T_I} \quad (3.14)$$

The signal-to-noise ratio (SNR) at the AP from the transmitted node located at (r, ϕ) is

$$\text{SNR}(r, \phi) = \frac{P|g|^2 F_M(\phi)}{(1 + r^a)\sigma^2} \quad (3.15)$$

where σ^2 is the noise power. Therefore,

$$\begin{aligned} P\{\text{SNR}(r, \phi) \leq x \mid P\} &= P\left\{\frac{P|g|^2 F_M(\phi)}{(1 + r^a)\sigma^2} \leq x \mid P\right\} \\ &= P\left\{|g|^2 \leq \frac{x(1 + r^a)\sigma^2}{PF_M(\phi)} \mid P\right\} \\ &= 1 - \exp\left(-x \frac{(1 + r^a)\sigma^2}{PF_M(\phi)}\right) \end{aligned} \quad (3.16)$$

Successful reception of the information message is possible if

$$R_I < W' \log_2(1 + \text{SNR}(r, \phi)) \quad (3.17)$$

where R_I is the information rate and W' the bandwidth allocated to a node. The information rate R_I equals D_I/T_I , where D_I is the amount of data (bits) that the node sends

to the AP and T_I is the transmission time interval ($T_I = T_S - T_H$). Using orthogonal signaling we assume that the available bandwidth W is equally divided to all nodes, and therefore

$$W' = \frac{W}{S_u} \quad (3.18)$$

with S_u an upper bound on the total number of nodes. Solving Equation (3.16) for $\text{SNR}(r, \phi)$ and using Equation (3.15), we obtain

$$\begin{aligned} p_s(r, \phi) &= P\{\text{successful information reception for a node located at } (r, \phi)\} \\ &= \exp\left(-\left(2^{R_I S_u/W} - 1\right) \frac{(1 + r^a)\sigma^2}{PF_M(\phi)}\right) \end{aligned} \quad (3.19)$$

Again, if the location of the sensor node is unknown we integrate over the spatial distribution of the nodes to find the average probability of successful information reception.

$$p_s = E_{\Phi}[p_s(r, \phi)] = \frac{1}{\theta \rho^2} \int_{-\theta}^{\theta} \int_0^{\rho} \exp\left(-\left(2^{R_I S_u/W} - 1\right) \frac{(1 + r^a)\sigma^2}{PF_M(\phi)}\right) r dr d\phi \quad (3.20)$$

Figure 3.5 depicts the probability of successful reception of messages vs. the available energy level for two nodes located at the edge of the network ($r = 10$). The first node is located at the axial direction of the beam (blue color) whereas the second node is located at the boundary of the sector (red color). The values of the parameters used are given in Table 3.1. Moreover, in Figure 3.5 the average probability of successful reception p_s (Equation (3.19)) is plotted with green solid line.

In the following we specialize the previous analysis for the cases of Random energy beamforming and the circular energy beamforming

3.2.2 Random Energy Beamforming

When a sensor node detects an event, it must transmit relative information to the AP with the minimum delay possible. When the sensor is in the serving sector, it first charges for a period $T_H + T_R$ and then transmits, using all its available power, at the end of the time slot over a period T_I . When the node is outside the serving area, it awaits until the AP switches the beam towards its direction. A node holding a message will use all its reserved battery energy to transmit it. Therefore, if the node's battery is at energy level $m\mathcal{E}_s$, the transmission power P is

$$P_m = \frac{m\mathcal{E}_s}{T_I}$$

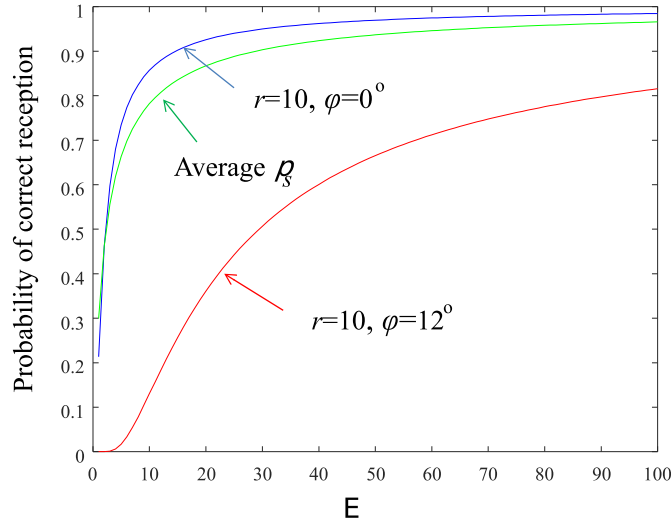


Figure 3.5: Probability of successful information reception. Green color: the average p_s , blue color: node located at $(10, 0^\circ)$, red color: node located at $(10, 12^\circ)$.

Therefore,

$$P\{\text{SNR} \leq x \mid P_m\} = 1 - \frac{1}{\theta \rho^2} \int_{-\theta}^{\theta} \int_0^{\rho} \exp\left(-x \frac{(1+r^a)\sigma^2}{P_m F_M(\phi)}\right) r dr d\phi \quad (3.21)$$

The probability that a node transmits with power P_m is

$$p_m = P\{P_m\} = \begin{cases} \sum_{j=0}^{\min\{\tau, m\}} \psi_j (F_{\mathcal{E}}((m+1-j)\mathcal{E}_s) - F_{\mathcal{E}}((m-j)\mathcal{E}_s)), & m = 0, \dots, N-1 \\ \sum_{j=0}^{\tau} \psi_j (1 - F_{\mathcal{E}}((N+1-j)\mathcal{E}_s)), & m = N \end{cases}$$

Note that the CDF $F_{\mathcal{E}}(\epsilon)$ used in the previous formula is given by Equation (3.12) with $T_H + T_R$ replacing T_H . Unconditioning on P_m , we obtain

$$F_{\text{SNR}}(x) = P\{\text{SNR} \leq x\} = 1 - \frac{1}{\theta \rho^2} \sum_{m=0}^N p_m \int_{-\theta}^{\theta} \int_0^{\rho} \exp\left(-x \frac{(1+r^a)\sigma^2}{P_m F_M(\phi)}\right) r dr d\phi \quad (3.22)$$

Therefore

$$p_{si}^r = P\{\text{successful information reception, random energy beamforming}\} = \frac{1}{\theta \rho^2} \sum_{m=0}^N p_m \int_{-\theta}^{\theta} \int_0^{\rho} \exp\left(-\left(2^{R_I S_u/W} - 1\right) \frac{(1+r^a)\sigma^2}{P_m F_M(\phi)}\right) r dr d\phi \quad (3.23)$$

The information rate R_I equals D_I/T_I , where D_I is the amount of data (bits) that the node sends to the AP, and T_I is the transmission time. In our case, $T_I = 1 - T_H - T_R$, and therefore, there is a trade-off between the charging time (transmission power) and the information rate.

3.2.3 Circular Energy Beamforming

When the AP beamforms in a round robin fashion and for a static channel, we have to consider two complementary cases. Assuming for simplicity that $\tau > S$, the first case refers to nodes that in one time slot harvest energy greater than $S\mathcal{E}_s$ energy units. These nodes manage to increase their battery energy level cycle-by-cycle until the threshold $\mathcal{E}_\tau$ (used for reporting) has been reached. After that, the nodes spend the amount of energy exceeding $\mathcal{E}_\tau$ for reporting and return to level $\mathcal{E}_\tau - (S-1)\mathcal{E}_s$ before they start to charge again. Note that $(S-1)\mathcal{E}_s$ energy units are lost due to the circular beamforming pattern.

The second case refers to nodes that in one time slot harvest energy less than $S\mathcal{E}_s$ energy units. Due to the circular nature of energy beamforming, these nodes deplete one energy unit per time slot and eventually return to the zero state before they start charging again.

For the probability of successful information reception using the circular energy-beamforming scheme, p_{si}^c , Equation (3.24) is still valid, but the transmission powers P_m and their corresponding probability $p_m = P\{P_m\}$ should be changed. The different cases are summarized in the following array

$$P_m = \begin{cases} \frac{m\mathcal{E}_s}{T_I}, & p_m = F_{\mathcal{E}}((m+1)\mathcal{E}_s) - F_{\mathcal{E}}(m\mathcal{E}_s), & m = 0, \dots, S-1 \\ \frac{(\tau-S+m)\mathcal{E}_s}{T_I}, & p_m = F_{\mathcal{E}}((m+1)\mathcal{E}_s) - F_{\mathcal{E}}(m\mathcal{E}_s), & m = S, \dots, N+S-1-\tau \\ \frac{N\mathcal{E}_s}{T_I}, & p_m = 1 - F_{\mathcal{E}}((N+S-\tau)\mathcal{E}_s), & m = N+S-\tau, \dots, N \end{cases} \quad (3.24)$$

Note that if no reporting is required, the parameter τ is set equal to N . In this case, the information transmission power is $N\mathcal{E}_s/T_I$ with probability $1 - F_{\mathcal{E}}(S\mathcal{E}_s)$. That is, if a sensor node charges in one time slot at energy levels greater than $S\mathcal{E}_s$, it will transmit the information message in full power.

3.2.4 Delay Analysis

In case of an event detection, the detecting node should report to the AP as soon as possible. An information message may reach the AP directly if the transmission of the detecting node is successful, or indirectly by relaying the message through neighboring nodes overhearing the transmission if the epidemic mode is on. This epidemic information dissemination is very robust but complicates the delay analysis. To this end, we present some basic delay analysis results, considering only the case of one-hop transmissions.

Delay of First Transmission Attempt for Random Energy Beamforming

Suppose an event takes place at a random time instance, and a nearby node detects the event. This node will transmit the information message at the end of the current time slot if the node is located in the serving sector, or at the end of an upcoming time slot for which the tagged sector is selected. Since the AP selects randomly the sectors with probability $q = \theta/\pi$, the time (in slots) until the first visit to the tagged sector is geometrically distributed with success probability q . Therefore, the average delay until transmission of the message is

$$E[\text{Delay for random energy beamforming}] = \frac{1}{2}q + (1-q) \sum_{n=1}^{\infty} \left(\frac{1}{2} + n \right) q(1-q)^{n-1} = \frac{1}{q} - \frac{1}{2} = S - \frac{1}{2} \quad (3.25)$$

where the term $1/2$ in the left side of the equation represents the average residual delay, that is, the time elapsed between detection and the end of the current time slot. Note that the first transmission attempt is successful with probability p_{si}^r .

Delay of First Transmission Attempt for Circular Energy Beamforming

Suppose again that an event takes place at a random time instance and that sectors are selected in a round robin fashion. Then, the average delay is $1/2$, which accounts for the average residual delay until the end of the current time slot, plus the average delay of a uniformly distributed random variable over the range $[0, \dots, S-1]$. Therefore,

$$E[\text{Delay for circular energy beamforming}] = \frac{1}{2} + \frac{S-1}{2} = \frac{S}{2} \quad (3.26)$$

which is almost half the value in Equation (3.26). Note that in this case, the first transmission attempt is successful with probability p_{si}^c .

3.2.5 Reporting Phase

The reporting phase is crucial to design alternative charging strategies. Knowledge (or estimation) of the energy reserves of nodes located in a sector may dictate specific actions to be taken by the AP. For example, lack of reports from nodes in the same sector

over several time slots is an indicator of heavy blockage. In this case, insisting on beamforming in the specific direction leads to a waste of resources and degrades the overall performance of the system. Nodes in the serving sector, after harvesting energy for a period T_H , report their ID to the AP provided that their battery energy exceeds a specific threshold $\mathcal{E}_\tau$. To be more specific, the nodes use the surplus (if any) battery energy $(m - \tau)\mathcal{E}_s$, $m = \tau + 1, \dots, N$ to report their presence to the AP. Needless to say that the reports are not always delivered to the AP due to the possible low transmitting power, bad channel conditions or link blockage. In the sequel, we estimate the probability of successfully delivering a report, under the assumption that the serving sector is selected randomly and in a circular fashion.

3.2.6 Probability of Successful Reporting in Case of Random Energy Beamforming

It is clear that only nodes with battery energy levels greater than $\mathcal{E}_\tau = \tau\mathcal{E}_s$ attempt to transmit report messages. Thus, the probability of reporting is

$$p_r^r = \sum_{i=0}^{\tau} \psi_i P\{\mathcal{E} > (\tau + 1 - i)\mathcal{E}_s\} = \sum_{i=0}^{\tau} \psi_i (1 - F_{\mathcal{E}}((\tau + 1 - i)\mathcal{E}_s)) \quad (3.27)$$

Given that a node reports to the AP, the probability that the sent message is received correctly by the AP, p_{sr}^r , is

$$p_{sr}^r = \frac{1}{\theta \rho^2 p_r^r} \sum_{i=0}^{\tau} \psi_i \sum_{\ell=1}^{N-\tau} p_{\ell} \int_{-\theta}^{\theta} \int_0^{\rho} \exp \left(-\frac{1 + r^a}{F_M(\phi)} \left(\frac{(2^{D_R/T_R W'} - 1)\sigma^2}{P_{\ell}} + \frac{\eta_{\tau+1-i}}{P_0} \right) - \beta r \right) r dr d\phi \quad (3.28)$$

with

$$p_{\ell} = \begin{cases} \frac{F_{\mathcal{E}}((\tau + \ell + 1 - i)\mathcal{E}_s) - F_{\mathcal{E}}((\tau + \ell - i)\mathcal{E}_s)}{1 - F_{\mathcal{E}}((\tau + 1 - i)\mathcal{E}_s)} & \ell < N - \tau \\ \frac{1 - F_{\mathcal{E}}((\tau + \ell + 1 - i)\mathcal{E}_s)}{1 - F_{\mathcal{E}}((\tau + 1 - i)\mathcal{E}_s)} & \ell = N - \tau \end{cases} \quad (3.29)$$

The proof is provided in Appendix A.

3.2.7 Probability of Successful Reporting in Case of Circular Energy Beamforming

If nodes are charged in a circular fashion, that is, every S time slots, then the probability of reporting is $1 - F_{\mathcal{E}}((S + 1)\mathcal{E}_s)$ provided that $\tau \geq S$ and $1 - F_{\mathcal{E}}((\tau + 1)\mathcal{E}_s)$ otherwise. These two cases are written in compact form as

$$p_r^c = P\{\mathcal{E} > (\min\{S, \tau\} + 1)\mathcal{E}_s\} = 1 - F_{\mathcal{E}}((\min\{S, \tau\} + 1)\mathcal{E}_s) \quad (3.30)$$

The reporting nodes form a point process, which is the original PPP thinned by the probability p_r^c . Following the same steps as in Appendix A, the probability that the sent message is received correctly by the AP, p_{sr}^c , is

$$p_{sr}^c = \frac{1}{\theta \rho^2 p_r^c} \sum_{\ell=1}^{N-\tau} p_\ell \int_{-\theta}^{\theta} \int_0^{\rho} \exp \left(-\frac{1+r^a}{F_M(\phi)} \left(\frac{(2^{D_R/T_R W'} - 1)\sigma^2}{P_\ell} + \frac{\eta_{\min\{S,\tau\}+1}}{P_0} \right) - \beta r \right) r dr d\phi \quad (3.31)$$

with

$$p_\ell = \begin{cases} \frac{F_{\mathcal{E}}((\min\{S, \tau\} + \ell + 1)\mathcal{E}_s) - F_{\mathcal{E}}((\min\{S, \tau\} + \ell)\mathcal{E}_s)}{1 - F_{\mathcal{E}}((\min\{S, \tau\} + 1)\mathcal{E}_s)} & \ell < N - \tau \\ \frac{1 - F_{\mathcal{E}}((\min\{S, \tau\} + \ell + 1)\mathcal{E}_s)}{1 - F_{\mathcal{E}}((\min\{S, \tau\} + 1)\mathcal{E}_s)} & \ell = N - \tau \end{cases} \quad (3.32)$$

A summary of chapter contributions is as follows:

- We derive analytical expressions for the average harvested energy per slot and the probability of successful information reception for a node.
- We model the energy level of a sensor battery as a finite Markov chain and derive its steady-state distribution for various blocking probabilities under the assumption of random energy beamforming.

4. MONITORING FOR RARE EVENTS IN A WIRELESS POWERED COMMUNICATION MMWAVE SENSOR NETWORK

We focus on the communication performance aspect of a WPCN network used to monitor an area of interest for possible rare events. The objective is to deliver the information message (in case of an event) successfully and with the minimum delay possible. Throughout this work, we consider a mmWave wireless power sensor network with randomly deployed sensor nodes. An AP at the center of the sensing area is responsible for wirelessly charging the sensors and collecting their information. Sensors monitor the environment for possible events that, upon detection, should be reported with minimum delay.

We introduce an optional reporting phase during which sensors, with energy storage exceeding a predefined threshold, report their status to the AP. Partial knowledge of the sensors energy status may prove helpful for the AP to select alternative and more efficient energy-beamforming strategies. Moreover, since transmissions in the mmWave band are susceptible to blockage, we consider a flooding technique for information message delivery. That is, nodes that intercept the message become information transmitters themselves in an effort to increase the reliability of the system and minimize the delivery delay. Finally, sector selection strategies are presented and their performance is assessed through simulations. Taking into account the number of reports received by the nodes of each sector, two strategies are proposed that identify and subsequently degrade energy beamforming towards sectors with heavy blockage. Periodic shifting of sectors is another proposed scheme that aims to boost nodes located at the edges of the beamforming pattern.

We study the system model as stated in Subsection 3.1.1 assuming the format of Figure 3.2 and the energy harvesting Markov chain model in subsection 3.1.3. For the phase information, the analysis in section 3.2 provides us with the probability of successful information reception in the case of random energy beamforming and the probability of successful information reception in the case of circular energy beamforming. Also, the analysis in section 3.2 provides us a mathematical expression for the delay of the first transmission attempt for random and circular energy beamforming

4.1 Sector Selection Strategies

In this section, we describe strategies that the AP can follow to select a sector for charging. It is clear that these strategies utilize the feedback provided by the reporting messages. The reporting or “presence” messages designate the number of nodes that have reached the charging energy threshold $\mathcal{E}_T$. A large number of successfully received reports from nodes in a sector indicates that the sector is sufficiently covered by charged nodes. Therefore, it is expected that upon detection of an event in the tagged sector, the information message will reach the AP promptly. The AP keeps a record of the reporting nodes per sector and directs its charging beam towards the sector that satisfies certain criteria.

In general, there are two mechanisms that influence the performance of the system. The first source of inefficiency is the prompt detection of the event itself and the successful transmission of the information message. Sensor nodes have a limited sensing area, and if the network is sparse, the monitored area is not sufficiently covered. In this case, and assuming that the event does not spread spatially over time, there is a substantial probability of an unnoticed event. Moreover, even if the event is detected promptly, there is no guarantee that the information message will reach the AP. This is due to possible blockage or bad channel conditions. Maximizing the covered area of a sector by sufficiently charged nodes and increasing the probability successful information transmission demands persistent beamforming towards sectors of high numbers of reporting nodes.

The second source of inefficiency is due to the fact that a node transmits an information message only if it is located in the serving sector. Therefore, if the AP spends its time to sectors other than the one that the event takes place, the delivery of information message suffers a considerable delay. In this case, fast (and fair) hopping between sectors is mandatory to reduce the information transmission delay. Note that the two inefficiency mechanisms demand different treatment by the AP. In the following, we join the two contradicting objectives into a reward function of the form

$$J = C_S + wC_D \quad (4.1)$$

where C_S denotes the reward of beamforming towards sectors of high numbers of reporting nodes, and C_D denotes the reward of not delaying energy beamforming of sectors. The factor w balances the relative weight of the two objectives. For C_S , we consider the average number of sufficiently charged sensor nodes per time slot (or sector selection), i.e., $C_S = E[\mathcal{S}]$, whereas two alternative reward functions are studied for C_D . Since the number of nodes that are capable of successfully conveying the information message to the AP is unknown, we replace it with the number of reporting nodes. It is clear that in order for a node to reach the reporting threshold, it must have encountered “good” channel conditions. Thus, reporting is a good indicator of the probability of successful information transmission.

Let us consider a policy of sector selection resulting (up to the time slot n) in the sequence of reports

$$R(n) = [R_{j_1}(n) \quad R_{j_2}(n) \quad \cdots \quad R_{j_n}(n)] \quad (4.2)$$

where the index $j_k \in \{1, \dots, S\}$ indicates the sector served at time slot k . Denote by $\nu_s(n)$ the number of times that sector s has been selected for service, that is

$$\nu_s(n) = \sum_{k=1}^n I(j_k = s) \quad (4.3)$$

with $I(\cdot)$ the indicator function. Using a time average instead of expectation, we seek a

sequential algorithm to maximize

$$\begin{aligned}\bar{R}(n) &= \frac{1}{n} \sum_{k=1}^n R_{j_k}(n) = \frac{1}{n} \sum_{s=1}^S \nu_s(n) \frac{\sum_{\ell=1}^n I(j_\ell = s) R_{j_\ell}(\ell)}{\nu_s(n)} \\ &= \sum_{s=1}^S \frac{\nu_s(n)}{n} \bar{R}_s(n) = \sum_{s=1}^S f_s(n) \bar{R}_s(n)\end{aligned}\quad (4.4)$$

where $f_s(n)$ is the frequency of serving sector S in the first n time slots and $\bar{R}_s(n)$ is the average number of reporting nodes in sector s over the $\nu_s(n)$ selections of the sector. The next sector to be served at time slot $n + 1$ is the one that maximizes $\bar{R}(n + 1)$, that is

$$j_{n+1}^* = \arg \max_{j_{n+1}} \bar{R}(n + 1) = \arg \max_{j_{n+1}} \sum_{s=1}^S f_s(n + 1) \bar{R}_s(n + 1) \quad (4.5)$$

To this end, we adopt a greedy algorithm that selects the next sector to be served as the one with the highest average of the product $f_s(\cdot) \bar{R}_s(\cdot)$. Thus, for each $s \in \{1, \dots, S\}$, we form the index

$$A_s(n + 1) = \frac{\sum_{k=1}^{n+1} I(j_k = s) f_s(k) \bar{R}_s(k)}{\nu_s(n + 1)} \quad (4.6)$$

and we serve the sector with the highest value of $A_s(n + 1)$. The index $A_s(n + 1)$ is computed recursively as

$$A_s(n + 1) = \frac{A_s(n) \nu_s(n) + (\bar{R}_s(n) \nu_s(n) + R_s(n + 1)) / (n + 1)}{\nu_s(n) + 1} \quad (4.7)$$

Note that the number of reporting nodes $R_s(n + 1)$, $s = 1, \dots, S$ is not known, since the sectors have not been served yet. To circumvent this problem, we replace $R_s(n + 1)$ with the most recent value, say $R_s^c(n)$, of known reporting nodes at time slot n . This choice is justified by the small differences in the numbers of reporting nodes for slowly varying channels.

We present now two alternative algorithms that take into account the delay reward C_D .

4.1.1 Algorithm 1

As was already stated, sectors with small reporting numbers should not be neglected at all. There is always a probability for an event to occur close to a sensor node with “good” channel conditions located in one of these “bad” sectors. Therefore, all sectors should be

served, although with different frequency. Our first attempt to maximize the delay reward C_D is to use the indices

$$B_s(n+1) = -\frac{1}{d_s(n+1)} \quad (4.8)$$

where $d_s(n+1)$ denotes the time elapsed since the last time sector s was selected for service. Sectors that have not been selected for a long period (large $d_s(n+1)$) exhibit large values of the index $B_s(n+1)$, thus forcing the AP to select them for service as soon as possible. Combining Equations (4.7) and (4.8), we propose the algorithm

$$j_{n+1}^* = \arg \max_s \{A_s(n+1) + wB_s(n+1)\} \quad (4.9)$$

A large value of the regulating parameter w will force the AP to select sectors in a round robin fashion, whereas a small value of the parameter w will force the AP to select sectors with the highest number of reporting nodes. Before summarizing the algorithm, we perform a final adjustment by replacing $R_s(n+1)$ in Equation (4.7) with $R_s^c(n)/\max_k R_k^c(n)$ in order to avoid the bias caused by large numbers of reporting nodes.

Algorithm 1 is described below, with the following defined vectors stored in AP.

- $R^c = [R_1^c(n) R_2^c(n) \dots R_S^c(n)]$, a vector holding the most recent number of reports per sector.
- $\bar{R} = [\bar{R}_1(n) \bar{R}_2(n) \dots \bar{R}_S(n)]$, a vector holding the average number of reports per sector.
- $\nu = [\nu_1(n) \nu_2(n) \dots \nu_S(n)]$, a vector holding the number of selections of each sector.
- $A = [A_1(n) A_2(n) \dots A_S(n)]$, a vector holding the indices up to the time n .
- $D = [d_1(n) d_2(n) \dots d_S(n)]$, a vector holding the time elapsed since the last service of each sector.

4.1.2 Algorithm 2

The second algorithm borrows ideas from the solution of the multiarmed bandit (MAB) [81] problem and specifically the upper confidence bound (UCB1) algorithm [3]. The MAB problem demonstrates the exploitation versus exploration dilemma and in many aspects fits the sector selection for energy-beamforming problem. In our case, exploitation reflects beamforming towards sectors of high numbers of reports, whereas exploration refers to beamforming towards sectors of bad channel conditions or heavy blockage.

