Long Term Sensing via Battery Health Adaptation

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Abstract—Energy Neutral Operation (ENO) has created the ability to continuously operate wireless sensor networks in areas such as environmental monitoring, hazard detection and industrial IoT applications. Current ENO approaches utilise techniques such as sample rate control, adaptive duty cycling and data reduction methods to balance energy generation, storage and consumption. However, the state of the art approaches makes a strong and unrealistic assumption that battery capacity is fixed throughout the deployment time of an application. This results in scenarios where ENO systems over allocate sensing tasks, therefore as battery capacity degrades it causes the system to no longer be energy neutral and then fail unexpectedly. In this paper, we formulate the problem to maximise the quality-of-service in terms of duty cycle and the battery capacity to extend the deployment lifetime of a sensing application. In addition, we develop a lightweight algorithm to solve the formulated problem. Moreover, we evaluate the proposed method using real sensor energy consumption data captured from micro-climate sensors deployed in Queen Elizabeth Olympic Park, London. Results show that a 307% extension of deployment lifetime can be achieved when compared to a traditional ENO solution without a reduction in the duty cycle of the sensor.

I. INTRODUCTION

The Internet of Things (IoT) has rapidly matured in the past decades and is becoming a viable solution for real world deployments. The major barriers to the practical adoption of IoT systems have been the limited deployment opportunities if run on mains power and limited operational lifetime on primary batteries [1]. The latter is compounded by the need for costly human intervention when batteries eventually need to be replaced, the environmental concerns of disposal of said batteries, and the introduction of errors when those batteries near end of life. Energy harvesting from sources, such as solar, wind, thermolectric and vibration have been put forth [2] as potential solutions to this problem when paired with a rechargeable battery. The introduction of energy harvesting to IoT brings improvements for system performance, however, gains from energy harvesting come with additional complexities, i.e. unpredictable energy generation.

Energy Neutral Operation (ENO) is introduced in [3] as a mode of operation of an IoT object where the energy consumption of a node is always less or equal to the energy harvested from the environment. However, the limitation of existing ENO approaches is the lack of consideration of the degradation of the capacity of the battery element. Specifically, the capacity of the battery is assumed [4] to be fixed throughout the lifetime of the deployment. In fact, battery capacity degrades over time and can only undergo a limited number of charge/discharge cycles before failure. In this paper, we aim to address the issue of how to incorporate awareness of this degradation into ENO optimisation formulations so that both the battery capacity and duty cycle of each sensor node in an arbitrary IoT application are maximised. As a result, the deployment time of an application can be extended, which results in reducing the associated costs of replacement and in field maintenance.

A. Contributions

To the best of our knowledge, this paper is the first to monitor the degradation of a battery element in node that is suitable for all battery chemistries. This allows existing ENO optimisation algorithms [3] to have an accurate awareness of battery states and the ability for IoT objects to flag failing batteries for replacement. The contributions of this paper are summarised as follows:

- We formulate the optimisation problem to maximise both the duty cycle of each individual node and the battery lifetime by considering the battery capacity degradation.
- We propose a novel lightweight algorithm to extend the lifetime of the deployment of an arbitrary IoT application.
- The proposed algorithm is verified by using the real world energy consumption data from micro-climate sensors deployed in Queen Elizabeth Olympic Park, London, UK.

The results show that an increase of deployment lifetime of 307% can be achieved without a without a reduction of duty cycle of the application.

B. Related Work

Prior to presenting our work it is necessary to provide background related to ENO systems and battery health modelling. ENO Systems: In the field of ENO, research has been conducted with consideration of power management [4] and data delivery [5], with an effort to intelligently reduce the energy burden on IoT devices and ensure sustainability of operation. The state of the art considers ENO such that optimisations can maximise data delivery of an entire network [6], efficiently utilise Residual Waste Energy (RWE) through in network data processing [7] and trade energy between networks when a surplus of energy exists [8].

The most relevant work to this paper comes from area of adaptive duty cycle [9] and duty cycle maximisation [10], which look at optimisation techniques to ensure energy is most effectively utilised to maximise sensing tasks while ensuring energy generation is greater than energy consumption. However, these work does not consider the dynamic capacity of a battery and therefore could not be applied to optimise battery lifetime.

Battery Health Modelling: The lifetime of primary (non-rechargeable) batteries has been an extensively covered area in IoT [11]. However, these approaches seek to conserve energy in a battery powered system rather than monitor the cycle lifetime of an energy harvested sensor with a rechargeable battery. Work has been undertaken to predict the lifetime of battery devices with renewable sources for home energy backup [12].

