Energy Management in Solar Powered WLAN Mesh Nodes Using Online Meteorological Data

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Abstract—Solar powered WLAN mesh nodes are assigned a solar panel and battery size based on power consumption profiles. If future loading exceeds the design target, then a node may not be able to achieve the outage performance for which it was configured. To prevent this from happening, forced power saving can be used to reduce node power consumption to acceptable levels. However, forced power saving generates a deficit in offered capacity which should be minimized as much as possible. In this paper we first formulate this as a non-linear control problem. An efficient Linear Programming approximation is then defined and solved based on an offline optimization where future solar insolation is known in advance. This provides a bound on the performance of any real control algorithm. We show that the LP solution is accurate in that it comes very close to achieving a no-control capacity deficit lower bound. A control algorithm is then proposed whose operation uses dynamic access to publicly available on-line meteorological data. The proposed approach uses this on-line data but could also benefit from on-line weather forecasting. Our results show that the proposed algorithm minimizes node outage and performs favorably compared to the offline and no-control lower bounds.

I. INTRODUCTION

WLAN mesh networks are used to provide IEEE 802.11 coverage by multihop relaying between mesh APs (MAPs) and mesh points (MPs). One of the costs in certain outdoor WLAN mesh deployments is that of providing these nodes with continuous electrical power. A cost effective alternative is to operate the mesh nodes using a sustainable energy power source, such as solar power [1]. For the past several years this approach has been used in the SolarMESH network deployment trials [1].

In solar powered WLAN mesh networks, node resource allocation includes assigning a panel and battery size to each mesh node. The panel/battery configuration is very important since together they can often be a significant fraction of the total node cost. This assignment must take into account the power consumption of the node based on the workload that the node is expected to encounter. If future loading exceeds this design, a node may not be able to achieve the outage performance for which it was originally configured. An alternative to increased outage is to withhold energy, which then incurs a capacity deficit. Control algorithms are needed to enforce an appropriate tradeoff between capacity deficit and outage so that the design performance is obtained.

In this paper we consider the problem of energy management in solar powered WLAN mesh networks. The problem is first formulated as a non-linear optimal control problem. A Linear Programming (LP) approximation is then given and solved based on an offline optimization where future solar insolation is known. This result gives a bound on the performance of any real control algorithm. We show that the LP solution is accurate in that it achieves results which are very close to a known no-control capacity deficit lower bound. A control algorithm is then proposed that uses access to publicly available meteorological databases. This approach uses on-line data but could also use data from weather forecasts. We show that the proposed algorithm minimizes node outage and performs favorably compared to the offline and no-control bounds.

II. BACKGROUND

A lot of previous work deals with energy-aware protocol design and routing. However, there is much less that deals with energy awareness in renewable-energy networks.

In [2] the design of solar-powered WLAN mesh networks was considered from a resource allocation and outage control point of view. A solar panel/battery configuration methodology was introduced based on a proposed AP power-aware version of IEEE 802.11. Public meteorological data is used to provision each node based on an averaged offered capacity profile. Results are presented which show the value of the proposed configuration methodology.

In [3] a power-aware routing algorithm is presented for wireless networks with renewable energy sources. The proposed algorithm is shown to be asymptotically optimal when compared to the full knowledge case (competitive analysis). No information is assumed regarding the arrival process and it is assumed that the node has full knowledge of the energy it will receive until the next renewal point by looking at previous data. The proposed routing algorithm uses a composite cost metric that includes power for transmission and reception, replenishment rate, and residual energy. The work also includes non-uniform energy replenishment rates and introduces a battery energy threshold scheme to decrease overhead.

Reference [4] presents an analysis of environmentally powered sensor networks. A model is provided for characterizing energy sources and includes a harvesting theory that governs
storage and power consumption requirements. The results are developed for constant and variable power operation. A communication protocol is described for sustainable performance of a network of sensors.

The problem of optimal energy allocation and admission control for solar powered communications satellites has been studied in [5]. The case is considered where each admitted request has an associated reward that is unknown a-priori but has a known pdf. The objective is to maximize the expected value of the reward while not exceeding the energy constraints. A dynamic programming approach is used to establish the optimal policy and was found to be characterized in terms of thresholds. Two heuristic approaches were provided (certainty equivalency, unlimited demand) to speed up the processing time since finding the optimal solution was found to be slow.

In [6] solar powered OFDM wireless mesh networks with sleep management and connection admission control were described. An analytic queuing model was formulated to evaluate the performance at the mesh nodes. Based on this model, the authors present an optimization problem formulation to determine the optimal sleep and wakeup parameters or the CAC threshold in order to meet the desired QoS constraints.

