2014 International Joint Conference on Neural Networks (IJCNN)
July 6-11, 2014, Beijing, China

Fuzzy Power Management for Environmental Monitoring Systems in Tropical Regions

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***Abstract*—Remote environmental monitoring systems require effective energy management to allow reliable long-term operation without frequent maintenance to replace or recharge batteries. To design and analyze relevant energy management strategies, we have developed Simulink-based models of a recently constructed monitoring device to evaluate its potential performance. The model uses long-term solar energy data from two locations, Chamela, Mexico, and Fairview, Canada, to estimate the energy harvesting capabilities of the device. Using the simulator, we have developed and evaluated a fuzzy energy management strategy that determines how the device should operate to match the solar energy profile in each location. Solar energy in Chamela, Mexico is abundant and consistent so an energy harvesting remote monitoring device could have a high activity level without risking device failure. Fairview, Canada, has limited solar resources in the winter but plenty in the summer; a device dependent upon this energy source must adapt its activity level to match energy availability or risk running out of energy. While the simulated device in Mexico outperforms the one in Canada, both succeed in matching the available environmental resources and largely avoid energy related device failure. In the future, their performance can be improved by optimizing the designed strategies and further improving the details of the simulation.**

I. Introduction

The human impact on various terrestrial ecosystems around the globe is a serious social concern and an issue for scientists and policy makers alike. In order to adequately determine this phenomena over large areas and sizable time spans, remote monitoring systems, particularity wireless sensor networks, are becoming more popular [1]–[3]. Such systems must be able to function without access to infrastructure or regular site visits [4]. In this article two remote locations, Fairview [5], Canada, near the EMEND Project site [3], and Chamela, Mexico, at the Tropi-Dry research site in the Chamela-Cuixmala Biosphere Reserve [2], are used to analyze and compare the performance of remote monitoring devices for two different environments in two very different climates: boreal forest and tropical dry forest.

The limited energy supplies of chemical and fuel based portable power sources pose a problem for wireless devices spread over large areas or in remote locations. The environment itself has a limited amount of power available, so some monitoring technologies have integrated energy harvesting to mitigate the problems related to finite energy storage techniques, but this comes with other challenges [6]–[8]. For example, solar energy is popular because of its reasonable energy density and commercial availability; however, it changes throughout the day and can vary with the season. This seasonality is largely dependent upon distance from the equator. Chamela is closer to the equator, where day length is similar year round, while Fairview is closer to the Arctic Circle, where daylight can disappear entirely during the winter [9]. This can be seen in Fig. 8 of Section V.

Remote monitoring devices must regularly collect data independent of weather and environmental conditions. Energy consumption is fixed by the required activities of the monitor, while the environment is constantly fluctuating. To operate in a desirable manner and minimize energy related failures, a device which depends on solar energy must adapt to its environment. This is the responsibility of the energy management strategy of the device. Strategies which are not suited to the environment produce less desirable data sets than those which change the operational level of the device to match available energy resources [10].

Distributing the abundant energy supply of daylight and summer time to the energy requirements of night and winter time requires energy storage [11], [12]. The energy management strategy is responsible for the effective allocation of the stockpiled energy to monitoring activities in a way that produces the most desirable data set. Given that monitoring devices have limited energy and computational resources, this strategy should be as simple as possible without giving up its effectiveness or robustness [9], [10].

Fuzzy rule based systems (RBS) can utilize intuitive human centric knowledge on a subject as a framework for control. An expert's opinion on how a device should operate is represented by the truthfulness of a set of governing logical statements. These statements, or rules, are then aggregated into a actions for the device [13], [14]. In this application it creates a mapping from what is happening to the remote monitor, to how actively it should monitor its environment. A good fuzzy RBS will map all possible states the remote monitor could be exposed to, to some actions which will produce good quality environmental measurements and avoid device failure [9].

A new wireless environmental remote monitoring device has been designed and constructed. This new hardware has been modelled in the Mathworks Simulink environment to test energy management strategies on the platform and

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to estimate how effective it will be when deployed. The simulation is tested using environmental data from the two locations mentioned above, Fairview and Chamela. Each simulation is equipped with an energy management strategy in the form of a lookup table derived from a fuzzy RBS and stored in the memory. The simulation covers two years of data to compare the results of energy management strategies in the two climates.

The simulated environmental monitoring platform used in this article is identical to [10]. The discussion of the platform and simulation has been included as necessary background, but is largely the same. The current article expands on the previous work by comparing the control technique in two separate, very different locations, as mentioned earlier.