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and electric vehicle cost analysis [13]. However, these methods are not designed to be run on resource constrained devices and have not previously been applied in-node to aid in ENO optimisations.

Multiple models of battery degradation, or battery health, have been proposed, such as the Rakhmatov and Virudhula method (RVM) [14] and the Peukert Lifetime Energy Throughput (PLET) [12]. The RVM method provides a more accurate measure of battery lifetime as it is derived from the physical principles of the battery chemistry. While this also narrows the scope of the model as it only takes into account lithium ion battery chemistries and would be computationally expensive if run on resource constrained devices. The PLET model, on the other hand, is appropriate for a wide range of battery elements, such as lithium-ion, nickelmetal hydride and nickelcadmium. This allows for a broader applicability of any optimisation built upon PLET. Adapting these battery health monitoring techniques to run on resource constrained devices and applying them to state of the art duty cycle maximisation methods will be the focus of this paper. This gives the unique ability to explore how energy degradation impacts performance in ENO systems.

II. SYSTEM MODEL

In this paper, we consider an energy harvesting wireless sensor that operates in discrete timeslots. Within each timeslot, the sensor node is capable to perform tasks, including sensing and wireless transmission.

\[ E^{sen} = (E^{tr} + E^{sc} + E^{co}), \]  

where \( E^{tr}, E^{sc} \) and \( E^{co} \) are the energy consumption per transmission, sensing, including energy overhead to sense energy harvested and energy consumed, and energy consumption of the active sensor node, including algorithm computation, respectively. These parameters are dependent on the hardware of the node.

At timeslot, \( t \), the battery state \( B_t \) of a node can be expressed as

\[ B_t = B_{t-1} + H_g - (E^{sen})D_t - E^{ce}, \]

where \( B_{t-1} \) is that battery state at the previous time slot, \( t-1 \), \( H_t \) is total energy generated from the energy harvesting source at timeslot, \( t \), \( D_t \) is the duty cycle of the node at \( t \), and \( E^{ce} \) is the energy consumption when the node turns into sleep mode.

As previously mentioned, traditional energy harvesting wireless sensors consider the battery to be of a fixed capacity. However, taking the depth of discharge of a lithium-ion storage element shown in Fig. 1 as an example, it is worth noting that the number of charge cycles that a battery can undertake decreases with increasing depth of discharge (DOD). This indicates that the maximum battery capacity \( B_{t}^{\text{max}} \) is not fixed, and it actually decreases as the battery degrades.

At timeslot, \( t \), the battery cycle lifetime, \( C_{\text{PLET}} \), which is adopted in the PLET approach [12], can be expressed as

\[ C_{\text{PLET}} = d_t^{kp}, \]

where \( kp \) is the Peukert Lifetime constant, \( n \) is the number of charge/discharge cycles of the battery, and \( d_t \) is the DOD percentage of the battery for timeslot \( t \), which is given by

\[ d = \begin{cases} B_t - B_{t-1}, & \text{if } B_t - B_{t-1} < 0. \\ 0, & \text{otherwise}. \end{cases} \]

The total lifetime of the battery \( C_{\text{PLET}} \) can be considered constant. Within the timeslot, \( t, n = 1 \) as the system will either be charging or discharging. Therefore, at timeslot \( t \), the maximum capacity of the battery, \( B_{t}^{\text{max}} \), can be updated by

\[ B_{t}^{\text{max}} = B_{t-1}^{\text{max}}(1 - d_t^{kp}) \frac{C_{\text{PLET}}}{C_{\text{PLET}}^{\text{max}}}. \]

Considering this new formulation, the degradation of a battery can be calculated in node. Consider an IoT scenario where an energy harvested node consisting of a solar energy source and a temperature sensor is transmitting data every 15 minutes to a Basestation (BS). As shown in Fig. 2, by monitoring the battery health in node, the degradation of the battery can be seen clearly over the course of a one-year period. Fig. 2 also highlights that the node failure percentage increases as the battery degrades. Here, the node failure percentage refers to the percentage that the system cannot perform the required tasks due to insufficient available energy over time window, \( N_w \).

III. POWER MANAGEMENT

To counteract the issues emerging from degrading battery, the PLET approach is considered to model the battery capacity more accurately and optimise both the duty cycle of an individual node and the battery health. In order to solve the formulated problem, we propose a novel lightweight algorithm for in-node implementation.

