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TESIS DOCTORAL

Statistical Models for Energy-Efficient Selective Communications in Sensor Networks

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El tribunal nombrado para juzgar la tesis doctoral arriba citada, compuesto por los doctores

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ABSTRACT

An inherent characteristic of Wireless Sensor Networks is their ability to operate with autonomy when sensor node devices are resource-constrained. Optimizing energy consumption with the goal of achieving longer sensor network lifetime is a major challenge. This thesis focuses on energy-efficient strategies based on the reduction of communication processes, the most energy expensive tasks by far. In particular, we analyze selective communication policies that allow sensor nodes to save energy resources at the same time that can assure the quantity and quality of the transmitted information.

This thesis proposes selective communication strategies for energy-constrained Wireless Sensor Networks, which are based on statistical models of the information flowing through the nodes. Assuming that messages are graded according to an importance/priority value (and whose traffic can be statistically modeled) and that the energy consumption patterns of each individual node are known (or can be estimated), the design and evaluation of optimal selective communication policies that maximize the quality of the information arriving to destination along the network lifetime are analyzed. The problem is initially stated from a decision theory perspective and later reformulated as a dynamic programming problem (based on Markov Decision Processes). The total importance sum of the transmitted, forwarded or finally delivered messages are used as performance measures to design optimal transmission policies. The proposed solutions are fairly simple and based on forwarding thresholds whose values can be adaptively estimated. Simulated numerical tests, including a target tracking scenario, corroborate the analytical claims and reveal that significant energy saving can be obtained to enlarge sensor network lifetime when implementing the proposed schemes.

RESUMEN EXTENDIDO EN CASTELLANO

INTRODUCCIÓN Y MOTIVACIÓN

Recientemente, las redes de sensores inalámbricas (*Wireless Sensor Network*, WSN) han recibido una gran importancia debido a su enorme potencial para mejorar y cambiar la forma en que las personas interactúan con el entorno. La naturaleza peculiar de las redes de sensores ha dado lugar a una intensa actividad investigadora en diferentes campos (electrónica, procesado de señal, comunicaciones) dado el potencial de sus aplicaciones y el gran número de desafíos tecnológicos que plantean.

En particular, el diseño de redes de sensores a gran escala, compuestas de dispositivos que deben funcionar con autonomía y alimentados únicamente a través de baterías (o, quizás, obteniendo energía del entorno), plantea muchos retos que no pueden resolverse con soluciones clásicas que funcionan para otro tipo de redes inalámbricas.

En concreto, la energía es un recurso escaso que juega un papel primordial en este tipo de redes ya que puede influir críticamente en las capacidades y condiciones de funcionamiento de los sensores. Por eso, buena parte de la investigación reciente en redes de sensores ha estado orientada a la búsqueda de soluciones hardware y software para optimizar la gestión y el consumo de energía en todas las capas de la WSN y prolongar así el tiempo de vida de la red. Gran parte de estas técnicas han estado orientadas a reducir el gasto energético global en comunicaciones (transmisión o recepción de información), al ser éstas las actividades que consumen mayor energía, aunque otras actividades del sensor (captura de datos y procesamiento) también implican un gasto energético, aunque mucho menor. Por eso, todas las decisiones del sensor que impliquen procesos de comunicación deben de tener en consideración los costes energéticos involucrados, pudiendo influir sobre las decisiones del nodo [Lee et al., 2006] or [Chelius et al., 2005].

Típicamente, los nodos de una red son forzados a transmitir cualquier señal capturada por sus sensores, o a reenviar cualquier señal bajo demanda de un nodo sensor vecino, mientras tengan baterías, lo que da lugar a una pérdida de capacidad para administrar sus propios recursos (y la consecuente ineficiencia en la utilización de la red). A pesar de la gran variedad de estrategias propuestas en el estado del arte para reducir el coste de las comunicaciones en las WSNs, apenas se han propuesto estrategias de ahorro de recursos basadas en la propia naturaleza de la información que se transmite, o en las expectativas de disponibilidad de recursos de los sensores que participan en la comunicación en cada momento.

Habitualmente, la red trata equitativamente la información de los diferentes nodos sensores. Sin embargo, existen numerosas situaciones donde cabe atribuir a cada mensaje a transmitir (o reenviar) un nivel de importancia [Wood and Stankovic, 2002], prioridad [Muraleedharan et al., 2006], utilidad [Athanassoulis et al., 2007] o relevancia [Wischhof et al., 2003]. Si nos centramos en estos escenarios, se puede asignar a los mensajes un indicador de importancia que refleje la prioridad del mensaje, la relevancia de la información, o un determinado nivel de Calidad de Información (*Quality of Information*, QoI). En el contexto de redes de sensores, se pueden encontrar ejemplos en diferentes campos: seguridad (informe de ataques [Wood and Stankovic, 2002]), atención médica (alertas críticas [Shnayder et al., 2005]), o sistemas de reconocimiento de caras [Muraleedharan et al., 2006], por citar algunos. En estos escenarios es donde cabe plantearse la cuestión de la viabilidad y eficiencia de dotar a los nodos de la red de capacidad para decidir sobre la conveniencia de la transmisión de un mensaje por la red, o por el contrario, su descarte en base a la importancia de su contenido, de los recursos energéticos del nodo y de sus patrones de consumo. Aparece, por tanto, el concepto de *comunicaciones selectivas* que consiste en reducir el tráfico menos importante de la red y reservar mejores recursos para información con mayor importancia (prioridad), permitiendo una mejor utilización de las capacidades de la red.

Hay algunos trabajos publicados en esta línea, ya sea a través del uso de heurísticos (que se basan típicamente en la modificación de un algoritmo existente) o bien teóricos. La idea de descarte de mensajes puede considerarse implícita en redes de sensores orientadas a sistemas de alertas (donde los sensores únicamente envían los datos que son indicios de eventos relevantes), o en sistemas de seguimiento (donde los sensores transmiten la información que supone un indicio de la presencia de un blanco en las proximidades).

Las propuestas teóricas basan el diseño en la resolución de un problema de optimización concreto. Así, el dilema entre transmitir y no hacerlo es la base de las redes de censores (*censor networks*) en detección descentralizada, que se remontan al trabajo original de Rago [Rago et al., 1996]. Los sensores transmiten solamente observaciones informativas al centro de fusión, y eliminan aquellos datos (no informativos) cuya verosimilitud local (basada en datos disponibles por el nodo) está dentro de un cierto intervalo, cuyo rango se selecciona para satisfacer unas restricciones a priori sobre la máxima tasa de comunicaciones permitida para el nodo. En [Patwari and Hero, 2003], advirtiendo que la tasa de transmisión no es una restricción adecuada para redes con limitaciones superiores en energía que en capacidad, se reemplaza la restricción sobre la tasa de bit por restricciones sobre la probabilidad de transmisión. Por estos mismos motivos, en el trabajo desarrollado en [Appadwedula et al., 2005] se impone una cota sobre el coste energético medio global (en toda la red) asociado a una detección.

En estos ejemplos, el ahorro energético se impone, directa o indirectamente, estableciendo cotas sobre la tasa de bit, la tasa de envíos, el coste energético de cada tarea u otras, pero el valor de dicha cota es un parámetro libre cuya asignación, en general, no es trivial porque estos parámetros especifican un punto de equilibrio entre las prestaciones del detector y el ahorro energético.

Por eso, en esta Tesis Doctoral se plantea como cuestión fundamental la búsqueda de un compromiso entre prestaciones de la red de sensores y el ahorro energético, donde está presente el problema de determinar la importancia relativa del consumo energético frente al valor de las actividades soportadas por la red. Para ello, se va a suponer que los datos están graduados de acuerdo a un valor que cuantifique su importancia (que se puede estimar localmente) y se conocen (o estiman) los patrones de consumo energético de cada sensor con la finalidad de maximizar las prestaciones globales de la red.

El problema de optimización de las prestaciones de una WSN durante su tiempo de vida, que además tenga en cuenta las limitaciones energéticas, se puede plantear matemáticamente utilizando el formalismo de los Procesos de Decisión de Markov (*Markov Decision Processes*, MDP) [Puterman, 2005], sus generalizaciones [Kaelbling et al., 1998]), o los modelos de aprendizaje por refuerzo [Sutton and Barto, 1998].

Los MDP's se han aplicado recientemente a la gestión eficiente de energía en redes de sensores. En [Williams et al., 2005b], [Williams et al., 2005a], [Williams et al., 2007] se plantea el compromiso entre el valor de la información contenida en un conjunto de medidas de red y el coste de capturarlas, procesarlas y enviarlas al nodo destino. Por ejemplo, se propone el uso de MDPs para resolver el problema de asignación del nodo líder (aquel que centraliza la recolección de los datos) en aplicaciones de seguimiento de blancos. También se utilizan como herramienta para encontrar un compromiso entre ahorro de energía en la agregación de datos y retardo de transmisión [Ye et al., 2009], o para optimizar una función objetivo que combina consumo de potencia, caudal y retardo [Munir and Gordon-Ross, 2009]. La teoría de MDPs proporciona un formalismo común para diferentes situaciones que pueden resolverse por procedimientos similares, ya que se basan en resolver un problema de optimización que caracteriza a una política de acciones óptimas. Dado que los parámetros estadísticos de un MDP raramente se conocen, y por tanto el diseño a priori de la estrategia óptima es pocas veces viable, en esta Tesis Doctoral se plantean dos alternativas: estimar los parámetros del modelo o bien aplicar técnicas de aprendizaje estadístico.

OBJETIVOS

De forma general, el objetivo principal de la Tesis consiste en diseñar y evaluar procedimientos que permitan dotar a los nodos de una red de sensores de capacidad para tomar decisiones autónomas sobre el tratamiento de los datos recibidos o detectados por el sensor, basándose en información capturada del entorno o recibida a través de otros nodos. Además, se pretende que las decisiones sean energéticamente eficientes buscando en todo momento un compromiso entre las prestaciones globales de la red y la prolongación de su tiempo de vida.

En lugar de utilizar aproximaciones heurísticas, el objetivo de esta Tesis Doctoral consiste en obtener resultados analíticos que elaborados sobre una base matemática proporcionen las pautas básicas para diseñar esquemas de comunicaciones selectivas que aseguren una QoI. Para ello, se hará uso de modelos de tipo MDP o sus generalizaciones.

De este modo, para extender el tiempo de vida de la red y optimizar las prestaciones de la misma, los nodos deberán sopesar dos factores: (i) los potenciales beneficios de transmitir información; y (ii) el coste de los subsiguientes procesos de comunicación. Para ello, el primer paso consistirá en cuantificar (o estimar) adecuadamente tanto los beneficios como los costes de la transmisión. Esto es posible en la práctica debido a que, por un lado, la energía consumida en cada tarea de comunicación (coste) está normalmente bien caracterizada y, por otro lado, la existencia de escenarios donde los mensajes están graduados de acuerdo a un indicador de importancia (beneficio) es habitual. A partir de esta información, los nodos tomarán decisiones de forma autónoma sobre el envío de los mensajes basándose en su importancia, permitiéndoles así ahorrar energía al adaptar sus decisiones al tráfico de importancias.

En esta Tesis Doctoral se abordará el diseño de políticas de comunicación eficientes en energía para redes de sensores, restringiéndose a aplicaciones donde: (i) la importancia de los mensajes se puede cuantificar apropiadamente, y (ii) los mensajes de baja importancia se pueden descartar eventualmente. De esta forma, la idea de comunicaciones selectivas se basa en el descarte de mensajes de baja importancia para ahorrar energía que se pueda utilizar para la transmisión de mensajes más importantes que lleguen en un futuro. Para tomar la decisión sobre la transmisión de los mensajes, los nodos tendrán en cuenta factores como los patrones de consumo en los diferentes estados del nodo, las baterías disponibles, la importancia de los mensajes recibidos, la distribución estadística de las importancias de los mensajes o el comportamiento de los nodos sensores vecinos.

El objetivo general se puede dividir en objetivos más específicos:

- *Identificar los aspectos clave a tener en cuenta en la toma de decisiones sobre la transmisión de mensajes* con la finalidad de reducir el consumo de energía en las redes se sensores. Para ello, es necesario tener una visión conjunta de las propuestas presentes en el estado del arte que nos permitirá situar y describir el ámbito de la Tesis.

- *Definir un modelo adecuado para los nodos sensores*, por lo que será necesario determinar las características esenciales de los nodos para incluirlas en el modelo.

- *Proponer esquemas óptimos de comunicación selectiva para diferentes escenarios* de acuerdo a las necesidades particulares de cada caso. Se pretende diseñar un esquema óptimo de transmisión selectiva y su posterior generalización, cumpliendo en todo momento los siguientes requisitos. En primer lugar, optimizar el consumo de energía a la vez que se mantengan las prestaciones de la red (incluida la QoI). En segundo lugar, que los procedimientos diseñados no conlleven una elevada complejidad y un alto coste computacional. Además, los nodos deberán tomar las decisiones sobre nuevos mensajes en el instante en que lleguen.

- *Evaluar los esquemas propuestos* (tanto teórica como experimentalmente), identificando las ventajas y desventajas de cada tipo de política de comunicación selectiva.
- *Analizar la idoneidad de las políticas de comunicación selectiva diseñadas* cuando se aplican a un escenario real, el seguimiento de blancos.

CONTRIBUCIONES

La Tesis Doctoral se ha centrado en desarrollar un formalismo matemático para analizar el problema de la gestión autónoma y automática de los recursos energéticos de cada uno de los nodos de una red de sensores y en estudiar el impacto que las limitaciones de recursos de un nodo tienen sobre sus procesos de comunicación e interacción con el entorno, especialmente cuando los mensajes tienen asignado un valor de importancia o prioridad y, por tanto, se pueden abordar políticas de comunicación selectiva. En particular, se han derivado y evaluado estrategias óptimas de comunicación selectiva con la finalidad de ahorrar recursos energéticos en redes de sensores con restricciones de energía al mismo tiempo que se ha garantizado una QoI. Los esquemas óptimos de transmisión (y reenvío) selectivo de mensajes desarrollados se han basado en modelos estadísticos del tráfico de las importancias (prioridades) de los mensajes. Así, en el diseño de las políticas de reenvío selectivo los sensores han tenido en cuenta tanto factores locales, como la energía que los nodos consumen en los diferentes estados del nodo (transmisión, recepción y escucha), las baterías disponibles en cada instante, la importancia de los mensajes recibidos (para asegurar una QoI a los usuarios) o el modelo estadístico de las importancias de los mensajes; además de factores no locales, como es la información sobre el comportamiento de los nodos vecinos.

A continuación se resumen las principales contribuciones de esta Tesis Doctoral, de forma que cada una de ellas se corresponde con un capítulo de la memoria de la Tesis.

Inicialmente, se ha caracterizado el sensor a través de un modelo que incluye todos los aspectos relevantes de un sensor real. Además de proponer un modelo estocástico de consumo de energía para poder abarcar una amplia variedad de escenarios, el nodo se ha modelado mediante un vector de estados (una de sus componentes es la energía disponible (nivel de baterías) mientras que la importancia del mensaje determina la posible recompensa por la acción de transmitir). Es preciso mencionar que el modelo de sensor es una abstracción de la realidad que considera ciertas simplificaciones: transmisiones perfectas, conocimiento de los recursos energéticos en cada instante y la distribución de importancias de los mensajes, entre otras. Algunas de estas suposiciones no son críticas, de forma que el modelo se puede modificar para incorporar escenarios más realistas. Sin embargo, otras plantean desafíos siempre que se quiera implementar esquemas de decisión selectiva prácticos. Pero, en cualquier caso, el modelo de sensor captura el comportamiento esencial de una política de comunicación selectiva y puede ser el punto de partida para otros diseños más apropiados para escenarios específicos.

Posteriormente, bajo la suposición de que los mensajes están graduados con un valor de importancia e inspirándose en la teoría de decisión bayesiana, se ha planteado la transmisión selectiva como un problema de decisión con costes (determinados por los consumos energéticos) y beneficios (determinados por las importancias de los mensajes), dando lugar a un esquema de transmisión selectiva basado en la minimización de un coste medio. La regla de decisión obtenida promovía la transmissión y reenvío de mensajes importantes mientras que descartaba los mensajes menos importantes. El esquema obtenido ha demostrado que filtrar los mensajes según su importancia puede ser eficiente cuando se pretende maximizar la eficiencia global de la red, medida en términos de la importancia acumulada de todos los mensajes llegados a destino durante su tiempo de vida. La regla de decisión se ha aplicado al diseño de dos nuevos algoritmos de encaminamiento, LPGR y Q-PR. En ellos ha quedado patente que los nodos sensores son capaces de aprender de decisiones de encaminamiento tomadas en el pasado para adaptar sus decisiones a condiciones futuras haciendo un uso eficiente de la energía.

Sin embargo, la aproximación anterior era inadecuada ya que el diseño del decisor no tenía en cuenta el carácter secuencial del problema. De hecho, una consecuencia indirecta es la aparición de un parámetro libre, que pondera el peso relativo del consumo energético respecto a la importancia del mensaje, cuyo valor debe asignarse a priori. Por eso, posteriormente se ha reformulado y resuelto el problema de la transmisión selectiva como un problema de decisión iterativo, determinando, a través de técnicas de programación dinámica estocástica, el decisor óptimo que maximiza la suma de importancias de todos los mensajes transmitidos por un nodo. En este caso, el equilibrio entre la minimización de los gastos de energía y la maximización de la suma de importancias se determina automáticamente, resultando la decisión óptima como una comparación entre la importancia del mensaje y un umbral variante en el tiempo. Además, la ganancia del esquema de transmisión selectiva dependía de los gastos de energía asociados a cada estado del nodo, entre otros factores. Por otro lado, se han desarrollado esquemas prácticos, que aunque son subóptimos, operan bajo condiciones menos exigentes que los óptimos. Así, el esfuerzo se ha dirigido en tres direcciones: 1) el análisis de políticas óptimas de transmisión para varias distribuciones de importancias estacionarias; 2) el diseño de un esquema de transmisión con umbral invariante que conllevaba optimalidad asintótica; y 3) el diseño de un algoritmo adaptativo que estimaba la distribución de importancias a partir de los mensajes realmente recibidos (o sensados). El análisis y evaluación de los distintos escenarios ha demostrado que las estrategias de transmisión selectiva mejoran las prestaciones de la red, medidas como la suma de importancias de los mensajes que llegan a destino, y el tiempo de vida de la red. Aunque no se hace explícito, el modelo utilizado es esencialmente un MDP, donde su uso resuelve completamente, al menos desde el punto de vista teórico, algunas dificultades de otras aproximaciones no secuenciales.

La optimización del transmisor selectivo se ha realizado a nivel de nodo, ya que maximiza la suma de importancias de los mensajes transmitidos por cada nodo, ignorando si estos mensajes enviados son seguidamente reenviados por sus vecinos o no, lo que conduce a algunas ineficiencias cuando se implementan en redes multisalto, porque algunos nodos pueden desperdiciar energía enviando mensajes que no son retransmitidos. Además, tampoco se atendía al destino final de los mensajes enviados, de forma que no se estaban garantizando las prestaciones a nivel global. Por este motivo, se abordó la generalización del modelo teórico anterior, posibilitando que los nodos usaran información no local, tanto de la vecindad como del destino, e incorporando dicha información al modelo estadístico para poder analizar su impacto en el comportamiento de la red. Con suposiciones menos restrictivas que en el caso anterior, se han diseñado y desarrollado esquemas de reenvío selectivo para tres escenarios diferentes: 1) cuando los sensores maximizan la importancia de sus mensajes transmitidos, que coincide básicamente con el modelo anterior de transmisión selectiva, aunque usando un modelo de consumo de energía más general; 2) cuando los sensores maximizan la importancia de los mensajes que son realmente reenviados por sus vecinos (optimización local); y 3) cuando los sensores maximizan la importancia de los mensajes que llegan de forma exitosa al destino (optimización global). Resultó especialmente importante la generalización de los resultados a costes energéticos estocásticos, ya que permitía incluir, por ejemplo, la idea de que los nodos podían consumir una cantidad de energía diferente en cada estado como consecuencia del tiempo que se permaneciera en ellos o de las distancias entre sensores (mayor gasto de energía cuanto más lejos estuvieran los nodos que se comunicaban). Desde una perspectiva práctica, el segundo escenario de los mencionados anteriormente, que es algo más complejo que el primero, puede ser el candidato para implementarse en la mayoría de los escenarios prácticos, ya que además requiere menos señalización que el escenario de optimización global.

En una aplicación práctica de este modelo se plantea si los criterios de optimización utilizados son o no adecuados para obtener buenas prestaciones desde el punto de vista de la aplicación. Por este motivo, se aplicó la política de comunicación selectiva a un escenario de seguimiento de blancos. Se ha comprobado que maximizar la suma de importancias permite mantener un error cuadrático medio bajo en la estimación de la posición de los blancos al tiempo que prolonga el tiempo de vida de la red. Adicionalmente, se ha demostrado su buen funcionamiento cuando el reenvío selectivo es combinado con otras técnicas de reducción de datos (como la agregación o fusión).

LÍNEAS FUTURAS

Finalmente, se indican futuras líneas de investigación que permiten extender el trabajo iniciado en esta Tesis Doctoral.

- Los teoremas propuestos en la Tesis se basan en la hipótesis de independencia entre observaciones (la secuencia de importancias es estadísticamente independiente). Esto es de gran utilidad porque simplifica el diseño algorítmico y, en general, aumenta la correlación entre la optimización de criterios aditivos (como la suma de importancias) y la mejora de las prestaciones globales de la aplicación. Sin embargo, aunque existen argumentos a favor de la hipótesis de independencia de observaciones en detección descentralizada, [Appadwedula et al., 2005], en un contexto general puede ser falsa, a causa de la posible correlación temporal y espacial entre observaciones.

  Desde el punto de vista del diseño de transmisores selectivos basados en MDPs, y aceptando el criterio de maximización de la suma de importancias, la hipótesis de independencia de importancias no es inherente al modelo. La teoría de MDPs solamente requiere que la secuencia de importancias sea markoviana, pero no independiente, y por tanto, los esquemas de comunicación selectiva que se han propuesto pueden generalizarse a observaciones dependientes, aunque en general los sensores deberán incorporar algún mecanismo de estimación de la correlación entre observaciones.

- Típicamente, los resultados obtenidos a través de simulación no se pueden aplicar directamente a motas reales debido a la frecuente aparición de problemas asociados a su implementación. Por eso, para constatar el verdadero potencial de las estrategias de comunicación selectiva y determinar, por tanto, su verdadero interés práctico, es imprescindible su implementación en plataformas reales. Además, esto nos permitiría analizar cómo se ajustan los datos a las predicciones de los modelos teóricos y determinar qué parámetros tienen mayor influencia sobre las prestaciones finales. En esta línea se han obtenido algunos resultados preliminares, [Hansen et al., 2010]. En particular, se han aplicado los algoritmos de transmisión selectiva sobre sensores TmoteSky [Tmo, 2009] con sistema operativo TinyOS [Levis et al., 2005] y un protocolo LPL (*Low Power Listening*) en la capa MAC.

- La aplicación de las estrategias de comunicación selectiva al seguimiento de blancos tiene aspectos cuestionables y mejorables. En particular, la elección de la función de importancia, basada en la potencia de señal detectada por el sensor, es sencilla y no tiene en cuenta la correlación con medidas previas. Una alternativa sería una elección basada en medidas de entropía condicional [Williams et al., 2007], donde la importancia mide esencialmente el grado de innovación del nuevo mensaje respecto a los anteriores.

- Las políticas de comunicación selectiva desarrolladas incluyen algunos parámetros libres, que están relacionados con la manera en que los nodos adquieren información sobre las políticas de reenvío de los vecinos y la frecuencia con la que los nodos comunican esta información. En la Tesis, la asignación de estos parámetros se ha realizado a través de la exploración de diferentes valores. Sin embargo, la optimización automática de estos parámetros tiene interés, fundamentalmente desde un punto de vista práctico.

- El análisis teórico ha permitido determinar una ecuación (de solución única) que establece el valor que, en caso de existir, debe tener el umbral asintótico. Nos podemos plantear si dicha existencia es una propiedad general, pero la respuesta es negativa: bajo ciertas condiciones, de escaso interés práctico, la función del umbral no converge a una constante, sino a una función de tipo oscilatorio. Hay, por tanto, un doble trabajo que realizar en esta línea: (i) analizar el comportamiento del umbral en estos casos, y (ii) determinar bajo qué condiciones puede garantizarse la existencia de un umbral asintótico. Sin embargo, esta línea de investigación tiene interés teórico, pero no cabe esperar de ella consecuencias prácticas, en la medida en que los casos de no convergencia son inusuales.

- El modelo desarrollado en esta Tesis no es aplicable a situaciones en las que los nodos pueden trabajar de forma indefinida en el tiempo (como es el caso de los sensores recargables), porque existen infinitas estrategias óptimas de suma de importancias. Para resolver este problema, sería necesario reemplazar el criterio de suma de importancias por alguna medida basada en promedios. La dificultad estriba no tanto en formular matemáticamente el modelo como en resolver el problema de optimización resultante para determinar la estrategia de transmisión óptima.

  Lei [Lei et al., 2009] ha propuesto recientemente un modelo de MDP que puede aplicarse a escenarios con sensores recargables o híbridos. Para resolver el problema de optimización, ha optado por discretizar todas las variables relevantes del problema: en particular, la importancia de los mensajes y el estado del nodo. Sin embargo, este modelo tiene algunas limitaciones importantes: está orientado a redes con un único salto, no es adaptativo (supone que los parámetros energéticos y de tasa de recepción de mensajes son conocidos a priori), supone que los gastos energéticos de transmisión son constantes y es sensible a errores de discretizacion. Por eso, la adaptación del modelo propuesto a este tipo de sensores es una línea futura de gran interés.

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A mis padres

A mi hermano

A mi abuela

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Chapter 1

Introduction

This chapter introduces the problem approach and the precedent related work of the state of the art, the motivation, and it formulates the objectives of this thesis. Moreover, the outline of the dissertation is described as well as the main contributions.

1.1 Problem approach

The high prominence recently given to Wireless Sensor Networks (WSNs) has been possible thanks to their potential to enhance and change the way people interact with technology and the world, revolutionizing many aspects of our economy and life, ranging from surveillance and environmental monitoring, to manufacturing and business asset management, automation in the transportation and health-care industries [Zhao and Guibas, 2004]. However, the origin lies in the users increasing demand of devices, appliances, and systems with better capabilities and higher levels of functionality. The sensor market is extremely diverse and sensors are used in most industries and so, sensors satisfy the continuous demand for more sophisticated applications [Hac, 2003].

The development of Sensor Networks requires technologies from three different research areas: sensing, communication and computing (including hardware, software and algorithms) [Chong and Kumar, 2003]. The separated and combined advancements in each of these areas have driven research in Sensor Networks and have been the key to originate the explosive growth in both academy and industry.

1.1.1 Sensor Networks overview

A Wireless Sensor Network can be defined as *a large-scale, ad hoc, multihop, unpartitioned network of largely homogeneous, tiny (hardly noticeable), resource-constrained, low-complexity, mostly immobile (after deployment) sensor nodes that would be randomly deployed in the area of interest* [Römer and Mattern, 2004] *and which communicate in short distances either directly or through other nodes by a wireless medium*. Although this first approach is quite general and valid for a huge variety of applications (specially those related to the military domain), it does not always characterize to an increasing number of applications.

A sensor is an autonomous electronic device with embedded data processing and communication capabilities, which is capable of detecting environmental conditions such as temperature, humidity, pressure, light, sound, vibration, motion, radiation, chemicals, pollutants or the presence of certain objects [Stojmenovic, 2005]. Each sensor has one or more sensing subsystems, an embedded processor, generally associated with a small memory for local data processing (processing subsystem), low-power radios for data communication (communication subsystem) and a power supply. Figure 1.1 shows the architecture of a common wireless sensor node. Sensing circuitry measures parameters from the observed phenomenon in the environment around the sensor and transforms them into digital signals. Processing the information captured by sensors can help researchers to draw conclusions about the properties of the located objects or events happening in the environment over a period of time. Fig. 1.2 shows a typical sensor node (Mica 2 mote) developed by researchers at University of California Berkeley.

In a WSN, a variable amount of sensor nodes ranging from hundreds to thousands may be densely deployed either directly inside the phenomenon of interest or close to it [Akyildiz et al., 2002]. Thus, sensors can be scattered on the ground, underground, in the air, under water, in vehicles, on human bodies and inside structures and buildings. Once sensor nodes are deployed, they require minimal external support for their functioning, since sensor networks are designed to withstand specific conditions. Under these working conditions and from application requirements and network management perspectives, sensor network protocols and algorithms must posses self-organizing capabilities. Nodes in their role as information sources interact with the physical environment and sense, measure and

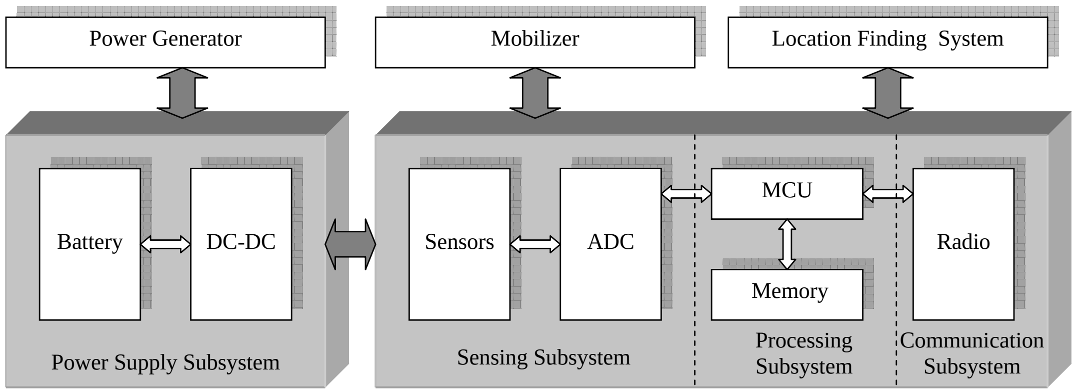


Figure 1.1: The architecture of a sensor node, taken from [Anastasi et al., 2009].

Figure 1.2: A sensor node (Mica2) developed by researchers at UC Berkeley, taken from [Cro, 2010].

gather detailed information from the entities of interest, performing simple processing on the extracted data, when required, and transmit it to remote locations, as it is shown in Fig. 1.3. Finally, the destination node (a.k.a. sink) uses data locally or communicates with the user through conventional network services, such as the Internet. In order for sensor nodes to accomplish their tasks, sensor nodes do not work independently, but cooperatively. As sensor nodes are often deployed in resource-constrained environments, i.e., they are usually battery-operated nodes, a considerable reduction in energy consumption can be easily obtained from node cooperation whenever nodes act as relays with messages originated from other nodes. Many sensing tasks require a sensor network system to process data cooperatively and combine information from multiple sources, despite the fact that sensors operate autonomously.

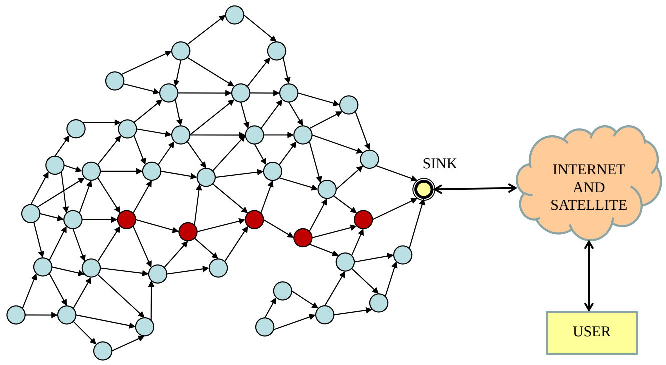


Figure 1.3: A multihop Wireless Sensor Network where sensors collect data and route them back to the sink and to the end user via infrastructureless architecture.

Commonly, it is used a single sink in a WSN, as depicted in Fig. 1.3. However, a more general scenario includes multiple sinks. A larger number of sinks will decrease the probability that nodes cannot deliver their data due to the signal propagation conditions or the presence of obstacles in the network. Therefore, the possibility of having multiple sinks ensures better network performance regarding the single-sink scenario (keeping constant the density of the network), but communication protocols must be more complex and should be designed according to suitable criteria. A common scenario where nodes require additional sinks is underground, where multiple sinks can be located on the ground to relay satisfactorily to the user data from sensors buried underground [Yick et al., 2008].

1.1.2 Sensor Network features

The discussion about sensor networks' features is based on the typical characteristics and requirements of the design space of WSNs proposed in [Römer and Mattern, 2004].

Cost and size

Typically, sensor nodes are inexpensive devices. Bearing in mind large-scale sensor networks, the cost of each sensor should be kept low to justify the use of sensor networks instead of other alternatives. However, it is also possible to find sensor devices of hundreds of euros in those networks that require few but powerful nodes.

Similarly and depending on the application needs, nodes can vary their physical size ranging from the almost invisibility (appropriated for military applications) to a shoe-box size (e.g. weather stations). Both, sensor node's size and cost constraints, have an impact on the battery size as well as on other resources such as computing, storage and communication.

Heterogeneity

Usually, sensor networks are composed of sensor devices identical from a hardware and software point of view. However, sensor networks composed of a variety of different devices with different abilities, such as computing power or sensing range, are starting to appear lately since they enhance energy capacity or communication capabilities, also increasing network reliability and lifetime [Yarvis et al., 2005].

Network topology

Regarding network topologies, sensor networks can be structured according to the common and basic ones, such as fully connected, star, ring, tree, bus, mesh or a combination of them. The mesh topology is stressed since it is the most appropriate model for large-scale WSNs. Information is usually sent via other sensors in a multihop manner towards other sensor nodes, or eventually, to the sink. Multihop communication is expected to consume less power than the traditional single-hop communication.

Transmission media

Generally, application requirements influence the choice of the transmission media. The most common among the communication modalities is the use of radio links due to their characteristics, such as a non-requiring free line-of-sight together with their low power consumption and relatively small antennae for transmitting over medium ranges.

Infrastructure and deployment

Typically, a WSN has little or no infrastructure. Therefore, WSNs can be categorized into structured or unstructured [Yick et al., 2008].

- Nodes in a *structured WSN* are deployed in a predefined location to provide coverage, so that only few nodes are deployed, keeping network maintenance and management costs at low values. Besides, sensor nodes can only directly communicate with the sink.

- An *unstructured WSN* is composed of a dense collection of sensor nodes. In this type of WSN, nodes are usually randomly deployed (ad-hoc manner), which is specially useful in hazardous, hostile and difficult access terrains (e.g. nodes on treetops or remote mountain areas), where nodes work unattended. The ad-hoc nature of the sensor deployment produces unpredictable patterns of connectivity and varied node density. Nodes can directly communicate with each other, acting as transmitters or as routers, being responsible for forwarding messages generated by other nodes up to the sink node over multiple hops. Nevertheless, network maintenance, and managing connectivity and detecting failures in particular, is more complicated than in structured WSN.

As the process of establishing an infrastructure is costly and sometimes not feasible due to the terrain characteristics, unstructured ad-hoc WSNs are preferred and desired for many applications.

Coverage

Since coverage is interrelated to sensor node placement, the degree of network coverage is determined by the number of sensors and their position in the sensor field. The execution of the sensing tasks requires an adequate sensor deployment. Mobile sensors can adaptively reposition and organize themselves in order to have a better coverage area or a uniform placement in the network, improving network connectivity compared with static sensor nodes [Bartolini et al., 2008].

High dynamism

On the other hand, densely deployed sensor networks have to handle with frequent topology changes. After the initial deployment, topology changes may be caused by changes in nodes' position as a consequence of their mobility (it can result from environmental influences, because sensors may be attached to or carried by mobile entities, or due to sensor node automotive capabilities), connectivity failures or the malfunctioning of some nodes (such as physical damage), changes in task dynamics, battery exhaustion or alterations in reachability because of jamming, noise, environmental interferences or moving obstacles [Akyildiz et al., 2002]. Despite the fact that nodes may fail, network topology needs to be built and updated in real time assuring fault tolerance. At this effect, different solutions have been proposed to improve robustness [Hoblos et al., 2000].

Types of data storage

Once data are collected, nodes should make data accessible to the user for future retrieval and data analysis. Different canonical ways can be adopted [Shenker et al., 2003]. In *external storage*, relevant captured data are routed back (and stored) to the sink for further processing. *Local storage*, where data are locally stored at the node that detects the phenomenon of interest. Or *data-centric storage*, characterized because the event information is stored in a specific node chosen to be responsible for that particular event.

From the above sensor network overview, it is clear that WSNs have to cope with different requirements and resource constrains (limited power and memory, computational and storage resources, short communication range and low bandwidth) that traditional networks (such as the Internet) do not have to. Table 1.1 contains a brief summary of some possible attributes of general sensor networks, most of them aforementioned. In WSNs, the entire protocol stack from the physical to the application layer must be designed on the basis of no fixed infrastructure. Even more, interdependencies among variables and parameters at different layers lead to the coupling among layers in order to obtain better results. Thus, to meet the requirements and reach WSN potential gains, a cross-layer protocol design that support adaptivity and optimization across multiple layers of the protocol stack is advisable [Goldsmith and Wicker, 2002]. Critical dependence on energy consumption makes sensor nodes consider energy as a first-order optimization goal, unlike traditional networks. Hence, all these aspects make traditional networks not directly applicable to WSNs.

Sensor Networks applications

The increase in popularity of Wireless Sensor Networks is based on the fact that they potentially provide low cost solutions to a great variety of real-world challenges. The fast

Table 1.1: Attributes of Sensor Nodes, taken from [Chong and Kumar, 2003].

Sensors	*Size:* small (e.g. micro-electro mechanical systems (MEMS)), large (e.g. radars, satellites) *Number:* small, large (hundreds or thousands) *Type:* passive (e.g. acoustic, seismic, video, IR, magnetic), active (e.g. radar, ladar) *Composition or mix:* homogeneous, heterogeneous *Spatial coverage:* dense, sparse *Deployment:* fixed and planned (e.g. factory networks), ad-hoc (e.g. air-dropped) *Dynamics:* stationary (e.g. seismic sensor), mobile (e.g. on robot vehicles, animals)
Sensing entities of interest	*Extent:* distributed (e.g. environmental monitoring), localized (e.g. target tracking) *Mobility:* static, dynamic *Nature:* cooperative (e.g. air traffic control), non-cooperative (e.g. military targets)
Operating environment	Benign (factory floor), adverse (battlefield)
Communication	*Networking:* wired, wireless *Bandwidth:* high, low
Processing architecture	Centralized (all data sent to a central site), Distributed (located at sensors or other sites), Hybrid
Energy availability	Constrained (e.g. small sensors), unconstrained (e.g. in large sensors)

deployment, self-organization and fault tolerance, among other characteristics, make them promising for a huge number of applications. Since their military beginnings as a means of battlefield surveillance, defense applications led research and development in WSNs but later, interests were widened to a range of civil applications which included environmental and habitat monitoring, natural disaster prediction and relief, health monitoring, fire detection, infrastructure security or industrial sensing, to name a few.

1.1.3 Wireless Sensor Network constraints

Among the many design challenges that have been identified, the ability of sensors to behave in an autonomous and self-organized manner using limited energy and computation resources has emerged as a key factor that requires novel solutions, where the limitation of resources at sensor nodes is often a critical factor that conditions the design of applications for sensor networks. The major sensor node constrains are listed below:

- *Limited power*: energy restrictions are raised due to its small physical size and lack

Table 1.2: Memory specifications of sensor network platforms.

René 1999	Mica-2 2002	Tmote Sky 2005	Imote2 2007
512B RAM 8KB Flash	4KB RAM 128KB Flash	10KB RAM 48KB Flash	32MB RAM 32MB Flash

of wires. As the absence of wires results in lack of a constant power supply, power solutions are limited.

- *Limited memory and storage restrictions*, due to its limited battery capacity, as well as its restriction in size, weight and cost. Usually, sensor node memory includes a flash memory used for storing downloaded application code, which is generally enough. Some of the state-of-the-art sensors have approximately a flash memory of 4 Mb [Ananda et al., 2006] and a RAM memory, which is used for storing application programs, sensor data and intermediate computation results [Sen, 2009]. The latter sometimes represents a real problem for some models, such as the 4KB (ATmega128L) or 10KB (MSP430), because after loading the operating system and the application code, there is not so much space left to run complex algorithms. Table1.2 contains the key memory specifications of four sensor nodes [Langendoen, 2007].

- *Low bandwidth and much lower transmission rate compared to wired networks*, originating a degradation in the Quality of Service (QoS), such as delays, jitter effect and longer connection set-up times.

- *Computational and processing resources*. Computation is closely linked to the available amount of power. As it is reasonable to understand, since there is a limited amount of power, computations are also constrained.

Efforts in WSNs are aimed at meeting the above constraints by introducing new design concepts, creating or improving existing protocols, building new applications, and developing new algorithms. Among the multiple limitations to consider, energy consumption emerges as a primary concern. While QoS is of paramount importance in traditional networks, sensor networks focus primarily on energy conservation.

1.1.4 The energy concern in Wireless Sensor Networks

Battery is the main power source in a sensor node. Once a WSN has been deployed, it is expected to operate for extended periods of time and typically without human intervention. It is practically unfeasible that sensor node batteries are (easily) refilled, either because sensor nodes are deployed in inaccessible terrains, the vast amount of deployed sensors or due to the sensor size limitation. This fact has a direct impact on the sensor node lifetime.

Energy constraints impact both the hardware operation and the signal transmission associated with the node operation. So much so that the energy concern has reached the industry and academy communities, since it has become the cornerstone in every ad-hoc sensor network design. No matter how much processors, memory or networks have improved if sensor node batteries die or have a really short lifetime to operate. At the beginning of the nineties, progress in battery technology, specifically in battery capacity, was forecast to undergo a maximum improvement of 20% within the following ten years [Sheng et al., 1992]. Nearly two decades later, new materials have appeared (nickel-cadmium, lithium-ion among others) which have led to an increase in energy capacity from 10 to 15 percent per year, but these technologies have already reached their ceiling since they were just capable of providing another 15 to 25 percent more [Paulson, 2003]. Therefore, battery capacity has slightly improved but it does not scale exponentially, rather, it proceeds along flattering [Paradiso and Starner, 2005], evolving (battery technology) very slowly compared to electronic technology. This limitation together with the fact that every task carried out by the WSN has an impact in terms of energy consumption, has led the proposal in literature of an enormous variety of solutions, both software and hardware, to optimize energy management and energy consumption. Even more, the explosion of terms, such as 'energy-aware', 'power-aware', 'energy-efficient' or 'energy-limited', in the recent sensor network literature denotes the increasing interest and concern for energy aspects in WSNs.

Therefore, the crucial question is: '*how to manage energy efficiently and thus, save energy resources to prolong the network lifetime of battery-powered sensors?*' Energy efficiency must watch over both the lifetime of each individual node and the overall network lifetime. In the next subsection we expose the more recent techniques of the state of the art to achieve this purpose.

1.1.5 State-of-the-art strategies for energy conservation

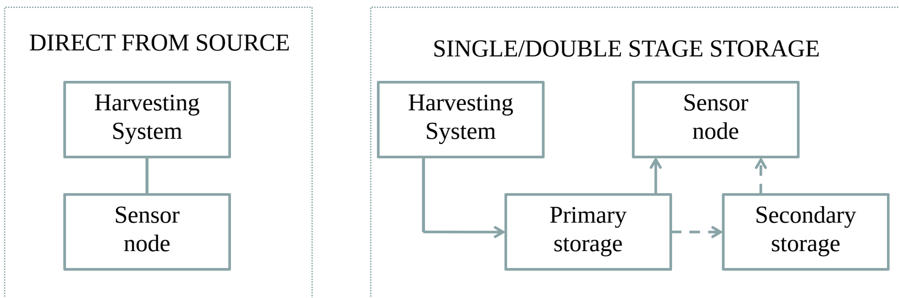
Sensor node energy consumption is split among the hardware and the different layers, such as the link layer, the Medium Access Control (MAC) layer, the network layer, etc. Optimizing simultaneously the energy consumption in all the layers is rather challenging. With a finite energy source, it is complicated to optimize all performance parameters at the same time (lifetime, cost, sensing reliability and sensing and transmission coverage). For instance, higher batteries imply increased cost and size, higher transmission range implies higher power requirements while lower transmission range implies more nodes taking part in the communication process and consuming energy, or low duty-cycle implies decreased sensing reliability. That is the reason why most up-to-date research is focused on optimizing communication and minimizing energy use independently in each layer.

Summarizing, the typical power-management design goal in battery-powered devices is to minimize energy consumption or maximize the lifetime while meeting certain performance requirements. Hence, to maximize the sensor node lifetime, aspects including circuits, architecture, algorithms, and protocols have to be energy-efficient.

In the remainder of the subsection, different approaches and strategies, extracted from the literature, that reduce power consumption or enlarge sensor network lifetime are listed.

1. **Energy scavenging.** A proper maintenance of batteries is a key requirement to extend sensor node lifetime in energy-constrained sensors. As it is not easy to replace or recharge batteries, acquiring the electrical power needed to operate is a major concern. Two alternatives may help sensor nodes to increase their functioning: A first approach considers *alternative types of energy sources to conventional batteries: energy harvesting or energy scavenging techniques*. It refers to methods that scavenge (harvest) energy from the environment or other energy sources (body heat, foot strike, finger strokes) available where the node lies to be later converted into electrical energy. Broadly, energy can either be harvested just in time for use (harvest-use architecture) to directly power the sensor device or harvested whenever possible and stored for future use (harvest-store-use architecture) to recharge the battery, as it is shown in Fig. 1.4.

