Optimal Power Control, Scheduling and Energy Harvesting for Wireless Networked Control Systems

by

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Koç University
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This is to certify that I have examined this copy of a master's thesis by

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and have found that it is complete and satisfactory in all respects,
and that any and all revisions required by the final
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To my mother

ABSTRACT

Communication system design for wireless networked control systems (WNCSs) requires strict timing, reliability and lifetime guarantees despite limited battery resources and the non-idealities introduced by wireless networking such as packet errors and delays. In this thesis, we introduce radio frequency (RF) energy harvesting paradigm into WNCS framework for the first time in the literature. We study the optimal power control, energy harvesting and scheduling problem with the objective of providing maximum level of adaptivity under periodicity, delay and reliability requirements. We show that the power allocation problem is separable from the scheduling problem at optimality and provide the exact expression for optimal power control. The scheduling problem is then formulated as a mixed integer linear programming (MILP) problem and proven to be NP-Hard. For the scheduling, we propose polynomial-time heuristic algorithms motivated by the analogy between scheduling sensor nodes with energy harvesting requirements over time units and jobs with sequence dependent setup times on identical machines. We prove the theoretical worst-case bound for the performance of these heuristics. We show via extensive simulations that the proposed algorithms perform close-to-optimal and significantly better than Earliest Deadline First (EDF) algorithm in terms of adaptivity, delay and average runtime.

ÖZETÇE

Kablosuz ağ tabanlı kontrol sistemleri (WNCS'ler) için haberleşme sistemi tasarımı, sınırlı batarya kaynaklarına ve paket hataları ve gecikmeler gibi kablosuz ağa ait ideal olmayan koşullara rağmen sıkı zamanlama, güvenilirlik ve batarya ömrü garantisi gerektirmektedir. Bu tezde, radyo frekanslı (RF) enerji hasatlama paradigması, literatürde ilk defa WNCS çerçevesine uygulanmaktadır. Bu kapsamda periyodiklik, gecikme ve güvenilirlik gereksinimleri kapsamında maksimum düzeyde uyarlanabilirlik sağlamak amacıyla optimum güç kontrolü, enerji hasatlama ve çizelgeleme sorunu incelenmektedir. Ayrıca, güç dağılımı probleminin en iyilik bağlamında çizelgeleme probleminden ayrı olduğu gösterilmekte ve optimum güç kontrolü için tam ifade ortaya konmaktadır. Daha sonra çizelgeleme problemi, tam sayı karışık doğrusal programlama (MILP) problemi olarak formüle edilmektedir ve bu problemin NP-Hard olduğu ortaya çıkarılmaktadır. Çizelgeleme için, enerji hasatlama gereksinimleri bulunan sensör düğümlerinin zaman birimleri üzerinde ve sıralama bağımlı kurulum süreleri bulunan işlerin özdeş makineler üzerinde çizelgelenmesi arasındaki paralelliği temel alan polinom zamanlı buluşsal algoritmalar önerilmektedir. İlgili buluşsal yöntemlerin performansı için en kötü teorik durum sınırı ortaya konulmaktadır. Kapsamlı simülasyonlar aracılığıyla, öne sürülen algoritmaların uyarlanabilirlik, gecikme ve ortalama çalışma süresi açısından optimuma yakın düzeyde ve En Erken Tamamlanma Zamanı (EDF) algoritmasından daha iyi sonuç verdiği gösterilmektedir.

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Chapter 1

INTRODUCTION

Wireless networked control systems (WNCSs) are spatially distributed systems in which sensors, actuators and controllers connect via a wireless network [Hespanha et al., 2007]. The usage of wireless communication in control systems results in flexible network architectures; eases diagnosis, installation and maintenance; brings agility; and reduces installation and maintenance costs. Consequently, WNCSs have been used in a broad range of applications, including industrial automation [Willig, 2008], building automation [Aswani et al., 2012], unmanned aerial vehicles [Seiler and Sengupta, 2001], automated highway [Varaiya, 1993] and smart grid [Li et al., 2012], with standardization efforts of industrial organizations, such as International Society of Automation (ISA) [Standard, 2009] and Highway Addressable Remote Transducer (HART) [WirelessHART, line]. Conventionally, WNCS nodes are assumed to operate on battery, therefore, most research efforts focus on energy saving mechanisms to prolong their lifetime. However, to overcome the battery lifetime limitation, these systems may additionally adopt energy harvesting capabilities. In particular, radio frequency (RF) energy harvesting networks (RF-EHN) stand out as a viable solution to support the strict delay and reliability requirements of WNCS applications due to fully controllable RF energy harvesting process of dedicated RF resources [Lu et al., 2015]. RF energy harvesting is a technique to convert radio signals with frequency range from 3 kHz to 300 GHz into electricity to have sustainable power supply. It has become increasingly prevalent due to its suitability for remote and mobile applications in the far-field, and recent hardware developments in the circuitry implementation, antenna design and receiver architecture.

1.1 Related Work

The scheduling frameworks proposed for WNCSs have been studied with three main objectives: provide low deterministic end-to-end delay for real-time traffic [Saifullah et al., 2014], [Saifullah et al., 2010], [Baldi et al., 2009], [Demirel et al., 2011]; adopt real-time scheduling algorithms used for the scheduling of both periodic and aperiodic controller tasks [Wu et al., 2014], [Sadi and Ergen, 2013]; and focus on optimization addressing the trade-off between energy consumption and performance of control systems [Yan et al., 2014], [Park et al., 2011], [Bai et al., 2012]. First, the scheduling algorithms designed for low deterministic end-to-end delay of real-time traffic are mainly based on recent communication standards such as WirelessHART [WirelessHART, line] and ISA-100.11a [Standard, 2009]. However, these algorithms do not exploit the periodic nature of data transmission. Second, real time scheduling algorithms used for the scheduling of both aperiodic and periodic controller tasks, such as Earliest Deadline First (EDF) [Liu et al., 2000], are adopted for the scheduling of periodic transmission of the sensor nodes in WNCSs [Wu et al., 2014], [Sadi and Ergen, 2013]. However, these algorithms do not compensate for the changes and imperfections of the wireless communication, thus, may not even guarantee timely packet delivery. Finally, the optimization problem formulations for WNCSs include maximizing end-to-end reliability under end-to-end delay guarantees [Yan et al., 2014]; minimizing energy consumption of the sensor nodes under packet loss probability and delay constraints [Park et al., 2011]; and maximizing control system performance by minimizing tracking error under network capacity and delay constraints [Bai et al., 2012]. However, they either do not consider the transmission power and packet length as a variable [Yan et al., 2014]; or ignore the dependency of energy consumption on the transmission power of the sensor nodes assuming fixed energy consumption [Park et al., 2011], [Bai et al., 2012]. More recently, the optimization problems have been extended to include the dependency of energy consumption on the transmission power of the nodes while exploiting the periodicity of the sensor node transmissions in WNCSs [Sadi and Ergen, 2013], [Sadi and Ergen, 2015]. These studies focus on maximizing adaptivity to the changes in the requirements of sensors and network topology. The adaptivity is attained by distributing the packet transmissions as uniformly as possible over time. Nonetheless, these works mostly assume battery powered sensor nodes and do not incorporate energy harvesting into the system.

As a plausible solution providing sustainable power supply from RF signals to sensor nodes, the literature on the optimization of RF-EHNs and wireless powered communication networks are immense [Lu et al., 2015]. The formulations for RF-EHNs are studied for single-hop, multi-hop and multi-antenna configurations. We will elaborate on multi-user scheduling in single-hop RF-EHNs as concerned by this thesis. The main goal of multi-user scheduling in RF-EHNs is to balance the trade-off in the usage of RF for energy transfer and information transmission. The formulations mostly aim at throughput fairness, throughput maximization or utility optimization under energy harvesting constraints. For instance, in [Ju and Zhang, 2014], authors propose a $harvest-then-transmit$ protocol, and then jointly optimize the time allocations of downlink energy transfer and uplink information transfer of the nodes to maximize the system throughput. In [Yang et al., 2015], a frame-based transmission protocol in a MIMO system optimizes time and energy allocation to maximize the minimum rate among users. In [Kang et al., 2015], two optimization problems, one maximizing total throughput under time constraints and the other minimizing total energy harvesting and transmission time under data transmission constraints, for a multi-user time allocation problem in a full-duplex TDMA-based RF-EHN are considered. However, these formulations are not suitable for WNCSs since they do not consider the specific requirements of these networks, including periodic nature of data transmissions. Moreover, they do not provide guaranteed performance in the case of changes in sensor node requirements and network topology by providing adaptivity.