This article is organized into six sections. Section II details the hardware of the device and briefly discusses popular environmental sensor options. The data sets used for the simulations, along with the simulation itself, is described in Section III. Section IV discusses the energy management strategies used to control the simulated monitor in the two simulated test locations. The results of this simulation, and a comparison to a previous study, are considered in Section V. To conclude, Section VI summarizes the results of the previous section and brings the paper to a close.

II. Monitoring systems and sensors

This section, adopted from [10], lays the groundwork for the current contribution by describing a general platform for environmental monitoring systems. An environmentally powered monitoring system contains several functional modules. The basic block diagram is shown in Fig. 1. Analog sensors are connected to the *analog preprocessing* module which provides signal conditioning. Data from digital sensors can be processed without signal conditioning. The *data processing and control unit* uses a microcontroller (MCU) to process the digital data from the sensor interfaces, and coordinate system operations like time keeping, data storage, and transmission. The *memory* block, implemented using non-volatile memory components, provides temporary or permanent storage of collected data. The *time tracking* module establishes the basis for precise timekeeping of the recorded values or events. The *power supply* block provides the energy to power the sensor platform by converting power from an energy source, usually batteries or another main supply, to the voltages required by other components in the system. Alternatively, the energy to power the system can be harvested from the environment and stored in secondary batteries or other energy storage devices. The sensor platform discussed in this document uses a pair of supercapacitors for short term energy storage [10].

The energy management strategy depends on sensors to measure internal state variables and external environmental conditions. In order to effectively manage the energy state of the platform, several major operational modes must be identified, and their energy demands described [10].

Common environmental conditions measured by remote monitors are: ambient temperature, solar irradiance, soil moisture, and atmospheric gases. Temperature can be measured using sensors based on a range of different technologies with different power demands, such as resistance temperature detectors, thermistors, thermocouples, bipolar junction transistors, and micro-electro-mechanical resonators [15]. Measurements of environmental light conditions can be further processed to estimate the fraction of incident photosynthetically active radiation absorbed by a plant canopy, and other ecosystem parameters [1], [16]. The actual sensing elements are based on thermopile or photovoltaic devices that generate voltage or current upon illumination [17], [18]. Soil moisture sensors are electromagnetic devices exploiting the dependence between soil water content and other electrical properties, such as conductivity or permittivity [19]. Gas sensing is usually based on light spectroscopy using nondispersive infrared gas sensors. The main disadvantage of these sensors is their relatively high power consumption of up to 500mW. Electrochemical sensors produce current or voltage proportional to the amount of a target gas (e.g. CO) in the atmosphere. Subsequently, their power consumption is the lowest among all gas sensors. They also have good linearity and selectivity, with excellent accuracy and repeatability [10], [20].

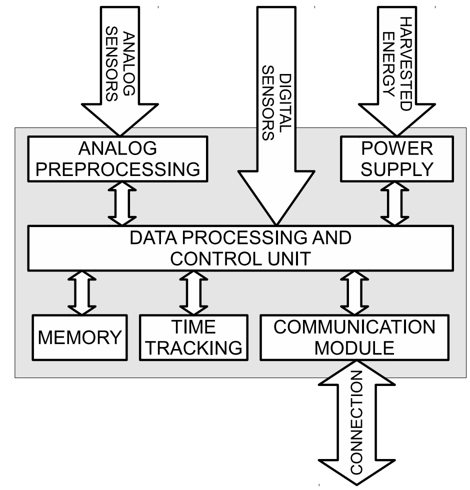

Fig. 1. A conceptual block diagram of the environmental monitoring system sensor platform (adopted from [10]).

III. Node simulator and data

The wireless remote monitoring device has been modeled using Simulink. The descriptions of the simulation's three modules: the energy harvesting solar panel simulation, the energy managing control module, and the energy consuming hardware model, are adopted from [10]. The results of using the data presented in this section with the simulation are presented in Section V.

The simulator requires environmental data to determine what conditions the presented platform will be exposed to when deployed. The results in Section V compare two years of data from the Tropi-Dry research site at the Chamela-Cuixmala Biosphere Reserve in Jalisco, Mexico with two years of data from ACIS "Fairview AGDM" site near the EMEND Project in the north-west part of Alberta, Canada [2], [3], [10]. The Tropi-Dry research site is located at 19.4877° latitude, -104.995° longitude, and 250.00m elevation and has solar irradiance measurements in W/m^2 from a pyranometer every 30 minutes from March 21, 2008, at 19:30, to April 18, 2013, at midnight. The data set was downloaded in its original form from the Environet portal [1]. The data set for the Fairview site is described in [10] and was downloaded from [5].