In UCB algorithms, the goal is the maximization of the cumulative reward $\sum_{t=1}^T R_s(t)$ over the set of actions S , where the random variable $R_s(t)$ has true mean Q_s and sample

Initialization;

Create initial values of $A, \nu, D, R^c, \bar{R}$ by serving sectors in a circular fashion for $n = 1, \dots, N$ time slots

Set parameter w

while no_information_message do

Calculate indices $A_s(n+1) + wB_s(n+1)$, $s = 1, \dots, S$ using equations (4.7) and (4.8);

Find $j_{n+1}^* = \arg \max_s \{A_s(n+1) + wB_s(n+1)\}$ Equation (4.9);

Energy beamform sector j_{n+1}^* ;

Receive reports $R_{j_{n+1}^*}(n+1)$;

/ Update */*

$R^c(j_{n+1}^*) = R_{j_{n+1}^*}(n+1)$;

$\bar{R}(j_{n+1}^*) = [\bar{R}(j_{n+1}^*)\nu(j_{n+1}^*) + R_{j_{n+1}^*}(n+1)/\max_s R^c(s)]/(\nu(j_{n+1}^*) + 1)$;

$A(j_{n+1}^*) = [A(j_{n+1}^*)\nu(j_{n+1}^*) + \bar{R}(j_{n+1}^*)/(n+1)]/(\nu(j_{n+1}^*) + 1)$;

$D(j_{n+1}^*) = 1$, $D(j) = D(j) + 1$ for $j \neq j_{n+1}^*$;

$\nu(j_{n+1}^*) = \nu(j_{n+1}^*) + 1$;

end

Algorithm 1: Dynamic Sector Energy Beamforming

mean $\bar{Q}_s(t) = 1/t \sum_{\tau=1}^t R_s(\tau)$. The algorithm at time step t selects the action that maximizes the upper confidence bound

$$s_t^* = \arg \max_{s \in S} \bar{Q}_s(t) + U_s(t) \quad (4.10)$$

where $U_s(t)$ is a carefully chosen upper confidence bound, so that the true value Q_s is less than $\bar{Q}_s(t) + U_s(t)$ with high probability. The UCB1 algorithm is based on a heuristic that makes use of Hoeffding's inequality [24] and sets the upper confidence bound to

$$U_s(t) = \sqrt{\frac{2 \log t}{\nu_s(t)}} \quad (4.11)$$

where $\nu_s(t)$ denotes the number of times action s was tried up to the time step t . Small values of $\nu_s(t)$ increase the upper bound $U_s(t)$ and consequently force the exploration of action s .

The second algorithm we propose uses the same principles as the UCB1 algorithm with a major modification. Since it is desirable to occasionally select sectors with low numbers of reporting nodes, we should not allow the upper bound $U_s(t)$ to vanish as t goes to infinity. We periodically “revive” the upper bound so that “bad” sectors have an opportunity to be

energy-beamformed. To this end, we define

$$B_s(n+1) = \sqrt{\frac{2 \log[(n+1)/f]}{\nu_s(n+1)/f}}, \quad f = \left\lceil \frac{n+1}{T_p} \right\rceil \quad (4.12)$$

where T_p is the time period that adjusts the upper bound and $\lceil \cdot \rceil$ denotes the ceiling operator. The parameter T_p has the opposite effect of the parameter w . For a large value of T_p , bad sectors are neglected in the long run, whereas for a small value of T_p , all sectors are selected sequentially.

Algorithm 2 is summarized as

$$j_{n+1}^* = \arg \max_s \{A_s(n+1) + B_s(n+1)\} \quad (4.13)$$

with $B_s(n+1)$ given by Equation (4.12) and all other parameters as in Algorithm 1.

Initialization;

Create initial values of $A, \nu, D, R^c, \bar{R}$ by serving sectors in a circular fashion for $n = 1, \dots, N$ time slots

Set parameter T_p ;

while no_information_message do

Calculate indices $A_s(n+1) + B_s(n+1)$, $s = 1, \dots, S$ using equations (4.7) and (4.12);

Find $j_{n+1}^* = \arg \max_s \{A_s(n+1) + B_s(n+1)\}$ Equation (4.13);

Energy beamform sector j_{n+1}^* ;

Receive reports $R_{j_{n+1}^*}(n+1)$;

/ Update */*

$R^c(j_{n+1}^*) = R_{j_{n+1}^*}(n+1)$;

$\bar{R}(j_{n+1}^*) = [\bar{R}(j_{n+1}^*)\nu(j_{n+1}^*) + R_{j_{n+1}^*}(n+1)/\max_s R^c(s)]/(\nu(j_{n+1}^*) + 1)$;

$A(j_{n+1}^*) = [A(j_{n+1}^*)\nu(j_{n+1}^*) + \bar{R}(j_{n+1}^*)/(n+1)]/(\nu(j_{n+1}^*) + 1)$;

$D(j_{n+1}^*) = 1$, $D(j) = D(j) + 1$ for $j \neq j_{n+1}^*$;

$\nu(j_{n+1}^*) = \nu(j_{n+1}^*) + 1$;

end

Algorithm 2: Dynamic Sector Energy Beamforming (MAB approach)

4.1.3 Shifting of Sectors Strategy

Due to the presence of the Fejér kernel in the received power formula, energy harvesting is maximum along the main direction of beamforming. Thus, nodes residing at the edges

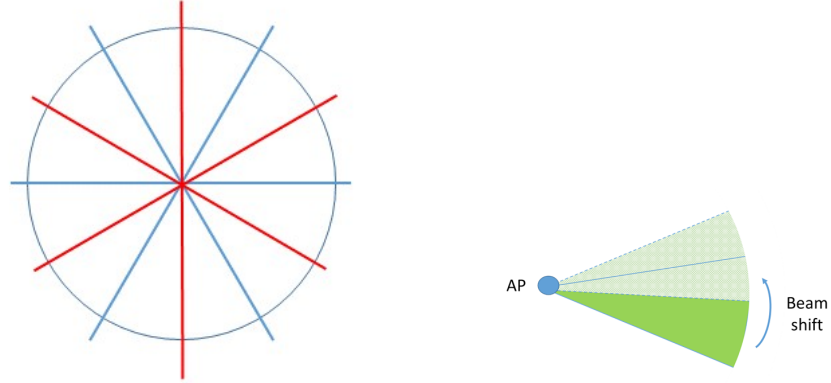


Figure 4.1: Shifting of sectors strategy.

Table 4.1: Parameters used in simulations.

Parameter	Value
$\zeta_1, \zeta_2, \gamma, N$	1500, 0.0022, 1, 100
ρ, θ, α, M	10 m, $\pi/15$, 2, 8
P_0, σ^2, λ	−10 db, −30 db, 1
D_I, D_R, W'	512 bits, 128 bits, 1 kHz

of a sector do not charge at the same level with the rest of the nodes even if they are at the same distance from the AP. A remedy to the problem is to periodically change the direction of the sectors as is shown schematically in Figure 4.1. For a predefined number of time slots, the AP beamforms according to the “blue” pattern and then switches to the “red” pattern and so on. It is conceivable that this technique can be combined with the aforementioned algorithms for sector selection.

4.2 Numerical Results and Simulations

In this section we assess, the performance of the proposed model and energy-beamforming strategies using simulations. The simulation platform was MATLAB. We used the parameter set of Table 4.1 taken from [54].

In our simulation model, a base station lies at the center of a cell of radius 10 m, and a linear antenna array of $M = 8$ elements is used to energy beamform 15 sectors. Sensor nodes are randomly deployed forming a Poisson Point Process with intensity $\lambda = 1$. That is, 314 nodes on average are scattered in the area of interest. Each node is equipped with a battery of $N = 100$ energy levels. Channel gains are modeled as independent random variables following the exponential distribution. However, the channels are slow-varying in the sense that the gains do not change throughout the simulation. All strategies were

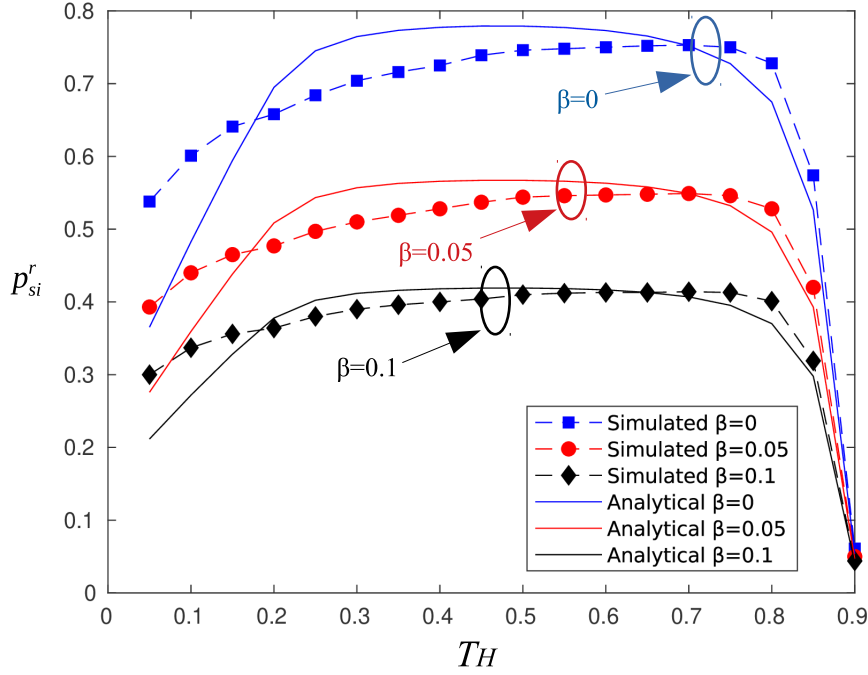


Figure 4.2: Probability of successful information reception p_{si}^r for random selected sectors.

simulated for 1000 different sensor deployments and channel gains. The simulation horizon is taken equal to 3000 time slots. For each simulation run, an event occurs randomly in the last 1000 time slots. It is further assumed that the event is detected immediately by the nearest node.

Figure 4.2 depicts p_{si}^r as a function of harvesting period T_H , for various values of the blocking parameter β . The parameter τ for reporting was set to 90. The analytical expression for p_{si}^r is given by Equation (3.23), and as is observed, there is a good match between the analytical and the simulation results. The p_{si}^r curve exhibits a plateau for T_H in the range $[0.3, 0.7]$. Smaller values of T_H mean less charging time, and therefore, the nodes do not transmit with sufficient power. Large values of T_H (greater than 0.8) remedy this problem, but the time period left to transmit the information message reduces considerably. As a result, the information rate increases and the probability of successfully delivering the information message drops. Figure 4.3 depicts p_{si}^c for the same parameter set of Figure 4.2. There is a deviation of the analytical and simulation results for high values of T_H , and as is observed, there is a slight increase in the probability of successful information reception compared to that of randomly selected sectors.

Figures 4.4 and 4.5 depict the probability of a successful report as a function of the threshold τ , for random and circular beamforming, respectively. The parameter T_H was set equal to 0.6. Note that Equations (3.28) and (3.31) expresses the conditional probability of successful report given that the node is sufficiently charged to attempt reporting,

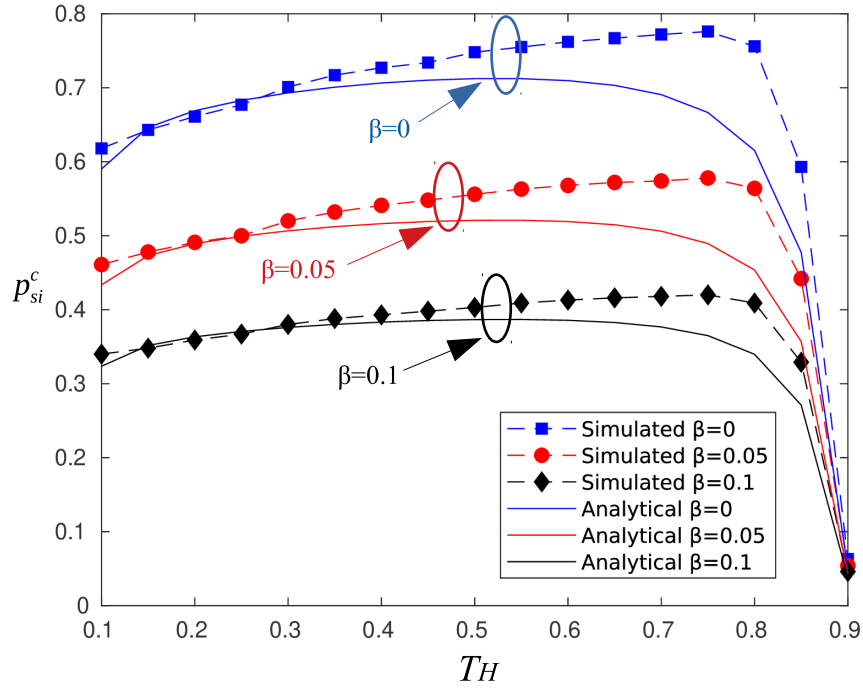


Figure 4.3: Probability of successful information reception p_{si}^c for circular selection of sectors.

whereas Equations (3.27) and (3.30) is the probability of reporting for the random (circular) selection of sectors. Thus, the analytical curves in Figure 4.4 were obtained using $P\{\text{success report, random}\} = p_{sr}^r p_r^r$ and those in Figure 4.5 were obtained using $P\{\text{success report, circular}\} = p_{sr}^c p_r^c$. The simulation and analytical results are in good agreement (error less than 3%) for values of τ less than 60. After $\tau = 60$, which is also the percentage of time a node is charging (T_H), the analytical curves start to deviate from the simulated ones. Comparing random and circular energy beamforming, it is clear that there are no major differences regarding the probabilities of successful information and reporting reception. However, as is shown by the simple delay analysis expressed by Equations (3.25) and (3.26), circular energy beamforming is superior regarding the average delay of message delivery. Thus, in the simulations that follow, we consider only the circular case as the benchmark solution.

4.2.1 Epidemic vs. No Epidemic

Figures 4.6 and 4.7 illustrate the effect of the epidemic dissemination of information on the probability and the delay of a successful message reception. As is observed, the probability of successful information reception increases by almost 30%. Neighboring nodes that receive the information transmission act as relays and retransmit the message at first chance. However, receiving the message from a relay node means an additional delay

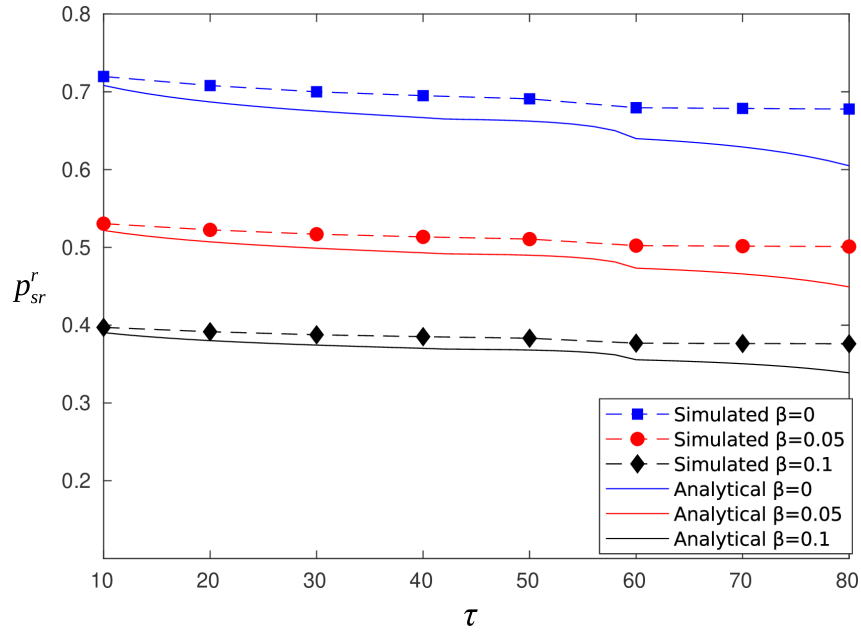


Figure 4.4: Probability of successful reporting, p_{sr}^r , for randomly selected sectors.

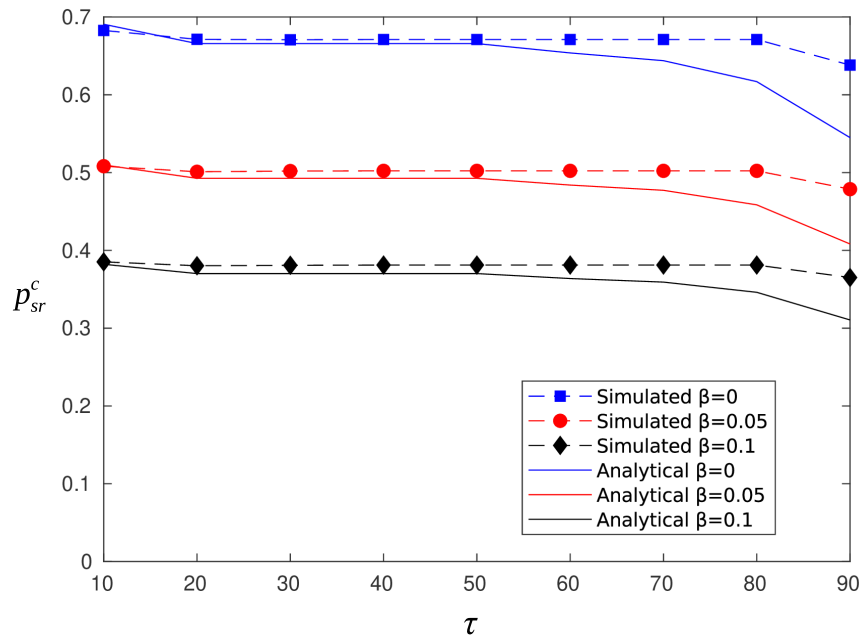
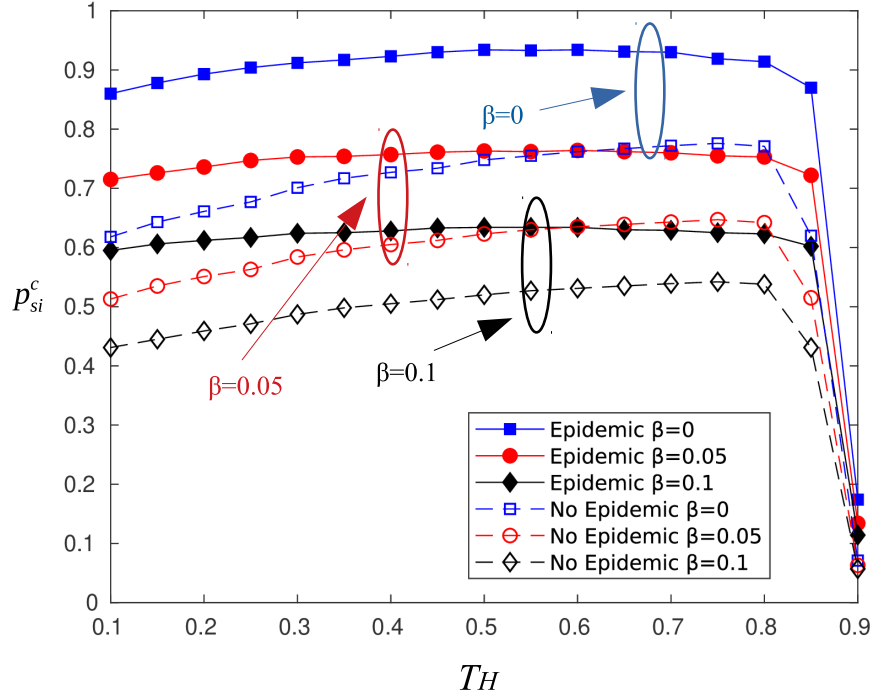


Figure 4.5: Probability of successful reporting, p_{sr}^c , for circular selection of sectors.

Figure 4.6: Effect of epidemic mechanism on p_{si}^c .

on the message delivery, which accounts for two time slots on average, as is shown in Figure 4.7.

4.2.2 Alternative Energy-Beamforming Strategies

In the rest of this section, we compare the circular energy-beamforming scheme with alternative strategies proposed in Section 4.1. In all cases, we did not consider relaying of the information messages.

Figures 4.8 and 4.9 depict the performance, in terms of the probability of successful information reception p_{si} , and the delay encountered for three strategies (the circular selection of sectors, Algorithms 1 and 2) and for various values of the parameter γ , that is, the charging efficiency of the sensor nodes. All nodes are in LoS with the AP, that is, $\beta = 0$, and the time duration for energy harvesting is $T_H = 0.7$. The parameter τ was set equal to 80 and $T_R = 0.05$. The simulations were obtained using 1000 runs, time horizon 5000 time slots, and an event taking place randomly in the last 15 time slots. It is observed, there are no differences regarding the probability of successful information reception, whereas an advantage seems to be revealed regarding the delay of the information delivery for the non-even selection of sectors. This advantage is expected to be magnified if some sectors are under heavy blockage. To this end, we have simulated two scenarios where, in the first scenario, consecutive sectors 1–5 are subject to blockage and, in the second scenario, equidistant sectors 1, 4, 7, 10, and 13 are subject to

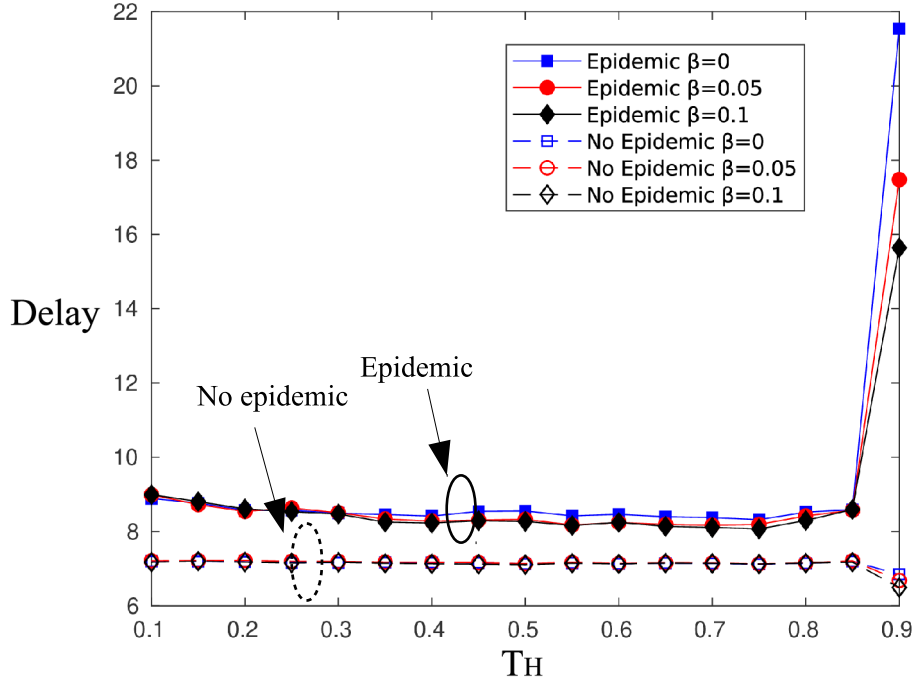


Figure 4.7: Effect of epidemic mechanism on delay.

blockage. Figure 4.10 is an illustration of the first scenario, with red color nodes indicating successfully reporting nodes and $\beta = 5$ for sectors under blockage.

Figures 4.11 and 4.12 depicts the frequency of sector selection by Algorithms 1 and 2 and for the two scenarios presented above and $\beta = 5$ for the sectors under blockage. For the first algorithm, the parameter w was set equal to 1, whereas $T_p = 1700$ for the second algorithm. For this choice of the parameter set, Algorithm 1 is more drastic in suppressing the selection of sectors that are subject to blockage.

Figures 4.13 and 4.14 compare the performance of Algorithm 1 and the circular selection of sectors scheme, in terms of the achievable p_{si} and delay, respectively. The scenario is that of equidistant sectors subject to blockage, and two values of the blockage parameter have been used, $\beta = 0.1$ and $\beta = 5$. As is observed, although both algorithms exhibit the same performance in terms of probability of successful information reception, Algorithm 1 is superior regarding the achievable delay. The gain is larger for greater values of β .

A similar performance is obtained using Algorithm 2. Figures 4.15 and 4.16 compare the performance of Algorithm 1 and the circular selection of sector scheme, in terms of the achievable p_{si} and delay, respectively. The simulation scenario is the same as in the previous case. Again, Algorithm 2 outperforms the circular sector selection scheme in terms of the achievable delay. In both proposed algorithms, blocked sectors are selected less often, and therefore, the residence time to these sectors is small, thus reducing the overall average delay. If an event occurs within a bad sector, then it is very likely to find

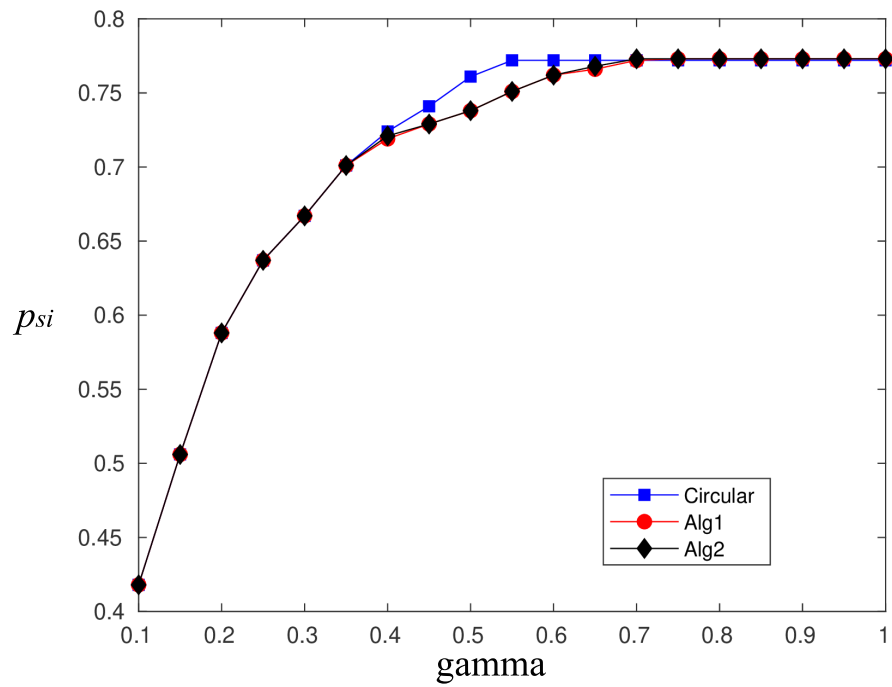


Figure 4.8: p_{si} —Compare sector selection strategies for $\beta = 0$.