1.2 Original Contributions

In this thesis, we are extending our work in [Karadag and Ergen, 2019] and propose a framework that incorporates energy harvesting paradigm into WNCSs for the first time in the literature. We study the optimal power control and scheduling algorithm with the objective of attaining maximum level of adaptivity while meeting the packet generation period, transmission delay, reliability and energy harvesting requirements of the sensor nodes in a WNCS. Our proposed scheduling framework provides adaptivity to packet losses, additional messaging events and changes in the requirements of sensors and network topology by uniformly distributing packet transmissions over time. Uniform scheduling allows the scheduling of retransmissions and event-driven packets with minimum delay. Moreover, the dependence of the energy consumption on the transmission power has been incorporated into the framework together with the energy causality constraint: The consumed energy by the nodes needs to be provided by the total energy transferred through RF. Furthermore, the power, scheduling and energy harvesting allocations of the nodes are jointly optimized due to their interdependency.

The novel contributions of this thesis are listed as follows.

- A novel scheduling problem has been formulated to provide maximum level of adaptivity while satisfying the packet generation period, transmission delay, reliability and energy harvesting requirements of WNCSs.

- The optimal power allocation has been proven to be independent of the optimal scheduling and energy harvesting problem. The exact expression for the optimal power allocation has been derived by exploiting the problem structure.

- The scheduling and energy harvesting problem is formulated as a mixed integer linear programming (MILP) problem following the analysis of the optimality conditions of the original problem, and proven to be NP-Hard. As a solution, two polynomial-time heuristic algorithms, Periodic List Scheduling (PLS) Algorithm and Periodic Alternative List Scheduling (PALS) Algorithm, are proposed. The heuristics are fundamentally grounded on the analogy between our framework and scheduling of jobs with sequence dependent setup times on identical machines to minimize the makespan. The difference in the allocation rules of these heuristics makes each preferable depending on the performance measure of choice. The asymptotic worst-case bounds for the performance of the heuristics are also derived analytically.

- The performance of the proposed heuristics is illustrated compared to the optimal solution and EDF algorithm in terms of adaptivity, delay and computational cost for various networks sizes and environments through extensive simulations.

1.3 Organization

The rest of the thesis is organized as follows. Chapter 2 describes the system model and assumptions used throughout the thesis. Chapter 3 presents the objective function, constraints and formulation of the optimization problem. Chapter 4 provides the analysis of the optimality conditions, exact expression of the optimal power allocation, and the formulation and NP-hardness of the scheduling and energy harvesting problem. Chapters 5 and 6 present the heuristic scheduling algorithms PLS and PALS, respectively, and analyze their worst case performance bounds. Chapter 7 gives the performance evaluation of the proposed algorithms. Finally, Chapter 8 concludes the thesis.

Chapter 2

SYSTEM MODEL AND ASSUMPTIONS

The system model and assumptions are detailed as follows.

1. The WNCS contains wireless sensor nodes, controllers and actuators, as illustrated in Fig. 2.1. Sensor nodes sample and transmit their sensed data from a real-time physical system or plant either periodically (time-triggered) or upon triggering of an event (event-triggered) to a controller via wireless channel [Xu and Jagannathan, 2013]. Controllers do not have multi-reception capability, i.e. each can receive one packet from one single node at a time. Upon reception of the sampled information, controllers compute and forward control commands to the actuators. Many controllers are collocated with the actuators because the control command is critical [Arampatzis et al., 2005]. Therefore, we assume that actuators receive the commands successfully.

2. We assume that each sensor node directly communicates with the corresponding controller, i.e. it is a single-hop network; and there are no concurrent transmis-

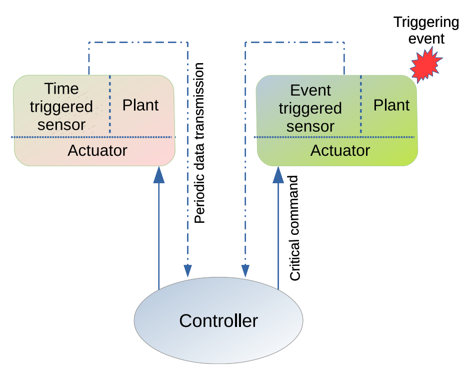


Figure 2.1: Simplified system architecture

sions, i.e. one single node can transmit at a time. The proposed framework can be extended for multi-hop networks and concurrent transmissions by adding routing constraints and modifying the transmission model in the optimization problem, respectively. To simplify the problem in the first step of the study and better focus on incorporating energy harvesting paradigm into the power control and scheduling of WNCSs, these extensions are out of the scope of this work and subject to future studies.

3. One of the controllers is selected as a central controller, as it is commonly envisioned in industrial control applications [WirelessHART, line]. The central controller is assumed to have complete topology information, and responsible for scheduling, resource allocation and synchronization of the active links based on the continuous monitoring of the received power and packet error rate of each link.

4. The terms *node* and *link* both indicate the connection between a sensor node and its controller, and are used interchangeably.

5. We consider Time Division Multiple Access (TDMA) as medium access control protocol. TDMA is frequently employed in industrial applications [Standard, 2009], since it is capable of both providing delay guarantee and decreasing energy consumption for the networks with preset topology and data generation characteristics [Ergen and Varaiya, 2006].

6. The sensors are either time-triggered or event-triggered. Time-triggered sensors generate their packet periodically. The packet generation period T_i is given for sensor $i \in \{1, ..., L\}$, where L is the number of sensor nodes. These nodes are assumed to have implicit delay tolerances, i.e. their transmission delay requirement is equal to their packet generation period. This implies that the nodes should complete their transmission before the next data generation. On the other hand, event-triggered sensors only generate packet upon a predetermined

event acting as a trigger. These sensors wait until the first unallocated part of the schedule large enough to accommodate their packet and then perform the transmission.

7. Time is divided into fixed length frames, which are further partitioned into a number of fixed length subframes. At the beginning of the frame and subframes, as needed, the beacon is transmitted by the central controller to ensure time synchronization within the network and broadcast the scheduling and resource allocation decisions. In case of stable channel conditions and acceptable level of packet error rate, the beacon is only used for time synchronization. Otherwise, it is used to broadcast updated scheduling, resource allocation and retransmission decisions. Subframes consist of a variable-length energy harvesting slot and a varying number of time slots, each time slot allocated to a sensor node depending on scheduling decisions. At the beginning of each subframe, during the energy harvesting slot, the nodes that are scheduled to transmit within the corresponding subframe harvest energy. These nodes then transmit their data during the allocated time slot announced in the beacon.

8. A subset of controllers transmit RF energy to the nodes simultaneously during the energy harvesting slot of the subframes. The nodes are assumed to be equipped with a rechargeable battery with low energy storage capacity and high discharge rate. Thus, all the harvested energy is assumed to be consumed or discharged within the corresponding subframe [Hadzi-Velkov et al., 2017]. The combined energy received by node i from this subset of controllers is modeled with downlink channel coefficient c_i.

9. The total energy harvested by a node i in subframe j is given by

$$e_{ij} = \zeta p_c c_i t_j^h, \tag{2.1}$$

where $\zeta \in (0, 1)$ is the energy harvesting efficiency of the sensor node, p_c is the transmit power of the RF sources, and t_j^h is the length of the energy harvesting slot in subframe j [Ju and Zhang, 2014], for $i \in \{1, ..., L\}$.

10. The packet generation period of a sensor is either a multiple or an aliquot of other packet generation periods, which can be given as a constraint to the control applications [Sadi and Ergen, 2015]. The choice of such a pattern allows the illustration of the robust scheduling idea more clearly, providing zero jitter in case of no packet loss. The methods proposed in the article can be easily applied for any arbitrary integral set of packet generation periods without loss of generality.