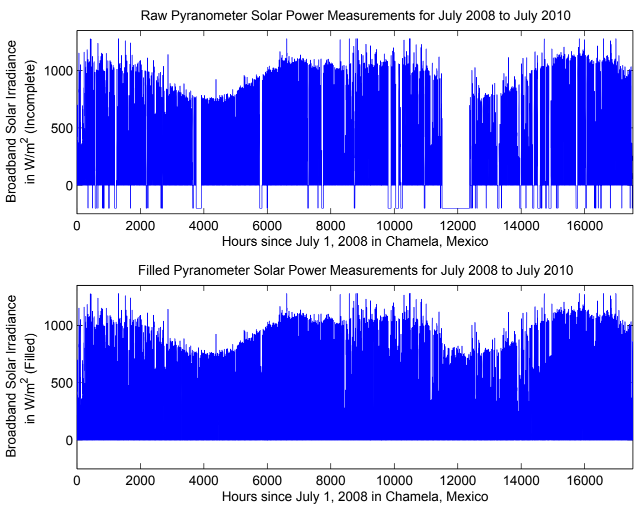

Fig. 2. The upper plot shows the solar power data from Chamela, Mexico, with missing data points represented as negative values. Every point with a negative value was filled with an estimate of the solar power at that time. The lower plot shows the final data set used by the simulator; the technique for filling missing points is outlined in Section III.

The Chamela data set was incomplete and had multiple large segments missing or only partially logged. To deal with this problem, and provide a sample of the data suitable for comparison with Fairview, the most complete two year segment, July 1, 2008, at midnight, to June 30, 2010, at 23:30 was used for the following simulations. To fill the missing data points in this two year period, the whole data set was averaged to form an estimated average year with very few missing segments. These segments were filled by using the average energy from the same time of day two and three weeks before and after the time segment in question. The average was spread over several weeks to ensure that weather affecting only a single day or week would be less influential on the filled points. The final, now complete estimated average year for the climate, was then used to fill the missing data points in the original two year data set starting at July 1, 2008. Combining the yearly data with the average data was more desirable than using the average data alone, because it forces the simulation to deal with environmental extremes which are missing in averaged climatological data. Averaged data would let the simulation adapt to the average reduction in solar energy during the year, rather than a full reduction in solar energy due to an individual weather event.

The solar panel simulator is responsible for modeling the energy harvesting subsystems of the sensor platform. The *solar panel* and *solar management* blocks of Fig. 3 make up this module. Environmental data from possible deployment locations, like those described above, are used to calculate approximately how much energy could be harvested by the sensor platform for a given deployment period. The solar panel simulator is separated from the energy-consuming back-end before the *DC/DC converter* block; the point immediately before energy is used to charge the energy buffer. The energy production computed from the environmental data before that point is unaffected by the actions of the simulator and does not need to be recomputed for each simulation. The separation between the solar panel simulator and the hardware module is as much for computational efficiency as it is for conceptual simplicity. Because the simulator is in its early stages, the solar panel model is still simple. It uses the solar irradiance, in W/m^2, and the solar cell area of the sensor platform, 8.46cm^2, along with the average efficiency of the solar cells, 22%, to estimate the energy available in the environment. As the simulator improves in detail and model complexity, a more suitable energy estimate will be used which will fully describe the two blocks in Fig. 3. The energy data provided by the solar panel module is required by the controller and hardware modules [10].

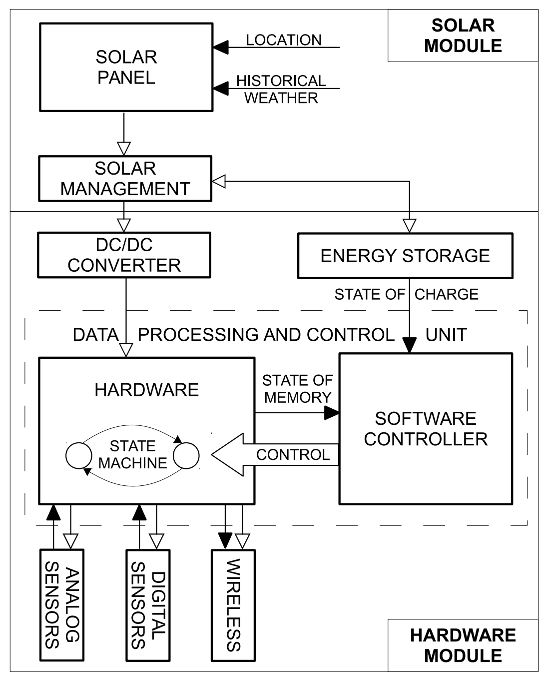

Fig. 3. A block diagram (adopted from [10]) of the simulator described in Section III. It contains three main modules: the solar panel, the hardware load, and the software controller responsible for balancing energy harvest with load consumption (▶ - data flows, ▷ - energy flows).

