Power Management for Controlling Event Detection Probability of Supercapacitor Powered Sensor Networks

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Abstract— **In this paper, the power management method of supercapacitor powered systems is developed for a complex sensor network system wherein the sensor footprint depends on the available energy of supercapacitor. With a radar sensor network as an example, it is proved that the event detection probability of the sensor network can be decoupled as the quality of service of each node. Accordingly, the problem of maintaining the event detection probability is formulated as a problem of tracking a reference quality of service value for each sensor node. In this problem formulation, the supercapacitor model and the in-network processing model are used as two of the constraints of the optimization problem, wherein the supercapacitor model captures both the self-discharge and charge-redistribution phenomena to achieve the full potential of the stored energy. Model predictive control is employed to solve the optimization problem with particle swarm optimization, and the simulation results demonstrate that the developed method can track the required quality of service while satisfying the system constraints and ensuring the terminal voltage of the supercapacitor to be within the normal working range.**

I. INTRODUCTION

Today, technologies like smart homes and smart grid are playing a more and more important role in civilian, commercial, and military applications. Behind the development of such systems, the concept of internet of things (IoT) is often considered a critical part. IoT devices connect the physical world to the information and communication infrastructure. Intelligent monitoring and management can be achieved via the wirelessly connected sensor networks, which usually consist of a large number of sensor nodes. Each node has limited sensing, communication and processing capabilities. But together they can achieve purposes like earthquake sensing, weather monitoring or wildlife monitoring [1].

Sensor nodes are equipped with various sensors to monitor the area of interest. Surveillance systems have used infrared, acoustic, and magnetic sensors for passive sensing, and optical and ultrasonic sensors for active sensing. Radar based sensors have also become an emerging solution with the radars becoming more efficient and compact. Compared with low data-rate sensors such as those for temperature and humidity, radar based sensors usually generate raw data at hundreds of kilobits or tens of megabits per second [2]. However, the per-node bandwidth of a wireless network is limited, thus imposing new challenges to the network operation. An efficient way to reduce bandwidth usage is via in-network data processing, wherein data is preprocessed at the node level. This also improves the efficiency and quality of overall data analytic by data filtering and dimensionality reduction. Therefore, it is important to balance the in-network processing and communication.

Moreover, the performance of the radar based sensors is known to be correlated with the energy level of the sensor node. Specifically, the sensor footprint area may be shrinking with the dropping of the energy level [3]. This coupling between available power and performance also exists in other types of sensors. For example, the maximum available frame rate is affected by the energy level of the storage device of the vision-based sensors. The performance of the radar sensor also depends on the probability of the radar being on. Due to the high power consumption of the sensor and the correlation of its performance with the available energy level, it is not efficient to keep the sensor on continuously. But if the radar is turned off when the critical event happens, then the event can't be detected. Thus, balancing the sensing ratio and the energy level is also critical to the performance of the sensor network.

These new challenges have brought forward new requirements for the power management of radar based sensor networks. Many research efforts have focused on developing energy saving methods for sensor networks. Pantazis *et al.* [4] presented a comprehensive survey of the passive and active power conserving mechanisms in wireless sensor networks. Anatasi *et al.* [5] summarized the main approaches to energy conservation of wireless sensor networks with a focus on reducing the power consumption on the sensor level. The existing research works typically assume the energy consumption of the communication to be much higher than the energy consumption due to sensing or processing. Many radio sensor network applications, however, have demonstrated that the power consumption of the sensor is comparable to that of the radio.

A duty cycle scheduling scheme is proposed to maintain a constant event detection probability for radar sensor networks [3]. In the paper, the decrease of effective sensor footprint caused by energy consumption is modeled and based on

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which the duty cycle scheduling method is developed. However, the authors only consider the sensing operation of the network and use a simple battery model to emulate the decline of energy level. For general radar sensor network applications, communication and in-network processing are also important factors. Moser *et al.* [9] proposed an adaptive power management framework based on the multiparametric programming techniques, which is capable of solving more general problems. The proposed method is developed to account for the unreliable nature of environmental energy and optimize the system performance while respecting the energy neutral operation condition. However, the simple battery model used in the paper can't capture the dynamic behavior of the other energy storage devices like supercapacitors. Moreover, the application performance model used in the paper doesn't account for more complex cases such as the radar sensor network, wherein the performance depends not only on the duty cycle but also on the available energy.