Potential energy sources used for harvesting include *ambient energies* such as sunlight [Alippi and Galperti, 2008] or wind [Weimer et al., 2006]; *Mechanical energy*, such as fluid flow [Starner, 1996], the human activity (walking) [Shenck and Paradiso, 2001] or vibration sources [Arms et al., 2009]; *Thermal energy* obtained from persons and animals, machines or other natural sources; *RF energy* harvesting converts radio waves into power [Visser et al., 2008]. *Other forms of motion* include energy harvested from body movements of humans (e.g. typing, cycling, etc.).



(a) Harvest-Use architecture

(b) Harvest-Store-Use architecture

Figure 1.4: Energy harvesting architectures.

Energy scavenging offers an additional mean to prolong the lifetime of sensor devices, but it may not be enough in the sense that the harvested power may be several orders of magnitude lower than the consumption of sensor devices.

A second alternative is the use of *secondary power supplies*. The maintenance problem is, however, still not solved. Actually, a possibility to recharge such kind of batteries is to harvest energy from the environment. In this way, energy harvesting is not trying to replace batteries but complements the maintenance issue.

2. **Hardware and power-aware computing approaches.** Other techniques that address the issue of energy efficiency consist of providing sensor nodes with low-power hardware components or including hardware optimization, such as dynamic optimization of voltage and clock rate. Thus, the development of ultra-low-power microprocessors or microcontrollers has been possible due to the advanced technology in VLSI circuits and system design [Raghunathan et al., 2002]. Besides, energy efficiency for

active states can be achieved by allowing processors to operate at different supply voltages to meet the instantaneous processing requirements. This is possible adopting the Dynamic Voltage Scaling (DVS) technique [Qu, 2001], an effective technique for reducing CPU (Central Processing Unit) energy. Also, additional energy saving can be significantly achieved if the system software, including the Operating System (OS), is energy-aware designed (e.g. introducing the task scheduler into the core of the OS [Raghunathan et al., 2001]).

3. **Physical Layer.** Minimizing energy consumption starts at the physical layer. Ignoring physical parameters may end in inefficient energy solutions. It is difficult to create energy-efficient algorithms and protocols that perform intelligent power management without the knowledge of the underlying computation and communication hardware. This is the origin of the work presented in [Shih et al., 2001], which proposes a physical-layer-driven approach to design protocols and algorithms with the aim of minimizing energy consumption. In [Marques et al., 2008], the authors minimize the average transmission power, subject to average rate and BER requirements, for coherent communications in a WSN, where sensors communicate with a fusion center using adaptive modulation and coding over a wireless fading channel.

4. **Data-driven approaches.** Data-driven approaches gather all techniques involving data that contribute to improve energy efficiency in sensor nodes, specially reducing the impact of data sensing on energy consumption. Here, we discuss the taxonomy proposed in [Anastasi et al., 2009]. Mainly, data-driven approaches are divided into two methods according the problem they address (see Fig. 1.5). Specifically, *data reduction schemes* face to unneeded samples, due to the fact that data have strong spatial and/or temporal correlations, resulting in redundant communications and useless energy consumption. On the other hand, *energy-efficient data acquisition schemes* focus on the sensing subsystem, trying to reduce the amount of sampled data while keeping sensing accuracy within reasonable levels (according to the application requirements).

   Belonging to the **data reduction schemes**, *in-network processing* basically consists in performing *data aggregation* while messages are routed towards the sink. Data aggregation techniques allow to combine data from different sources, decreasing communi-

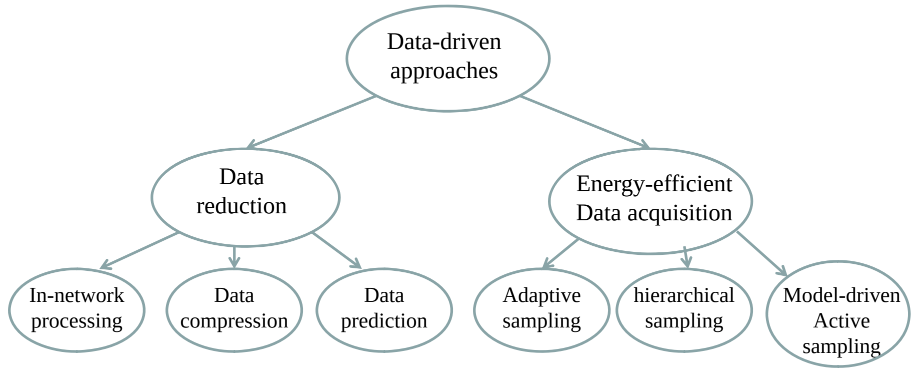


Figure 1.5: Taxonomy of data-driven approaches to save energy in sensor networks, taken from [Anastasi et al., 2009].

cation overhead for energy-saving purposes. Several algorithms have been proposed following this technique, such as [Fasolo et al., 2007], [Intanagonwiwat et al., 2003], or [Luo et al., 2009], to name a few. However, the intrinsic trade-off between energy and delay in aggregation operations characterizes this technique [Ye et al., 2009], [Zheng and Barton, 2007], apart from the fact that it is application-specific. Besides, in-network processing is also feasible through signal processing techniques, which is referred as *data fusion*. Apart from combining data from different sources, filtering and processing techniques help to eliminate the transmission of redundant data so that more accurate data are produced (e.g. [Wang et al., 2008]).

Data compression (encoding information at source nodes, and decoding it at the sink) can be applied to reduce the amount of data flowing through the network towards the sink. Some proposed methods are [Tang and Raghavendra, 2004], [Xiao et al., 2006] or [Pradhan and Ramchandran, 2003].

Data prediction techniques also reduce the amount of information sent by source nodes as well as the energy needed for communication. Continuous sensing and reporting of measures consumes not only energy but also memory. That is why these techniques are based on building a model that characterizes the phenomenon to be sensed, so that the sink can predict the values sensed by sensors within certain error bounds. If the model is accurate enough, the sink does not need the exact data.

On the other hand, **energy-efficient data acquisition** techniques are based on the assumption that, for some applications, the energy consumption of the sensing subsystem is relevant enough. In these cases, energy-saving approaches are aimed at reducing data samples acquired by sensors, by selecting a subset to deliver or reporting only those measurements falling outside or inside a certain interval, for instance. Moreover, reducing the number of samples implies decreasing the number of communications given that radio energy consumption reduces. Techniques belonging to this category can be split into three main groups:

Adaptive sampling exploits spatio-temporal correlations between data to reduce the amount of data acquired by sensors. In [Law et al., 2009], an adaptive sampling algorithm based on the Box-Jenkins approach in time series analysis is proposed. DOSA algorithm [Chatterjea et al., 2007], instead, exploits the high degree of spatial correlations of measurements of adjacent nodes in a densely deployed WSN and takes advantage of cross-layer information from the MAC protocol.

Hierarchical sampling is based on the idea that the sensor network is composed of different types of sensors, some of them are less accurate and low-energy consumption and the others quite the opposite. Triggered sampling applications [Xia and Zhao, 2007] or multi-scale sampling [Tseng et al., 2007] belong to this group.

Model-based active sampling follows a similar approach to data prediction (a model representing the sensing phenomenon is built) but unlike the latter approach, which periodically samples the medium to update the model, this technique reduces the sampling rate by using the computed model, see e.g. [A. Deshpande et al., 2004].

5. **Duty Cycling.** Another widely employed energy-saving technique consists of putting nodes in low-power sleep mode whenever communication is not needed and back to active modes as soon as new data are available, which is called as duty cycling. In a traditional sleep scheduling, sensors usually have to start up several times, consuming extra non-negligible amount of energy due to the state transitions.

   As an example, Table 1.3 lists the time and power consumption for a MICA2 mote with a CC1000 Transceiver regarding the different mote states [Ma et al., 2009]. The

Table 1.3: Time and power consumption in the startup process for a MICA2 mote with a CC1000 Transceiver.

Operation Process	Time	Power consumption
Sleep	–	90 μW
Radio Initialization	$0.35ms$	18 mW
Turn radio on	$1.50ms$	3 mW
Switch to RX/TX mode	$0.25ms$	45 mW
Receive 1 byte	$0.416ms$	45 mW
Transmit 1 byte	$0.416ms$	60 mW

startup process includes radio initialization, radio and its oscillator startup, and the switch of radio to receive/transmit state. In the example, the startup time is slow, 2.1 ms approximately, and consumes about 22 μJ. It consumes precious energy while doing nothing. As a consequence, switching the radio into sleep mode only saves energy if the state is kept during a long time.

Moreover, the cooperative nature of sensors highlights the need of a sleep/wake-up scheduling algorithm. Again, we discuss the taxonomy proposed in [Anastasi et al., 2009], which differentiates between two different duty cycling approaches (see Fig. 1.6).

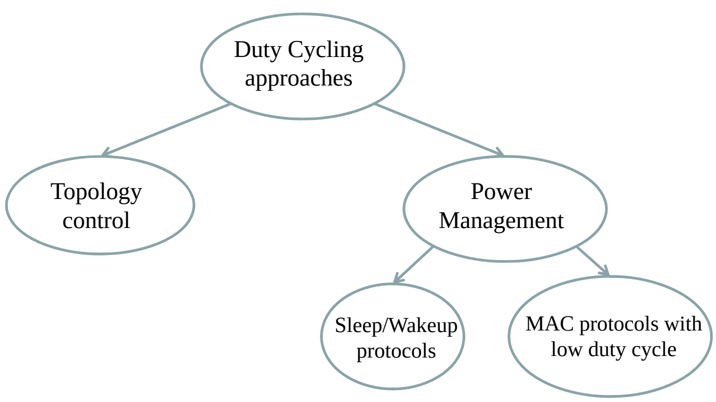


Figure 1.6: Taxonomy of duty-cycling approaches to save energy in sensor networks.

Topology control includes all protocols managing node redundancy. Protocols are aimed at dynamically adapting the network topology according to the application needs by only keeping active the minimum and optimum subset of sensors that ensures network connectivity. The remaining nodes (those that do not participate) transition to sleep state to save energy (e.g. GAF [Xu et al., 2001], SPAN protocol [Chen et al., 2002]). The main limitation of topology control protocols is the close dependency to the network density. That is why they are usually combined with other energy conservation approaches.

Dynamic Power Management (DPM) is the complementary technique to topology control that implements duty cycling. As the radio is the most power-consuming component of a typical sensor node, additional energy savings can be attained by using DPM to suitably shut down the sensor node radio if no events occur. The analytical model of [Chiasserini and Garetto, 2006] explores the trade-off between energy saving and network performance in terms of throughput and data delivery delay as the sensor dynamics in sleep/active mode vary. DPM can be classified into two different categories depending on the layer of the network architecture.

Sleep/wakeup protocols, the first group, implement sleep/wakeup protocols independently of the MAC layer. Different kinds of protocols belong to this group.

On-demand schemes are based on the idea that nodes only remain active whenever another node wants to communicate with them and spend the minimum time required for communication in that mode, maximizing the energy saving and hardly impacting on latency. Some examples are STEM [Schurgers et al., 2002] and its variation STEM-T or the PTW approach [Yang and Vaidya, 2004].

Scheduled rendez-vous schemes follow deterministic wakeup patterns because of the need of both the sender and the receiver to be awake at the same time. Nodes wake up periodically to check for potential communications, remain active for a predefined period of time and then, they come back to sleep state until the next rendez-vous (e.g. [Lin et al., 2004], [Cao et al., 2005] or [Keshavarzian et al., 2006]).

With *asynchronous approaches*, nodes can wake up independently of the others being still able to communicate with their neighbors through overlapped active periods within a specific number of cycles. The synchronization requirement is relaxed at the price of getting lower energy efficiency. In [Zheng et al., 2006], the problem of designing optimal asynchronous wakeup schedules to facilitate distributed power management is tackled. Other state-of-the art techniques are the RAW [Paruchuri et al., 2004] or the AWS [Vasanthi and Annadurai, 2006] algorithms.

MAC protocols with low duty-cycle compose the second category of the DPM techniques. In this second group, sleep/wakeup protocols are integrated into the MAC protocol, allowing the specific sleep/wakeup pattern to optimize medium access functions. As the MAC layer is here involved, let us first expose several factors that cause energy waste from a MAC perspective [Langendoen, 2007]:

- Collisions.
- Idle listening: the radio is on all the time to receive incoming data, but the cost is extremely high when nothing is sensed for a long period of time.
- Overhearing: as nodes are listening at incoming traffic, they can also receive packets intended for other neighboring nodes.
- Traffic fluctuations: the occasional peak loads can lead to network congestion or the use of long contention windows, rising energy consumption.
- Protocol overhead: MAC headers and control messages are considered overhead because they do not directly convey useful data, yet consume energy and reduce the effective throughput.

Properly designed MAC protocols should be intended to deal with the major sources of energy waste previously mentioned, implementing low duty-cycle schemes for power management. Thus, each MAC protocol has its own policy for controlling the use of the radio, switching it off to achieve a different trade-off.

A first group is composed of *schedule-based protocols*, such as *TDMA (Time Division Multiple Access)*, which are able to schedule transmissions and idle periods. Time is divided into periodic slots so that nodes transmit or receive during their own slots, fixed according to a certain scheduling algorithm, and go to sleep later. Thus, TDMA protocols may reduce energy expenditure and solve problems associated with interferences among nodes (transmissions of neighboring nodes can be scheduled at different time slots). LEACH [Heinzelman et al., 2000] or TRAMA [Rajendran et al., 2003] are some of the most well-known protocols. LEACH organizes nodes into cluster hierarchies and applies TDMA within each cluster, so that it directly extends the cellular TDMA model to sensor networks. TRAMA uses traffic-based scheduling to avoid wasting slots when nodes do not have data to transmit, switching to sleep mode when nodes are not target receivers of traffic.

A second group, *contention-based protocols*, does not require tight synchronization requirements and uses the Carrier-Sense Multiple Access (CSMA) technique. Its major disadvantage is its inefficient use of energy because of the incurred costs for idle listening and overhearing. However, contention-based MAC protocols are mainly proposed in the state-of-the-art approaches. B-MAC protocol [Polastre et al., 2004] provides collision avoidance and achieves low-power operation through the use of an adaptive preamble sampling scheme to reduce duty cycle and minimize idle listening. Another popular protocol is S-MAC [Ye et al., 2004]. It achieves collision avoidance and low-duty-cycle operation by putting nodes into sleep state. Adaptive listening reduces energy expenditure but increases latency and reduces throughput. Among the vast amount of MAC protocols, it is also worthy mentioning T-MAC (Timeout-MAC) [Van-Dam and Langendoen, 2003], DSMAC (Dynamic Sensor-MAC) [Lin et al., 2004], WiseMAC protocol [Enz et al., 2004], or DW-MAC protocol [Sun et al., 2008].

Finally, *hybrid approaches* combine the strength of both, as the Z-MAC protocol [Rhee et al., 2008].

6. **Routing protocols.** Sensor nodes play a dual role, as data sources and data routers. The continuous topology changes might require a network reorganization with the consequent message reroute, taking power conservation and power management additional importance. Hence, significant energy saving can be obtained by incorporating low-power strategies in the design of routing protocols. However, despite the huge number of routing protocols and variations, the current state of the art is specially rich in specialized routing protocols, concentrating on satisfying one or few requirements, but performing poorly under slightly different network conditions and

scenarios. Therefore, special interest will be put in energy-aware routing protocols, which mainly focus on two aspects: minimizing energy cost per message (or equivalently, maximizing sensor network lifetime) and balancing energy consumption in the network.

Data-centric routing algorithms. These protocols are query-based and depend on the naming of the desired data, which helps to eliminate many redundant transmissions (i.e. only sensors within a specified region are tasked to start collecting information). SPIN family protocols [Kulik et al., 2002] are one of the earliest works, which consider data negotiation among nodes to eliminate redundant data. Directed Diffusion [Intanagonwiwat et al., 2003] was developed later and became a breakthrough in data-centric routing since many proposed protocols are based on it.

Hierarchical routing algorithms. With the aim of decreasing the number of transmitted messages, the sensor network is divided into groups (clusters), where a representative node of each group (cluster head) gathers information of its group members and performs data aggregation and fusion. Many clustering protocols are enhancements or variations of the popular LEACH algorithm, in which nodes are chosen to be cluster heads based on a priori probability (e.g. PEGASIS [Lindsey and Raghavendra, 2002] or its extension hierarchical PEGASIS). TEEN [Manjeshwar and Agrawal, 2001] and its extension APTEEN, both also based on LEACH, reduce the number of transmissions by reporting only those measurements that exceed prefixed thresholds.

Location-based (or geographic) routing algorithms. Location-based protocols use position information to transmit data to the desired regions or to the sink. GPSR [Karp and Kung, 2000], one of the earliest and traditional works, relays the message to the neighboring node closest to the sink and solves the problem of holes following the perimeter of a planar graph to round the message around the void region. Another example is GEAR (Geographic and Energy Aware Routing) [Yu et al., 2001]. It disseminates queries to the desired geographical area without flooding using energy-aware and geographically informed neighbor selection heuristics. Within the region, it uses recursive geographic forwarding or restricted flooding to spread messages. A more recent work is LEARN [Wang et al., 2006], which theoretically guarantees the power efficiency of its routes.

Learning-based routing algorithms. Artificial intelligence techniques have started to appear lately to solve routing problems efficiently. Reinforcement learning is probably the most widely used machine learning technique for routing in WSNs because of its effective on-line decision making procedure, its flexibility and quick adaptability to changes. Some of the earliest works using reinforcement learning are Q-Routing [Boyan and Littman, 1994] or PQ-routing [Choi and Yeung, 1996] algorithms, which learn the best paths considering the least latency to the destinations. Other recent examples are CLIQUE [Förster and Murphy, 2009], IDR [Zhang et al., 2006] or the algorithm proposed in [Pandana and Liu, 2008], to name a few.

Energy Balanced Data Propagation algorithms. The approaches included in this category do not exactly propose routing algorithms but an algorithmic way of ensuring a balanced average energy consumption among all sensor nodes. The main goal is to avoid early energy depletion of sensors to enlarge sensor network lifetime by re-distributing network traffic without compromising network connectivity (e.g. TAEE load balanced energy-aware routing protocol [Liu and Hong, 2009]).

Another factor that contributes to increase energy expenditure in routing, and which deserves to be mentioned, is *link quality*. Link-level retransmissions could largely increase the energy cost, in the sense that, sometimes, retransmissions in a shorter path with low link quality may be even worse than a long multi-hop path provided with better link quality. Therefore, some works are aimed at including link quality in the routing metric (e.g. [Banerjee and Misra, 2002] or [Lal et al., 2003]); proposing procedures to estimate it since measuring instantaneous link quality is prohibitive (e.g. LQER [Chen et al., 2008] or SIR [Barbancho et al., 2006] routing algorithms).

7. **Storage.** Some works are devoted to evaluating and finding the most energy-efficient storage platform for WSN (e.g. [Mathur et al., 2006]).

8. **Mobility-based schemes.** In a multi-hop sensor network, nodes located closer to the sink usually deplete their batteries faster than their faraway counterparts, because they have to relay more messages. Adding mobility to sensor nodes may alter traffic flow whenever data collection is performed by mobile elements. Sensor nodes wait for having a mobile device in proximity to route messages directly to it, so that commu-

nication takes place in short distances and energy consumption is reduced. Providing with mobility to all sensor nodes is not energy convenient (energy expenditure of mobilizers is high). A best choice is to provide with mobility just some of them while the others remain static. Up to date, two tendencies are basically exploited.

The first includes *mobile sink-based approaches*. The unique (or multiple) sink moves in the network following different strategies (e.g. [Bi et al., 2009], [I. Chatzigiannakis and Nikoletseas, 2006] or [Wang et al., 2005]).

The second group, *mobile relay-based approaches*, includes the message ferrying [Zhao and Ammar, 2003] or data-MULE system approaches [Jain et al., 2006]. Both approaches consist in mobile entities, which follow a fixed or random trajectory, collecting data gathered by static sensors. Later, mobile entities forward data to the sink.

In summary, the concern about energy consumption in WSNs has given rise to an overwhelming amount of approaches in the literature, from the underlying hardware to the application software and different layer protocols. The energy optimization approaches presented above tackle lifetime enlargement of either sensor nodes or the sensor network, mainly reducing communications because of their high cost (from an energetic point of view). Without any doubt, it is more complex the latter case, since it involves not only the reduction of energy consumption in a single sensor, but also the maximization of the lifetime in the whole network. In any case, lifetime can be considerably increased if energy-awareness is incorporated into every stage of a WSN design and operation.

However, it is important not to leave *cross-layer design* perspectives aside. While traditional layered protocols may achieve very high performance in terms of the metrics related to each of these individual layers, they are not jointly optimized to maximize the overall network performance while minimizing energy expenditure. Thus, cooperation between layers by exchanging pertinent information is also exploited for optimizing algorithms. As a result, performance in sensor networks improves notably. Some authors suggest to classify the different techniques based on the network layers they aim at replacing in the classical OSI network stack [Melodia et al., 2005]. Some proposals are shown below, since the state of the art is also quite rich. The work in [Escudero-Garzás et al., 2007] proposes a model which tackles the minimization of the total transmission energy consumption in centralized networks, through a cross-layer design which involves the physical layer (selecting the modulation scheme adaptively) and the MAC layer (the allocation of the number of time slots to each sensor). Another cross-layer design perspective is also adopted in LESOP [Song and Hatzinakos, 2007] for high protocol efficiency, where direct interactions between the application and MAC layers are exploited; a cross-layer energy consumption model of the physical, data link, and network layer is analytically investigated in [Haapola et al., 2005]; or the cross-layer optimization problem proposed in [Yuan and Yu, 2006], a distributed optimization framework for multi-hop WSNs based on a game theoretic approach, which is decomposed into two subproblems corresponding to two separate layers (the physical and the application layers).

Therefore, joint optimization and design of networking layers (i.e. cross-layer design) stand as the most promising alternative to inefficient traditional layered protocol architectures. Nevertheless, the price we have sometimes to pay is an increase in complexity.

1.2 Motivation

Since communication processes are among the most energy-expensive tasks, the *cost of transmitting and receiving information* should influence node decisions; see, e.g., [Lee et al., 2006] or [Chelius et al., 2005]. Typically, nodes are compelled to transmit any signal captured by their sensors while batteries are alive. A similar situation occurs in scenarios where nodes act as relays that have to forward any message upon request from other neighboring node. This inability to apply autonomous transmission policies, thus preventing nodes from managing their own resources, hinders an efficient utilization of the network.

Despite the great variety of resource-saving strategies proposed in the literature contributing to reduce communication costs in WSNs, few approaches are based on the *nature of the information* that nodes have to transmit. Energy saving can also be obtained by taking a higher level approach and considering the different nature of the information and the expected available resources in sensors that take part in the communication at each moment.

Usually, data from different source nodes are handled equitably within the network. However, there exist many practical scenarios where it is feasible to attribute a particular significance [Wood and Stankovic, 2002]; priority [Muraleedharan et al., 2006]; relevance [Wischhof et al., 2003]; or utility [Athanassoulis et al., 2007] value to messages transmitted or forwarded by sensor nodes. Tailored to those scenarios, we may consider that messages can be valuated through an importance indicator which reflects the priority of the message, the relevance of the information conveyed or the required level of Quality of Service (QoS) or preferably, Quality of Information (QoI)[1]. Relevant examples in the context of sensor networks can be found in different fields. For instance, in a security scenario, nodes periodically report to the sink information related to battlefield conditions, tracking enemy troops movements, monitoring a secure zone for activity or measurement of damages and casualties. However, attack reports are sent to the sink as high importance (priority) messages [Wood and Stankovic, 2002]. Data priority in medical care area allow critical alerts from patients to have higher priority than others in presence of radio congestion (see, e.g., [Shnayder et al., 2005]). Another example is a face recognition system [Muraleedharan et al., 2006], where an image is transformed into some approximation coefficients and sets, which are categorized according to the level of detail. Coefficients are then transmitted considering different priorities assigned depending on the importance on the reconstruction (the higher level, the more influence and higher importance). Message priority/importance is also relevant in congested networks in order to not drop messages (see, e.g., [Kumar et al., 2006]) or in sensor networks that implement data aggregation. Message priority is also relevant in Wireless Multimedia Sensor Networks (WMSNs), in order to provide a required QoS. For example, a priority-based rate control mechanism for congestion control and service differentiation in WMSNs is presented in [Yaghmaee and Adjeroh, 2009] or the path priority scheduling algorithm [Chen et al., 2008], which considers message priority to satisfy the delay constraint of video frames while balancing energy and bandwidth usage among all the available paths.

In such scenarios, energy in WSNs can be saved providing sensor nodes with the ability to make intelligent importance-driven decisions about message transmission, adapting forwarding decisions to the message importance. In fact, this is the main goal of *selective*

[1]The concept of QoS was introduced in networking to provide different priority to different applications, users, or data flows according to a set of static predefined policies in order to guarantee a certain level of performance to the most important data flows (e.g. get first delivered). For sensor networks, the definition of QoS is inadequate because the notion of importance is associated not with a source, but with the data itself and moreover, with the value of the data to the end user of the application. This requires a form of dynamic QoS that translates the value of data from a node into its priority on-the-fly, which is called QoI [Charbiwala et al., 2009].

communications: some messages are transmitted while others discarded, according to certain criteria, to reduce the network load and increase the network lifetime by saving power of individual nodes. For instance, the idea of selective communications is the base of the work developed in [Chow et al., 2007]. The authors propose a selective transmission protocol to select and transmit images to a sink in an energy-efficient manner by comparing the similarity among images. It is worthy remarking the difference between selective communications when nodes act faithfully and decide not to transmit messages in exchange of optimizing network resources, and the fact that nodes act maliciously and refuse to forward certain messages, simply dropping them and ensuring that they are not propagated any further, which is known as the selective forwarding attack [Karlof and Wagner, 2003]. It is clear that the matter of study of this thesis is the first case. The idea of selective transmission is close to information-aware traffic reduction approaches [Ngai et al., 2009]. These approaches allow a better utilization of the network capacity by reducing the relatively less important traffic and reserving better resources for high priority data. Remark that these techniques are based on data reduction, so that they can be included in the taxonomy of data-driven approaches of Fig. 1.5. However, although information-aware approaches reduce unnecessary data traffic and consequently reduce the number of transmissions, they are mainly aimed at reducing network congestion adjusting the transmission rate control while providing QoI to the users without considering, explicitly, energy consumption issues.

Similar ideas to selective communications that also use the importance of messages as transmission criterion have been explored in the literature, either using a heuristic approach (typically focused on the modification of existing algorithms) or a theoretical one (aiming at the identification of basic guidelines for WSN design). Examples that fit in with the first category are mentioned next. The approach presented in [Ngai et al., 2009] wisely selects important data to be selectively transmitted to the sink according to their importance and the network load (it maximizes the information gain at the same time that controls the data rate in a node to be smaller than the maximum affordable) and reduces unnecessary routine data traffic without degrading the QoI. The PGR (Prioritized Geographical Routing) algorithm [Mujumdar, 2004] selects the appropriate routing technique depending on the priority of the message (low, medium or high). The RRR (Random Re-Routing) algorithm [Gelenbe and Ngai, 2008] gives a preferential treatment to high priority messages resulting from unusual events, routed along the shortest paths, and provides them with significantly better QoS (Quality of Service), opposite to background traffic, which is randomly shunted towards slower secondary paths.

Differently, theoretical approaches base the design of importance-driven schemes on the resolution of a specific optimization problem, as in [Lei et al., 2009], where a mathematical framework based on Markov chains is used to characterize an optimal policy for single hop transmission over a replenishable sensor network. The transmission/no transmission idea is also the base of censoring networks in decentralized detection [Rago et al., 1996]. Sensors only send informative observations to the fusion center, and do not transmit those deemed uninformative, i.e. whose local likelihood ratio falls in a certain single interval, which is fixed in order to satisfy a maximum communication rate constraint. In [Patwari and Hero, 2003], the authors argue that the appropriate constraint to bound energy consumption is the probability of transmission instead of the bit rate, as the communication rate is not a suitable constraint for WSN more limited in energy than in capacity. For the same reasons, the work in [Appadwedula et al., 2005] imposes a constraint on the expected cost arising from transmissions (sensor nodes to a fusion node) and measurements (at each sensor node) in a detection scenario.

In the examples mentioned above, energy saving is obtained, directly or indirectly, fixing constraints over the bit rate, the probability of transmission, the energy cost of each task, etc. However, the threshold value is a free parameter of the model whose assignment is not trivial because these parameters establish a trade-off between the detector performance and the energy saving.

In this thesis, however, the search of the trade-off between global performance and energy saving is stated as a fundamental matter. We will pose the problem from a general point of view: assuming that data are graded according to an importance value (whose distribution can be locally estimated), and knowing (or estimating) the energy consumption patterns of each sensor in order to maximize/optimize the global network performance.

Optimizing the performance of a WSN along the whole lifetime, also considering the energy constraints, can be mathematically stated using Markov Decision Processes (MDPs) [Puterman, 2005], some of its generalizations (Partially Observable Markov Decision Processes, POMDP [Kaelbling et al., 1998]), or Reinforcement Learning models

[Sutton and Barto, 1998].

MDPs have been recently applied to energy-efficient management in sensor networks. In [Williams et al., 2005b], [Williams et al., 2005a], [Williams et al., 2007], the trade-off between the value of the information held in a set of measures and the cost of capturing them, processing them and transmitting them to the sink is raised, proposing the use of MDPs to solve the leader assignment problem in target tracking applications. Besides, MDPs have been used as a tool to find a trade-off between energy saving of data aggregation and transmission delay [Ye et al., 2009]; to balance energy saving of low-power sensor states and the efficiency of the sensing, receiving and transmitting processes [Kianpisheh and Charkari, 2009]; or to optimize a reward function combining power consumption, throughput and delay [Munir and Gordon-Ross, 2009]. These works already highlight two fundamental questions related to the application of MDPs to selective communications in sensor networks: (i) how to assign locally the message importance (a problem pointed out in [Rago et al., 1996]); and (ii) how to build a global function based on local importances that weighs up the global network performance during its lifetime, and that can be optimized using decentralized procedures of low computational cost.

The theory of MDPs provides a common framework to different situations that can be solved using similar procedures, because they are based on solving an optimization problem that characterizes an optimal action policy. As the statistical parameters of a MDP are rarely known, and therefore, the a priori design of an optimal strategy is hardly feasible, two alternatives will be raised in this thesis: the estimation of the model parameters or the application of statistical learning techniques.

1.3 Objectives and main contributions

As stated above, the thesis is framed within the energy-constrained wireless sensor network field. According to the research and restriction problems described previously and the motivation of this work, the main and global objective pursued in this thesis consists of:

Designing energy-efficient methods that provide sensor nodes of a WSN with the ability to make autonomous decisions about the actions to be carried out on the received or sensed data (transmission, discarding, aggregation, fusion, etc.), based on information cap-

tured from the environment or coming from other sensor nodes, and entailing a trade-off between the global network performance, the quality of information and the enlargement of the network lifetime.

Thus, the application of selective policies to message transmission reduces considerably the number of energy-expensive communications, enlarging sensor network lifetime, which are relevant facts pursued in WSNs. Rather than using heuristic approaches, the aim of this thesis is to obtain analytical results that building on a mathematical formulation, provide basic guidelines to design energy-efficient selective communication schemes at the same time that assure a certain quality of information. To that purpose, we will make use of MDP models or their generalizations.

In order to enlarge the network lifetime and optimize the network performance, sensor nodes could weigh up: a) the potential benefits of transmitting information and b) the cost of the subsequent communication process. A first step to address such an optimum design is to properly quantify or estimate both costs and benefits. This is possible in practice because the energy consumed by every communication task (cost) is typically well-characterized and because applications where messages are scored according to an importance indicator (benefit) are frequent in WSNs. Once costs and benefits are properly quantified, energy can be saved by making intelligent importance-driven decisions about message transmission, in an autonomous and self-organized manner, adapting forwarding decisions to the traffic importance. This way, selective communication schemes allow nodes to keep the capacity for managing their own resources at the same time that optimize communication expenses by only transmitting the most relevant messages, while providing satisfactory quality of information to the users.

We will address the design of efficient communication policies for sensor networks, constraining ourselves to applications where: (i) *the importance of messages can be properly quantified*, and (ii) *low graded messages can be eventually discarded*. This way, the idea of selective communications consists of discarding low importance messages in order to save energy that can be used for transmitting more important upcoming messages. In order to make a decision (whether to transmit or not), sensors will take into account factors such as the energy consumed during the different states (transmission, reception, etc.), the available battery, the importance of the received message (to guarantee a certain level of QoI to the user), the statistical distribution of such importances, or the behavior of their neighbors.

The general objective is split into more specific objectives, which are listed below:

- To identify key aspects that should be taken into account when making transmission decisions in order to reduce energy consumption in sensor networks. To tackle this objective, it will be necessary to have a unifying view of several approaches present in the state of the art. That will allow us to situate and describe the scope of this work. Therefore, it will include the review of the literature with regard to proposed alternatives to reduce energy consumption.

- To define an appropriate model for sensor nodes. Before proposing any policy, it will be necessary to clearly expose those features of a sensor node that are essential and should be included in the model. To this aim, we will make use of the study of the state of the art made previously.

- To propose optimum selective communication schemes for different scenarios according to the needs of each particular case. Considering the key aspects and the sensor node model as a starting point, we will describe an initial optimal selective transmission scheme and its generalization, meeting both the following requirements. First, they will optimize energy consumption at the same time that will maximize the quality of information. Secondly, they will not entail high complexity and computational cost. And finally, communication policies will be applied on-the-fly, i.e., sensor nodes will not require to store all previous received messages to make decisions about new incoming messages.

- To evaluate the proposed schemes, identifying advantages and disadvantages of each type of policy. Differences among the proposed schemes will be quantified both from a theoretical and numerical perspective. Moreover, this evaluation will allow us to extract conclusions that will be useful for future research.

- To analyze the suitability of the selective communication policies in specific and realistic scenarios. The first step so as to fulfill this objective will be to identify a scenario where the selective transmission policies can be applied. After that, the scenario will be reproduced in order to analyze the performance of sensor networks composed of selective forwarders.

From the aforementioned objectives, the main contributions of this thesis can be summarized as follows:

- The definition of a sensor model that brings together the relevant characteristics of a real sensor node, including its energy consumption model.

- The development of a selective communication model based on decision theory, as a first approach to develop optimal energy-aware transmission schemes with quality of information.

- The derivation of *optimum selective communication schemes* for three different scenarios: 1) when sensors maximize the importance of *their own* transmitted messages (selective transmitter) ; 2) when sensors maximize the importance of their messages that are actually *retransmitted* by their neighbors (selective forwarder with local optimization); and 3) when sensors maximize the importance of the messages that successfully *arrive to the sink* (selective forwarder with global optimization). Clearly, from an overall network efficiency perspective the first scenario performs worse than its counterparts, but it requires less signaling overhead. On the contrary, the last scheme optimizes the overall network performance, but it requires full coordination among the nodes of the WSN. Performance evaluation is quantified, both theoretically and numerically. The derivation and evaluation of these schemes are the central contributions of this thesis since it links several of the previous specific objectives.

- The development of *suboptimal schemes* that operate under less demanding conditions than those for the optimal ones and entail reduced computational cost.

- The application of selective forwarding policies to a particular application scenario: target tracking in Wireless Sensor Networks.

1.4 DISSERTATION OVERVIEW

The dissertation is divided into 7 chapters and 2 appendix. Once exposed the relevant state of the art in WSNs concerning energy conservation techniques, the motivation and the objectives, Chapter 2 describes the sensor model used in the subsequent chapters. Later, Chapter

3 proposes a selective communication model based on decision theory. This initial proposal leads us to the main contributions of this thesis, which are detailed in Chapter 4 and 5. Optimal selective message forwarding schemes to economize on energy and extend the lifetime of WSNs are developed using stochastic tools. Chapter 6 includes the study and analysis of selective forwarding policies applied to a target tracking scenario in energy-constrained sensor networks. Finally, Chapter 7 draws the conclusions of this dissertation as well as points out future research lines. Below is a more detailed overview of each chapter.

- Chapter 2 describes the sensor model used in the thesis. Initially, we will discuss the main ways of expending energy in a sensor node. The drawn conclusions will be later used to characterize the sensor through a model that details the different states of a sensor node, its possible actions or dynamics, together with a generic energy consumption model.

- Chapter 3 provides a selective communication model based on decision theory: nodes decide to transmit or discard a message according to a decision rule that minimizes a cost, which depends on the energy expenses as well as the message importance.

  The main contributions of this chapter are published in [Arroyo-Valles et al., 2006], [Arroyo-Valles et al., 2007b] and [Arroyo-Valles et al., 2007a].

- Chapter 4 presents an optimum selective message transmission scheme based on a statistical model of the message importances (the Selective Transmitter). More specifically, optimal decisions that maximize the importance sum of the transmitted messages at each node are derived and the node behavior is analyzed under different importance distributions. Using asymptotic analysis, gains with regard to a nonselective scheme are theoretically quantified. Furthermore, in scenarios where nodes do not know the statistical importance distribution of messages, an alternative method that does not require a priori knowledge of the statistical information is developed. Numerical results quantify the gain of implementing the selective transmission scheme.

  The main contributions of this chapter are published in [Arroyo-Valles et al., 2009] and [Arroyo-Valles et al., 2010b].

- Chapter 5 generalizes the model presented in Chapter 4, allowing the use of information from other nodes and analyzing the impact of using non-local information on the network behavior. The selective forwarding schemes are studied under three different scenarios: 1) when sensors maximize the importance of their own transmitted messages (which basically coincides with the model presented in Chapter 4, though using a more general energy consumption model); 2) when sensors maximize the importance of their messages that are actually retransmitted by their neighbors (selective forwarder with local optimization); and 3) when sensors maximize the importance of the messages that successfully arrive to the sink (selective forwarder with global optimization). Suboptimal schemes that rely on local estimation algorithms and entail reduced computational cost are also considered. Theoretical results will be complemented with numerical simulations.

The main contributions of this chapter are published in [Arroyo-Valles et al., 2008a] and [Arroyo-Valles et al., 2010a].

- Chapter 6 proposes an application case study. Selective forwarding sensor nodes are deployed in an energy-constrained sensor field to perform target tracking. We will analyze and evaluate the behavior and performance of selective sensors in this scenario with and without the simultaneous application of other data reduction approaches.

  The main contributions of this chapter are published in [Arroyo-Valles et al., 2008b] and [Arroyo-Valles et al., 2010c].

- Chapter 7 summarizes the main results and contributions of the thesis, discusses the basic assumptions considered in the thesis and points out further research lines.

  The main contribution of this chapter is published in [Hansen et al., 2010].

- To conclude the dissertation, two appendix are included in order to show the mathematical proofs of the theorems stated in the thesis. Particularly, Appendix A includes the proofs of the theorems corresponding to the Optimal Selective Transmitter (Chapter 4) whereas Appendix B contains those proofs of the Optimal Selective Forwarder (Chapter 5).

CHAPTER 2

SENSOR MODEL

In the precedent chapter, we discussed a classification of the state-of-the-art energy conservation strategies for Wireless Sensor Networks. However, we did not include a detailed accounting of the main ways in which sensor nodes may consume energy. Identifying the representative activities performed by sensor nodes will contribute to properly characterize energy consumption. Thus, the analysis and drawn conclusions will be essential in the sense that they will be later integrated into the sensor model proposed for the selective communication policies. Apart from specifying a generic energy consumption model, the definition of the sensor model will also include other relevant information such as the different states of a sensor node, or its possible actions or dynamics.

The rest of the chapter is organized as follows. Initially, a discussion about the energy expenditure in sensor nodes will be raised. After exposing the differences between power and energy consumption, the chapter will be closed describing the general sensor model.

2.1 ENERGY EXPENDITURE IN SENSOR NODES

According to the work presented in [Ephremides, 2002], sensor nodes can be in four different operational modes in a WSN:

- *Transmission*. In this mode, energy can be spent on two major different ways. In the front-end amplifier that supplies the power for the actual RF transmission (transmission energy) and in the node processor implementing the signal generation, formatting, encoding, modulation, memory access and other signal processing functions (processing energy).

- *Reception*. Energy is consumed completely by the processor, including the low noise amplifier that boots the output of the receiving antenna to suitable levels for demodulation, decoding, buffering, etc.

- *Idle, or 'on'*. In this state, sensor nodes are not actively receiving but listening to the channel. Again, energy is consumed by the processors, since the Voltage Control Oscillator (VCO) is operating to be ready to start demodulating an incoming signal and all circuits are properly initialized and charged being ready to operate. But sometimes, a listening node requires that the network protocol transmits periodical beacon signals consuming, therefore, transmission energy. It is usually the default mode in nodes of a sensor network.

- *Sleep*. In the sleep mode, some parts of the sensor circuitry (e.g., microprocessor, memory, radio frequency (RF) components) are turned off. The more circuitry components are switched off, the more the power consumption as well as the operational capabilities of the sensor decrease.

The previous operational modes involve all sensor node components, including both hardware and software. The first two types of operational modes are grouped into the active mode, where the node is fully working and is able to transmit and receive data. Energy spent in idle listening is quite small compared to active modes. But it consumes a non-negligible amount of energy in applications where sensors must spend most of their time without transmitting and receiving, just listening to the medium. Usually, the highest energy consumption corresponds to the transmission mode and the lowest to the sleep mode, when the node turns off the transceiver. In the latter mode, a node can not take part in the network activity, neither transmitting nor receiving, until it is woken up.

A summary of the power consumption of some of the most commonly used motes is presented in Table 2.1 [Sen, 2010]. According to data in Table 2.1, power consumption for transmitting messages is the same as for receiving. However, it is very often to consider higher values for transmissions, as in the examples shown below. It is also remarkable how power consumption drops drastically in the sleep state. On the other hand, the exact cost of

Table 2.1: Power consumption for different sensor motes.

	Mica-2	Tmote Sky	Imote	BTnod	TinyNode 584
sleep	0.054 mW	0.0153 mW	9 mW	9.9 mW	0.0195 mW
idle listening	66 mW	65.4 mW	62.1 mW	82.5 mW	48 mW
receive	117 mW	58.5 mW	112.5 mW	102.3 mW	186 mW
transmission	117 mW	58.5 mW	112.5 mW	102.3 mW	186 mW

the idle listening depends on the radio hardware and the operation mode. It is known that for long-distance radios (0.5 km or more) transmission power dominates receiving and listening costs, however several generations of short-range radios have listening costs of the same order of magnitude as transmission or reception cost [Ye and Heidemann, 2003]. For example, Stemm and Katz measured the power consumption ratios of idle:receive:transmission on the 915MHz Wavelan card [Stemm and Katz, 1997], 1:1.05:1.4, while the Digitan 2 Mbps Wireless LAN module (IEEE 802.11/2Mbps) specification showed ratios of 1:2:2.5 [Ye and Heidemann, 2003].

Looking at the operational modes of the sensor nodes, it is clear that communication processes are energy-expensive (e.g., the transmission or reception of a message). But power consumption is not only present in communication tasks but also in data processing and sensing events of interest. In the sensing activity, the main sources of power consumption are signal sampling and conversion of physical signals to electrical signals, signal conditioning, and analog to digital conversion (ADC) [Halgamuge et al., 2009]. The sensing subsystem consumes a different amount of power depending on the specific type of sensor and the specific application, so that it might be another source of power consumption. However, experimental measurements have shown that the wireless communication task is the major power consumer during the node operation [Raghunathan et al., 2002]. Specifically, the energy cost of transmitting a single Kb of information is approximately the same as the energy needed for processing three million operations in a typical sensor node [Pottie and Kaiser, 2000]. As presented in [Raghunathan et al., 2002], an analysis of the power consumption for the WINS Rockwell seismic sensor indicates power consumption between 0.38 - 0.7 W for transmitting, 0.36 W for receiving, 0.34 W for the idle state and 0.03 W in sleep state, while the power consumed for the sensing task is 0.02 W. For this particular type of sensor, an interesting observation is that the receive and idle modes may require as much power as transmitting, whereas in the traditional ad-hoc wireless networks, transmitting may use as high as twice the power of receiving. Another observation concerns the communication/computation power usage ratio, which can be higher than 1000 (e.g., for the WINS Rockwell sensor, it is from 1500 to 2700). Therefore, local data processing is preferable to communication tasks.

2.2 Power versus Energy consumption

Consumption values in Table 2.1 are expressed in terms of power (energy per unit time) reported from the data sheets of motes. Other typical way of expressing consumption in mote data sheets is current values. However, the term 'energy consumption' is probably more widely used in the literature. Obviously, energy and power consumption terms are not the same but they are close related. Looking at the values of Table 2.1, the instantaneous power consumption of transmissions and receptions is identical (or similar in other motes). Nevertheless, energy consumption (which is essentially the product of power and time) may be significantly different because of its dependence on the amount of time spent in each state or operational mode. This fact clearly entails that the average energy consumption of transmission and reception processes may strongly depend on features from the network design at all levels (the power control strategies, the choice of the MAC layer protocol, the routing algorithm, etc.) and also on the current network deployment and conditions (the density of nodes, the traffic patterns, the link quality, fading channels, environmental influences, etc.). For instance, implementing a Low Power Listening (LPL) MAC layer, a transmitter repeatedly sends the same packet for a duration longer than the sleep interval to guarantee that the receiver is awake during transmission. Thus, the length of the transmission varies accordingly to whenever the receiver wakes up and acknowledges a successful reception. Clearly, it also depends on the LPL interval versus the data rate. On the other hand, the length of a reception varies with the number of received packets, and so, it does the reception cost. Another example is a WSN where errors induce packet losses and nodes implement automatic repeat request (ARQ) schemes to combat them. In those networks, the energy required for a successful transmission may vary with certain probability due to the additional cost that retransmissions entail. The same idea applies to low link quality networks. But in any case, the energy consumption for transmissions is considerably higher than for receptions. In practice, sometimes it is not easy to compute energy consumption associated to each operational mode. For instance, the transmission of a packet can interfere with the idle and receive modes so the computation of the transmission energy consumption is quite involved.