The hardware module holds the models for the physical components of the sensor platform. In Fig. 3 the *DC/DC converter*, *energy storage*, *hardware*, *wireless*, and *sensors* blocks are all within this module. It focuses on the energy consumption of individual hardware components, and the energy available in the platform's storage elements. This is done by constructing a small state machine which keeps track of the length of time each hardware component is operational, what operational mode it is in, and how much energy is consumed over its operational period. While the solar panel model is concerned with energy production through energy harvesting, the hardware module is the load which consumes this energy to produce and store data through sensor measurements. It is the module which actually executes the exchange of energy for data [9]. The hardware module computes the "state" of the sensor platform for the controller. This "state" is a relative indicator of what is happening to the sensor platform; the simulations described in Section V have two important state values: the percentage of the energy buffer (supercapacitor charge) remaining for consumption, and the percentage of the data buffer (EEPROM non-volatile memory) filled by sensor measurements [10].

The wide range of sensors outlined in Section II would each need to be modeled in the hardware module if they were attached to the sensor platform. The amount of time and power required to actively take measurements would be used to compute the energy required to capture a single data point. Additionally, the energy overhead required to have the sensor attached to the platform in its idle or sleep modes must also be accounted for. These values together can be used to estimate the sensor's energy consumption and relate it to its data production for manipulation by the control module's energy management strategy. In its present form, the simulator assumes that there are digital gas sensors along with a few low power analog electrochemical sensors available for manipulation by software [10].

The controller module is contained in software in the microcontroller unit of the hardware module's *data processing and control unit*. The *software controller* block in Fig. 3 is separate due to the conceptual division between the hardware module and the control module. The *software controller* block interprets the energy management strategies for the simulator and determines what actions the hardware module should execute. The controller uses state information as an input and does not directly interact with the hardware. This abstracts the controller from the details of device operation and makes it largely self contained. The controller's output is also abstracted from the hardware and provides relative instructions, like operational duty cycle, for the hardware. This is described further in Section IV. After future improvements, the control module should be able to usefully control the hardware module even if the hardware module is modified. This would not be easy to do if control was not abstracted from the hardware [10].

IV. Energy Management Strategy

The objective of the energy management strategy is to allocate the energy available to the device, harvested from the environment or previously stored in the energy buffer, to the activities which will allow the best quality data set to be collected by the remote monitoring device. In this application, collecting the most data points over a two year period with as few device failures as possible produces the "best quality data". Any point where the device does not have enough energy to take a measurement is considered a failure. If the device does fail, consecutive failures negatively impact data quality more than individual failures. What defines "best data quality" will change depending upon the application.

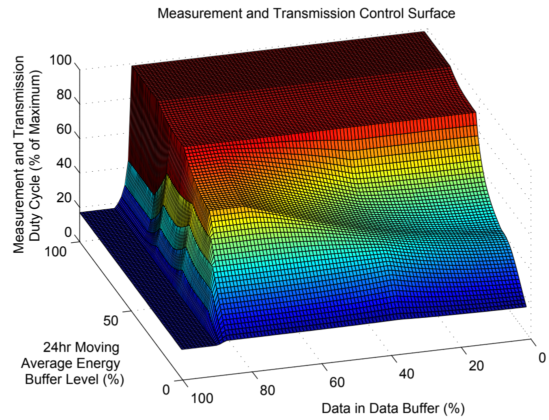

Fig. 4. The continuous output of the fuzzy RBS used to determine the measurement and transmission duty cycle as a percent of the maximum possible activity level. This surface was generated using the same technique as Fig. 3 of [10]; however, it has been modified to suit the environment of Chamela, Mexico.

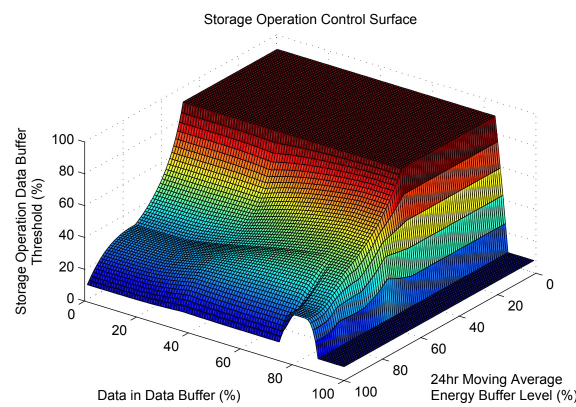

Fig. 5. The continuous output of the fuzzy RBS used to determine storage actions by the hardware module. This surface was generated using the same technique as Fig. 4 of [10]; however, it has been modified to suit the environment of Chamela, Mexico.