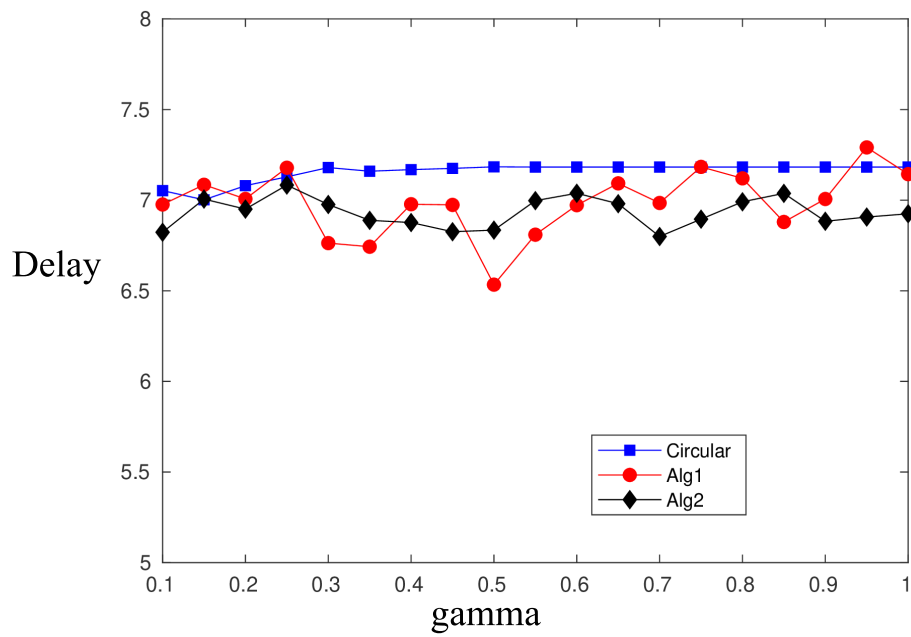


Figure 4.9: Delay—Compare sector selection strategies for $\beta = 0$.

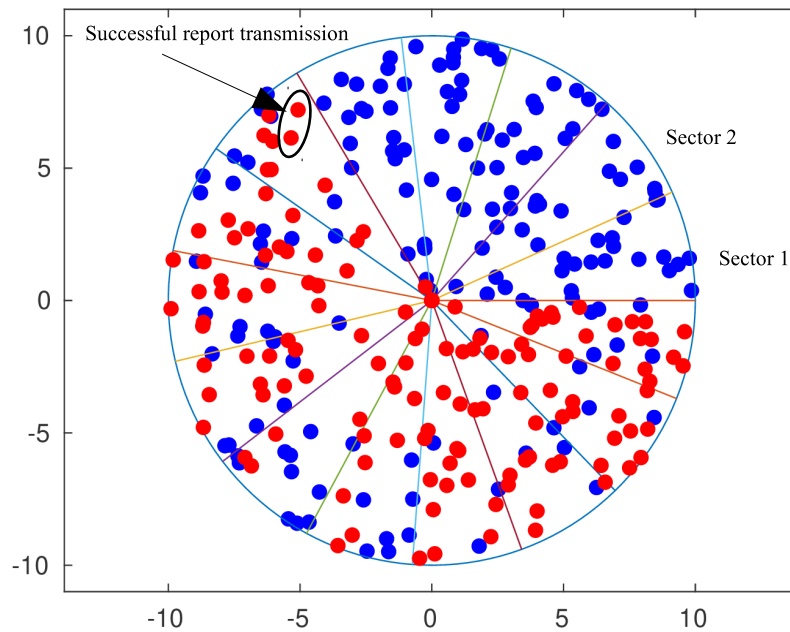


Figure 4.10: Sensors deployment (red denotes sensors with successful report transmissions).

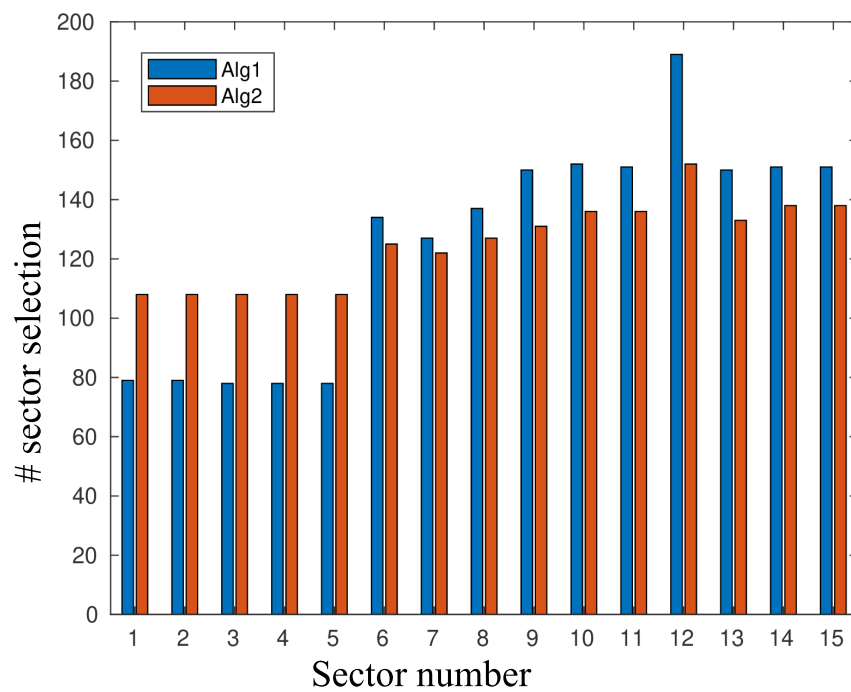


Figure 4.11: Sector selection distribution, where sectors 1–5 are subject to blockage with $\beta = 5$.

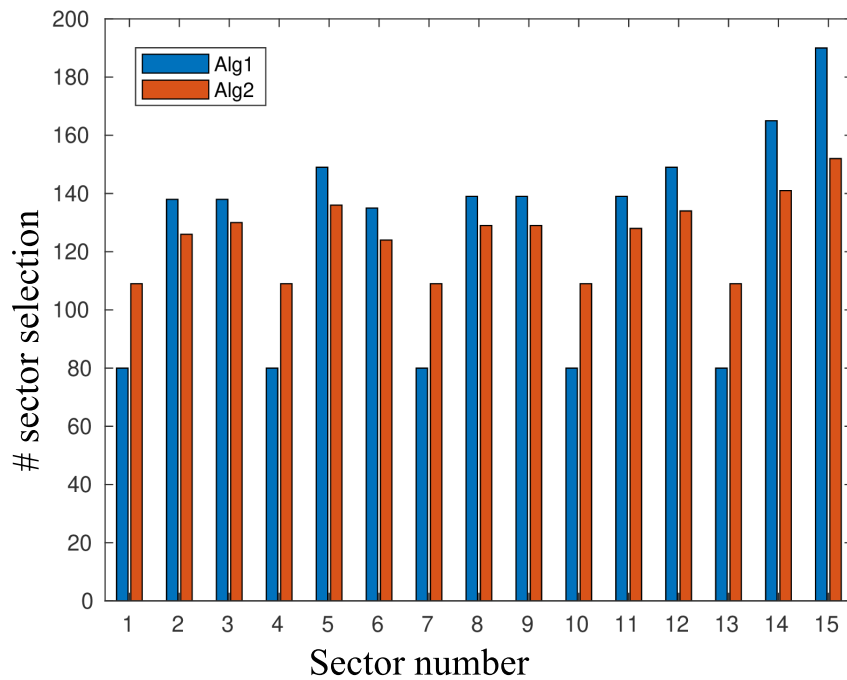


Figure 4.12: Sector selection distribution, where sectors 1, 4, 7, 10, and 13 are subject to blockage with $\beta = 5$.

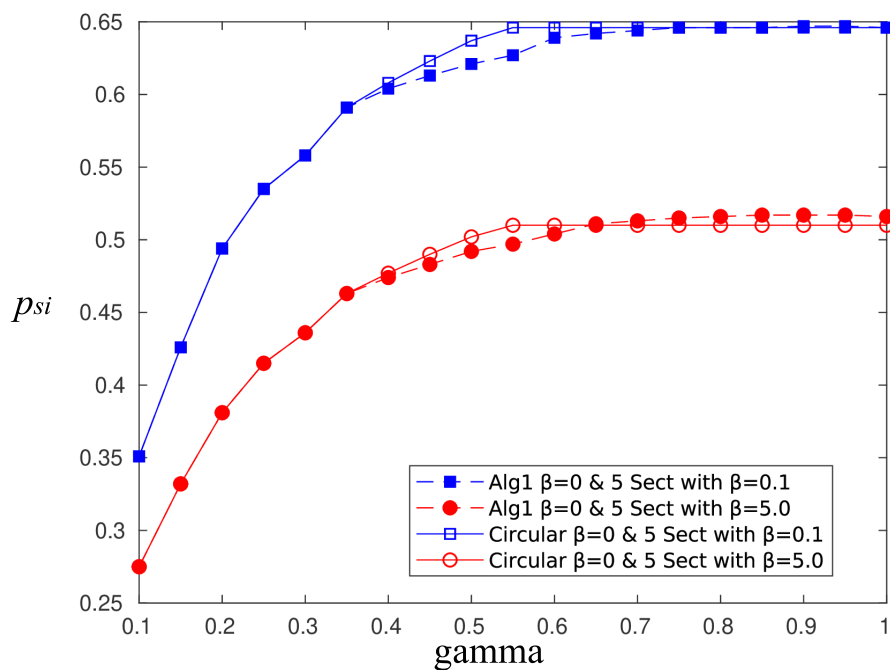


Figure 4.13: Probability of successful information reception, p_{si} , Algorithm 1 vs. circular selection of sectors.

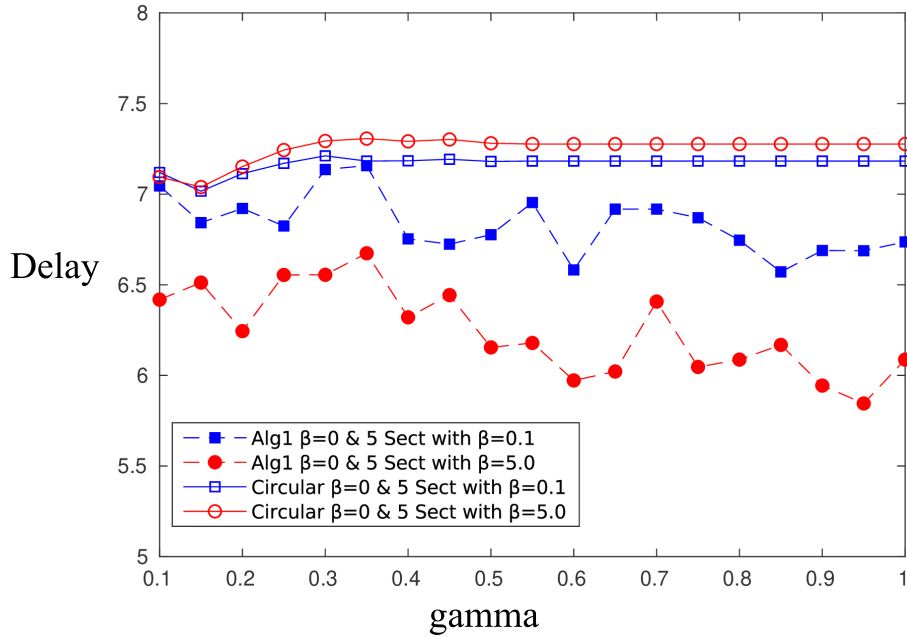


Figure 4.14: Delay of information reception, Algorithm 1 vs. circular selection of sectors.

depleted sensor nodes, and thus, a successful transmission of the information message is impossible anyway. In the rare case that the event occurs near a node that is capable of transmitting the message successfully, the delay will be large, but its contribution to the average delay is small. Therefore, it is preferable to insist on beamforming “good” sectors, whose sensors have a good chance to transmit successfully, and occasionally give the opportunity to nodes in “bad” sectors to charge and transmit.

Next, we assess the performance of the shifting of sectors strategy proposed in Subsection 4.1.3. Figures 4.17 and 4.18 depict the achievable probability of successful information reception and the average delay, respectively. The simulation parameters are the same as those used to test the epidemic mechanism. The pattern of circular selected sectors is shifted every 15 time slots.

The shifting of sectors strategy outperforms the circular selection in terms of p_{si} . Nodes located at the edges of a sector benefit from the shift of the beam pattern, but nodes located at the main direction of the beam become beam edge nodes. Alternating the beam pattern has the overall effect of making battery charging levels independent of the angular position of nodes. It turns out that more nodes are capable of successfully transmitting the information message to the AP, thus increasing p_{si} . However, shifting sectors comes with a penalty on latency, and as is observed, there is an increase of 1–4 time slots in the delay of information message delivery.

A summary of chapter contributions is as follows:

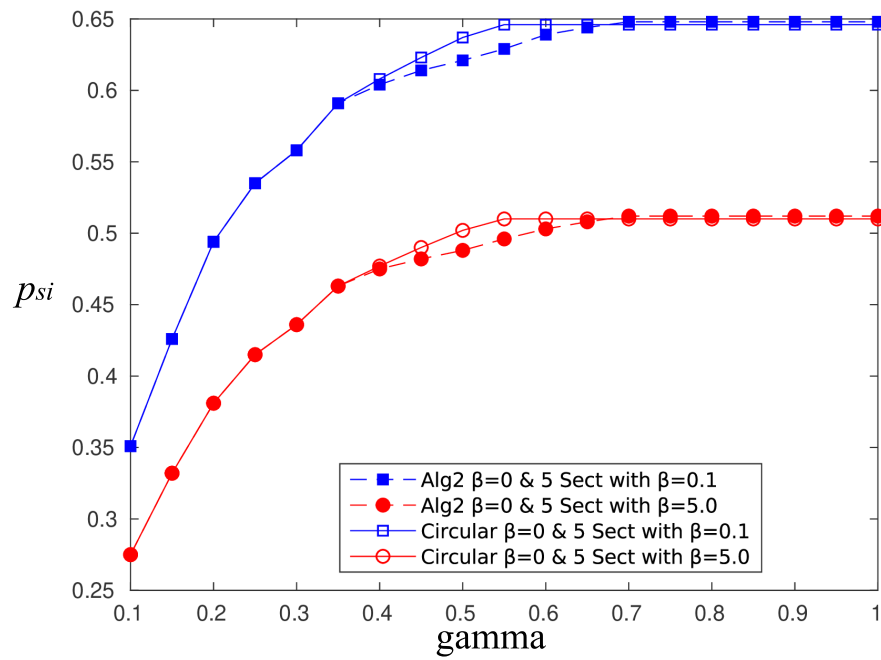


Figure 4.15: Probability of successful information reception, p_{si} , Algorithm 2 vs. circular selection of sectors.

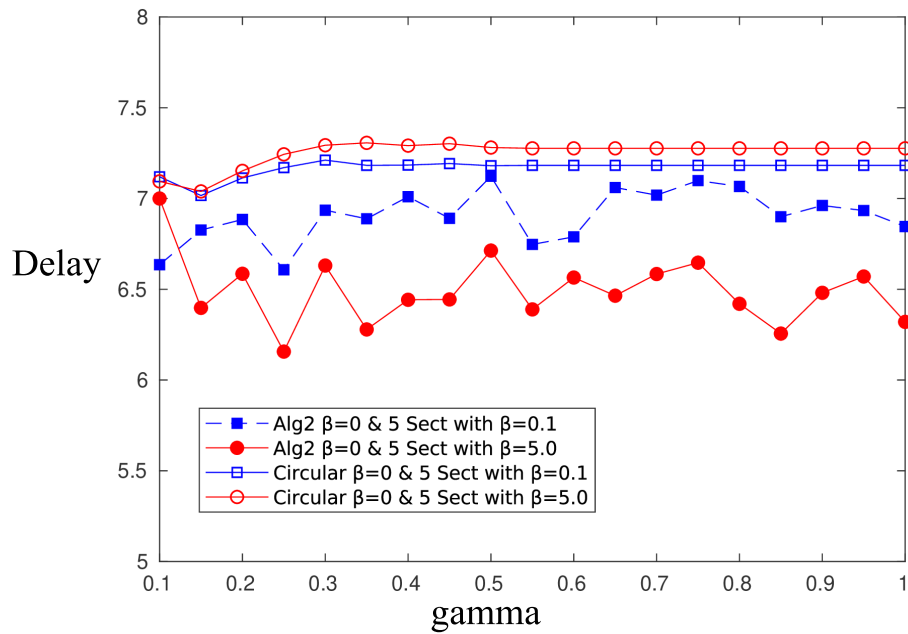


Figure 4.16: Delay of information reception, Algorithm 2 vs. circular selection of sectors.

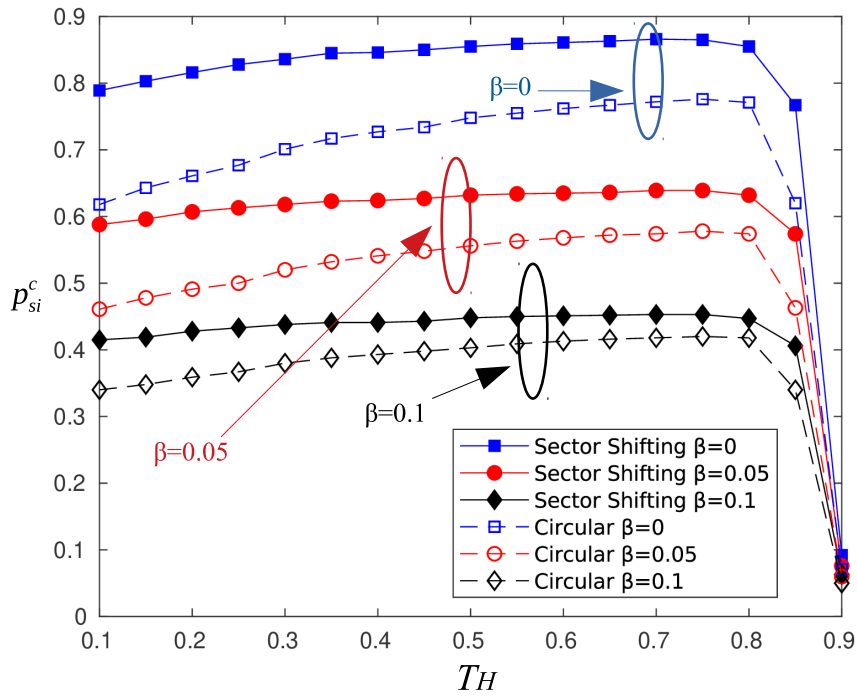


Figure 4.17: Probability of successful information reception using the sector shifting scheme.

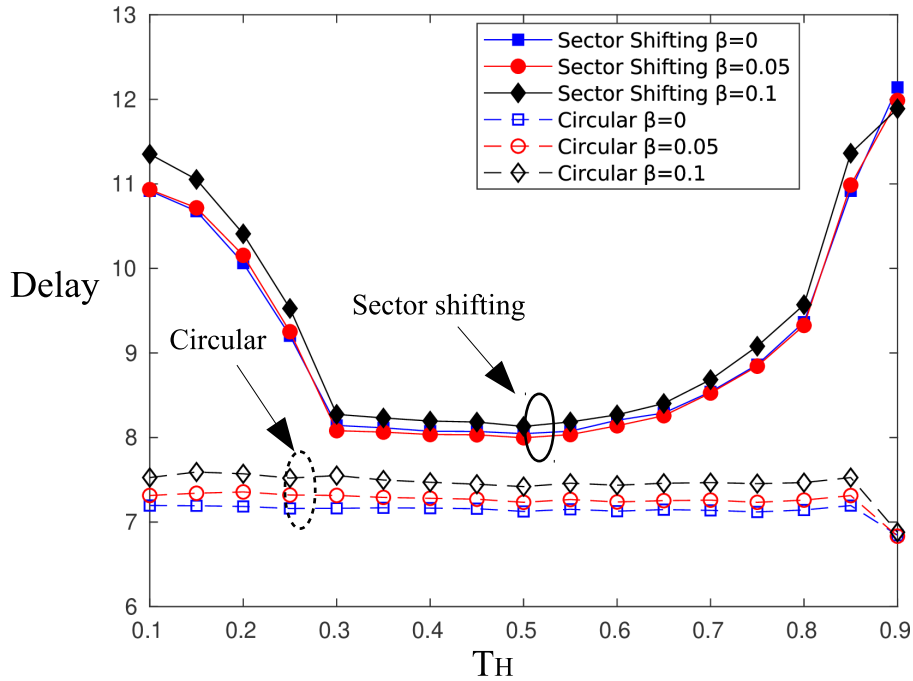


Figure 4.18: Delay of information reception using the sector shifting scheme.

- In case of an event, we derive an analytical expression for the probability of successful information reception, using stochastic geometry tools for two cases: random and circular selection of sectors.
- We provide the probability that the sensors' status report messages are received correctly by the AP for the two cases mentioned above.
- Simple sector selection strategies are presented and their performance is assessed through simulations. Taking into account the number of reports received by the nodes of each sector, two strategies are proposed that identify and subsequently degrade energy beamforming towards sectors with heavy blockage. Periodic shifting of sectors is another proposed scheme that aims to boost nodes located at the edges of the beamforming pattern.

5. EVENT DETECTION IN WPCN WITH NOISY MEASUREMENTS

An access point (AP), equipped with a mmWave antenna, orchestrates the information exchange with the nodes and the charging process. Each sensor takes measurements from the environment and tries to detect a possible change in the distribution of the monitored parameter. In case of an event, the sensor transmits the available information at the time to the AP with as much energy as possible. As sensor measurements may be noisy due to the nature of the monitored phenomenon or the quality of the sensors themselves, the detection process may result in an extremely large number of false alarms. The sensor nodes treat each alarm as a true event and try to pass relative information to the AP. This in turn exhausts frequently the node's stored energy since increasing the probability of successful message reception demands transmissions using all the available power. Harvesting energy from scratch regularly (especially with a small charging efficiency index) leads to partially charged nodes at any time, thus jeopardizing the functionality of the system. The aim of this work is to reduce the number of false alarms, which deplete the node energy (because of multiple unnecessary transmissions), and at the same time reduce the delay of detecting the critical event.

We study the system model as stated in subsection 3.1.1 assuming the format of Figure 3.2. At the energy harvesting phase, we follow the analysis presented in subsection 3.1.2. For the information phase, the analysis in section 3.2 provides us with the probability of successful information reception in the case of circular energy beamforming.

5.1 Sensing Model

A very simple sensing model is adopted for this work. A sensor node senses all events within a distance r_s from its location. The situation is shown schematically in Figure 5.1 where nodes #1 and #2 detect the event while nodes #3 and #4 fail to do so. More sophisticated models, like the one in [44], can be used but their added value for this work is limited.

A distribution $f_0(\cdot)$ is used to model sensor measurements prior to the event. The same distribution, but with different parameters, say $f_1(\cdot)$, is used to model measurements after the event. For the rest of this paper, $f_0(\cdot)$ and $f_1(\cdot)$ are assumed to be Gaussian with means 0 and 1 respectively and standard deviation equal to 0.4. The large value of the standard deviation, compared to the difference of the means, indicates extremely noisy measurements.

A well-known optimal stopping technique due to Shirayev [63] is used for event detection and described in Section 5.2. As the involved posterior probabilities are highly noisy, a Beta Particle Filter is introduced in Section 5.3 to smooth them. Finally, data fusion principles that could improve the system's performance are presented in Subsection 5.3.3.

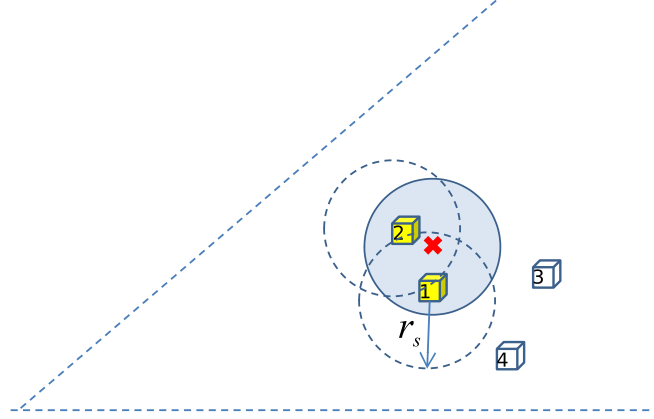


Figure 5.1: Nodes within a distance r_s from the event (like nodes #1 and #2) can sense it.