Note that selective communication strategies assume that the cost of transmission is much higher than that of reception, otherwise the benefits of discarding messages may be negligible. Under these conditions (hence, considering energy consumption values), the benefits of a selective transmission algorithm become apparent.

2.3 Sensor Model

For the purpose of the analysis that follows from now on, we consider a sensor network as a collection of sensor nodes $\mathcal{N} = \{n|n = 0, \ldots, N-1\}$. Next, we will characterize each sensor through a model that gathers all the relevant characteristics of a real sensor. The sensor model here proposed will be used for the derivation of the Selective Transmitter (Chapter 4) and the Selective Forwarder (Chapter 5), although a slight adaptation will be performed to the latter. Remind that the sensor model has to be rich enough so that different real scenarios can be fit into. On the other hand, it has to be simple enough so that the mathematical formulation will be tractable and closed-form solutions can be derived.

2.3.1 Sensor node state information

For the time being, we will focus on the behavior of each sensor node, which receives a sequence of requests to transmit messages (no matter how the network topology is). The node state will be characterized by two variables:

- e_k : available energy (battery level) at time k. It reflects the "internal state" of the node; and
- x_k : importance of the message to be sent at time k. It reflects the "external input" to the node.

The “time” variable k requires an explanation. Strictly speaking, it does not represent physical time, but a counter of epochs. An epoch is every time period that starts when the node acquires some data (from the sensing devices or from other nodes) with a request to forward them to the sink, ends when the node discards the message or completes the transmission to a neighboring node, and contains all time instants devoted to receive, process and (eventually) forward these data. In practice, this may happen in a non-continuous time period (e.g., if new messages arrive to the node before completing the transmission of previous messages), and different epochs may be intertwined in the real time line. The identification of the time periods that correspond to each epoch (and the further assignment of energy consumption to epochs) is an important step for implementing a selective scheme in true networks, but goes beyond the scope of this thesis.

In addition to this, it may happen that a node has no pending messages, and stays in idle state or listening to the channel. For the mathematical model, these periods can be interpreted as requests to transmit null messages with zero importance (i.e. $x_k = 0$), while true messages will have $x_k > 0$.

2.3.2 Sensor node location information

Sensor nodes must address messages to a unique sink. It is widely recognized that performance can be improved if nodes have (possibly local) information about their own geographical position and that of other nodes. Therefore, each node n knows its location, the location of its neighbors and the location of the sink, but global knowledge of the network topology is not needed. Location information could be dispensable in the model whenever sensor nodes do not use geographical routing.

2.3.3 Sensor node actions

The network routing algorithm (whatever it is) has defined (possibly, in a decentralized manner) a set of neighbors for each sensor node, in such a way that, any sensor node holding a message at time k has to make a decision d_k about sending or not the current message to a neighbor. The message is sent if $d_k = 1$, while it is discarded if $d_k = 0$.

2.3.4 Operational modes and sensor node dynamics

Sensor nodes consume energy at each time epoch by an amount that depends on the operational mode (node state). According to the analysis exposed in Section 2.1, four different energy expenses are typically considered:

- e_I: energy expenditure corresponding to the "idle" state, i.e., when there is no message reception or sensing activity and the node keeps listening;

- e_R: energy expenditure corresponding to the reception state, which may include the reception of a single or multiple messages;

- e_T: energy expenditure corresponding to the transmission state. It embraces the energy expense of the whole transmission process, which may also include the energy cost of a waiting period for acknowledgments (ACKs); and

- e_S: energy expenditure on data collection by a sensing device.

Remark that energy consumption due to the sleep mode is not considered since it was shown that its energy cost was almost negligible.

The value of these parameters will depend on the system specifications and the specific application. For example, for static dense networks, e_T and e_R values may be very similar, while for mobile networks operating over fading channels, $e_T >> e_R$ is expected because sensors usually beamform their transmitted symbols to mitigate the degradation effects in the communication performance due to fading (e.g. [Marques et al., 2008]).

Two energy consumption models are proposed. As a first approach, a *constant energy consumption model*. This model will be used for the derivation of the selective transmitter (Chapter 4). Energy at time k can be expressed recursively as

$$e_{k+1} = e_k - d_k E_1(x_k) - (1 - d_k) E_0(x_k), \tag{2.1}$$

where $E_1(x_k)$ is the energy consumed when the node decides to transmit the message, and $E_0(x_k)$ is the energy consumed when the message is discarded. Assuming that the energy consumption is constant for any node state, the mean consumption patterns are given by

$E_S = e_S$, $E_R = e_R$, $E_T = e_T$, $E_I = e_I$. For positive values of importance, energy consumption is independent of the message importance, and we have

$$E_1(x_k) = E_T + E_R, \qquad x_k > 0 \tag{2.2}$$

$$E_0(x_k) = E_R, \qquad x_k > 0. \tag{2.3}$$

Recalling that $x_k = 0$ means that no messages are received, we also have

$$E_1(0) = E_0(0) = E_I. \tag{2.4}$$

When the sensor node is the source of the message, E_R comprises the energy cost of the message generation process (possibly by a sensing device), i.e. $E_S = E_R$. When the sensor node acts as a forwarder, E_R comprises the energy expense of receiving the message from other node. Thus, for simplicity we assume that E_R is the same no matter if the node is the source of the message or it has been requested to forward a message from other node (i.e. E_R represents the energy consumption associated to the data capture event, integrating both reception and sensing). Constant parameters E_T, E_R and E_I are perfectly known by sensor nodes. It is important to mention that although the energy consumption model is given by (2.2)-(2.4), we will formulate the selective transmitter considering the general case in (2.1) by assuming that both consumption profiles, $E_1(x_k)$ and $E_0(x_k)$, may arbitrarily depend on x_k.

However, the model can be even applied to situations where E_T and E_R are random or time-variant (e.g., a WSN transmitting over fading channels, where the energy consumption is a random variable that depends on the fading realization; see, e.g., [Marques et al., 2008]) by substituting E_T and E_R by their respective mathematical expectations. This way we can deal with a broader range of scenarios, and actually, be more realistic. This idea leads to the second approach, the *stochastic energy consumption model*. This case is a generalization of the first model and it will be used for the derivation of the selective forwarder (Chapter5). Now, the available energy at time k is expressed as

$$e_{k+1} = e_k - d_k c_{1,k} - (1 - d_k) c_{0,k}, \tag{2.5}$$

where $c_{1,k}$ is the energy consumed when the node decides to transmit the message, and $c_{0,k}$ is the energy consumed when the message is discarded. The latter may include the cost of sensing the data (if the sensor device is the source of the message), the cost of data reception (when data come from other nodes) or the cost of the idle state (if there are no data to transmit, which is formally equivalent to receive a virtual zero importance message). Parameter $c_{1,k}$ accounts for all the previous costs plus the cost of forwarding the message. In general, we assume that energy consumption may depend on x_k and may have some random components, so that $c_{1,k}$ and $c_{0,k}$ are stochastic processes. Note also that the fact that $c_{1,k}$ and $c_{0,k}$ are stochastic allows integrating in the sensor model the idea of nodes consuming a different amount of energy at every state, being able to include explicitly in the model the dependence on other features of the network design. Energy consumption may depend on factors such as the amount of time spent in each state (which in fact may be linked to messages of different lengths as a consequence (or not) of having different priorities, for instance) or the inter-sensor distances (transmitting a message to faraway nodes implies a higher consumption).

Besides, assuming that energy consumption costs are stochastic for any node state, and defining the mean consumption patterns as $E_R = \mathbb{E}\{e_R\}$ (or $E_R = \mathbb{E}\{e_S\}$, as E_R represents the energy consumption associated to a data capture event), $E_T = \mathbb{E}\{e_T\}$, $E_I = \mathbb{E}\{e_I\}$, we can express $c_{1,k} = E_T + E_R$ and $c_{0,k} = E_R$ for $x_k > 0$, and $c_{1,k} = c_{0,k} = E_I$ for $x_k = 0$, so that this model is equivalent to the previous one.

Finally, we assume that energy functions are perfectly known by sensor nodes.

2.3.5 Additional sensor node characteristics

A sensor node is able to overhear any message sent by a node within its transmission radius. As wireless networks usually use a single frequency for communication purposes, a message intended for a node is also heard by all neighbors within the sender transmission radius [Stojmenovic, 2002]. However, we neglect to consider overhearing energy costs because we assume early overhearing avoidance techniques (e.g. the work in [Hu and Motani, 2009]), which is able to reduce the impact on energy consumption to low values.

Sensors are assumed to have a single omnidirectional antenna. Hence, reciprocity between coverage areas is assumed (i.e. node j is neighbor of node i and vice versa).

2.4 Concluding remarks

This chapter has listed the main sources of energy expenditure in a sensor node. The drawn conclusions were crucial to characterize the sensor through a model appropriated for the design of the selective communication policies.

Remark that the sensor model is an abstraction of reality, which makes some simplifying assumptions: perfect transmissions, perfect knowledge of energy resources and energy costs, and some others. Some of them are likely not critical and the model can be modified in order to incorporate more realistic situations. Some others state some challenges in order to obtain more practical selective decision schemes. In any case, we believe that the model captures the essential behavior of a selective sensor and can be used as a starting point for other designs more accurately adapted to specific scenarios.

CHAPTER 3

SELECTIVE COMMUNICATIONS BASED ON DECISION THEORY

In the introductory chapter, it was remarked that one of the main goals in WSNs consisted of designing energy-efficient schemes that reduce considerably communication tasks for being extremely costly, energetically speaking. It was also stated that making intelligent importance-driven decisions about message transmission in WSNs may notably contribute to reduce communication expenses by only transmitting the most relevant messages (selective transmission), while a level of QoI is assured.

This chapter considers a selective forwarding scheme that uses a probabilistic approach as a first attempt to develop optimal selective communication policies. Thus, the decision to transmit or discard a message at each node will be made by means of a Bayesian decision model that tries to minimize a cost which will depend on the energy expenses and the energy availability as well as the importance of the current message.

Furthermore, adding sensor nodes the capability to learn in a distributed way from previous decisions together with cooperation patterns may help to improve the adaptation of sensor nodes to changing conditions, which on the other hand, are so common in WSNs. For instance, applying the potential benefits of machine learning techniques to a routing scenario, sensor nodes may learn from the success or failure of past decisions in order to make intelligent decisions according to future conditions.

Hereunder, a selective transmission scheme inspired from Bayes decision theory and based on learning patterns will be developed as a manner of preserve energy whereas guarantees QoI.

3.1 Decision model inspired by Bayes decision theory

As it was mentioned in the motivation section in Chapter 1, the basis of selective communications consists of selecting, according to a criterion or a rule, which messages will be transmitted and which discarded in order to save energy of individual nodes. Hence, based on selective communication principles, in this section we derive a transmission decision rule based on energy expenses, energy availability, cooperation patterns and message importance.

Whenever a sensor node receives a message, it should make a decision that implies accomplish an action, i.e. transmit or discard the message. To make the right decision in order to extend network lifetime while not discarding relevant information (important messages), each node should assess the consequences derived from each action. The node should evaluate the risk assumed when forwarding the message to a neighboring node (and thus, the energy expenditure associated to the possible transmission) and the probability that the message will not be eventually retransmitted from a neighboring node (either for energy problems or selfish reasons), opposite to discarding the incoming message to wait for future highly graded messages.

Sensors are able to make better decisions if they have some kind of information that contributes to assess the action effects. Defining $\phi(i)$ as the neighbors of sensor node i, decisions at node i will be based on the following variables:

- Energy expenditure associated to the operational modes/node states: E_T, E_R, E_I.
- The importance of the message to be transmitted at time k, x_k. The assessment of the message importance is a responsibility of the source node, so that the importance value should be transmitted along with the message.
- Profiles of neighboring nodes (cooperation patterns and an estimation of the available energy at neighbors, $\{\hat{E}_{ij}, j \in \phi(i)\}$), learnt from previous experiences and statistics.

Variables x_k and $\hat{E}_{ij}$ are grouped into observation vector **y** (i.e. $\mathbf{y} = [\hat{E}_{ij} \quad x_k]^T$). Based on **y**, each node with a message to be transmitted states the decision as the result of solving a hypothesis testing problem with two hypothesis: $q = 0$ or $q = 1$, where:

- $q = 1$ if at least one neighboring node will forward the message.
- $q = 0$ if no neighboring node will forward the message (thus, saving energy to transmit future high important messages).

Depending on its belief about the value of q, node i will make decision $\mathcal{D}_1$ (the message is transmitted, $d = 1$) or $\mathcal{D}_0$ (the message is not transmitted, $d = 0$).

To do so, we define cost $C(\mathcal{D}_i, z) = c_{iz}$ as the cost of deciding $\mathcal{D}_i$ when the true hypothesis is $q = z$ (where $i, z \in \{0, 1\}$). The table of costs associated to the transmission decision problem is shown in Table 3.1.

Table 3.1: Table of costs associated to the transmission decision problem.

$C(\mathcal{D}_i, q)$	$q = 0$	$q = 1$
$\mathcal{D}_0$	$c_{00} = E_I$	$c_{01} = E_I$
$\mathcal{D}_1$	$c_{10} = E_T$	$c_{11} = E_T - \gamma x_k$

Note that the cost of rejecting a forwarding request ($c_{0,q}$) is the energy expenditure due to the listening state. The cost for node i when it decides not to transmit a message is independent of the decision made by neighboring nodes. The cost of deciding to forward a message when at least a neighbor retransmits (c_{11}) is reduced according to the message importance x_k. As message importance x_k is not scaled as regards energy consumption, parameter γ modulates the trade-off between the transmission energy (cost) and the message importance (benefit).

According to this, the conditional risks (mean costs) associated to decide in favor of transmitting ($\mathcal{D}_1$) or discarding ($\mathcal{D}_0$) are given by

$$C(\mathcal{D}_0|\mathbf{y}) = E_I P(q = 0|\mathbf{y}) + E_I(q = 1|\mathbf{y}) = E_I \tag{3.1}$$

$$C(\mathcal{D}_1|\mathbf{y}) = E_T P(q = 0|\mathbf{y}) + (E_T - \gamma x_k)P(q = 1|\mathbf{y}) = E_T - \gamma x_k P(q = 1|\mathbf{y}), \tag{3.2}$$

respectively. Note that we have used $P(q = 0|\mathbf{y}) = 1 - P(q = 1|\mathbf{y})$. As the goal is to minimize the mean cost, which consists of making the decision that minimizes the conditional risk (i.e. $\arg\min_i E\{C(\mathcal{D}_i|\mathbf{y}), \mathbf{i} = \mathbf{0}, \mathbf{1}, ..., \mathbf{L}\}$, which translates into $C(\mathcal{D}_1|\mathbf{y}) \gtrless^{D_0}_{D_1} C(\mathcal{D}_0|\mathbf{y})$ because it is a binary decider), the final decision is given by

$$P(q = 1|\mathbf{y}) \underset{0}{\overset{1}{\gtrless}} \frac{E_T - E_I}{\gamma x_k}. \tag{3.3}$$

3.1.1 Computation of the posterior probability

In order to estimate the posterior probability of each hypothesis, $P(q = 1|\mathbf{y})$, node i makes two simplifying assumptions:

a1) The probability of node j forwarding a message is independent of the forwarding decision made by any other node.

a2) The probability of node j forwarding a message is independent of the state information at any other node.

Defining the random variable q_j equal to 1 if node j will forward the message and 0 otherwise, we can rely on a1) to write

$$p_{ij} = P(q = 1|\mathbf{y}) = 1 - P(q = 0|\mathbf{y}) = 1 - \prod_{\substack{j=1 \\ j \in \phi(i)}}^{L} (1 - P(q_j = 1|\mathbf{y})). \tag{3.4}$$

In order to compute (3.4), we make use of the simplifying assumption a2), which states that the posterior probability of transmitting only depends on local information of node j. Thus, noting that the local information of node j is given by $\mathbf{y}_j = [\hat{E}_{ij} \quad x_k \quad 1]^T$ (the last component, equal to unity, has been included for mathematical convenience), we can write

$$P(q_j = 1|\mathbf{y}) = P(q_j = 1|\mathbf{y}_j). \tag{3.5}$$

Since a closed-form expression for (3.5) is unknown, we may assume a truncated logistic model

$$P(q_j = 1|\mathbf{y}_j) = \frac{1}{1 + \exp\left(-\mathbf{w}_j^T \mathbf{y}_j\right)} u(\hat{E}_{ij} - E_T), \tag{3.6}$$

where u is the Heaviside step function. Note that a direct consequence of (3.6) is that node i assigns a zero probability of retransmission to any node that (according to its estimate) does not have energy to transmit the message.

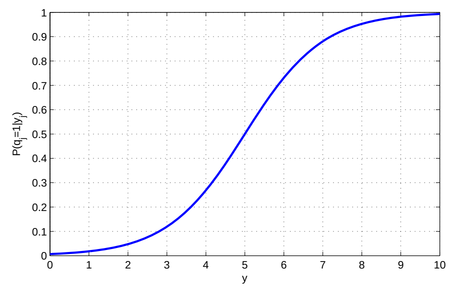


Figure 3.1: Logistic model to compute the probability of forwarding by neighboring nodes, $P(q_j = 1|\mathbf{y}_j)$.

We have chosen the logistic sigmoid because it is bounded by 0 and 1, and its S-shaped continuous output, which assigns higher output values to higher x-coordinate values. This function captures the intuition that nodes have about the probability that neighboring nodes will forward the message, since the higher the message importance and the estimation of the available energy at neighboring nodes is, the higher the probability of forwarding is. Fig. 3.1 represents the logistic sigmoid function.

The probabilistic dependencies which define the decision process at each node are illustrated in Fig. 3.2 for the case of 3 nodes. Each transmitting node "builds" a graphical model including the most relevant variables in the node decision: namely, the message importance and the estimation of the energy at neighboring nodes. Though each node makes the simplifying assumption that the decision of a neighboring node will not depend on the energy at other nodes, it learns existing probabilistic dependencies through the logistic model.

3.1.2 Learning neighbors' profile

Each node is able to estimate parameters $\mathbf{w}_j$ of the logistic neighbors' profile in (3.6) without exchanging any information among nodes, just overhearing retransmissions.

Let us define d_j as the decision of node j to forward a message from node i (i.e. d_j is a binary variable equal to 1 if node i listens to node j forwarding its message, and 0

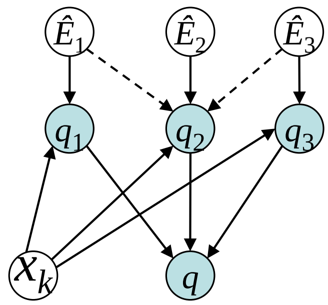


Figure 3.2: The graphical model built by a transmitting node including the message importance and the estimation of energy at neighboring nodes. Each node makes the simplifying assumption that the decision of a neighboring node will not depend on the energy at other nodes (thus omitting dependencies given by the dashed arrows, which may appear if neighbors of a node are neighbors among themselves).

otherwise). Parameters $\mathbf{w}_j$ are estimated in order to minimize a loss function capable of providing adequate estimates of the posterior probability, such as the cross entropy loss function [Miller et al., 1993], a loss function commonly used in neural network training algorithms and which is given by

$$L(p_{ij}, d_j) = -d_j \ln p_{ij} - (1 - d_j) \ln(1 - p_{ij}), \tag{3.7}$$

where p_{ij} represents the estimated probability that node i transmits the message through node j. This cost function is widely used for learning problems.

Applying stochastic gradient learning rules, node i updates parameters after a transmission as

$$\mathbf{w}_j(k+1) = \mathbf{w}_j(k) + \eta(d_j(k) - p_{ij}(k))u(\hat{E}_{ij} - E_T)\mathbf{y}_j(k), \tag{3.8}$$

where η is the adaptive step and k represents the epochs. Clearly, the selection of η entails a trade-off between the speed of convergence (higher for large η) and the stability of the adaptive rule (better for small η).

3.1.3 Updating information from statistics

Based on node dynamics, node i can estimate the profile information of its neighbors, such as the remaining energy ($\widehat{E}_{ij}, j \in \phi(i)$). Even though it could be possible to include this information in periodical "keep alive" beacons, we would rather consider that sensor nodes have incomplete information so they need getting it from statistics, with the consequent imprecisions that it implies. Thus, energy at node j can be estimated by node i (whenever it hears a retransmission by node j or when it is aware node j receives a message) using the general energy model proposed in (2.1) in Chapter 2 (but substituting e_k by $\widehat{E}_{ij}$).

There are, however, messages received by node j that node i is not aware of. Experimental results showed that this slight energy overestimation seems to affect neighboring nodes concentrated in a local region in a similar way, so it does not result significant to make forwarding decisions. Moreover, if energy expenditure is similar in reception and idle states, the overestimation is considerably reduced.

3.1.4 Application of the Decision Model to Routing in WSN

The decision model was incorporated into the design of two new energy-aware routing algorithms, namely Learning-based Prioritized Geographical Routing (LPGR) [Arroyo-Valles et al., 2007b] and Q-Probabilistic Routing (Q-PR) [Arroyo-Valles et al., 2007a], to verify its validity. Nevertheless, as the decision rule is the key and starting point of the work that follows in the remainder of the dissertation, we are not including the description and performance evaluation of both routing algorithms. We urge the reader to have a look at the references cited above to go into detail. However, we briefly resume the main findings below.

Using the decision model, nodes are able to make intelligent forwarding decisions discarding low importance messages to save energy for higher importance incoming messages. Thus, each node observes if neighboring nodes forward its messages and based on these observations and exploiting local information from the signals detected at them, sensor nodes can learn to route messages in order to improve the communication performance of the overall network and minimize the need of coordination or signaling protocols among nodes. The resulting protocols transmit messages selectively according to a given importance value, promoting the transmission of highly graded messages, which is efficient to maximize the overall importance of the messages arriving to the sink during the whole network lifetime. Furthermore, both protocols ensure successful message transmissions entailing a low loss rate.

CHAPTER 4

OPTIMAL SELECTIVE TRANSMISSION

In the previous chapter, a probabilistic selective communication model based on decision theory was proposed. The transmit/discard decision was quantified according to a cost which depended on energy expenses and the message importance so that the final decision was made with the aim of minimizing a mean cost. Thus, the resulting decision rule tended to promote the transmission of highly graded messages and, as a result, the overall importance of the transmitted messages during the full node lifetime was higher than the corresponding to nonselective transmission schemes. However, this model does not take into account the sequential nature of the problem. Besides, the cost model is, to some extent, arbitrary. The dynamical adjustment of parameter γ in (3.3), which balances the importance of the message (benefit) regarding the energy expenses (cost), should be properly refined. According to (3.3), a high value of parameter γ will promote the transmission of messages while a low value will have the opposite effect. But, what is the appropriate value of parameter γ? That is why the relative influence of energy expenses and importance values in the overall cost is a free parameter of the model, whose value is difficult to optimize.

The goal pursued in this chapter is to re-formulate and solve the selective transmission problem as an iterative decision problem in such a way that the balance between minimizing energy expenses and maximizing the importances of the transmitted messages is determined automatically by the optimization process. Specifically, we derive a selective transmission policy maximizing the importance sum of the messages transmitted by each node from the sensor node information (e.g. energy expenses, available batteries, the importance of messages, etc.), and analyze the node behavior under different importance distributions. Using asymptotic analysis, the gain with regard to a nonselective scheme is theoretically quantified. Furthermore, in scenarios where nodes do not know the statistical importance distribution of messages, an alternative method that does not require a priori knowledge of the statistical information is developed.

It will be shown that in most cases, the optimal transmission scheme is fairly simple. Particularly, it will turn out that the optimal decision is made comparing the message importance with a time-variant threshold. It will be also shown that the gain of the selective transmission scheme, compared to a nonselective one, will critically depend on energy expenses, among other factors. Theoretical results will be complemented with numerical simulations that not only will corroborate the theoretical claims but also will help us to quantify the gains of implementing the selective scheme for a broad range of practical scenarios.

Noticeably, the statistical model of the selective transmission scheme here presented exhibits similarities to other problems in Operations Research and Stochastic Dynamic Programming (see, e.g., [Sennott, 1997]), and the equations describing the energy evolution at the sensor node and the importance sum can be restated as a particular type of Markov Decision Process, as it will be further stated in the next chapter.

The chapter is organized as follows: Section 4.1 focuses on the optimal selective transmitter, obtaining a general formula to compute the optimal time-variant threshold, which is thereafter particularized for specific operating conditions and different importance distributions. Section 4.2 describes a selective transmission policy based on a constant threshold. The asymptotic analysis in Section 4.3 provides a gain formula as well as some illustrative examples. In Section 4.4, an adaptive method that does not require any knowledge of the importance distribution, but estimates it on-the-fly is presented. Section 4.5 discusses the experimental study and results for a single node scenario. Finally, the chapter ends with some concluding remarks.

4.1 Optimal selective transmission

The sensor model used for the mathematical formulation was described in Chapter 2. Remind that the derivation of the selective transmitter is made considering that the node has a constant energy consumption model (although may arbitrarily depend on the importance value x_k) given by (2.1).

To derive the optimal transmission policy we will consider that node decisions do not depend on the state and actions of neighboring nodes, but only on the available information at each node. Therefore, at each time k, the node decision depends on the internal state and the external input

$$d_k = d_k(e_k, x_k), \tag{4.1}$$

(note that, with some abuse of notation, we adopt the same notation for the decision variable and the decision function), with the constraint

$$d(e_k, x_k) = 0, \text{ if } e_k < E_1(x_k) \tag{4.2}$$

reflecting that, if the sensor node does not have enough energy to receive and transmit the message, it cannot decide $d_k = 1$.

Decisions at each node will be made with *infinite horizon*, i.e., by maximizing (on average) the importance sum of *all* transmitted messages

$$t_\infty = \sum_{k=0}^{\infty} d_k x_k. \tag{4.3}$$

Since nodes have limited energy resources, this sum only contains a finite number of nonzero values (eventually, for some k, $e_k < \min_k E_1(x_k)$, and $\forall k' \geq k$, we have $d_{k'} = 0$).

Since the design focuses on the performance of each single node, decisions made at other nodes are not explicitly taken into account, but only implicitly through messages actually received from its neighbors. Although this approach fits into the design philosophy of sensor networks where the complexity of each node should be kept as low as possible, it is worth remarking that from an overall network perspective, it may entail a loss of performance. Therefore, a generalization of the selective transmission model proposed in this chapter, which will also consider the behavior of neighboring nodes, will be proposed in Chapter 5.

The following result provides the optimal selective transmitter.

Theorem 1 *Let $\{x_k, k \geq 0\}$ be a statistically independent sequence of importance values, and e_k the energy budget at time k, whose energy process is given by (2.1). Consider the sequence of decision rules in the form*

$$d_k = u(x_k - \mu_k(e_k, x_k))u(e_k - E_1(x_k)), \tag{4.4}$$

where $u(x)$ stands for the Heaviside step function (with the convention $u(0) = 1$) and threshold μ_k is defined recursively through the pair of equations

$$\mu_k(e, x_k) = \lambda_{k+1}(e - E_0(x_k)) - \lambda_{k+1}(e - E_1(x_k)) \tag{4.5}$$

$$\lambda_k(e) = \left(\mathbb{E}\{\lambda_{k+1}(e - E_0(x_k))\} + \mathbb{E}\{(x_k - \mu_k(e, x_k))^+ u(e - E_1(x_k))\}\right) u(e), \tag{4.6}$$

where

$$(x_k - \mu_k(e, x_k))^+ = (x_k - \mu_k(e, x_k))u(x_k - \mu_k(e, x_k)). \tag{4.7}$$

Sequence $\{d_k\}$ is optimal in the sense of maximizing $\mathbb{E}\{t_\infty\}$ (with $d(e_k, x_k) = 0$ for $e_k < E_1(x_k)$ and t_∞ given by (4.3)) among all sequences in the form $d_k = d_k(e_k, x_k)$.

*The auxiliary function $\lambda_k(e)$ represents the expected increment of the total importance (*expected reward*) at time k , i.e.,*

$$\lambda_k(e) = \sum_{i=k}^{\infty} \mathbb{E}\{d_i x_i | e_k = e\}. \tag{4.8}$$

Proof See Appendix A.1.

Although the result of Theorem 1 is general and holds for any energy cost and importance value, it does not provide a clear intuition about the impact of $E(x)$ and the distribution of x_k on the design of the optimal transmission scheme. Moreover, the direct application of this result is difficult, because (4.5) and (4.6) state a time-reversed recursive relation: to make optimal decisions, the node should know the future importance distributions in advance. For these reasons, in the reminder of this chapter we will focus special attention on several particular cases that will lead us to tractable closed-form solutions.

4.1.1 Stationarity

If all variables $x_1, \ldots, x_k$ have the same distribution, then μ_k does not depend on k [c.f. (4.5) and (4.6)]. In this case, the following result can be shown:

Theorem 2 *Under the conditions of Theorem 1, if the importance values* $\{x_k, k \geq 0\}$ *are identically distributed and* $\inf_x\{E_i(x)\} > 0$*, for* $i = 0, 1$*, the sequence of decision rules*

$$d = u(x - \mu(e, x))u(e - E_1(x)), \tag{4.9}$$

where

$$\mu(e, x) = \lambda(e - E_0(x)) - \lambda(e - E_1(x)) \tag{4.10}$$

$$\lambda(e) = \left(\mathbb{E}\{\lambda(e - E_0(x))\} + \mathbb{E}\{(x - \mu(e, x))^+ u(e - E_1(x))\}\right) u(e), \tag{4.11}$$

is optimal in the sense of maximizing $\mathbb{E}\{t_\infty\}$ *(with* $d(e, x) = 0$ *for* $e < E_1(x)$ *and* t_∞ *given by (4.3)) among all sequences in the form* $d = d(e, x)$*.*

Proof See Appendix A.2.

It is important to stress that in most scenarios involving multiple sensors, the stationarity assumption, strictly speaking, is not true. For example, the distribution of messages arriving to a node depends on the transmission policy used by forwarding nodes. Since the optimal policy presented here is energy-dependent [c.f. either (4.5) or (4.10)] and the available energy clearly changes along time for all nodes, the importance distribution of the received messages will also change along time. However, it will be shown in the next sections that the simplification obtained in (4.10) is not only useful from a theoretical perspective, but also valid from a practical point of view for large networks. This (almost) stationary behavior can be justified based on different reasons. First, although the optimal transmission policy varies along time, this variation turns out to be negligible during most of the time (i.e., it is almost-stationary). The underlying reason is that for medium to high values of available energy the optimal transmission scheme is not very sensitive to energy changes. Only when nodes are close to run out of batteries, the decision threshold varies significantly as a function of the remaining energy. Second, even if the behavior of a single node is not stationary, the aggregate effect of the entire network may be stationary. In other words, the approximation given by (4.10) will be accurate during most of the time, and the discrepancy will only arise when the network is close to expire. Theoretical analysis and numerical results will corroborate this intuition.

4.1.2 Constant energy profiles

Under the constant energy profile model given by (2.2)-(2.4), the optimal threshold can be written as

$$\mu_k(e,x) = \mu_k(e) I_{x>0}, \tag{4.12}$$

where $I_{x>0}$ is an indicator function (equal to unity if the condition holds and zero otherwise), and using (4.5) we have

$$\mu_k(e) = \lambda_{k+1}(e - E_R) - \lambda_{k+1}(e - E_T - E_R). \tag{4.13}$$

Also, defining the probability of being in idle state as $P_I = P(x_k = 0)$, (4.6) becomes

$$\begin{aligned}\lambda_k(e) &= P_I \lambda_{k+1}(e - E_I) + (1 - P_I)\lambda_{k+1}(e - E_R) - P_I \mu_k(e,0) u(-\mu_k(e,0)) u(e - E_I) \\ &\quad + (1 - P_I)\mathbb{E}\{(x_k - \mu_k(e,x_k))^+ | x_k > 0\} u(e - E_T - E_R) \\ &= P_I \lambda_{k+1}(e - E_I) + (1 - P_I)\lambda_{k+1}(e - E_R) \\ &\quad + (1 - P_I)\mathbb{E}\{(x_k - \mu_k(e,x_k))^+ | x_k > 0\} u(e - E_T - E_R). \end{aligned} \tag{4.14}$$

Furthermore, defining

$$H_k(\mu) = \mathbb{E}\{(x_k - \mu)^+ | x_k > 0\}, \tag{4.15}$$

we can write

$$\lambda_k(e) = P_I \lambda_{k+1}(e - E_I) + (1 - P_I)\lambda_{k+1}(e - E_R) + (1 - P_I) H(\mu_k(e)) u(e - E_T - E_R). \tag{4.16}$$

Thus, the optimal transmission policy for a sensor with a constant energy profile is described by (4.13) and (4.16). In order to analyze the influence of idle times and the relation between transmission and reception energy expenses separately, in the following examples we consider the case of $P_I = 0$ and/or $E_I = 0$. Note that if any of these conditions holds, the expected importance sum in (4.16) can be rewritten as

$$\lambda_k(e) = \lambda_{k+1}(e - E_R) + H(\mu_k(e))u(e - E_T - E_R). \tag{4.17}$$

4.1.3 Examples

As we have already mentioned, there is no general explicit solution to the pair of equations (4.5) and (4.6), not even for the stationary case in (4.13) and (4.16). For this reason, in this section we focus on systems satisfying the operating conditions that gave rise to (4.17) (constant energy profiles, stationarity and zero idle energy) and solve the recursive relations for several importance distributions[1]. This simplification will lead to tractable expressions, providing insight into the behavior of the optimal transmission scheme.

- **Uniform Distribution**: Let $U(0, 2)$ denote the uniform distribution between 0 and 2 whose probability density function (PDF) is

  $$p(x) = \frac{1}{2}(u(x) - u(x - 2)). \tag{4.18}$$

  By substituting (4.18) into (4.15), we have

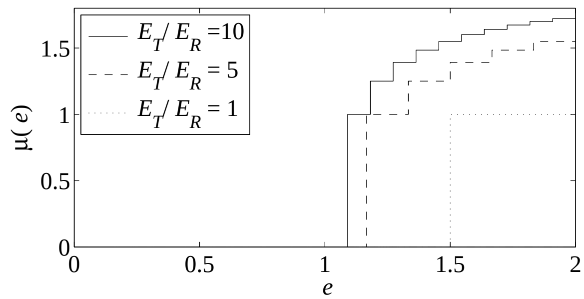
  $$H(\mu) = \mathbb{E}\{(x - \mu)^+\} = \frac{1}{4}(2 - \mu)^2, \tag{4.19}$$

  and therefore, the expected reward is given by

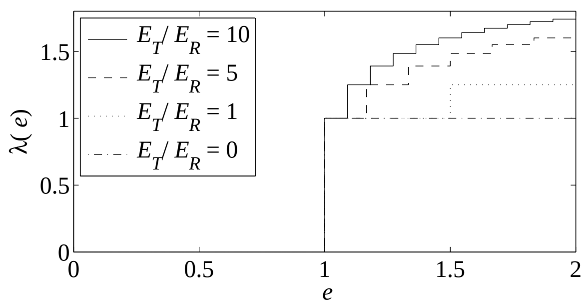
  $$\lambda(e) = \lambda(e - E_R) + \frac{1}{4}(2 - \mu(e))^2 u(e - E_T - E_R). \tag{4.20}$$

  Fig. 4.1(a) plots the threshold for *extremely small* values of available energy, e. $E_1(x) = 1$ and different values of the ratio E_T/E_R are considered. Note that, for values of e lower than 1, in spite of the threshold value is 0, there is no actual transmission because $u(e - E_T - E_R) = 0$. For $1 < e < E_T + E_R$ there is only one opportunity to send the message, so the threshold is also 0, which means that the message will be transmitted whatever its importance value is. For larger energy values,

[1] In the following, free parameters will be set so that importance distributions have a mean value equal to 1.



(a)



(b)

Figure 4.1: Variation of the decision threshold (a) and the expected importance sum (b) for low values of available energy, e. A uniform importance distribution $U(0,2)$ with $E_1(x) = E_R + E_T = 1$ is assumed. Different plots correspond to different values of E_T/E_R.

the threshold increases, meaning that the transmission can be made more selective. Note, also, that $\mu(e)$ evolves in a staircase manner, because any energy amount in excess of a multiple of E_R is useless.

Fig. 4.1(b) represents the expected reward ($\lambda(e)$). Note that the case $E_T = 0$ is equivalent to a nonselective transmitter (because, according to (4.13), the optimal threshold is 0, which means that no messages are discarded). Despite that, for e close to 2, there is not energy for a second transmission, the selective transmitter provides a significant expected income with respect to the nonselective one.

Fig. 4.2(a) shows the optimal threshold for $E_T = 4$, $E_R = 1$ and *high* values of available energy. Note the sawtooth shape of the transmission threshold: as the available energy is reduced to a value close to a multiple of the energy required to transmit, the

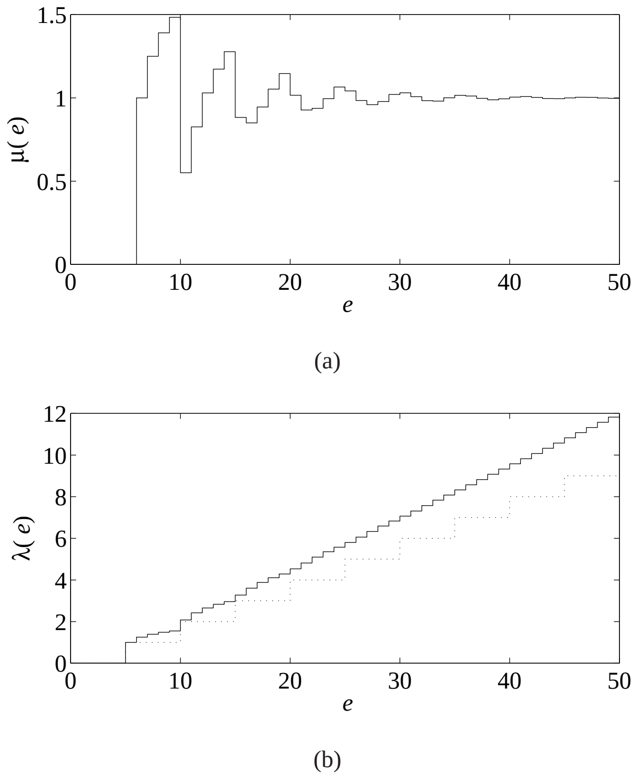


Figure 4.2: Variation of the decision threshold (a) and the expected importance sum (b) (continuous line) as a function of the available energy. A uniform importance distribution $U(0,2)$ with $E_T = 4$ and $E_R = 1$ is assumed. The stepwise function (dotted line) reflects the behavior of a nonselective transmitter, which transmits any message whatever its importance value is.

transmission threshold decreases, because if there is not any transmission, the total number of possible messages to be sent is reduced by a unity.

Fig. 4.2(b) represents the expected reward of the selective transmitter (continuous line) and the nonselective one (dotted line), which transmits all messages regardless of the importance value, until energy is used up.

- **Exponential**: For an exponential distribution of free parameter a, we have

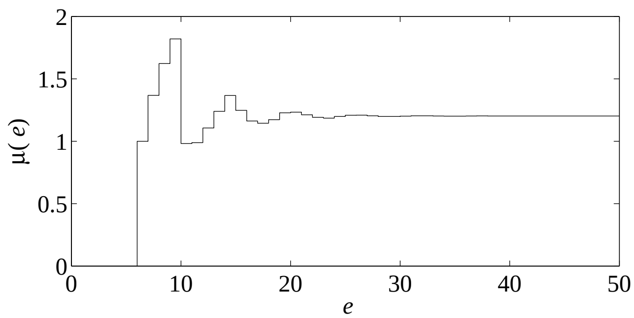
$$p(x) = \frac{1}{a} \exp\left(-\frac{x}{a}\right) u(x), \tag{4.21}$$

and

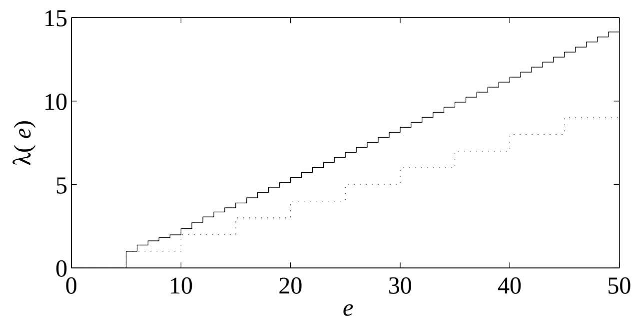
$$H(\mu) = a \exp\left(-\frac{\mu}{a}\right), \tag{4.22}$$

so that

$$\lambda(e) = \lambda(e - E_R) + a \exp\left(-\frac{\mu(e)}{a}\right) u(e - E_T - E_R). \tag{4.23}$$



(a)



(b)

Figure 4.3: Variation of the decision threshold (a) and the expected importance sum (b) (continuous line) with respect to the available energy. An exponential importance distribution with $a = 1$, $E_T = 4$ and $E_R = 1$ is assumed. The dotted line represents the expected importance sum of the nonselective transmitter.

The variation of μ and λ for an exponential distribution with $a = 1$, $E_T = 4$ and $E_R = 1$ is illustrated in Fig. 4.3. The more restrictive threshold (Fig. 4.3(a)), compared to that one shown in Fig. 4.2(a) for the uniform distribution, gives rise to a higher increase in the expected reward with regard to the nonselective transmitter (Fig. 4.3(b)).

- **Pareto**: For the Pareto-type distribution with PDF

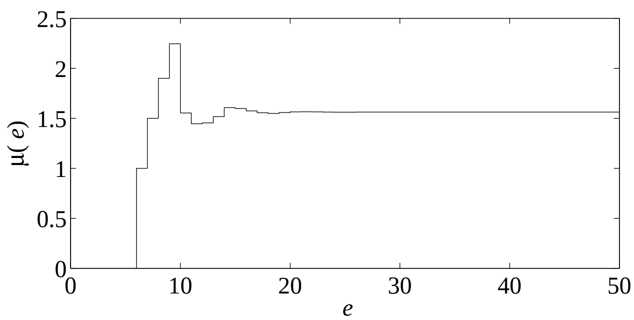
$$p(x) = \frac{a-1}{(1+x)^a} u(x), \tag{4.24}$$

we have

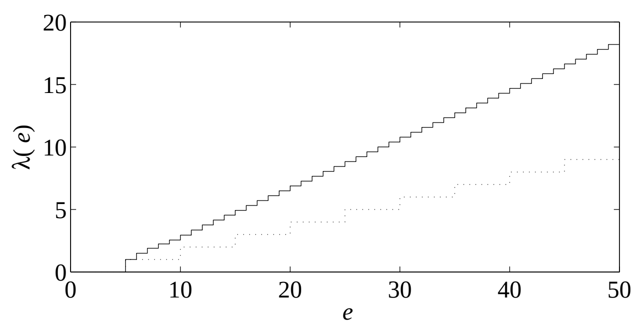
$$H(\mu) = \frac{1}{a-2} \frac{1}{(1+\mu)^{a-2}} \tag{4.25}$$

so that

$$\lambda(e) = \lambda(e - E_R) + \frac{1}{a-2} \frac{1}{(1+\mu(e))^{a-2}} u(e - E_T - E_R). \tag{4.26}$$



(a)



(b)

Figure 4.4: Variation of the decision threshold (a) and the expected importance sum (b) (continuous line) with respect to the available energy. A Pareto importance distribution with $a = 3$, $E_T = 4$ and $E_R = 1$ is assumed. The dotted line shows the behavior of the nonselective transmitter.

The evolution of μ and λ for a Pareto distribution with $a = 3$, $E_T = 4$ and $E_R = 1$ is depicted in Fig. 4.4. Similar conclusions can be applied to this type of distribution.

4.2 THE CONSTANT THRESHOLD TRANSMITTER

For comparative purposes in the following sections, we will derive some expressions relative to selective transmission policies based on constant thresholds. Let us assume that node decisions are given by

$$d_k = u(x_k - \mu_c)u(e_k - E_1(x_k)), \tag{4.27}$$

where μ_c is a constant threshold. Note that if $\mu_c = 0$, the constant threshold transmitter reduces to the nonselective transmitter. Following an analysis similar to that exposed in Appendix A.1, we can write the expected reward of the constant threshold transmitter as

$$\begin{aligned}\lambda_k(e) &= \mathbb{E}\{d_k x_k | e_k = e\} + \mathbb{E}\{(1-d_k)\lambda_{k+1}(e - E_0(x_k))\} + \mathbb{E}\{d_k \lambda_{k+1}(e - E_1(x_k))\} \\ &= \mathbb{E}\{u(x_k - \mu_c)u(e - E_1(x_k))x_k\} \\ &+ (1 - P(x_k \geq \mu_c, e \geq E_1(x_k)))\mathbb{E}\{\lambda_{k+1}(e - E_0(x_k))|(x_k < \mu_c) \text{ OR } (e < E_1(x_k))\} \\ &+ P(x_k \geq \mu_c, e \geq E_1(x_k))\mathbb{E}\{\lambda_{k+1}(e - E_1(x_k))|x_k \geq \mu_c, e \geq E_1(x_k)\}. \end{aligned} \tag{4.28}$$

In particular, for large e (i.e., $e > \max_x\{E_1(x)\}$) and the stationary case,

$$\begin{aligned}\lambda(e) =& \mathbb{E}\{u(x - \mu_c)x\} + P(x < \mu_c)\mathbb{E}\{\lambda(e - E_0(x))|x < \mu_c\} \\ &+ P(x \geq \mu_c)\mathbb{E}\{\lambda(e - E_1(x))|x \geq \mu_c\}.\end{aligned} \tag{4.29}$$

Interestingly, for the constant energy profile case with $P_I = 0$, $E_1(x) = E_T + E_R$ and $\mu_c = 0$, $\lambda(e)$ can be computed explicitly using (4.8) as

$$\lambda_k(e) = \sum_{i=k}^{\infty} \mathbb{E}\{u(e_i - E_1(x_i))x_i | e_k = e\} = \left\lfloor \frac{e}{E_T + E_R} \right\rfloor \mathbb{E}\{x\}, \tag{4.30}$$

where $\lfloor y \rfloor$ denotes the largest integer which is lower than y. So that (4.30) reflects the stepwise form shown in the example of Fig. 4.2.