In [7] improved communication energy efficiency is considered for networks powered by renewable energy sources. The work analyzes the energy consumption in the one transmitter, multiple receiver, case. Optimal scheduling algorithms are presented for data transmission at different rates such that the throughput is maximized under given time limits and energy constraints.

III. SOLAR POWERED WLAN MESH NETWORKS

Figure 1 shows a simplified block diagram of a solar powered WLAN mesh node. The solar panel and battery are connected to the AP through a charge controller which performs functions such as battery over-/under-charge protection. In the energy flow model we define $E_{\text{panel}}(k)$ to be the energy produced in the solar panel over the time increment $[(k - 1)\Delta, k\Delta]$, where $\Delta$ is the time-step length considered.

In photovoltaic (PV) systems designed using publicly available meteorological data, data collection and modeling is done in discrete time, and more than sufficient accuracy is obtained using 1 hour $\Delta$ increments [8]. The solar panel size is given by $S_{\text{panel}}$, and is usually rated in Watts at peak solar insolation. We also define $B(k)$ to be the residual battery energy stored at time $k\Delta$, and $B_{\text{max}}$ is defined to be the total battery capacity. If we assume that $L(k)$ is the load energy demand over the time duration $[(k - 1)\Delta, k\Delta]$, then we can write that [9]

$$B(k) = \min\{\max\{B(k - 1) + E_{\text{panel}}(k)
- L(k), B_{\text{outage}}, B_{\text{max}}\},$$

(1)

where $B_{\text{outage}}$ is the maximum allowed depth of discharge based on safety and battery life considerations [10]. When $B(k) < B_{\text{outage}}$, the charge controller will disconnect the MAP/MP load and the node will experience a radio outage. The above model is easily modified to incorporate more sophisticated battery models such as those that include temperature effects. These can be included in the methodology we present in this paper.

Solar powered node resource allocation includes assigning a panel and battery size to each mesh node. When this configuration is performed, a load profile for each node is determined. The load profile is a time function which represents the peak workload for which the node in question is designed. For a given geographic location, public meteorological data is then used to design the node subject to a target outage probability [2]. For a given power dissipation workload a continuum of battery and panel sizes can be determined and a cost-optimal assignment can be found. Using data for Toronto, Canada for example, the cost-optimal panel and battery sizes for $P_{\text{Out}} = 10^{-4}$ are 40.6 Ah and 38 W [2] for a (short-term) average power consumption of 2 Watts. Thus, the solar panel and battery sizes represent a significant fraction of the node cost [2].

Power consumption is a major factor affecting the node cost due to the panel/battery configuration. Unfortunately, IEEE 802.11 does not include procedures that would allow an access point to achieve power saving, and this aspect of IEEE 802.11 is an impediment to the development of real power saving WLAN infrastructure. In classical IEEE 802.11, power saving has dealt with end user stations, since access points are assumed to have continuous power connections [11]. In [12] a power saving WLAN mesh architecture is proposed based on simple extensions to IEEE 802.11e [13]. In conventional IEEE 802.11, APs broadcast beacon packets periodically to announce the presence of the access point and to maintain synchronization with its associated stations. In the proposed power saving protocol, the AP includes a network allocation map (NAM) in its beacon broadcasts which specifies periods of time within the superframe when it is in a power saving state [12]. In this paper we assume that such power saving techniques are available and therefore the AP can choose to force a level of power saving activity regardless of mobile station transmission requirements. This is referred to as forced
power saving (FPS). When FPS is used the bandwidth offered by the AP is artificially reduced and when this is less than that required by the load the system incurs a capacity deficit. The objective of a control algorithm is to try to meet the target outage requirements of the system while keeping the capacity deficit as low as possible. In the following section we present the optimization problem formulation and consider an efficient LP approximation for the offline optimization problem.