A. Problem Formulation

By considering the dynamic maximum battery capacity, an ENO optimisation formulation seeks to achieve the following problem:

\[ \text{(P1)} \quad \max \sum_{t=1}^{N_w} D_t. \]
Subject to:

\[ 0 \leq B_t \leq B_t^{\max}, \]
\[ D_{\min} \leq D_t \leq D_{\max}, \] (7)

where \( D_t \) is the duty cycle for timeslot \( t \), \( D_{\min} \) is the minimum duty cycle that is normally defined by scenario requirements, \( D_{\max} \) is a maximum duty cycle over which there is no added value to sensing in a timeslot as the additional sensing would only add congestion to a network. The objective function (6) seeks to achieve a maximum duty cycle of a node over time window \( N_w \). The constraint (7) ensures that the minimum and maximum capacity characteristics of the battery are met by considering the dynamic maximum battery capacity, in which \( B_t^{\max} \) is given in (5). Constraint (8) defines the duty cycle bounds of operation. Here, we define \( B_1 = B_0 \), where \( B_0 \) is the starting residual energy in the battery.

Using (5), the new capacity of the battery can be calculated and used to create a better model for the optimisation. In addition to (P1), a new optimisation formulation should also be considered with the objective to maximise battery life, and therefore extend the deployment time of a sensor node. The formulated problem is given by

\[ \text{(P2)} \quad \max \sum_{t=1}^{N_w} B_t^{\max}. \] (9)

Subject to:

Constraints (2), (5), (7), and (8).

**B. Proposed Lightweight Algorithm**

In order to extend the lifetime of an ENO deployment, maximise the duty cycle and satisfy all the constraints of the system, (P1) and (P2) should be solved jointly. We propose a lightweight algorithm, which we call ENO-BA. We start with the assertion

\[ \max \sum_{t=1}^{N_w} B_t^{\max} = \max B_t^{\max}. \] (10)

Then the optimisation problem can be reformulated in such a way as to be solved by a lightweight linear algebra solution that can be performed in node per timeslot \( t \). By updating the objective function of (P2) and maximise \( B_t^{\max} \), \( d_t \) should be minimised. According to (4), we can narrow the range of \( D_t \) for (P1) after solving the updated (P2), which results in a lightweight solution and does not require the storage and computation over the entire \( N_w \) for solving (P2).

From this a lightweight distributed algorithm can be created that constrains the application maximum and minimum duty cycle in every timeslot \( t \). This results in a narrow range of \( D_t \), where battery degradation is minimised. The summary of the proposed lightweight algorithm can be found in Algorithm 1. With the updated \( D^u \) from Algorithm 1, (P1) becomes

\[ \text{(P3)} \quad \max \sum_{t=1}^{N_w} B_t^{\max}. \] (11)

The Algorithm 1 results in a narrow range for \( D_t \), and then the duty cycle over a long term observation period can be maximised inside the new range of \( D_t \). One benefit of this approach is that Algorithm 1 can be applied to multiple existing research involving duty cycle maximisation in ENO systems.

In order to further understand the dynamics of this system an evaluation has been undertaken.

**IV. EVALUATION**

To evaluate the improvement of lifetime, the following methods are compared in this section:

- Fixed duty cycle sensor (Polled);
- ENO adaptive duty cycling using the Kansal Method [3] (ENO-Kansal);
- The proposed lightweight lifetime extension algorithm (ENO-BA) with adaptive duty cycling;

Fig 3. plots the degradation of the battery over time for two solar energy harvesting IoT microclimate sensors, one utilising...
the ENO-Kansal method and one with our ENO-BA method. It can be clearly seen that our proposed approach can achieve an increase in deployment of 2.5 years in comparison with the Kansal-ENO method.

To begin the data sources for the model are described, then testing for robustness to variation in energy harvesting sources is undertaken, followed by variation of energy consumption metrics for different applications. Finally, the impact of variation of the system parameters are explored and discussed to highlight the benefits and limitations of this work.

A. Data Sources

To accurately show the benefits of a battery health aware ENO, the ability to accurately represent energy generation over multiple years is needed. Unfortunately, existing simulators, such as Cooja and TOSSIM, are not designed to handle such long term simulations. To solve this problem, a python based simulator has been created, which models energy generation and consumption over long term periods.