4.3 ASYMPTOTIC ANALYSIS

4.3.1 Large energy threshold

The above examples show that for large energy values e, the threshold converges to a constant value, and the expected reward tends to grow linearly. Both behaviors are closely related because, as (4.5) shows, the optimal threshold is the difference between two expected rewards. But this is also a general behavior of the constant threshold transmitter. In this section, we discuss the asymptotic behavior of any selective transmitter in the stationary case. To do so, we first define the *income rate* of a selective transmitter.

Definition 1 The income rate of a selective transmitter with expected reward $\lambda(e)$ is defined as

$$\tau = \lim_{e\to\infty} \frac{\lambda(e)}{e}. \tag{4.31}$$

We start with the income rate of the constant threshold transmitter, providing a formula and a proof for bounded energy profiles.

Theorem 3 *Consider the selective transmitter given by (4.27), constant threshold μ_c, and energy profiles with upper bound, B, such that $E_0(x) \leq B$, and $E_1(x) \leq B$, for all x. Then, the income rate is given by*

$$\tau_{\mu_c} = \frac{\mathbb{E}\{u(x-\mu_c)x\}}{(1-P_{\mu_c})\mathbb{E}\{E_0(x)|x<\mu_c\} + P_{\mu_c}\mathbb{E}\{E_1(x)|x\geq\mu_c\}} \tag{4.32}$$

where $P_{\mu_c} = P(x \geq \mu_c)$.

Proof See Appendix A.3.

As a reference for comparison, we will consider the particular case of the nonselective transmitter, the particular case of the constant threshold transmitter with $\mu_c = 0$, in such a way that (4.32) reduces to

$$\tau_0 = \frac{\mathbb{E}\{x\}}{\mathbb{E}\{E_1(x)\}}. \tag{4.33}$$

The following theorem provides a way to compute the income rate of the optimal selective transmission policy:

Theorem 4 *The only threshold function $\mu(e, x)$ which is a solution of (4.10) and (4.11) and is constant with e is given by*

$$\mu(e, x) = \mu(x) = (E_1(x) - E_0(x))\tau, \tag{4.34}$$

where τ is a solution of

$$\mathbb{E}\{E_0(x)\}\tau = \mathbb{E}\{(x - (E_1(x) - E_0(x))\tau)^+\}. \tag{4.35}$$

Moreover, if $E_1(x) \geq E_0(x)$, for all x, this solution is unique.

Proof See Appendix A.4.

An important consequence of Theorem 4 is that, if $\lim_{e\to\infty} \mu(e, x)$ exists, it must be equal to (4.34). Even though we will not show any theoretical convergence result, we have found a systematic empirical convergence and we guess that this could be a general result for any importance distribution, provided it is stationary.

For the constant energy profile case, the asymptotic threshold (4.34) becomes

$$\mu(x) = E_T \tau I_{x>0}. \tag{4.36}$$

The recursive expression in (4.35) can be written as a function of $\mu^* = E_T\tau$ as

$$(P_I E_I + (1 - P_I)E_R)\mu^* = (1 - P_I)E_T H(\mu^*), \tag{4.37}$$

where $H(\mu^*)$ is given by (4.15). Defining

$$\rho = \frac{(1 - P_I)E_T}{P_I E_I + (1 - P_I)E_R}, \tag{4.38}$$

we get

$$\mu^* = \rho H(\mu^*). \tag{4.39}$$

4.3.2 Gain of a selective transmission scheme

In this section, we analyze asymptotically the advantages of the optimal selective scheme with regard to the nonselective one. To do so, we define the *gain* of a selective transmitter as the ratio of its income rate τ and that of the nonselective transmitter τ_0,

$$G = \frac{\tau}{\tau_0}. \tag{4.40}$$

For the optimal selective transmitter with constant energy profile, combining (4.34) and (4.33), we get

$$\begin{aligned} G =& \frac{\mu^* \mathbb{E}\{E_1(x)\}}{E_T \mathbb{E}\{x\}} = \frac{\mu^* (P_I E_I + (1 - P_I)(E_T + E_R))}{E_T \mathbb{E}\{x\}} \\ =& (1 - P_I)(1 + \rho^{-1}) \frac{\mu^*}{\mathbb{E}\{x\}} = \frac{1 + \rho}{\rho} \frac{\mu^*}{\mathbb{E}\{x|x > 0\}}. \end{aligned} \tag{4.41}$$

In the following, we compute the gain for several importance distributions.

4.3.3 Examples

Let us illustrate some examples taken from the constant energy profile as follows:

- **Uniform Distribution**: Substituting (4.19) into (4.39), we get

$$\mu^* = \frac{1}{4} \rho (2 - \mu^*)^2, \tag{4.42}$$

which can be solved for μ^* as

$$\mu^* = 2 \left(\frac{1 + \rho}{\rho} - \sqrt{\left(\frac{1 + \rho}{\rho} \right)^2 - 1} \right) \tag{4.43}$$

(the second root is higher than 2, which is not an admissible solution). Note that, for $\rho = 4$, we get $\mu^* = 1$, which agrees with the observation in Fig.4.2(a).

Therefore, the gain is given by

$$G = 2 \frac{1 + \rho}{\rho} \left(\frac{1 + \rho}{\rho} - \sqrt{\left(\frac{1 + \rho}{\rho} \right)^2 - 1} \right). \tag{4.44}$$

- **Exponential**: Using (4.22) we find that μ^* is the solution of

$$\mu^* = a W(\rho), \tag{4.45}$$

where $W(x) = y$ is the real-valued Lambert's W function, which solves the equation $ye^y = x$ for $-1 \leq y \leq 0$ and $-1/e \leq x \leq 0$ [Corless et al., 1996]. Thus,

$$G = (1 + \rho^{-1})W(\rho). \tag{4.46}$$

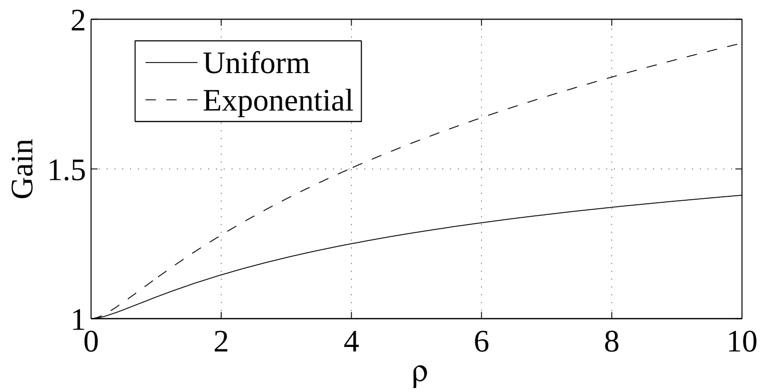


Figure 4.5: Gain of the selective transmission policy under uniform and exponential distributions as a function of ρ.

Fig. 4.5 compares the gain of the uniform and the exponential distributions as a function of ρ. The graphic remarks that, under exponential distributions, the difference between the selective and the nonselective transmission scheme is much more significant. The better performance of the exponential distribution compared to the uniform may be attributed to the tailed shape. We may think that, for a long-tailed distribution, the selective transmitter may be highly selective, saving energy for rare but *extremely important* messages. This intuition is corroborated by the following example.

- **Pareto** (one-sided): For this distribution, (4.25) can be used to conclude that μ^* is the solution of

$$\mu^* = \frac{\rho}{(a-2)(1+\mu^*)^{a-2}}. \tag{4.47}$$

Although for a generic a, this equation does not have an analytical solution (closed-form solutions for specific values of a are possible), it can always be solved numerically. Fig. 4.6 shows the gain of the optimal selective transmission policy under a

Pareto distribution, for different values of parameter a. As stated before, it is corroborated that the gain achieves higher values for a Pareto distribution regarding the other two types of distributions. Besides, for the Pareto distribution, the higher the distribution parameter *a* is, the lower the gain is.

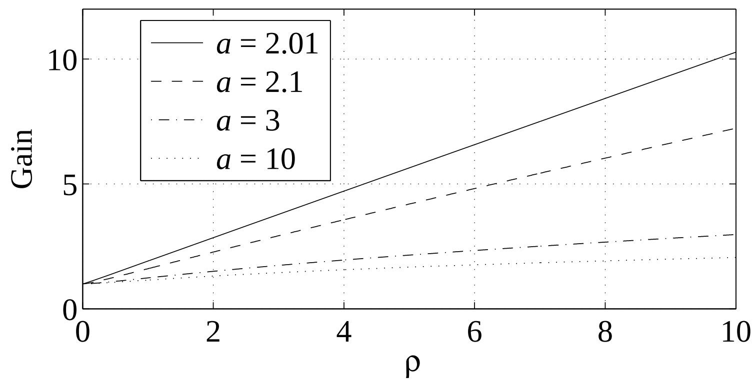


Figure 4.6: Gain of the selective transmission policy under a Pareto distribution, for different values of parameter a. For values higher than 10, the gain is approximately equal to the case $a = 10$.

4.3.4 Bounding the gain of a selective transmitter

We can bound the gain of the optimal selective transmitter on a constant energy profile scenario by noting that, for any $\mu^* \geq 0$ and any importance distribution, $(x-\mu^*)u(x-\mu^*) \leq \frac{x^2}{4\mu^*}$. Therefore,

$$H(\mu^*) = \mathbb{E}\{(x-\mu^*)u(x-\mu^*)|x>0\} \leq \frac{\mathbb{E}\{x^2|x>0\}}{4\mu^*}. \tag{4.48}$$

Using (4.39), we get

$$\mu^* \leq \frac{1}{2}\sqrt{\rho\mathbb{E}\{x^2|x>0\}}. \tag{4.49}$$

Thus, the gain in (4.40) can be bounded as

$$G \leq \frac{\sqrt{\mathbb{E}\{x^2|x>0\}}}{\mathbb{E}\{x|x>0\}}\frac{1+\rho}{2\sqrt{\rho}}. \tag{4.50}$$

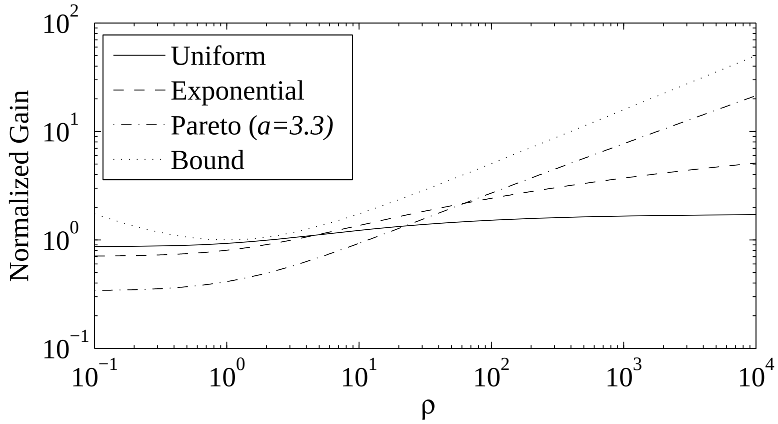


Figure 4.7: Comparison of the normalized gain with the theoretical bound, for different importance distributions.

Fig. 4.7 compares the normalized gain given by

$$\overline{G} = \left(\frac{\sqrt{\mathbb{E}\{x^2|x>0\}}}{\mathbb{E}\{x|x>0\}} \right)^{-1} G \tag{4.51}$$

with the theoretical bound, for different distribution types, in a log-log scale. Note that, for large values of ρ, the bound has the same tendency than the Pareto distribution.

4.3.5 Influence of idle states

The above examples show that the gain of the optimal selective transmitter increases with ρ. By noting that ρ in (4.38) is a decreasing function of P_I and E_I, the influence of idle states becomes clear: as soon as the frequency of idle states or the idle energy expense increases, the gain of the selective transmission scheme reduces. This effect will be observed in the experiments.

4.4 Algorithmic design

4.4.1 Estimating Importance Distributions

To obtain the optimal transmission threshold, the importance distribution of messages is required. However, in many practical scenarios, $p(x_k)$ is either unknown or may change along time. On the other hand, the computation of μ_k for a given value of available energy e must be carried out iteratively. Moreover, the recursions in (4.5) and (4.6) proceed forward, from lower energy values to higher values. This is undesirable because, in practice, the available energy at a given node reduces with time, so we cannot take advantage of previous computations with energy $e = e_{k-1}$ to compute λ_k and μ_k for energy $e = e_k$. To bypass these problems, $p(x_k)$ can be estimated in real time based on available data $\{x_\ell, \ell = 0, \ldots, k\}$ at time k.

We consider an approach based on a parametric estimation of $p(x_k)$ given by the Gamma distribution (see Fig. 4.8)

$$p(x|v,\theta) = x^{v-1}\frac{e^{-x/\theta}}{\theta^v\Gamma(v)}, \qquad x, v, \theta > 0. \tag{4.52}$$

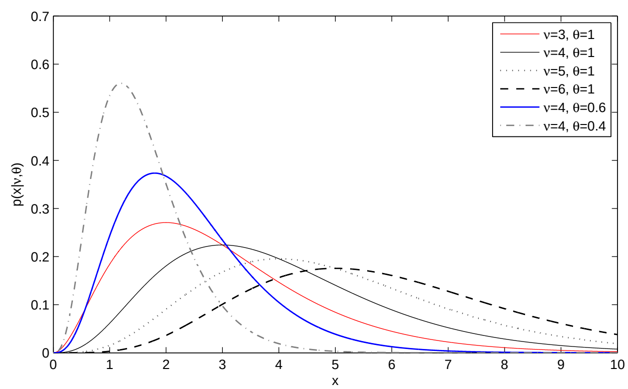


Figure 4.8: Probability density function of the Gamma distribution for different values of parameters v and θ.

Obviously, many other (non) parametric methods can be used to estimate $p(x_k)$, such as the nonparametric estimate given by

$$\mathbb{E}\{(x-\mu)u(x-\mu)\} \approx \frac{1-\alpha^{k+1}}{1-\alpha}\sum_{\ell=0}^{k}\alpha^{k-\ell}(x_\ell-\mu)u(x_\ell-\mu), \tag{4.53}$$

where $\alpha = 0$ if $p(x_k)$ does not depend on k (i.e., the importance distribution is stationary), and $0 < \alpha < 1$ otherwise.

However, the main reason for actually selecting (4.52) is that it does not require to store all importance values at each time, and so, the estimation is not too much expensive computationally. Thresholds can be computed analytically by using the upper and lower incomplete gamma distribution ($\Gamma(a,x)$ and $\gamma(a,x)$, respectively),

$$\begin{aligned}
\mathbb{E}\{(x-\mu)u(x-\mu)\} &= \frac{1}{\theta^v\Gamma(v)}\int_{\mu}^{\infty}(x-\mu)x^{v-1}e^{-x/\theta}dx \\
&= \frac{1}{\theta^v\Gamma(v)}\int_{\mu}^{\infty}x^{v}e^{-x/\theta}dx - \frac{\mu}{\theta^v\Gamma(v)}\int_{\mu}^{\infty}x^{v-1}e^{-x/\theta}dx \\
&= \frac{\theta}{\Gamma(v)}\int_{\mu/\theta}^{\infty}x^{v}e^{-x}dx - \frac{\mu}{\Gamma(v)}\int_{\mu/\theta}^{\infty}x^{v-1}e^{-x}dx \\
&= \frac{1}{\Gamma(v)}\left(\theta\Gamma(v+1,\mu/\theta) - \mu\Gamma(v,\mu/\theta)\right) \\
&= \frac{1}{\Gamma(v)}\left(\theta\left(\Gamma(v+1) - \gamma(v+1,\mu/\theta)\right) - \mu\left(\Gamma(v) - \gamma(v,\mu/\theta)\right)\right).
\end{aligned} \tag{4.54}$$

Let us define

$$\hat{m}_k = \frac{1}{k+1}\sum_{\ell=0}^{k} x_\ell,, \tag{4.55}$$

$$\hat{n}_k = \frac{1}{k+1}\sum_{\ell=0}^{k} \ln(x_\ell). \tag{4.56}$$

While the maximum-likelihood (ML) estimate $\hat{\theta}_k$ (ML estimate of θ at time k) is calculated as

$$\hat{\theta}_k = \frac{\hat{m}_k}{\hat{v}_k}, \tag{4.57}$$

the ML estimate of parameter v at time k, denoted by $\hat{v}_k$, can be obtained as the solution of $\ln(\hat{v}_k) - \psi(\hat{v}_k) = \ln(\hat{m}_k) - \hat{n}_k$, where $\psi(\hat{v}_k) = \Gamma'(\hat{v}_k)/\Gamma(\hat{v}_k)$ is the digamma function. Although there is not a closed-form solution for $\hat{v}_k$, it can be approximated as [Maddah et al., 2007]

$$\hat{v}_k \approx \frac{3 - z_k + \sqrt{(z_k-3)^2 + 24z_k}}{12z_k}, \tag{4.58}$$

where $z_k = \ln(\hat{m}_k) - \hat{n}_k$.

If accuracy were critical, closer approximations would be obtained iterating

$$\hat{v}_k \leftarrow \hat{v}_k - \frac{\ln(\hat{v}_k) - \psi\left(\hat{v}_k\right) - z_k}{1/\hat{v}_k - \psi'(\hat{v}_k)}, \tag{4.59}$$

where $\psi'\left(\cdot\right)$ denotes the trigamma function, the derivative of the digamma function (see [Choi and Wette, 1969] for further details).

Note that $\hat{m}_k$ and $\hat{n}_k$ can be computed accumulatively so that the importance sequence x_l is not required to be stored (saving memory resources). Also note that both sums in these equations can be exponentially weighted so as to cope with nonstationary importance distributions as

$$\hat{m}_k = \frac{1-\alpha^{k+1}}{1-\alpha}\sum_{\ell=0}^{k}\alpha^{k-\ell}x_\ell, \tag{4.60}$$

$$\hat{n}_k = \frac{1-\alpha^{k+1}}{1-\alpha}\sum_{\ell=0}^{k}\alpha^{k-\ell}\ln\left(x_\ell\right). \tag{4.61}$$

The design of optimal/efficient algorithms to estimate the importance distributions and calculate the optimal decision threshold is a complex problem that has to be thoroughly addressed. The scheme proposed in this section is a simple implementation, which, besides achieving good performance, can be used to gauge the influence of using estimates instead of the true statistics. Another alternative, considerably less expensive computationally speaking, consists of estimating the optimal threshold function by its asymptotic limit, which is also computed in real time based on the received data. Further details will be exposed in Chapter 5.

4.5 Experiments and results

In this section we test the selective message transmission scheme in a scenario where the node is isolated. As this scenario is quite simple, the next chapter includes a more complex setup where nodes are integrated into a sensor network. Simulations have been conducted using Matlab.

4.5.1 Isolated node

The scenario simulates an isolated energy-limited node. At each time k, the node receives a message of importance x_k randomly generated according to a distribution $p(x)$. This distribution is known and independent of k (stationary case). Next, a decision about transmitting the message is made. Three importance distributions have been considered: uniform, exponential, and Pareto. Distribution parameter a is set to 1.8 and 3.5 for exponential and Pareto distributions, respectively. Samples belonging to the uniform distribution are generated according to $U(0, 10)$. Recall, $x_k = 0$ represents a silent time.

Performance of four different types of sensors is compared as follows:

- *Nonselective sensor* (NS). The threshold is set to $\mu = 0$, so that the node transmits all incoming or generated messages.

- *Optimal selective Transmitter* (OT). Threshold μ is computed according to (4.13) and (4.16). The node knows the importance distribution $p(x)$.

- *Constant threshold Transmitter* (CT). The sensor node establishes a constant threshold, which is set to the asymptotic value of the optimal threshold given by (4.39).

- *Adaptive selective Transmitter* (AT). The threshold is also computed following (4.13) and (4.16). Nevertheless, the node is unaware of $p(x)$ and it uses the estimation strategy exposed in Section 4.4 to know $p(x)$, so that μ is computed according to (4.54).

The initial battery of the sensor is set to $E = 2,000$ units. Energy expenses are also set to $E_T = 4$, $E_R = 1$ and $E_I = 0$ units. A simulation finishes when the node runs out of battery. Results are averaged over 50 simulation runs.

Fig. 4.9 depicts the optimal selective transmitter and the decision-making process given by the optimal transmission decision rule. In case of an affirmative decision, the next forwarder is chosen according to the routing algorithm.

Performance is assessed in terms of the importance sum of all transmitted messages, the mean value of the transmitted importances and the total number of transmitted messages. Results are summarized in Tables 4.1, 4.2 and 4.3.

The first observation is that the nonselective node transmits more messages than any type of selective transmitters: approximately 17% more in the uniform distribution, 32% in the exponential distribution and 47% in the Pareto distribution. Bearing in mind that the NS sensor forwards all the messages it receives, it is hardly surprising that the number

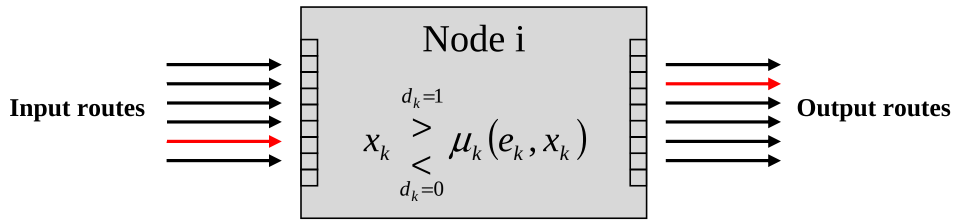


Figure 4.9: Sketch of the optimal selective transmitter.

Table 4.1: Averaged performance of a sensor node considering that importance values are generated according to a uniform importance distribution.

Type of sensor	Avg. Total Imp. Tx $\pm$ std. deviation	Importance mean value	Total Transmitted messages
NS	1988.22 ± 53.17	4.97	400
OT	**2486.03 ± 35.98**	7.48	332.50
CT	2485.22 ± 35.84	7.48	332.22
AT	2480.40 ± 37.87	**7.59**	326.82

of transmitted messages is the same no matter the importance distribution (as opposed to selective transmitters). Nevertheless, on the one hand, the importance sum of all transmitted messages in a NS sensor is the lowest in comparison with the selective transmitters. On the other hand, the mean value of the transmitted messages is lower for the NS transmitter for all types of importance distributions. The mean importance value of the exponential and Pareto importance distributions is conditioned by the parameter selection, since it influences on the threshold, as it was shown in Section 4.3.3. Therefore, the simulated results confirm the less efficient behavior of the NS transmitter. Besides, as selective transmitters maximize the importance sum of all transmitted messages, they provide QoI since the most important messages are always transmitted.

Focusing on the selective transmitters, we observe that OT/CT nodes outperform the AT node. Clearly, estimation errors penalize the AT node performance compared to the optimal. In spite of that, its performance is close to the one achieved by the OT sensor. Furthermore, it always yields a better result than the NS transmitter. With regard to the CT node, results are similar to those of the OT node (differences only appear when the node is

Table 4.2: Averaged performance of a sensor node considering that importance values are generated according to an exponential importance distribution.

Type of sensor	Avg. Total Imp. Tx $\pm$ std. deviation	Importance mean value	Total Transmitted messages
NS	719.47 ± 34.25	1.80	400
OT	**1087.15 ± 43.70**	**3.98**	273.46
CT	1086.85 ± 43.91	**3.98**	272.92
AT	1084.39 ± 42.21	3.94	275.34

Table 4.3: Averaged performance of a sensor node considering that importance values are generated according to a Pareto importance distribution.

Type of sensor	Avg. Total Imp. Tx $\pm$ std. deviation	Importance mean value	Total Transmitted messages
Type NS	262.94 ± 24.20	0.66	400
Type OT	**473.47 ± 38.35**	**2.23**	212.20
Type CT	473.40 ± 38.23	**2.23**	211.82
Type AT	469.06 ± 40.79	2.05	230.30

close to use up its batteries). Performance clearly depends on the importance values of those messages arrived at the node when the battery level is scarce.

With the aim of obtaining a better comparison between both types of selective sensors (OT and CT), their behavior under low battery resources is studied. In this case, the battery level is limited to 13 units, so that the maximum number of possible transmissions is two. Fig. 4.10 illustrates that, when batteries are scarce and the importance of the messages arriving at the sensor is low, the OT sensor slightly outperforms the CT sensor. This is because for small energy values, the optimal transmitter is more sensitive to energy changes.

Study of the influence of frequencies of idle states

Threshold variations as a function of the remaining energy e under the influence of different frequencies of idle states (P_I) are depicted in Fig. 4.11 for an AT sensor.

Reception and idle energy expenses are fixed to the same amount ($E_R = E_I = 1$ units) and the node is initially provided with $E = 2,000$ units. The importance of messages fol-

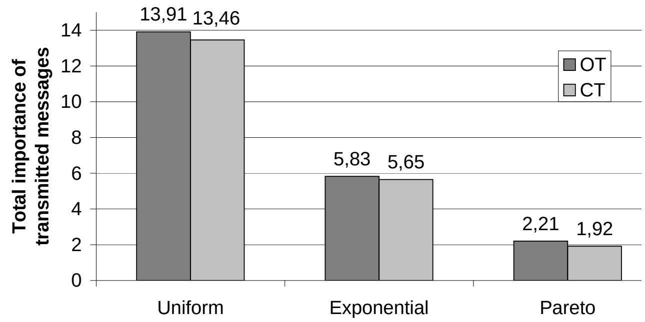


Figure 4.10: Comparison between the optimal selective transmitter and the asymptotically optimal selective transmitter with low battery level.

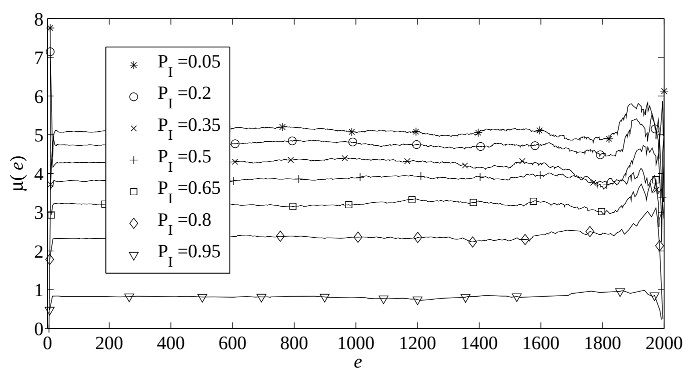


Figure 4.11: Threshold evolution regarding the remaining battery level *e* in an isolated AT sensor node for a uniform importance distribution $U(0, 10)$. Different frequencies of being in idle mode have been considered in a single run.

lows a uniform distribution $U(0, 10)$. As it can be observed, the more frequent the idle states is, the lower the decision threshold is. The node is less selective when the opportunities to send true messages decrease, corroborating the theoretical results presented above. Moreover, for high values of energy e, we observe strong oscillations in threshold μ. This oscillation occurs because during the first time instants, the AT node does not have enough samples to properly estimate the importance distribution. As the number of received messages increases, nearly constant thresholds are obtained and changes only appear when the node's battery is close to use up. The duration of the transitory phase will depend on the specific application. For instance, monitoring activities will not entail a long transitory phase.

The reason is that during most of the time, sensors are reporting a high number of consistent measurement values (the network is typically dense and the environment usually remains unchanged). On the other hand, in applications where nodes are not always collaborative, more time is needed to reach the long-term behavior of the network. A transitory phase might also appear if the importance distribution varies too drastically, since nodes would need some time to learn the new distribution (smooth changes should easily be tracked by the learning algorithm). Regardless of its duration, the impact of the transitory phase on the overall network performance is not necessarily critical, since high importance messages will be always transmitted.

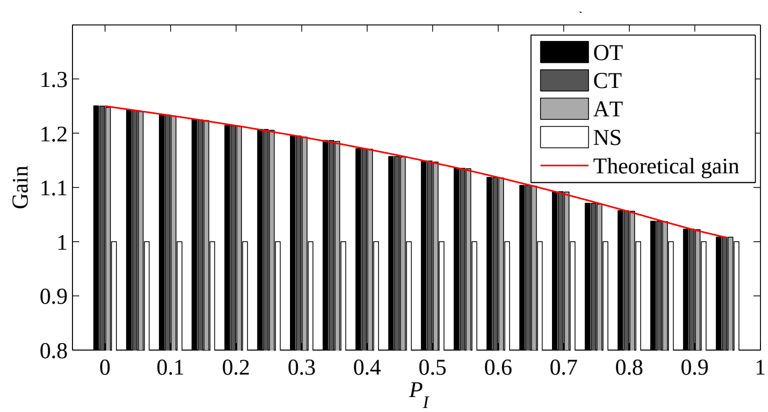


Figure 4.12: Gain of the selective transmitting policy under a uniform importance distribution $U(0, 10)$ for different values of P_I.

Fig. 4.12 shows the gain of the different types of selective transmitters regarding the nonselective transmitter for a uniform importance distribution and for different frequencies of idle states. As mentioned in Section 4.3.5, the gain of the selective transmission scheme decreases as P_I increases. Intuitively, it is easy to see that as P_I approaches one (i.e., the node is in idle mode most of the time), the selective transmitter converges to the NS transmitter. The same behavior is appreciated in the exponential and the Pareto importance distributions (see Fig. 4.13 and 4.14). In these cases, the gain is even higher than in the uniform case, what corroborates the theoretical study.

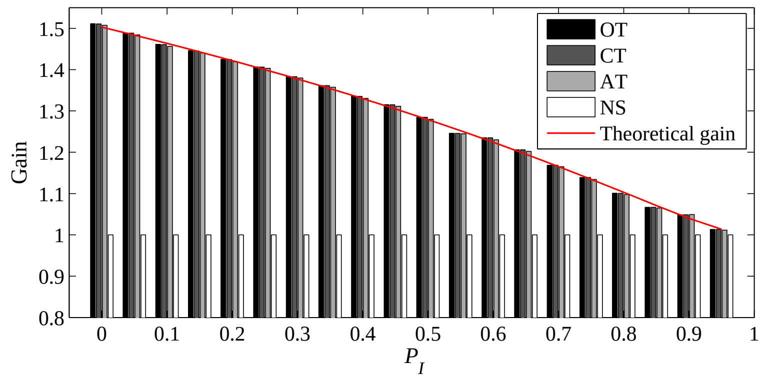


Figure 4.13: Gain of the selective transmission policy under an exponential importance distribution with $a = 1.8$ for different values of P_I.

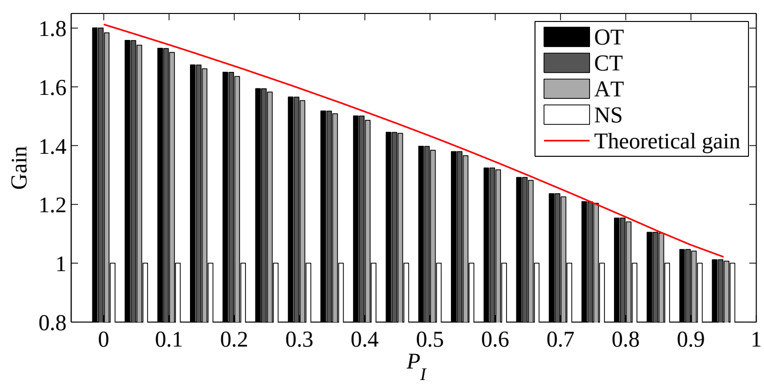


Figure 4.14: Gain of the selective forwarding policy under a Pareto importance distribution with $a = 3.5$ for different values of P_I.

Analysis of different constant energy consumption models

We have also investigated the behavior of the performance of the various transmission strategies for a wide variety of constant energy consumption patterns. The study will help us to explore how our findings are influenced by the relative values of the energy consumptions. First of all, the gain of the aforementioned transmission strategies is analyzed for different values of E_R. Besides considering a uniform importance distribution, the transmission expense is set to $E_T = 4$, the idle expense to $E_I = 1$, and $P_I = 0.5$. Fig. 4.15 shows a decreasing behavior in the gain for all types of selective transmitters when the value E_R

approaches to E_T. This behavior is expected since ρ in (4.38) is a decreasing function of E_R. Note that this result is in agreement with the general assumption made by selective communication strategies (exposed in Chapter 2): benefits of a selective transmission algorithm become apparent when the cost of transmission is much higher than that of reception. On the other hand, the NS transmitter is not affected by the value E_R since it will transmit the incoming messages in any case.

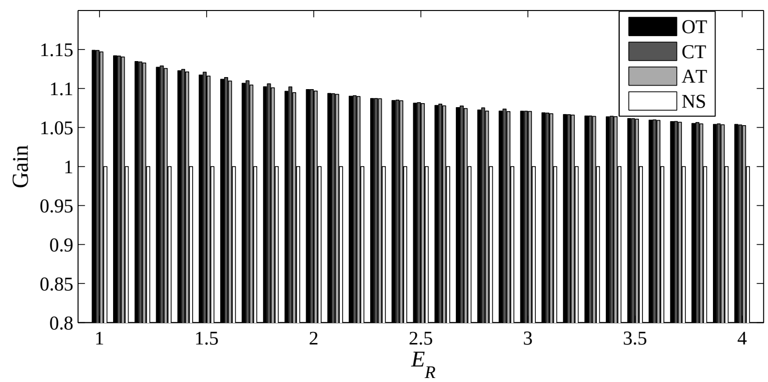


Figure 4.15: Gain of the selective transmission policy under a uniform importance distribution $U(0, 10)$ for different values of E_R and $P_I = 0.5$.

Fig. 4.16 focuses on the OT sensor in order to examine the gain behavior under the influence of the frequency of idle states and for different values of E_R. As it can be expected, as the frequency of idle states and the reception energy expenses increases, the gain of the selective transmission scheme reduces, according to (4.38).

Now, the gain of the selective transmission policy for different values of E_I is studied. Again, we consider a uniform importance distribution, and node state expenses are set to $E_T = 4$, $E_R = 1$, and $P_I = 0.5$. Parameter E_I varies from 0.05 to 1.5, since it was shown in Chapter 2 that energy consumption due to idle listening mode is usually lower than the energy expenditure corresponding to the transmission/reception state. Fig. 4.17 corroborates the idea previously stated in Section 4.3.5: the gain of the different types of selective transmitters reduces as soon as E_I increases because ρ in (4.38) is a decreasing function of E_I.

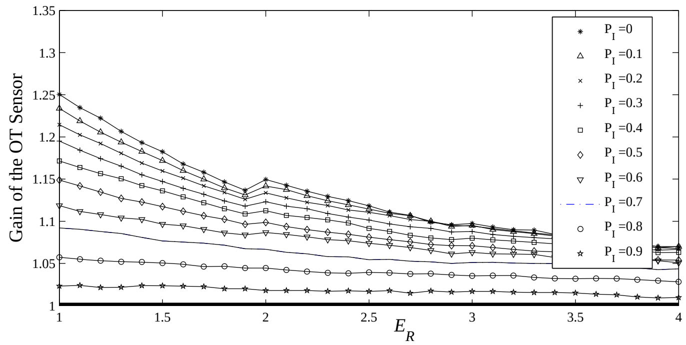


Figure 4.16: Gain of the OT sensor under a uniform importance distribution $U(0, 10)$ for different values of E_R and P_I.

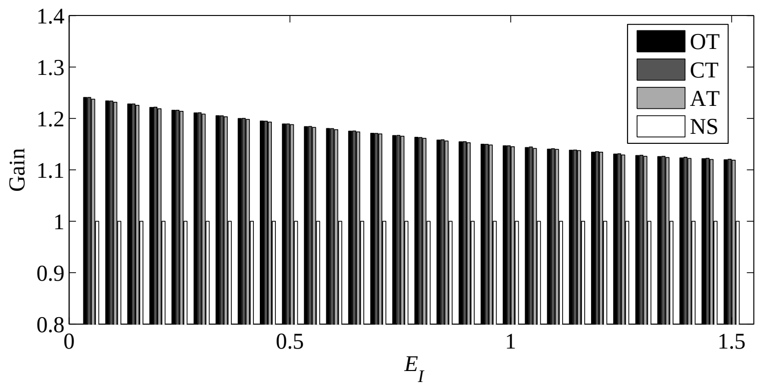


Figure 4.17: Gain of the selective transmission policy under a uniform importance distribution $U(0, 10)$ for different values of E_I and $P_I = 0.5$.

Analysis under different importance distribution patterns

Finally, the evolution of the transmission threshold under different importance distribution patterns also allows us to illustrate the behavior of the selective transmitter.

Firstly, a *bimodal importance distribution* is analyzed. The importance distribution arriving to the node follows a bimodal uniform distribution ($U(1, 6)$ and $U(10, 15)$, whose PDF is given by $p(x) = \frac{1}{10}(u(x-1) - u(x-6)) + \frac{1}{10}(u(x-10) - u(x-15))$). The node is provided with $E = 2,000$ units. Energy expenses are set to $E_T = 4$, $E_R = 1$ and $E_I = 0$ units. The decision threshold evolution as a function of the battery level *e* for an AT node is depicted in Fig. 4.18 (only a sampled set of importance values is shown).

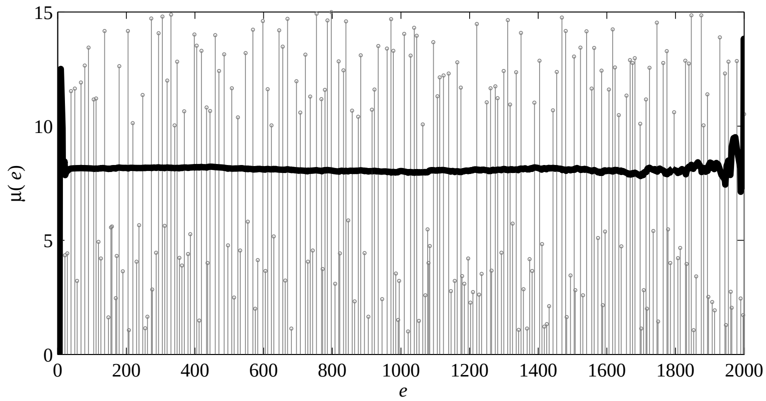


Figure 4.18: Threshold evolution regarding the remaining battery level *e* in an isolated AT sensor node for a bimodal uniform importance distribution.

From the analysis of the plot, it can be observed that low importance messages are discarded in favor of high importance messages. Only those messages whose importances are generated according to $U(10, 15)$ are transmitted because they contribute to maximize the importance sum of the transmitted messages. The same behavior will appear under different bimodal importance distributions. A direct consequence of this behavior is the better performance of the selective transmitter versus the nonselective regarding the metric to maximize (see Table 4.4, whose results are averaged over 50 experimental runs). The selective transmission policy (AT node) gets 30% higher importance sum than the achieved by the nonselective node, assuring QoI since the most importance messages are transmitted (remark also the higher importance mean value).

Table 4.4: Averaged performance of a sensor node considering that importance values are generated according to a uniform bimodal distribution.

Type of sensor	Avg. Total Imp. Tx $\pm$ std. deviation	Importance mean value	Total Transmitted messages
NS	3190.86 ± 90.55	7.98	400
AT	**4159.05 $\pm$ 59.94**	**12.49**	333.04

Secondly, a *non-stationary importance distribution* is studied. In this case, the importance follows a $U(10, 15)$ distribution but it changes to a $U(1, 6)$ distribution at a certain time epoch. The threshold evolution regarding the remaining battery level for an AT node provided with $E = 4,000$ units is depicted in Fig. 4.19.

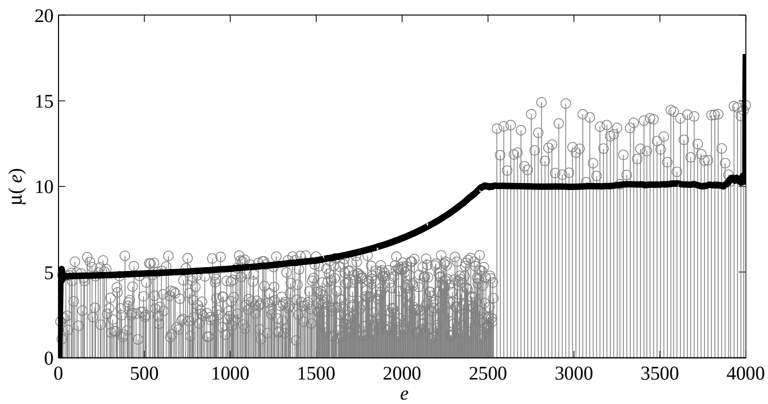


Figure 4.19: Threshold evolution regarding the remaining battery level *e* in an isolated AT sensor node for a non-stationary importance distribution.

Importance values arriving to the node are also represented. Initially, the decision threshold is set according to the received importance values. Nevertheless, as soon as the node notices a change in the importance distribution, the threshold decreases to adapt to the new received importance values. Note, however, the appearance of a transitory phase when the importance distribution changes, as the node needs some time to learn the new distribution. Also, remark the higher concentration of received importance samples during the initial phase of the threshold adaptation because the node rejects the transmission of any message.

4.6 Concluding remarks

This chapter has exposed an optimal selective transmission policy in WSNs as an energy-efficient scheme for data transmission that also provide QoI. Messages, which were assumed to be graded with an importance value and which could be eventually discarded, were transmitted by sensor nodes according to a transmission policy, which considered consumption patterns, available energy resources in nodes, the importance of the current message and the statistical description of such importances.

The optimal selective transmitter was derived, leading to an expression for the optimal decision that turned out to compare the received importance with a transmission threshold, whose optimal value varied with time. Under certain simplifying operating conditions, a constant transmission threshold, which did not change along time and entailed asymptotic optimality, was also developed and closed-form expressions were obtained. Moreover, the gain of the selective transmission policy compared to a nonselective one was quantified and it was proved to have a strong dependence on the energy expenses, the frequency of idle states and the statistical importance distribution. Finally, for cases were the importance distribution of messages was unknown or it varied with time, an adaptive algorithm that caught this distribution on-the-fly and based on the the received messages was proposed.

The study has also motivated the application of the selective communication model to an evaluation case: an isolated node. Numerical results validated the analytical claims and corroborated that the selective transmission scheme clearly outperforms the nonselective one, even when idle states are considered. Results also evidenced that the simplified developed designs obtained a performance close to the optimal transmitter.

Besides the theoretical value of this work: (i) the developed schemes can eventually be incorporated into many existing routing protocols; and (ii) the approach can also be easily integrated with a variety of existing data collection approaches, including schemes that support in network data aggregation.

Chapter 5

A Generalization: Optimal Selective Forwarding

Chapter 4 introduced, from theoretical considerations, an optimal selective transmission policy in WSN as an energy-efficient scheme for data transmission. Assuming that messages have an importance value (apart from being independent among themselves) and based on energy consumption patterns and the availability of energy resources in a node, the selective transmission model optimizes the communication performance of each node considered individually. However, nodes do not behave independently but they take part in a sensor network. Hence, as the selective transmission scheme does not pay attention to the final destination of the transmitted messages, it does not guarantee global performance of the sensor network, measured in terms of the quantity and quality of those messages actually arriving to the sink.

The selective transmission model offers powerful insights and guidelines for the design of schemes able to exploit the trade-off between the importance of messages and energy consumption. However, it does not allow the transmission policy of a given node to depend on parameters of other nodes. As nodes are integrated into a sensor network, it may be useful to incorporate information coming from the neighborhood (or the sink) into the statistical model. Generalizing the model to allow the use of information from other nodes and analyzing the impact of using nonlocal information on the behavior of the network are the main goals of this chapter. To do so, we develop optimal forwarding schemes for three different scenarios: 1) when sensors maximize the importance of *their own* transmitted messages (which basically coincides with the setup in Chapter 4, though using a more general energy consumption model); 2) when sensors maximize the importance of their messages that are actually *retransmitted* by their neighbors; and 3) when sensors maximize the importance of the messages that successfully *arrive to the sink*. Upon properly selecting the formulation, all three cases can be tackled in parallel. The motivation to consider those three scenarios is twofold. First, since each scenario requires different operating conditions, designers can chose the one that best fits their WSN at hand. Second, by comparing the importance performances of the different schemes, the impact of accessing to nonlocal information can be evaluated.

The design of the selective transmission policy was formulated as a stochastic sequential decision problem, proposing a mathematical model that, as we stated in the previous chapter, is a particular case of a MDP [White, 1993] [Puterman, 2005]. The application of MDP models to sequential decisions in WSNs has attracted recent attention in the literature, as it was mentioned in Section 1.2. Nevertheless, the approach presented in Chapter 4 was content-driven: the importance value is used to decide whether transmit or discard a message, so that the accumulated importance of all transmitted messages is maximized. In this chapter, however, we will raise the sequential decision problem from a MDP framework.