In this paper, we extend the previous work and propose a power management method for supercapacitor powered embedded systems to optimize the system operation while respecting the energy limitation and system constraints. In particular, a radar sensor network is investigated as an example. The radar sensor network is optimized to maintain a satisfactory event detection probability. The decrease of the radar sensor footprint due to power decay is analyzed and the in-network processing is employed to reduce the communication overhead. The event detection probability of the sensor network is controlled with the developed method by first decomposing it as the quality of service of each sensor node, and then formulating an optimization problem for the sensor node, which can be solved with model predictive control (MPC) based on Particle Swarm Optimization (PSO). By adjusting the sensing, receiving/transmitting, and processing rates, the quality of service of the sensor node is controlled to track a reference value, throughout the lifetime. This ensures that the overall event detection probability of the sensor network is around or greater than the reference value.

The next section presents the system model of the radar sensor network. The probability of event detection is analyzed in Section III. Section IV proposes the adaptive power management method based on model predictive control. The simulation results are discussed in Section V and the paper is concluded in Section VI.

II. SYSTEM DESCRIPTION AND MODEL

Consider a radar sensor network randomly deployed within a domain $\mathcal{D} \subset \mathbb{R}^2$ such that the location of each sensor is independent of all the other sensors' locations. The sensors' locations can be modeled as a spatial Poisson point process. The sensor network operates in a finite-horizon consisting of discrete time slots $t \in \{0, 1, 2, \ldots, t_{end}\}$, $t_{end} < \infty$ and is used to detect events in $\mathcal{D}$. Each radar sensor has a considerable processing power to perform the following five operations: collecting raw sensor readings, performing pre-processing on the data in the data queue, transmitting or receiving data packets over wireless links and performing online calculation of the optimal operation status.

A. Energy Storage Model

Supercapacitor is employed as the energy storage device. Such devices have the benefit of very long charging-discharging cycles and are therefore able to achieve much longer operation time when being fed by harvested power sources [6]. Additional advantages of supercapacitor are its high power density, simple charging requirement and robustness to temperature changes, shock, and vibration. In this paper, we use a fully charged supercapacitor to power the sensor node. Energy harvester is often incorporated into this kind of system as power source, but we neglect it for the purpose of simplification. Besides the self-discharge phenomenon of supercapacitor, charge redistribution could also have a significant impact on power management. As such, to take full potential of the stored energy, both self-discharge and charge redistribution of the supercapacitor have to be taken into consideration. The two branch equivalent circuit model [7] provides a way to model the effect of both self-discharge and charge redistribution. Based on which, the model proposed by Chai *et al.* [10] is used to predict the terminal behavior of supercapacitor.

$$V_1[n] = V_1[n-1] + T * \frac{V_{est}[n-1] - V_1[n-1]}{R_1 C_0 + R_1 K_V V_1[n-1]}, \quad (1)$$

$$V_2[n] = V_2[n-1] + \frac{T}{R_2 C_2}(V_{est}[n-1] - V_2[n-1]), \quad (2)$$

$$\begin{aligned} V_{est}[n] = & \frac{R_M}{2}(V_1[n] + \frac{R_1}{R_2}V_2[n]) \\ & + \sqrt{\frac{1}{4}R_M^2(V_1[n] + \frac{R_1}{R_2}V_2[n])^2 + R_M R_1 P[n]}. \end{aligned} \quad (3)$$

In which, n is used to represent the predicted future time step and $V_1[n]$, $V_2[n]$ represent the predicted supercapacitor internal state at nth step. $V_{est}[n]$ is the predicted terminal voltage at time n. R_1, C_0, K_v are the first branch parameters that represent the fast charging/discharging characteristics and R_2, C_2 are the second branch parameters that represent the delayed characteristics. $P[n]$ is the future charging/discharging power. R_M can be calculated as

$$R_M = \frac{R_2 R_3}{R_2 R_3 + R_1 R_2 + R_1 R_3}. \quad (4)$$

Thus, given the current supercapacitor state $V_1[0]$, $V_2[0]$, and the future charging/discharging power P, the terminal voltage of the supercapacitor can be predicted recursively.