To model energy generation, the National Solar Radiation Data Base (NSRDB) [15] is utilised. This provides 14 years of solar radiation, wind, temperature and other environmental variables in 30 minute timeslots. For solar energy generation, the methodologies in [16], [17] are employed to transform incoming energy from the sun, solar zenith and temperature to calculate accurate energy generation metrics. Similarly, the methods in [17], [18] are utilised to derive accurate wind energy production from wind speed, direction and atmospheric pressure. Fig. 4 presents an example output using this approach, it can be seen here that the relationship between wind and solar energy can be both correlated (e.g. A sunny and windy day) and uncorrelated (e.g. a cloudy and windy day).

As part of our smart cities project, energy harvesting micro-climate sensors have been designed and characterised. This allows energy consumption to be modelled accurately. As can be seen in Fig. 5, these sensors are deployed in Queen Elizabeth Park, London, UK to test the methodologies described here. These nodes are based on the TI CC2650 sensor tag and consist of temperature, relative humidity, light and atmospheric pressure sensors.

This characterisation allows for more representative energy consumption data. Energy characterisation is undertaken using with an Agilent Technologies N6705B DC Power Analyser. (2) is then used to model the energy consumption and battery state when implementing solution (9). Fig. 6, shows an example of the energy profile of a TI CC2650 sensor tag.
Table I: Metrics used in simulator

<table>
<thead>
<tr>
<th>Metric</th>
<th>Value</th>
</tr>
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<tbody>
<tr>
<td>Wind swept area</td>
<td>5.4 × 8.8 cm</td>
</tr>
<tr>
<td>Solar cell area</td>
<td>5.4 × 8.8 cm</td>
</tr>
<tr>
<td>$E_{in}$</td>
<td>0.16 mA</td>
</tr>
<tr>
<td>$E_{out}$</td>
<td>0.02 mA</td>
</tr>
<tr>
<td>$E_{eco}$</td>
<td>0.008 mA</td>
</tr>
<tr>
<td>$B_{max} t = 0$</td>
<td>10 mAh</td>
</tr>
<tr>
<td>$D_{min}$</td>
<td>2</td>
</tr>
<tr>
<td>$D_{max}$</td>
<td>30</td>
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<tr>
<td>$k_p$</td>
<td>1.14</td>
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<tr>
<td>$C_{P, M, W}^0$</td>
<td>97260</td>
</tr>
<tr>
<td>$N_w$</td>
<td>48</td>
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Table II: Results of testing of energy harvesting on lifetime

<table>
<thead>
<tr>
<th>Solar</th>
<th>Polled</th>
<th>ENO-Kansal</th>
<th>ENO-BA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lifetime</td>
<td>1.12</td>
<td>0.26</td>
<td>3.79</td>
</tr>
<tr>
<td>Increase from Polled</td>
<td>n/a</td>
<td>12.47%</td>
<td>237.54%</td>
</tr>
<tr>
<td>Avg$q_{tx}$</td>
<td>15</td>
<td>17.79</td>
<td>10.08</td>
</tr>
<tr>
<td>Variability</td>
<td>0</td>
<td>184.1</td>
<td>155.38</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Wind</th>
<th>Polled</th>
<th>ENO-Kansal</th>
<th>ENO-BA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lifetime</td>
<td>0.6</td>
<td>1.92</td>
<td>2.19</td>
</tr>
<tr>
<td>Increase from Polled</td>
<td>n/a</td>
<td>21.96%</td>
<td>265%</td>
</tr>
<tr>
<td>Avg$q_{tx}$</td>
<td>15</td>
<td>2.31</td>
<td>2.19</td>
</tr>
<tr>
<td>Variability</td>
<td>0</td>
<td>4.18</td>
<td>3.19</td>
</tr>
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</table>

<table>
<thead>
<tr>
<th>Solar-Wind</th>
<th>Polled</th>
<th>ENO-Kansal</th>
<th>ENO-BA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lifetime</td>
<td>1.1</td>
<td>1.26</td>
<td>3.79</td>
</tr>
<tr>
<td>Increase from Polled</td>
<td>n/a</td>
<td>21.06%</td>
<td>248%</td>
</tr>
<tr>
<td>Avg$q_{tx}$</td>
<td>15</td>
<td>18.08</td>
<td>10.54</td>
</tr>
<tr>
<td>Variability</td>
<td>0</td>
<td>180.13</td>
<td>158</td>
</tr>
</tbody>
</table>

