Integrated fuzzy control to power management on event-based sensor node

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This paper demonstrates how a fuzzy controller based dynamic power management (FCDPM) model for wireless sensor node saves a significant amount of power than traditional systems. The stochastic behavior of input event arrival is modeled with first-in-first-out (FIFO) queue and single server handled with FCDPM that improves lifetime and minimizes the delay in servicing the events. Compared with the previous research on power consumption of a wireless sensor node, this SimEvents model gives an easier implementation of sensor node with its system-level performance metrics in terms of power consumption, delay, lifetime and processor utilization for non-stationary workloads. The power saving of a single sensor node is analysed for forest fire detection and it can be further implacable in several energy-hungry wireless sensor network applications.

Keywords: fuzzy control, lifetime improvement, power consumption, sensor node, Simulink model, wireless sensor networks

1. INTRODUCTION

Most of the forest fire events in Indian states/Union Territories are reported in Orissa, Chhattisgarh, Assam, Madhya Pradesh and Mizoram between 2009 to 2014 [1]. A survey on forest fire states that the 50% to 70% area of the Indian forest is prone to fire [2]. The fire response time after getting fire information through any means is compared and reported 5-7 minutes for urban and 20 minutes for rural areas in India [3]. Definitely, this will be more in forest, remote or unattended areas and need an immediate attention to reduce severe damage. In first phase, pre-fire planning for fire-prone areas can effectively contribute to forest-fire decision support system. Next phase during fire requires fire detection, spreading its information and control on fire. The recent trends of the fire data collection are geographical information system and satellite remote sensing. An Indian-Forest-Fire-Response-and-Assessment-System (INFFRAS) deals with the preparation and management of forest fire control [4]. These techniques give poor resolution in the denser areas and delay the prediction due to slow sampling. The use of wireless sensor network along with the satellite-based forest fire monitoring can effectively and efficiently reduce the fire fatal. The nodes in a wireless sensor network are deployed in the fire-sensitive area and detect the fire in its early stage [5], [6] and help in transmitting the fire information for controlling center through a satellite system. Thus, the cooperative WSNs with satellite system can save a large area from severe damage or loss due to fire.

Typically, a sensor node consists of minimum four functional blocks; sensing, storing, computing, controlling and power blocks. Lifetime improvement in wireless sensor networks (WSNs) is the biggest barrier for its application advancement such as critical patient monitoring to disaster prediction. Day to day, researchers are contributing for

power consumption reduction techniques to increase the lifespan of a sensor network [7], [8]. Authors in [9] have presented different energy conservation techniques to reduce consumption from sensor node components to the network perspective. The limitations of MAC layer protocol, which can decrease the lifetime of a sensor node are found out for IEEE 802.15.4 technology-based WSNs [10]. Consequently, an improvement in the MAC protocol is implemented to sensor node hardware for optimizing the energy consumption and loss of information within the network. A model for elderly healthcare application is simulated using OPNET [11]. On the other hand, the nodes, which are used to detect chemical agent, biological agent, seismic and acoustic sensor nodes require very much power for their operations. Dynamic power management techniques are very effective in prolonging the lifetime of an individual sensor node and thus the entire wireless sensor network. They help in application based decision making on the operation of low power components of the sensor node and their implementation require low power components with multiple operating modes, low sleep power and fast switching between power modes to reduce energy and time overheads. The switching between different power modes depends on the arrived workload pattern and speed on sensor input. The dynamic decision-making on its non-stationary operation/workload is a challenging task for resource-constrained sensor node and remained unsolved.

This paper presents a stochastic event dependent sensor node model for fuzzy controller based dynamic power management (called FCDPM) and focuses on system-level energy consumption. The state-based Markov model reveals the effect of non-stationary event arrival and threshold on the power consumption of sensor node. The sensor node model is simulated and analyzed for forest-fire detection application, taking temperature as fire detection threshold. This approach can overcome the low resolution and large scanning period drawbacks of satellite-based forest fire monitoring application. Thus, reduces the major loss of lives and forest for a long period after WSN deployment. The improvement in power and delay matrices help in forecasting the fire before it spreads in an uncontrollable manner. Next, section 2 discusses emerging techniques for dynamic power management. Section 3 illustrates system model of power management based sensor node and describes the related subsystems. Section 4 gives the performance analysis in terms of power and delay parameters. Finally, section 5 concludes the above-mentioned sections.