The current internal state $V_1[0] = V_1(t)$, $V_2[0] = V_2(t)$ can be updated at each time step according to the terminal voltage measured at previous step $V_t(t-1)$ [11].

$$V_1(t) = V_1(t-1) + T * \frac{V_t(t-1) - V_1(t-1)}{R_1 C_0 + R_1 K_V V_1(t-1)}, \quad (5)$$

$$V_2(t) = V_2(t-1) + \frac{T}{R_2 C_2}(V_t(t-1) - V_2(t-1)). \quad (6)$$

Here, t represents the current time slot. (5) and (6) essentially serve as the state observer for the supercapacitor system.

Based on the calculated V_1, we can estimate the quickly available energy in the supercapacitor via

$$E_{QA}(t) = \frac{1}{2}C_0 V_1^2(t) + \frac{1}{3}K_V V_1^3(t). \quad (7)$$

Unlike the battery, the supercapacitor has a more significant voltage variation. Thus an interface circuit is usually used to provide a stable supply voltage to the embedded system. The interface circuit requires the output voltage of the supercapacitor to be within a certain range, which is normally set to be from $1\ Volt$ to $2.7\ Volts$. Therefore, to guarantee efficient operation, the terminal voltage of the supercapacitor has to be modeled. Moreover, as what will be stated in the following context, the supercapacitor voltage also has a direct connection with the performance of the radar sensor.

B. Sensing and Communication Model

At each time slot t, each node collects raw sensor data readings at a rate of $r_s(t) \geq 0$. The maximum sensing rate is represented as r_{max}. We denote the per packet energy cost for sensing operation as $p_s(t)$.

For radar or RF type sensors, the size of sensor footprint is proportional to the available energy of the sensor node. The footprint of sensor node i located at x_i can be represented as a close ball centered at x_i with a radius of $r(t)$. The footprint of a sensor is the region in which an event can be detected. The event is detected with a boolean model, i.e. events are only detected if they are in the footprint and the sensor is turned on. It is shown that if the sensor range model is based on the RF power density function for an isotropic antenna, the sensor footprint is proportional to the available energy of the sensor node [12], i.e.

$$r^2(t) = \zeta E(t), \quad (8)$$

where ζ is the coefficient of proportionality. Hence, the area of the sensor footprint at time t is

$$A(t) = \pi r(t)^2 = \alpha E(t), \quad (9)$$

where $\alpha = \zeta\pi$ is a constant. According to Hsin *et al.* [13], for sensors that are randomly deployed with uniform distribution within a large region, the probability of an event being detected is given by

$$P_d = 1 - \exp(-\lambda\pi r^2 q), \quad (10)$$

as the number of sensors goes to infinity. In (10), q represents the expected value of sensor being on.

The communication scheduling within a network is conducted by computing the contention free link with maximum aggregated weights

$$\mu^*(t) = \arg\max_{\mu(t)\in\mathbb{L}^f} \sum_{(x,y)\in\mu(t)} w_{x,y}(t), \quad (11)$$

where $\mathbb{L} \in 2^{\mathcal{L}}$ is the set of all contention-free links. For general interference relations, the optimal solution of the scheduling problem is centralized and NP-hard, which is therefore intractable in practice. Fully distributed suboptimal scheduler is often used to solve the problem in practice. For example, the lightweight Longest Queue First (LQF), which have the potential to achieve a near-optimal performance in practice. After the communication links are scheduled, the data forwarding rate rate $f_{x,y}(t)$ over each link $(x,y) \in \mathcal{L}$ is set between 0 and link capacity $c_{x,y}(t)$, i.e. the maximum number of data packets that can be successfully transmitted from x to y during slot t.