Table III: Results of testing of energy harvesting on lifetime

<table>
<thead>
<tr>
<th>Metric</th>
<th>Polled</th>
<th>ENO-Kansal</th>
<th>ENO-BA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lifetime</td>
<td>0.79</td>
<td>0.81</td>
<td>2.62</td>
</tr>
<tr>
<td>Increase from Polled</td>
<td>n/a</td>
<td>5%</td>
<td>231%</td>
</tr>
<tr>
<td>Avg$q_{tx}$</td>
<td>15</td>
<td>15.46</td>
<td>7.92</td>
</tr>
<tr>
<td>Variability</td>
<td>0</td>
<td>194.38</td>
<td>129.41</td>
</tr>
</tbody>
</table>

Fig. 7: Impact of $N_w$ on lifetime

D. Discussion on System Parameters

A number of parameters were varied to understand their impact on the ability of the algorithms proposed to extend lifetime of IoT applications. As Table II showed robustness to different energy sources and Table III shows robustness to different energy consumption profiles, a single example of an IoT sensor is chosen here. Specifically, a solar powered micro-climate sensor is chosen for the following evaluation. The parameters changed in the subsequent experiments are:

- window size, $N_w$, to understand how variations would impact the robustness of the algorithms;
- average duty cycle per timeslot $t$, to investigate how increasing the energy burden would impact performance;
- initial battery capacity $B_{max}$, to highlight the impact of this parameter on the system;

Fig. 7 shows the impact of window size $N_w$, it can be seen that varying the window size has a minor impact on the performance of the algorithm. As ENO-BA is calculated per timeslot, it would naturally follow that varying $N_w$ would have a small impact on overall performance from a lifetime perspective. For the ENO-Kansal method it can be seen that increasing $N_w$ has a negative impact on lifetime; this could be a result larger $N_w$ having a negative impact on (P1). Varying $N_w$ would not have an impact on the Polled method; the duty cycle is fixed and this is reflected in Fig. 7.

Fig. 8 shows how a larger average duty cycle impacts the system lifetime. The Polled method does not adapt the duty cycle to the environment, therefore an increase in this static duty cycle does degrade the battery lifetime, however as the Polled method does not adapt it’s $D_t$ to long periods of low energy production, this would cause the main source of battery degradation for this method. The positive benefit of our ENO-BA algorithm can be seen here over the ENO-Kansal method.
boundaries of our solution can also be noted, as average \( D \) is increased sufficiently to strain the battery, a convergence to IoT objects. Therefore, battery capacity choice therefore will both financially in terms of increasing the physical size of a minimum lifetime is observed.

Furthermore, the benefit of a given task will be smaller, this can be seen in Fig. 9 increasing initial capacity will improve deployment as DOD increases so does the algorithms ability to improve the deployment of the ENO-BA method can be seen here, as battery capacity is increased sufficiently to strain the battery, a convergence to IoT objects. Therefore, battery capacity choice therefore will both financially in terms of increasing the physical size of the ENO optimisations. By using our novel lightweight battery capacity optimisation method the operational lifetime of an IoT sensor can be extended by 307%. The ability to increase the longevity of deployments reduces the need for costly replacement and maintenance and improves the robustness of said systems. Next steps for this work involve undertaking real world experimentation on our energy harvesting platform in Queen Elizabeth Olympic Park, London.

At very low duty cycle levels the two methods have a similar performance in terms of battery lifetime, as the battery is not burdened relative to the tasks it needs to undertake. However a significant benefit can be seen here, lifetime is preserved for much larger average \( D_t \) with our lightweight solution. The boundaries of our solution can also be noted, as average \( D_t \) is increased sufficiently to strain the battery, a convergence to a minimum lifetime is observed.

Fig. 9. Shows how initial battery capacity influences these systems. For a given system with a given energy profile, increasing initial capacity will improve deployment as DOD for a given task will be smaller, this can be seen in Fig. 9 as lifetime increases for all methods. Furthermore, the benefit of the ENO-BA method can be seen here, as battery capacity increases so does the algorithms ability to improve the deployment lifetime. However, increasing battery capacity is costly both financially in terms of increasing the physical size of IoT objects. Therefore, battery capacity choice therefore will become a trade-off between physical size, cost and lifetime for a given application.

V. Conclusions

Battery cycle lifetime can be a major issue in the development of IoT solutions. We have shown that battery degradation can be monitored in node. Furthermore, we are the first to integrate battery degradation methodologies with ENO optimisations. By using our novel lightweight battery capacity optimisation method the operational lifetime of an IoT sensor can be extended by 307%. The ability to increase the longevity of deployments reduces the need for costly replacement and maintenance and improves the robustness of said systems. Next steps for this work involve undertaking real world experimentation on our energy harvesting platform in Queen Elizabeth Olympic Park, London.

REFERENCES