The energy management strategy requires some information to determine how to allocate its resources. This information is its state, while the allocation process is its actions. The two state dimensions indicate to the monitor how much energy is available for use and how much data can be stored. The energy allocation process, the platform's actions, consist of collecting data and safely storing it. In this simulation, the device will measure and wirelessly transmit data at various intervals, or perform data storage operations to move data from the buffer to long term data storage. To produce desirable data, the remote monitor must collect data at a certain energy cost, however, if the storage operation is neglected to save energy and the data buffer overflows, data is lost and the energy to collect it is wasted. The energy management strategy must select an acceptable balance between these two actions based upon the available state information.

The energy buffer of the device is a pair of supercapacitors recharged by solar cells to extend the life of the sensor platform, while the data buffer is a small, low power, non-volatile EEPROM memory, which protects the collected data from device failure [10]. Because the solar energy harvest data from Fig. 8 oscillates daily, the energy buffer cycles as well. This periodic change in the energy buffer makes energy management difficult, so the buffer level is passed through a twenty four hour moving average operation to filter out daily changes and access seasonal trends in solar energy [10]. Fig. 9 shows the resultant energy state information over a two year period, while the data buffer state is in Fig. 10.

A fuzzy RBS was used to construct two controllers, one for each action, which were then discretized and stored as lookup tables. The fuzzy RBS allowed "expert opinion", intuitive knowledge on how the remote monitor should allocate its energy and data resources, to be quickly and easily passed to the controller. The fuzzy RBS covered each of the two state dimensions with five triangular membership functions, sized by an "expert", to process incoming state information. The membership functions were related using twenty-five automatically generated rules which were then weighted using one of five membership functions for each of the two possible action dimensions. The "expert" determined which membership function should be used to weight each fuzzy rule and tuned them using trial and error [4]. For example, if the energy buffer is full and the data buffer is empty, the RBS has been tuned to collect and store data often, consuming energy and preventing waste, while keeping the data buffer empty to prepare for future energy shortages. The control surfaces from the fuzzy RBS used for the Chamela site are available in Fig. 4 and Fig. 5.

The surfaces produced for each location by the fuzzy RBS were discretized to represent complete actions and stored as lookup tables in the simulated device's memory. The lookup tables map the simulators state information directly to the actions to be executed. Fig. 6 and Fig. 7, show the "ideal" activity level for the two actions in the environment of the Chamela site for every possible input state. The data in Fig. 9 and Fig. 10 are used directly by the lookup tables in Fig. 6 and Fig. 7. These two sets of data make up the state information for the energy management strategy and provide the control module with a sufficiently complete perspective on the device. By computing the lookup tables before running the simulation, the complexity of executing the energy management strategy on the device is reduced to two lookup operations: so simple any microcontroller with memory should be able to use it. Using this technique, control is always a simple process for the monitor, while the complexity of determining a good strategy can be abstracted to iterative development using a simulation or passed off to a human [9], [10]. Section V and Fig. 11 demonstrate the effectiveness and shortcomings of this approach. The strategies used here have not been optimized, but are still useful for this application. This is validated in Sections V of [10] and this article. In the future, various optimization techniques could be used to improve the performance of this energy management strategy [9].

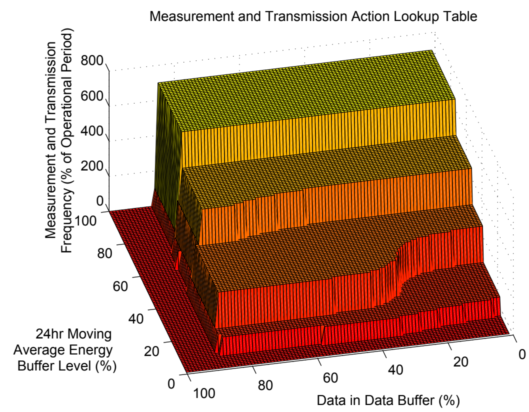

Fig. 6. A 3D representation of the lookup table for the measurement and transmission control output. The vertical axis is the desired measurement and transmission duty cycle relative to the hourly operational period of the simulation. The input parameters are in the upper plots of Fig. 9 and 10 while the output is in the upper plot of Fig. 11.