5.2 Event Detection

In the problem considered we assume for simplicity that the time at which an event occurs, $\mathcal{T}$, follows the geometric distribution with probability of success ϱ . The parameter ϱ is assumed known, for example from historical data. We furthermore denote the prior probability that an event happened before starting time by π . That is

$$P\{\mathcal{T} = 0\} = \pi \quad (5.1)$$

$$P\{\mathcal{T} = n\} = (1 - \pi)(1 - \varrho)^{n-1}\varrho \quad (5.2)$$

The time instant n represents the n th period of beamforming the tagged sensor node. Let τ be the time at which the sensor node decides to transmit its information (measurements) to the BS. There are three risk functions associated with τ . First is the risk function $J_1(\tau) = P\{\tau < \mathcal{T}\}$ which is interpreted as the probability of false alarm. Second is the risk function $J_2(\tau) = E[\max(\tau - \mathcal{T}, 0)]$ which is the average delay of transmission after occurrence of the event. Third is the risk function $J_3(\tau) = P\{\text{unsuccessful transmission at } \tau\}$. Minimizing the aforementioned risks has adversary effects on the selection of τ . For example, to maximize the probability of a successful transmission we have to postpone it until the sensor node is sufficiently charged to overcome bad channel conditions or even bad location conditions (distant node or edge beamforming node). This postponement imposes in turn a large delay on information reporting to the BS. If the nodes act alone, that is they do not relay information by other nodes, then it is crucial to transmit with as much power as possible in order to increase the probability the successful information reception by the BS. Thus, we formulate the problem as

$$\begin{aligned} \min & P\{\tau < \mathcal{T}\} + \lambda_d E[\max(\tau - \mathcal{T}, 0)] \\ \text{s.t.c. } & P_{ui} < \psi \end{aligned} \quad (5.3)$$

where P_{ui} denotes the probability of unsuccessful information reception and λ_d is a weight factor balancing the importance between false alarm rate and detection delay. Let us first focus on the constraint and reveal the role of τ in it. Successful reception of the information message is possible if Equation (3.17) is satisfied. Using Equation (3.19) and defining for notation simplicity

$$Q(r, \phi) = \frac{(2^{R_I/W'} - 1)(1 + r^a)\sigma^2}{F_M(\phi)} \quad (5.4)$$

we obtain

$$P_{ui} < \psi \Leftrightarrow 1 - \exp\left\{-\frac{Q(r, \phi)}{P^\tau}\right\} < \psi \Leftrightarrow P^\tau > -\frac{Q(r, \phi)}{\ln(1 - \psi)} \quad (5.5)$$

where P^τ is the transmission power at time instant τ . Moreover, P^τ is equal to $\mathcal{E}^\tau/T_I$, where $\mathcal{E}^\tau$ is the total energy harvested by the node up to time τ and T_I is the signaling period. Thus, the constraint of the optimization problem (5.3) imposes a lower bound on the selected time τ' to transmit. The node has to postpone its transmission at least until the accumulated stored energy satisfies

$$\mathcal{E}^{\tau'} > -\frac{T_I Q(r, \phi)}{\ln(1 - \psi)} \quad (5.6)$$

Inequality (5.6) presupposes knowledge of the location of the node. If this is not possible, the threshold on the right side of (5.6) may be replaced by an average over the possible locations of the sensor nodes, that is

$$\mathcal{E}^{\tau'} > \frac{1}{\theta \rho^2} \int_{-\theta}^{\theta} \int_0^{\rho} -\frac{T_I Q(r, \phi)}{\ln(1 - \psi)} r dr d\theta \quad (5.7)$$

We turn now to the minimization of the objective function in (5.3). To this end we define the posteriori probability of the event occurring before time n

$$\pi_n = P\{\mathcal{T} \leq n | \mathcal{F}_n\}, \quad \pi_0 = \pi \quad (5.8)$$

where $\mathcal{F}_n = \sigma\{X_1, X_2, \dots, X_n\}$ is the σ -algebra characterizing the information before time n . Sensor measurements $X_1, X_2, \dots$ are assumed independent having pdf $f_0(\cdot)$ prior to the event and pdf $f_1(\cdot)$ after occurrence of the event. Using Bayes' formula

$$\pi_{n+1} = \frac{(\pi_n + (1 - \pi_n)\varrho)f_1(X_{n+1})}{(\pi_n + (1 - \pi_n)\varrho)f_1(X_{n+1}) + (1 - \pi_n)(1 - \varrho)f_0(X_{n+1})} \quad (5.9)$$

Noting that

$$P\{\tau < \mathcal{T}\} = E[1 - \pi_\tau] \quad (5.10)$$

and following Shiryaev [63], the objective function in the optimization problem (5.3) can be transformed into the more convenient form

$$\begin{aligned} J(\tau) &= P\{\tau < \mathcal{T}\} + \lambda_d E[\max(\tau - \mathcal{T}, 0)] \\ &= E \left[1 - \pi_\tau + \lambda_d \sum_{k=0}^{\tau-1} \pi_k \right] \end{aligned} \quad (5.11)$$

For a given prior π , we seek an optimal stopping time τ^* that satisfies $J^*(\tau^*) = \min J(\tau)$. It turns out that the optimal stopping time is independent of π and can be found by a simple thresholding rule

$$\tau^* = \min\{n \geq 0 : \pi_n \geq \Gamma\} \quad (5.12)$$

Indeed, according to the results of Shiryaev [63] (Theorem 2.23) the minimum risk function satisfies the equations

$$J^*(\pi) = \min\{1 - \pi, \lambda_d \pi + E[J^*(\pi_1)]\} \quad (5.13)$$

$$= \lim_n Q^n(1 - \pi) \quad (5.14)$$

where π_1 is the posterior probability given by (5.9) (one step forward after the current prior π) and the expectation is over the pdf

$$f(x) = (\pi_n + (1 - \pi_n)\varrho)f_1(x) + (1 - \pi_n)(1 - \varrho)f_0(x) \quad (5.15)$$

The operator $Q(\cdot)$ is defined as

$$Q(h(\pi)) = \min\{h(\pi), \lambda_d \pi + E[h(\pi_1)]\} \quad (5.16)$$

The $Q(\cdot)$ function is concave as the pointwise minimum of concave functions. Repeating this argument, $Q^n(1 - \pi)$ is concave and therefore $J^*(\pi)$ is concave. The optimal stopping time τ^* is given by

$$\tau^* = \min\{n \geq 0 : J^*(\pi_n) = 1 - \pi_n\} \quad (5.17)$$

and due to the concavity of the risk function it assumes the form given by (5.3). The threshold Γ can be found using the equation

$$1 - \Gamma = \lambda_d \Gamma + J^*(\Gamma) \quad (5.18)$$

Figure 5.2 depicts $J^*(\pi)$ for three values of λ_d . As λ_d decreases more emphasis is given in minimizing the false alarm rate and therefore the threshold Γ drifts to larger values.

It is clear at this point that the choice of τ (the time at which the sensor node decides to transmit its information) is affected by two independent criteria. The first one is the energy criterion (5.6) which depends on the location of the sensor node, the probability of

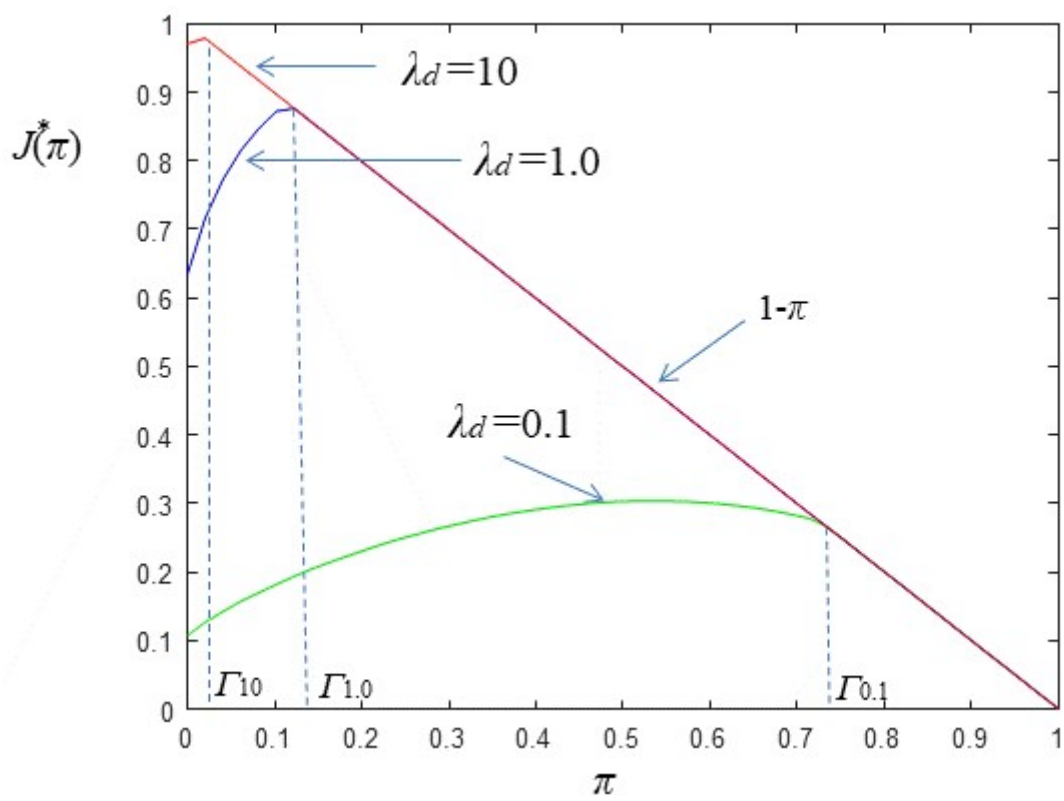


Figure 5.2: $J^*(\pi)$ and related thresholds.

successful transmission $1 - \psi$, and the charging parameter γ . The second criterion, say false-alarm/delay criterion, is described by (5.12) and it depends, among other things, on λ_d and the “frequency” parameter ϱ . Combining these two criteria into one is a matter of the nature of the events and the system’s parameters. For example, for false-alarm and successful reporting critical events, both criteria should be satisfied, so we can combine them as

$$\tau_o = \max\{\tau', \tau^*\} \quad (5.19)$$

whereas for delay critical events we can simply set

$$\tau_o = \tau^* \quad (5.20)$$

which means that the sensor-node transmits as soon as possible regardless of its accumulated energy. Moreover, the values of the parameters of the system play a major role in the decision process, as it is demonstrated next. Consider the aforementioned network topology with $\rho = 10$ m, $S = 15$, sensing area of radius $r_s = 1$ m, and the parameter ϱ set to 0.01. This means that events happen every 100 system time slots on average, which is quite high for rare events. If the events are uniformly distributed in the network area, then a specific sensor node will be “hit” with probability $\varrho r_s^2 / \rho^2 = 0.0001$, that is every 10,000 time slot on average. Setting the successful transmission constraint to $1 - \psi = 0.9$, then approximately $\mathcal{E}_{av,s} = 30$ (eyeball Figure 3.5). Using the curve of the smallest γ ($=0.01$) in Figure 3.3 and for the worst case of $r = 10$, $\phi = 12^\circ$, we find that $30/0.1 = 300$ time slots are needed for the node to charge at the value of 30 energy units starting from zero conditions. Since the tagged sensor is charged every $S = 15$ time slot (round-robin beamforming), the number of system time slots that are needed for the sensor to reach its target energy level is $300 \times 15 = 3500$. Thus the event, with high probability, will find the node sufficiently charged for transmission. In cases like this, the constraint of the optimization problem (5.3) can be neglected.

5.3 Smoothing the Posterior Probability

Measurements of the posterior probability of the event occurring before time n , as they are described by Equation (5.9) may be highly unstable. Thus, for example, a low valued threshold as Γ_{10} or $\Gamma_{1.0}$ in Figure 5.2 may be crossed several times before the occurrence of an event. This in turn will impose unnecessary sensor node transmissions which will deplete its energy reserve. Therefore, if the energy harvesting process has a low rate compared to ϱ (the events’ occurrence rate), it is highly probable that at the time of an event the sensor node will be uncharged. This implies a large delay in information reporting. To remedy this problem we resort to posterior probability smoothing and we test two techniques. The first technique is straightforward and relies on the use of an AR filter whereas the second technique is a novel one and relies on particle filter principles.

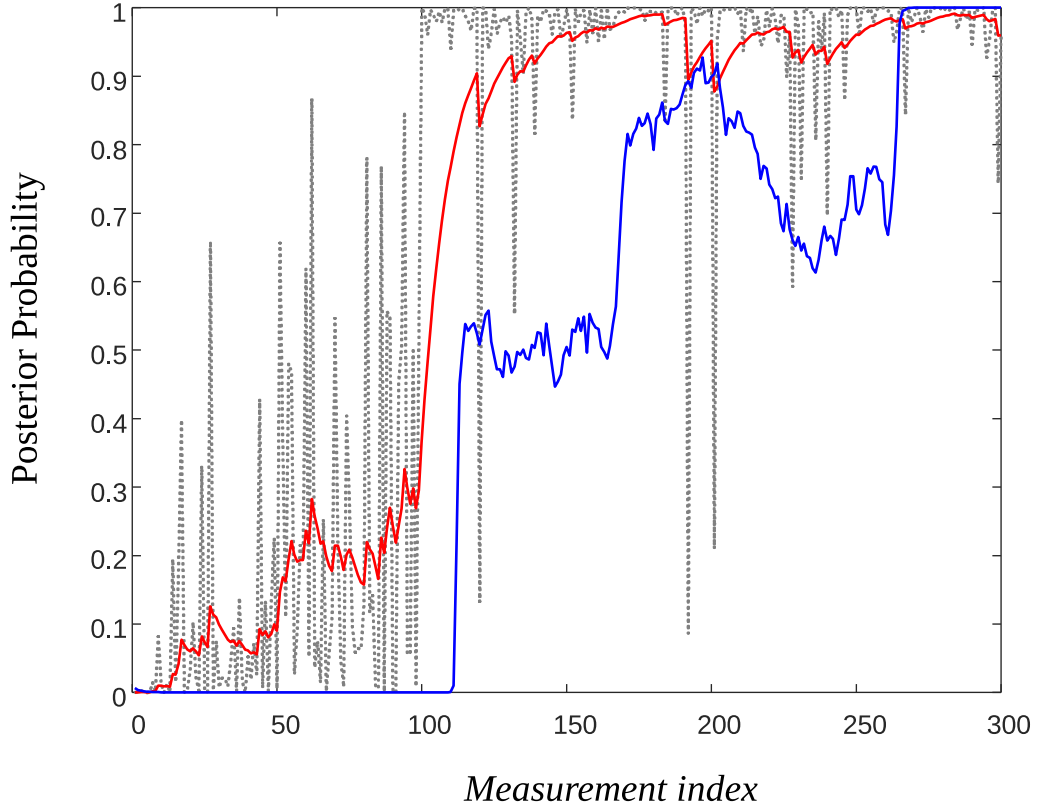


Figure 5.3: Smoothed posterior probabilities: Original π_n (dotted-black), AR filter $\tilde{\pi}_n$ for $\alpha = 0.9$ (solid-red), and Beta Particle Filter $\hat{\pi}_n$ (solid-blue).

5.3.1 AR Smoothing

For simplicity we consider an AR filter of order one to smooth the posterior probability π_n . Thus,

$$\tilde{\pi}_n = \alpha \tilde{\pi}_{n-1} + (1 - \alpha) \pi_n \quad (5.21)$$

where $\alpha \in (0, 1)$ determines the degree of smoothing. Using a value α , we have essentially an average over the last $1/(1 - \alpha)$ values of the posterior probability.

Figure 5.3 shows a trace of the posterior probability π_n (Equation (5.9), dotted black line) generated using $\varrho = 0.01$, $f_0 \sim \mathcal{N}(0, 0.4^2)$ and $f_1 \sim \mathcal{N}(1, 0.4^2)$. The time of the event was taken at $\mathcal{T} = 100$. As it is observed there are large false spikes both prior to the event and after. The red solid line depicts $\tilde{\pi}_n$ for $\alpha = 0.9$. Although there is some sort of smoothing there are substantial high values of the posterior probability prior to the event which may lead to several false detections. Decreasing α improves smoothing but the slope of the curve after the event decreases. This means that an extra delay may be introduced before detecting the event.

5.3.2 Beta Particle Filter Smoothing

The second technique relies on the use of particle filtering and specifically the sampling-importance-resampling (SIR) method. In Bayesian filtering, such as Kalman or particle filtering, estimating the system state $\mathbf{x}_n$ based on observations up to the time n , $\mathbf{y}_{1:n}$, involves two steps. A prediction step to compute the prior $p(\mathbf{x}_n|\mathbf{y}_{1:n-1})$, followed by a filtering step to compute the posterior $p(\mathbf{x}_n|\mathbf{y}_{1:n})$. Thus

$$\text{Prediction: } p(\mathbf{x}_n|\mathbf{y}_{1:n-1}) = \int p(\mathbf{x}_n|\mathbf{x}_{n-1})p(\mathbf{x}_{n-1}|\mathbf{y}_{1:n-1})d\mathbf{x}_{n-1} \quad (5.22)$$

$$\text{Filtering: } p(\mathbf{x}_n|\mathbf{y}_{1:n}) \propto \int p(\mathbf{y}_n|\mathbf{x}_n)p(\mathbf{x}_n|\mathbf{y}_{1:n-1}) \quad (5.23)$$

In the proposed smoothing technique, the posterior probabilities π_n , given by Equation (5.9), play the role of the observations $\mathbf{y}_n$ while the smoothed values $\hat{\pi}_n$ will represent the unknown internal system state $\mathbf{x}_n$. In both the prediction step and filtering step we use the Beta distribution to model the state transition probability distribution $p(\mathbf{x}_n|\mathbf{x}_{n-1}) = p(\hat{\pi}_n|\hat{\pi}_{n-1})$ and the likelihood $p(\mathbf{y}_n|\mathbf{x}_n) = p(\pi_n|\hat{\pi}_n)$. The Beta distribution is given by

$$\text{Beta}_x(a, b) = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} x^{a-1}(1-x)^{b-1} \quad (5.24)$$

with the shape parameters a and b controlling the peak and the sharpness of the peak and $\Gamma(\cdot)$ is the Gamma function. Since the filtered value $\hat{\pi}_n$ has to be close to $\hat{\pi}_{n-1}$ we model the state transition probability as

$$p(\hat{\pi}_n|\hat{\pi}_{n-1}) \sim \text{Beta}_{\hat{\pi}_n}(\nu_1\hat{\pi}_{n-1}, \nu_1(1-\hat{\pi}_{n-1})) \quad (5.25)$$

with the parameter ν_1 taking a large value, to guarantee $a > 1$ and $b > 1$. Similarly, we model the likelihood as

$$p(\pi_n|\hat{\pi}_n) \sim \text{Beta}_{\pi_n}(\nu_2\hat{\pi}_n + 1, \nu_2(1-\hat{\pi}_n) + 1) \quad (5.26)$$

with the parameter ν_2 having a relatively small value. The bias term (+1) was introduced to avoid numerical problems when π_n assumes small values. The Beta Particle Filtering algorithm is presented in Algorithm 3.

The solid-blue line in Figure 5.3 depicts the smoothed value $\hat{\pi}_n$ using the Beta Particle Filter method. The plot was obtained using $K = 200$ particle streams and the parameters $(\nu_1, \nu_2) = (500, 1)$. As it is observed, prior to the event the smoothed posterior probability stays close to zero but there is a substantial delay after the event to reach the true value one.

5.3.3 Fusion of the Sensor Measurements

From the discussion in the previous subsection, it becomes clear that more reliable estimates of the posterior probability are needed before the sensor nodes decide to transmit

Initialization

- Select the number of particle streams K
- Generate K samples for the initial state $\hat{\pi}_0 = \pi$
 - For** $k = 1, \dots, K$
 - draw $\hat{\pi}_0^k \sim \text{Beta}_{\hat{\pi}_0}(\nu_1 \pi, \nu_1(1 - \pi))$
 - set $w_0^k = 1/K$ % set initial weights

end for**Main Loop**

- For** $n = 1, 2, \dots$
 - For** $k = 1, 2, \dots, K$
 - draw $\hat{\pi}_n^k \sim \text{Beta}_{\hat{\pi}_n}(\nu_1 \hat{\pi}_{n-1}^k, \nu_1(1 - \hat{\pi}_{n-1}^k))$
 - $w_n^k = w_{n-1}^k \text{Beta}_{\pi_n}(\nu_2 \hat{\pi}_n^k + 1, \nu_2(1 - \hat{\pi}_n^k) + 1)$
- end for**
- $W_n^k = w_n^k / \sum_k w_n^k$ % normalize weights
- $K_{\text{eff}} = 1 / \sum_k (W_n^k)^2$
- If** $K_{\text{eff}} < K_T$ % K_T was taken equal to $0.85K$
 - Resample $\{\hat{\pi}_n^k, W_n^k\}_{k=1}^K$ to obtain $\{\bar{\pi}_n^k, 1/K\}_{k=1}^K$
 - Set $\hat{\pi}_n^k = \bar{\pi}_n^k, W_n^k = 1/K$
- end if**
- Estimate $\hat{\pi}_n = \sum_k \hat{\pi}_n^k W_n^k$

end for**Algorithm 3:** The Beta Particle Filter smoothing algorithm.

their information. This may be achieved by fusing the measurements of the sensors that cover the same area. To this end, sensor nodes utilize the second time-slot format and exchange measurement information during T_F prior to any transmission.

Figure 5.4 shows the smoothed posterior probabilities of three sensors and as it is observed false alarm probabilities (prior to the event and for the AR filtering technique), have been reduced by a factor 2 to 3 compared to that of Figure 5.3. Note that if m sensors are involved in the fusion process, the posterior probabilities (Equation (5.9)) are given by

$$\pi_{n+1} = \frac{(\pi_n + (1 - \pi_n)\rho) \prod_{i=1}^m f_1^{(i)}(X_{n+1}^{(i)})}{(\pi_n + (1 - \pi_n)\rho) \prod_{i=1}^m f_1^{(i)}(X_{n+1}^{(i)}) + (1 - \pi_n)(1 - \rho) \prod_{i=1}^m f_0^{(i)}(X_{n+1}^{(i)})} \quad (5.27)$$

However, there is a price to pay for the advantages of fusion. Covering an area of interest by more than one sensor node is not always feasible and it depends mainly on the type of sensors used. For example, an optical sensor has a much larger sensing radius compared to a temperature sensor but nevertheless, line-of-sight blocking limits the size of the monitored area. Let us assume that the distribution of the sensor nodes is a homogeneous Poisson Point Process (PPP) with intensity λ . If it is desirable for the event to be detected by at least two sensors with a probability higher than α_c , then

$$P\{\#\text{sensors} \geq 2\} \geq \alpha_c \Rightarrow 1 - (e^{-\lambda A_s} + e^{-\lambda A_s} \lambda A_s) \geq \alpha_c \quad (5.28)$$

with $A_s = \pi r_s^2$. Setting $r_s = 1$ m and $\alpha_c = 0.5$ results in 168 nodes on average that have to be deployed over an area of radius 10 m. If the sensing radius is reduced to 0.5 m then the number of nodes has to be quadrupled. Moreover, using an extra time period T_F in the time slot format in order for the sensors to exchange their measurements, reduces either the harvesting period T_H , or the transmission period T_I , or both. One may neglect T_F and resort to centralized information fusion by letting all the sensors sensing an event independently transmit their measurements to the AP.

There are also certain advantages to introducing the time period T_F . During this period sensor nodes may exchange information, beyond measurements for data fusion, such as their energy reserves. In this case, more sophisticated transmission strategies may be explored. For example, among two or more sensor nodes that detect an event, only the node with the higher energy level transmits the information to the AP. The rest of the nodes delay their transmission either for extra charging purposes or to increase time diversity. Since for neighboring nodes the channel gains are highly correlated, postponing the transmission for a period greater than the time coherence of the channel may prevent nodes transmitting under the same (possibly bad) channel conditions.

5.4 Simulation Results

In this section, some simulation results are presented that corroborate the analysis of the previous section. The values of the system parameters are given in Table 3.1 taken

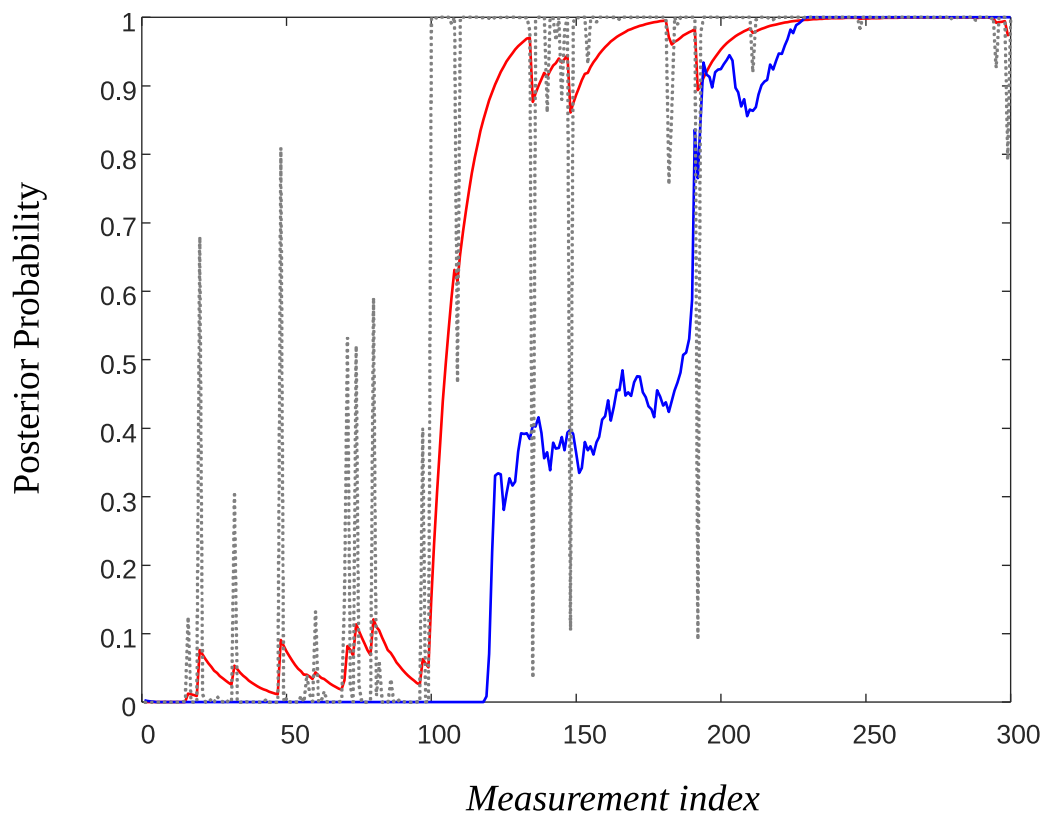


Figure 5.4: Data fusion of three sensors for smoothing the posterior probabilities: Original π_n (dotted-black), AR filter $\tilde{\pi}_n$ for $\alpha = 0.9$ (solid-red) and Beta Particle Filter $\hat{\pi}_n$ (solid-blue).

from [54] and the simulation platform was MATLAB.