In this paper, we simplify this process by assuming all data coming from a single virtual node and all data are send to another single virtual node. Thus the details of communication scheduling are abstracted. Moreover, we assume we can control the data rate of sending $f_t(t)$ and receiving $f_r(t)$. This simplifies the details of data forwarding mechanism. In a real sensor network, where there are multiple sender and receiver, this method developed in this paper can be used to calculate the average number of data packets to be sent or received after the communication link is scheduled. At the next time slot, when the communication link is rescheduled, we can modify the link capacity $c_r(t)$ and $c_t(t)$ accordingly and apply the power management method again with the updated constraints. The node throughput $c_r(t)$ and $c_t(t)$ generally don't have abrupt changes, therefore the method developed in this paper can be utilized to obtain better performance.

Denote $p_t(t)$ and $p_r(t)$ as energy prices for the transmission and reception at time slot t respectively. For a successful transmission over node i at time slot t, the total energy costs for transmitting and receiving are $f_t(t)p_t(t)$ and $f_r(t)p_r(t)$ respectively.

C. Data Processing Model

For the radar sensor, each scan produce tens of Megabytes of raw data, which is much higher than the bandwidth available to each radar sensor in a multi-hop mesh network [2]. Therefore, the raw data must be preprocessed prior to transmission. After preprocessing, the number of reduced data packets is represented as data change rate. It is important to build a model that describes the relation between data change rate and the energy consumption caused by data processing.

Each sensor node x maintains a data queue $\mathcal{Q}_x(t)$ to store its own scanned data, the data packets preprocessed by itself, and the data packets received from its neighbors, assuming each data packet in the network has a unique identifier that identifies its source ID, data attributes, etc. Let $Q_x(t) \geq 0$ be the length of queue $\mathcal{Q}_x(t)$. Due to the limited RAM size of the sensor node, the data queue $\mathcal{Q}_x(t)$ has a limited size, which can be represented as Q_{max}.

The data change rate is represented as $f_{dp}(t)$, and the maximum amount of data can be reduced is denoted as $c_{dp}(t)$. The energy consumption of data processing $EC_{dp}(t)$ can be represented as a function of the data change rate as $EC_{dp}(t) = g(f_{dp}(t))$.

Previous work [14] employs a simple averaging technique to down-sample data, through which, neighboring readings are averaged and replaced by their mean. The larger the number of neighboring readings over which the mean is computed, the greater the data change rate. Simple processing operations such as aggregations that are required to compute the maximal, minimal, and average data values normally result in a linear $g(\cdot)$. Let e^1 and e^2 be the energy costs of the atomic operations respectively, then the energy consumption of average filtering can be easily obtained:

$$EC_{dp}(t) = e_1 f_{dp}(t) + e_2. \tag{12}$$

The function $g(\cdot)$ could also be a nonlinear function for more complex processing operations such as Kalman-filter based data fusion, and compression algorithms like SPIHT [2].

III. PROBABILITY OF EVENT DETECTION

In this section, we analyze the event detection probability of the sensor network and its relation with the operation of each sensor node.

Consider a domain $\mathcal{D}$ where sensors are randomly deployed. The sensor deployment can be modeled as a stationary spatial Poisson point process with constant intensity λ. Given a sub space in $\mathcal{D}$ with area A, the probability of having n sensors in this area can be calculated as

$$P_n = \frac{(\lambda A)^n e^{-\lambda A}}{n!}. \tag{13}$$

To analyze the event detection process, we assume the total number of sensor nodes in $\mathcal{D}$ is very large. All the sensor nodes are radar based. The footprint of each sensor i is a closed ball of radius $r(t)$, centered at x_i, which is the position of the sensor. The union of these footprints form the germ-grain model of stochastic geometry. The sensor is *on* with probability q. For an event to be detected, it should happen within the footprint of at least one *on* sensor.

Let a non-persistent event happens at location $x_e \in \mathcal{D}$. If the network is non-decaying, i.e. the sensor footprints A does not change with time. The probabilities of *on* q is also a constant. The probability of a non-persistent event not being detected can be calculated as

$$P_{un} = \exp(-\lambda A q). \tag{14}$$

With a decaying network, the sensor nodes' energy is consumed when they are on, resulting in a decrease in the area of the sensor footprints. This decrease is proportional to the energy decay. The area of a sensor footprint at time t can be represented as (9). According to Jaleel *et al.* [15], the probability of an event being detected by a decaying network is given by

$$P_d(t) = 1 - \exp(-\lambda \hat{A}(t) q(t)), \tag{15}$$

in which, $\hat{A}(t)$ is the expected coverage of all the sensor nodes.