11. We consider the energy consumption during the data transmission only. The energy consumption in sleep mode, i.e. radio is in sleep state when the node is not scheduled, and transient mode, i.e. the node switches from sleep mode to active mode and vice versa, is much lower than that in the data transmission, therefore, is ignored [Cui et al., 2005]. On the other hand, the energy harvesting for the the reception of the beacon packets can be separately optimized and is out of scope of this work.

12. We assume all devices in the network are equipped with a single omnidirectional antenna and operate over the same frequency.

13. We use constant rate transmission model [Sadi and Ergen, 2014], in which each node i transmits successfully at constant rate r if link i satisfies a fixed Signal-to-Noise-Ratio (SNR) threshold, given by

$$\frac{p_i g_i}{N_0} \geq \beta_i, \tag{2.2}$$

where p_i is the transmit power of link i, β_i is the SINR ratio to be kept by the link i to achieve constant rate r, g_i is the uplink channel gain, and N_0 is the background noise power, for $i \in [1, L]$. This implies that the length of the time slot t_i, which is given by the ratio of the packet length of sensor i, L_i, to constant data rate r, is the same in all periods.

14. We assume slow fading uplink and downlink channels such that c_i and g_i are fixed during the scheduling frame for $i \in [1, L]$ [Sadi and Ergen, 2014]. This is commonly assumed for minimum length scheduling in wireless ad-hoc networks. The extension of this work to fast-fading channels is beyond the scope of this work and subject to future studies.

Chapter 3

DESCRIPTION OF THE OPTIMIZATION PROBLEM

3.1 Objective Function of Optimization Problem

The objective of the joint power control, energy harvesting and scheduling problem is to provide maximum level of adaptivity. In the following, we summarize the adaptivity metric from [Sadi and Ergen, 2015].

Adaptivity of a schedule is defined as the ability of accommodating unscheduled changes in the network, such as a retransmission of a time-triggered sensor, transmission of an event-triggered sensor and inclusion of a new sensor. This requires the distribution of node transmissions as uniformly as possible over time. The time unit over which the transmissions are distributed in our framework is *subframe.* The *total active length of a subframe* l is originally defined as the sum of the length of the time slots allocated to subframe l. This definition is extended here to additionally include the length of the energy harvesting slot. The subframe length and the frame length are determined as the minimum and the maximum of the packet generation periods of all nodes in [Sadi and Ergen, 2013], denoted by S and F, respectively. The objective of maximizing adaptivity is then quantified as minimizing the maximum total active length over all M subframes, where $M = F/S$.

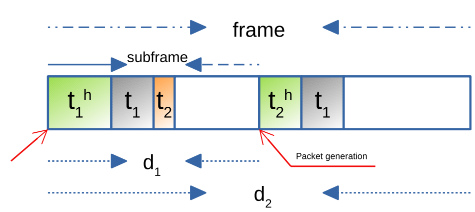


Figure 3.1: Time slot allocation of two transmitting sensor nodes

Fig. 3.1 depicts the example of an allocation of two sensor nodes. The packet generation periods are given as $T_1 = 1ms$ and $T_2 = 2ms$. The time slot lengths are given as $t_1 = 0.2ms$ and $t_2 = 0.1ms$. Subframe and frame lengths are given by the minimum packet generation period, i.e. $S = 1ms$, and the maximum packet generation period, i.e. $F = 2ms$, respectively. In this allocation, the length of the energy harvesting slots required for the transmission of the corresponding nodes for subframe 1 and subframe 2 are given as $t_1^h = 0.3ms$ and $t_2^h = 0.2ms$, respectively. Then, the total active lengths of subframe 1 and subframe 2 are calculated as the sum of the total active lengths of the time slots and energy harvesting slots in subframe 1 and subframe 2, i.e. $a_1 = t_1^h + t_1 + t_2 = 0.6ms$ and $a_2 = t_2^h + t_1 = 0.4ms$, respectively. Now, let a sensor 3 with parameters $T_3 = 2ms$ and $t_3 = 0.4ms$, which requires $0.1ms$ of energy harvesting be given for assignment. If subframe 1 is chosen, then there is no room left for any additional messaging or retransmissions in subframe 1, with $a_1 = 0.6 + t_3 = 1ms$. With the aim of maximizing adaptivity, subframe 2 should be chosen so that the transmissions are distributed as uniformly as possible over time to allow room, with $a_2 = 0.4 + t_3 = 0.8ms$.

3.2 Constraints of Optimization Problem

The optimization problem have the constraints of energy harvesting, transmission delay and periodic data generation for individual sensor nodes. The energy harvesting constraint requires the energy harvesting slot allocated at the beginning of a subframe to suffice for the data transmission of all the sensors assigned to transmit in the corresponding subframe. The transmission delay constraint requires the generated packet to be transmitted before the next packet generation in T_i time unit for node i, i.e. the sensors have implicit delay tolerances. The periodic data generation constraint requires that the data generation of all sensors occur periodically, separated by T_i time unit for node i.

Let s_i be the ratio of packet generation period T_i to the subframe length S. We now show that the periodic data generation and transmission delay requirements can be achieved by the allocation of fixed-length time slot once in every s_i subframes.

Lemma 1 *The periodic data generation and delay requirements are satisfied by allocating a time slot of length t_i once in every s_i subframes to node i, where $i \in [1, L]$.*

Proof: *Let the k^{th} data generation of sensor i occur at the beginning of subframe j at time $t_g^{(k)} = S(j-1)$. The $(k+1)^{st}$ data generation will occur T_i units after the k^{th} data generation at time $t_g^{(k+1)} = S(j-1)+T_i = S(j-1)+Ss_i = S(j-1+s_i)$ due to the periodic data generation requirement. Also, the k^{th} data transmission time, defined as $t_t^{(k)}$ must take place before $(k+1)^{th}$ data generation, due to the delay requirement. Resultantly, we have $S(j-1) \leq t_t^{(k)} \leq S(j-1+s_i)$, which corresponds to allocating a time slot of length t_i for node i between subframes j and $(j+s_i)$, i.e. once in every s_i subframes.* □

3.3 Formulation of Optimization Problem

The optimal energy harvesting, scheduling and power control problem is mathematically formulated as follows:

minimize

$$\max_{j\in[1,M]} \sum_{i=1}^{L} z_{ij} t_i + t_j^h \tag{3.1a}$$

subject to

$$\sum_{j=ks_i+1}^{(k+1)s_i} z_{ij} = 1, \quad k \in [0, \frac{M}{s_i} - 1], i \in [1, L] \tag{3.1b}$$

$$\sum_{i=1}^{L} z_{ij} t_i + t_j^h \leq S, \quad j \in [1, M] \tag{3.1c}$$

$$z_{ij} t_i p_i \leq \zeta p_c c_i t_j^h, \quad i \in [1, L], j \in [1, M] \tag{3.1d}$$

$$p_i \leq p_{max}, \quad j \in [1, M] \tag{3.1e}$$

$$\frac{p_i g_i}{N_0} \geq \beta_i, \quad i \in [1, L] \tag{3.1f}$$

variables

$$p_i \geq 0,\ z_{ij} \in \{0, 1\},\ t_j^h \geq 0,\ i \in [1, L],\ j \in [1, M] \tag{3.1g}$$

where p_{max} is the maximum allowed transmission power; z_{ij} is an integer variable that takes value 1 if sensor i is allocated to subframe j and 0 otherwise.

Eqn. (3.1a) aims to minimize the maximum total active length of all subframes. Eqns. (3.1b) and (3.1d) represent the periodic packet generation and delay requirements, and energy harvesting requirement, respectively. Eqn. (3.1c) is a feasibility condition that states that the maximum total active length over all subframes cannot exceed the subframe length. Eqn. (3.1e) states that the transmission power of link i cannot exceed maximum allowed transmit power. Eqn. (3.1f) represents the SNR requirement for constant rate transmission with no concurrent transmissions. The variables of the problem are given as follows: 1) $z_{ij}, i \in [1, L], j \in [1, M]$ for scheduling; 2) $p_i, i \in [1, L]$ for power allocation; and 3) $t_j^h, j \in [1, M]$ for energy harvesting slot allocation.