In our simulation model, a base station lies at the center of a cell of radius 10 m and a linear antenna array of $M = 8$ elements is used to energy beamform 15 sectors in a round-robin fashion. The location of the event is selected randomly in the monitored area and the event interarrival time follows the geometric distribution. Channel gains are modeled as independent random variables following an exponential distribution. We assume fast varying channels in the sense that the gains change at every time slot.

We focus on the behavior of two sensor nodes located at the edge of the network, that is at a distance $r = 10$ m from the AP. The first node lies along the direction of the beam pattern ($\phi = 0^\circ$), whereas the second sensor node lies at $\phi = 12^\circ$, which is at the edge of the beam pattern. Sensor information transmission and charging are possible only when the AP beamforms towards the tagged sector. However, the nodes continuously sense the environment for possible events and run the detection algorithm. The simulation horizon is large enough to ensure the creation of several events in the neighborhood of the sensors.

We present two sets of simulations. In the first set we illustrate the effects of smoothing, charging efficiency γ , and event probability ϱ on the false alarm rate and the accumulated node energy prior to information transmission. In the second set, we deal with the effects of the aforementioned parameters on the information reporting delay.

5.4.1 Charging and False Alarm Rate

Figure 5.5 shows the average accumulated energy for various values of the threshold parameter Γ (Criterion 5.20). The averages were obtained using 200 runs, the charging efficiency was set to $\gamma = 0.01$ and AR smoothing of the posterior probabilities was used. A few observations are immediate. First of all, the node at the edge of the beam pattern fails to reach high energy levels as it is with the node along the main direction of the beam. A remedy to this problem is to offset the direction of the beam (by half of the beam width) before starting a new charging cycle. Secondly, the energy storage from one value onwards remains constant. Values of the threshold Γ greater than 0.3 do not affect the charge percentage of the sensors. For small values of Γ , the threshold is exceeded several times forcing the sensor to transmit and therefore to deplete regularly its energy storage. Figure 5.6 repeats the experiment with a larger value of the charging efficiency parameter γ . In this case, sensors charge at a tenfold rate and manage to recover from false transmissions.

The effect of smoothing the posterior probabilities is more obvious for small values of the threshold Γ . As it is observed from Figures 5.5 and 5.6, high smoothing ($\alpha = 0.9$) prevents, to some extent, false alarms and moderates unnecessary threshold crossings.

Figure 5.7 compares the performance of the Beta Particle Filter smoother with that of the AR filter using $\alpha = 0.9$. The threshold Γ was set equal to 0.15 and the accumulated energy prior to information transmission is plotted vs. the charging efficiency γ . Note that for this experiment $\varrho = 1$, which means a high rate of events. One event occurs in the

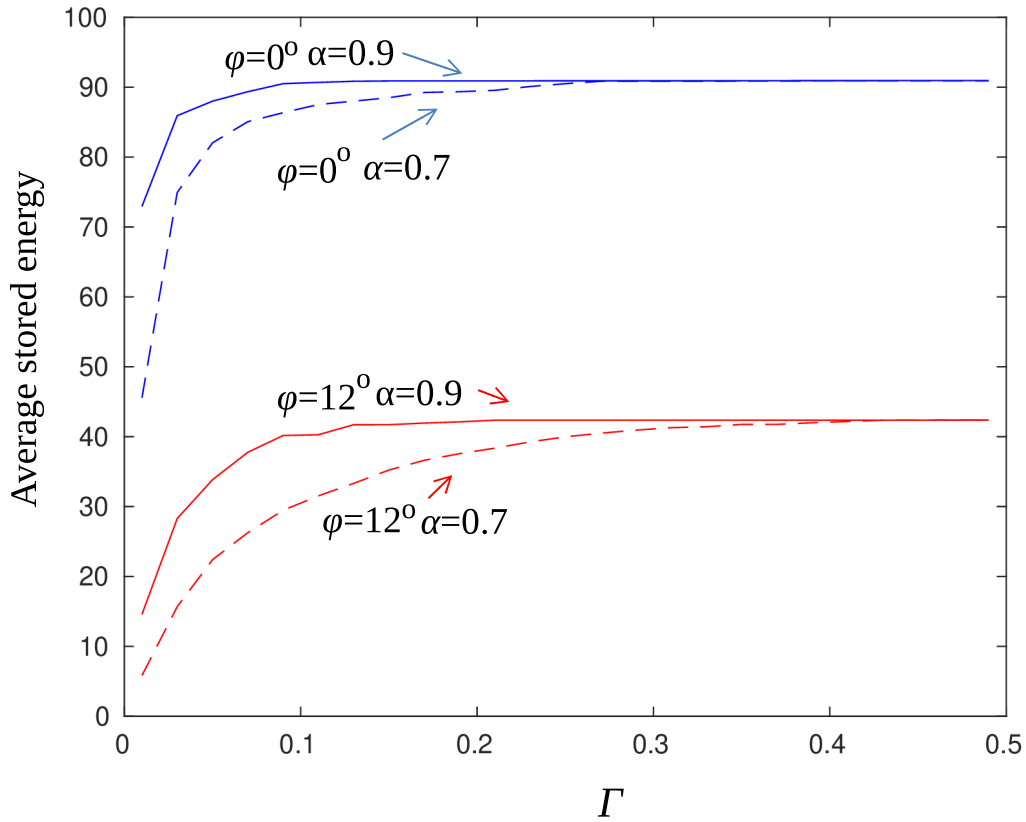


Figure 5.5: AR filter—average stored energy for $\gamma = 0.01$, $\varrho = 0.1$.

monitored network area every one time slot on average. It is conceivable from the figure that BPF outperforms AR smoothing by almost 10%. Figure 5.8 compares the performance of the smoothing filters under detection criteria 5.19 and 5.20. Black lines correspond to the case of a sensor that lies on the main direction of the beam pattern $\phi = 0^\circ$. The target probability of unsuccessful transmission was set equal to $\psi = 0.05$. There are two observations that reveal the superiority of the BPF against AR smoothing regarding the treatment of false alarms. Firstly, using BPF the sensor node reaches higher values of accumulated energy that are almost independent on the threshold parameter Γ . Secondly, Criterion 5.19, that is postponement of information transmission until both energy and detection threshold constraints are satisfied, does not have a major impact on the accumulated energy. This is justified by the fact that the BPF smoother is not “fooled” by temporary ripples of the posterior probabilities and therefore the sensor node does not discharge for unnecessary transmissions. Red lines correspond to the case of a sensor that lies at the edge of the beam pattern $\phi = 12^\circ$. Although the BPF smoother has steadily better performance than the AR filter, the differences are not that large. An edge sensor is hard to charge and therefore it is difficult to recover after false alarms. In cases like this, it is preferable to postpone transmissions until the sensor is sufficiently charged in order to guarantee the successful transmission of the information message.

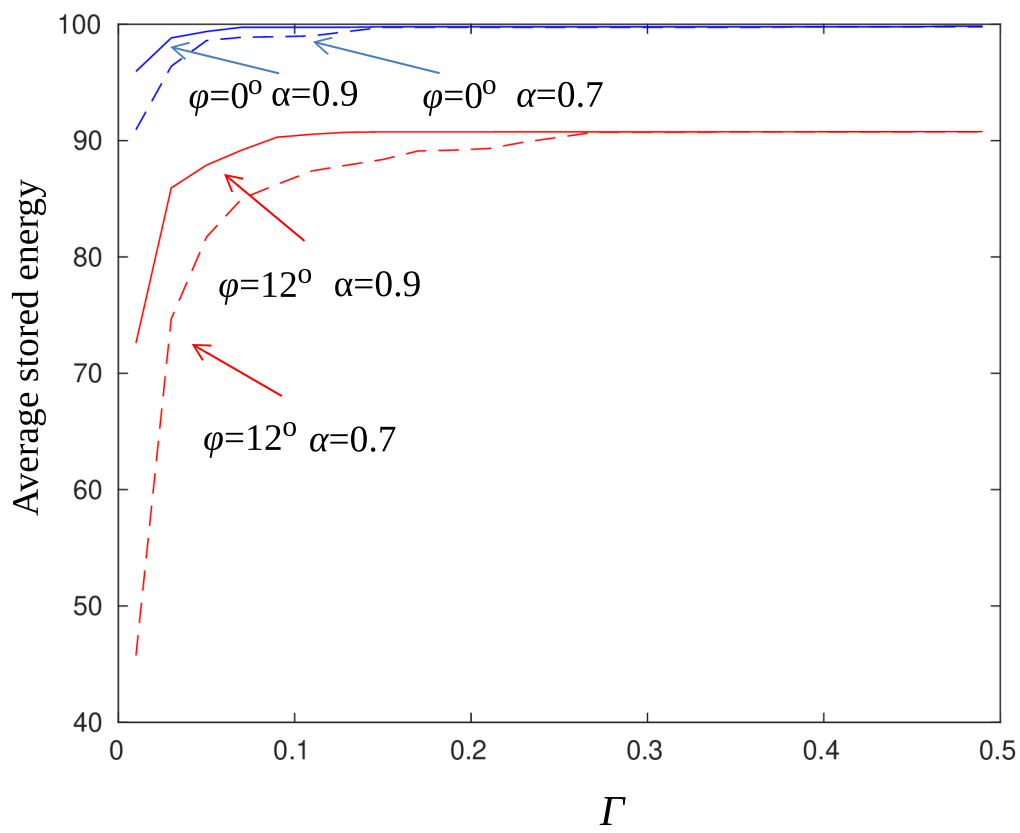


Figure 5.6: AR filter—average stored energy for $\gamma = 0.1, \varrho = 0.1$.

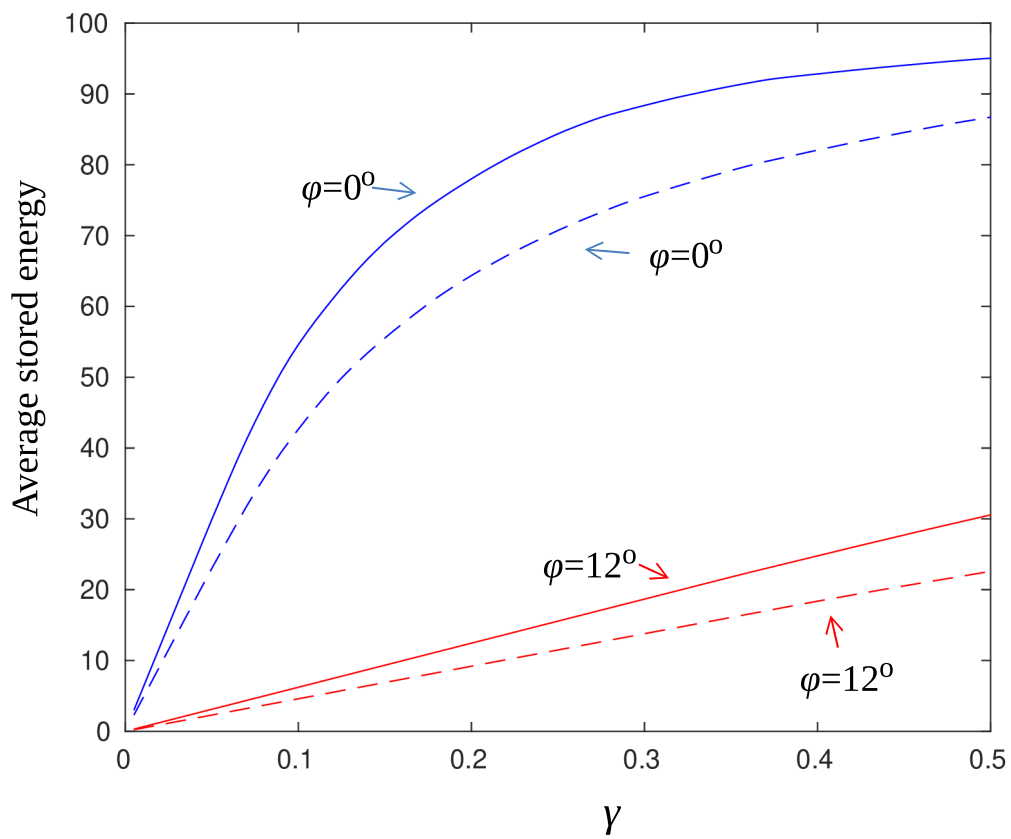


Figure 5.7: Average stored energy for $\Gamma = 0.15$, $\varrho = 1$, $\alpha = 0.9$, and $r = 10$ m. Solid line: Particle filter method, dashed line: AR filtering.

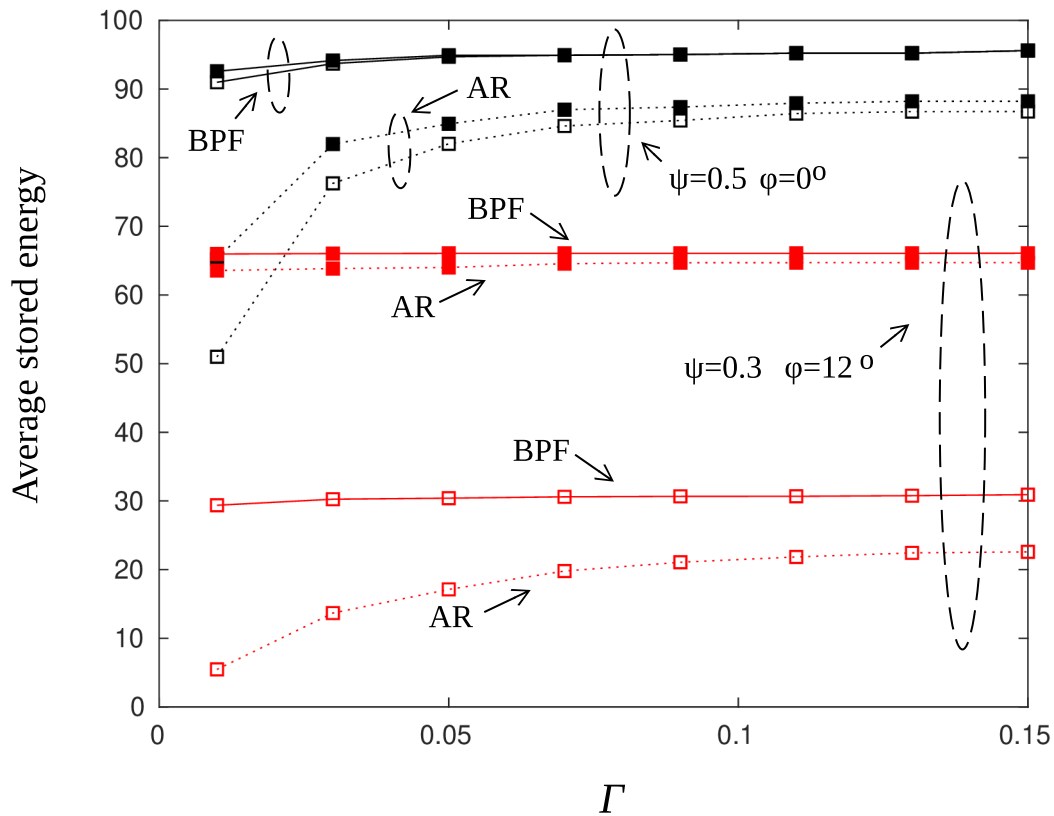


Figure 5.8: Average stored energy for particle filter (solid line) and AR filter (dotted line), with parameters $\gamma = 0.5$, $\varrho = 1$, $r = 10$ m, $\psi = 0.05$, $\phi = 0^\circ$ (black lines), and $\psi = 0.3$, $\phi = 12^\circ$ (red lines). Filled squares mark both threshold and energy criteria (Cr. 5.19), squares mark only threshold criteria (Cr. 5.20).

5.4.2 Charging and Detection Delay

Figure 5.9 plots the detection delay, measured in time slots, for a sensor that charges well ($\phi = 0^\circ$ and high values of the charging efficiency parameter γ). An immediate observation is that the use of BPF results in larger delays compared to that of AR filter by almost 25–30 time slots. This is in agreement with the results of Figures 5.3 and 5.4, where it is demonstrated that the response of the BPF to the changes of the posterior likelihood is delayed. Another, rather obvious, observation is that smaller values of threshold parameter Γ produces smaller delays. Indeed, comparing the circle marked curves, which correspond to $\Gamma = 0.3$, to the square marked curves, which correspond to $\Gamma = 0.15$, we note a difference in the detection delay of 10 time slots for the BPF and 4 time slots for the AR filter. The criterion selection, i.e., criterion 5.19 or 5.20, does not have a major impact on the detection delay for nodes that charge easily. As it is observed from Figure 5.9 criterion 5.19 (filled square and circle markers) provides the same performance with criterion 5.20 (empty markers). However, this is not the case for sensor nodes that are difficult to charge, as is shown next. Figure 5.10, depicts the detection delay performance for a node that lies at the edge ($\phi = 12^\circ$) of the charging beam. Unless the charging efficiency γ is high enough, detection delays reach large values if the node has to postpone its transmission (criterion 5.19, filled markers). Thus, in such cases alternative solutions must be sought. For example, one may take off edge sensors from their unfavorable position by beamforming using an angle offset or by letting sensor nodes relay the information of their neighbors. In the latter scheme, nodes transmit using less power since the objective is to reach a neighbor node that is well charged and capable to relay the information to the AP. Figure 5.11 summarizes some comparative results for the case of a sensor that charges well ($\phi = 0^\circ$). The left column of figures corresponds to criterion 5.20 whereas the right column corresponds to criterion 5.19. The first row of figures is for AR filtering ($\alpha = 0.9$) and the second row is for Beta Particle Filter smoothing. The average number of false alarms is depicted with bars, whereas the detection delay is depicted with filled diamond marks. As it is observed, for very small values of the threshold parameter Γ , the Beta Particle Filter smoothing results in considerably smaller values (tenfold reduction) of false alarms compared to AR filtering. However, the situation is reversed regarding the detection delay. Using criterion 5.19, although the detection delay is not affected, the false alarm rates are reduced by a factor of three (or more) for small values of the parameter Γ .

A summary of chapter contributions is as follows:

- We define the optimal stopping problem and show that the node has to postpone its transmission, at least until the accumulated energy satisfies a specific criterion.
- We propose two solutions to overcome the posterior probability measurement variability problem. The first relies on the use of an AR filter, whereas the second uses a novel technique based on the particle filter theory.
- We assess the performance of the proposed solutions through simulations.

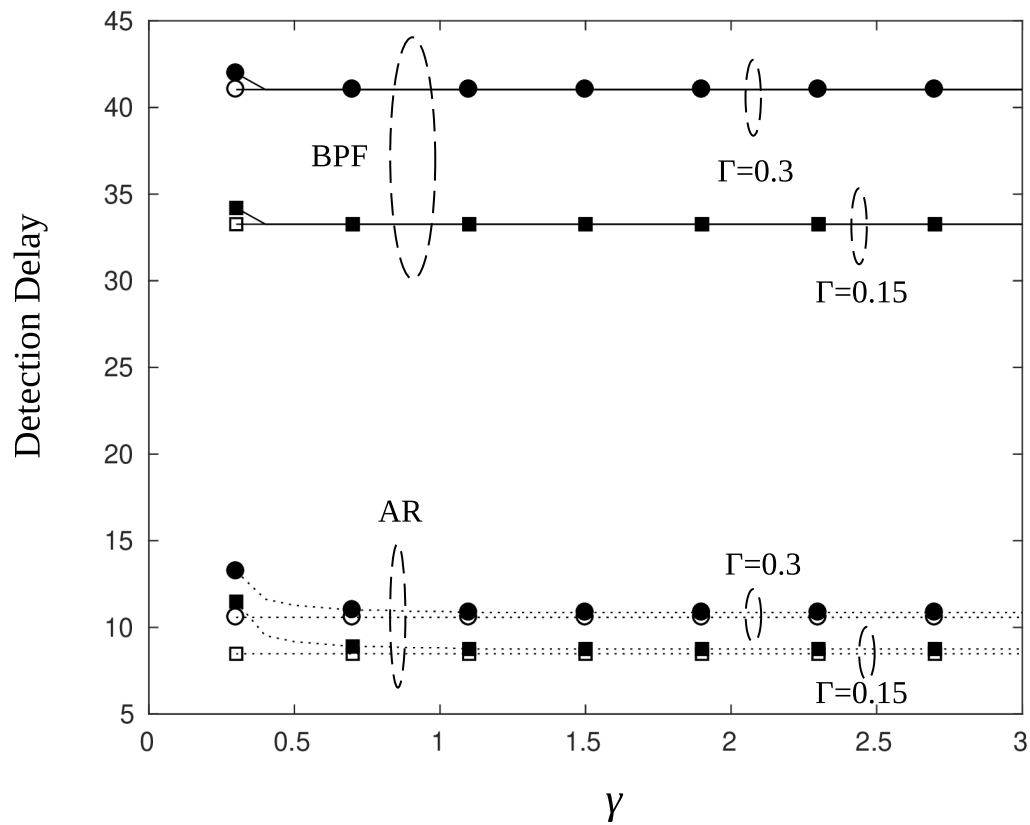


Figure 5.9: Detection delay for particle filter (solid line) and AR filter (dotted line), with parameters $\phi = 0^\circ$, $\varrho = 1$, $\psi = 0.05$, $r = 10$ m, $\Gamma = 0.15$ (square), and $\Gamma = 0.3$ (circle). Filled squares mark both threshold and energy criteria (Cr. 5.19), squares mark only threshold criteria (Cr. 5.20).

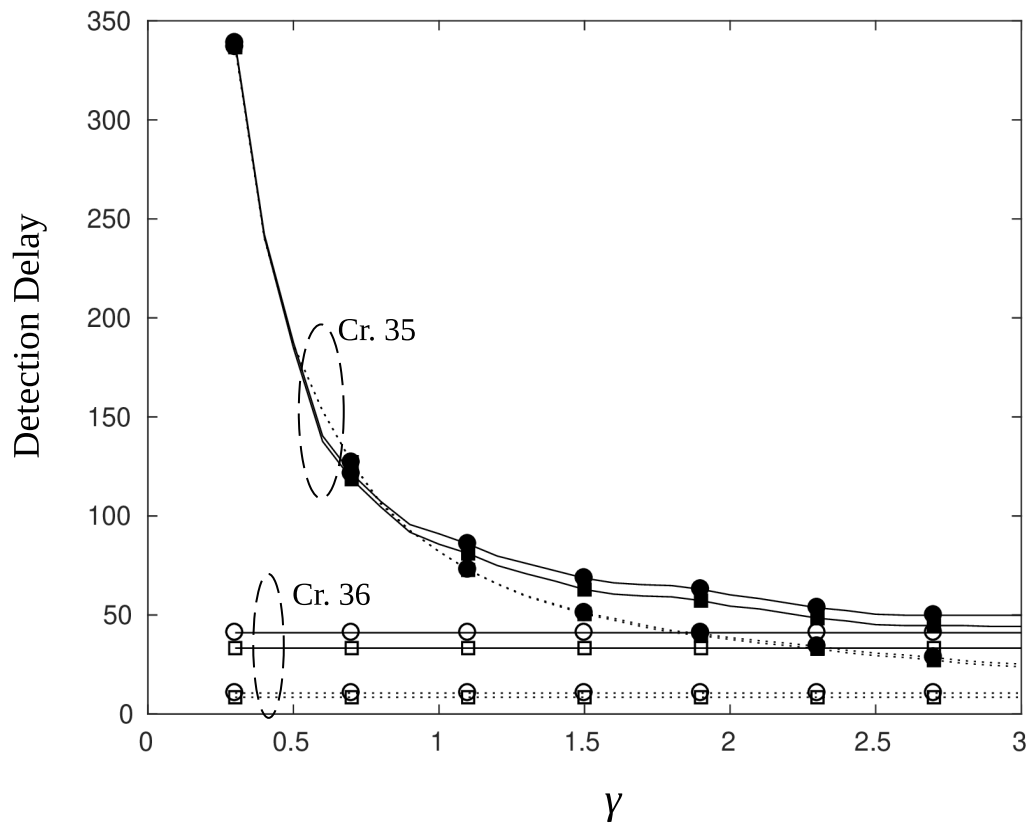


Figure 5.10: Detection delay for particle filter (solid line) and AR filter (dotted line), with parameters $\phi = 12^\circ$, $\varrho = 1$, $\psi = 0.3$, $r = 10$ m, $\Gamma = 0.15$ (square), and $\Gamma = 0.3$ (circle). Filled squares mark both threshold and energy criteria (Cr. 5.19), squares mark only threshold criteria (Cr. 5.20).