IV. OPTIMIZATION PROBLEM FORMULATION

The problem can be formulated as a stochastic control problem. As before \( \mathcal{L}(k) \) is defined to be the energy loading of the AP during the time interval \([ (k-1)\Delta, k\Delta] \). We then define the actual (or delivered) energy loading during the interval \([(k-1)\Delta, k\Delta] \) to be \( \mathcal{E}_a(k) \). In the absence of any control and outage, \( \mathcal{E}_a(k) = \mathcal{L}(k) \), but when a control mechanism is in place, the activity level of the AP may sometimes be artificially reduced to save power, i.e.,

\[
\mathcal{E}_a(k) = \min(\mathcal{L}(k), \mathcal{E}_{\text{max}}(k)),
\]

where \( \mathcal{E}_{\text{max}}(k) \) is a control variable that specifies the maximum energy consumption in the next interval. The actions of the control variable lead to an energy deficit, \( \mathcal{E}_{\text{def}}(k) \), defined by

\[
\mathcal{E}_{\text{def}}(k) = \mathcal{L}(k) - \mathcal{E}_a(k).
\]

In addition to an outage requirement, we assume that the normalized level of offered AP capacity should never drop below some acceptable design value, \( U_{\text{min}} \), otherwise the operation of the AP would be too impaired. We will constrain \( \mathcal{E}_a(k) \) so that it does not drop below the value needed to provide \( U_{\text{min}} \) AP activity level, i.e., \( \mathcal{E}_a(k) \geq \mathcal{F}(U_{\text{min}}) \). The function \( \mathcal{F}[\cdot] \) translates the average activity of the AP into an average energy consumption over \([(k-1)\Delta, k\Delta] \).

The objective of the control scheme is to satisfy the target outage rate while reducing the capacity deficit as much as possible. For a given loading condition, the optimum control scheme is to select \( \mathcal{E}_a(k) \) for all \( k \), such that the energy deficit over all time is minimized, i.e.,

\[
\min_{\{\mathcal{E}_{\text{max}}(k)\}} \sum_{k=0}^{K_{\text{max}}} \mathcal{E}_{\text{def}}(k),
\]

such that

\[
B(k) = \min\{\max[B(k-1) + \mathcal{E}_{\text{panel}}(k) - \mathcal{E}_a(k), B_{\text{outage}}], B_{\text{max}}\},
\]

\[
Pr\left\{\bigcap_k (B(k) > B_{\text{outage}})\right\} \geq 1 - P_{\text{outage}},
\]

and

\[
\mathcal{E}_a(k) \geq \mathcal{F}(U_{\text{min}}).
\]

Equation 5 is the modified energy flow equation for the system, Equation 6 is the outage requirement and Equation 7 is the constraint on minimum AP activity. Normally the AP will be designed to a zero outage probability target and in this case Equation 6 is equivalent to the requirement that \( B(k) > B_{\text{outage}} \) for all \( k \). Unfortunately Equation 4 describes an extraordinarily hard optimal control problem.

A. Optimal Offline Formulation and LP Approximation

In this section we show a simplified formulation of the offline version of the control problem and an LP approximation in order to solve large-scale system runs. We assume that we have full knowledge of the future solar insolation and load, which will result in a bound on performance for any realizable algorithm.

Let us first assume that \( \mathcal{E}_a(k) \) is the control variable to be optimized. We introduce a new variable, \( S(k) \) which serves a dual purpose; it can be used to represent the surplus amount of energy received by the system that cannot be stored by the battery or it can take a negative value when the battery charge is found to be negative, i.e.,

\[
S(k) = \begin{cases} 
0 & \text{if } 0 \leq B(k) \leq B_{\text{max}} \\
-B(k) & \text{if } B(k) < 0 \\
B_{\text{max}} - B(k) & \text{if } B(k) > B_{\text{max}}.
\end{cases}
\]

The problem can now be re-written as

\[
\min_{\{\mathcal{E}_a(k)\}} \sum_{k=0}^{K_{\text{max}}} \mathcal{E}_{\text{def}}(k)
\]

such that

\[
\mathcal{E}_{\text{def}}(k) = \mathcal{L}(k) - \mathcal{E}_a(k)
\]

\[
\mathcal{F}(U_{\text{min}}) \leq \mathcal{E}_a(k) \leq \mathcal{L}(k)
\]

\[
S(k) + B(k) = B(k-1) + \mathcal{E}_{\text{panel}}(k) - \mathcal{E}_a(k)
\]

\[
B(k) = \min\{\max[S(k) + B(k), B_{\text{outage}}], B_{\text{max}}\}
\]

We notice that all the constraints and the objective are linear except for the condition

\[
B(k) = \min\{\max[S(k) + B(k), B_{\text{outage}}], B_{\text{max}}\}.
\]

The outage constraint has been dropped by specifying that \( B_{\text{outage}} < B(k) \).