To break down the event detection probability of the sensor network, we first define the quality of service of each sensor node.

Definition 3.1: The quality of service of sensor node x is defined as

$$1 - \exp(-\lambda A_x(k) q_x(k)). \tag{16}$$

Then we show that the average quality of service of all sensor nodes is the lower bound of the sensor network event detection probability.

Theorem 3.1: The event detection probability of a decaying network with M sensor nodes is greater than or equal to

$$\frac{1}{M}\sum_{x=1}^{M}\big(1 - \exp(-\lambda A_x(k) q_x(k))\big) \tag{17}$$

as M goes to infinity.

Proof: For a decaying sensor network, consider all the sensors of footprint area $A_i(k)$ and sensing ratio $q_j(k)$. Let's assume the ratio of such sensors is $\delta_{ij}(k)$.

Let $N(k)$ be the total number of combinations of footprint $A_i(k)$ and sensing ratio $q_j(k)$ at time k. So $\sum_{i,j=1}^{N(k)} \delta_{ij}(k) = 1$ and $\delta_{ij}(k)\lambda$ is the intensity of sensors with footprint area $A_i(k)$ and sensing ratio $q_j(k)$.

The probability of having n sensors with footprint area $A_i(k)$ and sensing ratio $q_j(k)$ in a given set with area $A_i(k)$ is

$$P_n^{ij}(k) = \frac{(\delta_{ij}(k)\lambda A_i(k))^n \exp(-\delta_{ij}(k)\lambda A_i(k))}{n!}. \tag{18}$$

The probability of an event going undetected by all the sensors of footprint area $A_i(k)$ and sensing ratio $q_j(k)$ can be calculated as

$$\begin{aligned} &P_u^{ij}(k) \\ &= \sum_{n=0}^{\infty}(1 - q_j(k))^n \frac{(\delta_{ij}(k)\lambda A_i(k))^n \exp(-\delta_{ij}(k)\lambda A_i(k))}{n!} \\ &= \exp(-q_j(k)\delta_{ij}(k)\lambda A_i(k)). \end{aligned} \tag{19}$$

The total probability of an event going undetected by all the sensors is

$$P_u(k) = \exp(-\lambda[\sum_{i,j=1}^{N(k)} q_j(k)\delta_{ij}(k)A_i(k)]). \tag{20}$$

Since

$$\sum_{i,j=1}^{N(k)} q_j(k)\delta_{ij}(k)A_i(k) = \frac{1}{M}\sum_{x=1}^{M} A_x(k)q_x(k) \to \overline{(qA)}, \tag{21}$$

we have

$$P_u(k) = \exp(-\frac{\lambda}{M}\sum_{x=1}^{M} A_x(k)q_x(k)). \tag{22}$$

Therefore, the event detection probability of the sensor network is

$$1 - P_u(k) = 1 - \exp(-\frac{\lambda}{M}\sum_{x=1}^{M} A_x(k)q_x(k)). \tag{23}$$

The theorem is equivalent to

$$\begin{aligned} 1-\exp(-\frac{\lambda}{M}\sum_{x=1}^{M}A_x(k)q_x(k)) \\ \geq \frac{1}{M}\sum_{x=1}^{M}(1-\exp(-\lambda A_x(k)q_x(k))). \end{aligned} \quad (24)$$

To prove (24), we have to prove

$$\exp(-\frac{\lambda}{M}\sum_{x=1}^{M}A_x(k)q_x(k)) \leq \frac{1}{M}\sum_{x=1}^{M}\exp(-\lambda A_x(k)q_x(k)). \quad (25)$$

Let

$$f(x)=e^{-\lambda x}. \quad (26)$$

$f(x)$ is convex function, since

$$f''=(\lambda)^2 e^{-\lambda x}>0. \quad (27)$$

Then according to Jensen's inequality, we have

$$\begin{aligned} \exp(-\lambda\frac{\frac{1}{M}\sum_{x=1}^{M}A_x(k)q_x(k)}{\sum_{x=1}^{M}\frac{1}{M}}) \\ \leq \frac{\frac{1}{M}\sum_{x=1}^{M}\exp(-\lambda A_x(k)q_x(k))}{\sum_{x=1}^{M}\frac{1}{M}}, \end{aligned} \quad (28)$$

which is equivalent of (25). This completes our proof. ■

With the Theorem 3.1, the event detection probability of the whole network can be decoupled as the quality of service of single node.