We now show that power allocation can be separated from the scheduling and energy harvesting problem at optimality, so as to simplify the energy harvesting constraints.

Chapter 4

ANALYSIS OF THE OPTIMALITY CONDITIONS

4.1 Optimal Power Allocation

Let us assume that $\frac{\beta_i N_0}{g_i} \leq p_{max}$ is satisfied to have a non-empty feasible region for the problem. Then the lower and upper bounds of p_i value are given by $\frac{\beta_i N_0}{g_i}$ and p_{max}, using Eqns. (3.1f) and (3.1e), respectively. Since the energy consumption so the lower bound for t_j^h decreases as p_i decreases by Eqn. (3.1d), the optimal value of power p_i is equal to its lower bound, as given by

$$p_i^* = \frac{\beta_i N_0}{g_i}, \quad i \in [1, L] \tag{4.1}$$

4.2 Energy Harvesting Slot Allocation

Let us define h_i as the energy harvesting time required for the transmission of link i. Let us replace p_i by the its optimal value p_i^*. Then, $h_i = \frac{(t_i)(\frac{\beta_i N_0}{g_i})}{\zeta p_c c_i}$ for $i \in [1, L]$. Let us also define the sets I_j and H_j, $I_j = \{i | z_{ij} = 1\}$ and $H_j = \{h_i | i \in I_j\}$, for $j \in [1, M]$. In other words, I_j is the index set of the sensors assigned to subframe j, and H_j is the set of the energy harvesting time values of the sensors assigned to subframe j. In any feasible solution, based on Eqn. (3.1d), we have $t_j^h \geq h_i, i \in I_j$.

The optimal value of t_j, denoted by t_j^{h*}, satisfies $t_j^{h*} \in H_j$, $t_j^{h*} = \max_{i \in I_j} h_i$ for $j \in [1, M]$.

4.3 Simplified Model

The simplified formulation is given as follows:

minimize

$$W \tag{4.2a}$$

subject to

$$\sum_{j=ks_i+1}^{(k+1)s_i} z_{ij} = 1, \quad k \in [0, \frac{M}{s_i} - 1], i \in [1, L] \tag{4.2b}$$

$$t_j^h \geq z_{ij} h_i, \quad i \in [1, L], j \in [1, M] \tag{4.2c}$$

$$S \geq W \geq \sum_{i=1}^{L} z_{ij} (\frac{L_i}{r}) + t_j^h, \quad j \in [1, M] \tag{4.2d}$$

variables

$$W \geq 0,\ z_{ij} \in \{0, 1\},\ t_j^h,\ i \in [1, L],\ j \in [1, M] \tag{4.2e}$$

Eqn. (4.2a) is used to transform the objective from a nonlinear form of minimizing $max_x f(x)$ to a linear form and merged with Eqn. (3.1c) to obtain Eqn. (4.2d). The variables of the problem are $z_{ij}, i \in [1, L], j \in [1, M]$, continuous variable W, and $t_j^h \in H_j, j \in [1, M]$. The resultant problem is MILP.

4.4 NP-hardness of Optimization Problem

Theorem 1 *The scheduling problem formulated in Section 4.3 is NP-hard.* Proof: *We reduce the NP-hard minimum makespan scheduling (MSP) on identical machines to our scheduling problem, by employing a similar methodology to [Sadi and Ergen, 2013]. Given a set of n jobs with processing times $pt_i, i \in [1, n]$, and m identical machines, the MSP aims to find an assignment of jobs to the machines with the goal of minimizing the time it takes all jobs to finish processing, i.e. the makespan.*

Let us define a problem instance where we are to schedule $n + 1$ sensors with packet generation periods $T_2 = T_3 = ... = T_{n+1} = mT_1$, where m is an integer greater *than 1, and energy harvesting requirements $h_1 \geq h_i, i \in [2, n+1]$. Since frame and subframe lengths are equal to maximum and minimum of the packet generation periods, the number of subframes is m. Obviously, the sensor with packet generation period T_1 is allocated a time slot of t_1 in each subframe. Since that particular sensor is allocated to all subframes and has the maximum energy harvesting requirement among all sensors, $t_j^h = h_1, j \in [1, M]$, based on the optimality condition of energy harvesting slot allocation derived in Section 4.2. Also, let $t_{i+1} = pt_i, i \in [1, n]$. The problem is to allocate n sensors of different time slot lengths to m subframes such that the maximum total active length of all subframes is minimized. Assuming that the optimal solution to this problem is less than S, it is equal to $h_1 + t_1$ plus the optimal solution of aforementioned MSP. Since we can reduce the NP-hard MSP to an instance of the scheduling problem that was formulated in Section 4.3, the scheduling problem in Section 4.3 is also NP-hard.* $\square$

4.5 Solution Strategy

Because the optimization problem (7) is NP-hard, we propose two polynomial-time heuristic algorithm in Chapters 5 and 6.

- We establish an analogy between our scheduling framework and task scheduling on identical machines with sequence-dependent setup times. Setup times and minimizing makespan correspond to energy harvesting requirements of nodes relative to each other, and minimizing the maximum total active length of the subframes in our framework, respectively.

- Motivated by this analogy, PLS and PALS are inspired from list scheduling algorithm [Ovacik and Uzhoy, 1993] and alternative list scheduling algorithm [Schutten, 1996] proposed in the literature for MSP, respectively.

- PLS assigns time slots to the subframe with smallest total active length and repeats allocation periodically. PALS, on the other hand, assigns time slots to the subframe in which they will finish transmission the earliest. For zero or equal-length energy harvesting slots, PLS and PALS would yield the same schedule. In general, however, they produce schedules with different maximum total active lengths.

Chapter 5

PERIODIC LIST SCHEDULING (PLS) ALGORITHM

In this chapter, we propose a heuristic for Optimization Problem (4.2) based on a heuristic proposed for minimum makespan scheduling (MSP) on identical machines by exploiting the analogy between them. For this purpose, we adopt a concept existent in machine scheduling problems, called *sequence-dependent setup times*, or shortly, *setup times*. In machine scheduling problems, *sequence-dependent setup time* s_{ij} is the required setup time of a machine when task j is to be executed immediately following task i. Then, the modified processing time of a task j following task i on a machine is given by the sum of its processing time t_j and the setup time s_{ij}. Similarly, in our scheduling framework, the processing time of a task j on subframe k depends on the other nodes that have been scheduled on subframe k prior to task j. The processing time of node j is its time slot length t_j plus the additional harvesting time it requires, which depends on the other nodes that have been scheduled priorly on subframe k. s_{ij} corresponds to the additional harvesting requirement of sensor j with respect to sensor i. If sensor j is assigned to subframe k where sensor i has already been assigned, sensor j will require additional s_{ij} time units of energy harvesting upon assignment. In other words, sensor j requires $s_{ij} = max(0, h_j - h_i), i \neq j$ units of additional harvesting time when it is to be allocated to subframe k where sensor i has been previously allocated. $s_{jj}, j \in [1, L]$ is defined to be the inherent energy harvesting requirement of sensor j, and consequently set to h_j. In other words, if the subframe is empty so far, then sensor j will require s_{jj} units of harvesting time. Then, processing time of sensor j on subframe k is given by $p_j^k = t_j + \min_{i \in I_k} s_{ij}$. To complete this analogy, we need to introduce the list scheduling algorithm proposed for the MSP on parallel identical machines with sequence-dependent setup times. The list scheduling (LS) algorithm schedules the next job on a given list to the next available machine for processing [Ovacik and Uzhoy, 1993], i.e. machine with the minimum current load at that time.

In the following, we propose the scheduling algorithm PLS that assigns sensors to the subframe with the smallest total active length and perform the analysis for the performance of PLS.