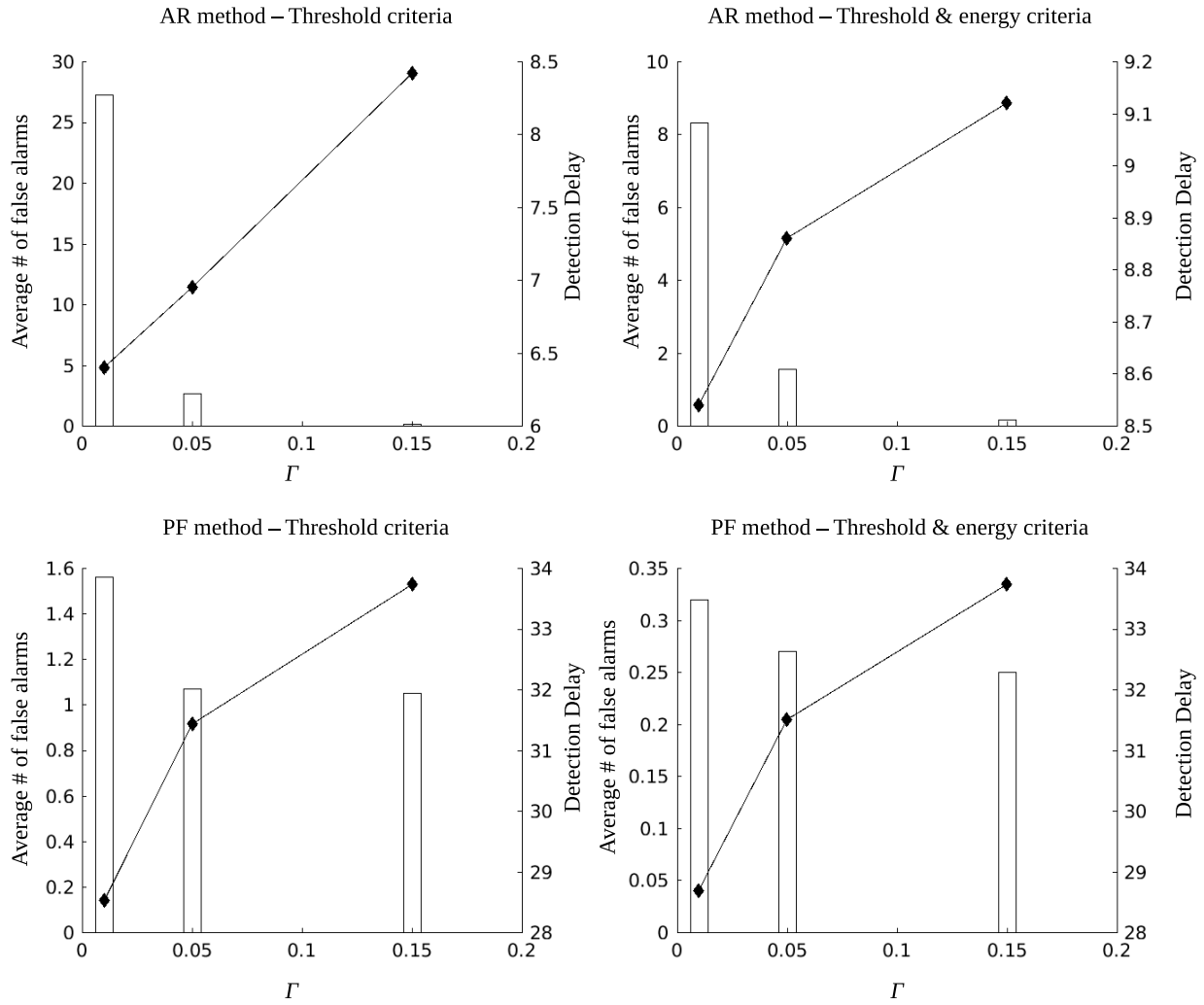


Figure 5.11: Detection delay—average number of false alarms before the event, with parameters $\phi = 0^\circ$, $\varrho = 1$, $\psi = 0.05$, $r = 10$ m, $\gamma = 0.5$, and $\alpha = 0.9$.

6. AN MDP APPROACH TO TRANSMISSION SCHEDULING IN WPCN NETWORKS

In this work, the emphasis is on the design of a WPCN network whose sensor nodes periodically report their measurements to the AP. The transmission period is application dependent, and there are no guarantees that report messages will reach AP successfully. There are several reasons that this may happen. First of all, the charging efficiency of the nodes may be low, and thus for relatively short inter-transmission periods, the stored battery energy may not reach an adequate level for successful transmission. Secondly, a node may lie at an unfavorable location regarding charging. That is, it might be a distant node or a node located at the edge of the charging beam. A third reason is the underlying channel conditions during transmission. A low channel gain due to the multipath effect, or blockage by obstacles, may prevent the node from charging at a sufficient level for successful transmission. To overcome these problems, we resort to an MDP approach, allowing nodes the choice to transmit or refrain from the transmission and continue the charging process. In a sense, we follow the saying “better late than never” allowing a regularizing parameter of the MDP process to take care of extremely delayed transmissions.

6.1 System Model

We study the system model as stated in Subsection 3.1.1. Figure 6.1 shows graphically an ideal beamforming sector and a sensor node located at (r, ϕ) . Switching among sectors is performed circularly, assuming the format of Figure 6.2. In this work, we use T_F to convey feedback from AP to the nodes regarding the success of their transmission. Sensor nodes use all their stored energy for transmission to maximize the probability of successful reception of the information message by the AP.

6.1.1 Energy Harvesting

For the energy harvesting period, we model the charging process as stated in Subsection 3.1.2.

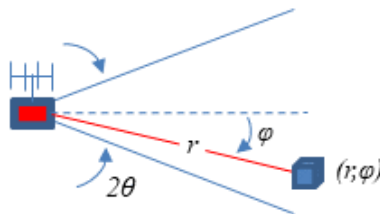


Figure 6.1: Idealized beamforming sector with a sensor node located at (r, ϕ) .

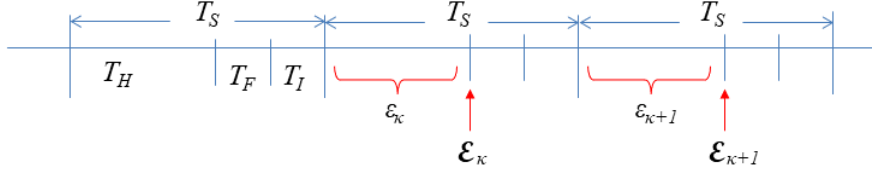


Figure 6.2: Format of system's timeslot. The slot duration T_s equals to the residence time of the charging beam to each sector.

To describe the channel gain g we adopt a Finite State Markov Channel (FSMC) model [70]. Specifically, the variations of the received power can be captured by the factor $|g|^2$. By partitioning the range of $|g|^2$ into a finite number of intervals, let us say using steps of 2db, a finite-state model for the fading channel is built. For a slow fading channel, only state transitions between neighboring states are allowed. Since harvesting energy is an increasing function of the received power, the energy increments, ε , inherit the Markovian property. To ease the presentation and with no loss of generality we round the energy increments to the nearest integers. This rounding in effect reduces the number of Markov chain (MC) states. The resultant number of states depends on the efficiency factor γ . For example, for a small value of γ rounding may result in only two states, 0 and 1, whereas a large value of γ may preserve the original number of states of the Markov Channel model.

6.1.2 Message Transmission Phase

Following the analysis of Subsection 3.2.1 for the calculation of the probability of successful information reception for a node located at (r, ϕ) Figure 6.3 depicts the probability of successful reception of messages vs. the available energy level for two nodes located at $r = 10$. The first node is located close to the axial direction of the beam, 1° offset, (red color) whereas the second node is located close to the boundary of the sector, 11° offset (blue color). The values of the parameters used are given in Table 4.1.

6.2 MDP formulation and proposed algorithm

We consider a 2-D Markov Chain with state space $\mathcal{S}$, that is the set of states $\mathbf{s}_k = (\mathcal{E}_k, \varepsilon_k)$. $\mathcal{E}_k$ denotes the stored energy of the sensor node at time index k prior to decision. It assumes the values $0, \dots, \mathcal{E}_b$ where $\mathcal{E}_b$ is the maximum energy battery capacity of the nodes. The variable ε_k denotes the energy harvested during the k^{th} time slot. As it was assumed in the previous section, ε_k takes integer values and the cardinality of the set of values is denoted by ε_b . Thus, $|\mathcal{S}| = (\mathcal{E}_b + 1) \times \varepsilon_b$ and one can vectorize the 2-D states to obtain a 1-D MC with $|\mathcal{S}|$ states. In MDP, at each time step k the process is in some state $\mathbf{s}_k$ and at the next step the process moves to some state $\mathbf{s}_{k+1}$. This movement is influenced by node's decision action α . We consider two actions: continue

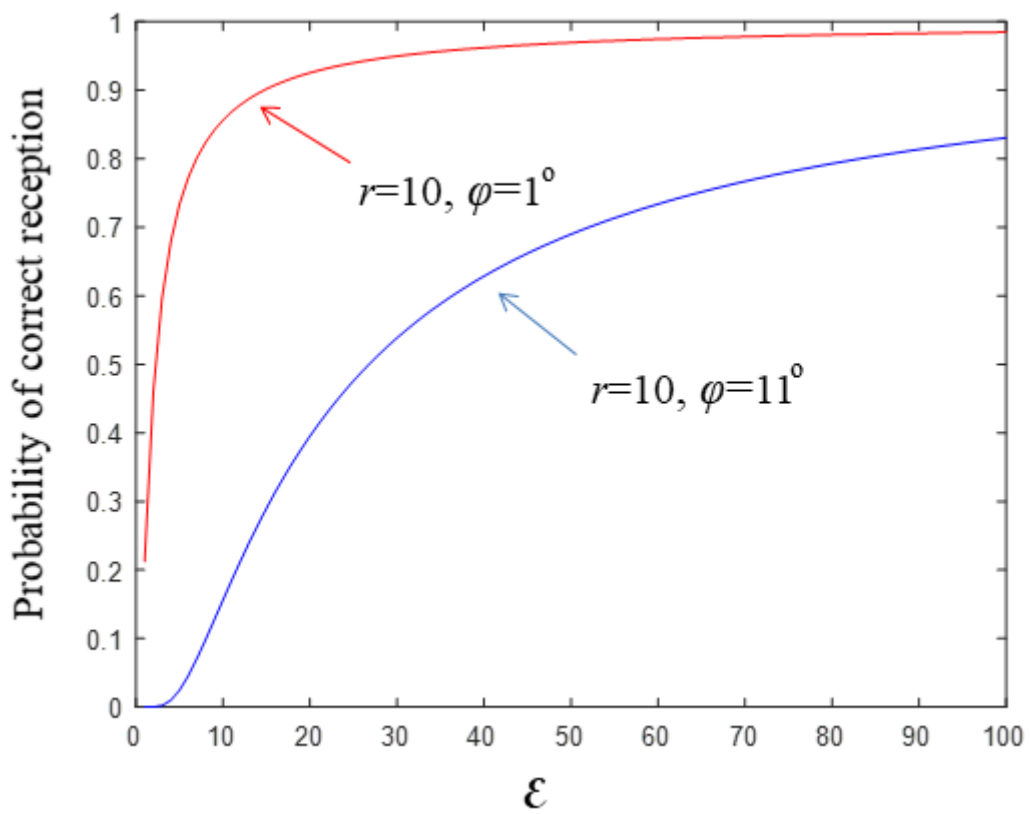


Figure 6.3: Probability of successful information reception. Red color: node located at $(10, 1^\circ)$, blue color: node located at $(10, 11^\circ)$.

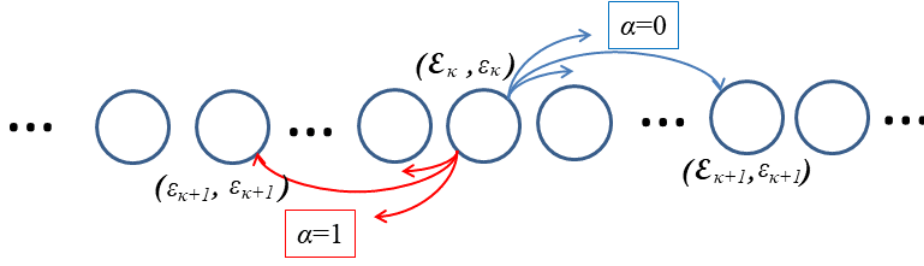


Figure 6.4: State transition diagram, red color: action $\alpha = 1$, blue color: action $\alpha = 0$.

charging, denoted by $\alpha = 0$ and transmit, denoted by $\alpha = 1$. If the node decides to continue, $\alpha = 0$, then

$$\begin{aligned} & P_0 \{(\mathcal{E}_{k+1}, \varepsilon_{k+1}) = (\ell, m) \mid (\mathcal{E}_\tau, \varepsilon_\tau), \tau \leq k\} \\ &= P_0 \{(\mathcal{E}_{k+1}, \varepsilon_{k+1}) = (\ell, m) \mid (\mathcal{E}_k, \varepsilon_k) = (n, \nu)\} \\ &= \delta(\ell - (n + m)) P \{\varepsilon_{k+1} = m \mid \varepsilon_k = \nu\} \end{aligned} \quad (6.1)$$

where $\delta(\cdot)$ is the Kronecker delta function. If the node decides to transmit then it will use all its available energy, in an effort to maximize the probability of successful reception by the AP, and the state transition probability is given by

$$\begin{aligned} & P_1 \{(\mathcal{E}_{k+1}, \varepsilon_{k+1}) = (\ell, m) \mid (\mathcal{E}_\tau, \varepsilon_\tau), \tau \leq k\} \\ &= P_1 \{(\mathcal{E}_{k+1}, \varepsilon_{k+1}) = (\ell, m) \mid (\mathcal{E}_k, \varepsilon_k) = (n, \nu)\} \\ &= \delta(\ell - m) P \{\varepsilon_{k+1} = m \mid \varepsilon_k = \nu\} \end{aligned} \quad (6.2)$$

Note that we define the states after the charging period T_H . Thus, even though after transmission the node depletes its energy, at the next time slot it will be charged by an amount $\varepsilon_{k+1} = m$, which in this case is also its total energy $\mathcal{E}_{k+1}$. Therefore, for $\alpha = 1$ the MC moves to one of the states $(\varepsilon_{k+1}, \varepsilon_{k+1})$ with probability $P\{\varepsilon_{k+1} \mid \varepsilon_k\}$. Figure 6.4 shows schematically the state transitions under the different actions.

Each movement from state $\mathbf{s}_k$ to $\mathbf{s}_{k+1}$ gives the sensor node a corresponding reward $R_\alpha(\mathbf{s}_k, \mathbf{s}_{k+1})$. A policy ρ is a mapping from $\mathcal{S}$ to the action set $A = \{0, 1\}$. The objective is to find the optimal policy that will maximize some function of the rewards. A typical function is the expected discounted sum

$$E \left[\sum_{k=0}^{\infty} \delta^k R_{\alpha_k}(\mathbf{s}_k, \mathbf{s}_{k+1}) \right] \quad (6.3)$$

where $\alpha_k = \rho(\mathbf{s}_k)$ and the expectation is over the distribution $\mathbf{s}_{k+1} \sim P_{\alpha_k}\{\mathbf{s}_k, \mathbf{s}_{k+1}\}$. The discount factor δ regularizes the delay of the actions. If δ is small then low emphasis is given to future rewards and the action is taken as early as possible. On the other hand, a large value of δ postpones actions. A policy that maximizes (6.3) is called an optimal

policy and it is denoted by ρ^* . To find the optimal policy ρ^* we use an iterative method, the *Value Iteration*, proposed by Bellman [4]. The value V is an array, indexed by state, that contains for each state the discounted sum of rewards to be earned in the future (on the average) starting from state $\mathbf{s}$.

$$V(\mathbf{s}) = \sum_{\mathbf{s}'} P_{\rho(\mathbf{s})}\{\mathbf{s}, \mathbf{s}'\} (R_{\rho(\mathbf{s})}(\mathbf{s}, \mathbf{s}') + \delta V(\mathbf{s}')) \quad (6.4)$$

In the Value Iteration algorithm, the policy $\rho(\mathbf{s})$, is not calculated explicitly and its impact is taken into account by a maximization process over states. To be more specific, if $V^{(i)}$ denotes the value array at iteration step i , then

$$V^{(i+1)}(\mathbf{s}) = \max_{\alpha} \left\{ \sum_{\mathbf{s}'} P_{\alpha}\{\mathbf{s}, \mathbf{s}'\} (R_{\alpha}(\mathbf{s}, \mathbf{s}') + \delta V^{(i)}(\mathbf{s}')) \right\} \quad (6.5)$$

Starting at $i = 0$ with an initial value $V^{(0)}$, the Value Iteration algorithm will converge to the true value array solution and as a byproduct it will provide the optimal value of the action α for each state $\mathbf{s}$.

The reward function $R_{\alpha}(\mathbf{s}, \mathbf{s}')$ depends on the action chosen by the node, the current state and possibly the next state to be visited. A reasonable reward should involve, among other things, the average number of successful node transmissions. If $N_1(\mathbf{s})$ denotes the number of successful transmissions, under action $\alpha = 1$, when node is in state $\mathbf{s}$, then

$$E[N_1(\mathbf{s})] = 1 \cdot p_s(r, \phi) + 0 \cdot (1 - p_s(r, \phi)) = p_s(r, \phi) \quad (6.6)$$

whereas, under action $\alpha = 0$, $E[N_0(\mathbf{s})] = 0$. Thus, a simple reward function assumes the form

$$R_1(\mathbf{s}, \mathbf{s}') = p_s(r, \phi), \quad R_0(\mathbf{s}, \mathbf{s}') = 0 \quad (6.7)$$

Using, (6.7) nodes are forced to transmit immediately, at least for small values of δ . For large values of δ , nodes “explore” further into the future but transmissions are not postponed enough for nodes to be sufficiently charged. We may change $R_0(\mathbf{s}, \mathbf{s}')$ to a threshold value, i.e, $R_0(\mathbf{s}, \mathbf{s}') = p_a$. In this case, the MDP algorithm will postpone transmissions until node is sufficiently charged to guarantee a successful transmission with probability p_a . In the simulations part of the next section we adopt the latter reward function as proof of concept of using the MDP algorithm. Of course, more sophisticated approaches are possible. For example, if we allow sensor nodes to relay information of their neighboring nodes, we may reward transmissions that reach a neighbor node instead the AP itself. Moreover, depending on the application, there is no always a clear borderline between delay and data loss preferences. The decision algorithm should be flexible enough to accommodate most of the cases. Consider for example the case that sensor node's data are by nature of graded importance. Powerful coding techniques may be used to protect the most significant data whereas the less significant data are transmitted uncoded. In this case, we may relax strict requirements on the successful reception of the entire message and trade off data loss for data delay performance.

Table 6.1: Parameters used in simulations.

Parameter	Value
$\zeta_1, \zeta_2, \mathcal{E}_b, \theta, \alpha, M$	1500, 0.0022, 100, $\pi/15$, 2, 8
$P_0, \sigma^2, T_H, T_I, D_I, W'$	−10 db, −30 db, 0.85, 0.1, 1024 bits, 1 KHz
$a_{11}, a_{22}, a_{33}, a_{44}, a_{55}, a_{66}, a_{77}$	0.4, 0.3, 0.3, 0.2, 0.2, 0.1, 0.05
$a_{23}, a_{34}, a_{45}, a_{56}, a_{67}$	$\frac{2}{3}(1 - a_{22}), \frac{2}{3}(1 - a_{33}), \frac{1}{2}(1 - a_{44}), \frac{1}{2}(1 - a_{55}), \frac{1}{3}(1 - a_{66})$

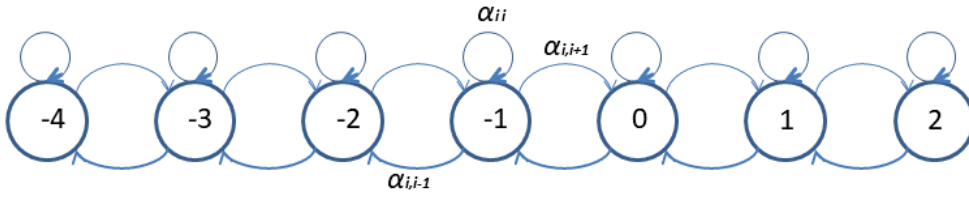


Figure 6.5: FSMC model of the downlink channel gains.

From the previous discussion in this section, it is clear that each sensor node has to estimate the number of states of the underlying Markov Chain, the state transition probabilities, the reward function, and the optimal policy. Thus, a training period should precede nodes' normal operation. During the training period, nodes keep track of the charging increments in order to form the MDP's state transition probability matrix using statistical estimation. Moreover, the probability of successful uplink transmissions should be estimated for deciding the reward function. Since uplink and downlink transmissions use different frequency bands, nodes transmit default messages, using different power levels, and receive feedback from the AP on the successfulness of their attempts. This feedback is sent to the nodes, lying in the serving beam, during the T_F field of the timeslots. After sufficiently accurate estimations have been obtained, nodes run the Value Iteration algorithm in order to find the optimal policy and switch to normal operation.

6.3 Simulation results

In our simulation model, a base station equipped with a linear antenna array of $M = 8$ elements is used to energy beamform 15 sectors in a round-robin fashion. The ideal beamwidth is 24° . We focus on the behavior of two sensor nodes located at a distance $r = 10$ m from the AP. The first node lies close to the direction of the beam pattern ($\phi = 1^\circ$), whereas the second sensor node lies at $\phi = 11^\circ$, which is close to the edge of the beam pattern. Table 6.1 shows the values of the parameters used in simulations

The downlink channel is a slow fading channel with gains $|g|^2$ modeled as an MC process with 7 states as it is shown in Figure 6.5. The states assume the values $-4, -3, \dots, 1, 2$

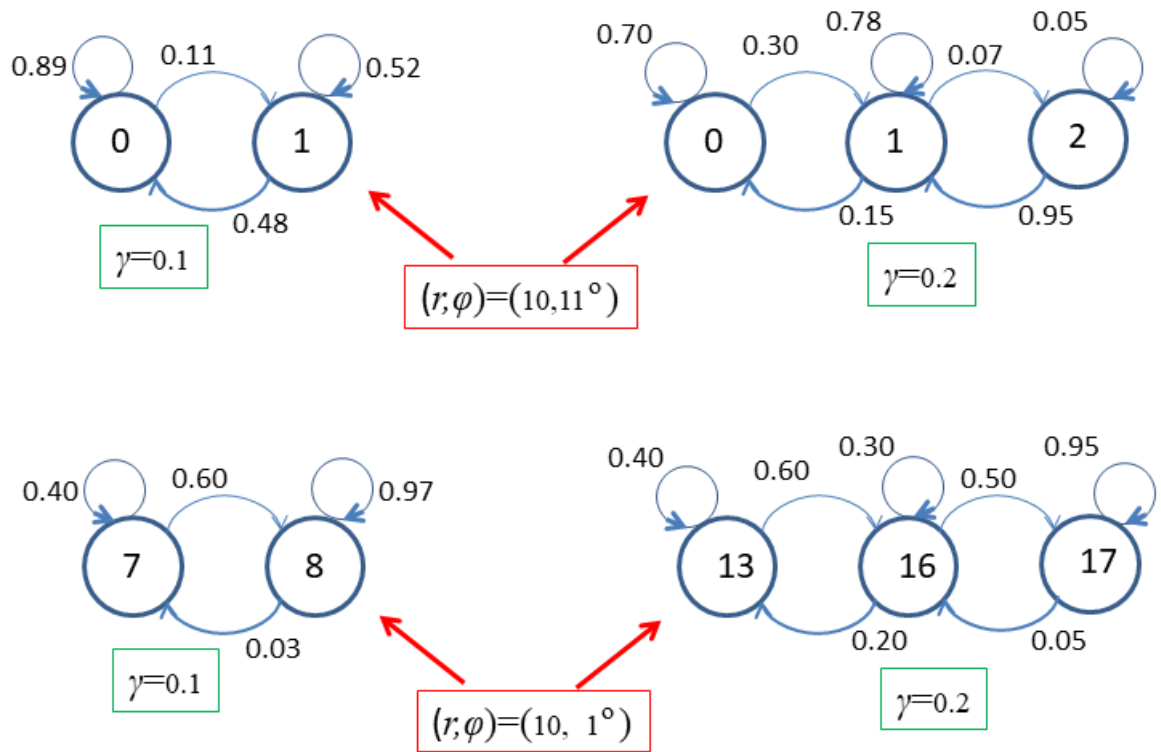


Figure 6.6: Induced MC for the energy increments ε_k . Top row corresponds to $(r, \phi) = (10, 11^\circ)$ and $\gamma = 0.2, 0.8$ respectively. Bottom row corresponds to $(r, \phi) = (10, 1^\circ)$ and $\gamma = 0.1$

dB and only transitions to neighboring states are allowed. The transition probabilities of the channel MC model are given in the bottom two lines of Table 6.1. The steady state probabilities of the channel Markov chain and the average channel gain are respectively

$$P_{ss} = [0.0385, 0.0990, 0.1980, 0.2310, 0.2310, 0.1540, 0.0486] \quad (6.8)$$

$$E[|g|^2] = 0.8752 \quad (6.9)$$

The state transition diagram of the energy increments ε_k induced Markov Chain is shown in Figure 6.6 for several cases. The state numbers denote the rounded incremental energy per charging timeslot. The top row is for the sensor node located at $(r, \phi) = (10, 11^\circ)$. The top left diagram corresponds to charging efficiency $\gamma = 0.1$, whereas the top right diagram corresponds to $\gamma = 0.2$. The bottom row depicts the state transition diagrams for the node located at $(r, \phi) = (10, 1^\circ)$ with a charging efficiency equal to $\gamma = 0.1$ and $\gamma = 0.2$ respectively. As it is observed from the figure, a well charging sensor node, located at the direction of the charging beam, induces Markov chains with large value states. The same effect is obtained by increasing the charging efficiency γ .