IV. ADAPTIVE POWER MANAGEMENT BASED ON MODEL PREDICTIVE CONTROL

A. System Dynamics

Based on the system models described above, the system dynamics includes the dynamics of data queue and the dynamics of energy storage device.

Consider the sensing, transmitting, receiving and data processing operations, the data queue dynamics of a sensor node can be described as

$$Q(t+1)=\left|Q(t)-f_t(t)-f_{dp}(t)\right|_{+}+r_s(t)+f_r(t). \quad (29)$$

Moreover, the size of data queue is limited by the RAM size Q_{max}.

The transmitting and receiving rate are limited by the link capacity $c_r(t)$ and $c_t(t)$.

The data change rate $f_{dp}(t)$ is limited by the maximum number of data change $c_{dp}(t)$ within a time slot.

The sensing, transmitting and receiving operations all consume energy. Their energy prices are $p_s(t)$, $p_t(t)$, $p_r(t)$ respectively. The energy consumption of the data processing can be different for different applications. In this paper, we take the liner model as in (12) as an example, which corresponds to the average filtering process. Let $EC(t)$ be the amount of energy consumption at time slot t. It can be represented by

$$EC(t)=p_s(t)r_s(t)+EC_{dp}(t)+p_t(t)f_t(t)+p_r(t)f_r(t). \quad (30)$$

With the supercapacitor model depicted in (1), (2), and (3), the supercapacitor terminal behavior can be estimated. What is to be noted is that the terminal voltage of supercapacitor has to be within $[1, 2.7]$ V to guarantee continuous operation.

B. Objective Function

The objective of the proposed power management method is to track a reference value of the quality of service r via controlling the sensing, transmitting, receiving and data processing operations of each sensor node. According to Theorem 3.1, the average quality of service of all sensor nodes in the network is the lower bound of the event detection probability of the sensor network. Therefore, forming an optimization problem to track r ensures that the event detection probability of the sensor network is around or greater than r.

The quality of service of each sensor node could also be maximized to achieve the maximum event detection probability of the whole sensor network. However, it leads to high sensing rate during the lifetime of the sensor node, which is not efficient for energy conservation.

Therefore, in this paper we formulate the objective function of the optimization as

$$\underset{r_s,f_{dp},f_t,f_r}{\text{minimize}} \sum_t (1-\exp(-\lambda\alpha E_{QA}\frac{r_s(t)}{r_{max}})-r)^2. \quad (31)$$

C. Model Predictive Control

Based on the system dynamics and objective function presented above, the power management problem can be formulated as an optimization problem and solved with model predictive control. The model predictive control method has the advantage of explicitly handling the constraints and achieving optimal performance within a finite horizon. It also prevents the performance degradation caused by the uncertainty of communication scheduling.

The control inputs of the MPC are the sensing rate r_s, transmitting and receiving rates f_t and f_r and the data processing rate f_{dp}. The state variables are the data queue length $Q(t)$ and the internal states of supercapacitor $V_1(t)$ and $V_2(t)$. By adjusting r_s, f_t, f_r and f_{dp}, the objective function as in (31) can be minimized. The optimization formulation can be represented as

$$\begin{aligned} \underset{r_s,f_{dp},f_t,f_r}{\text{minimize}} \quad & \sum_{t=1}^{k}(1-\exp(-\lambda\alpha E_{QA}(t)\frac{r_s(t)}{r_{max}})-r)^2 \\ \text{subject to} \quad & \textit{supercapacitor dynamics } (1)(2)(3) \\ & \textit{data queue dynamics } (29) \\ & 1\leq V_{est}(t)\leq 2.7 \\ & 0\leq Q(t)\leq Q_{max} \\ & 0\leq r_s(t)\leq r_{max} \\ & 0\leq f_{dp}(t)\leq c_{dp}(t) \\ & 0\leq f_t(t)\leq c_t(t) \\ & 0\leq f_r(t)\leq c_r(t) \end{aligned} \quad (32)$$

In which, k represents the prediction horizon of the MPC.