5.1 Description of PLS

PLS algorithm, as given in Algorithm (1), is described in detail as follows. At the initialization, the nodes in the list are ordered in increasing packet generation periods (Line 2). The next node j on the list is assigned to the subframe with the minimum total active length with processing time indexed by k (Line 5). The corresponding processing time p_j^k is then calculated by including both the transmission time and the additional harvesting time required for the transmission of node j on subframe k (Line 6). Finally, the time slot assignment is repeated every s_j subframes for $j \in [1, L]$, to satisfy the periodicity requirement (Line 7).

Allocation of four nodes by PLS algorithm is depicted in Fig. 5.1. The parameters are given as $T_1 = 1ms$, $t_1 = 0.1ms$, $h_1 = 0.1ms$, $T_2 = 2ms$, $t_2 = 0.1ms$, $h_2 = 0.4ms$, $T_3 = 2ms$, $t_3 = 0.2ms$, $h_3 = 0.1ms$, $T_4 = 4ms$, $t_4 = 0.2ms$, $h_4 = 0.4ms$. The scheduling order of nodes is 1-2-3-4. For this network, frame length $F = 4ms$ and subframe length $S = 1ms$. Initially, all subframes are empty. Sensor 1 is allocated to subframe 1 with its energy harvesting time $s_{11} = h_1 = 0.1ms$ and extended periodically. Then, all subframes have the same length and sensor 2 is allocated to subframe 1 with its additionally required harvesting time $s_{12} = max(0, h_2 - h_1) = h_2 - h_1 = 0.3ms$ and extended periodically. Afterwards, sensor 3 is allocated to the subframe with smallest total active length, subframe 2, with $s_{13} = max(0, h_3 - h_1) = 0$ and extended periodically. Finally, sensor 4 is allocated to the subframe with smallest total active length, subframe 2, with $\min_{i \in \{1,3\}} s_{i4} = s_{14} = max(0, h_4 - h_1) = 0.3ms$ and extended periodically. The resultant schedule yields a maximum active length of

$a_2 = h_1 + s_{31} + s_{41} + t_1 + t_3 + t_4 = 0.9ms$.

The overall complexity of PLS is $O(LM + L^2)$. The allocation of each sensor requires determining the subframe of smallest total active length, periodic repetition of the allocation over the frame, and update of the subframe total active lengths, each of which is of $O(M)$ complexity. Finding the additionally required harvesting time required by the sensor to be allocated to the subframe with smallest total active length is also of $O(L)$ complexity. For L sensors, the overall complexity is polynomial since $(L + M)^2 \geq (LM + L^2)$.

input : T_i, t_i, h_i, for $i \in [1, L]$
output: z_{ik}, t_k^h, for $i \in [1, L]$, $k \in [1, M]$

begin
    order the nodes in increasing T_i ;
    $S = T_1$, $F = T_L$, $M = F/S$;
    for $j = 1 : L$ **do**
        find index k of the subframe of smallest total active length ;
        allocate p_j^k to subframe k ;
        repeat allocation of sensor j every s_j subframes ;
    end
end

Algorithm 1: PLS Algorithm

5.2 Analysis of PLS

In this section, we will analyze the properties of PLS. We will define two auxiliary optimization problems to derive worst case theoretical bound of PLS algorithm using the worst case bound of the list scheduling algorithm for jobs with sequence-dependent setup times on identical machines provided in [Ovacik and Uzhoy, 1993].

We now continue with the properties of the PLS algorithm.

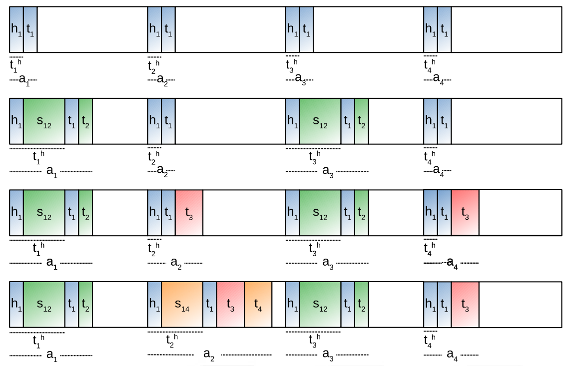


Figure 5.1: Allocation of four nodes by PLS algorithm

Lemma 2 *The subframes to which a sensor i is allocated by PLS have the same total active lengths just before the scheduling of sensor i.*

Proof: *The proof follows from Lemma (2) in [Sadi and Ergen, 2013]. It is based on a contradiction argument that assumes two subframes to which sensor i is assigned have different active lengths. Then, there must be a previously assigned higher priority sensor k with T_k assigned to one of the subframes to which sensor i is assigned but not to the other. However, because of the separation of allocation of sensor i by s_i subframes and s_i being a multiple of s_k due to the order of scheduling in PLS, if sensor k is allocated to one of the subframes, it must also be allocated to the other, which yields a contradiction.* □

Before we move on to the remaining properties, we define two auxiliary optimization problems, $P1$ and $P2$, to help us use the bound provided in [Ovacik and Uzhoy, 1993] to establish the bound of PLS.

Definition 1 *Let us define two problems, $P1$ and $P2$. In $P1$, consider Optimization Problem (4.2), i.e. the optimal scheduling problem of L sensors with time slots t_i, energy harvesting times h_i, and therefore the relative energy harvesting requirements s_{ij} over F/S subframes with the requirement of seperation of time slot allocations by s_i. In $P2$, consider the MSP such that F/T_i jobs with processing times t_i for each and every $i \in [1, L]$ and sequence-dependent setup times s_{ij} on F/S identical machines.*

Now that we have defined the two problems, let us show the relation between their the optimal values when there there are no energy harvesting (and setup time) requirements.

Lemma 3 *Denote the optimal value of* $P1$ *and* $P2$ *by* OPT_{P1} *and* OPT_{P2}*, respectively, for the case* $s_{ij} = 0$*,* $h_i = 0$*,* $i, j \in [1, L]$*. Then,* $OPT_{P2} \leq OPT_{P1}$*.*

Proof: *$P1$ and $P2$ are equivalent except for the additional requirement of allocation once in every s_i subframes in $P1$. Then, $OPT_{P2} \leq OPT_{P1}$ because $P1$ has an additional constraint that narrows down its feasible region.* $\square$

Now, we will take a closer look into the outcomes of PLS and LS on $P1$ and $P2$, respectively.

Lemma 4 *Let* $C_{P1,PLS}$ *and* $C_{P2,LS}$ *denote the maximum active length of the schedule of* $P1$ *produced by PLS and the makespan of* $P2$ *produced by LS algorithm proposed for solving MSP with sequence-dependent setup times [Ovacik and Uzhoy, 1993], respectively. Then,* $C_{P1,PLS} \leq C_{P2,LS}$*.*

Proof: *The LS algorithm proposed for solving MSP with sequence-dependent setup times assigns the next job on the list to the machine with the minimum current load, along with the required setup time of the task. The PLS similarly finds the subframe of minimum total active length for the assignment of each sensor, along with the additionally required harvesting time. The periodic extension of the time slot allocation also assigns to the subframes of minimum total active length due to Lemma 2. Thus, the only difference between PLS and LS is the way of determining the required setup time. In LS, when task j follows task i, the setup time is s_{ij} by definition. In PLS, however, we require the energy harvesting slot of the corresponding subframe to be sufficient for all assigned nodes to the corresponding subframe. Therefore, the additionally required harvesting time should be determined by comparing the harvesting requirement of sensor j (h_j) to the maximum of the harvesting requirements of the nodes that have been allocated to the corresponding subframe* ($\max_{i \in I_k} h_i$)*. Therefore, the corresponding s_{ij} is the smallest value possible over all $i \in I_k$. In other words,*

$s_{ij} = max(0, h_j - \max_{i \in I_k} h_i) \leq max(0, h_j - h_i)$, $i \in I_k$. *Hence, in each assignment, PLS yields a better schedule in terms of maximum total active length compared to the makespan produced by LS.* $\square$

Now, we are ready to establish the worst case bound of PLS.