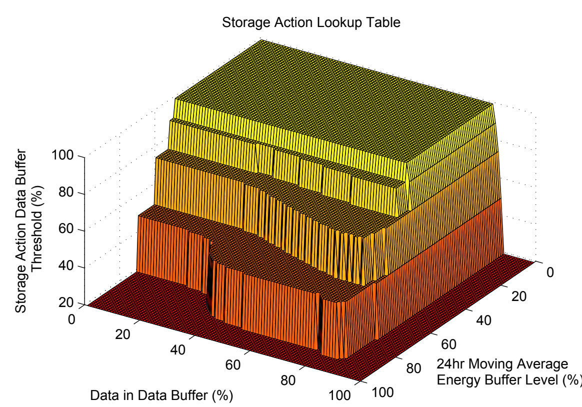

Fig. 7. A 3D representation of the lookup table provided to the simulated remote monitor to determine when to execute storage operations. The vertical dimension acts as a threshold: if the data buffer is more full than this value, a storage operation is executed. Notice that this is a discretized version of Fig. 5. The two input parameters are plotted in Fig. 9 and 10.

V. RESULTS

The two solar energy data sets in Fig. 8, from Chamela, Mexico, and Fairview, Alberta, were used by the simulation to estimate the remote monitor performance in each location. This simulation is described in Section III. During the simulations, the energy management strategy from Section IV determined how the monitor would expend its collected energy at any given time. Both strategies attempted to adapt the operational level of the simulated device to match the solar energy available in the environment throughout the year. While both succeeded, the remote monitor appears to perform much better in Chamela, Mexico, than Fairview, Alberta. Some values used to evaluate the performance of the simulations are presented in Table I.

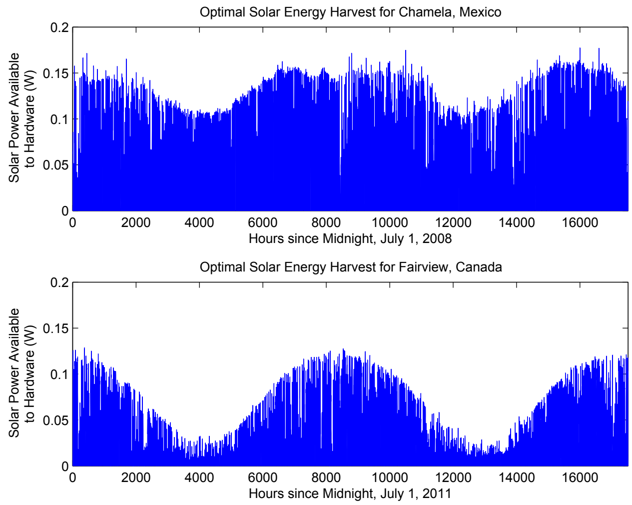

Fig. 8. The maximum amount of electrical energy provided by the remote monitor's solar cells for each of the two locations. The figure appears solid due to the diurnal cycle of the data set. The upper plot in this figure matches the lower plot of Fig. 2, but has had its magnitude scaled to down based on solar cell size and efficiency.

The solar energy profile of the Chamela data set is more even than the Fairview profile, and generally provides more energy, even during its low sections, than Fairview does at its peak. The solar cell in Chamela can provide approximately 591.30Wh over the entire year. Chamela's solar energy changes slightly with the seasons, but Fig. 9 shows that this has little effect on the energy buffer of the simulated device; the supercapacitor holds around 79% charge on average. The energy management strategy only needs to take individual weather events into consideration, and small adjustments to the operational level of the device are sufficient to handle them in most cases, as shown in Fig. 10 and Fig. 11. Table I shows that the device failed for nine data points. The large drop in average stored energy in Fig. 9 near 14000 hours is due to a sudden weather event during an otherwise high energy period, which reduced the available solar energy for a few days. The 24hr average energy buffer works as a low pass filter and prevents daily operational oscillations, but does so by giving up some sensitivity to environmental conditions. This is an acceptable exchange and the Chamela data set remains very consistent.

The Fairview location has much less solar energy to utilize than Chamela; the solar cell in Fairview can only provide 348.19Wh, about 59% of that available to Chamela. The remote monitor has far less energy to invest in data collection, storage, and transmission. However, according to Fig. 11, it is still able to provide a reasonably consistent set of measurements. Figs. 10 and 11 show that it is much harder to adapt to its changing environment. To avoid failure, the simulated monitor must reduce the frequency of its measurements and delay storage operations during the winter. Given the high average level of the energy buffer during the summer, the device could increase its activity level above its present maximum of four activities per hour, but only for the highest energy period. The high

TABLE I. A COMPARISON OF REMOTE MONITOR PERFORMANCE FOR TROPICAL DRY FOREST AND BOREAL FOREST

Property	Fairview [10]	Chamela
Measurements per Hour	1 to 4	1 to 7
Maximum Possible Measurements	70080	122640
Collected Measurements	61731	121696
Number of Failures	91	8
Failure as Percent of Collected	0.1474%	0.0066%
Optimal Total Solar Harvest	348.193Wh	591.297Wh
Measurements per Watt Hour	177.3	205.8

average energy buffer values during the summer indicated that the harvested solar energy was lost due to energy buffer overflow and wasted.