This optimization problem is solved over a finite interval of k future time slots, which starts at the current time slot. Only the calculated control inputs corresponding to the first predicted time slot are actually applied to the system. The remaining control inputs are discarded. At the next time slot, a new optimization problem with updated constraints is solved over a shifted prediction horizon. At each time slot, the control input applied to the system depends on the most recent measurements and the model deviation is minimized.

Due to the nonlinear nature of the constraints and objective function, particle swarm optimization (PSO) is employed to solve the optimization problem at each time slot. PSO is a population based stochastic approach for solving optimization problems. The algorithm generates a group of random particles in the search space representing the candidate solutions to the optimization problem. Each particle searches for better solutions in the search space by adjusting its velocity based on two values. The first one is the best solution it has achieved so far, which we represent as p_{best}. The second one is the best solution that has been obtained so far by all particles in the population, which we represent as g_{best}. The PSO algorithm can be summarized as Algorithm 1. In which, η_1 and η_2 represent the two random numbers.

Algorithm 1 Particle Swarm Optimization

Require: Number of particles N_p, number of iterations N_i

for k=1 : N_p **do**
    Initialize particle k;
end for
$i \leftarrow 1$;
for i=1 : N_i **do**
    for k=1 : N_p **do**
        Calculate fitness value of particle k;
        if Current solution is better than p_{best} **then**
            $p_{best} \leftarrow$ current solution;
        end if
    end for
    $g_{best} \leftarrow$ best solution in the generation;
    for k=1 : N_p **do**
        $v_k = v_k + c_1 * \eta_1 * (p_{best} - x_k) + c_2 * \eta_2 * (g_{best} - x_k)$;
        $x_k = x_k + v_k$;
    end for
end for

The PSO algorithm has the benefit of global search, parallel capabilities, limited memory consumption, and it is easy to implement since there is no need to calculate gradient. Xu *et al.* [16] solve the MPC of a fast dynamic systems using the PSO implemented on a FPGA. For the power management problem formulated as (32), the control frequency can be much lower. Moreover, the trade-off of solution performance and the computational time can be explored to further reduce the computation time at each step. More specifically, due to the fast convergence of PSO, the generated solution could have satisfactory performance after a few generations. Thus the number of generations to be executed can be reduced depending on the remaining time and energy. This won't cause significant performance degradation when system dynamics does not vary very fast, since only solution corresponding to next time slot is actually applied and the other solutions are discarded. Furthermore, to accelerate the algorithm execution, each time when the optimization problem is solved, the calculated solution can be stored and used to initialize one of the particles for the next run.

V. SIMULATION STUDIES

To demonstrate the effectiveness of the proposed power management method, we simulate a radar based sensor network that is powered by supercapacitor. Sensors are deployed in the field according to a spatial stationary Poisson point process with constant intensity per unit area of $\lambda = 5$. Events are generated randomly at each time instant throughout the area of interest. Each sensor is equipped with a 310 F supercapacitor with parameters listed as in Table I.

TABLE I
MODEL PARAMETER OF A 310 F 2.7 V SUPERCAPACITOR

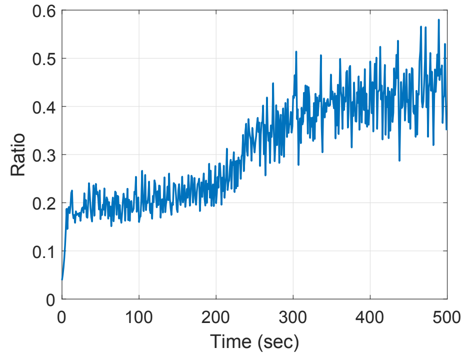
$R_1(Ohm)$	$R_2(Ohm)$	$C_0(Farad)$	K_V	$C_2(Farad)$
0.00224	10	298.37960	29.994	12.077

The proportional coefficient α between the sensor footprint and the available energy is 0.00077858. For the radar sensing, the time varying sensing price was randomly generated using a uniform distribution over the range of $[0.008, 0.016]$ (J per packet) for each sensor node at each time slot. The maximum sensing rate of the radar sensor is set to be 20 packets. In the MPC formulation, we set $p_s(t)$ to be the average 0.012 J per packet.