2. RELATED WORK

Today, advancement in the WSNs has emerged towards ultra-low-power hardware/software design. Every day researchers and academicians are trying to devise new technologies in architecture, logic, battery, circuit, system and network level to mitigate the energy limitation in wireless sensor networks [12-15]. As discussed in the literature, the energy problem can be solved either with energy efficient protocols at network level or power management strategies at system level [16-17]. The system/node power management contribute to power saving by reducing the wasteful and inefficient activities and operating components only for desired event at input of sensor node. A viewpoint on energy-aware protocols, energy harvesting issues, energy-aware sampling and sensing represents how sensor node operations and communications save the energy [18]. Most of the available sensor nodes (e.g. Wec, TelosB, IRIS, Dot, Mica, MicaZ, Mica2Dot, Tmote Sky, WaspMote Lotus and Shimmer etc.) have their inbuilt low power microcon-

troller (AT90LS8535, ATmega163, ATmega128 and TI MSP430) to work on different power modes such as active, sleep, deep-sleep etc. The fast switching of the microprocessor (from sleep to active or vice versa) not necessarily provides the more power saving in Atmega128L processor of Mica2 mote than Intel PXA-255 processor [19]. The overall power consumption depends on so many other factors such as energy consumed per instruction, number of operating power modes, event arrival and processing rate, event scheduling before processing, its duty cycle and many more. Therefore, the specific power management techniques facilitate the dynamic power mode selection of sensor node components to achieve the energy efficiency in low duty cycle applications [20]. The low-power node (hardware) provides intelligent decision-making on its operation when working in collaboration with power management software [21-23]. In the most relevant state of the art, the network lifetime is calculated based on two important factors; one is node failure and another is battery depletion. The system/node fault has been detected on component failure. Authors proposed a DPM scheme, which saves the power consumption by operating a minimum number of sensor nodes with their minimum number of active components [24]. Such modeling techniques need to be explored in terms of other performance parameters such as delay, power consumption, processor utilization etc. There is a need for a wake-up mechanism, which can keep track on the sensor node activities and threshold-based event that can occur during sensor is idle or off. An onboard radio wake-on at sensor hardware was proposed to detect an event at sensor input or radio [25]. This wake-on triggers the sensor controller and transceiver on the occurrence of an event. The wake-on implementation on sensor node requires hardware change and thus the overall power consumption of the including wake-on component is also required.

So far, several fuzzy logic based clustering approaches are proposed and implemented at routine and network layer [26-29], while an efficient node power management based on fuzzy controller need to be addressed and explored to mitigate the decision-making hurdles on DPM. The fuzzy logic for forest fire detection for a wireless sensor network is presented in [30-31]. Another work shows the climate control using fuzzy approach [32]. As per our knowledge, none has presented the power consumption analysis with the application intelligence in system. We present a model that does not require the change in hardware; it controls the fuzzy logic based switching of sensor node components at operational level and thus reduces the power consumption. As per our knowledge, this is the first time when FIS has been used for controlling power and performance of sensor node. Apart from the traditional communication/ transmission strategies of power saving, our approach increases the lifetime of sensor node and thus, can increase the energy efficiency in energy-hungry sensor applications (e.g. ocean water, pollution, fire detection, target monitoring and health control etc.).

3. SYSTEM DESIGN

This section presents an FCDPM model consisting of a sensing unit to detect and filter the arrived events, FIFO queue for input buffering, single server for event processing, a dynamic power-managing unit and delay analyser for performance evaluation, see figure 1. The sensing unit not only detects the occurrence of stochastic event but its corresponding magnitude (ex. threshold value of smoke, temperature, vibration etc.) too.

The stochastic event arrival/workload is non-stationary. A DPM implemented single node is not able to receive any information when it is off. This problem is formulated using fuzzy inference system (FIS) to control the power flow in the power manager block. For real-time fire detection, the fuzzy system has capability of detecting event arrival rate and temperature threshold, which is useful in intelligent decision making on power management. The fuzzy control provides precise control and does not require accurate mathematical model for power and performance than traditional methods [30-31]. The Fuzzy Inference Systems (FIS) are simpler in designing, more flexible in functionality and computationally faster. Compared to other techniques, they require lesser development time, lesser memory and lesser research efforts in implementing on resource constrained sensor nodes. The simpler IF-THEN rules have been used to handle unreliable and imprecise data values from sensor inputs and controlling power consumption.