Because both energy management strategies were based on one "expert opinion", optimal results were not expected. However, thanks to the stable nature of Chamela's environment, control was easier to design. If the control strategy of both locations were optimized, as described in [9], the average energy left in the energy buffer would be reduced for the Fairview location, because it would be used more effectively and wasted less often. The periods around 4000 and 13000 hours correspond to the winter periods of the two consecutive years and are more interesting for the Fairview location.

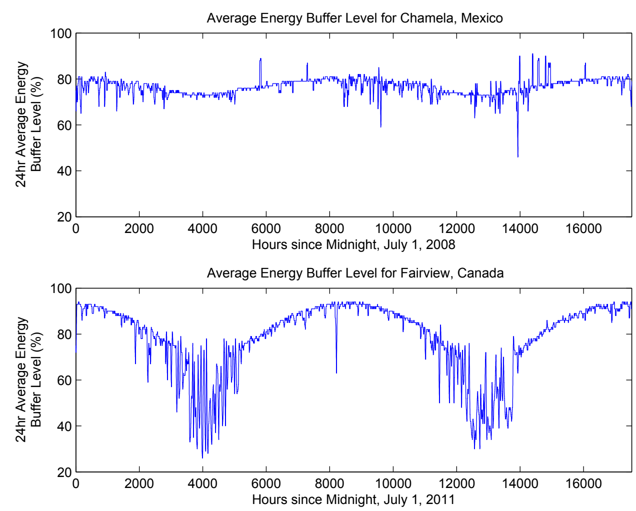

Fig. 9. The 24hr average energy buffer level for each of the two locations for the duration of the simulation. This value acts as one input to the lookup tables in Figs. 6 and 7. The average acts as a low pass filter to the lookup table, which would otherwise use the data from Fig. 8. The energy buffer from the Fairview simulation (lower plot) becomes unstable as the device adapts to the decrease in solar energy [10].

Given the significant difference in solar energy availability between the two locations, a direct comparison between the number of measurements and transmissions made by the simulated remote monitors are an inappropriate measure of comparative performance and do not provide insight into the energy management strategy at work. In Chamela the simulated device captures almost twice the total number of measurements compared to the one in Fairview, 121696 to 61731, but it has access to about 1.7 times more solar energy. The Fairview location has less solar energy for potential devices, and given that energy is the limiting factor in the energy for data exchange, it makes sense that the device also collects less data than it would in Chamela. Data would be the limiting factor in the energy for data exchange if data storage was extremely limited, or if sensors could not be used arbitrarily. To compare the performance of the two simulations, the number of measurements collected per watt hour of solar energy harvested by the solar panels is used. The simulation for Chamela captures 205.81 measurements per watt hour compared to 177.29 measurements per watt hour for the Fairview simulation. From this perspective, a remote monitor in Chamela has only improved its performance by a factor of 1.16. While both strategies are exchanging energy for data sub-optimally, Chamela is still superior. These results are available in Table I.

An earlier inquiry into this issue [10], showed that dynamically adjusting the duty cycle of the simulated monitoring device significantly improved performance. The important concept observed for that case and the one at hand is that the duty cycle of the device suits its environmental energy profile. A static strategy would perform well in Chamela because it has static energy profile; dynamically changing Fairview's duty cycle is necessary because its energy profile is dynamic. If the energy management strategies for both locations were optimized, the number of data points captured per unit of energy would likely move towards some similar point. The energy management strategy for Fairview would benefit the most, as the energy wasted during the summer could be eliminated and energy buffer oscillations during the winter could be more appropriately dealt with. Performance in Chamela would also improve, because the few points where it did fail could be fixed by improving the resolution of the fuzzy RBS near 79% in the energy input dimension. Regardless of optimization, the peak value of measurements per unit energy is presently dependent upon the simulation parameter values, but when the remote monitors are deployed, this value will depend on their hardware.

It should also be mentioned that this simulation only models the energy buffer provided by the supercapacitors and assumes that the simulated devices have no other protection from energy related failure. If a battery, or some other reserve energy source, was attached to the system it could completely eliminate the failures observed in both simulations. While this reserve would require maintenance, if it lasted long enough to match the regular maintenance the remote monitor would receive anyway, it would improve device performance without becoming an inconvenience [10].

VI. Conclusion

The performance of a simulated wireless remote monitoring device was evaluated in two different environments: a tropical dry forest from Chamela, Mexico, and boreal forest from Fairview, Canada. The simulated device used solar energy data from the two locations to estimate how much energy was available for harvest in the environment. A fuzzy RBS was used to construct an energy management strategy for the simulated remote monitor in both locations so that it could adapt its activity level to variant environmental conditions.