Figures 6.7 and 6.8 show the optimal policy, as it is obtained using the MDP algorithm with $\delta = 0.99$ and $\delta = 0.01$ respectively, and for the node located at $(r, \phi) = (10, 11^\circ)$

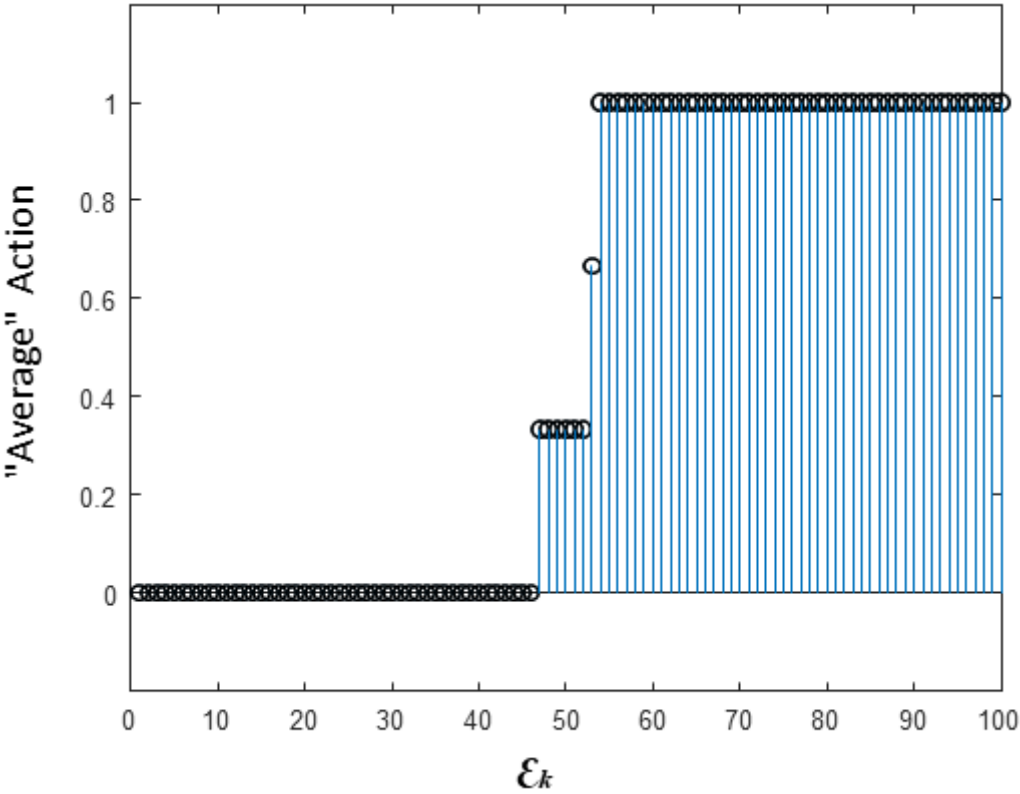


Figure 6.7: The actions taken by the sensor node when $\delta = 0.99$

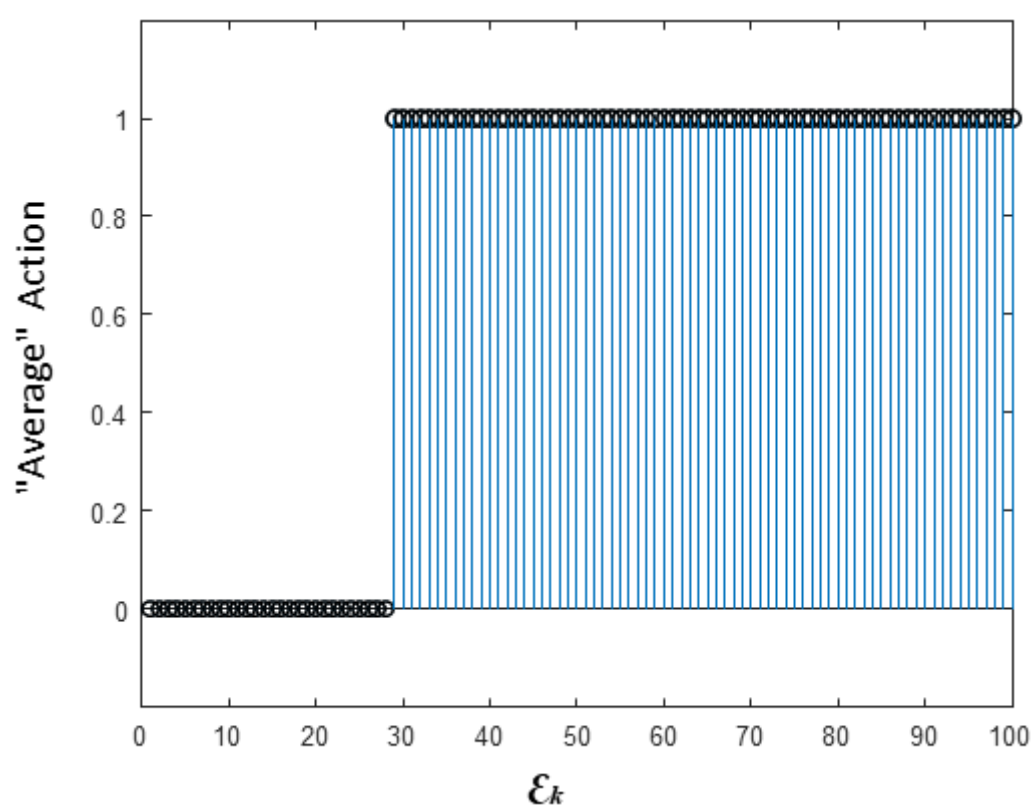


Figure 6.8: The actions taken by the sensor node when $\delta = 0.01$

	$(r, \phi) = (10, 11^\circ), p_a = 0.5$			
	$\gamma = 0.1$		$\gamma = 0.2$	
	Delay	Success Prob	Delay	Success Prob
$\delta = 0.01$	148	0.517	38	0.501
$\delta = 0.99$	209	0.650	66	0.651

Table 6.2: Delay and success probability performance for a sensor node located at $(r, \phi) = (10, 11^\circ)$ and with a charging efficiency $\gamma = 0.1$ and $\gamma = 0.2$ respectively. The MDP algorithm is used with parameters $\delta = 0.01$ and $\delta = 0.99$.

with $\gamma = 0.2$. In both cases $p_a = 0.5$, and as it is observed, the action takes the value $\alpha = 1$ for energy levels $\mathcal{E}_k > 30$, in agreement with the results of Figure 6.3. However, the large value of δ forces the algorithm to delay actions. Moreover, since there are states $(\mathcal{E}_k, \varepsilon_k)$ with the same $\mathcal{E}_k$ but different actions, we have plotted the “average” action per energy level $\mathcal{E}_k$.

Finally, in Table 6.2 we provide some simulation results on the average delay per transmission and the probability of successful transmission. We consider the node located at $(r, \phi) = (10, 11^\circ)$ with a reward probability threshold $p_a = 0.5$. The simulation results were obtained by averaging over 10 sets of 10000 samples each. In all cases the probability of a successful transmission exceeds the set threshold of $p_a = 0.5$. Moreover, large delays are induced for $\delta = 0.99$ since the MDP algorithm explores future states and postpones actions. Note that for $\gamma = 0.1$ the induced incremental energy MC has steady state probability vector $P_{ss} = [0.8056, 0.1844]$ and therefore the average energy increment per charging cycle is $0 \times 0.8056 + 1 \times 0.1844 = 0.1844$. From Figure 6.3, we deduce that for a success probability equal to 0.5 the energy level should be at least 28 units. Thus, $28/0.1844 = 152$ charging cycles are needed to reach this value in accordance to the results of Table 6.2. Similarly, for $\gamma = 0.2$, the steady state probability vector is $P_{ss} = [0.3290, 0.6303, 0.0407]$ and therefore the average energy increment per charging cycle is $0 \times 0.3290 + 1 \times 0.6303 + 2 \times 0.0407 = 0.7117$. In this case, at least $28/0.7117 = 39$ charging cycles are needed to reach an energy level of $\mathcal{E} = 28$.

A summary of chapter contributions is as follows:

- We propose a Markov Decision Process (MDP) algorithm that allows nodes the choice of transmitting or refraining from transmitting and continuing charging.
- We assess the performance of the proposed solutions through simulations.

7. SUMMARY AND FUTURE WORK

In the communication performance aspect of a WPCN network, a simple sensor reporting protocol for a WPCN network has been proposed. Theoretical expressions for the probability of successful information and successful reporting were provided and verified via model simulations. Sector selection strategies were proposed based on sensor reporting information, and their performance was assessed using simulations. Having the probability of successful information message reception as a figure of merit, the random selection scheme and the circular selection of sectors exhibit comparable performance to the proposed sector selection strategies. The performance, in terms of the delay of message delivery, is environment-dependent. For environments characterized by diverse blockage, the proposed algorithms outperform the circular (and consequently the random) selection of sectors. Future work will focus on exploiting the proposed reporting mechanism for other crucial tasks than simply declaring the presence of charged nodes. For example, early event indications may be notified to the AP using the proposed reporting mechanism. In this case, the AP may temporarily abandon beamforming all sectors and steer its beam towards the area of interest.

On event detection application, a thorough study was conducted on the performance aspects of a WPCN network used to detect events under the assumption of noisy sensor measurements. Detecting changes in the distribution of environmental parameters were based on the Optimal Stopping Theory by Shiryaev. The unstable nature of the involved likelihoods imposes smoothing on the posterior estimates, and to this end, a Beta Particle Filter was proposed and tested against a classical AR filter. Analytical and simulation results show that performance indices, such as false alarm rate, detection delay, and probability of successful transmission rely heavily on the charging efficiency and the location of the sensor nodes. Future work is oriented toward incorporating mechanisms, such as data/information fusion and relaying of information, that alleviate the problem of partly charged sensor nodes in an effort to increase the reliability of the system.

Finally, in the case of a WPCN network whose sensors' task is periodically transmitting their measurements to the AP, a proposed MDP algorithm is employed to postpone transmissions so that specific performance criteria are met optimally. Results show that the method is flexible enough to accommodate a variety of reward functions and offers a degree of trade-off between exploitation and exploration. However, the method's main disadvantage is its long training period to estimate the underlying MC and rewards for all possible channel variations. Future work will focus on WPCN networks with nodes possessing relay capabilities using the MDP algorithm.

ABBREVIATIONS - ACRONYMS

WSN	Wireless sensor network
MCU	Microcontroller unit
WPT	Wireless power transfer
WET	Wireless energy transfer
EH	Energy harvesting
SR	Separate Receiver
TS	Time Switching
PS	Power Splitting
AS	Antenna Switching
IoT	Internet of Things
3GPP	3rd Generation Partnership Project
ITU	International Telecommunication Union
e-MBB	Enhanced mobile broadband
m-MTC	Massive machine-type communications
u-RLLC	Ultra-reliable and low-latency communications
M2M	Machine-to-machine
RFID	Radio Frequency Identification
MIMO	Massive multiple-input multiple-output
BS	Base station
AP	Access point
WPCN	Wireless powered communication network
SWIPT	Simultaneous wireless information and power transfer
NOMA	Non orthogonal multiple access
UAV	Unmanned aerial vehicles
CUSUM	Cumulative sum
MDP	Markov decision process

MC	Markov chain
IID	Independent and identically distributed

APPENDIX A. PROOF OF EQUATION FOR THE PROBABILITY OF SUCCESSFUL REPORTING

The reporting nodes form a point process, say Φ_2 , which is the original PPP thinned by the probability p_r . For this thinned process, the spatial distribution of the reporting nodes is given by

$$f_R(r, \phi) = \frac{\lambda_{\Phi_2}(r, \phi)}{\mu_{\Phi_2}} = \frac{\lambda_{\Phi_2}(r, \phi)}{\int_{-\theta}^{\theta} \int_0^{\rho} \lambda_{\Phi_2}(r, \phi) r dr d\phi} \quad (\text{A.1})$$

where $\lambda_{\Phi_2}(r, \phi)$ is the intensity function

$$\lambda_{\Phi_2}(r, \phi) = \lambda \sum_{i=0}^{\tau} \psi_i P\{\mathcal{E}(r, \phi) > (\tau + 1 - i)\mathcal{E}_s\} \quad (\text{A.2})$$

and μ_{Φ_2} the intensity measure of the process. The harvested energy $\mathcal{E}(r, \phi)$ over the period T_H , for a sensor located at (r, ϕ) is given by

$$P_k^{\text{RF}} = -\frac{1}{\zeta_1} \ln \left(\frac{T_H L - \mathcal{E}(r, \phi)}{T_H L + \mathcal{E}(r, \phi) \exp(\zeta_1 \zeta_2)} \right)$$

with

$$P_k^{\text{RF}} = \frac{P_0 |g_k|^2 F_M(\phi)}{1 + r^a}$$

Hence, $\mathcal{E}(r, \phi) > (\tau + 1 - i)\mathcal{E}_s$ provided that

$$P_k^{\text{RF}} > -\frac{1}{\zeta_1} \ln \left(\frac{T_H L - (\tau + 1 - i)\mathcal{E}_s}{T_H L + (\tau + 1 - i)\mathcal{E}_s \exp(\zeta_1 \zeta_2)} \right) = \eta_{\tau+1-i}$$

or equivalently

$$|g_k|^2 > \frac{\eta_{\tau+1-i}(1 + r^a)}{P_0 F_M(\phi)}$$

Since $|g_k|^2$ is exponentially distributed, and incorporating the LOS probability, we have

$$\begin{aligned} P\{\mathcal{E}(r, \phi) > (\tau + 1 - i)\mathcal{E}_s\} &= P\left\{|g_k|^2 > \frac{\eta_{\tau+1-i}(1 + r^a)}{P_0 F_M(\phi)}\right\} \exp(-\beta r) \\ &= \exp\left(-\frac{\eta_{\tau+1-i}(1 + r^a)}{P_0 F_M(\phi)} - \beta r\right) \end{aligned} \quad (\text{A.3})$$

Substituting Equation (A3) in Equations (A2) and (A1), we obtain

$$f_R(r, \phi) = \frac{\lambda_{\Phi_2}(r, \phi)}{\mu_{\Phi_2}} = \frac{\lambda \sum_{i=0}^{\tau} \psi_i \exp\left(-\frac{\eta_{\tau+1-i}(1+r^a)}{P_0 F_M(\phi)} - \beta r\right)}{\lambda \theta \rho^2 p_r^r} \quad (\text{A.4})$$

Note that

$$\begin{aligned} \mu_{\Phi_2} &= \int_{-\theta}^{\theta} \int_0^{\rho} \lambda \sum_{i=0}^{\tau} \psi_i \exp\left(-\frac{\eta_{\tau+1-i}(1+r^a)}{P_0 F_M(\phi)} - \beta r\right) r dr d\phi \\ &= \lambda \sum_{i=0}^{\tau} \psi_i \int_{-\theta}^{\theta} \int_0^{\rho} \exp\left(-\frac{\eta_{\tau+1-i}(1+r^a)}{P_0 F_M(\phi)} - \beta r\right) r dr d\phi \\ &= \lambda \sum_{i=0}^{\tau} \psi_i \theta \rho^2 P\{\mathcal{E} > (\tau + 1 - i)\mathcal{E}_s\} \\ &= \lambda \theta \rho^2 p_r^r \end{aligned} \quad (\text{A.5})$$

We return now to the calculation of the probability of successfully receiving a report message, p_{sr}^r . The message is received correctly by the AP provided that

$$R_R = \frac{D_R}{T_R} < W' \log_2(1 + \text{SNR}) \quad (\text{A.6})$$

where D_R is the message length (bits), T_R is the time to transmit the report message, W' is the bandwidth allocated to a node, and SNR is the signal to noise ratio at the AP. Clearly, the SNR for a node located at (r, ϕ) is

$$\text{SNR} = \frac{P_{\ell} |g|^2 F_M(\phi)}{(1 + r^a) \sigma^2} \quad (\text{A.7})$$

with $P_{\ell} = \ell \mathcal{E}_s / T_R$, $\ell = 1, \dots, N - \tau$. As in the case of calculating p_{si}^r ,

$$\begin{aligned} P\{\text{SNR} \leq x \mid P_{\ell}\} &= P\left\{\frac{P_{\ell} |g|^2 F_M(\phi)}{(1 + r^a) \sigma^2} \leq x \mid P_{\ell}\right\} \\ &= P\left\{|g|^2 \leq \frac{x(1 + r^a) \sigma^2}{P_{\ell} F_M(\phi)} \mid P_{\ell}\right\} \\ &= 1 - E_{\Phi_2} \left[\exp\left(-\frac{x(1 + r^a) \sigma^2}{P_{\ell} F_M(\phi)}\right) \right] \end{aligned} \quad (\text{A.8})$$

In the last equation, the average is over the thinned process, for which the nodes are distributed according to $f_R(r, \phi)$. Thus,

$$\begin{aligned}
P\{\text{SNR} \leq x \mid P_\ell\} &= 1 - \int_{-\theta}^{\theta} \int_0^{\rho} \exp\left(-\frac{x(1+r^a)\sigma^2}{P_\ell F_M(\phi)}\right) f_R(r, \phi) r dr d\phi \\
&= 1 - \frac{1}{\theta \rho^2 p_r^r} \int_{-\theta}^{\theta} \int_0^{\rho} \sum_{i=0}^{\tau} \psi_i \exp\left(-\frac{1+r^a}{F_M(\phi)} \left(\frac{x\sigma^2}{P_\ell} + \frac{\eta_{\tau+1-i}}{P_0}\right) - \beta r\right) r dr d\phi
\end{aligned} \tag{A.9}$$

The probability of successfully receiving a report message p_{sr}^r is simply

$$p_{sr}^r = P\{\text{SNR} > 2^{R_R/W'} - 1\} = P\{\text{SNR} > 2^{D_R/T_R W'} - 1\}$$

Substituting it in Equation (A9) and unconditioning on P_ℓ , we obtain

$$p_{sr}^r = \sum_{\ell=1}^{N-\tau} P\{\text{SNR} > 2^{D_R/T_R W'} - 1 \mid P_\ell\} P\{P_\ell\} \tag{A.10}$$

The probability of transmitting the report message with power P_ℓ , given that the node's energy level after harvesting exceeds the threshold τ , equals

$$p_\ell = P\{P_\ell\} = \begin{cases} \frac{F_{\mathcal{E}}((\tau + \ell + 1 - i)\mathcal{E}_s) - F_{\mathcal{E}}((\tau + \ell - i)\mathcal{E}_s)}{1 - F_{\mathcal{E}}((\tau + 1 - i)\mathcal{E}_s)} & \ell < N - \tau \\ \frac{1 - F_{\mathcal{E}}((\tau + \ell + 1 - i)\mathcal{E}_s)}{1 - F_{\mathcal{E}}((\tau + 1 - i)\mathcal{E}_s)} & \ell = N - \tau \end{cases} \tag{A.11}$$

APPENDIX B. MARKOV DECISION PROCESS (MDP)

In this appendix, we highlight the basic principles of the Markov chain (MC) and the Markov decision process (MDP). Throughout this section, we refer only to the finite discrete time case following the exposition of [57].

Markov Chain (MC)

Let X_t be a random variable denoting the state of a process at time t . Assuming that process consists of S different states, the process is always in some state $X_t < S$. The process is characterized as stochastic if the transition from one state to another is stochastic. Any move from a state i to j has a transition probability $p_{i,j}$ which does not change over time.

The process has the Markov property if the probability of moving from state i to another state j is independent of the states visited before i . Markov chain is a type of stochastic process that satisfies the Markov property. So Markov chain is characterized by a state space, a transition matrix describing the probabilities of particular transitions, and an initial state across the state space.

Depending on the probability of revisiting state i while you are in state i , there are two kind of states: Transient states if the above mention probability is not equal to one, recurrent states if the above mention probability is equal to one. Recurrent state means that the process after reaching state i it will be visited i infinitely.

Let $p_{i,j}^n$ denote the probability of moving from i to j in n steps. In order to calculate this probability, taking advantage of the total probability law and the Markov property, we only have to sum the probabilities of all the intermediate steps between i and j . (Chapman - Kolmogorov equation)

Markov Decision Process (MDP)

Markov decision processes are an extension of Markov chains. Instead of a self-transitioning process, as in a Markov chain, in MDP, we have a decision-making agent responsible for the progress of the process. So at each time step of the process agent choose how to proceed from a set of actions. After the action has been taken, the agent moves to the next state and receives a reward. Formally a Markov decision process is a 4-tuple (S, A, P_a, R_a) where

- S is the state space
- A is the action state
- P_a is the probability that an action a in state s at time t will forward to s' at $t + 1$

$$P_a(s, s') = P_r(s_{t+1} = s' \mid s_t = s, a_t = a) \quad (\text{B.1})$$

- R_a is the reward after moving from state s to state s' by action a

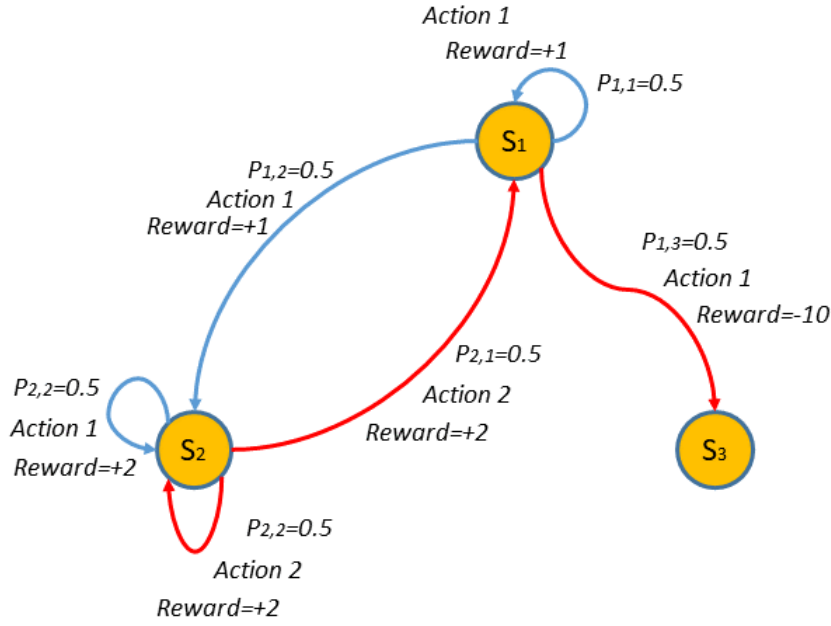


Figure B.1: Example of a simple MDP with three states, two action and three rewards.

The agent, as the process progresses, will have a starting state and some absorbing terminal state. Therefore, we define a policy and denote it with π , as the subset of state-action that passes from a starting state to a terminal state.

A Markov decision process aims to identify a proper "policy" for the decision maker. A function π that defines the action $\pi(s)$ the decision maker will select when the agent is in state s .

The objective is to choose a policy π that maximizes the cumulative function of the random rewards

$$\mathbb{E} \left[\sum_{t=0}^{\infty} \gamma^t R_{\pi(s_t)}(s_t, s_{t+1}) \right] \quad (\text{B.2})$$

where γ is the discount factor satisfying $0 \leq \gamma \leq 1$. A lower discount factor encourages the decision-maker to favor immediate action over long-term deferral. A policy that maximizes the function above is called an optimal policy π and is usually denoted by π^* .

For the calculation of optimal policies for finite states and actions, the general algorithms require storing two arrays, named value and policy. This arrays are repeatedly updated using older estimations of the value and the policy arrays until no other change in the process takes place.

$$V(s) := \sum_{s'} P_{\pi(s)}(s, s') R_{\pi(s)}(s, s') + \gamma V(s') \quad (\text{B.3})$$

$$\pi(s) := \operatorname{argmax}_a \left\{ \sum_{s'} P_a(s, s') R_a(s, s') + \gamma V(s') \right\} \quad (\text{B.4})$$

The most common algorithms are Value iteration, policy iteration, and prioritized sweeping.

Value iteration

We calculate the optimal policy and state value by iteratively revising the estimate $V(s)$ in the value iteration method. We start with a random value function, and at each step, we update it.

$$V(s) := \max_a \left\{ \sum_{s'} P_a(s, s') R_a(s, s') + \gamma V(s') \right\} \quad (\text{B.5})$$

We note that the calculation of $\pi(s)$ is within $V(s)$.

Data: states S , actions A

Result: Convergence of $V(s)$

/ textbfInitialization $V(s)$ initialized with random values;*

while *maximum difference between two iterations* $< \delta$ **do**

for all $s \in S$ **do**

for all $a \in A$ **do**

$Q(s, a) \leftarrow \sum_{s'} P_a(s, s') R_a(s, s') + \gamma V(s')$

end

$V(s) \leftarrow \max V(s);$

end

end

Algorithm 4: Value iteration Algorithm

APPENDIX C. PARTICLE FILTERS

A particle filter is a method to solve estimation problems. Numerous applications use particle filter algorithms, such as fault detection in critical infrastructures or position estimation, like finding a robot position based on a known map [5]. In this appendix, we concentrate on the use of particle filters to resolve recursive estimation problems. The reason for recursive estimation is that in a sensor network, the state information is a dynamic process due to the nature of the environment. In order to estimate the state sequence x_n we need:

- A prior knowledge of state x_n evolution over time
- Measurements of the state x_n

An advantage of Particle filters is that they allow us to handle efficient inputs like above that are nonlinear compared to other methods like Kalman filters.

We define the posterior state as the state estimation at time n considering previous information up to time n :

$$p(x_n | y_{1:n}) \quad (\text{C.1})$$

where $y_{1:n}$ denote the measurements up to time n .

If we express the state space as a Markov Chain, assuming all information needed from the previous step is summarized at the state x_{n-1} , the particle filter is a Bayesian filter.

$$p(x_n | x_{1:n-1}, y_{1:n-1}) = p(x_n | x_{n-1}) \quad (\text{C.2})$$

$$p(y_n | x_{1:n}, y_{1:n-1}) = p(y_n | x_n) \quad (\text{C.3})$$

Estimating a state using Baye's theorem, we combine the measurement process (likelihood) with a prior probability of the state process. The solution stages include updating the state model by executing the following two steps at each time step.

Step1: Computation of the prior at time n

$$p(x_n | y_{1:n-1}) = \int p(x_n | x_{n-1}) p(x_{n-1} | y_{1:n-1}) dx_{n-1} \quad (\text{C.4})$$

Step2: Based on the measurements, we calculate the posterior

$$p(x_n | y_{1:n}) = \frac{p(y_n | x_n) p(x_n | y_{1:n-1})}{p(y_n | y_{1:n-1})} \quad (\text{C.5})$$

Where the measurement likelihood is expressed as $p(y_n | x_n)$ and the marginal likelihood is computed using:

$$p(y_n | y_{1:n-1}) = \int p(y_n | x_n) p(x_n | y_{1:n-1}) dx_n \quad (\text{C.6})$$

In order to solve equations (C.5) and (C.6), particle filter algorithms use a discrete approximation that transforms the integrals into summations over N_s samples. The samples are referred to as particles. In our case, the posterior that must be approximate is unknown, so we choose another distribution for sampling to overcome the problem. This distribution is defined as importance density q . So given the importance of density, we can compute the weights:

$$w_n^i \propto w_{n-1}^i \frac{p(y_n|x_n^i)p(x_n^i|x_{n-1}^i)}{q(x_n^i|x_{n-1}^i, y_n)} \quad (\text{C.7})$$

Where w_{n-1}^i represents the weight at the previous time step and continuing, we compute the posterior:

$$p(x_n|y_{1:n}) = \sum_{i=1}^{N_s} w_k^i \delta(x_n - x_n^i) \quad (\text{C.8})$$

The basic steps described above define the sequential importance sampling algorithm.