Theorem 2 *Let $C_{P1,PLS}$ be the maximum active length of the schedule obtained by PLS, C^* be the optimal value of Optimization Problem (4.2), i.e. $P1$, and $F/S = M$ be the number of subframes. Also, assume that $s_{ij} \leq t_j, \forall i, j$. Then,*

$$\frac{C_{P1,PLS}}{C^*} \leq 4 - \frac{2}{M}. \tag{5.1}$$

Proof: *In [Ovacik and Uzhoy, 1993], the approximation bound is provided as $\frac{C_{P2,LS}}{OPT_{P2}} \leq 4 - \frac{2}{M}$ is provided. By Lemma 3, $OPT_{P2} \leq OPT_{P1}$. By Lemma 4, $C_{P1,PLS} < C_{P2,LS}$. Moreover, OPT_{P1} is a lower bound on the optimal value of Optimization Problem (4.2) since it considers the same problem without the harvesting times, i.e $OPT_{P1} \leq C^*$. Then,*

$$\frac{C_{P1,PLS}}{C^*} \leq \frac{C_{P1,PLS}}{OPT_{P1}} \leq \frac{C_{P2,LS}}{OPT_{P1}} \leq \frac{C_{P2,LS}}{OPT_{P2}} \leq 4 - \frac{2}{M} \tag{5.2}$$

$\square$

Chapter 6

PERIODIC ALTERNATIVE LIST SCHEDULING (PALS) ALGORITHM

Periodic Alternative List Scheduling (PALS) Algorithm is inspired from alternative list scheduling algorithm proposed for MSP. The alternative list scheduling (ALS) [Schutten, 1996] schedules the next job on a given list to the machine on which it will be completed first. List scheduling and alternative list scheduling are the same for machines with no setup times yet produce different schedules when setup times are involved.

In the following, we propose the scheduling algorithm PALS that assigns the sensor to the subframe on which it will complete transmission the earliest.

6.1 Description of PALS

PALS algorithm, as given in Algorithm (2), is described in detail as follows. The only difference between PALS and PLS is that PALS assigns the next job on the ordered list to the subframe on which it will finish transmission the earliest, instead of the shortest subframe (Line 6). PALS allocates the next sensor on the list to the subframe on which its transmission will be completed the earliest, taking into account both the total active length of the corresponding subframe, its own time slot length and additionally required harvesting time in case it is allocated to the corresponding subframe.

Fig. 6.1 depicts the allocation by PALS algorithm of the same network as Fig. 5.1. Allocation of the first three sensors yield the same schedule as PLS. Sensor 4 is allocated to the subframe on which it will complete transmission the earliest (subframe 1), instead of the subframe with smallest total active length (subframe 2). The resultant schedule yields a maximum active length of $a_1 = h_1 + s_{21} + s_{42} + t_1 + t_2 + t_4 = 0.8ms$.

Overall complexity of PALS is $O(LM + L^2M)$. Allocation of each sensor requires determining the subframe on which its time slot will complete the earliest. Finding the additionally required harvesting time for each subframe is of $O(L)$ complexity, which yields $O(LM)$ for selecting the subframe for allocation. Periodic repetition of allocation over the frame, and update of the subframe total active lengths are of $O(M)$ complexity. For L sensors, the overall complexity is $O(L^2M + LM)$.

input : T_i, t_i, h_i, for $i \in [1, L]$
output: z_{ik}, t_k^h, for $i \in [1, L]$, $k \in [1, M]$

begin
    order the nodes in increasing T_i ;
    $S = T_1$, $F = T_L$, $M = F/S$;
    for $j = 1 : L$ **do**
        find index k on which sensor j finishes transmission the earliest ;
        allocate p_j^k to the subframe k ;
        repeat allocation of sensor j every s_j subframes ;
    end
end

Algorithm 2: PALS Algorithm

6.2 Analysis of PALS

In this section, we will analyze the properties of PALS. With a similar method followed in Section 5.2, we will derive the worse case theoretical bound of PALS algorithm.

Lemma 5 *The subframes to which a sensor i is allocated by PALS have the same total active lengths just before the scheduling of sensor i.*

Proof: *The same arguments in the proof of Lemma 2 hold for PALS.* □

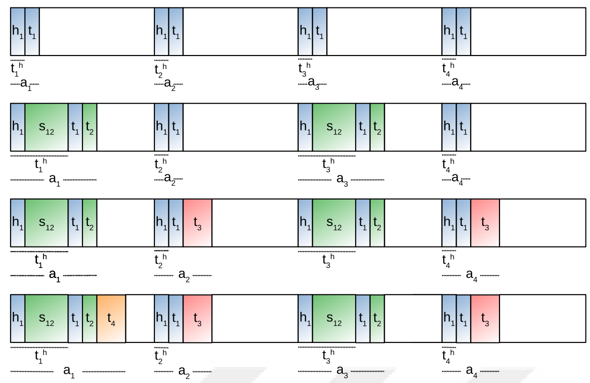


Figure 6.1: Allocation of four nodes by PALS algorithm

To proceed with the establishment of the worst case bound of PALS, we will benefit from the methodology followed in [Ovacik and Uzhoy, 1993] thats derives the worst-case bound of list scheduling for MSP on identical machines with sequence-dependent setup times bounded by processing times of tasks.

Lemma 6 *Let $C_{P2,PALS-ap}$ be the makespan of the schedule obtained by PALS-ap, the counterpart of PALS without the periodic allocation property. Also, let M_h be the set of tasks already scheduled on machine h, i.e the counterpart of I_k, and the setup time incurred for task j on machine h be $max(0, h_j - max_{i \in M_h} h_i)$. Also, assume that $s_{ij} \leq t_j, \forall i, j$. Then,*

$$\frac{C_{P2,PALS-ap}}{OPT_{P2}} \leq 4 - \frac{2}{M}. \tag{6.1}$$

Proof: *Let us start by establishing some facts about OPT_{P2}, which will be useful in establishing the worst case bound. Since OPT_{P2} is the optimal value of P2 when $s_{ij} = 0$ by definition, $\forall i, j$, we can write*

$$OPT_{P2} \geq \max_i t_i \tag{6.2}$$

$$OPT_{P2} \geq \frac{1}{M} \sum_i t_i \tag{6.3}$$

Eqn. (6.2) states that OPT_{P_2} *is greater than or equal to processing time of the job with maximum processing time, which holds since the job with maximum processing time has to be assigned to a machine. Eqn. (6.3) states that* OPT_{P_2} *is greater than or equal to the average of processing times of all jobs, which refers to the case where the sum of processing times of all jobs were allowed to be evenly distributed on the machines.*

We now continue with taking a closer look at a direct implication of the scheduling rule of ALS. Let n *be the last job on the list to be scheduled by ALS. Also let* H_h *be the time at which processing stops on machine* h *before scheduling* n*. As stated, ALS schedules the next job on the list to the machine on which it will complete the earliest. This implies that if job* n *were to be assigned to another machine than the one it has been assigned to, it would have been completed at a later time. This would yield a makespan greater than or equal to the current makespan. Then, for* $i \in M_h$*, we have*

$$H_h + s_{in} + t_n \geq H_h + mins_{in} + t_n \geq C_{P2,PALS-ap}, \tag{6.4}$$

In Eqn. (6.4), the right-hand side represents the current makespan. The expression in the middle represents the makespan if job n *were to be assigned to any machine* h*. The left-hand side is a mathematical fact due to* $s_{in} \geq mins_{in}$ *for* $i \in M_h$*.*

Also, by the left-hand and right-hand sides of Eqn. (6.4) and using the relation $s_{ij} \leq t_j$*, we can write*

$$H_h \geq C_{P2,PALS-ap} - 2t_n \tag{6.5}$$

Let us now take a look at Fig. 6.2. Since $s_{ij} \leq t_j$*, a job can take at most* $2t_j$ *amount of time on a given machine. Then, we have*

$$\sum_{h=1}^{M} H_h \leq 2\sum_{i=1}^{n-1} t_i \tag{6.6}$$

Eqn. (6.6) represents that the sum of all processing and setup times on all machines would be less than or equal to two times the sum of all processing times of all tasks before allocation of job n*.*