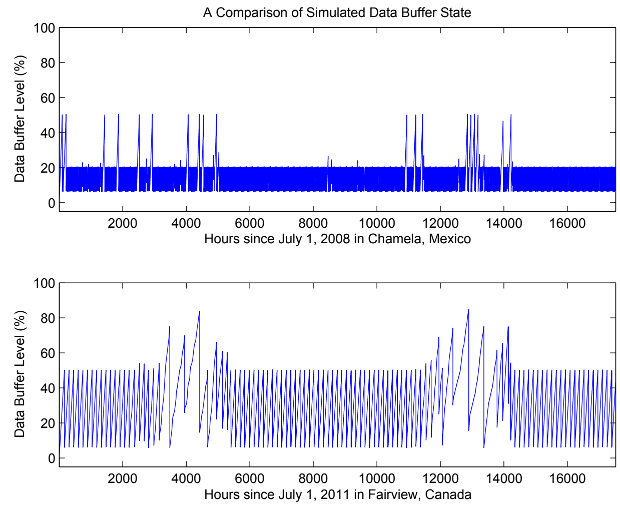

Fig. 10. The data buffer level of the simulated remote monitor over a two year period. Measurement actions fill the buffer while storage operations empty it. Fairview collects less data, and thus stores it at a lower frequency than Chamela. Chamela rarely needs to delay storing data due to its abundance of solar energy. The Fairview plot is presented from [10] for comparison.

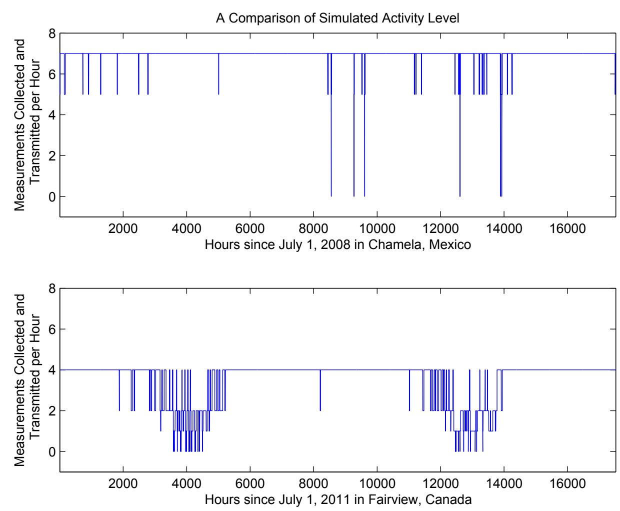

Fig. 11. A plot of the measurement and transmission actions of the simulated remote monitor in each location. Any points where this value falls to zero is considered a device failure. The Fairview location must significantly reduce its operational level during the winter months to mitigate failures due to seasonal energy constraints. The Chamela location has far more solar energy, so it can take measurements more often. It only needs to reduce its measurements for isolated weather events. The bottom plot is based on Fig. 6 of [10].

In this study, both energy management strategies attempted to match the energy consumption of the simulated remote monitor to the environmental energy profile of its respective location. The environment of Chamela, Mexico, was high energy and mostly invariant. Only small changes in activity level were required, and the energy management strategy could have been simplified with no reduction in performance. The environment of Fairview, Canada, changed significantly through the year and provided less energy for the simulated monitor. Estimating a fuzzy RBS to manage the problem was more difficult, and it did not perform as effectively as the other location. The simulation for Fairview made less measurements per watt hour of environmental energy available. The Canadian environment required many changes in activity level and would benefit from optimizing its energy management strategy more than the Mexican location. The Canadian environment also shows that an energy management strategy which increases or decreases device activity to match environmental energy resources can reduce device failure [10].

If the controllers are automatically generated and optimized in the future, the simulation should allow them to adapt to a location's environment and eliminate all but the most unusual energy related failures. It may even allow the sensor platform to dynamically adapt to changes in sensor or hardware configuration. Ideally two locations as diverse as the two shown here, with different sensor and energy storage configurations, should be able to have their energy management strategies constructed from the same automatic technique.

The simulated remote monitor was based on a hardware platform which is being developed. The results show that present estimates of the device's performance are encouraging. Presently the simulation only emulates some of the hardware platform's functionality, the rest of which will be explored more thoroughly in the future as development continues.

ACKNOWLEDGMENT

This work has been supported by the Natural Science and Engineering Research Council (NSERC) of Canada, TECTERRA project 1209-UNI-013, and by project SP2014/156 "Microprocessor Based Systems for Control and Measurement Applications" of Student Grant System, VSB-TU Ostrava.

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