Regarding practical implementations, it will turn out that the optimal forwarding scheme is fairly simple: the decision maker must compare the importance of the received message with a time-variant threshold. Furthermore, under some stationarity conditions, a constant threshold can be nearly optimal and can be estimated adaptively. The results obtained in this chapter generalize those exposed in Chapter 4 because not only are two additional scenarios (optimality criteria) considered, but also the assumptions are less restrictive. Especially important is the generalization of the results to stochastic energy costs. Moreover, the adaptive/suboptimal schemes are more robust and require less a priori information than those proposed in the previous chapter.

From a generalization point of view, it is worth noting that although the schemes in this chapter solve well-defined problems and are derived using a self-contained formulation, they can be adapted to address problems different than those specifically considered in the thesis.

For example, our approach can be easily integrated with a variety of existing data collection approaches, including schemes that support in network data aggregation. On the other hand, although the chapter has a strong theoretical component, the results are also useful from a practical point of view. Because not only can they provide basic guidelines for the design of future systems, but also the developed schemes can eventually be incorporated into many existing routing protocols.

The chapter is organized as follows: Section 5.1 describes some additional remarks about the sensor model to adapt the notation to MDP terminology. The optimization problem formulated in this chapter is solved in Section 5.2. Assuming that the distribution of importances is stationary and that the available energy is large, an asymptotically optimal scheme that gives rise to a constant threshold that does not vary along time is also developed. Adaptive methods to estimate the forwarding thresholds and that do not require the knowledge of the importance distribution are proposed in Section 5.3. Theoretical results will be complemented with numerical simulations in Section 5.4. Results not only will corroborate the theoretical claims but also will help us to quantify the gains of implementing the selective forwarding schemes for a broader range of practical scenarios and the impact of nodes accessing to nonlocal information. Conclusions in Section 5.5 wrap-up this chapter.

5.1 Additional remarks about the sensor model

In this section, we make some additional remarks to adapt the sensor model proposed in Chapter 2 to the MDP framework, at the same time that we include some generalizations.

5.1.1 State vector

Besides e_k and x_k, the node may use additional information to make decisions: this includes information about the packet (e.g., the packet length, which could be relevant to estimate the energy cost of forwarding it) and some data about the state or the eventual actions of neighboring nodes (e.g., information about the forwarding policy of other nodes). All this additional information (together with x_k) is collected into vector $\mathbf{z}_k$. Following a usual terminology in MDP models, the node state vector is defined as $\mathbf{s}_k = (e_k, \mathbf{z}_k)$; i.e., the state vector contains all and only the information that is available at the node to make a decision at time k. The set of all possible states is denoted as $\mathcal{S}$.

5.1.2 Actions and policies

At time k, the sensor must make a decision d_k about transmitting ($d_k = 1$) or discarding ($d_k = 0$) the current message. A forwarding policy $\pi = \{d_1, d_2, \ldots\}$ at a given node is a sequence of decision rules, which are functions of the state vector; i.e.,

$$d_k = d_k(\mathbf{s}_k) = d_k(e_k, \mathbf{z}_k). \tag{5.1}$$

5.1.3 State dynamics

Each node consumes energy at each time epoch according to the stochastic energy consumption model given by (2.5).

With respect to the other component of the state vector, $\mathbf{z}_k$, we assume that it is a statistically independent sequence, and independent of e_{k-n} or d_{k-n}, for any $n > 0$. Our goal is to use the previous assumptions to characterize the probability of any state transition from k to $k+1$. More specifically, we want to find $p(\mathbf{s}_{k+1}|\mathbf{s}_k, d_k)$, which denotes the probability of reaching the state s_{k+1} given that at time k the state was s_k and the decision made was d_k. To do so, let $p_{0,k}$, $p_{1,k}$ and p_{k+1} denote the probability density functions of $c_{0,k}$, $c_{1,k}$ and $\mathbf{z}_{k+1}$, respectively. Taking into account that the energy consumed during time $k+1$ is $e_k - e_{k+1}$ and that the energy dynamic is given by (2.5), the transition probability $p(\mathbf{s}_{k+1}|\mathbf{s}_k, d_k)$ can be expressed as

$$p(\mathbf{s}_{k+1}|\mathbf{s}_k, d_k) = \left(d_k p_{1,k}(e_k - e_{k+1}|\mathbf{z}_{k+1}) + (1-d_k)p_{0,k}(e_k - e_{k+1}|\mathbf{z}_{k+1})\right) p_{k+1}(\mathbf{z}_{k+1}). \tag{5.2}$$

In other words, if $d_k = 1$, then $p_{1,k}(e_k - e_{k+1}|\mathbf{z}_{k+1})p_{k+1}(\mathbf{z}_{k+1})$; while if $d_k = 0$, then $p_{0,k}(e_k - e_{k+1}|\mathbf{z}_{k+1})p_{k+1}(\mathbf{z}_{k+1})$. Although for the theoretical analysis we assume that the distributions $p_{0,k}$, $p_{1,k}$ and p_{k+1} are known, we will see that only some of its statistics, which may be estimated from data, are required to implement the selective forwarder.

5.1.4 Rewards

Let $q_k \in \{0, 1\}$ denote the *success index*: a binary variable taking value 1 if the transmission is successful, and zero otherwise. With $u(\cdot)$ standing for the Heaviside step function (with the convention $u(0) = 1$), the *reward* at time k for a node that decides to transmit a message will be

$$r_k = x_k q_k u(e_k - c_{1,k}). \tag{5.3}$$

The “success” of a transmission can be measured in different ways. In the thesis we consider three different measures:

- *Global success index.* Since each message must travel through several nodes before arriving to destination, the transmission of a message is completely successful ($q_k = 1$) if the message arrives to the sink, and zero otherwise.

- *Local success index.* If the transmitting node does not have a way to know if the message arrives to the sink, the global success index is not accessible. However, it may be the case that the transmitting node may know if the neighboring node receiving the message forwards it to other nodes or not (by overhearing, or because the neighboring node returns a confirmation message). The local success index is $q_k = 1$ if a neighboring node forwards the message, and zero otherwise.

- *Zero-order success index.* As a degenerate case, we can take any transmission as successful, so that $q_k = 1$ in any case. This amounts to say that every node maximizes the importance of its own transmitted messages, which is the problem dealt in Chapter 4.

In summary, if d_k denotes the decision at node i, (5.3) states that the node receives a reward equal to the message importance if $d_k = 1$ (the node decides to transmit the message), $q_k = 1$ (the transmission is successful) and $e_k \geq c_{1,k}$ (the node has enough energy for the transmission). Otherwise, the reward is zero. In all three previous cases we have assumed that when a node transmits a message, the message is always received by the destination. This free-loss assumption can be accurate when losses are extremely small or when nodes implement ARQ schemes. Nevertheless, transmission losses can be easily accommodated in (5.3). In fact, the only modification is to scale q_k by $(1 - p_k^{loss})$, where p_k^{loss} stands for the packet loss probability.

The figure of merit to design the selective forwarder will be given by the accumulated importance of all messages *successfully* transmitted by nodes. Accordingly, the total reward up to time k is defined as

$$t_k = \sum_{i=0}^{k} d_i r_i = \sum_{i=0}^{k} d_i q_i x_i u(e_i - c_{1,i}). \tag{5.4}$$

The selective forwarding policy is chosen in order to maximize the total expected reward, defined as

$$\mathbb{E}\{t_\infty\} = \mathbb{E}\left\{\lim_{k\to\infty} t_k\right\}. \tag{5.5}$$

Note that, since nodes have limited energy resources, the sum in (5.5) only contains a finite number of nonzero values (eventually, for some k, $e_k < \min_k c_{1,k}$, and $\forall k' \geq k$, we have $r_{k'} = 0$).

5.2 OPTIMAL SELECTIVE FORWARDING

5.2.1 Markov Decision Process

The tuple defined by $(\mathcal{S}, \mathcal{A}, P, r)$, where $\mathcal{S}$ is the set of states, $\mathcal{A} = \{0, 1\}$ is the set of possible decisions (actions), P is the transition probability measure given by (5.2) and r is the reward function, has the structure of a MDP. Moreover, since the action set $\mathcal{A}$ is finite, an optimal policy exists and it is Markovian. This means that there is an optimal policy such that, at any time k, the decision rule only depends on the state $\mathbf{s}_k$ [Puterman, 2005]. Therefore, the sensor does not need to save in memory the state history to make optimal decisions.

The following result, which provides an optimal selective forwarder, can be derived using some standard results from MDP models. Our proof is, however, self-contained. All expectations in the following are taken over $\mathbf{z}_k$, $c_{0,k}$, $c_{1,k}$ and q_k (which are the primary random variables in the model), unless otherwise stated through the conditional operators.

Theorem 5 *Let $\{\mathbf{z}_k, k \geq 0\}$ be a statistically independent sequence of importance values, and e_k the energy process given by* (2.5). *Consider the sequence of decision rules in the form*

$$d_k = u(Q_k(e_k, \mathbf{z}_k)x_k - \mu_k(e_k, \mathbf{z}_k)), \tag{5.6}$$

where $Q_k(e_k, \mathbf{z}_k) = \mathbb{E}\{q_k u(e_k - c_{1,k})|e_k, \mathbf{z}_k\}$ *and threshold* μ_k *is defined recursively through the pair of equations*

$$\mu_k(e, \mathbf{z}_k) = \mathbb{E}\{\lambda_{k+1}(e - c_{0,k}) - \lambda_{k+1}(e - c_{1,k})|\mathbf{z}_k\} \tag{5.7}$$

$$\lambda_k(e) = \left(\mathbb{E}\{\lambda_{k+1}(e - c_{0,k})\} + \mathbb{E}\{(Q(e, \mathbf{z}_k)x_k - \mu_k(e, \mathbf{z}_k))^+\}\right) u(e), \tag{5.8}$$

with $(z)^+ = zu(z)$*, for any* z*.*

Sequence $\{d_k\}$ *is optimal in the sense of maximizing* $\mathbb{E}\{t_\infty\}$ *(with* t_∞ *given by (5.5)) among all sequences in the form* $d_k = d_k(e_k, \mathbf{z}_k)$*.*

The auxiliary function $\lambda_k(e)$ *represents the increment of the total importance that can be expected at time* k*, i.e.,*

$$\lambda_k(e) = \sum_{i=k}^{\infty} \mathbb{E}\{d_i q_i x_i u(e_i - c_{1,i})|e_k = e\}. \tag{5.9}$$

Proof See Appendix B.1.

It is interesting to rewrite (5.6) as $d_k = u\left(Q_k(e_k, \mathbf{z}_k) - \mu_k(e_k, \mathbf{z}_k)/x_k\right)$, which expresses the node decision as a comparison of Q_k with a threshold inversely proportional to the importance value x_k. Remark that this result is in agreement with the transmission rule based on decision theory (3.3) obtained in Chapter 3.

Note that (5.7) and (5.8) do not state a forward recursion (λ_{k+1} vs. λ_k) but a backward recursion (λ_k vs. λ_{k+1}). This makes the direct application of these equations impossible in a general non-stationary environment, because to compute λ_0 the importance distribution $\forall k$ should be known at time $k = 0$. The boundary conditions determining the solution to these recursive equations are given by $\lambda_k(e) = 0$, for any k and any $e < 0$, which are implicit in the factor $u(e)$ in (5.8).

Theorem 5 is general and holds for any energy cost and importance distributions, but it does not provide a clear intuition about the impact of the available energy and the distribution of x_k on the design of the optimal forwarding scheme. Due to this, and as it was done for the selective transmitter, in the reminder of this chapter we will pay attention to several particular cases that will lead us to tractable closed-form solutions and useful insights.

5.2.2 Stationarity

If the statistical distributions of $\mathbf{z}_k$, $c_{0,k}$ and $c_{1,k}$ do not depend on k, then μ_k does not depend on k [c.f. (5.7) and (5.8)]. In this case, the following result can be shown:

Theorem 6 *Under the conditions of Theorem 5, if the following conditions hold: (i) the statistical distribution of $\mathbf{z}_k$, $c_{0,k}$ and $c_{1,k}$ is independent of k; (ii) $P(c_{i,k} > \epsilon) = 1$, for $i = 0, 1$, some $\epsilon > 0$ and any $k \geq 0$; and (iii) $Q_k(e, \mathbf{z}) = Q(e, \mathbf{z})$ (i.e., Q_k does not depend on k), then the sequence of decision rules*

$$d_k = u(Q(e_k, \mathbf{z}_k)x_k - \mu(e_k, \mathbf{z}_k)), \tag{5.10}$$

where

$$\mu(e, \mathbf{z}_k) = \mathbb{E}\{\lambda(e - c_{0,k})|\mathbf{z}_k\} - \mathbb{E}\{\lambda(e - c_{1,k})|\mathbf{z}_k\} \tag{5.11}$$

$$\lambda(e) = \left(\mathbb{E}\{\lambda(e - c_{0,k})\} + \mathbb{E}\{(Q(e, \mathbf{z}_k)x_k - \mu(e, \mathbf{z}_k))^+\}\right) u(e), \tag{5.12}$$

is optimal in the sense of maximizing $\mathbb{E}\{t_\infty\}$ (with t_∞ given by (5.5)), among all sequences in the form $d_k = d_k(e_k, \mathbf{z}_k)$.

Proof See Appendix B.2.

Theorem 6 implies that, under stationarity assumptions, μ_k and λ_k do not depend on k, so that the optimal policy is characterized by a the pair of functions (5.11) and (5.12). But as it was remarked for the selective transmitter, the stationarity assumption, strictly speaking, is not true. However, from a computational point of view, the stationarity assumption is a good alternative to make the design of forwarding policies tractable.

5.2.3 Asymptotic analysis: constant threshold

Experimental work in Chapter 4 shows that, for large values of available energy e and for $Q(e, \mathbf{z}) = 1$ (i.e. for situations where neighboring nodes always transmit the incoming messages), the optimal threshold converges to a constant value and the expected reward tends to grow linearly. Both behaviors are closely related because, as (5.7) shows, the optimal threshold is the difference between two expected rewards. This situation can also be observed when $Q(e, \mathbf{z})$ does not depend on e, so that we can write $Q(\mathbf{z}) = Q(e, \mathbf{z})$. In this section, we discuss the asymptotic behavior of any selective forwarder in the stationary case. To do so, we prove the following:

Theorem 7 *Assume that the conditions of Theorem 6 hold and* $\mathbb{E}\{x_k\} < \infty$. *If* $\lim_{e\to\infty} \mu(e, \mathbf{z})$ *and* $\lim_{e\to\infty} Q(e, \mathbf{z})$ *exist, then*

$$\lim_{e\to\infty} \mu(e, \mathbf{z}) = (\mathbb{E}\{c_1|\mathbf{z}\} - \mathbb{E}\{c_0|\mathbf{z}\})\tau, \tag{5.13}$$

where τ *is a solution of*

$$\mathbb{E}\{c_0\}\tau = \mathbb{E}\{(Q(\mathbf{z})x - (\mathbb{E}\{c_1|\mathbf{z}\} - \mathbb{E}\{c_0|\mathbf{z}\})\tau)^+\}. \tag{5.14}$$

Moreover, if $\mathbb{E}\{c_1|\mathbf{z}\} \geq \mathbb{E}\{c_0|\mathbf{z}\}$*, for any* $\mathbf{z}$*, this solution is unique.*

Proof See Appendix B.3.

An important consequence of Theorem 7 is that, if $\lim_{e\to\infty} \mu(e, \mathbf{z})$ exists, it must be equal to (5.13). The main idea behind the selective forwarding algorithm consists of replacing the optimal rules in (5.10) - (5.12) by their asymptotic approximations based on (5.13) and (5.14). Experimental work in Chapter 4 suggested that this is a good choice provided that there is enough energy for a reasonable number of transmissions. If the node has battery for only a few transmissions, the forwarding threshold should start to oscillate and decreases in some way defined by (5.10) and (5.11), but the computational cost of computing such threshold is high. The design of computationally efficient forwarding policies for low batteries is an open issue.

Thus, (5.13) is the basis of the adaptive procedure proposed in the next section.

5.3 Parameter estimates

5.3.1 Estimating asymptotic thresholds

The optimal threshold depends on the distribution of message importances, which may be unknown in practice. To bypass this problem, apart from estimating it (which was the solution proposed in Chapter 4), we can try to estimate parameter τ in (5.14) and replace the optimal threshold function by its asymptotic limit. Parameter τ can be estimated in real time based on the available information at time k: $\{(\mathbf{z}_\ell, q_\ell), \ell = 0, \ldots, k\}$.

Defining the mean energy difference

$$\Delta(\mathbf{z}) = \mathbb{E}\{c_1|\mathbf{z}\} - \mathbb{E}\{c_0|\mathbf{z}\}, \tag{5.15}$$

we can estimate the expected value on the right-hand side of (5.14) as

$$\mathbb{E}\{(Q(\mathbf{z})x - \Delta(\mathbf{z})\tau)^+\} \approx m_k, \tag{5.16}$$

where

$$m_k = \frac{1}{k}\sum_{i=1}^{k}(Q(\mathbf{z}_i)x_i - \Delta(\mathbf{z}_i)\tau)^+ = \left(1 - \frac{1}{k}\right)m_{k-1} + \frac{1}{k}(Q(\mathbf{z}_k)x_k - \Delta(\mathbf{z}_k)\tau)^+. \tag{5.17}$$

According to (5.14), we can then estimate τ at time k as $\tau_k = m_k/\epsilon_0$, where $\epsilon_0 = \mathbb{E}\{c_0\}$. Using (5.17) we get

$$\tau_k = \left(1 - \frac{1}{k}\right)\tau_{k-1} + \frac{(Q(\mathbf{z}_k)x_k - \Delta(\mathbf{z}_k)\tau)^+}{k\epsilon_0}. \tag{5.18}$$

Unfortunately, the above estimate is not feasible because the right-hand side depends on τ, which is unknown. But we can replace it by τ_{k-1}, so that

$$\tau_k = \left(1 - \frac{1}{k}\right)\tau_{k-1} + \frac{(Q(\mathbf{z}_k)x_k - \Delta(\mathbf{z}_k)\tau_{k-1})^+}{k\epsilon_0}. \tag{5.19}$$

If the mean energy difference $\Delta(\mathbf{z})$ is unknown, it can be estimated from data. Making the simplifying assumption that energy cost does not depend on $\mathbf{z}$ (which may be realistic, for instance, if $\mathbf{z}$ only contains the importance value), it can be estimated as the difference of the average costs of past decisions. For instance, $\mathbb{E}\{c_1\} \approx \left(\sum_{i=1}^{k} d_i c_1^i\right) / \left(\sum_{i=1}^{k} d_i\right)$.

5.3.2 Estimating the success index

A simple estimate of the selective communication policy $Q_k(e_k, \mathbf{z}_k) = \mathbb{E}\{q_k u(e_k - c_{1,k})|e_k, \mathbf{z}_k\}$ can be derived by assuming that: a) it does not depend on e_k (i.e., the subsequent forward/discard decision made at the receiving node is independent of the energy state at the transmitting node), and b) each node can know about the success of the transmission. When q_k represents the local success index, each node is able to listen to the retransmission of a message that has been previously sent (i.e., each node can observe q_k when $d_k = 1$). Similarly, when q_k represents the global success index, it requires the sink to acknowledge the reception of messages back through the routing path, so as to provide nodes with a set of observations q_k for the estimation algorithm. Following an approach similar to that exposed in Chapter 3, Q_k can be estimated by means of the parametric model

$$Q_k(\mathbf{z}_k, w, b) = P(q_k = 1 | x_k, w, b) = \frac{1}{1 + \exp[-w(x_k - b)]}. \tag{5.20}$$

Note that the only component of $\mathbf{z}_k$ which has some influence on Q_k in (5.20) is x_k. For positive values of w, Q_k increases monotonically with x_k, as expected from the node behavior. We estimate parameters w and b via ML using the observed sequence of neighbor decisions $\{q_k\}$ and importance values $\{x_k\}$, by means of stochastic gradient learning rules

$$w_{k+1} = w_k + \eta(q_k - Q_k(x_k, w_k, b_k))(x_k - b_k) \tag{5.21}$$

$$b_{k+1} = b_k - \eta(q_k - Q_k(x_k, w_k, b_k))w_k, \tag{5.22}$$

where the learning step, η, is a free parameter of the rules.

5.4 Numerical Experiments and Results

In this section we analyze the performance of selective forwarders in different network scenarios through simulation experiments carried out using Matlab. First, we describe some common features of the experimental setup.

1. Initially, we have used a simple deterministic energy model given by three constant and known parameters: E_I, E_R and E_T. According to this, for $x_k > 0$, energy consumption in (2.5) is constant and deterministic, so that $c_{1,k} = E_T + E_R$ and $c_{0,k} = E_R$. On the other hand, if $x_k = 0$, $c_{1,k} = c_{0,k} = E_I$. Again, for simplicity, we assumed that the value of E_R is the same no matter if the data have been taken from the sensing device or received from other node. Energy values are set to $E_T = 4$, $E_R = 1$ and $E_I = 0$.

2. Nodes are homogeneous and initially charged with the same batteries except for the sink, which has unlimited power supply. Nodes keep working until their batteries expire. The network dies when all the sink neighbors have died.

3. Sources are selected at random. Nodes are assumed to have identical transmission radii. They can communicate only if they are within mutual transmission range. As coverage areas are reciprocal and nodes can overhear, nodes are able to update their information estimates. Moreover, remind that each node knows the location of its neighbors, the sink, and itself.

4. Though the selective forwarding strategies can be implemented in any routing algorithm, we have used the greedy forwarding scheme [Karp and Kung, 2000]. This scheme selects the neighbor geographically closest to the sink as the next hop of the message. Although the greedy forwarding algorithm has well-known disadvantages (e.g., when there is a void or the network is sparse), we choose it for simplicity, to minimize the influence of the routing algorithm on the final results. With the same aim, link losses have not been included in the model.

5. Up to our knowledge, there are no other proposals in the literature oriented to maximize the important sum or any related measure. The only exception may be the work in [Lei et al., 2009], which uses the same paradigm (MDP), but it is oriented to a completely different scenario (replenishable sensors) and cannot be expected to have a good behavior in sensors with finite lifetime. Therefore, to evaluate the behavior of the developed schemes, different types of selective nodes are implemented:

   - *Nonselective sensor* (NS). The sensor does not censor any message.
   - *Adaptive selective Transmitter* (AT), which uses the zero-order success index.
   - *Local selective Forwarder* (LF). It computes the forwarding threshold according to (5.7) and (5.8), considering the local success index.
   - *Global selective Forwarder* (GF), which uses the global success index.

   The only information used by nodes to make decisions is the importance value. In other words, $\mathbf{z}_k = x_k$. Moreover, selective sensors compute the forwarding threshold adaptively via (5.19).

6. Performance is assessed in terms of the importance sum of all messages received by the sink (Total Import. Received), the mean value of the received importance (Importance mean value), the number of message receptions at the sink (Number of receptions), and the number of *generated* messages (Number of gen. Messages). The latter amounts to measure the network lifetime.

7. Experimental results are averaged over 50 topologies with different traffic patterns.

5.4.1 Nodes with full information

Chain network

With the aim of illustrating the merits of the selective forwarding policies, we have selected a first simplified setup where 30 nodes are equidistantly placed in a row. Nodes are numbered from 1 to 30 from left to right, being node 30 the sink, located at the end of the chain. Each node can only communicate with its two adjoint neighbors. This simple configuration emulates in a certain way the scenario where nodes placed closer to the sink have more activity than those far-off located (they have to route their own messages and those coming from remote nodes), thus representing a bottleneck in the routing path. In this setting, we assume that selective forwarding nodes (LF and GF) know the forwarding threshold used by their neighbors. Node batteries are initially charged with $3,000$ units. All nodes generate messages whose importance values follow a uniform distribution $U(0,1)$, except for node 29 (the one connected to the sink), which generates importance values according to a $U(1,2)$ distribution. Fig. 5.1 illustrates a sketch of the sensor network deployment.

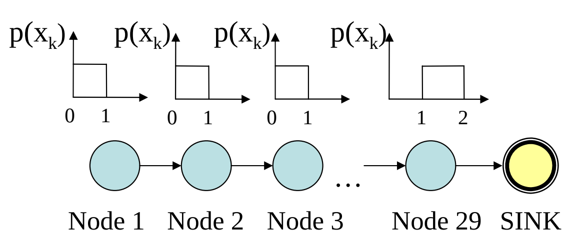


Figure 5.1: Chain network of 30 equally-spaced nodes.

This scenario has been designed ad-hoc to make clear the differences among the diverse tested types of sensors. Numerical results are listed in Table 5.1, and reveal that:

Table 5.1: Averaged performance results in a chain network of 30 equally-spaced nodes. Importance values are generated according to a uniform distribution.

Type of sensor	Total Import. Received	Importance mean value	Number of Receptions	Number of gen. Messages
NS	321.04	0.54	**599.00**	600.00
AT	552.44	0.96	577.42	2623.60
LF	**910.66**	**1.60**	567.58	**21170.40**
GF	**910.66**	**1.60**	567.58	**21170.40**

- All selective communication strategies (AT, LF and GF) outperform nonselective forwarding (NS). Despite the fact that the latter delivers more messages to the sink, the total importance sum is lower (many delivered messages have a low importance value), and so the network lifetime (NS nodes waste energy sending low importance messages).

- The two selective forwarding policies (LF and GF) get around 65% higher importance sum than that achieved by the selective transmission in AT. Also, the higher mean value of the messages received by the sink implies that the selective forwarders are much more selective, what guarantees a level of QoI. This is also reflected in the fact that the number of generated messages is considerably higher for the selective forwarders, enlarging the network lifetime. This is not surprising: AT nodes do not pay attention to the final destination of the messages they transmit, and keep sending messages that will not be delivered to the sink (node 29 generates more important messages, hence tends to reject most messages arriving from other nodes). On the contrary, GF nodes are aware of the higher selectivity of node 29, and inhibit transmissions that they know will not succeed.

- Interestingly, LF and GF results are identical. GF nodes are aware of the higher selectivity of node 29, and inhibit transmissions that will not be successful. LF nodes have no direct access to the threshold set by node 29, but this information is propagated backwards: nodes notice that node 29 is not forwarding messages below a certain threshold and set their own threshold accordingly. This is first appreciated by node

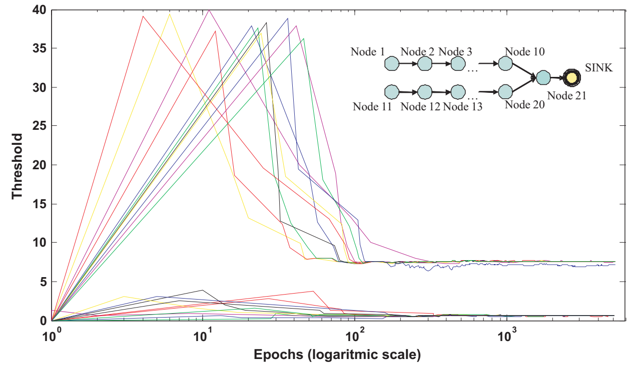
28, and then by node 27, and so on. As a consequence, despite the fact that LF nodes only use local information, the state of node 29 propagates backwards to further nodes with the global effect of removing all nonimportant traffic from the network. Besides, we do not have taken into account the eventual costs due to the propagation of the success index. Clearly, it would be a more realistic implementation and we may hope that LF nodes outperform GF nodes.

Threshold evolution in a double branch network

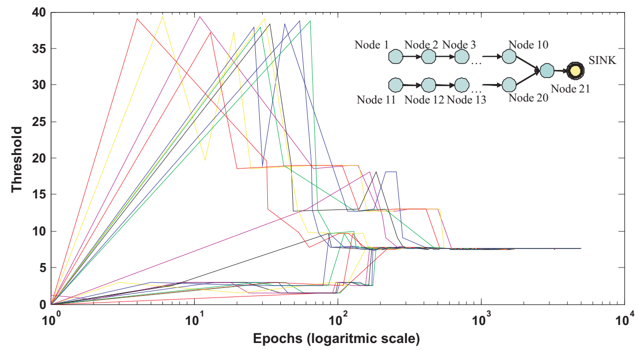
The time evolution of the forwarding threshold in a two-branch network is also illustrative of the behavior of selective sensors. The network sketch is represented at the top-right corner of both plots in Fig. 5.2. Nodes 1-10 and 11-20 form two branches of nodes placed equidistantly in a line. Nodes 10 and 20 are connected to node 21, which delivers all network messages to the sink. While nodes 1-10 generate low importance messages ($U(0, 1)$), nodes 11-20 generate messages of high importance ($U(9, 10)$). Node 21 generates a mixture of both distributions. This scenario represents the arrival of two flows of different prioritized messages at a common node in the routing path to the sink.

Figures 5.2(a) and 5.2(b) plot the threshold evolution for AT and LF nodes, respectively. Fig. 5.2(a) shows that the lines of nodes 1-10 converge to a low threshold, while those of nodes 11-20 converge to a high threshold. The threshold of node 21 converges to a high value, which means that all messages arriving at node 21 from the low importance branch will not be delivered to the sink. Moreover, analyzing the nodes of the low importance branch at a lower scale (see Fig. 5.3), we observe that the furthest node from the sink (which only has to transmit its own generated traffic) sets the lowest threshold. The threshold of subsequent nodes increases slightly as a consequence of receiving messages with clipped importances from their previous nodes. This means that most nodes in the network waste energy receiving messages that will not be forwarded.

In contrast, all nodes in Fig. 5.2(b) follow a similar trend. Thresholds tend to converge to the value established by node 21, as a consequence of the same backward propagation mechanism observed in the chain network. Low prioritized traffic is again removed from the network.



(a)



(b)

Figure 5.2: Decision threshold evolution for Adaptive Transmitters (a) and Local Forwarders (b) as a function of time in a simulation run, represented in a X-axis logarithmic scale. Uniform importance distributions are assumed.

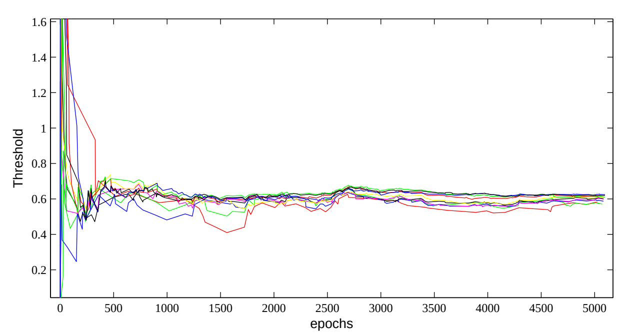
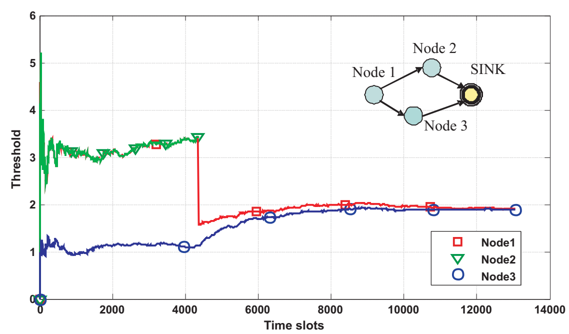


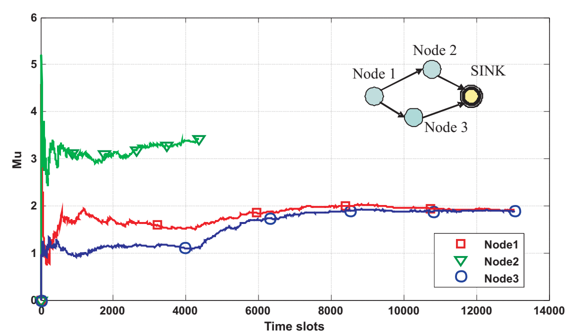
Figure 5.3: Zoom of the decision threshold evolution for Adaptive Transmitters in the branch where messages have low importance.

Threshold evolution after battery depletion

Another simple setup will serve to show how selective forwarders adapt their thresholds to network topology changes. Fig. 5.4 shows the threshold evolution of a sensor network (sketched at the top-right) with 3 nodes and the sink. With the aim of analyzing the adaptive behavior of thresholds, nodes 1 and 3 are charged with more batteries than node 2. Nodes 1, 2 and 3 generate messages according to exponential importance distributions with means $m_1 = 1.59$, $m_2 = 2.57$ and $m_3 = 0.95$, respectively (note that $m_3 < m_1 < m_2$, the specific values of the means not being relevant).



(a)



(b)

Figure 5.4: Decision threshold (a) and mu evolution (b) for Local Forwarders as a function of time in a network topology composed of 4 nodes. Different exponential importance distributions are assumed.

Although node 1 can transmit messages to nodes 2 and 3 (which are linked to the sink), it will do it initially to node 2 (according to the greedy forwarding routing policy). Since nodes are LF, thresholds of nodes 1 and 2 get rapidly coupled (i.e., they converge to the same value); Fig. 5.4(a) illustrates this fact. Once node 2 runs out of battery, node 1 starts routing messages to the sink via node 3, which still has energy. From that point on, node 1 reduces its threshold, because node 3 is less selective, and node 3 adapts its threshold according to the new messages arriving from node 1, which have higher importance values (because $m_3 < m_1$). As a result, nodes 1 and 3 get coupled.

5.4.2 Nodes with incomplete information

In more realistic settings, nodes must acquire the information about neighboring thresholds, either by estimating (learning) it from side information or by paying some cost (energy, bandwidth) to learn it. Here, the aim is to analyze the performance of sensors with incomplete information and compare it with results of sensors with full information (-FI).

The setup is the same linear arrangement of 30 nodes depicted in Fig. 5.1, but with message importances drawn from exponential distributions. The mean of each distribution is taken from the increasingly sorted samples generated randomly from another exponential distribution with mean 2. Nodes manage to get threshold information from their neighbors following two different approaches:

- *Based on learning*. Nodes estimate the parameters of the probability model Q_k in (5.20) using learning rules, (5.21) and (5.22) (-EST). The success index, q_k, of previous transmissions, which is required to apply these rules, can be obtained in different ways: we assume that LF nodes overhear any message forwarding made by a neighboring node, and also, GF nodes receive acknowledgments from the sink whenever a message arrives successfully.

- *Based on feedback*. Nodes transmit threshold values to their neighbors. Since transmitting the threshold every time it changes is energy expensive, we have explored two ways to reduce communication overheads: (i) to send the threshold to all their neighbors every time the current value differs more than a certain fixed amount (denoted by β_μ) from the last transmitted value (-VAR), or (ii) to broadcast the threshold to all neighbors periodically using beacons (-BEAC).

In the experiments, the value of β_μ is set to 3.5, the beacon interval to $2,500$ epochs and the value of η in (5.21) and (5.22) to 0.04 for LF nodes and 0.009 for GF nodes. These values have been adjusted off-line to gauge the potential advantages of schemes relying on incomplete information. The automatic assignment of these parameters, which is certainly important from a practical implementation perspective, goes beyond the scope of this thesis.

Results are summarized in Table 5.2. As expected, the best performance among LF nodes is achieved by LF-FI networks. The approaches that rely on feedback to obtain the thresholds of the neighbors also provide good performance, always exceeding the results of the AT: an improvement around 5.7% for the estimate-based approach and around 6.7% for the use of beacons. Increasing the frecuency of beacons causes a significant decrease of the importance sum due to the fast energy expense. On the other hand, selective forwarders with a beacon interval approaching to infinity behave as AT nodes (nodes do not have any information from their neighbors).

Table 5.2: Averaged performance results in a chain network of 30 equally-spaced nodes. Importances follow exponential distributions.

Type of sensor	Total Import. Received	Importance mean value	Number of Receptions	Number of gen. Messages
NS	1074.02	1.79	**599.00**	600.00
AT	6962.02	14.55	480.44	15638.10
LF-FI	7698.31	15.73	491.54	20563.78
LF-EST	7356.90	15.76	468.56	19911.62
LF-VAR	7696.91	**16.80**	459.32	**24661.00**
LF-BEAC	7429.23	15.41	484.10	19243.56
GF-FI	**7699.94**	15.73	491.40	20597.22
GF-EST	7319.05	15.13	485.82	17415.22

Reporting significant threshold variations (-VAR) provides an improvement around 10.5%, performing similarly to LF-FI sensor networks. Decreasing the value of β_μ causes very frequent threshold update reports due to the initial instability in thresholds, reducing quickly the batteries. In all cases, the lifetime of LF sensor networks is higher than that of AT sensor networks, as the higher number of generated messages shows. Even more, in some cases the number of messages received by the sink is slightly higher than for AT networks. Moreover, in selective forwarding networks high prioritized messages arrive easier to the sink than in AT networks. We just need to look at the importance mean value of the messages received by the sink. The same conclusions can be extrapolated to GF networks.

LF-FI and GF-FI results are practically identical. GL-EST results are slightly worse than those achieved by the LF nodes, but very close to LF-EST.

5.4.3 Networks with arbitrary topologies

To analyze the behavior of selective forwarders in a more realistic scenario, we simulate a network of 140 nodes scattered in a square field with corners (0,0) and (L,L), with $L = 150$. Nodes are denser deployed near the sink, tailing off towards the edges. Nodes report the information to a unique sink, located at (L,$L/2$). Fig. 5.5 illustrates a sketch of the sensor network deployment.

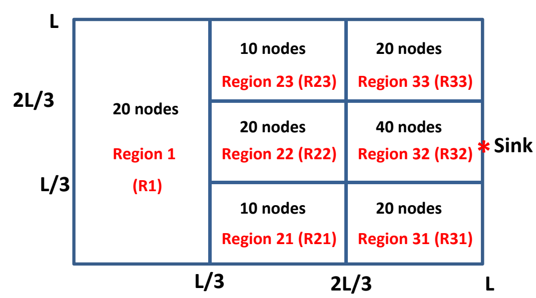


Figure 5.5: Sensor Network deployment sketch.

Each node generates importances following an exponential distribution with different mean, whose values were randomly generated from another exponential distribution with mean 2. Messages are equally generated in the three regions and node batteries are charged to $1,500$ units. In this case, results are averaged over 20 different topologies, where the average depth of the network (number of hops required to reach the edges from the sink) is 7. Note that if the depth of the network increases substantially, threshold information in LF nodes will propagate slower towards the edges of the sensor field and could eventually cause a degradation in the results, especially when batteries are close to run out, compared with GF nodes.

Table 5.3 compares the performance for all types of nodes. Parameter η is fixed to 0.008 for LF and GF nodes. The value of β_μ is set to 3.5, and the beacon interval to $13,000$ epochs. Conclusions are similar to those of section 5.4.2. The importance sum of messages arriving to the sink in AT networks is around 280% higher than that of NS networks.

The improvement is even higher when deploying selective forwarders (around 293% for LF estimate-based nodes and 343% for LF-FI nodes). Also, note that the network lifetime is at least 6 times longer than that of NS networks.

Table 5.3: Averaged performance results in an arbitrary network topology of 140 nodes. Importances are generated according to exponential distributions of different mean.

	Total Import. Received	Importance mean value	Number of Receptions	Number of gen. Messages
NS	10328.62	1.92	**5414.00**	9292.20
AT	39105.03	10.13	3934.35	66630.15
LF-FI	**45786.56**	11.04	4223.95	101537.35
LF-EST	40578.81	10.36	3992.50	72406.10
LF-VAR	40075.74	**11.32**	3619.00	**102801.30**
LF-BEAC	40955.17	11.05	3766.90	86856.55
GF-EST	40957.99	10.42	4007.50	72997.05

The comparative analysis of selective sensors shows again that LF nodes outperform AT nodes. Not only are the most relevant messages prioritized to arrive earlier to the sink (shown through the importance mean value of messages received by the sink), but also the sensor network lifetime is enlarged, beating the average value obtained by selective AT networks. Specifically, the best performance corresponds to LF-FI sensor networks. The importance sum is 17% better than that of AT sensors. As nodes initially lack of information from their neighbors, the approximate approaches also yield a reasonable performance. Among the proposed techniques, we would like to emphasize the good performance achieved by the estimate-based proposal, both with local and global optimization. Even, GF-EST results are slightly better than those of LF with incomplete information.

We have also analyzed the threshold values in different regions of the sensor field for the same setup. Averaged results for AT and LF-FI sensor nodes are shown in Table 5.4. In general, AT nodes belonging to regions closer to the sink set higher thresholds than those faraway located. As AT nodes set threshold values independently, the furthest nodes (which only have to transmit their own generated traffic) set the lowest thresholds. Insofar as nodes approach to the sink, threshold values are slightly increased as a consequence of receiving messages with clipped importances from the furthest nodes.

Table 5.4: Averaged threshold value in different regions of an arbitrary network topology of 140 nodes. Importances are generated according to exponential distributions of different mean.

	R1	R21	R22	R23	R31	R32	R33
AT	2.79	3.36	3.85	3.63	3.05	4.88	3.39
LF-FI	11.20	9.34	10.48	10.85	7.42	7.89	8.56

On the contrary, the opposite effect is observed for LF-FI nodes, i.e., threshold values are lower in those regions placed near the sink. It would not make sense that nodes approaching to the sink set high thresholds because faraway generated messages will be never forwarded. Naturally, the most selective nodes in the field are those located near the edges because they ensure the forwarding of their own generated traffic and thus, they avoid wasting energy transmitting messages that will not be forwarded. Recall that nodes generate messages of different importances and moreover, set their thresholds also taking into account neighbor behavior (whose information is backward propagated).

Finally, Table 5.5 lists the sensors remaining battery (averaged) for each region. Results are shown for AT and LF-FI nodes. Clearly, AT nodes do their best concerning energy consumption but LF-FI nodes are those that make a better use of energy resources.

Table 5.5: Averaged remaining battery in different regions of an arbitrary network topology of 140 nodes. Importances are generated according to exponential distributions of different mean.

	R1	R21	R22	R23	R31	R32	R33
AT	0	7.07	6.65	6.45	237.20	113.16	244.84
LF-FI	0	221.13	199.42	222.40	641.16	289.81	659.52

Analysis of different constant energy consumption models

Now, we study the performance of the forwarding policies under different energy models. The network topology consists of 150 nodes randomly scattered in a square field with corners (0,0) and (L,L), with $L = 150$. The sink is located at (L,$L/2$). Parameters η, β_μ and the beacon interval as well as the node batteries are the same than those used in the previous subsection.

Initially, let us define the gain as

$$G_{NS} = \frac{\lambda}{\lambda_{NS}}, \tag{5.23}$$

where λ and λ_{NS} stand for the importance sum of those messages succesfully arrived at the sink when nodes use a selective and nonselective communication policy, respectively. Alternatively, we may redefine the gain in order to compare the importance sum of the received messages by the sink using selective forwarders versus selective transmitter (i.e., $G_{AT} = \frac{\lambda}{\lambda_{AT}}$).

Firstly, the value of E_R is varied to analyze the effect on the gain. $E_T = 4$, $E_I = 0$, and $P_I = 0$. Averaged results are shown in Fig. 5.6. Fig. 5.6(a) plots the G_{NS} gain. Not surprisingly, the gain decreases for all types of selective sensors when E_R approaches to the E_T value. The reason is the same than the stated in the previous chapter: the gain increases with parameter ρ (defined by (4.38)) and ρ decreases with E_R. However, the gain of selective nodes is undoubtedly higher than that achieved by NS nodes.

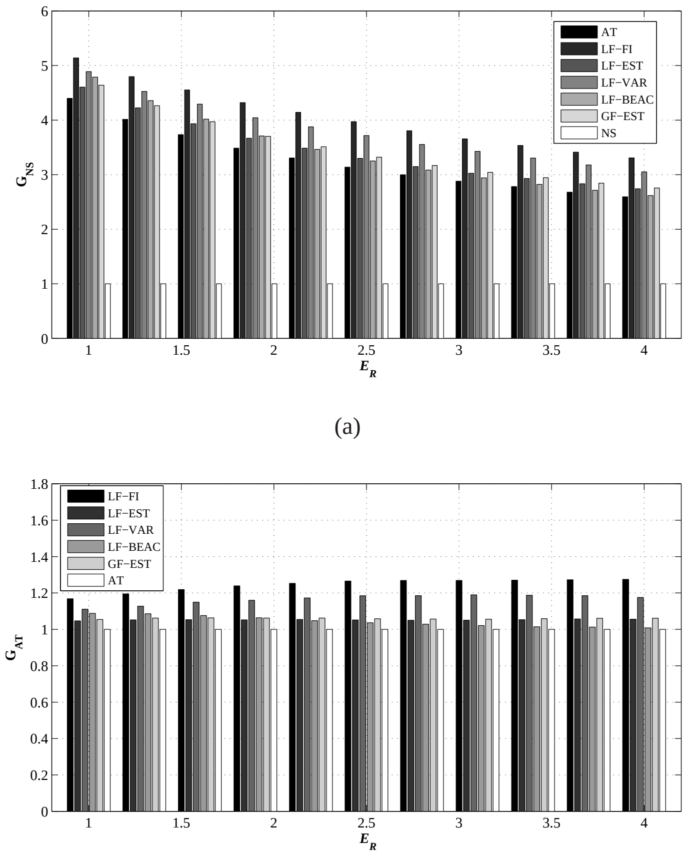
Fig. 5.6(b) plots the G_{AT} gain. Looking at the graph, we can conclude that the selective forwarding nodes (LF and GF) yield a higher gain than selective transmitters (AT nodes), even if the cost associated to the receiving state increases. Moreover, a tendency in the gain behavior can be appreciated for selective forwarders: it increases slightly insofar as E_R grows. This fact is specially remarked by LF-FI and LF-VAR nodes. Therefore, changes in the energy cost associated to the receive state have less effects on selective forwarders (LF and GF) than on selective transmitters (AT).