Now, we will manipulate the expressions above to obtain the worst-case bound. First, extracting H_M and adding $t_n + s_{in}$ to both sides in Eqn. (6.6), we have

$$2\sum_{i=1}^{n} t_i \geq 2\sum_{i=1}^{n-1} t_i + t_n + s_{in} \geq \sum_{h=1}^{M-1} H_h + H_M + t_n + s_{in} \tag{6.7}$$

Second, without loss of generality, we assume $C_{P2,PALS-ap}$ is given by machine M. Then, after allocation of job n, there are two possibilities: 1) if job n is allocated to machine M, we have $H_M + t_n + s_{in} = C_{P2,PALS-ap}$ and 2) if job n is allocated to another machine than M, we have $H_M + t_n + s_{in} > C_{P2,PALS-ap} = H_M$. Using this observation, extracting H_M in Eqn. (6.5) and performing the summation over h in Eqn. (6.7), we obtain

$$2\sum_{i=1}^{n} t_i \geq \sum_{h=1}^{M-1} H_h + H_M + t_n + s_{in} \geq (M-1)(C_{P2,PALS-ap} - 2t_n) + C_{P2,PALS-ap} \tag{6.8}$$

Then, combining Eqns. (6.2), (6.3) and (6.8), we have

$$2MOPT_{P2} \geq 2\sum_{i=1}^{n} t_i \geq (M-1)(C_{P2,PALS-ap} - 2OPT_{P2}) + C_{P2,PALS-ap} \tag{6.9}$$

Finally, by rearranging the left-hand and right-hand sides of Eqn. (6.9) we obtain,

$$\frac{C_{P2,PALS-ap}}{OPT_{P2}} \leq 4 - \frac{2}{M} \tag{6.10}$$

□

Now, we will take a closer look to the maximum active length and makespan produced by $PALS$ and $PALS - ap$ on $P1$ and $P2$, respectively.

Lemma 7 *Let $C_{P1,PALS}$ be the maximum active length of the schedule of $P1$ produced by PALS. Also, let $C_{P2,PALS-ap}$ be the makespan of $P2$ produced by alternative list scheduling algorithm described in Lemma 6. Then, $C_{P1,PALS} = C_{P2,PALS-ap}$.* Proof: *Both algorithms make assignment based on the completion of a task in with respect to*

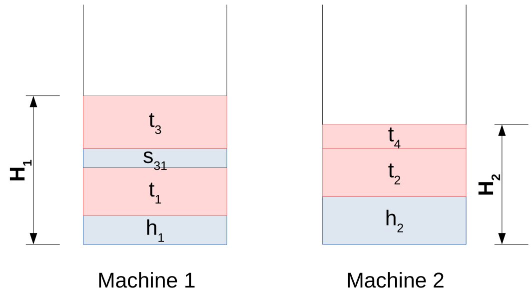


Figure 6.2: Allocation of four tasks using ALS on two machines. Note that $s_{42} = max(0, h_4 - max_{i \in M_2} h_i) = 0$.

a given list. Moreover, the additionally required harvesting time for the next sensor and the setup time needed for the next job are the same and equal to $max(0, h_j - \max_{i \in I_k} h_i)$. *The periodic extension of sensor allocation also assigns to the subframes on which it will complete the earliest due to Lemma 5. Hence, in each assignment, PALS yields the same schedule in terms of maximum total active length compared to the makespan produced by PALS-ap.* □

Now, we are ready to establish the worst-case bound of PALS.

Theorem 3 *Let* $C_{P1,PALS}$ *be the maximum active length of the schedule obtained by PALS,* C^* *be the optimal value of the Optimization Problem (4.2), i.e.* $P1$, *and* $F/S = M$ *be the number of subframes. Also, assume that* $s_{ij} \leq t_j, \forall i, j$. *Then,*

$$\frac{C_{P1,PALS}}{C^*} \leq 4 - \frac{2}{M}. \tag{6.11}$$

Proof: *By Lemma 6,* $\frac{C_{P2,PALS-ap}}{OPT_{P2}} \leq 4 - \frac{2}{M}$. *By Lemma 7,* $C_{P1,PALS} = C_{P2,PALS-ap}$. *Moreover,* OPT_{P1} *is a lower bound on the optimal value of the Optimization Problem (4.2) since it considers the same problem without the harvesting times, i.e* $OPT_{P1} \leq C^*$. *Then,*

$$\frac{C_{P1,PALS}}{C^*} \leq \frac{C_{P1,PALS}}{OPT_{P1}} \leq \frac{C_{P2,PALS-ap}}{OPT_{P1}} \leq \frac{C_{P2,PALS-ap}}{OPT_{P2}} \leq 4 - \frac{2}{M} \tag{6.12}$$

□

It is important to note that the worst case approximation bounds for PLS and PALS algorithms are established under the condition that setup times are bounded by time slot lengths. Now, let us present a channel condition where the worst case bounds are guaranteed to hold.

Lemma 8 *If the channel gains of the nodes satisfy $g_j c_j \geq \frac{\beta_j N_0}{p_c \zeta}$, the setup times are bounded by time slots, i.e. $s_{ij} \leq t_j, j \in [1, L]$.*

Proof: *Clearly, if $h_j \leq t_j$, $s_{ij} = max(0, h_j - h_i) \leq t_j$ holds. Then, replacing the expression for h_j and manipulating,*

$$\frac{h_j}{t_j} = \frac{\frac{\frac{\beta_j N_0}{g_j}}{p_c c_j \zeta} t_j}{t_j} \leq 1 \tag{6.13}$$

corresponds to

$$g_j c_j - \frac{\beta_j N_0}{p_c \zeta} \geq 0 \tag{6.14}$$

□

Chapter 7

PERFORMANCE EVALUATION

The goal of this chapter is to evaluate the performance of the proposed scheduling algorithms PLS and PALS, compared to the optimal algorithm and the commonly used Earliest Deadline First algorithm in terms of maximum total active length; maximum aperiodic delay, which is defined as the worst-case delay that an aperiodic packet experiences until it completes transmission in the unallocated part of the schedule [Sadi and Ergen, 2013]; average runtime; and average number of missed deadlines, which is the average number of packets that cannot be successfully transmitted within their delay tolerance even after retransmissions in the unallocated parts of the schedule. The optimal algorithm is obtained by choosing the best maximum total active length amongst the evaluations of all feasible allocations, and denoted by OPT. EDF algorithm [Liu et al., 2000] is a real-time scheduling algorithm that assigns priorities to tasks inversely proportional to their deadlines and schedules them as they arrive. In our framework, we consider the non-preemptive counterpart of EDF [Guan et al., 2008] to allow fair comparison, where a running task is uninterrupted until completion.

Simulation results are obtained based on 100 independent random network topologies. The distances between sensor nodes and corresponding controller are randomly distributed in the range $[0.1, 1]$ m. The packet generation periods and the packet lengths are uniformly chosen from the set $\{1, 5, 10, 50, 100, 200\}$ ms and the interval [10,20] bytes, respectively. All simulations are performed in MATLAB where IBM CPLEX solver is used for the optimal algorithm. The simulation parameters are based on the parameters of existing RF implementations, such as the Powerharvester [Powercast, line], and practical values provided in [Lu et al., 2015], as listed in

Table 7.1: Simulation Parameters

α	3.5	σ_z	4 dB	$\beta_i, \forall i$	10 dB
N_0	10^{-8} W/Hz	f	915 MHz	d_0	1 m
ζ	0.7	p_c	4 W	r	2 Mbps

Table 7.1.

The attenuation of the links are determined by considering both large and small-scale statistics. The large scale-statistics is modeled as

$$PL_{dB}(d) = PL_{dB}(d_0) + 10\alpha log_{10}(d/d_0) + Z \tag{7.1}$$

where d is the distance between the sensor node and the controller, $PL(d)$ is the path loss at distance d, $PL(d_0)$ is the free space path loss at reference distance d_0, α is the path loss exponent [Cui et al., 2005] and Z is a Gaussian random variable with zero mean and standard deviation σ_z [Khader et al., 2011]. The small scale fading has been modeled as Rayleigh fading with scale parameter Ω set to the mean power level determined by Eqn. (7.1) [Sadi and Ergen, 2015], [Khader et al., 2011].