Input: $\{x_{n-1}^i, w_{n-1}^i\}_{i=1}^{N_s}, y_n$
Output: $\{x_n^i, w_n^i\}_{i=1}^{N_s}, y_n$
for $i = 1, \dots, N_s$ **do**
 /*Step 1: propagate particle
 draw sample $x_n^i \sim q(x_n^i|x_{n-1}^i, y_n)$
 /* Step 2: update weight
 assign weight w_n^i using (C.7)
end

Algorithm 5: Sequential Importance Sampling

The most straightforward resampling algorithm includes resampling at each time step. Even though resampling has computational cost is the most popular because it overcomes a critical issue, the degeneracy problem. The problem consists of when we run the SIS algorithm, after a few iterations, one of the weights will take the value of one, and all the rest weight the value of zero. The algorithm pseudocode is presented next.

Input: $\{x_{n-1}^i, w_{n-1}^i\}_{i=1}^{N_s}, y_n$
Output: $\{x_n^i, w_n^i\}_{i=1}^{N_s}, y_n$
 $w_{sum} = 0$
for $i = 1, \dots, N_s$ **do**
 /*Step 1: propagate particle
 draw sample $x_n^i \sim q(x_n^i | x_{n-1}^i, y_n)$
 /* Step 2: update weight
 assign weight w_n^i using (C.7)
 /* Step 3: cumulative weights $w_{sum} = w_{sum} + w_n^i$
end
/* Normalize weights
for $i = 1, \dots, N_s$ **do**
 $w_n^i = w_n^i / w_{sum}$
end
/* Resample
Resample N_s particles with replacement
/* Reset weights
for $i = 1, \dots, N_s$ **do**
 $w_n^i = 1/N_s$
end

Algorithm 6: Sequential Importance Resampling

APPENDIX D. MULTI-ARMED BANDIT

The multi-armed bandit (MAB) problem was firstly described by Robinson [56] as a problem where a gambler enters a casino and must decide how many times he will play each slot machine and in what order to increase the total payouts received. If a gambler knows which slot machine is the most profitable and its payouts vary depending on how often it is chosen, she will keep pulling from that machine. Even without this information, a gambler can still estimate the machines' profitability by watching each arm pull's results. The gambler must choose between "exploiting" the machine with the highest expected reward and "exploring" other machines to learn more about their profitability.

Initially, multi-armed bandit theory problems are used in clinical tests where, despite different available cures, one must decide which treatment to employ on a patient. In recent years new applications have used this theory to solve problems in which the monitor parameter space is not fixed in advance but is a function of the observations involving time. Examples are:

- in digital web ad placement which advertisement to display
- how to manage research projects in a large organization

There are three fundamental formulations of the bandit problem depending on the assumed nature of the reward process: stochastic, adversarial, and Markovian.

For each category, there is a corresponding algorithm as a baseline to solve each model:

- In the stochastic case, the principal solution algorithm is the Upper Confidence Bound (UCB)
- In the adversarial case, the principal solution algorithm is the Exp3 randomized algorithm
- In the Markovian case, the principal solution algorithm is the so-called Gittins indices.

In this appendix, we focus on stochastic bandits.

A bandit problem consists of K 's possible user actions. Each time we take an action, we get a reward visible to the user. Assuming that each action follows a different reward distribution that does not change over time, the user must decide what series of actions must follow, called policy.

In stochastic MAB we focus on problems where the reward process of each action is independent and identically distributed (IID), and the rewards across different actions may be dependent. In this type of problem, the optimal policy the user must follow is to play the arm with the highest expected reward the entire time. In general, all bandit algorithms attempt to minimize regret. Regret is defined as:

$$\text{regret}(n) = \mu^* n - \sum_{j=1}^K \mathbb{E}[T_j(n)] \quad (\text{D.1})$$

where μ^* is the expected reward of the best action dictated by the optimal policy, K is the number of arms, and $T_j(n)$ is the number of times we have chosen action j over n played actions.

A simple example that presents the importance of the trade-off between exploring and exploiting is. Suppose there are 3 slot machines in a casino, and you are trying to figure out which machine has the highest payout. The first time you play each machine, you get the following payouts: Machine A: 10 euro Machine B: 5 euro Machine C: 8 euro Based on these initial payouts, you estimate that Machine A has the highest payout, and you start playing that machine exclusively to maximize your profits. However, there is a chance that your initial estimates are wrong, and another machine actually has a higher payout. If you were to play each machine multiple times, you would eventually converge on the true payout rate of each machine through a process called "exploration." However, if you are overly confident in your initial estimates and do not continue to explore, you may miss out on a better payout rate and end up with suboptimal profits. For example, let's say that after 10 plays on Machine A, you have won 70 euros, which reinforces your belief that it has the highest payout. However, during this time, the other machines may have had better payouts that you missed out on. Perhaps Machine B had a higher payout rate, but you only played it once and then abandoned it. To avoid this problem, you need to balance your exploration of new options with your exploitation of current options. In the context of the multi-armed bandit problem, this means occasionally trying out other machines to see if they have a better payout rate, even if you are relatively confident in your current estimate of the best machine.

In order to increase our belief in our reward estimates, bandit theory introduces a well know statistical notion of the confidence interval. So the average reward of each action will lie between a value range with some probability. Consequently, we expect a wide confidence interval if an action is not chosen often and a narrow confidence interval when we repeatedly try a specific action. So Upper confidence algorithm (UCB), instead of trying the action with the highest mean, chooses the action with the highest upper bound on its confidence interval. In order to calculate the upper bound, we rely on the Chernoff-Hoeffding bound theory. Let $X_1, X_2, \dots, X_n$ be independent random variables in the range $[0, 1]$ with $\mathbb{E}[X_i] = \mu$. Then for $a > 0$,

$$P \left(\frac{1}{n} \sum_{i=1}^n X_i \geq \mu + a \right) \leq e^{-2a^2 n} \quad (\text{D.2})$$

and

$$P \left(\frac{1}{n} \sum_{i=1}^n X_i \leq \mu - a \right) \leq e^{2a^2 n} \quad (\text{D.3})$$

By solving $p = e^{2a^2 n}$ we calculate the theoretical upper bound of the average reward. UCB1, achieving logarithmic regret uniformly over n and without any preliminary knowledge about the reward distributions.

Deterministic policy: UCB1.

Initialization: Play each machine once.

Loop:

- Play machine j that maximizes $\bar{x}_j = \sqrt{\frac{2 \ln n}{n_j}}$ where $\bar{x}_j$ is the average reward obtained from machine j , n_j is the number of times machine j has been played so far, and n is the overall number of plays done so far.

Algorithm 7: UCB1 policy algorithm

REFERENCES

- [1] Alireza Abdollahi, Karim Rejeb, Abderahman Rejeb, Mohamed M Mostafa, and Suhaiza Zailani. Wireless sensor networks in agriculture: Insights from bibliometric analysis. *Sustainability*, 13(21):12011, 2021.
- [2] Muhammad Yeasir Arafat and Sangman Moh. Bio-inspired approaches for energy-efficient localization and clustering in uav networks for monitoring wildfires in remote areas. *IEEE Access*, 9:18649–18669, 2021.
- [3] Nicolo Cesa-Bianchi Auer, Peter and Paul Fischer. Finite-time analysis of the multi-armed bandit problem. *Machine Learning*, 47.2-3:235–256, 2002.
- [4] Richard Bellman. A markovian decision process. *Journal of mathematics and mechanics*, pages 679–684, 1957.
- [5] Hilal Bello, Zeng Xiaoping, Rosdiadee Nordin, and Jian Xin. Advances and opportunities in passive wake-up radios with wireless energy harvesting for the internet of things applications. *Sensors*, 19(14):3078, 2019.
- [6] Sofiane Benzid and Ahmed Belhani. A study of wireless sensor networks based adaptive traffic lights control. In *International Conference on Artificial Intelligence and its Applications*, pages 406–417. Springer, 2022.
- [7] Tadilo Endeshaw Bogale, Xianbin Wang, and Long Bao Le. mmwave communication enabling techniques for 5g wireless systems: A link level perspective. In *MmWave Massive MIMO*, pages 195–225. Elsevier, 2017.
- [8] Elena Boshkovska, Derrick Wing Kwan Ng, Nikola Zlatanov, and Robert Schober. Practical non-linear energy harvesting model and resource allocation for swipt systems. *IEEE Communications Letters*, 19(12):2082–2085, 2015.
- [9] Benjamin L Cannon, James F Hoburg, Daniel D Stancil, and Seth Copen Goldstein. Magnetic resonant coupling as a potential means for wireless power transfer to multiple small receivers. *IEEE transactions on power electronics*, 24(7):1819–1825, 2009.
- [10] Kae Won Choi, Lorenz Ginting, Phisca Aditya Rosyady, Arif Abdul Aziz, and Dong In Kim. Wireless-powered sensor networks: How to realize. *IEEE Transactions on Wireless Communications*, 16(1):221–234, 2016.
- [11] Kae Won Choi, Phisca Aditya Rosyady, Lorenz Ginting, Arif Abdul Aziz, Dedi Setiawan, and Dong In Kim. Theory and experiment for wireless-powered sensor networks: How to keep sensors alive. *IEEE Transactions on Wireless Communications*, 17(1):430–444, 2017.

- [12] Angelo Coluccia and Alessio Fascista. A review of advanced localization techniques for crowdsensing wireless sensor networks. *Sensors*, 19(5):988, 2019.
- [13] Linglong Dai, Bichai Wang, Mugen Peng, and Shanzhi Chen. Hybrid precoding-based millimeter-wave massive mimo-noma with simultaneous wireless information and power transfer. *IEEE Journal on Selected Areas in Communications*, 37(1):131–141, 2018.
- [14] Zhiguo Ding, Pingzhi Fan, and H Vincent Poor. Random beamforming in millimeter-wave noma networks. *IEEE access*, 5:7667–7681, 2017.
- [15] Russell Ford, Menglei Zhang, Marco Mezzavilla, Sourjya Dutta, Sundeep Rangan, and Michele Zorzi. Achieving ultra-low latency in 5g millimeter wave cellular networks. *IEEE Communications Magazine*, 55(3):196–203, 2017.
- [16] Mingjin Gao, He Henry Chen, Yonghui Li, Mahyar Shirvanimoghaddam, and Jinglin Shi. Full-duplex wireless-powered communication with antenna pair selection. In *2015 IEEE Wireless Communications and Networking Conference (WCNC)*, pages 693–698. IEEE, 2015.
- [17] Gordana Gardašević, Konstantinos Katzis, Dragana Bajić, and Lazar Berbakov. Emerging wireless sensor networks and internet of things technologies—foundations of smart healthcare. *Sensors*, 20(13):3619, 2020.
- [18] Amin Ghazanfari, Hina Tabassum, and Ekram Hossain. Ambient rf energy harvesting in ultra-dense small cell networks: Performance and trade-offs. *IEEE Wireless Communications*, 23(2):38–45, 2016.
- [19] Sravanthi Godala and Rama Prasad V Vaddella. A study on intrusion detection system in wireless sensor networks. *International Journal of Communication Networks and Information Security*, 12(1):127–141, 2020.
- [20] Vehbi C Gungor and Gerhard P Hancke. Industrial wireless sensor networks: Challenges, design principles, and technical approaches. *IEEE Transactions on industrial electronics*, 56(10):4258–4265, 2009.
- [21] Jing Guo, Xiangyun Zhou, and Salman Durrani. Wireless power transfer via mmwave power beacons with directional beamforming. *IEEE Wireless Communications Letters*, 8(1):17–20, 2018.
- [22] Olympia Hadjiliadis, Hongzhong Zhang, and H Vincent Poor. One shot schemes for decentralized quickest change detection. *IEEE Transactions on Information Theory*, 55(7):3346–3359, 2009.
- [23] Longzhuang He, Jintao Wang, and Yahong Rosa Zheng. On the energy coverage of low power wide area networks (lpwans) wireless powered by ultra-dense mmwave small cells. In *2018 IEEE International Conference on Communications Workshops (ICC Workshops)*, pages 1–6. IEEE, 2018.

- [24] Wassily Hoeffding. *Probability inequalities for sums of bounded random variables*. Springer, NY, 1994.
- [25] Y-W Peter Hong, Teng-Cheng Hsu, and Pradeep Chennakesavula. Wireless power transfer for distributed estimation in wireless passive sensor networks. *IEEE Transactions on Signal Processing*, 64(20):5382–5395, 2016.
- [26] Zhongwei Hu, Chaowei Yuan, Fengchao Zhu, and Feifei Gao. Weighted sum transmit power minimization for full-duplex system with swipt and self-energy recycling. *IEEE Access*, 4:4874–4881, 2016.
- [27] Jun Huang, Yide Zhou, Zhaolong Ning, and Hamid Gharavi. Wireless power transfer and energy harvesting: Current status and future prospects. *IEEE Wireless Communications*, 26(4):163–169, 2019.
- [28] Kaibin Huang and Erik Larsson. Simultaneous information and power transfer for broadband wireless systems. *IEEE Transactions on Signal Processing*, 61(23):5972–5986, 2013.
- [29] Yiming Huo, Xiaodai Dong, Tao Lu, Wei Xu, and Marvin Yuen. Distributed and multi-layer uav networks for next-generation wireless communication and power transfer: A feasibility study. *IEEE Internet of Things Journal*, 2019.
- [30] Gervais N Kamga and Sonia Aïssa. Wireless power transfer in mmwave massive mimo systems with/without rain attenuation. *IEEE Transactions on Communications*, 67(1):176–189, 2018.
- [31] Dionisis Kandris, Christos Nakas, Dimitrios Vomvas, and Grigorios Koulouras. Applications of wireless sensor networks: an up-to-date survey. *Applied System Innovation*, 3(1):14, 2020.
- [32] Sun-Woong Kim and Dong-You Choi. Analysis of beamforming antenna for practical indoor location-tracking application. *Sensors*, 19(14):3040, 2019.
- [33] Michael Koutsoumpos, Evangelos Zervas, Efstathios Hadjiefthymiades, and Lazaros Merakos. Monitoring for rare events in a wireless powered communication mmwave sensor network. *Sensors*, 20(12):3341, 2020.
- [34] Ioannis Krikidis, Themistoklis Charalambous, and John S Thompson. Buffer-aided relay selection for cooperative diversity systems without delay constraints. *IEEE Transactions on Wireless Communications*, 11(5):1957–1967, 2012.
- [35] Ioannis Krikidis, Shigenobu Sasaki, Stelios Timotheou, and Zhiguo Ding. A low complexity antenna switching for joint wireless information and energy transfer in mimo relay channels. *IEEE Transactions on Communications*, 62(5):1577–1587, 2014.
- [36] Ioannis Krikidis, Stelios Timotheou, Symeon Nikolaou, Gan Zheng, Derrick Wing Kwan Ng, and Robert Schober. Simultaneous wireless information and power

- transfer in modern communication systems. *IEEE Communications Magazine*, 52(11):104–110, 2014.
- [37] Dileep Kumar, Jani Saloranta, Jarkko Kaleva, Giuseppe Destino, and Antti Tölli. Reliable positioning and mmwave communication via multi-point connectivity. *Sensors*, 18(11):4001, 2018.
- [38] Gilwon Lee, Youngchul Sung, and Junyeong Seo. Randomly-directional beamforming in millimeter-wave multiuser miso downlink. *IEEE Transactions on Wireless Communications*, 15(2):1086–1100, 2015.
- [39] Hoon Lee, Kyoung-Jae Lee, Hanjin Kim, Bruno Clerckx, and Inkyu Lee. Resource allocation techniques for wireless powered communication networks. In *2016 IEEE International Conference on Communications (ICC)*, pages 1–6. IEEE, 2016.
- [40] Xin Lin, Lei Huang, Chongtao Guo, Peichang Zhang, Min Huang, and Jihong Zhang. Energy-efficient resource allocation in tdms-based wireless powered communication networks. *IEEE Communications Letters*, 21(4):861–864, 2016.
- [41] Gary Lorden et al. Procedures for reacting to a change in distribution. *The Annals of Mathematical Statistics*, 42(6):1897–1908, 1971.
- [42] Lu Lu, Geoffrey Ye Li, A Lee Swindlehurst, Alexei Ashikhmin, and Rui Zhang. An overview of massive mimo: Benefits and challenges. *IEEE journal of selected topics in signal processing*, 8(5):742–758, 2014.
- [43] Xiao Lu, Ping Wang, Dusit Niyato, and Zhu Han. Resource allocation in wireless networks with rf energy harvesting and transfer. *IEEE Network*, 29(6):68–75, 2015.
- [44] Dimitris V Manatakis and Elias S Manolakos. Estimating the spatiotemporal evolution characteristics of diffusive hazards using wireless sensor networks. *IEEE Transactions on Parallel and Distributed Systems*, 26(9):2444–2458, 2014.
- [45] Deepak Mishra, Swades De, Soumya Jana, Stefano Basagni, Kaushik Chowdhury, and Wendi Heinzelman. Smart rf energy harvesting communications: Challenges and opportunities. *IEEE Communications Magazine*, 53(4):70–78, 2015.
- [46] George V Moustakides et al. Optimal stopping times for detecting changes in distributions. *Annals of Statistics*, 14(4):1379–1387, 1986.
- [47] Derrick Wing Kwan Ng, Ernest S Lo, and Robert Schober. Wireless information and power transfer: Energy efficiency optimization in ofdma systems. *IEEE Transactions on Wireless Communications*, 12(12):6352–6370, 2013.
- [48] Derrick Wing Kwan Ng, Ernest S Lo, and Robert Schober. Robust beamforming for secure communication in systems with wireless information and power transfer. *IEEE Transactions on Wireless Communications*, 13(8):4599–4615, 2014.

- [49] Maryam Olyaei, Mohsen Eslami, Hadi Hashemi, and Javad Haghighat. Performance of wireless energy transfer efficiency in mm-wave communications. In *2019 27th Iranian Conference on Electrical Engineering (ICEE)*, pages 1611–1615. IEEE, 2019.
- [50] Tharindu D Ponnimbaduge Perera, Dushantha Nalin K Jayakody, Shree Krishna Sharma, Symeon Chatzinotas, and Jun Li. Simultaneous wireless information and power transfer (swipt): Recent advances and future challenges. *IEEE Communications Surveys & Tutorials*, 20(1):264–302, 2017.
- [51] Zhouyue Pi and Farooq Khan. An introduction to millimeter-wave mobile broadband systems. *IEEE communications magazine*, 49(6):101–107, 2011.
- [52] Manuel Piñuela, Paul D Mitcheson, and Stepan Lucyszyn. Ambient rf energy harvesting in urban and semi-urban environments. *IEEE Transactions on microwave theory and techniques*, 61(7):2715–2726, 2013.
- [53] K Premkumar and Anurag Kumar. Optimal sleep-wake scheduling for quickest intrusion detection using wireless sensor networks. In *IEEE INFOCOM 2008-The 27th Conference on Computer Communications*, pages 1400–1408. IEEE, 2008.
- [54] Constantinos Psomas and Ioannis Krikidis. Energy beamforming in wireless powered mmwave sensor networks. *IEEE Journal on Selected Areas in Communications*, 37(2):424–438, 2018.
- [55] Vasanthan Raghavan and Venugopal V Veeravalli. Quickest change detection of a markov process across a sensor array. *IEEE Transactions on Information Theory*, 56(4):1961–1981, 2010.
- [56] Herbert Robbins. Some aspects of the sequential design of experiments. *Bulletin of the American Mathematical Society*, 58(5):527–535, 1952.
- [57] Sheldon M Ross. *Introduction to probability models*. Academic press, 2014.
- [58] Mahmood Safaei, Shahla Asadi, Maha Driss, Wadii Boulila, Abdullah Alsaedi, Hassan Chizari, Rusli Abdullah, and Mitra Safaei. A systematic literature review on outlier detection in wireless sensor networks. *Symmetry*, 12(3):328, 2020.
- [59] M Series. Imt vision–framework and overall objectives of the future development of imt for 2020 and beyond. *Recommendation ITU*, 2083:21, 2015.
- [60] Chao Shen, Wei-Chiang Li, and Tsung-Hui Chang. Simultaneous information and energy transfer: A two-user miso interference channel case. In *2012 IEEE Global Communications Conference (GLOBECOM)*, pages 3862–3867. IEEE, 2012.
- [61] Yuan-Yao Shih, Wei-Ho Chung, Ai-Chun Pang, Te-Chuan Chiu, and Hung-Yu Wei. Enabling low-latency applications in fog-radio access networks. *IEEE network*, 31(1):52–58, 2016.

- [62] Albert N Shiryaev. On optimum methods in quickest detection problems. *Theory of Probability & Its Applications*, 8(1):22–46, 1963.
- [63] Albert N Shiryaev. *Optimal stopping rules*, volume 8. Springer Science & Business Media, 2007.
- [64] A Sofi, J Jane Regita, Bhagyesh Rane, and Hieng Ho Lau. Structural health monitoring using wireless smart sensor network—an overview. *Mechanical Systems and Signal Processing*, 163:108113, 2022.
- [65] Xiaoli Sun, Weiwei Yang, Yueming Cai, Liwei Tao, Yang Liu, and Yongming Huang. Secure transmissions in wireless information and power transfer millimeter-wave ultra-dense networks. *IEEE Transactions on Information Forensics and Security*, 14(7):1817–1829, 2018.
- [66] Alexander G Tartakovsky, Boris L Rozovskii, Rudolf B Blažek, and Hongjoong Kim. Detection of intrusions in information systems by sequential change-point methods. *Statistical methodology*, 3(3):252–293, 2006.
- [67] Alexander G Tartakovsky and Venugopal V Veeravalli. Change-point detection in multichannel and distributed systems. *Applied Sequential Methodologies: Real-World Examples with Data Analysis*, 173:339–370, 2004.
- [68] Venugopal V Veeravalli. Decentralized quickest change detection. *IEEE Transactions on Information theory*, 47(4):1657–1665, 2001.
- [69] Chwei-Sen Wang, Grant A Covic, and Oskar H Stielau. Power transfer capability and bifurcation phenomena of loosely coupled inductive power transfer systems. *IEEE transactions on industrial electronics*, 51(1):148–157, 2004.
- [70] Hong Shen Wang and Nader Moayeri. Finite-state markov channel-a useful model for radio communication channels. *IEEE transactions on vehicular technology*, 44(1):163–171, 1995.
- [71] Jin Wang, Yu Gao, Kai Wang, Arun Kumar Sangaiah, and Se-Jung Lim. An affinity propagation-based self-adaptive clustering method for wireless sensor networks. *Sensors*, 19(11):2579, 2019.
- [72] Jin Wang, Yu Gao, Xiang Yin, Feng Li, and Hye-Jin Kim. An enhanced pegasis algorithm with mobile sink support for wireless sensor networks. *Wireless Communications and Mobile Computing*, 2018, 2018.
- [73] Jin Wang, Chunwei Ju, Yu Gao, Arun Kumar Sangaiah, and Gwang-jun Kim. A pso based energy efficient coverage control algorithm for wireless sensor networks. *Comput. Mater. Contin*, 56(3):433–446, 2018.
- [74] Qingqing Wu, Wen Chen, and Jun Li. Wireless powered communications with initial energy: Qos guaranteed energy-efficient resource allocation. *IEEE Communications Letters*, 19(12):2278–2281, 2015.

- [75] Yao Xie and David Siegmund. Sequential multi-sensor change-point detection. In *2013 Information Theory and Applications Workshop (ITA)*, pages 1–20. IEEE, 2013.
- [76] Lu Yang, Yong Zeng, and Rui Zhang. Wireless power transfer with hybrid beamforming: How many rf chains do we need? *IEEE Transactions on Wireless Communications*, 17(10):6972–6984, 2018.
- [77] Chun-Han Yao, Yin-Yi Chen, Biswa PS Sahoo, and Hung-Yu Wei. Outage reduction with joint scheduling and power allocation in 5g mmwave cellular networks. In *2017 IEEE 28th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC)*, pages 1–6. IEEE, 2017.
- [78] Evangelos Zervas, A Mpimpoudis, Christos Anagnostopoulos, Odysseas Sekkas, and Stathes Hadjiefthymiades. Multisensor data fusion for fire detection. *Information Fusion*, 12(3):150–159, 2011.
- [79] Daosen Zhai, Ruonan Zhang, Jianbo Du, Zhiguo Ding, and F Richard Yu. Simultaneous wireless information and power transfer at 5g new frequencies: Channel measurement and network design. *IEEE Journal on Selected Areas in Communications*, 37(1):171–186, 2018.
- [80] Rui Zhang and Chin Keong Ho. Mimo broadcasting for simultaneous wireless information and power transfer. *IEEE Transactions on Wireless Communications*, 12(5):1989–2001, 2013.
- [81] Rong Zheng and Cunqing Hua. *Sequential Learning and Decision-Making in Wireless Resource Management*. Springer International Publishing, 2016.
- [82] Xun Zhou, Rui Zhang, and Chin Keong Ho. Wireless information and power transfer: Architecture design and rate-energy tradeoff. *IEEE Transactions on communications*, 61(11):4754–4767, 2013.
- [83] Xun Zhou, Rui Zhang, and Chin Keong Ho. Wireless information and power transfer in multiuser ofdm systems. *IEEE Transactions on Wireless Communications*, 13(4):2282–2294, 2014.