Now, let us analyze the gain of the selective forwarding policy for different values of E_I. In this case, $E_R = 1$ while E_T remains unchanged. The probability of idle state, P_I, is computed based on the number of idle states and the number of data events (DE),

$$P_I = \frac{\#idle}{\#slots} = \frac{\#idle}{\#idle + \#DE}, \tag{5.24}$$

where DE includes locally generated messages, successfully received messages from neighbors and message transmissions.

Results are shown in Fig. 5.7. Fig. 5.7(a) represents the G_{NS} gain. An abrupt drop in the gain of selective nodes is observed when parameter E_I differs from 0, although the



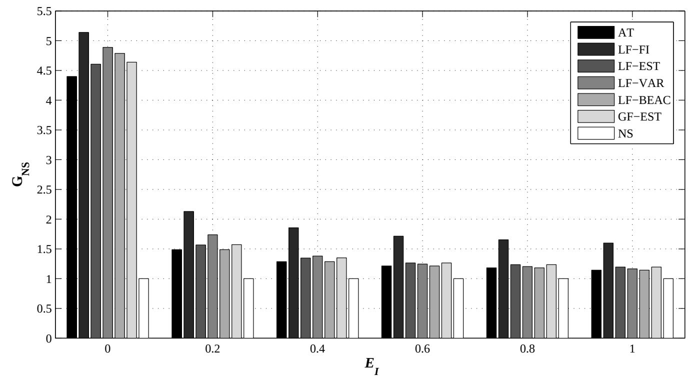
(a)

(b)

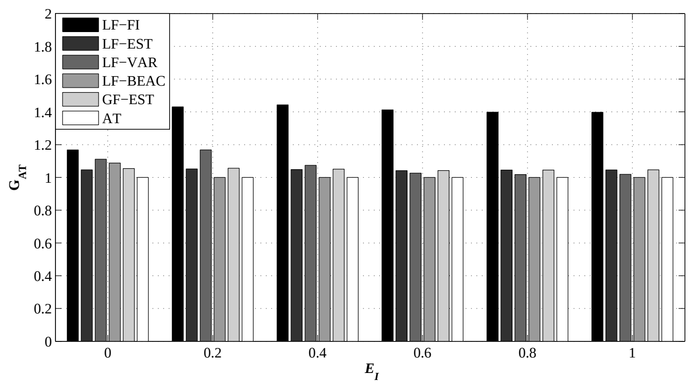
Figure 5.6: Gain of the selective communication policies regarding the NS node (a) and the AT node (b) under exponential importance distributions for different values of E_R.

gain always exceeds the value obtained by NS nodes. This behavior is expected from theory since the gain increases with parameter ρ and ρ is a decreasing function of E_I and P_I.

Finally, we analyze the G_{AT} gain (Fig. 5.7(b)). The gain of LF and GF nodes reduces, regarding the AT node, when the value of E_I increases. As it can be observed, the potential gain of the local forwarder (established by LF-FI node) is not depreciable, but it reduces when nodes have incomplete information. This fact can be partly due to the free parameter assignment, which may not be appropriated and should be properly adjusted.



(a)



(b)

Figure 5.7: Gain of the selective communication policies regarding the NS node (a) and the AT node (b) under exponential importance distributions for different values of E_I.

Stochastic energy costs

Up to this point, a simple deterministic energy model with constant energy costs was assumed. But $c_{1,k}$ and $c_{0,k}$ can be stochastic processes (see (2.5)). In this section we consider that energy costs vary along time: energy costs (E_T, E_R and E_I) are samples of noncentral Chi-square distributions of one degree of freedom. The other free parameter of the distribution takes the value 3.5 for E_T, 1 for E_R and 2 for E_I. The estimation of E_I from the idle states is straightforward as well as the estimation of E_T. Parameter E_R is updated according to the cost of receiving messages from neighbors during a reception state as well as from energy consumed during local data generation. To compute the forwarding threshold, the average value of the energy costs is needed. To save memory resources, all estimates are based on an Exponential Weighted Moving Average (EWMA),

$$E_s(n+1) = \left(1 - \frac{1}{n}\right) E_s(n) + \frac{1}{n} e_{new}, \tag{5.25}$$

where n is an increasing counter for the specific estimate, E_s corresponds to the energy estimate (E_T, E_R or E_I) and e_{new} is the current cost of the transmitting, receiving or idle state. P_I estimate is computed according to (5.24).

In the experiments, the network is composed of 150 nodes provided with $E = 10,000$ units and they are randomly scattered in a square field. Parameter η is fixed to 0.1 for LF and GF nodes. The value of β_μ is set to 1.5 and the beacon interval to $2,000$ epochs. Results are averaged over 50 different topologies and the depth of the network is, on average, 8 hops.

The gain for different types of sensors is depicted in Fig. 5.8. It highlights the advantage of including selective nodes in sensor networks. The best performance corresponds to the LF-FI node. Nevertheless, remark the good behavior achieved by LF-VAR and LF-BEAC nodes, which approach to the results got by the LF-FI node. GF-EST gets a slightly better results than LF-EST, what makes good sense to the fact that the global forwarder performs rather better than the other two types of selective nodes.

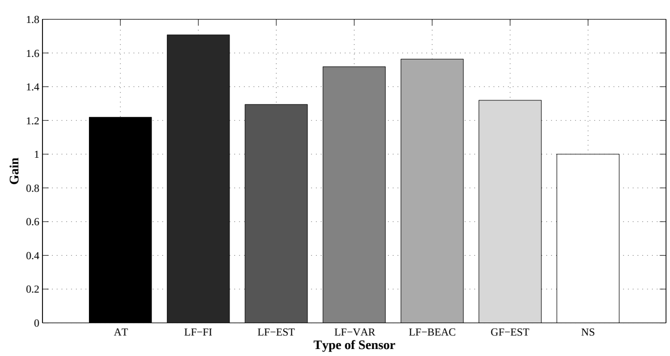


Figure 5.8: Gain of the selective forwarding policies under exponential importance distributions when energy costs are stochastic.

5.5 Concluding remarks

This chapter has introduced several selective message forwarding policies, formulated via MDP notation, that were obtained as the optimal solution of a formulated problem in order to save energy and extend the lifetime of WSNs. Messages were transmitted by sensor nodes according to a forwarding policy, which considered consumption patterns, available energy resources in nodes, the importance of the current message, the statistical description of such importances and the behavior of neighboring nodes.

Forwarding schemes were optimally designed for three different scenarios: 1) when sensors maximize the importance of their own transmitted messages (no information from other nodes is available); 2) when sensors maximize the importance of messages that have been successfully retransmitted by at least one of its neighbors (nodes need to know/estimate if the message was retransmitted); and 3) when sensors maximize the importance of the messages that successfully arrive to the sink (nodes need to know if the message arrived to the sink). Interestingly, the structure of the optimal scheme was the same in all three cases and consisted of comparing the received importance to a forwarding threshold (in fact, the expression for the optimal forwarding threshold turned into a general expression of the optimal selective transmitter stated in Chapter 4). The expression to find the optimal threshold varies with time and is slightly different for each scenario. The developed schemes were optimal from an importance perspective, efficiently exploited the energy resources, entailed very low computational complexity and were amenable to distributed implementation, all desirable characteristics in WSNs.

The three schemes have been compared under different criteria. From an overall network efficiency perspective, the first scheme performed worse than its counterparts, but it required less signaling overhead. On the contrary, the last scheme was the best in terms of network performance, but it required the implementation of feedback messages from the sink to the nodes of the WSN. Numerical results showed that the proposed selective forwarding schemes improved the global performance in terms of quantity and quality of the messages that really arrive at the sink. Particularly, for the tested cases they showed that differences among the three schemes were small - with schemes two and three performing evenly but better than scheme one. From a practical perspective, this suggests that the second scheme, which is just slightly more complex than the first one, can be the best candidate in most practical networks (especially in new deployments). Similarly, from a modeling point of view, the results indicate that when nodes have access to nonlocal information, information of first order neighbors may be enough. On the other hand, the variation of the energy consumption patterns has the same impact than the observed for the selective transmitter: an increase of E_R or E_I values reduces the advantage of selective communications, but exceeds the behavior of nonselective communications by far. Finally, the gain enhancement introduced by selective forwarders was also corroborated even considering stochastic energy costs.

CHAPTER 6

AN APPLICATION SCENARIO: TARGET TRACKING

As a case study, we have identified a scenario within WSNs where the selective forwarding policy can be useful: target tracking. Target tracking has received considerable attention in the literature. The ability to track a target is essential in many military (e.g., tracking enemy vehicles, detecting illegal border crossings) and commercial applications (e.g., tracking the movement of wild animals, highway traffic monitoring, etc.). In a target tracking system, the object of interest is a single (or multiple) target that moves in a field of sensors, which measure signal power, and the objective is the estimation of its trajectory and velocity.

Most of the research work in target tracking in WSNs is focused on providing energy saving techniques to avoid the early battery exhaustion of sensor nodes (see, e.g., [Wang et al., 2010], [Pattem et al., 2003]). That is why we consider that the application of the selective forwarding policy (together with other in-network data processing techniques) to sensors aimed at tracking deserves some attention. From the optimal selective forwarding scheme based on the statistical model of the message importance (defined in Chapter5), in this chapter we analyze and validate the performance of selective sensors that initially apply other data reductions techniques (data aggregation or fusion) for a centralized and distributed tracking architecture. We compare results with those extracted from nonselective sensors to assess the advantages in terms of tracking accuracy, network lifetime and resource usage, among other parameters. Particularly, only those sensors with essential information about the target, i.e., whose message importance is over a time-variant decision threshold, transmit their measurements/estimates in order to determine the target location. Consequently, communication processes reduce considerably, having an impact on the network lifetime enlargement without compromising the application performance.

The rest of the chapter is structured as follows. Section 6.1 details the general procedure for the joint application of the selective forwarding policy and the data aggregation/fusion methods to sensor networks designed to track targets. Section 6.2 describes the tracking algorithm, the data reduction techniques and the computation of the importance values. Later, Section 6.3 shows the experimental study and results, considering both selective and nonselective sensor nodes. Finally, some concluding remarks are drawn in Section 6.4.

6.1 Tracking with selective forwarders

The more nodes collaborate in tracking, the more data measurements are collected, and the better the estimate of the target position and velocity is. Nevertheless, nodes consume a valuable amount of battery performing measurement collection and communication tasks, increasing the congestion of the limited bandwidth. Data aggregation schemes can be used to improve energy efficiency, but it states a major problem: sensor nodes may combine redundant data or data that may not contain relevant information about the target, consuming a non-negligible bandwidth. This weakness is, to some extent, alleviated using fusion schemes since data are partially processed to compute target parameters, reducing power consumption. Nevertheless, target estimations should be routed to the sink in order to let the sink handle the collected information.

The key idea developed in this chapter is the combination of data reduction schemes with the selective forwarding policy in such a way that nodes selectively report the most informative information only, which suffices to obtain an accurate target parameter estimate, saving energy resources that enlarge network lifetime.

6.1.1 The general procedure

For the sake of clarity, let us first expose the general procedure that we propose to follow.

1. At time k, nodes sense some specific parameters (i.e., take measurements), $l_{n,k}$, which are somehow related to the target state $\mathbf{y}_k$ (position, velocity,...): $l_{n,k} = f(\mathbf{y}_k)$. Variable n denotes the node index.

2. Some nodes, which vary depending on the particular scenario, compute estimates of the moving target position recursively, considering the available observations at every time instant, $\hat{\mathbf{y}}_k = g(l_{n,k}, \hat{\mathbf{y}}_{k-1})$.

3. Nodes acting as source forwarders or cluster-heads compute and assign an importance value to messages based on the available measurements or state estimates respectively, $x_k = h(l_{n,k}, \hat{\mathbf{y}}_k)$. The importance value remains invariable once it is set.

4. Sensor nodes apply selective communication policies to decide whether to transmit messages or not according to the importance value as well as other factors, such as the remaining energy resources, $d_k = d_k(e_k, x_k)$.

The computation of the importance value based on the available information at each time k is a major issue in the design of a selective communication policy, and it is application-dependent. The importance functions used in the experiments will be detailed in Sec.6.2.5. Remark that the procedure is general enough to consider any type of sensor. The next sections detail the target motion model, tracking method, and data reduction approaches.

6.2 Target Location and Tracking Methods

6.2.1 Target Motion Model

Generally, target tracking problems can be stated in terms of the estimation of an unobserved discrete-time random signal in a dynamic system of the form

$$\mathbf{y}_k = f\left(\mathbf{y}_{k-1}, \mathbf{u}_k\right) \tag{6.1}$$

$$\mathbf{l}_k = g\left(\mathbf{y}_k, \mathbf{v}_k\right), \tag{6.2}$$

where $\mathbf{y}_k = [y_{1,k}, y_{2,k}, \dot{y}_{1,k}, \dot{y}_{2,k}] \in R^4$ is a state vector whose elements are the position and the velocity of the target in a two dimensional Cartesian coordinate system at time instant

k, $\mathbf{u}_k$ is the noise component, and function $f(\cdot)$ relates the current state vector with the previous one and the noise (i.e., the state transition function). $\mathbf{l}_k$ is the sensor measurement at time k, $g(\cdot)$ is the observation function (which will be defined in the next subsection), and $\mathbf{v}_k$ is the observation noise. $\mathbf{u}_k$ and $\mathbf{v}_k$ are assumed to be statistically independent.

We have focused on models that are linear in the state dynamics. The model is described in [Gustafsson et al., 2002] as:

$$\mathbf{y}_k = \mathbf{G}_y\, \mathbf{y}_{k-1} + \mathbf{G}_u\, \mathbf{u}_k, \tag{6.3}$$

where $\mathbf{G}_y$ and $\mathbf{G}_u$ are known matrices defined by

$$\mathbf{G}_x = \begin{pmatrix} 1 & 0 & T_s & 0 \\ 0 & 1 & 0 & T_s \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \quad \mathbf{G}_u = \begin{pmatrix} \frac{T_s^2}{2} & 0 \\ 0 & \frac{T_s^2}{2} \\ T_s & 0 \\ 0 & T_s \end{pmatrix}, \tag{6.4}$$

where T_s denotes the sampling period of $\mathbf{l}_k$, and $\mathbf{u}_k$ is a 2×1 vector that represents a Gaussian noise process with zero mean and known covariance matrix $\mathbf{C}_u = diag\left(\sigma^2_{u_1}, \sigma^2_{u_2}\right)$, which accounts for the acceleration of the target (assumed to be unknown).

6.2.2 Type of Sensor: Acoustic Amplitude Sensor

The formulation of the measurement model is in agreement with the type of sensor deployed in the network. Microphones, apart from being low-cost devices, are affordable and simple in computation, what makes them attractive to study. An acoustic amplitude sensor node measures sound amplitude at each microphone and estimates the distance to the target based on the physics of the sound attenuation [Zhao and Guibas, 2004].

Assuming that the target is a point source and acoustic signals propagate lossless and isotropically, the acoustic amplitude measurement $l_{n,k}$ performed by n-sensor is related to the sound source position $o_k^T = [y_{1,k}, y_{2,k}]$ by

$$l_{n,k} = \frac{a}{\|\mathbf{o}_k - \mathbf{r}_n\|^{\alpha/2}} + v_{n,k} \tag{6.5}$$

where a is a given random variable representing the amplitude of the signal at the target (uniformly distributed in the interval $[a_{lo}, a_{hi}]$), α is an unknown attenuation coefficient and $\|\cdot\|$ is the Euclidean distance. Measurement noise is modeled as Gaussian with zero mean and variance σ_v^2. Both, the noise variance and the sensor position $\mathbf{r}_n$, are typical characteristics about sensors, together with its energy reserve [Zhao and Guibas, 2004].

To tackle the problem of selective forwarding, nodes set the importance of the information according to the relevance of the measures taken by each node along time, $x_k = l_{n,k}$.

6.2.3 Tracking Algorithm

Target location is crucial in distributed tracking. The aim at target tracking is to obtain a good estimate of the moving target position at time k, $\mathbf{y}_k$, from the measurement history up to time k, $\overline{\mathbf{l}_k} = \{\mathbf{l}_0, \mathbf{l}_1, \ldots, \mathbf{l}_k\}$, within a sensor field monitored by a sensor network. Among all possible methods to locate targets from the measurements sensed by nodes, we have selected a statistical approach: the sequential Bayesian filtering. We would like our estimate $\hat{y}(\overline{\mathbf{l}_k})$ to be, on average, as close to the true value $\mathbf{y}_k$ as possible, trying to minimize the Minimum Mean Squared Error (MMSE) estimator [Liu et al., 2003],

$$\hat{\mathbf{y}}_k = E\left[\mathbf{y}_k|\overline{\mathbf{l}_k}\right] = \int \mathbf{y}_k\, p\left(\mathbf{y}_k|\overline{\mathbf{l}_k}\right) d\mathbf{y}_k. \tag{6.6}$$

where $p\left(\mathbf{y}_k|\overline{\mathbf{l}_k}\right)$ is the current a posteriori distribution or belief, which in this application corresponds to the target position and velocity.

Specifically, we have made use of the particle filter Monte Carlo technique [Doucet et al., 2000] [Ristic et al., 2004] to compute the corresponding Bayesian estimates and target prediction. It approximates the belief by a set of particle streams $\mathbf{y}_k^{(m)}$, $m = 1, 2, \ldots, M$, and their weights $w_k^{(m)}$, which are normalized such that $\sum_{m=1}^{M} w_k^{(m)} = 1$. Particles have the same structure than the state vector presented in Section 6.2.1, $\mathbf{y}_k^{(m)} = \left[y_{1,k}^{(m)}, y_{2,k}^{(m)}, \dot{y}_{1,k}^{(m)}, \dot{y}_{2,k}^{(m)}\right] \in R^4$. Thus, the belief can be approximated as follows

$$p\left(\mathbf{y}_k|\overline{\mathbf{l}_k}\right) = \sum_{m=1}^{M} w_k^{(m)}\, \delta(\mathbf{y}_k - \mathbf{y}_k^{(m)}), \tag{6.7}$$

a discrete weighted approximation of the true posterior, $p\left(\mathbf{y}_k|\overline{\mathbf{l}_k}\right)$.

The basic operation of a particle filter is summarized next: when new observations are available, the set of particles $\mathbf{y}_{k-1}^{(m)}$ is expanded to $\mathbf{y}_k^{(m)}$ and their weights $w_{k-1}^{(m)}$ are updated to $w_k^{(m)}$. At least three steps can be easily identified: a) new particle generation; b) weights update; and c) resampling. The last step is necessary to avoid a degeneracy of random measurements and it is based on the replication of particles that have larger weights.

The steps of the particle filtering algorithm can be summarized as follows:

1. *Initialization* $\Rightarrow$ Particles $\mathbf{y}_0^{(m)}$, $m = 1, 2, \ldots, M$, are initially drawn from a priori distribution $\pi(\mathbf{y}_0)$ (a Gaussian distribution, whose mean is the sensor position that particles have and variance σ_n^2), and the weights of the particles are set to $\frac{1}{M}$.

2. *New particle generation* $\Rightarrow$ A new set of particles, $\mathbf{y}_k^{(m)}$, $m = 1, 2, \ldots, M$, is computed according to the distribution $p\left(\mathbf{y}_k|\mathbf{y}_{k-1}\right)$, and can be expressed as
$$\mathbf{y}_k^{(m)} = f\left(\mathbf{y}_{k-1}^{(m)}\right) + \mathbf{n}_k, \tag{6.8}$$
where $\mathbf{n}_k$ is the noise component which produces a random particle movement.

3. *Weights Update* $\Rightarrow$ Update weights by means of the likelihood
$$w_k^{(m)} = w_{k-1}^{(m)}\, p\left(\mathbf{l}_k|\mathbf{y}_k^{(m)}\right). \tag{6.9}$$

4. *Position Estimate* $\Rightarrow$ An approximation of (6.6) is computed in order to estimate the target position. Note that weights are normalized to sum up to 1.
$$\hat{\mathbf{y}}_k \approx \sum_{m=1}^{M} w_k^{(m)}\, \mathbf{y}_k^{(m)}. \tag{6.10}$$

5. *Resampling* $\Rightarrow$ Sampling importance resampling (SIR) technique, explained in detail in [Arulampalam et al., 2002], is applied. It takes samples with replacement from the set $\left\{\mathbf{y}_k^{(m)}\right\}_{m=1}^{M}$, where the probability to take sample m is $w_k^{(m)}$. Let $w_k^{(m)} = \frac{1}{M}$.

6. Let $k := k + 1$ and go to step 2.

6.2.4 Data reduction schemes

One of the main problems stated in tracking moving objects is the huge amount of messages to be transmitted to the sink when sensors detect a target, and the possibility of collision and interference in the shared media. With the aim of improving energy efficiency, data reduction schemes are commonly used in target tracking to reduce communications in the network. We consider two in-network processing approaches: data aggregation and sensor fusion.

Data Aggregation Scheme

Basically, data aggregation allows sensors to combine data from different sources and report them to the sink. Later, the sink applies a location algorithm to the information gathered from all sensors to update the target track. Figure 6.1 shows an example of data aggregation. Data from the two sources are aggregated by node c and the combined data (labeled D_1+D_2) are sent from node c to the sink. It results in energy saving, as fewer transmissions are required to send the information from both sources to the sink.

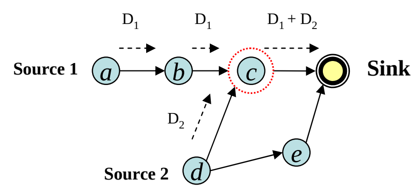


Figure 6.1: Example of data aggregation.

Though data aggregation can be done with some data processing, we have applied a simple *packaging* scheme [Nakamura et al., 2007]: each node groups p measurements (observations sensed by itself or coming from other nodes), generating a packet to be routed through the network. This avoids the overhead of the MAC protocol when transmitting several packets. The selection of the packet size p must take into account the potential delay incurred because data from nearer sources may have to be held back at an intermediate node in order to be aggregated with data coming from further sources. This fact can be seen by referring back to Fig. 6.1. There, node c is only one hop from source node d, but two from source a. If both sources transmit measurements simultaneously, data from source 2 will get to node c before data from source 1, and take longer to get to the sink than it would in no aggregation schemes. For simplicity reasons, we have arbitrarily set a fix packet size without further optimization.

We have integrated the data aggregation scheme into two different approaches:

- *Centralized approach*: every sensor of the network field wakes up periodically to take a measurement, and informs the sink. The sink updates the belief state using the sequential Bayesian filtering technique presented in Section 6.2.3, considering at every time the N measurements sent by sensors. Clearly, it is a simple but very energy-expensive method.

- *Leader approach*: this approach is more energy-efficient because sensor activation only affects a localized area in the sensor field, reducing communication overhead. It is based on a cluster-leader scheme, particularly, the information-driven sensor querying (IDSQ) approach. At each time, the leader and its m neighbors are active while all the remaining nodes are sleeping. The leader requests the measurements to all its neighbors, packages all collected data in groups of p measurements, and routes them towards the sink, which estimates the target position based on this reduced set of $m \ll N$ measurements at each time. As the target moves continuously in the sensor field, the leader role should be constantly updated. The process of leader selection is based on an information-driven criterion: the most informative sensor (i.e., the neighbor with the best measurement) is selected in the next round. The process is repeated until the task is completed. In the initialization phase, some sensors, elected at random, are assigned to weak up periodically and scan the network for detecting possible targets. When a sensor measurement exceeds the power threshold, the corresponding node becomes the initial leader and the tracking algorithm starts to run. Additionally, it is a leader requirement to have enough energy to accomplish the task.

Sensor Fusion Scheme

The approach presented above is based on a fully centralized processing approach performed by the sink. The main drawback of transmitting every measurement to the sink is the high cost in terms of communication energy in any nontrivial size network. Moreover, aggregating data (packaging) does not exploit synergies among data. Other simple functions (such as the average, maximum or minimum) are not appropriate, because information related to sensor position is completely lost. Fusion schemes decrease communication overhead, and save energy by combining data from different sources and by reducing the amount of information, so that new data are improved (greater quality or relevance). In distributed fusion, measurements are fused before sending them to the sink. Intermediate nodes only route the packet, do not fuse incrementally.

The experimental work is specially focused on distributed sensor fusion based on the

IDSQ tracking algorithm. Besides collecting measurements, the leader node fuses the information to obtain an estimate of the target position, which is later routed to the sink. Again, we use sensor fusion based on Bayesian Inference and particle filtering. Figure 6.2 shows the flowchart of the tracking algorithm in this scenario.

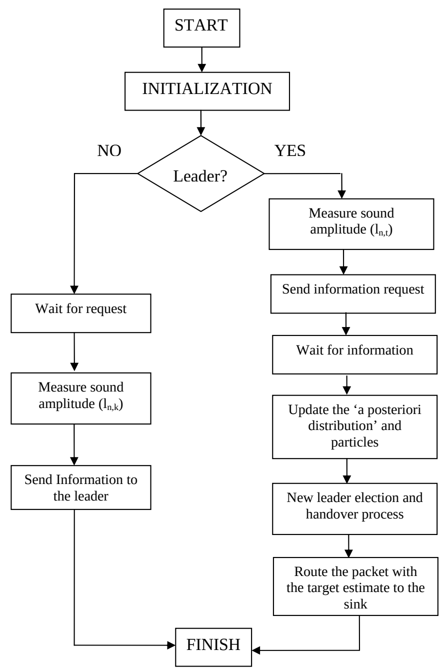


Figure 6.2: Flowchart of the tracking algorithm in a distributed sensor fusion scheme.

6.2.5 Computing the importance values

To avoid communicating uninformative messages, nodes will apply selective communication strategies. To do so, an importance function assigning an importance value to every message to be transmitted must be computed. In the tracking scenario, since observations $l_{n,k}$ represent signal power measures from microphones, and large values of $l_{n,k}$ can be expected to be more informative than low values, the importance value of a single measure will be taken as $x_k = l_{n,k}$.

In case of data aggregation, the importance of the aggregated packet will be computed as the sum of importances of each individual measurement. According to the selective forwarding policy, the aggregated packet may be discarded. However, the whole packet is not dropped, but only the least important measurement (based on the signal power). A new measurement can be added to the rest of the packet, and a new decision will be made. Any intermediate node receiving a message repeats again the process.

In case of data fusion, the target position is estimated at leaders, and this estimation can be used to compute the importance values. In our experiment, the message importance is

$$x_k = \|\hat{\mathbf{y}}_k - \check{\mathbf{y}}_k\|^2, \tag{6.11}$$

where $\hat{\mathbf{y}}_k$ is the position estimate carried out by the leader node, and $\check{\mathbf{y}}_k$ is the position estimate that would be estimated by the sink without the current message (which is the result of applying the target motion model to the last previous estimate).

When the sink receives a report message, it processes the information by means of a tracking algorithm (the particle filter which was described in Section 6.2.3), or directly reconstructs the target trajectory, bearing in mind the time when nodes detected the target and assuming that all sensors are initially synchronized. Whenever the sink does not receive any estimate or any measurement for any particular time instant, it applies the target movement equation to the precedent received or computed estimate, respectively. Fig. 6.3 helps to clarify the sink behavior.

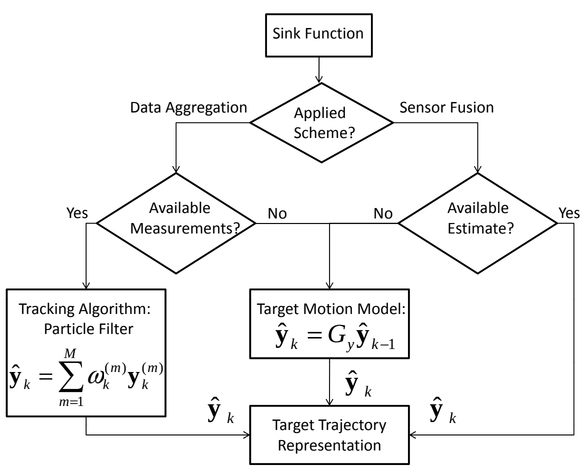


Figure 6.3: Flowchart of the sink behavior depending on the applied data reduction scheme, and the availability of measurements and estimates in nonselective and selective networks.

6.3 Experimental Results

In this section we analyze and validate through simulations the performance of the selective forwarding policy applied to target tracking. Experimental results are conducted using Matlab. Results are focused on comparing two types of sensors: local selective forwarders based on learning (LF-EST) and nonselective (NS) sensors.

The sensor network field is considered as a square area of 250 x 250 m^2, where 64 sensor nodes have been deployed in a grid structure. Nodes are initially charged with the same batteries, $E = 15,000$ units, except for the sink, which has unlimited power supply. The sink is placed at the up right-hand corner in the sensor field. Nodes keep working until their batteries expire and the network dies after the death of the fist node, or when a predefined simulation time is over (at $t = 30,000s$). We have used the constant energy model given by (2.1), where energy values are set to $E_T = 5$, $E_R = 2$ and $E_I = 0$.

Assuming acoustic sensors (6.5), parameter a is uniformly distributed in the interval [60, 80], and the target moves continuously in the sensor field at variable speed between [0, v_{max}] m/s, where v_{max} is 2 or 5. Whenever the target arrives at any side of the field, the target is reflected guaranteeing its position in the field. The signal attenuation coefficient α in (6.5) is set to 2. As in the previous chapter, we have used the greedy forwarding routing algorithm for simplicity. Moreover, link losses have not been included in the model.

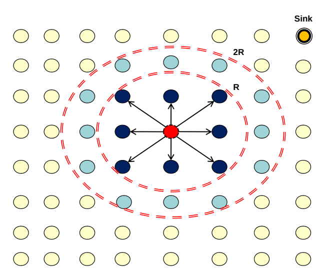


Figure 6.4: Sensor network deployment and communication range.

The transmission radius R is adjusted so that nodes can communicate with eight neighbors, as it is shown in Figure 6.4. By overhearing, nodes are able to update their information parameter estimate according to (5.21) and (5.22). Besides, we have also tested tracking scenarios with higher transmission radius. Particularly, nodes can enlarge their transmission range up to 2R. In this case, the cost for transmitting to neighbors placed to a distance between R and 2R increases accordingly, $2E_T$.

For tracking applications, performance is assessed in terms of tracking accuracy (tracking error) and resource usage (energy consumption). In multi-hop routing protocols, performance is also stated in terms of energy consumption and network lifetime. As the selective forwarding policy maximizes the importance sum of the forwarded messages, performance will be also assessed in terms of the importance sum of messages received by the sink.

Experimental results are averaged over 50 simulation runs, where different target trajectories are tracked. The same trajectories are tracked for both types of sensors (NS and LF-EST) under three different scenarios: (i) no in-network processing technique; (ii) data aggregation based on centralized or leader methods; and (iii) data fusion based on cluster-leader schemes. The starting point of target trajectories is different in all simulation runs.

6.3.1 Tracking without in-network processing

This scenario is aimed at showing the benefits of including selective sensors. Initially, nodes do not perform any in-network processing technique, i.e., every time sensor nodes collect an acoustic amplitude measurement, it is routed back to the sink to estimate target parameters.

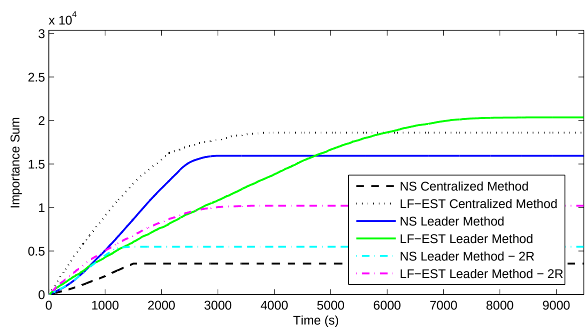
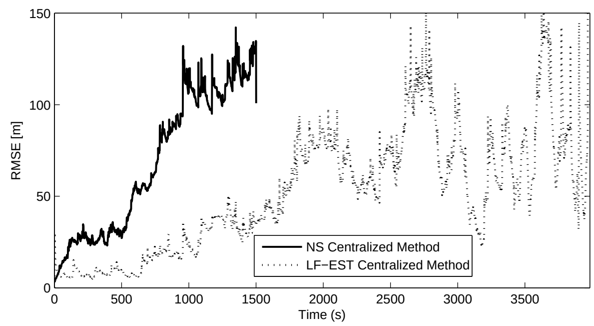
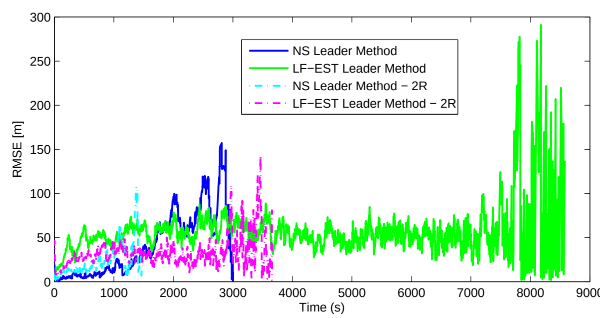


Figure 6.5: Evolution of the importance sum of messages received by the sink for tracking methods without in-network processing.

Figure 6.5 depicts the evolution of the importance sum received by the sink along time when the target is moving at $v_{max} = 2m/s$. For the sake of clarity, we have kept the importance sum constant once the network lifetime has expired. As expected, those networks composed of selective forwarders achieve a higher importance sum regarding its corresponding nonselective counterpart method, and also a higher network lifetime. Comparing the performance of the different tracking methods, leader-based method with radius R yields the best performance, as it reduces the number of transmissions. In this scenario, increasing the transmission radius does not improve the importance sum because energy consumption drops faster as more nodes are involved in tracking. However, the best improvement regarding its nonselective counterpart corresponds to the centralized method. Multiple sensor nodes perceive similar observations, which results in inherent redundancy of sensory data. Including LF nodes reduces not only redundancy, but also inhibits the transmission of non-relevant data while the network lifetime is prolonged. This scheme performs even better than the leader-based method with NS nodes, and approaches the best performance.



(a)



(b)

Figure 6.6: Average RMSE for NS and LF-EST sensor networks that implement centralized (a) and leader-based schemes (b) without applying any data reduction schemes.

Figure 6.6 shows the Root Mean Square Error (RMSE) of the target estimation. Note that we show average results; however, each trajectory has a different duration. Hence, we average those trajectories that are alive at every time instant. Tests for the centralized scheme (see Fig. 6.6(a)) show that localization errors for LF sensor networks are lower than for NS networks. However, the tracking error is rather high in both, and increases progressively due to the fast battery exhaustion, forcing the sink to use the target motion model. Therefore, tracking error achieves non admissible values for a tracking application. The drastic drops of the error at the last time instants in LF sensor networks are caused by the reception of informative measurements by the sink, which clearly contributes to get a better target estimate. Besides, the lifetime of LF sensor networks is two times longer than the NS network lifetime. This is also observed in leader-based methods (see Fig. 6.6(b)). Whereas LF sensor networks with transmission range $2R$ achieve a lower error in the short term, LF sensor networks with transmission radius R get a better performance in the long term because less nodes are involved in the measurement capture, and the network lasts longer. In general, error results still reach non admissible values, though. Finally, let us point out the higher lifetime of the leader-based approach with radius R regarding the centralized ones.

6.3.2 Tracking methods with data aggregation

In this section, nodes are provided with data aggregation capabilities. We have arbitrarily considered two packet sizes: $p = 3$ and $p = 5$ (i.e., nodes have to wait up to fill a packet with the required amount of measurements). Note that results exposed in the previous section are a particular case of those presented here by considering $p = 1$.

Table 6.1 summarizes the average network lifetime for LF and NS sensor networks provided with aggregation capabilities, for different packet sizes and target speeds. As expected, higher packet size increases network lifetime, because it reduces communication processes. Concerning the use of selective nodes, the enlargement of network lifetime is remarkable. Specifically, lifetime is increased more than 2 times in centralized methods, around 1.5 in leader-based method with transmission radius R, and 1.7 in leader-based method with transmission range $2R$. Again, the best improvement, regarding its NS counterpart, corresponds to the centralized method because of the huge filtering of redundant and non-important information. However, network lifetime values are still far from the results achieved by the leader-based approach with transmission radius R, which undoubtedly yields the best performance. Note also how network lifetime of centralized approaches is higher than for leader-based method with radius $2R$.

Method	Network Lifetime (s)			
	$v_{max} = 2m/s$		$v_{max} = 5m/s$	
	$p = 3$	$p = 5$	$p = 3$	$p = 5$
Centralized method with NS nodes	1502	1503	1502	1503
Centralized method with LF nodes	**3339**	**3575**	**4085**	**4230**
Leader method with NS nodes	2924	3716	3075	3881
Leader method with LF nodes	**4577**	**4601**	**5039**	**4963**
Leader method with range 2R and NS nodes	1147	1298	1380	1553
Leader method with range 2R and LF nodes	**1932**	**1962**	**2340**	**2316**

Table 6.1: Average network lifetime (s) for nodes with aggregation capabilities and for different tracking methods, packet size (p) and velocities of the target (v_{max}).

It is interesting to observe how the enlargement of the network lifetime is consistent with energy expenditure. Fig. 6.7 plots the average energy per node along time for packet size 5 and $v_{max} = 2m/s$. The slope of the different plots shows that selective sensors balance their energy expenditure (smoothness in the slope) to carry out the tracking and routing tasks. This fact is particularly noticed making a comparison between centralized methods. The abrupt slope in NS sensor networks is consequence of a faster battery depletion due to the intrinsic nonselective nature of these sensors.

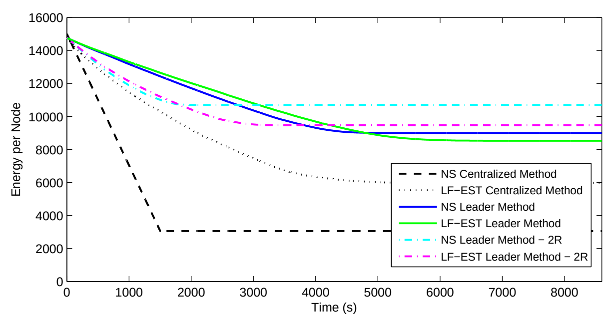
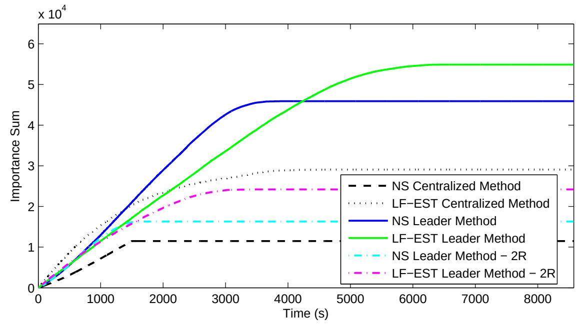
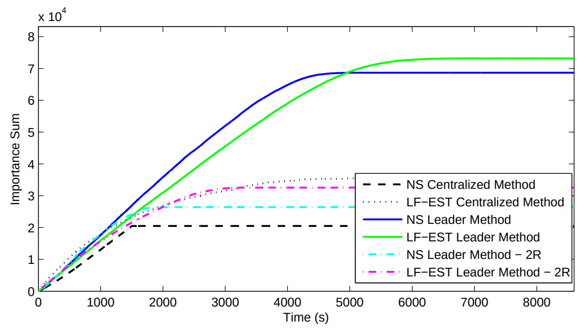


Figure 6.7: Evolution of the average energy per node for tracking methods performing data aggregation with $p = 5$ and for $v_{max} = 2m/s$.

Fig. 6.8 depicts the evolution of the importance sum of the received messages at the sink when the target is moving at maximum speed $2m/s$, and for different packet sizes. Again, experimental results validate the theoretical claims. Basically, LF networks outperform their



(a)

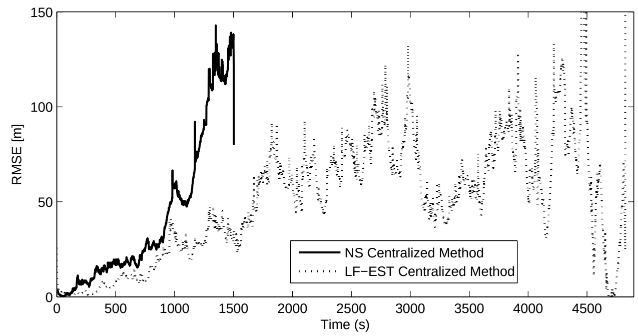


(b)

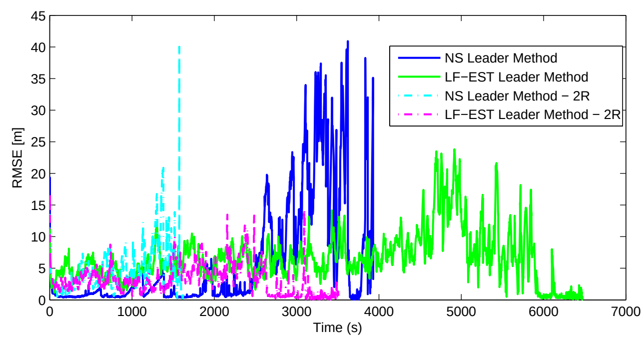
Figure 6.8: Importance sum evolution for tracking methods performing data aggregation with $p = 3$ (a) and $p = 5$ (b) when $v_{max} = 2m/s$.

corresponding nonselective ones, whatever the aggregation method and packet size is. The same conclusions got for Section 6.3.1 apply here: the leader-based aggregation method with radius R yields better results than the centralized ones in terms of importance sum, although the higher relative improvement compared to its NS counterpart corresponds to centralized aggregation methods with LF sensors. The improvement of LF networks compared to its NS counterpart reduces slightly in so far as the packet size increases. It may be due to the proposed message discarding technique what makes that, sometimes, nodes have to wait longer to fill in a packet, particularly if measurements have low importance.

To analyze the influence of selective policies on the tracking performance, Fig. 6.9 shows the average RMSE for NS and LF networks that implement aggregation with $p = 3$, and $v_{max} = 2m/s$. Fig. 6.9(a) shows the outcome for the centralized approach. Again, it is observed a significant lower tracking error for LF networks. However, even though the tracking error reaches lower values than for packet size 1 (i.e., no aggregation scheme is used), the error is still high. On the other hand, the error obtained by leader-based aggregation schemes (see Fig. 6.9(b)) keeps at low values, so that LF networks perform better along the whole sensor network lifetime.



(a)



(b)

Figure 6.9: Average RMSE for NS and LF sensor networks that implement centralized (a) and leader-based (b) aggregation schemes with $p = 3$ and $v_{max} = 2m/s$.

The trade-off between network lifetime and tracking error can be observed in Fig. 6.10, which shows the RMSE of each individual simulation run for the leader-based aggregation scheme. Network lifetime of each simulation run is enlarged whereas the tracking error yields at low values and comparable to those of NS networks.

The benefits of selective policies are even clearer for packet size 5, as it is shown in Fig. 6.11, and similar conclusions arise for different target speed, as shown in Fig. 6.12. Increasing the packet size helps to keep the good performance longer, as the decrease in

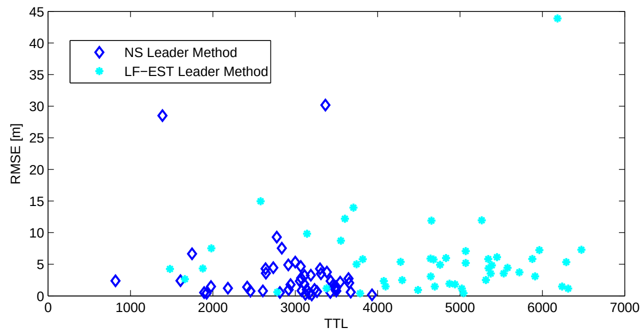


Figure 6.10: RMSE of each individual run for NS and LF sensor networks that implement the leader-based aggregation scheme with $p = 3$ and $v_{max} = 2m/s$.

the amount of transmissions also saves energy used for ulterior transmissions. However, the increase of the target speed yields a worse initial performance in LF networks. As the target is moving faster, nodes involved in capturing measurements change more often, needing more time to set an appropriate decision threshold.

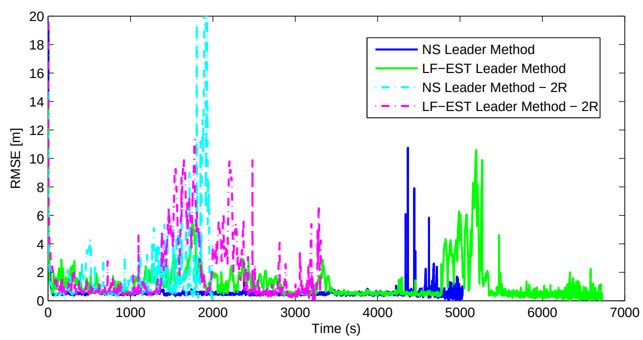
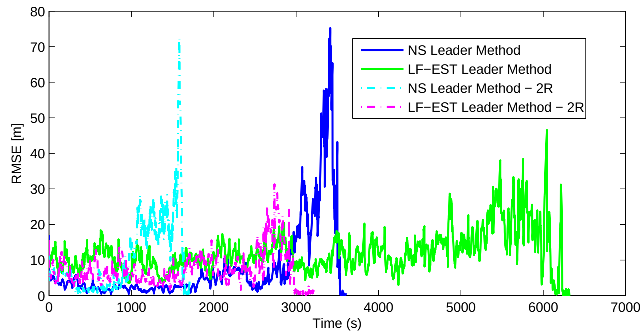


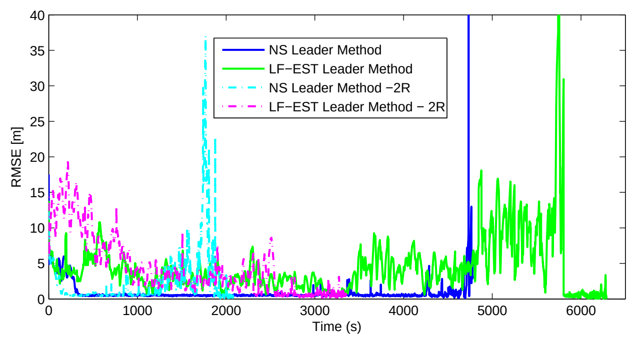
Figure 6.11: Average RMSE for NS and LF sensor networks that implement leader-based aggregation schemes with $p = 5$ and $v_{max} = 2m/s$.