7.1 Maximum Total Active Length

Fig. 7.1 shows the maximum total active length of the subframes for different numbers of nodes for PLS, PALS, EDF and OPT algorithms. The performances of PLS and PALS are very close to the optimal solution with maximum approximation ratios of 1.0556 and 1.0410, which are much less than the approximation ratios proved in Theorems (2) and (3), respectively. They both outperform EDF since EDF schedules tasks as they arrive.

Fig. 7.2a and Fig 7.2b show the maximum total active length of the algorithms for environments with different path loss characteristics for two distinct network sizes. As the path loss exponent increases, the received signal power of the nodes decreases

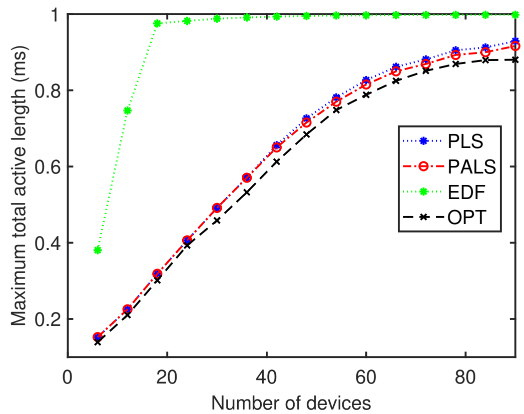
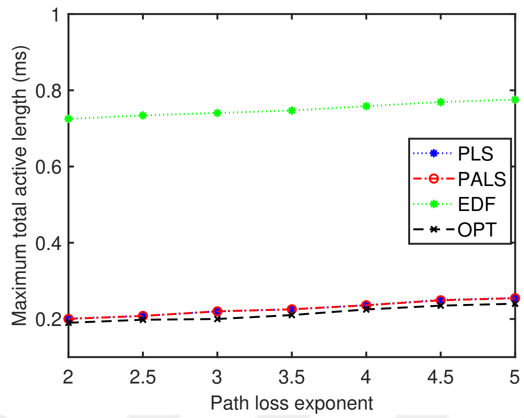


Figure 7.1: Maximum total active length of the subframes of PLS, PALS, EDF, OPT algorithms for different number of devices.

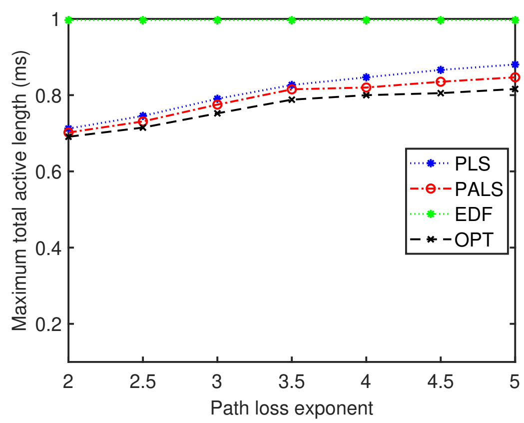
due to the lossy environment; and therefore, the amount of energy harvesting time that the nodes require for transmission and maximum total active length increase. This effect becomes more significant with increasing network size, as expected.

7.2 Maximum Aperiodic Delay

Fig. 7.3 shows the performance of the scheduling algorithms in terms of maximum delay experienced by an aperiodic packet. PLS and PALS outperform EDF with a close-to-optimal performance. EDF schedules the tasks are as they arrive, leaving almost no room in some of the subframes for the allocation of additional packets. As the number of nodes increases, the number of fully or near-to-fully allocated subframes that the additional packets have to wait to transmit increases. On the other hand, PLS and PALS distribute the allocations as uniformly as possible over the subframes, allowing the allocation of additional messaging.



(a) Number of sensor nodes = 12



(b) Number of sensor nodes = 60

Figure 7.2: Maximum total active length of subframes of PLS, PALS, EDF, OPT algorithms for different path loss exponents

7.3 Average Number of Missed Deadlines

Table 7.2 illustrates average number of missed deadlines for the scheduling algorithms. The proposed algorithms PLS and PALS considerably outperform EDF algorithm. The average number of missed deadlines is nonzero in all cases for EDF and increases drastically with increasing packet loss probability due to the nonuniform distribution of transmissions over time units. The number of missed deadlines becomes significant for PLS and PALS when the packet loss probability and the number of nodes are

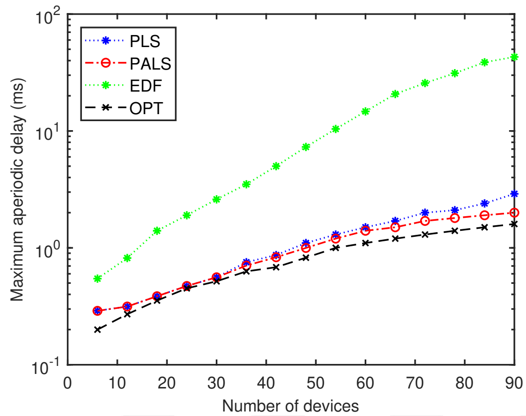


Figure 7.3: Maximum aperiodic delay of PLS, PALS, EDF, OPT algorithms for different number of devices.

Table 7.2: Average number of missed deadlines of PLS, PALS, EDF and OPT for different number of nodes and packet loss probabilities (PLP)

PLP	$\#ofnodes$	PLS	$PALS$	EDF	OPT
10^{-4}	42	0.001	0	0.008	0
10^{-4}	84	0.025	0	0.2515	0
10^{-3}	42	0.019	0.007	0.127	0
10^{-3}	84	0.205	0.087	3.299	0
10^{-2}	42	0.170	0.085	1.458	0
10^{-2}	84	8.916	5.352	41.662	0
10^{-1}	42	40.155	39.407	51.893	0.149
10^{-1}	84	1235.2	1234.2	1340.1	2.672

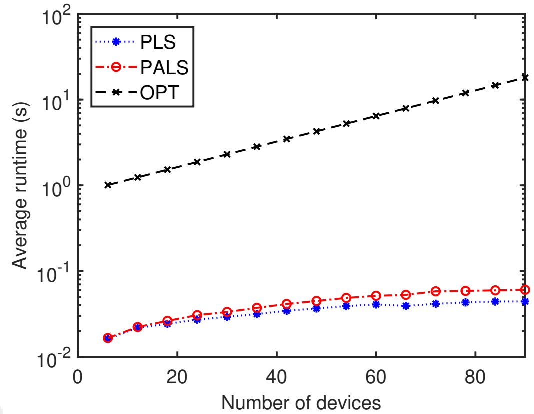


Figure 7.4: Average runtime of PLS, PALS, OPT algorithms for different number of devices.

both large at 10^{-2} and 84, respectively, or when packet loss probability is very large at 10^{-1}.

7.4 Average Runtime

Fig. 7.4 shows the average runtime of the proposed algorithms with respect to the optimal algorithm. The average runtime of both heuristics is negligible due to their polynomial complexity when compared to that of the optimal, which exhibits exponential increase as the number of nodes increases.

Chapter 8

CONCLUSION

In this thesis, we study the optimal power control and scheduling of an energy harvesting wireless networked control system. The objective of the problem is to provide maximum level of adaptivity to accommodate the changes in transmission time, retransmissions, and allocation of additional messages whereas the constraints include the packet generation period, transmission delay, and energy harvesting requirements of the individual sensor nodes. We show the power allocation problem can be separated from the scheduling and energy harvesting problem at optimality. The resultant simplified scheduling problem formulated as MILP, and proven to be NP-hard. We first propose two polynomial time scheduling heuristics, PLS and PALS, for our sensor node scheduling framework over time units with energy harvesting requirements, inspired by list scheduling algorithms proposed for job scheduling on identical machines with sequence-dependent setup times. We then derive the worst case approximation bounds for the two heuristics. Finally, through simulations, we illustrate the very close-to-optimal performance and superiority of the proposed heuristic compared to commonly used EDF and optimal algorithm in terms of adaptivity, maximum delay, and average runtime for various network sizes.

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