The above formulation can be used to find the offline solution to the problem. It can also be used to establish a performance benchmark and to establish the conditions necessary for the optimization to exist. The optimizer will be able to find an optimal system run that leads to the minimum capacity deficit. The disadvantage of the off-line optimization is that although it can determine the existence of an optimal solution, and it provides the full-knowledge solution, no insight is given as to how to develop an algorithm to find an optimal causal run.

Since non-linear optimization problems are difficult to solve for large scale problems, an approach is to approximate it by an LP or a convex problem for which there are several efficient large scale solvers [14]. We notice that \( S(k) \) is obtained via a non-linear expression, however, by careful examination we notice that we want to minimize its absolute value for all cases with the exception of the case when the non-linear constraint
is active. Therefore, the problem can be re-formulated as the following LP problem

$$\max_{\{E_a(k), B(k), S(k)\}} \sum_{k=0}^{K_{\text{max}}} E_a(k) - \lambda t(k)$$

(15)

such that

$$F(U_{\text{min}}) \leq E_a(k) \leq L(k)$$

(16)

$$B(k) + S(k) = B(k-1) + E_{\text{panel}}(k) - E_a(k)$$

(17)

$$B_{\text{outage}} < B(k) \leq B_{\text{max}}$$

(18)

$$-t(k) \leq S(k) \leq t(k),$$

(19)

where $\lambda$ is a control factor that is set so as to not interfere with the operation of the original objective. $t(k)$ is a dummy variable used to linearize the absolute value operation of $S(k)$.

### B. Performance Results

For the off-line optimization problem, the cvx [15] and the Matlab linprog toolboxes were used to generate the following results. Both tools were found to achieve the same results. In the following results we first show a sample comparison of the output of the offline optimization (OOC) with that of the no control lower bound (NCLB) on capacity deficit [2]. The presented results are typical of what we have found in that the computed version achieves CD values very close to the lower bound. Then in the next section we propose a control algorithm which uses on-line access to meteorological database information.

We assume that the battery and panel have been designed for a nominal 2 Watt power consumption load with an outage probability $P_{\text{Out}} = 10^{-2}$. We then subject the node to a constant load power of 4 W (i.e., double its design value), with $B_{\text{outage}} = 0.1067$, $U_{\text{min}} = 0.1$. The system was then simulated for 3000 hours using meteorological data for the city of Toronto.

Figure 2 shows an example of the results obtained for the offline optimizer in addition to a comparison to the no control case. The figure shows the battery charge, admitted load, and the received solar insolation as they evolve over time. We notice that the battery charge never dips below $B_{\text{outage}}$ and the admitted load never dips below $U_{\text{min}}$, as required. We can also see that the admitted load is evenly distributed as opposed to the no control case, which simply turns the system on and off. For example, we see that between the 125th hour and the 250th hour, the offline optimizer withheld energy from the load by only supplying 3 W instead of 4 W. On the other hand, the no control algorithm provided the complete load but it started with an empty battery and ended with an empty battery. If we examine the hours between 250-275, we notice that the solar insolation dips down to zero and the no control case is incapable of satisfying requests while the offline optimizer has accumulated enough energy in the battery so that it can supply 3 W over the no insolation period. These results qualitatively motivate the advantage obtained of using both past and predictive meteorological data. An algorithm based on this is introduced in Section V.

### V. Energy Control Algorithm

A control algorithm is now proposed. The mechanism updates decisions at discrete time periods, $k$, which would typically be 1 hour increments. Since decisions are based on such long intervals, any forced power saving can easily be applied to both best effort traffic and connection oriented traffic admission.

It is assumed that the algorithm has access to historical meteorological data for the current geographic location. In the
description below we refer to the algorithm running on the mesh node itself. However this would probably be undesirable due to processing constraints at the node. A more likely scenario is that the algorithm is executed on a networked server which receives input and communicates results to the mesh node through the WLAN mesh network.

The proposed mechanism is shown as Algorithm 1. At each decision point, \( k \), the node must decide what energy it is willing to consume over the next \( \Delta \) time increment, \([k)\Delta, (k + 1)\Delta]\). Using the historical data, simulation runs of the energy balance equation are done for \( W \) time increments (i.e., hours) into the future. The results of these runs are used to determine the energy that can be offered over this time increment.

The algorithm exploits solar cyclostationarity, and indexes each year in \( \Delta \) time increments (e.g., we assume that \( \Delta = 1 \) hour). It then accepts as an input the current hour \( p \), the window of prediction \( W \), and the load that is being considered for admission, i.e., “originalload”. At the corresponding time \( p \) in the historical database, the controller performs a simulation based on Equation 1 for a given past year, from \([p, p + W] \) using the data in question. This procedure is repeated for multiple years in the meteorological database for this location.