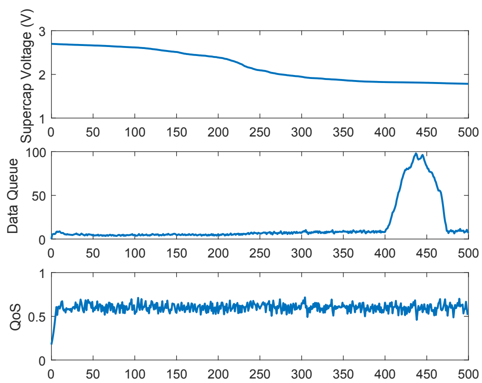
For the communication between sensor nodes, the channel capacity c_{max} is set to be 40 packets. The energy prices of transmitting and receiving over each wireless link have a linear relation with a ratio of 0.6, according to the datasheet of a IEEE 802.15.4 transceiver (AT86RF231). So the receiving energy price is set to be 0.025 J per packet and the transmitting energy price is 0.015 J per packet. The details of communication scheduling are simplified, we assume the number of receiver nodes and transmitter nodes are randomly generated using a uniform distribution over the range of $[1, 4]$. In the optimization formulation, we set $p_t(t)$ and $p_r(t)$ as the expectation of transmitting and receiving energy price, which are 0.0375 and 0.0625 J per packet respectively. The power management algorithm then calculates the average number of packets sent to or received from the neighboring nodes.

The data processing is assumed to be the simple averaging process with $e_1 = 0.001$ J per packet and $e_2 = 0.0005$ J per packet. The maximum data size change caused by data processing is $c_{dp} = 30$.

Initially, the supercapacitor is fully charged, i.e. the terminal voltage is 2.7 $Volts$ and $V_1 = V_2 = 2.7$ $Volts$. The data queue is empty, so $Q(0) = 0$ packets. At each time slot, the MPC controller calculates the sensing rate of the radar sensor $r'_s(t)$, the transmitting and receiving rate $f_t(t)$



(a)



(b)

Fig. 1. (a) The terminal voltage of the supercapacitor, the length of data queue, and the quality of service of each sensor node. (b) The sensing ratio of r_s/r_{max}.

and $f_r(t)$, and the data processing rate f_{dp}. The solution is searched within $\pm 30\%$ of the solution found in the previous time step.

Figure 1(a) shows the terminal voltage of the supercapacitor, length of data queue, and the quality of service of the sensor node. The event detection probability of the whole sensor network is around or above the quality of service of each single node, which is tracking a reference signal of 60%. The supercapacitor voltage is within the range $(1, 2.7]$ $Volts$. The length of data queue is within the range $[0, 100]$ packets. Figure 1(b) shows the calculated sensing ratio r_s/r_{max} of the radar sensor. It can be seen that the sensing ratio gradually increase to compensate for decrease of energy level. The length of data queue also shows slow increase, which is due to the decrease of transmitting rate as a result of energy saving for sensing operation.

VI. CONCLUSIONS

Supercapacitor powered systems have the advantages of very long charging/discharging cycles and high power density. The power management method, however, have to be designed specifically to achieve the full potential of the stored energy. The paper proposed a power management method based on the model predictive control and the supercapacitor model that captures no only the self-discharge but also the charge redistribution phenomenon. Radar sensor network is used as an example. The event detection probability of the sensor network is decomposed as the quality of service of each sensor node, which depends on the available energy of the node and the sensing rate. The developed method achieves the goal of tracking a reference event detection probability while satisfying the constraint of continuous operation. With the simulation study, it is demonstrated that as the available energy decreases with the operation, the sensor node has to increase the sensing rate in order to track the reference quality of service, which ensures a satisfactory event detection probability.

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