6.3.3 Tracking methods with data fusion

The last set of simulations analyzes the distributed sensor fusion scheme. Table6.2 shows the longer average lifetime for LF networks with respect to NS networks with data fusion,



(a)



(b)

Figure 6.12: Average RMSE for NS and LF sensor networks that implement leader-based aggregation schemes with $p = 3$ (a) and $p = 5$ (b) when $v_{max} = 5m/s$.

for different transmission ranges. It also evidences the benefits of data fusion schemes with respect to data aggregation. Particularly, let us highlight the lifetime enlargement achieved by LF nodes with communication range R, 40.6%.

Other important fact to evaluate is the importance sum of packets received by the sink (Fig. 6.13). In this scenario, NS networks perform evenly and achieve a performance significantly inferior than LF networks. We do not compare importance sum values between aggregation and fusion schemes because the importance is set in a different way, hence, having different meaning.

Finally, we analyze tracking accuracy. Fig. 6.14 illustrates the average tracking error for the fusion method when the target moves at maximum velocity $2m/s$. Comparing with NS networks, LF networks sacrifice slightly accuracy to estimate the target position in exchange

Method	Network Lifetime (s)	Improvement (%)
Leader with NS nodes	4378	17.8
Leader with LF nodes	**6468**	40.6
Leader with range 2R and NS nodes	2157	66.1
Leader with range 2R and LF nodes	**2719**	38.6

Table 6.2: Average network lifetime for the fusion method, and improvement of the fusion approach versus the aggregation method with $p = 5$ and $v_{max} = 2$.

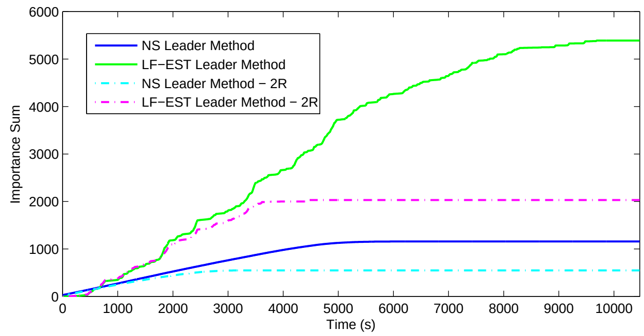


Figure 6.13: Importance sum evolution for tracking methods performing sensor data fusion when $v_{max} = 2m/s$.

of an increase in the network lifetime, specially LF networks with communication radius R. On the other hand, selective networks with radius $2R$ have better accuracy, achieving error values close to those of NS networks, but they keep it for a shorter period of time due to their quicker battery exhaustion. The higher initial error in both selective networks is a consequence of the selective node needs to set the decision threshold according to the received information. As leaders transmit estimates instead of measurements, sensors need receiving more packets to set the threshold properly. Perhaps a better approach would be the use of LF nodes capable of switching adaptively between the two different communication ranges, depending on the needs and the current tracking error, but the exploration of this idea is left as a future research line.

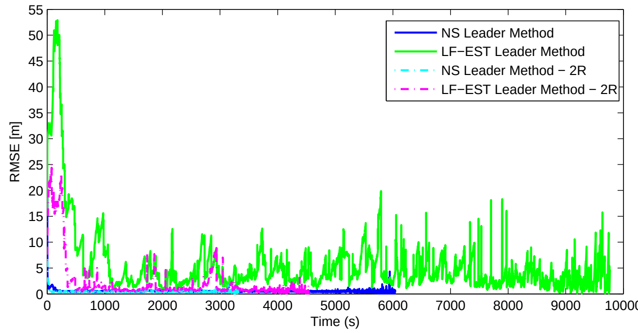


Figure 6.14: Average RMSE for NS and LF sensor networks that implement leader-based fusion schemes when $v_{max} = 2m/s$.

6.4 CONCLUDING REMARKS

In this chapter, the selective communication policy was applied to target tracking in order to save energy resources, particularly by reducing communication tasks. The selective forwarding scheme, due to its easy capacity of integration, was jointly applied with other data reduction techniques, such as data aggregation and sensor fusion, in centralized and distributed architectures. Sensor nodes were able to make the appropriate decision about message forwarding according to an estimated stationary asymptotic threshold. Besides, we have also defined a scheme to assign importance values to packets in the target tracking application.

Three different scenarios have been tested for selective and nonselective nodes: 1) sensors without in-network processing capabilities; 2) sensors with aggregation capabilities; and 3) sensors with data fusion abilities. From an overall perspective, the application of selective forwarding policies enlarged sensor network lifetime, as a consequence of a more balanced and optimized energy expenditure. Clearly, the first scenario was the simplest, but the tracking error achieved non admissible values. On the contrary, the other two scenarios were more complex, but tracking accuracy was not compromised. Particularly, sensors in the third scenario achieved the longest lifetime but performed slightly worse, regarding the tracking error, than sensors in the second scenario.

To conclude, we would like to remark the simplicity of the importance function, which is based on the power of the signal detected by sensors. Hence, this work can be improved taking into account the degree of correlation of the current measure with the previous ones. In that sense, an importance function based on measures of conditional entropy seems more suitable, as it is considered in [Williams et al., 2007].

CHAPTER 7

CONCLUSIONS

The main conclusions derived from the thesis are outlined here, and some of the new lines of work that this thesis has opened are drawn.

7.1 CONCLUSIONS AND DISCUSSION

The nature of Wireless Sensor Networks has originated a number of new challenging and interesting research topics. In particular, the design of large-scale sensor networks composed of battery-powered devices provided with a high degree of autonomy states many challenges that cannot be solved with classical solutions working out for other wired or wireless networks. Specifically, energy is of paramount importance in these networks because it may critically impact on operating conditions and sensor capabilities, as it imposes the main constraint. Therefore, a prerequisite for achieving either longer sensor node lifetime or longer sensor network lifetime is the development of energy-efficient strategies dealing with a reduction in communication processes, which are the most energy expensive tasks. Hence, a selective policy for processing and transmitting at nodes allows optimizing energy consumption and maximizes the quantity and quality of the transmitted information.

In this context, this thesis has been aimed at analyzing the problem of energy resource self-management in nodes belonging to Wireless Sensor Networks, and studying the impact that resource constraints had on communication processes, especially when messages were graded according to an importance/priority value and we could tackle with selective transmission policies. In particular, it has been developed and evaluated optimal selective communication policies in order to save energy resources in Wireless Sensor Networks while providing satisfactory quality of information. With this purpose, optimum selective message forwarding schemes based on the statistical model of the traffic importances (message priorities) were developed for energy-limited Sensor Networks. In order to design the selective forwarding policies, sensor nodes took into account both local factors, such as the energy consumed during the different node states (transmission, reception, idle listening), the available battery, the importance of the received message (to assure a certain level of quality of information to the user) or the statistical model of such importances, and non-local factors, such as information behavior of other nodes.

The main contributions of this thesis are summarized hereunder. Each of them actually corresponds to a chapter of this dissertation.

Initially, in Chapter 2 we characterized the sensor through a model, which gathered all the relevant features of a real sensor. Among them, we remark the stochastic energy consumption model proposed to deal with a broad range of scenarios.

Later in Chapter 3, under the assumption that messages are graded with an importance value, a selective transmission scheme inspired by Bayes decision theory was proposed. The scheme tried to minimize a cost, which depended on the energy expenses and the importance of the current message. The obtained decision rule tended to promote the transmission of highly graded messages while all messages with lower importances were discarded. As a result, the proposed scheme showed that filtering messages according a given importance value may be efficient to maximize the overall importance of the messages arriving to the sink during the whole network lifetime. The proposed decision rule has been applied to two new routing algorithms, named LPGR and Q-PR. It was proved that nodes were able to learn from previous routing decisions in order to adapt their decisions to future conditions, making an efficient energy use.

From the previous work, and using ideas that have many similitudes with others in Stochastic Dynamic Programming and Markov Decision Processes, the problem of selective transmission of graded messages in energy-constrained sensors was theoretically analyzed in Chapter 4. The problem of selective transmission was reformulated (and solved) so that the balance between minimizing the node energy expenses and maximizing the importance sum of all transmitted messages was automatically determined. It turned out that the optimal decision was made comparing the message importance with a time-variant threshold. Moreover, the gain of the selective transmission scheme depended on the energy expenses, among other factors. Albeit suboptimal, practical schemes that operated under less demanding conditions than those for the optimal one were developed. Effort was placed into three directions: 1) the analysis of the optimal transmission policy for several stationary importance distributions; 2) the design of a transmission policy with invariant threshold that entailed asymptotic optimality; and 3) the design of an adaptive algorithm that estimated the importance distribution from the actual received (or sensed) messages. The analysis demonstrated that selective transmission strategies had the potential to provide improvements of the network performance, measured as the sum of importances of all messages arriving to destination, apart from an enlarged lifetime.

In the selective transmission model proposed in Chapter 4, optimization was at node level, focusing on optimizing the transmission efficiency made at each node, without paying any attention if transmitted messages successfully arrived to the sink. Hence, global performance was not guaranteed. Therefore, Chapter 5 dealt with a generalization of the previous theoretical model, allowing nodes to use nonlocal information (coming from the neighborhood or the sink), which was incorporated into the statistical model to analyze its impact on the network behavior. Under less restrictive assumptions, optimum forwarding schemes for three different scenarios were developed: 1) when sensors maximized the importance of their own transmitted messages (which basically coincided with the policy presented in Chapter 4, though using a more general energy consumption model); 2) when sensors maximized the importance of their messages that were actually retransmitted by their neighbors (local optimization); and 3) when sensors maximized the importance of the messages that successfully arrived to the sink (global optimization). Especially important was the generalization of the results to stochastic energy costs because it integrated in the model the idea of nodes consuming a different amount of energy at every state depending on the amount of time spent in each state and/or the inter-sensor distances, for instance. From a practical perspective, the second scenario, which was just slightly more complex than the first one, can be the best candidate in most practical networks, since it required less signaling overhead than the global one.

Finally, the selective communication policy was applied to the target tracking scenario in Chapter 6 to optimize the application performance while saving energy resources. An importance assignment scheme to messages was defined from the available information that nodes had about the application layer. By applying selective communication strategies, communication costs and energy consumption could be minimized, enlarging the network lifetime consequently. Furthermore, the easiness of the selective forwarding scheme to be integrated with other variety of existing data collection approaches, favored its jointly application to data aggregation and sensor fusion schemes, in centralized and distributed architectures. The analysis of the findings proved that scenarios where only selective communication policies were applied (i.e., no other data reduction scheme was simultaneously applied) achieved a poor performance, measured in terms of tracking error. On the contrary, the joint implementation with data aggregation or data fusion techniques did not compromise tracking accuracy as well as increased the network lifetime.

Summarizing, the work of this thesis allowed us to find a suitable mathematical formalism to solve the problem of energy-efficient management in communication processes in a WSN. However, we are conscious that the potential advantages of the selective forwarding strategies stand on a wide set of assumptions about the sensor network model:

1. Battery levels can be accurately measured and they are not rechargeable.
2. Sensor node lifetime can be divided into different predefined states: idle, reception, sensing and transmission.
3. Sensor node states can be precisely identified by each node to efficiently attribute energy consumptions to tasks in real time.
4. The energy consumption of each state does not depend on the selective transmission policy used by the sensor node.
5. The energy cost of a transmission process is higher than the energy cost of reception states.
6. Messages are graded with an importance value.
7. Low importance messages can be discarded.

8. The sensor can only take two actions whenever it receives or senses data: transmitting them immediately or discarding them.

9. The cumulative importance sum is a useful and good performance measure.

10. The importance sequence is statistically independent.

11. The importance distribution is stationary.

12. The constant threshold provides a good approximation to the optimal (variable) threshold, etc.

We have tried to make all these assumptions explicit in the dissertation, focusing on providing a solid theoretical support to the algorithms emanated from the basic assumptions. Testing the validity of these assumptions is of major importance to validate the application of the selective communication policies to real settings. This is, in fact, part of the current research work. The first findings obtained from implementing the selective transmission policy in real sensors (to test assumptions (1)-(5), which are related to the energy consumption of a sensor) show that the potential advantages of selective transmitters depend on multiple factors, including physical variables (power consumptions for each task) as well as the chosen MAC protocol.

In the introductory chapter, several examples from the literature were mentioned to justify the feasibility of attributing a particular priority, relevance, utility or importance value to messages transmitted or forwarded by sensor nodes (assumption 6). Assumption (7) may not be reasonable in some applications, where the importance can be related to priority values, and where all messages are expected to arrive at the sink (maybe with different delays). However, there are some applications where the outtake of less relevant messages for the shake of saving energy is admissible, as in [Chow et al., 2007] or even, the proposed target tracking application explored in Chapter 6, where discarding weak measurements from nodes faraway located from the targets can be perfectly done with a very low cost in estimation accuracy. Assumption (8) is considered in those works that deal with selective communications as a dilemma between transmitting or discarding the information. However, other alternatives may include: the configuration of the transmitter so that sensors always transmit messages but using a power or modulation according to the sensor state

[Munir and Gordon-Ross, 2009]; routing all messages so that the sensor should decide the appropriate path depending on the message importance and the energy state of nodes (as in the PGR [Mujumdar, 2004] or RRR [Gelenbe and Ngai, 2008] priority-based routing algorithms); or keeping the discarded message in memory waiting for more relevant messages with whom it can be aggregated or fused [Ye et al., 2009].

The assumption about the validity of the cumulative importance sum as a good performance measure (assumption 9) may be also arguable in situation where the value of the information is not additive (for instance, if long messages are fragmented in smaller ones, which have no value separately but when joined to reconstruct the original message).

Assumption (10) is likely wrong in many practical settings, for instance, in target tracking scenarios where nodes sense at a high rate so that measurements are likely correlated, or in a data aggregation scenario. However, we believe that it can be relaxed in the theoretical model. In fact, the selective communication policy (based on the statistical independence assumption) has been applied to data aggregation schemes in the target tracking scenario with a satisfactory result. Assumption (11) is clearly application-dependent.

7.2 Future research lines

Let us end this dissertation by adding some potential open issues that may contribute to extend the work exposed in this thesis. Some of them are directly derived from the discussion started above, and for some others, we have already had some preliminary results that guarantee its feasibility and interest. Some of them are briefly described hereafter:

- All the theorems proposed in this thesis assume that the importance sequence is statistically independent. However, the generalization of the optimal selective forwarding scheme with statistical dependence of the importance sequence can be tackled using MDP tools, since the MDP theory only establishes that the state sequence (and consequently, the importance sequence) is a Markov process. This would have interest in the sense that we can rigorously deal with data aggregation or tracking scenarios, for instance. Moreover, in these scenarios, it could be also interesting to include in the selective forwarding model a factor to penalize for the delay incurred. Some works in the literature are aimed at optimizing it (some are even formulated in terms of MDPs), so to integrate these models with the one proposed in this thesis could be explored.

- There are some free parameters in the optimal selective forwarding policy. These parameters are related to the way nodes acquire information about neighboring thresholds, and the frequency of nodes communicating their thresholds (e.g., parameter η, β, beacon interval, etc.). Up to now, the assignment of these parameters has been adjusted off-line (exploring different values). The optimization of these parameters so that neighboring nodes will be able to automatically update their threshold value is raised as a future research line because it is certainly important from a practical implementation perspective.

- Although the proof of the optimal selective forwarding exposed in the dissertation is self-contained, the sensor model is stated as a special case of a MDP (with the particularity that the state space is infinite and an expected non-discounted sum over a potentially infinite horizon, which is actually finite). An extension of this work could be to find and explore other MDP models so that they fit and are useful in sensor network scenarios.

- Results obtained through simulation are typically not directly applicable to operational networks because many new issues arise when working with real-world experiments or deployments. As the final aim of the selective policy exposed in this thesis is to implement it in real motes, it would be essential to test results in real setups to analyze its behavior. Furthermore, theoretical and simulation work would be completed and complemented with real-world experiments. Therefore, another future work (although actually it is a current line) is to test the implementation of the selective transmission strategy. Preliminary results can be found in [Hansen et al., 2010]. Thus, to go into preliminary results in depth and to think about more complex setups are of interest.

- Another future research work was mentioned in the previous chapter. The application of the selective communication strategies to target tracking can be improved. Particularly, the choice of the importance function, which is based on the power of the signal detected by sensors, is simple and does not consider the correlation with previous measures. Therefore, an importance function based on measures of conditional entropy seems more suitable, as it is considered in [Williams et al., 2007], where the importance reflects the degree of innovation of the incoming message regarding the previous ones.

- The model developed in this thesis is not suitable for scenarios where nodes can work indefinitely in time (as for renewable or rechargeable sensors), because there are infinite optimal strategies for the importance sum. To solve this problem, it would be necessary to replace the importance sum criterion by another one based on averages. The difficulty mainly stems from solving mathematically the optimization problem to obtain the optimal transmission strategy.

  Recently, Lei [Lei et al., 2009] has proposed a model for replenishable sensors based on MDPs. To solve the optimization problem, the authors formulated the problem as a discrete time Markov chain, and considered as discrete the main variables of the problem: the message importance and the node state. However, the model has some important restrictions: to make the problem tractable, they consider a single-hop transmission, the model is not adaptive (the energy replenishment rate and the message arrival rate are known a priori), and the model assumes that the energy transmission costs are constant, among others. Hence, the adaptation of the models proposed in the thesis to this kind of scenarios is a future line of great interest.

- Finally, other research lines are basically theoretical, as to prove the convergence of parameter τ in (5.14) or trying to find a constant asymptotic threshold close in performance to the optimal threshold for those 'particular' cases where the optimal threshold does not converge to a constant value when energy is infinite.

APPENDIX A

MATHEMATICAL PROOFS: OPTIMAL SELECTIVE TRANSMISSION

A.1 PROOF OF THEOREM 1

Defining the cumulative importance at time k as

$$t_k = \sum_{i=0}^{k} d_i x_i, \tag{A.1}$$

the dynamics of the cumulative importances and energy can be described by the pair of equations

$$t_k = t_{k-1} + d_k x_k \tag{A.2}$$

$$e_{k+1} = e_k - d_k E_1(x_k) - (1 - d_k) E_0(x_k), \tag{A.3}$$

and $d_k = d(e_k, x_k)$ with the constraint $d(e_k, x_k) = 0, \text{ if } e_k < E_1(x_k)$.

Note that the accumulated importance can be expressed as

$$t_\infty = \sum_{i=0}^{\infty} d_i x_i = t_{k-1} + \sum_{i=k}^{\infty} d_i x_i. \tag{A.4}$$

Since, for any k, $\mathbb{E}\{t_\infty\} = \int \mathbb{E}\{t_\infty | e_k, x_k\} dP(e_k, x_k)$, maximizing $\mathbb{E}\{t_\infty\}$ is equivalent to maximize, for each k, $\mathbb{E}\{t_\infty|e_k,x_k\}$,[1] which can be expressed as

$$\mathbb{E}\{t_\infty|e_k,x_k\} = \mathbb{E}\{t_{k-1}|e_k,x_k\} + d_k x_k + \sum_{i=k+1}^{\infty} \mathbb{E}\{d_i x_i|e_k,x_k\}. \tag{A.5}$$

Since d_k is a deterministic function of e_k and x_k, we can write for any $i > k$,

$$\begin{aligned}
&\mathbb{E}\{d_i x_i|e_k,x_k\}\\
&=P(d_k=0|e_k,x_k)\mathbb{E}\left\{d_i x_i|e_k,x_k,d_k=0\right\} + P(d_k=1|e_k,x_k)\mathbb{E}\left\{d_i x_i|e_k,x_k,d_k=1\right\}\\
&=(1-d_k)\mathbb{E}\left\{d_i x_i|e_k,x_k,d_k=0\right\} + d_k\mathbb{E}\left\{d_i x_i|e_k,x_k,d_k=1\right\}\\
&=(1-d_k)\mathbb{E}\left\{d_i x_i|e_{k+1}=e_k-E_0(x_k),e_k,x_k\right\} + d_k\mathbb{E}\left\{d_i x_i|e_{k+1}=e_k-E_1(x_k),e_k,x_k\right\},
\end{aligned} \tag{A.6}$$

thus, replacing (A.6) into (A.5)

$$\begin{aligned}
\mathbb{E}\{t_\infty|e_k,x_k\} &= \mathbb{E}\{t_{k-1}|e_k,x_k\}\\
&+ \quad d_k\left(x_k + \sum_{i=k+1}^{\infty}\mathbb{E}\{d_i x_i|e_{k+1}=e_k-E_1(x_k),e_k,x_k\}\right)\\
&+ \quad (1-d_k)\sum_{i=k+1}^{\infty}\mathbb{E}\{d_i x_i|e_{k+1}=e_k-E_0(x_k),e_k,x_k\}.
\end{aligned} \tag{A.7}$$

Since (i) for $i > k$ both d_i and x_i are independent of x_k (the importance sequence, x_k, is statistically independent) and (ii) e_{k+1} is fixed; we can remove x_k and e_k in the conditional expectations. Thus, we can use the definition of λ_{k+1} in (4.8), to rewrite (A.7) as

$$\begin{aligned}
\mathbb{E}\{t_\infty|e_k,x_k\} &= \mathbb{E}\{t_{k-1}|e_k,x_k\} + \lambda_{k+1}(e_k-E_0(x_k))\\
&+ \quad \left(x_k - \left[\lambda_{k+1}(e_k-E_0(x_k)) - \lambda_{k+1}(e_k-E_1(x_k))\right]\right)d_k.
\end{aligned} \tag{A.8}$$

Since the two first terms are fixed and do not depend on d_k, focus has to be placed on the third term. Defining $\mu_k(e_k,x_k)$ as in (4.5), the third term in (A.8) can be written as

[1] An intuitive explanation for the equivalence between maximizing $\mathbb{E}\{t_\infty\}$ and $E\{t_\infty|e_k,x_k\}$is the following: no matter what a selective transmission scheme has done up to time $k-1$, the best that can be done at time k is maximizing $E\{t_\infty|e_k,x_k\}$. If this rule is applied at every time k, the unconditional expectation, $\mathbb{E}\{t_\infty\}$, is maximized.

$$(x_k - \mu_k(e_k, x_k))\, d_k. \tag{A.9}$$

Clearly, the decision rule given by $d_k = 1$ as soon as $x_k \geq \mu_k(e_k, x_k)$ (so as to maximize (A.9)) and $e_k \geq E_1(x_k)$ (so as to satisfy the constraint in (4.2)) and $d_k = 0$ otherwise, is optimal in the sense of maximizing $\mathbb{E}\{t_\infty|e_k, x_k\}$.

The recursive computation of $\lambda_k(e)$ in (4.6) is the only result that remains to be proved. To do so we note that, for any $i > k$,

$$\begin{aligned}\mathbb{E}\{d_i x_i|e_k\} &= P(d_k = 0|e_k)\mathbb{E}\{d_i x_i|e_k, d_k = 0\} + P(d_k = 1|e_k)\mathbb{E}\{d_i x_i|e_k, d_k = 1\}\\ &= (1 - P(x_k \geq \mu_k(e_k, x_k), e_k \geq E_1(x_k)|e_k))\mathbb{E}\{\mathbb{E}\{d_i x_i|e_{k+1} = e_k - E_0(x_k), e_k, d_k = 0\}\}\\ &\quad + P(x_k \geq \mu_k(e_k, x_k), e_k \geq E_1(x_k)|e_k)\mathbb{E}\{\mathbb{E}\{d_i x_i|e_{k+1} = e_k - E_1(x_k), e_k, d_k = 1\}\},\end{aligned} \tag{A.10}$$

(where the external expectation must be taken over $x_k|e_k, d_k$). Using the definition of $\lambda_k(e)$ in (4.8) and capitalizing on (A.10), we find

$$\lambda_k(e) = \sum_{i=k}^{\infty} \mathbb{E}\{d_i x_i|e_k = e\} = \mathbb{E}\{d_k x_k|e_k = e\} + \sum_{i=k+1}^{\infty} \mathbb{E}\{\mathbb{E}\{d_i x_i|e_k = e, x_k\}\} \tag{A.11}$$

where the outer expectation applies over x_k. Taking into account that d_k only depends on e_k and x_k, the conditions in the inner expectation operators determine uniquely d_k and, thus, we can write

$$\begin{aligned}\lambda_k(e) &= \mathbb{E}\{d_k x_k|e_k = e\} + \sum_{i=k+1}^{\infty} \mathbb{E}\Big\{(1 - d_k)\mathbb{E}\{d_i x_i|e_{k+1} = e - E_0(x_k), x_k\}\\ &\qquad + d_k \mathbb{E}\{d_i x_i|e_{k+1} = e - E_1(x_k), x_k\}\Big\}\\ &= \mathbb{E}\{d_k x_k|e_k = e\} + \mathbb{E}\{(1 - d_k)\lambda_{k+1}(e - E_0(x_k))\} + \mathbb{E}\{d_k \lambda_{k+1}(e - E_1(x_k))\}\\ &= \mathbb{E}\{d_k x_k|e_k = e\} - \mathbb{E}\{d_k \mu_{k+1}(e, x_k)\} + \mathbb{E}\{\lambda_{k+1}(e - E_0(x_k))\}\\ &= \mathbb{E}\{d_k(x_k - \mu_k(e_k, x_k))|e_k = e\} + \mathbb{E}\{\lambda_{k+1}(e - E_0(x_k))\}\\ &= \mathbb{E}\{\lambda_{k+1}(e - E_0(x_k))\} + \mathbb{E}\{(x_k - \mu_k(e, x_k))^+ u(e - E_1(x_k))\}.\end{aligned} \tag{A.12}$$

The initial value can be computed using (4.2): if there is no available energy, transmissions are not possible. Mathematically, if $e_k = 0$, $d_i = 0$ for $i > k$, so that (4.8) becomes

$$\lambda_k(0) = 0, \qquad \text{for any } k. \tag{A.13}$$

Combining (A.12) and (A.13) we get (4.6), completing the proof.

A.2 Proof of Theorem 2

Let us define the minimum energy consumed per time as $\epsilon = \min_{i,x}\{E_i(x)\}$. We prove the theorem by induction, by showing that $\lambda_k(e)$ does not depend on k for $e \leq n\epsilon$, for any n. This is true for $n = 0$, because $\lambda_k(0) = 0$. Now, let us assume that $\lambda_k(e)$ does not depend on k for $e \leq n\epsilon$. If $n\epsilon < e \leq (n+1)\epsilon$, by (4.5) we find that $\mu_k(e, x)$ does not depend on k. Thus, using (4.6), and taking into account that expectations are taken over x_k, whose distribution does not depend on k, we find that $\lambda_k(e)$ does not depend on k, which completes the proof.

A.3 PROOF OF THEOREM 3

Defining

$$z(e) = \lambda(e) - \tau_{\mu_c} e \cdot u(e), \tag{A.14}$$

where τ_{μ_c} is given by (4.32), we have, for large e (i.e., $e > B$)

$$\begin{aligned}
z(e) =& \mathbb{E}\{u(x-\mu_c)x\} - \tau_{\mu_c} e \\
&+ P(x<\mu_c)\mathbb{E}\{\lambda(e - E_0(x))|x<\mu_c\} + P(x \geq \mu_c)\mathbb{E}\{\lambda(e-E_1(x))|x \geq \mu_c\} \\
=& \mathbb{E}\{u(x-\mu_c)x\} - \tau_{\mu_c} e \\
&+ P(x<\mu_c)\mathbb{E}\{z(e-E_0(x))|x<\mu_c\} + P(x<\mu_c)\tau_{\mu_c}\mathbb{E}\{e-E_0(x)|x<\mu_c\} \\
&+ P(x\geq\mu_c)\mathbb{E}\{z(e-E_1(x))|x\geq\mu_c\} + P(x\geq\mu_c)\tau_{\mu_c}\mathbb{E}\{e-E_1(x)|x\geq\mu_c\} \\
=& \mathbb{E}\{u(x-\mu_c)x\} \\
&+ P(x<\mu_c)\mathbb{E}\{z(e-E_0(x))|x<\mu_c\} + P(x<\mu_c)\tau_{\mu_c}\mathbb{E}\{E_0(x)|x<\mu_c\} \\
&+ P(x\geq\mu_c)\mathbb{E}\{z(e-E_1(x))|x\geq\mu_c\} + P(x\geq\mu_c)\tau_{\mu_c}\mathbb{E}\{E_1(x)|x\geq\mu_c\} \\
=& P(x<\mu_c)\mathbb{E}\{z(e-E_0(x))|x<\mu_c\} + P(x\geq\mu_c)\mathbb{E}\{z(e-E_1(x))|x\geq\mu_c\}.
\end{aligned} \tag{A.15}$$

Defining the random variable

$$\epsilon = E_0(x) I_{x<\mu_c} + E_1(x) I_{x \geq \mu_c}, \tag{A.16}$$

we have

$$z(e) = \mathbb{E}\{z(e-\epsilon)\} = P(\epsilon = 0) z(e) + P(\epsilon > 0)\mathbb{E}\{z(e-\epsilon)|\epsilon > 0\}. \tag{A.17}$$

Thus,

$$z(e) = \mathbb{E}\{z(e-\epsilon)|\epsilon > 0\}. \tag{A.18}$$

Since $z(e)$ is a weighted average of previous values, there should exist some values $\epsilon_l > 0$ and $\epsilon_u > 0$ such that

$$z(e-\epsilon_l) < z(e) < z(e-\epsilon_u). \tag{A.19}$$

Applying these inequalities iteratively, we can prove by induction that

$$z(e_l) \leq z(e) \leq z(e_u), \qquad \text{for some } e_l, e_u \leq B. \tag{A.20}$$

But, since λ is finite for finite e, λ is bounded in $[0, B]$; so z is also bounded in $[0, B]$. Thus, using (A.20), we conclude that $z(e)$ is bounded in $\mathbb{R}$. Therefore, we can compute the income rate as

$$\lim_{e \to \infty} \frac{\lambda(e)}{e} = \lim_{e \to \infty} \frac{z(e) + \tau_{\mu_c} e}{e} = \tau_{\mu_c}. \tag{A.21}$$

A.4 Proof of Theorem 4

Let us assume that the threshold function does not depend on the energy level, so that $\mu(e, x) = \mu(x)$. Then, using (4.10), we can write

$$\lambda(e) = \lambda(e - \Delta(x)) + \mu(x), \tag{A.22}$$

where

$$\Delta(x) = E_1(x) - E_0(x). \tag{A.23}$$

Defining

$$g_x(e) = \lambda(e) - \frac{\mu(x)}{\Delta(x)} e, \tag{A.24}$$

(A.22) implies that $g_x(e)$ is a periodic function with period $\Delta(x)$. But this is impossible if $\frac{\mu(x)}{\Delta(x)}$ varies with x (because the difference between two periodic functions cannot be a (nonconstant) linear function. Thus,

$$\mu(x)/\Delta(x) = \tau \tag{A.25}$$

for some constant τ, and

$$g_x(e) = g(e) = \lambda(e) - \tau e. \tag{A.26}$$

Combining (4.11), (A.22) and (A.26), we can write

$$g(e) + \frac{\mu(x)}{\Delta(x)} e = \mathbb{E}\left\{g(e - E_0(x)) + \tau(e - E_0(x))\right\} + \mathbb{E}\{(x - \mu(x))^+\}. \tag{A.27}$$

Thus,

$$g(e) - \mathbb{E}\{g(e - E_0(x))\} = -\,\mathbb{E}\left\{\tau E_0(x)\right\} + \mathbb{E}\{(x - \mu(x))^+\}. \tag{A.28}$$

Integrating the above equation with respect to e over a full period and noting that $\int_{\Delta(x)} g(e) de = \int_{\Delta(x)} g(e - E_0(x)) de$, we get

$$\tau\mathbb{E}\left\{E_0(x)\right\} = \mathbb{E}\{(x - \Delta(x)\tau)^+\}, \tag{A.29}$$

which is equivalent to (4.35). To show that the solution of (A.29) is unique, note that the left-hand side is a strictly growing function of τ while the right-hand side is a nonincreasing function, because

$$\frac{d\mathbb{E}\{(x-\Delta(x)\tau)^{+}\}}{d\tau} = -\mathbb{E}\{\Delta(x)u(x-\Delta(x)\tau)\}, \tag{A.30}$$

which is always nonpositive. Since a strictly increasing function intersects with a nonincreasing function in at most one single point, the solution is unique.

Appendix B

Mathematical Proofs: Optimal Selective Forwarding

B.1 Proof of Theorem 5

The cumulative importance at time k, given by (5.4), can be expressed recursively as $t_k = t_{k-1} + d_k r_k$ and, for any $k > 0$, the accumulated importance can be expressed as

$$t_\infty = \sum_{i=0}^{\infty} d_i r_i = t_{k-1} + \sum_{i=k}^{\infty} d_i r_i. \tag{B.1}$$

Since, for any k, $\mathbb{E}\{t_\infty\} = \int \mathbb{E}\{t_\infty|e_k, \mathbf{z}_k\} dP(e_k, \mathbf{z}_k)$, maximizing $\mathbb{E}\{t_\infty\}$ is equivalent to maximize, for each k, $\mathbb{E}\{t_\infty|e_k, \mathbf{z}_k\}$, which can be expressed as

$$\mathbb{E}\{t_\infty|e_k, \mathbf{z}_k\} = \mathbb{E}\{t_{k-1}|e_k, \mathbf{z}_k\} + d_k \mathbb{E}\{r_k|e_k, \mathbf{z}_k\} + \sum_{i=k+1}^{\infty} \mathbb{E}\{d_i r_i|e_k, \mathbf{z}_k\}, \tag{B.2}$$

where we have used the fact that d_k is a deterministic function of e_k and $\mathbf{z}_k$. Also, it is useful to write, for any $i > k$,

$$\mathbb{E}\{d_i r_i|e_k, \mathbf{z}_k\} = (1 - d_k)\mathbb{E}\left\{d_i r_i|e_k, \mathbf{z}_k, d_k = 0\right\} + d_k \mathbb{E}\left\{d_i r_i|e_k, \mathbf{z}_k, d_k = 1\right\}. \tag{B.3}$$

Taking into account that

$$\begin{aligned}\mathbb{E}\{d_i r_i|e_k = e, \mathbf{z}_k, d_k = 0\} &= \int \mathbb{E}\{d_i r_i|e_k = e, \mathbf{z}_k, d_k = 0, c_{0,k}\} dP(c_{0,k}|e_k = e, \mathbf{z}_k, d_k = 0) \\ &= \int \mathbb{E}\{d_i r_i|e_{k+1} = e - c_{0,k}\} dP(c_{0,k}|\mathbf{z}_k) = \mathbb{E}\{\mathbb{E}\{d_i r_i|e_{k+1} = e - c_{0,k}\}|\mathbf{z}_k\}\end{aligned} \tag{B.4}$$

where we have used the fact that the data sequence, $\mathbf{z}_k$ is statistically independent, so that both d_i and r_i are independent of $\mathbf{z}_k$, for $i > k$, and we can remove $\mathbf{z}_k$ in the inner conditional expectations in (B.4). The outer expectation should be taken over $c_{0,k}$. Proceeding in an analog manner with $\mathbb{E}\{d_i r_i | e_k = e, \mathbf{z}_k, d_k = 1\}$, we arrive at

$$\begin{aligned} \mathbb{E}\{d_i r_i | e_k = e, \mathbf{z}_k\} = (1-d_k)\mathbb{E}\{\mathbb{E}\{d_i r_i | e_{k+1} = e - c_{0,k}\} | \mathbf{z}_k\} \\ + d_k \mathbb{E}\{\mathbb{E}\{d_i r_i | e_{k+1} = e - c_{1,k}\} | \mathbf{z}_k\}. \end{aligned} \tag{B.5}$$

Upon defining $Q_k(e_k, \mathbf{z}_k) := \mathbb{E}\{q_k u(e_k - c_{1,k}) | e_k, \mathbf{z}_k\}$ and replacing (B.5) into (B.2), we get

$$\begin{aligned} \mathbb{E}\{t_\infty | e_k = e, \mathbf{z}_k\} &= \mathbb{E}\{t_{k-1} | e_k = e, \mathbf{z}_k\} \\ &+ (1-d_k) \sum_{i=k+1}^{\infty} \mathbb{E}\{\mathbb{E}\{d_i r_i | e_{k+1} = e - c_{0,k}\} | \mathbf{z}_k\} \\ &+ d_k x_k Q_k(e, \mathbf{z}_k) + d_k \sum_{i=k+1}^{\infty} \mathbb{E}\{\mathbb{E}\{d_i r_i | e_{k+1} = e - c_{1,k}\} | \mathbf{z}_k\} \end{aligned} \tag{B.6}$$

Using the definition of λ_{k+1} in (5.9), the expected accumulated importance can be written as

$$\begin{aligned} \mathbb{E}\{t_\infty | e_k = e, \mathbf{z}_k\} &= \mathbb{E}\{t_{k-1} | e_k = e, \mathbf{z}_k\} + (1-d_k)\mathbb{E}\{\lambda_{k+1}(e - c_{0,k}) | \mathbf{z}_k\} \\ &+ d_k x_k Q_k(e, \mathbf{z}_k) + d_k \mathbb{E}\{\lambda_{k+1}(e - c_{1,k}) | \mathbf{z}_k\}. \end{aligned} \tag{B.7}$$

Defining $\mu_k(e, \mathbf{z}_k)$ as in (5.7), we get

$$\begin{aligned} \mathbb{E}\{t_\infty | e_k = e, \mathbf{z}_k\} = \mathbb{E}\{t_{k-1} | e_k = e, \mathbf{z}_k\} + \mathbb{E}\{\lambda_{k+1}(e - c_{0,k}) | \mathbf{z}_k\} \\ + d_k(x_k Q_k(e, \mathbf{z}_k) - \mu_k(e, \mathbf{z}_k))). \end{aligned} \tag{B.8}$$

Clearly, the decision rule given by $d_k = 1$ as soon as $x_k Q_k(e, \mathbf{z}_k) \geq \mu_k(e, \mathbf{z}_k)$ (so as to maximize the third term in (B.8)) and $d_k = 0$ otherwise, is optimal in the sense of maximizing $\mathbb{E}\{t_\infty | e_k, \mathbf{z}_k\}$. Therefore, $d_k = u(x_k Q_k(e_k, \mathbf{z}_k) - \mu_k(e_k, \mathbf{z}_k))$, where $u(\cdot)$ is the step function.

The recursive computation of $\lambda_k(e)$ in (5.8) is the only result that remains to be proved. To do so, we note that, for any $i > k$,

$$\begin{aligned}\mathbb{E}\{d_i r_i | e_k = e\} &= P_{0,k}(e)\mathbb{E}\{\mathbb{E}\{d_i r_i | e_k = e, d_k = 0\}\} + P_{1,k}(e)\mathbb{E}\{\mathbb{E}\{d_i r_i | e_k = e, d_k = 1\}\} \\ &= P_{0,k}(e)\mathbb{E}\{\mathbb{E}\{d_i r_i | e_{k+1} = e - c_{0,k}\} | e_k\} + P_{1,k}(e)\mathbb{E}\{\mathbb{E}\{d_i r_i | e_{k+1} = e - c_{1,k}\} | e_k\}\end{aligned} \tag{B.9}$$

where $P_{0,k}(e) = P(d_k = 0 | e_k = e)$ and $P_{1,k}(e) = 1 - P_{0,k}(e)$. The outer expectations must be taken over $c_{0,k}$ and $c_{1,x}$. Using the definition of $\lambda_k(e)$ in (5.9) and capitalizing on (B.9), we find

$$\lambda_k(e) = \sum_{i=k}^{\infty} \mathbb{E}\{d_i r_i | e_k = e\} = \mathbb{E}\{d_k r_k | e_k = e\} + \sum_{i=k+1}^{\infty} \mathbb{E}\{\mathbb{E}\{d_i r_i | e_k = e, \mathbf{z}_k\}\} \tag{B.10}$$

where the outer expectation applies over $\mathbf{z}_k$. Taking into account that d_k only depends on e_k and $\mathbf{z}_k$, the conditions in the inner expectation operators determine uniquely d_k and, thus, we can write

$$\begin{aligned}\lambda_k(e) =& \mathbb{E}\{d_k r_k | e_k = e\} + \sum_{i=k+1}^{\infty} \mathbb{E}\Big\{(1 - d_k)\mathbb{E}\{d_i r_i | e_{k+1} = e - c_{0,k}, \mathbf{z}_k\} \\ &+ d_k \mathbb{E}\{d_i r_i | e_{k+1} = e - c_{1,k}, \mathbf{z}_k\} | e_k = e\Big\} \\ =& \mathbb{E}\{d_k r_k | e_k = e\} + \mathbb{E}\{(1 - d_k)\lambda_{k+1}(e - c_{0,k}) | e_k = e\} + \mathbb{E}\{d_k \lambda_{k+1}(e - c_{1,k}) | e_k = e\} \\ =& \mathbb{E}\{\lambda_{k+1}(e - c_{0,k})\} + \mathbb{E}\{d_k(r_k - \mu_k(e, \mathbf{z}_k)) | e_k = e\} \\ =& \mathbb{E}\{\lambda_{k+1}(e - c_{0,k})\} \\ &+ \mathbb{E}\{(x_k q_k u(e - c_{1,k}) - \mu_k(e, \mathbf{z}_k)) u(x_k Q_k(e, \mathbf{z}_k) - \mu_k(e, \mathbf{z}_k)) | e_k = e\} \\ =& \mathbb{E}\{\lambda_{k+1}(e - c_{0,k})\} + \mathbb{E}\{(x_k Q_k(e, \mathbf{z}_k) - \mu_k(e, \mathbf{z}_k)) u(x_k Q_k(e, \mathbf{z}_k) - \mu_k(e, \mathbf{z}_k))\}.\end{aligned} \tag{B.11}$$

Using (5.9), and taking into account that, if there is no available energy, no transmissions are possible, we can write $\lambda_k(e) = 0$, for any k and $e \leq 0$. Combining the latter with (B.11), we get (5.8), completing the proof.

B.2 PROOF OF THEOREM 6

Take $\epsilon > 0$ such that, with probability 1, $c_{1,i} > \epsilon$ for any i. We prove the theorem by induction, by showing that $\lambda_k(e)$ does not depend on k for $e \leq n\epsilon$, for any n. This is true for $n = 0$, because $\lambda_k(0) = 0$. Now, let us assume that $\lambda_k(e)$ does not depend on k for $e \leq n\epsilon$. If $n\epsilon < e \leq (n+1)\epsilon$, by (5.7) we find that $\mu_k(e, \mathbf{z})$ does not depend on k. Thus, using (5.8), and taking into account that expectations are taken over $\mathbf{z}_k$, whose distribution does not depend on k, we find that $\lambda_k(e)$ does not depend on k, which completes the proof.