Once the charge values are generated \( W \) hours into the future, they can be examined in order to make a decision on the admissible load. The controller sets a threshold \( L_{th} \) on the battery charge, and finds the lowest point \( \delta \) below \( L_{th} \) in the simulated run. The controller then sets the admissible load to be the original demand load reduced so that the lowest point is above \( L_{th} \). The admissible load will be termed “admissibleload”. As seen in the algorithm, if the total admissible load is less than \( U_{min} \), it is left at \( U_{min} \) since the priority is to always supply \( U_{min} \) as discussed above.

Finally, the ensemble average value of the admissible load across all the years available on record is taken and this will be the load actually admitted by the system.

**Algorithm 1 Control Algorithm (PC)**

1. **Initialization:**
   - \( \text{Current time} = p \)
   - \( W = 24 \)

2. **For each year \( j \):**
   - \( j = 1 \) to Number of years
   - \( i = p+1 \) to \( p+W \)
   - \( \text{if} \) \( \text{BatteryCharge}(i) < L_{th} \)
     - \( \delta(i) = L_{th} - \text{BatteryCharge}(i) \)
     - \( \text{else} \)
     - \( \delta(i) = 0 \)
   - \( \text{end if} \)
   - \( \text{end for} \)
   - \( \text{if} \) \( \text{admissibleload}(j) < U_{min} \)
     - \( \text{admissibleload}(j) = U_{min} \)
   - \( \text{end if} \)

3. **Return average of admissible load over \( j \)***

1) **Performance Results:** Many experiments have been performed using publicly available meteorological data for many North American cities. In the results presented below we use 20 years of data for the city of Toronto, Canada. The data was split into even-numbered and odd-numbered years. The odd-numbered years were used for the actual system simulation, while the even years were used in the weather simulations. The experiments were repeated for \( P_{out} = 10^{-2}, 10^{-3}, \) and \( 10^{-4} \). We assumed that \( W = 24 \) (i.e., 24 hour prediction window), \( L_{th} = 10\% \), and \( U_{min} = 0.1 \) W.

Figures 4 and 5 show the results of our experiments. The simulations assume an initially half full battery. Here we assume the system was allocated enough resources (battery and panel) for a constant 2 W power consumption, therefore the excess load is \( C_{Excess} = 2W \).

Figure 4 plots the CD versus the excess load applied to the system. In the figure, we compare the capacity deficit for the control scheme (PC) to the theoretical lower bound on capacity deficit. Although the scheme cannot achieve the lower bound as seen in the OOC case, the capacity deficit tracks the bound well. On the other hand, Figure 5 plots the outage probability versus the excess load for the PC scheme and the NCLB case. We can see that the PC scheme has successfully eliminated the outage events completely.

It is clear that the compromise made by the controller is to sacrifice some of the system capacity. However, this CD is very close to the theoretical lower bound. For example, the CD for the \( P_{out} = 10^{-2} \) case for the PC scheme is about 0.11 while it is equal to 0.0865 for the NCLB and 0.0868 for the OOC case. We also notice the large reduction in outage probability achieved by the control scheme. When the controller is active the outage probability goes down to...
virtually zero for all designs. On the other hand, the outage probability for the no control case goes up from 0.01 to 0.125 for the $P_{Out} = 0.01$ case, which is a significant increase.

The above results are typical of many others that have been obtained which show the excellent performance of the proposed algorithm.

![Graph 1](image1.png)

**Fig. 4.** Capacity Deficit versus Excess Load (with control)

![Graph 2](image2.png)

**Fig. 5.** $P_{Out}$ versus Excess Load (with control)

VI. CONCLUSIONS

This paper considered the use of forced power saving control for outage prevention in solar powered WLAN mesh nodes. We first formulated the control objective as a non-linear control problem. An accurate Linear Programming (LP) approximation was then defined and solved based on an offline optimization where future solar insolation is known. This gives a bound on the performance of any real algorithm which was used to compare with a proposed control scheme.

A control algorithm was proposed whose operation uses dynamic access to publicly available meteorological data. We showed that the proposed algorithm eliminates node outage events completely in the case when the system is heavily overloaded beyond its nominal design value. The outage elimination came at the expense of an increase in the capacity deficit. However, the scheme’s capacity deficit performed favorably when compared to the formulated offline and no-control bounds. This demonstrates the effectiveness of forced power saving as a tool for reducing outage for solar powered IEEE 802.11 WLAN mesh networks.

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