B.3 Proof of Theorem 7

Let define $h(e) = \mathbb{E}\{(Q(e, \mathbf{z}_k)x_k - \mu(e, \mathbf{z}_k))^+\}$ and note that

$$\mathbb{E}\{\lambda(e - c_0)\} = \int \lambda(e - c)p_{c_0}(c)dc = \lambda(e) * p_{c_0}(e) \tag{B.12}$$

where '$*$' denotes the convolution operator and $p_{c_0}(e)$ is the probability density function of c_0. Then, (5.12) can be written as

$$(\delta(e) - p_{c_0}(e)) * \lambda(e) = h(e)u(e), \tag{B.13}$$

where subindex k in e_k and $c_{0,k}$ has been omitted for simplicity. Similarly, (5.11) can be written as

$$\mu(e, \mathbf{z}) = \lambda(e) * (p_{c_0|\mathbf{z}}(e) - p_{c_1|\mathbf{z}}(e)). \tag{B.14}$$

Applying a convolution with $\delta(e) - p_{c_0}(e)$ to (B.14), and using (B.13), we get

$$(\delta(e) - p_{c_0}(e)) * \mu(e, \mathbf{z}) = (h(e)u(e)) * (p_{c_0|\mathbf{z}}(e) - p_{c_1|\mathbf{z}}(e)) \tag{B.15}$$

Once again, applying a convolution with $u(e)$ to (B.15),

$$(u(e) - P_{c_0}(e)) * \mu(e, \mathbf{z}) = (h(e)u(e)) * (P_{c_0|\mathbf{z}}(e) - P_{c_1|\mathbf{z}}(e)) \tag{B.16}$$

where P_{c_0}, $P_{c_0|\mathbf{z}}$ and $P_{c_1|\mathbf{z}}$ are distribution functions. Defining $d_\mu(e, \mathbf{z}) = \mu(e, \mathbf{z}) - \mu(\mathbf{z})$, where $\mu(\mathbf{z}) = \lim_{e\to\infty} \mu(e, \mathbf{z})$, the left-hand side of (B.16) can be written as

$$\begin{aligned}(u(e) - P_{c_0}(e)) * \mu(e, \mathbf{z}) &= \int_0^e (u(\alpha) - P_{c_0}(\alpha))\mu(e - \alpha, \mathbf{z})d\alpha \\ &= \mu(\mathbf{z}) \int_0^e (u(\alpha) - P_{c_0}(\alpha))d\alpha + \int_0^e (u(\alpha) - P_{c_0}(\alpha))d_\mu(e - \alpha, \mathbf{z})d\alpha. \end{aligned} \tag{B.17}$$

Now we compute the limit of (B.17) for large e. After some algebra, it can be shown that

$$\lim_{e\to\infty} \int_0^e (u(\alpha) - P_{c_0}(\alpha))d\alpha = \mathbb{E}\{c_0\}. \tag{B.18}$$

To compute the limit of the second term in (B.17), note that, since the limit in (B.18) is $\mathbb{E}\{c_0\}$, for any $\epsilon > 0$ we can take some q_ϵ such that, for any $e > q_\epsilon$ it holds that $\int_0^e (u(\alpha) - P_{c_0}(\alpha))d\alpha > \mathbb{E}\{c_0\} - \epsilon$. Also, since $\lim_{e\to\infty} \mu(e, \mathbf{z}) = \mu(\mathbf{z})$, we can take e large enough to get $|\mu(e', \mathbf{z}) - \mu(\mathbf{z})| < \epsilon$ for any $e' > e + q_\epsilon$. Thus,

$$\left|\int_0^e (u(\alpha) - P_{c_0}(\alpha))d_\mu(e-\alpha,\mathbf{z})d\alpha\right| \leq \int_0^{q_\epsilon} (u(\alpha) - P_{c_0}(\alpha))|d_\mu(e-\alpha,\mathbf{z})|d\alpha$$
$$+ \int_{q_\epsilon}^e (u(\alpha) - P_{c_0}(\alpha))|d_\mu(e-\alpha,\mathbf{z})|d\alpha < \ \mathbb{E}\{c_0\}\epsilon + \int_{q_\epsilon}^e (u(\alpha) - P_{c_0}(\alpha))|d_\mu(e-\alpha,\mathbf{z})|d\alpha. \tag{B.19}$$

If we can prove that $|d_\mu(e, \mathbf{z})|$ is bounded by some $B_\mathbf{z} < \infty$ for any $e \geq 0$ we get

$$\left|\int_0^e (u(\alpha) - P_{c_0}(\alpha))d_\mu(e-\alpha,\mathbf{z})d\alpha\right| < \ (\mathbb{E}\{c_0\} + B_\mathbf{z})\epsilon \tag{B.20}$$

so that

$$\lim_{e\to\infty}\int_0^e (u(\alpha) - P_{c_0}(\alpha))d_\mu(e-\alpha,\mathbf{z})d\alpha = 0 \tag{B.21}$$

and, joining (B.17), (B.18) and (B.21), we arrive at

$$\lim_{e\to\infty}((u(e) - P_{c_0}(e)) * \mu(e,\mathbf{z})) = \mu(\mathbf{z})\mathbb{E}\{c_0\}. \tag{B.22}$$

To prove that $|d_\mu(e, \mathbf{z})|$ is bounded, take an arbitrary $\epsilon > 0$. Since $\lim_{e\to\infty} \mu(e, \mathbf{z}) = \mu(\mathbf{z})$, there exists some q such that $|d_\mu(e, \mathbf{z})| < \epsilon$ for any $e > q$. For $e < q$,

$$|d_\mu(e,\mathbf{z})| \leq |\mu(e,\mathbf{z})| + |\mu(\mathbf{z})| = |\lambda(e) * (p_{c_0|\mathbf{z}}(e) - p_{c_1|\mathbf{z}}(e)| + |\mu(\mathbf{z})| \leq \lambda(q), \tag{B.23}$$

where the last inequality uses the fact that $\lambda(e)$ is a nondecreasing function of e. Thus, for any $e \geq 0$, $|d_\mu(e, \mathbf{z})| \geq B = \max\{\epsilon, \lambda(q)\}$, which completes the proof of (B.22).

The right-hand side of (B.16) can be analyzed in a similar way: defining $d_h(e) = h(e) - h_\infty$, where $h_\infty = \lim_{e\to\infty} h(e)$, we can write

$$(h(e)u(e)) * (P_{c_0|\mathbf{z}}(e) - P_{c_1|\mathbf{z}}(e)) = \int_0^e (P_{c_0|\mathbf{z}}(\alpha) - P_{c_1|\mathbf{z}}(\alpha))h(e-\alpha)d\alpha$$
$$= h_\infty \int_0^e (P_{c_0|\mathbf{z}}(\alpha) - P_{c_1|\mathbf{z}}(\alpha))d\alpha + \int_0^e (P_{c_0|\mathbf{z}}(\alpha) - P_{c_1|\mathbf{z}}(\alpha))d_h(e-\alpha)d\alpha. \tag{B.24}$$

The same reasoning used to prove (B.21) can be used to prove that

$$\lim_{e\to\infty}\int_0^e (P_{c_0|\mathbf{z}}(e) - P_{c_1|\mathbf{z}}(e))d_h(e-\alpha)d\alpha = 0. \tag{B.25}$$

Defining $\Delta(\mathbf{z}) = \mathbb{E}\{c_1|\mathbf{z}\} - \mathbb{E}\{c_0|\mathbf{z}\}$ and substituting (B.25) into (B.24), in the limit we get

$$\lim_{e\to\infty}((h(e)u(e)) * (P_{c_0|\mathbf{z}}(e) - P_{c_1|\mathbf{z}}(e))) = h_\infty \int_0^e (P_{c_0|\mathbf{z}}(\alpha) - P_{c_1|\mathbf{z}}(\alpha))d\alpha = h_\infty\Delta(\mathbf{z}). \tag{B.26}$$

Combining (B.16), (B.22) and (B.26), we have that $\mu(\mathbf{z})\mathbb{E}\{c_0\} = h_\infty\Delta(\mathbf{z})$, which shows that $\tau = \mu(\mathbf{z})/\Delta(\mathbf{z})$ does not depend on $\mathbf{z}$. Thus

$$\tau\mathbb{E}\{E_0(\mathbf{z})\} = \mathbb{E}\{(xQ(\mathbf{z}) - \Delta(\mathbf{z})\tau)^+\}, \tag{B.27}$$

which is equivalent to (5.14). To show that, for $\Delta(\mathbf{z}) > 0$ the solution of (B.27) is unique, note that the left-hand side is a strictly increasing function of τ while the right-hand side is a non-increasing function, because $d\mathbb{E}\{(xQ(\mathbf{z}) - \Delta(\mathbf{z})\tau)^+\}/d\tau = -\mathbb{E}\{\Delta(\mathbf{z})u(xQ(\mathbf{z}) - \Delta(\mathbf{z})\tau)\}$, which (for $\Delta(\mathbf{z}) > 0$) is always non positive. Since a strictly increasing function intersects with a non-increasing function in at most one single point, the solution is unique.

Bibliography

[Tmo, 2009] (2009). Tmote Sky Low Power IEEE 802.15.4 Wireless Sensor Module datasheet. http://sentilla.com/files/pdf/eol/tmote-sky-datasheet.pdf.

[Cro, 2010] (2010). Crossbow technologies web site. http://www.xbow.com/.

[Sen, 2010] (2010). Sensor Network Museum. http://www.snm.ethz.ch/Main/HomePage.

[A. Deshpande et al., 2004] A. Deshpande, A., Guestrin, C., Madden, S. R., Hellerstein, J. M., and Hong, W. (2004). Model-driven data acquisition in sensor networks. In *Proc. 30th Int'l conf. on Very large data bases (VLDB'04)*, pages 588–599.

[Akyildiz et al., 2002] Akyildiz, I. F., Su, W., Sankarasubramaniam, Y., and Cayirci, E. (Aug. 2002). A Survey on Sensor Networks. *IEEE Comm. Magazine*, 40(8):102–114.

[Alippi and Galperti, 2008] Alippi, C. and Galperti, C. (2008). An Adaptive System for Optimal Solar Energy Harvesting in Wireless Sensor Network Nodes. *IEEE Trans. on Circuits and Systems I: Regular Papers*, 55(6):1742–1750.

[Ananda et al., 2006] Ananda, A., Chan, M., and Ooi, W. (2006). *Mobile, Wireless, and Sensor Networks: Technology, Applications, and Future Directions*. Wiley.

[Anastasi et al., 2009] Anastasi, G., Conti, M., Di-Francesco, M., and Passarella, A. (2009). Energy conservation in wireless sensor networks: A survey. *Ad Hoc Networks*, 7(3):537 – 568.

[Appadwedula et al., 2005] Appadwedula, S., Veeravalli, V., and Jones, D. (2005). Energy-efficient detection in sensor networks. *IEEE Journal on Selected Areas in Communications*, 23(4):693 – 702.

[Arms et al., 2009] Arms, S., Townsend, C., Churchill, D., Hamel, M., Augustin, M., Yeary, D., and Phan, N. (2009). *Medium Access Control in Wireless Networks, Volume II: Practice and Standards*, chapter Energy Harvesting Technologies, pages 195–208. Springer.

[Arroyo-Valles et al., 2007a] Arroyo-Valles, R., Alaiz-Rodriguez, R., Guerrero-Curieses, A., and Cid-Sueiro, J. (2007a). Q-Probabilistic Routing in Wireless Sensor Network. In *Proc. 3th Int'l Conf. Intelligent Sensor, Sensor Networks and Information Processing (ISSNIP '07)*.

[Arroyo-Valles et al., 2007b] Arroyo-Valles, R., Marqués, A. G., and Cid-Sueiro, J. (2007b). Energy-aware Geographic Forwarding of Prioritized Messages in Wireless Sensor Networks. In *Proc. 4th IEEE Int'l Conf. on Mobile Ad-hoc and Sensor Systems (MASS '07)*.

[Arroyo-Valles et al., 2008a] Arroyo-Valles, R., Marques, A. G., and Cid-Sueiro, J. (2008a). Energy-efficient Selective Forwarding for Sensor Networks. In *Proc. Workshop on Energy in Wireless Sensor Networks (WEWSN'08), in conjunction with DCOSS'08*.

[Arroyo-Valles et al., 2009] Arroyo-Valles, R., Marques, A. G., and Cid-Sueiro, J. (2009). Optimal Selective Transmission under Energy Constraints in Sensor Networks. *IEEE Trans. on Mobile Computing*, 8(11):1524–1538.

[Arroyo-Valles et al., 2010a] Arroyo-Valles, R., Marques, A. G., and Cid-Sueiro, J. (2010a). Optimal Selective Forwarding for Energy Saving in Wireless Sensor Networks. *Accepted, IEEE Trans. on Wireless Communications*.

[Arroyo-Valles et al., 2010b] Arroyo-Valles, R., Marques, A. G., and Cid-Sueiro, J. (2010b). *Wireless Sensor Networks*, chapter Energy-aware Selective Communications in Sensor Networks. IN-TECH.

[Arroyo-Valles et al., 2006] Arroyo-Valles, R., Marqués, A. G., Vinagre-Díaz, J., and Cid-Sueiro, J. (2006). A Bayesian Decision Model for Intelligent Routing in Sensor Networks. In *Proc. 3rd IEEE Int'l Symp. on Wireless Comm. Systems (ISWCS '06)*.

[Arroyo-Valles et al., 2010c] Arroyo-Valles, R., Pino-Povedano, S., and Cid-Sueiro, J. (2010c). Selective Forwarding for Energy-efficient Target Tracking in Sensor Networks. *submitted to IEEE Journal on Selected Areas in Communications*.

[Arroyo-Valles et al., 2008b] Arroyo-Valles, R., Pino-Povedano, S., Cid-Sueiro, J., and Gonzalez-Serrano, F. (2008b). Distributed Target Tracking with Selective Transmitters in energy-constrained Sensor Networks. In *Proc. 4th Int. Conf. on Intelligent Sensors, Sensor Nertworks and Information Processing (ISSNIP'08)*.

[Arulampalam et al., 2002] Arulampalam, M., Maskell, S., Gordon, N., and Clapp, T. (2002). A Tutorial on Particle Filters for Online Nonlinear/Non-Gaussian Bayesian Traking. *IEEE Trans. on Signal Processing*, 50(2):174–188.

[Athanassoulis et al., 2007] Athanassoulis, M., Alagiannis, I., and Hadjiefthymiades, S. (2007). Energy Efficiency in Wireless Sensor Networks: A Utility-Based Architecture. In *Proc. 13th European Wireless Conf. (EW'07)*.

[Banerjee and Misra, 2002] Banerjee, S. and Misra, A. (2002). Minimum energy paths for reliable communication in multi-hop wireless networks. In *Proc. ACM Int'l Symp. on Mobile Ad Hoc Networking and Computing*, pages 146–156.

[Barbancho et al., 2006] Barbancho, J., Leon, C., Molina, J., and Barbancho, A. (2006). SIR: A New Wireless Sensor Network Routing Protocol Based on Artificial Intelligence . In *Proc. Advanced Web and Network Technologies, and Apps. (APWeb 2006) Intl. Lecture Notes in Computer Science*, volume 3842, pages 271–275.

[Bartolini et al., 2008] Bartolini, N., Calamoneri, T., Fusco, E. G., Massini, A., and Silvestri, S. (2008). Snap and Spread: A Self-deployment Algorithm for Mobile Sensor Networks. In *Proc. IEEE Int'l Conf. on Distributed Computing in Sensor Systems (DCOSS 08). Lecture Notes in Computer Science*, pages 451–456.

[Bi et al., 2009] Bi, Y., Sun, L., and Li, N. (2009). Boss: a moving strategy for mobile sinks in wireless sensor networks. *Int'l Journal Sensor Networks*, 5(3):173–184.

[Boyan and Littman, 1994] Boyan, J. and Littman, M. (1994). Packet Routing in Dynamically Changing Networks: A Reinforcement Learning Approach. In *Advances in Neural Information Processing Systems 6*, pages 671–678.

[Cao et al., 2005] Cao, Q., Abdelzaher, T., He, T., and Stankovic, J. (2005). Towards optimal sleep scheduling in sensor networks for rare-event detection. In *Proc. 4th Int'l Symp. on Information Processing in Sensor Networks (IPSN'05)*, pages 20–27.

[Charbiwala et al., 2009] Charbiwala, Z., Zahedi, S., Kim, Y., Srivastava, M., and Cho, Y. (2009). Toward Quality of Information Aware Rate Control for Sensor Networks. In *Proc. 4th Int'l Workshop on Feedback Control Implementation and Design in Computing Systems and Networks (FeBID'09)*, page 8.

[Chatterjea et al., 2007] Chatterjea, S., Nieberg, T., Zhang, Y., and Havinga, P. (2007). Energy-Efficient Data Acquisition Using a Distributed and Self-organizing Scheduling Algorithm for Wireless Sensor Networks. In *Proc. IEEE Int'l Conf. on Distributed Computing in Sensor Systems (DCOSS 07). Lecture Notes in Computer Science*, volume 4549, pages 368–385.

[Chelius et al., 2005] Chelius, G., Fleury, E., and Mignon, T. (2005). Lower and upper bounds for minimum energy broadcast and sensing problems in sensor networks. In *Proc. 11th Int'l Conf. Parallel and Distributed Systems*, volume 2, pages 88–92.

[Chen et al., 2002] Chen, B., Jamieson, K., Balakrishnan, H., and Morris, R. (2002). Span: an energy-efficient coordination algorithm for topology maintenance in ad hoc wireless networks. *Wireless Networks*, 8(5):481–494.

[Chen et al., 2008] Chen, J., Lin, R., Li, Y., and Sun, Y. (2008). LQER: A Link Quality Estimation based Routing for Wireless Sensor Networks. *Sensors*, 8(8):1025–1038.

[Chiasserini and Garetto, 2006] Chiasserini, C.-F. and Garetto, M. (2006). An Analytical Model for Wireless Sensor Networks with Sleeping Nodes. *IEEE Trans. Mobile Computing*, 5(12):1706–1718.

[Choi and Wette, 1969] Choi, S. and Wette, R. (1969). Maximum Likehood Estimation of the Parameters of the Gamma Distribution and Their Bias. *Technometrics*, 2(4):683–690.

[Choi and Yeung, 1996] Choi, S. and Yeung, D.-Y. (1996). Predictive Q-Routing: A Memory-based Reinforcement Learning Approach to Adaptive Traffic Control. In *Proc. Neural Information Processing Systems (NIPS'96)*, pages 945–951.

[Chong and Kumar, 2003] Chong, C.-Y. and Kumar, S. (2003). Sensor Networks: Evolution, Opportunities, and Challenges. In *Proc. IEEE*, volume 91, pages 1247–1256.

[Chow et al., 2007] Chow, K.-Y., Lui, K.-S., and Lam, E. (2007). Efficient selective image transmission in visual sensor networks. In *Proc. 65th IEEE Vehicular Technology Conf. (VTC'07-Spring)*, pages 1 –5.

[Corless et al., 1996] Corless, R. M., Gonnet, G. H., Hare, D. E. G., Jeffrey, D. J., and Knuth, D. E. (1996). On the Lambert W function. *Advances in Computational Mathematics*, 5:329–359.

[Doucet et al., 2000] Doucet, A., Godsill, S., and Andrieu, C. (2000). On sequential monte carlo sampling methods for bayesian filtering. *Statistics and Computing*, 10(3):197–208.

[Enz et al., 2004] Enz, C., El-Hoiydi, A., Decotignie, J.-D., and Peiris, V. (2004). WiseNET: An Ultralow- Power Wireless Sensor Network Solution. *IEEE Computer*, 37(8):62–70.

[Ephremides, 2002] Ephremides, A. (2002). Energy Concerns in Wireless Networks. *IEEE Wireless Comm.*, 9(4):48–59.

[Escudero-Garzás et al., 2007] Escudero-Garzás, J., Bousńo-Calzón, C., and Garcia-Armada, A. (2007). An energy-efficient adaptive modulation suitable for wireless sensor networks with ser and throughput constraints. *EURASIP Journal Wireless Commununication and Networking*, 2007(1):23–23.

[Fasolo et al., 2007] Fasolo, E., Rossi, M., Widmer, J., and Zorzi, M. (2007). In-network aggregation techniques for wireless sensor networks: a survey. *IEEE Wireless Comm.*, 14(2):70–87.

[Förster and Murphy, 2009] Förster, A. and Murphy, A. (2009). Clique: Role-Free Clustering with Q-Learning for WSNs. In *Proc. 29th Int'l Conf. on Distributed Computing Systems (ICDCS'09)*, pages 441–449.

[Gelenbe and Ngai, 2008] Gelenbe, E. and Ngai, E. C.-H. (2008). Adaptive random re-routing for differentiated QoS in sensor networks. In *Proc. Visions of Computer Science Conf.*, pages 343–354.

[Goldsmith and Wicker, 2002] Goldsmith, A. and Wicker, S. (2002). Design Challenges for Energy-Constrained Ad Hoc Wireless Networks. *IEEE Wireless Comm.*, 9(4):8–27.

[Gustafsson et al., 2002] Gustafsson, F., Gunnarsson, F., Bergman, N., Forssell, U., Jansson, J., Karlsson, R., and Nordlund, P. (2002). Particle filters for positioning, navigation, and tracking. *IEEE Trans. on Signal Processing*, 50(2):425 –437.

[Haapola et al., 2005] Haapola, J., Shelby, Z., Pomalaza-Raez, C., and Mahonen, P. (2005). Cross-layer energy analysis of multi-hop wireless sensor networks. In *Proc. 2nd European Conf. on Wireless Sensor Networks (EWSN'05)*, pages 33 – 44.

[Hac, 2003] Hac, A. (2003). *Wireless Sensor Network Designs*. Wiley.

[Halgamuge et al., 2009] Halgamuge, M., Zukerman, M., Ramamohanarao, K., and Vu, H. (2009). An estimation of sensor energy consumption. *Progress in Electromagnetics Research B*, 12:259–295.

[Hansen et al., 2010] Hansen, M. T., Arroyo-Valles, R., and Cid-Sueiro, J. (2010). Testing Selective Transmission with Low Power Listening. In *Proc. 4th Workshop on Real-World Wireless Sensor Networks. Lecture Notes in Computer Science*, pages 158–165.

[Heinzelman et al., 2000] Heinzelman, W., Chandrakasan, A., and Balakrishnan, H. (2000). Energy-Efficient Communication Protocol for Wireless Microsensor Networks. In *Proc. 33rd Hawaii Int'l Conf. on System Sciences (HICSS'00)*, volume 8, page 8020.

[Hoblos et al., 2000] Hoblos, G., Staroswiecki, M., and Aitouche, A. (2000). Optimal Design of Fault Tolerant Sensor Networks. In *Proc. IEEE Int'l Conf. on Control Applications*, pages 467–472.

[Hu and Motani, 2009] Hu, S. and Motani, M. (2009). Early overhearing avoidance in wireless sensor networks. In *Proc. 7th Int'l IFIP-TC6 networking Conf. on AdHoc and sensor networks, wireless networks, next generation internet (NETWORKING'08). Lecture Notes in Computer Science.*, pages 26–35. Springer-Verlag.

[I. Chatzigiannakis and Nikoletseas, 2006] I. Chatzigiannakis, A. K. and Nikoletseas, S. (2006). Sink mobility protocols for data collection in wireless sensor networks. In *Proc. 4th ACM/IEEE Int'l Workshop on Mobility Management and Wireless Access Protocols (MobiWac'06)*, pages 52–59.

[Intanagonwiwat et al., 2003] Intanagonwiwat, C., Govindan, R., Estrin, D., Heidemann, J., and Silva, F. (2003). Directed diffusion for wireless sensor networking. *IEEE/ACM Trans. on Networking*, 11(1):2–16.

[Jain et al., 2006] Jain, S., Shah, R., Brunette, W., Borriello, G., and Roy, S. (2006). Exploiting mobility for energy efficient data collection in wireless sensor networks. *ACM/Springer Mobile Networks and Applications*, 11(3):327–339.

[Kaelbling et al., 1998] Kaelbling, L. P., Littman, M. L., and Cassandra, A. R. (1998). Planning and acting in partially observable stochastic domains. *Artificial Intelligence*, 101(1-2):99 – 134.

[Karlof and Wagner, 2003] Karlof, C. and Wagner, D. (2003). Secure routing in wireless sensor networks: attacks and countermeasures. In *Proc. 1st IEEE Int'l Workshop on Sensor Network Protocols and Applications*, pages 113 – 127.

[Karp and Kung, 2000] Karp, B. and Kung, H. (2000). Greedy Perimeter Stateless Routing for Wireless Networks. In *Proc. 6th Annual ACM/IEEE Int'l Conf. on Mobile Computing and Networking (MobiCom 2000)*, pages 243–254.

[Keshavarzian et al., 2006] Keshavarzian, A., Lee, H., and Venkatraman, L. (2006). Wakeup scheduling in wireless sensor networks. In *Proc. 7th ACM Int'l Symp. on Mobile ad hoc networking and computing (MobiHoc'06)*, pages 322–333.

[Kianpisheh and Charkari, 2009] Kianpisheh, S. and Charkari, N. (2009). Dynamic Power Management for Sensor Node in WSN Using Average Reward MDP. In *Proc. 4th Int'l Conf. on Wireless Algorithms, Systems, and Applications*, page 61. Springer.

[Kulik et al., 2002] Kulik, J., Heinzelman, W., and Balakrishnan, H. (2002). Negotiation-based protocols for disseminating information in wireless sensor networks. *Wireless Networks*, 8(2/3):169–185.

[Kumar et al., 2006] Kumar, R., Rowaihy, H., Cao, G., Anjum, F., Yener, A., and Porta, T. L. (2006). Congestion Aware Routing in Sensor Networks. Technical Report NAS-TR-0036-2006, Network and Security Research Center, Department of Computer Science and Engineering, Pennsylvania State University, University Park, PA, USA.

[Lal et al., 2003] Lal, D., Manjeshwar, A., Herrmann, F., Uysal-Biyikoglu, E., and Keshavarzian, A. (2003). Measurement and Characterization of Link Quality Metrics in Energy Constrained Wireless Sensor Networks. In *Proc. IEEE Globecom*, pages 446–452.

[Langendoen, 2007] Langendoen, K. (2007). *Medium Access Control in Wireless Networks, Volume II: Practice and Standards*, chapter Medium Access Control in Wireless Networks. Nova Science Publishers.

[Law et al., 2009] Law, Y., Chatterjea, S., Jin, J., Hanselmann, T., and Palaniswami, M. (2009). Energy-efficient data acquisition by adaptive sampling for wireless sensor networks. In *Proc. Int'l Conf. on Wireless Communications and Mobile Computing (IWCMC'09)*, pages 1146–1151.

[Lee et al., 2006] Lee, S., Kwak, K., and Campbell, A. (2006). Solicitation-based Forwarding for Sensor Networks. In *Proc. 3th Annual IEEE Comm. Society Conf. on Sensor and Ad Hoc Comm. and Networks (SECON'06)*, pages 90–99.

[Lei et al., 2009] Lei, J., Yates, R., and Greenstein, L. (2009). A generic model for optimizing single-hop transmission policy of replenishable sensors. *IEEE Trans. on Wireless Comm.*, 8(2):547 –551.

[Levis et al., 2005] Levis, P., Gay, D., Handziski, V., Hauer, J.-H., Greenstein, B., Turon, M., Hui, J., Klues, K., Sharp, C., Szewczyk, R., Polastre, J., Buonadonna, P., Nachman, L., Tolle, G., Culler, D., and Wolisz, A. (2005). T2: A second generation os for embedded sensor networks. Technical report, Telecommunication Networks Group, Technische Universität Berlin.

[Lin et al., 2004] Lin, E.-Y., Rabaey, J., and Wolisz, A. (2004). Power-efficient rendez-vous schemes for dense wireless sensor networks. In *Proc. IEEE Int'l Conf. on Communications*, volume 7, pages 3769–3776.

[Lindsey and Raghavendra, 2002] Lindsey, S. and Raghavendra, C. (2002). Pegasis: Power-efficient gathering in sensor information systems. In *Proc. IEEE Aerospace Conf.*, volume 3, pages 1125–1130.

[Liu and Hong, 2009] Liu, J. and Hong, X. (2009). An online energy-efficient routing protocol with traffic load prospects in wireless sensor networks. *Int'l Journal of Sensor Networks*, 5(3):185–197.

[Liu et al., 2003] Liu, J., Reich, J., and Zhao, F. (2003). Collaborative In-Network Processing for Target Tracking. *EURASIP Journal on Applied Signal Processing*, 4:378–391.

[Luo et al., 2009] Luo, J., Wang, D., and Zhang, Q. (2009). Double Mobility: Coverage of the Sea Surface with Mobile Sensor Networks. In *Proc. 28th IEEE Conf. on Computer Comm. (INFOCOM 2009)*, pages 118–126.

[Ma et al., 2009] Ma, J., Lou, W., Wu, Y., Li, X., and Chen, G. (2009). Energy Efficient TDMA Sleep Scheduling in Wireless Sensor Networks. In *Proc. 28 Annual Joint Conf. of the IEEE Computer and Comm. Societies (INFOCOM 2009)*, volume 1, pages 630–638.

[Maddah et al., 2007] Maddah, M., III, W. W., Warfield, S., Westin, C., and Grimson, W. (2007). Probabilistic Clustering and Quantitative Analysis of White Matter Fiber Tracts. In *Proc. 20th Int'l Conf. on Information Processing in Medical Imaging (IPMI 2007)*, pages 372–383.

[Manjeshwar and Agrawal, 2001] Manjeshwar, A. and Agrawal, D. (2001). Teen: a routing protocol for enhanced efficiency in wireless sensor networks. In *Proc. 15th Int'l Parallel and Distributed Processing Symp.*, pages 2009 –2015.

[Marques et al., 2008] Marques, A. G., Wang, X., and Giannakis, G. B. (2008). Minimizing Transmit-Power for Coherent Communications in Wireless Sensor Networks with Finite-Rate Feedback. *IEEE Trans. on Signal Processing*, 56(8):4446–4457.

[Mathur et al., 2006] Mathur, G., Desnoyers, P., Ganesan, D., and Shenoy, P. (2006). Ultra-low power data storage for sensor networks. In *Proc. 5th Int'l Conf. on Information processing in sensor networks (IPSN'06)*, pages 374–381.

[Melodia et al., 2005] Melodia, T., Vuran, M., and Pompili, D. (2005). The State of the Art in Cross-layer Design for Wireless Sensor Networks. In *Proc. EuroNGI Workshops on Wireless and Mobility. Springer Lecture Notes in Computer Science*, volume 3883, pages 78–92.

[Miller et al., 1993] Miller, J. W., Goodman, R., and Smyth, P. (1993). On Loss Functions Which Minimii to Conditional Expected Values and Posterior Probabilities. *IEEE Trans. on Information Theory*, 39(4):1404–1408.

[Mujumdar, 2004] Mujumdar, S. (2004). Prioritized Geographical Routing in Sensor Networks. Master's thesis, Vanderbilt University, Tennessee.

[Munir and Gordon-Ross, 2009] Munir, A. and Gordon-Ross, A. (2009). An mdp-based application oriented optimal policy for wireless sensor networks. In *Proc. 7th IEEE/ACM Int. Conf. on Hardware/Software Codesign and System Synthesis (CODES+ISSS '09)*, pages 183–192.

[Muraleedharan et al., 2006] Muraleedharan, R., Yan, Y., and Osadciw, L. A. (2006). Increased Efficiency of Face Recognition System Using Wireless Sensor Network. *Journal of Cybernetics, Systemics, and Informatics*, 4(6):38 – 46.

[Nakamura et al., 2007] Nakamura, E., Loureiro, A., and Frery, A. (2007). Information fusion for wireless sensor networks: Methods, models, and classifications. *ACM Compututing Surveys*, 39(3):9.

[Ngai et al., 2009] Ngai, E. C.-H., Gelenbe, E., and Humber, G. (2009). Information-Aware Traffic Reduction for Wireless Sensor Networks. In *Proc. 34th Annual IEEE Conf. on Local Computer Networks (LCN'09)*, pages 1–8.

[Pandana and Liu, 2008] Pandana, C. and Liu, K. (2008). Robust connectivity-aware energy-efficient routing for wireless sensor networks. *IEEE Trans. on Wireless Comm.*, 7(10):3904 – 3916.

[Paradiso and Starner, 2005] Paradiso, J. A. and Starner, T. (2005). Energy Scavenging for Mobile and Wireless Electronics. *IEEE Pervasive Computing*, 4(1):18–27.

[Paruchuri et al., 2004] Paruchuri, V., Basavaraju, S., Durresi, A., Kannan, R., and Iyengar, S. (2004). Random asynchronous wakeup protocol for sensor networks. In *Proc. First Int'l Conf. on Broadband Networks*, pages 710–717.

[Pattem et al., 2003] Pattem, S., Poduri, S., and Krishnamachari, B. (2003). Energy-Quality Trade-offs for Target Tracking in Wireless Sensor Networks. *Lecture Notes on Computer Science. IPSN 2003*, pages 32–46.

[Patwari and Hero, 2003] Patwari, N. and Hero, A. (2003). Hierarchical Censoring for Distributed Detection in Wireless Sensor Networks. In *Proc. IEEE Int'l Conf. Acoustics, Speech, and Signal Processing (ICASSP'03)*, volume 4, pages 848–851.

[Paulson, 2003] Paulson, L. D. (2003). Will Fuel Cells Replace Batteries in Mobile Devices? *Computer*, 36(11):10–12.

[Polastre et al., 2004] Polastre, J., Hill, J., and Culler, D. (2004). Versatile low power media access for wireless sensor networks. In *Proc. 2nd Int'l Conf. on Embedded networked sensor systems (SenSys'04)*, pages 95–107.

[Pottie and Kaiser, 2000] Pottie, G. and Kaiser, W. (2000). Wireless integrated network sensors. *Communications of the ACM*, 43(5):51 – 58.

[Pradhan and Ramchandran, 2003] Pradhan, S. and Ramchandran, K. (2003). Distributed source coding using syndromes (discus): Design and construction. *IEEE Trans. on Information Theory*, 49(3):626–643.

[Puterman, 2005] Puterman, M. (2005). *Markov decision processes*. Wiley-Interscience.

[Qu, 2001] Qu, G. (2001). What is the limit of energy saving by dynamic voltage scaling? In *Proc. IEEE/ACM Int'l Conf. Computer Aided Design (ICCAD 2001)*, pages 560–563.

[Raghunathan et al., 2002] Raghunathan, V., Schurgers, C., Park, S., and Srivastava, M. (2002). Energy-aware wireless microsensor networks. *IEEE Signal Processing Magazine*, 19(2):40–50.

[Raghunathan et al., 2001] Raghunathan, V., Spanos, P., and Srivastava, M. (2001). Adaptive power-fidelity in energy-aware wireless embedded systems. In *Proc. 22nd IEEE Real-Time Systems Symp. (RTSS'01)*, pages 106 – 115.

[Rago et al., 1996] Rago, C., Willett, P., and Bar-Shalom, Y. (1996). Censoring sensors: a low-communication-rate scheme for distributed detection. *IEEE Trans. on Aerospace and Electronic Systems*, 32(2):554 –568.

[Rajendran et al., 2003] Rajendran, V., Obraczka, K., and Garcia-Luna-Aceves, J. (2003). Energy-efficient collision-free medium access control for wireless sensor networks. In *Proc. 1st Int'l Conf. on Embedded networked sensor systems (SenSys'03)*, pages 181–192.

[Rhee et al., 2008] Rhee, I., Warrier, A., Aia, M., Min, J., and Sichitiu, M. (2008). Z-MAC: A Hybrid MAC for Wireless Sensor Networks. *IEEE/ACM Trans. on Networking*, 16(3):511–524.

[Ristic et al., 2004] Ristic, B., Arulampalam, S., and Gordon, N. (2004). *Beyond the Kalman Filter: Particle Filters for Tracking Applications*. Artech House.

[Römer and Mattern, 2004] Römer, K. and Mattern, F. (2004). The Design Space of Wireless Sensor Networks. *IEEE Wireless Comm.*, 11(6):54–61.

[Schurgers et al., 2002] Schurgers, C., Tsiatsis, V., Ganeriwal, S., and Srivastava, M. (2002). Topology management for sensor networks: exploiting latency and density. In *Proc. 3rd ACM Int'l Symp. on Mobile ad hoc networking & computing (MobiHoc'02)*, pages 135–145.

[Sen, 2009] Sen, J. (2009). A Survey on Wireless Sensor Network Security. *Int'l Journal of Comm. Networks and Information Security*, 1(2):59–82.

[Sennott, 1997] Sennott, L. (1997). *Stochastic Dynamic Programming and the Control of Queueing Systems*. Wiley-Interscience.

[Shenck and Paradiso, 2001] Shenck, N. and Paradiso, J. (2001). Energy scavenging with shoe-mounted piezoelectrics. *IEEE Micro*, 1(3):30–42.

[Sheng et al., 1992] Sheng, S., Chandrakasan, A., and Brodersen, R. (1992). A Portable Multimedia Terminal. *IEEE Comm. Magazine*, 30(12):64–75.

[Shenker et al., 2003] Shenker, S., Ratnasamy, S., Karp, B., Govindan, R., and Estrin, D. (2003). Data-centric Storage in Sensornets. *SIGCOMM Comput. Commun. Rev.*, 33(1):137–142.

[Shih et al., 2001] Shih, E., Cho, S.-H., Ickes, N., Min, R., Sinha, A., Wang, A., and Chandrakasan, A. (2001). Physical layer driven protocol and algorithm design for energy-efficient wireless sensor networks. In *Proc. 7th annual Int'l Conf. on Mobile computing and networking (MobiCom'01)*, pages 272–287.

[Shnayder et al., 2005] Shnayder, V., Chen, B., Lorincz, K., Fulford-Jones, T., and Welsh, M. (2005). Sensor networks for medical care. In *Proc. 3rd Int'l Conf. on Embedded networked sensor systems (SenSys'05)*, pages 314–314.

[Song and Hatzinakos, 2007] Song, L. and Hatzinakos, D. (2007). A Cross-Layer Architecture of Wireless Sensor Networks for Target Tracking. *IEEE/ACM Trans. on Networking*, 15(1):145 –158.

[Starner, 1996] Starner, T. (1996). Human-powered Wearable Computing. *IBM Systems Journal*, 35(3):618–629.

[Stemm and Katz, 1997] Stemm, M. and Katz, R. (1997). Measuring and reducing energy consumption of network interfaces in hand-held devices. *IEICE Trans. on Communications*, E80-B(8):1125–1131.

[Stojmenovic, 2002] Stojmenovic, I. (2002). Position-based routing in ad hoc networks. *IEEE Comm. Magazine.*, 40(7):128 –134.

[Stojmenovic, 2005] Stojmenovic, I. (2005). *Handbook of Sensor Networks: Algorithms and Architectures*. Wiley.

[Sun et al., 2008] Sun, Y., Du, S., Gurewitz, O., and Johnson, D. (2008). Dw-mac: a low latency, energy efficient demand-wakeup mac protocol for wireless sensor networks. In *Proc. 9th ACM Int'l Symp. on Mobile ad hoc networking and computing (MobiHoc'08)*, pages 53–62.

[Sutton and Barto, 1998] Sutton, R. and Barto, A. (1998). *Reinforcement learning*. MIT Press.

[Tang and Raghavendra, 2004] Tang, C. and Raghavendra, C. (2004). Compression techniques for wireless sensor networks. pages 207–231.

[Tseng et al., 2007] Tseng, Y., Wang, Y., Cheng, K., and Hsieh, Y. (2007). iMouse: An Integrated Mobile Surveillance and Wireless Sensor System. *IEEE Computer*, 40(6):60–66.

[Van-Dam and Langendoen, 2003] Van-Dam, T. and Langendoen, K. (2003). An adaptive energy-efficient mac protocol for wireless sensor networks. In *Proc. 1st Int'l Conf. on Embedded networked sensor systems (SenSys'03)*, pages 171–180.

[Vasanthi and Annadurai, 2006] Vasanthi, N. and Annadurai, S. (2006). Aws: asynchronous wakeup schedule to minimize latency in wireless sensor networks. In *Proc. IEEE Int'l Conf. on Sensor Networks, Ubiquitous, and Trustworthy Computing*, volume 1, pages 7 pp.–.

[Visser et al., 2008] Visser, H., Reniers, A., and Theeuwes, J. (2008). Ambient RF Energy Scavenging: GSM and WLAN Power Density Measurements. In *Proc. 38th European Microwave Conf. (EuMC 2008)*, pages 721–724.

[Wang et al., 2010] Wang, X., Ma, J., Wang, S., and Bi, D. (2010). Distributed Energy Optimization for Target Tracking in Wireless Sensor Networks. *IEEE Trans. on Mobile Computing*, 9(1):73–86.

[Wang et al., 2008] Wang, X., Wang, S., Ma, J.-J., and Bi, D.-W. (2008). Energy-efficient Organization of Wireless Sensor Networks with Adaptive Forecasting. pages 2604–2616.

[Wang et al., 2006] Wang, Y., Song, W.-Z., Wang, W., Li, X.-Y., and Dahlberg, T. (2006). LEARN: Localized Energy Aware Restricted Neighborhood Routing for Ad Hoc Networks. In *Proc. 3rd Annual IEEE Comm. Society on Sensor and Ad Hoc Communications and Networks (SECON'06)*, volume 2, pages 508 –517.

[Wang et al., 2005] Wang, Z., Basagni, S., Melachrinoudis, E., and Petrioli, C. (2005). Exploiting Sink Mobility for Maximizing Sensor Networks Lifetime. In *Proc. 38th Annual Hawaii Int'l Conf. on System Sciences (HICSS'05)*, volume 9.

[Weimer et al., 2006] Weimer, M., Paing, T., and Zane, R. (2006). Remote area wind energy harvesting for low-power autonomous sensors. In *Proc. 37th IEEE Power Electronics Specialists Conf. (PESC '06)*, pages 1–5.

[White, 1993] White, D. (1993). *Markov Decision Processes*. Wiley-Interscience.

[Williams et al., 2005a] Williams, J., Fisher, J.W., I., and Willsky, A. (2005a). An approximate dynamic programming approach to a communication constrained sensor management problem. In *Proc. 8th Int'l Conf. on Information Fusion*, volume 1, page 8 pp.

[Williams et al., 2005b] Williams, J., Fisher, J., and Willsky, A. (2005b). An approximate dynamic programming approach for communication constrained inference. In *Proc. 13th IEEE Workshop on Statistical Signal Processing*, pages 1202–1207.

[Williams et al., 2007] Williams, J., Fisher, J., and Willsky, A. (2007). Approximate dynamic programming for communication-constrained sensor network management. *IEEE Trans. on Signal Processing*, 55(8):4300 –4311.

[Wischhof et al., 2003] Wischhof, L., Ebner, A., Rohling, H., M.Lott, and Halfmann, R. (2003). SOTIS - A Self-Organizing Traffic Information System. In *Proc. 57th IEEE Semiannual Vehicular Technology Conf. (VTC'03)*, volume 4, pages 2442 – 2446.

[Wood and Stankovic, 2002] Wood, A. D. and Stankovic, J. A. (2002). Denial of Service in Sensor Networks. *IEEE Computer*, 35(10):54–62.

[Xia and Zhao, 2007] Xia, F. and Zhao, W. (2007). Flexible Time-Triggered Sampling in Smart Sensor-Based Wireless Control Systems. *Sensors*, 7(11):2548–2564.

[Xiao et al., 2006] Xiao, J., Ribeiro, A., Luo, Z., and Giannakis, G. (2006). Distributed compression-estimation using wireless sensor networks. *IEEE Signal Processing Magazine*, 23(4):27 – 41.

[Xu et al., 2001] Xu, Y., Heidemann, J., and Estrin, D. (2001). Geography-informed energy conservation for ad hoc routing. In *Proc. 7th annual Int'l Conf. on Mobile Computing and Networking (MobiCom'01)*, pages 70–84.

[Yaghmaee and Adjeroh, 2009] Yaghmaee, M. and Adjeroh, D. (2009). Priority-based rate control for service differentiation and congestion control in wireless multimedia sensor networks. *Computer Networks*, 53(11):1798 – 1811.

[Yang and Vaidya, 2004] Yang, X. and Vaidya, N. (2004). A wakeup scheme for sensor networks: achieving balance between energy saving and end-to-end delay. In *Proc. 10th IEEE Real-Time and Embedded Technology and Applications Symp. (RTAS'04)*, pages 19–26.

[Yarvis et al., 2005] Yarvis, M., Kushalnagar, N., Singh, H., Rangarajan, A., Liu, Y., and Singh, S. (2005). Exploiting Heterogeneity in Sensor Networks. In *Proc. 24th Annual Joint Conf. of the IEEE Computer and Comm. Societies (INFOCOM 05)*, volume 2, pages 878–890.

[Ye and Heidemann, 2003] Ye, W. and Heidemann, J. (2003). Medium Access Control in Wireless Sensor Networks. Technical Report ISI-TR-580, USC/Information Sciences Institute.

[Ye et al., 2004] Ye, W., Heidemann, J., and Estrin, D. (2004). Medium access control with coordinated adaptive sleeping for wireless sensor networks. *IEEE/ACM Trans. Networking*, 12(3):493–506.

[Ye et al., 2009] Ye, Z., Abouzeid, A., and Ai, J. (2009). Optimal Stochastic Policies for Distributed Data Aggregation in Wireless Sensor Networks. *IEEE/ACM Trans. on Networking*, 17(5):1494–1507.

[Yick et al., 2008] Yick, J., Mukherjeea, B., and Ghosal, D. (2008). Wireless sensor network survey. *Computer Networks*, 52(12):2292–2330.

[Yu et al., 2001] Yu, Y., Govindan, R., and Estrin, D. (2001). Geographical and energy aware routing: A recursive data dissemination protocol for wireless sensor networks. Technical Report UCLA/CSD-TR-01-0023, Univ. California, Los Angeles.

[Yuan and Yu, 2006] Yuan, J. and Yu, W. (2006). Distributed cross-layer optimization of wireless sensor networks: a game theoretic approach. In *Proc. IEEE Global Telecommunications Conf. (GLOBECOM'06)*.

[Zhang et al., 2006] Zhang, Y., Liu, J., and Zhao, F. (2006). *Combinatorial optimization in communication networks*, chapter Information-directed routing in sensor networks using real-time reinforcement learning, pages 259–288. Springer Berlin / Heidelberg.

[Zhao and Guibas, 2004] Zhao, F. and Guibas, L. (2004). *Wireless Sensor Networks. An Information Processing Approach*. ELsevier.

[Zhao and Ammar, 2003] Zhao, W. and Ammar, M. (2003). Message Ferrying: Proactive Routing in Highly-Partitioned Wireless Ad Hoc Networks. In *Proc. 9th IEEE Workshop on Future Trends of Distributed Computing Systems (FTDCS'03)*, page 308.

[Zheng and Barton, 2007] Zheng, R. and Barton, R. (2007). Toward Optimal Data Aggregation in Random Wireless Sensor Networks. In *Proc. 26th IEEE Int'l Conf. on Computer Communications (INFOCOM 2007)*, pages 249–257.

[Zheng et al., 2006] Zheng, R., Hou, J., and Sha, L. (2006). Optimal Block Design for Asynchronous Wake-Up Schedules and Its Applications in Multihop Wireless Networks. *IEEE Trans. Mobile Computing*, 5(9):1228–1241.