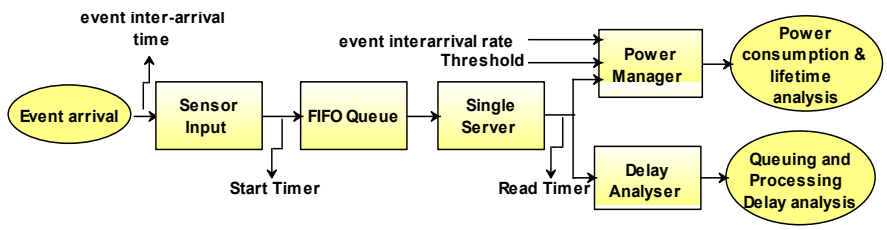

Fig. 1. Basic architecture for event-based sensor node model

The Markov process is used to compute and analyze the two crucial performance parameters of wireless sensor node (i.e. power consumption and latency). The timer is used to analyze the delay introduces in handling the event between queueing and processing. In our Markov model, the power states change according to number of active components in the sensor node. Four power states (P_{s0} - P_{s3}) are to represent the complete system. The decision on the switching between different power states is modeled with Markov process while decision on the processor power levels is modeled with fuzzy based system. The analyzer subsystem is capable of operating the node components at different power levels. We have presented a review on the stochastic modeling techniques for dynamic power management in wireless sensor networks [33]. An application-based taxonomy for the applications of Markov decision process is shown [34]. The model flexibility in dynamic optimization problems is also illustrated. A detailed description about subsystems is presented in the next sections. Before proceeding, the notations are presented in table 1, which has been used in the subsequent sections.

Table 1. Notations

Symbol	Name	Symbol	Name
λ_i	i^{th} arrival rate of events	$\bar{P}_e$	Node power consumption
β_i	i^{th} servicing rate of events	LT_e	Node lifetime
γ_i	i^{th} intergeneration time of events	P_{S_0}	Event monitoring power consumption
K_i	Queue length at i^{th} event rate	E_e	Average node energy
$p_j(i)$	Probability of j number of events at i^{th} arrival rate	T_e	Average event time
ρ_i	Processor utilization	α or alfa	Change detection probability
$E[n_i]$	Average queue length	P_{S_1}	Power state when analyser ON
$E[d_i]$	Average queue delay	P_{S_2}	Power state when analyser

			and processor are ON
T_a	Analysing time	P_{S_3}	Power state when all sensor node components are ON
T_p	Processing time	C_P	Main processor energy cost
T_t	Transmission time	C_R	Transceiver unit energy (wake up) cost
X	Temperature threshold	μ	Membership function
$E_{resource}$	Battery energy		

3.1 Queuing Events

For wireless sensor node, the event arrival is assumed Poisson distributed with arrival rate "λ_i" and servicing rate "β_i". The event intergeneration time is assumed as exponentially distributed. The sensor input receives the incoming events and schedules them as first-in-first-out manner in the finite queue of length K_i. The M/M/1/K_i Markov model is simulated and analyzed for processing and computing the power consumption of a sensor node. At steady state, the probability of j number of events at i^{th} arrival rate i.e. $p_j(i)$ in the queue is presented in equation (1). Then, the processor utilization "ρ_i", average queue length $E[n_i]$ and average queue delay $E[d_i]$ are computed using Little's formula, equations (2 &3) respectively.

$$p_j(i) = \frac{1-\rho_i}{1-\rho_i^{K_i+1}}\,\rho_i^{\,j}, \qquad 0 \le j \le K_j \qquad \left(\text{where, } \rho_i = \frac{\lambda_i}{\beta_i} = \frac{1}{\beta_i \gamma_i}\right) \tag{1}$$

$$E[n_i] = \sum_{j=1}^{K_i} j\, p_j(i) = \frac{\rho_i}{1-\rho_i} - \frac{(K_i+1)\,\rho_i^{\,K_i+1}}{1-\rho_i^{\,K_i+1}} \tag{2}$$

$$E[d_i] = \frac{E[n_i]}{\lambda_i} = E[n_i]\gamma_i \tag{3}$$

The average queue length is taken from the time when first event arrives at FIFO queue until the end of simulation. The average queue delay is computed from the time first event enter the queue to the time event leaves the queue. The total delay time is computed adding server delay to the queuing delay.

3.2 Power Management

The power management unit consists of a fuzzy based controller, which works as an analyser of desired events and reduces the communication overheads. The power consumption depends on the number of active components on the sensor node. The communication plays a very important role in power consumption of a sensor node. In order to meet the application requirement of wireless sensor networks, the input data should be categorized according to the priority level. The fuzzy controller provides flexibility in processing and communication speed and thus the power consumption based on the priority requirement of application. The analyser unit is used to detect change in the previously detected value from sensor input and consider it as a threshold for decision making on component power level switching. An analyser-based model [35] improves significantly the energy efficiency of an event-driven sensor node and this has been compared with existing model [36]. This paper follows the work on sensor node model presented in [35]. We have introduced fuzzy based analyser before processing and communication that intelligently reduces the undesired event processing; thus saves the power consumption. Equations (4-7) presents that the node power consumption "$\bar{P}_e$" and lifetime "LT_e", which depend on the event arrival rate, event monitoring power consumption "P_{S_0}", average node energy "E_e" and average event time "T_e".

$$\bar{P}_e = \frac{P_{S_0} + \lambda(E_e)}{1+\lambda(T_e)} \tag{4}$$

$$E_e = \overline{T_a} P_{S_1} + \alpha\, \overline{T_p} P_{S_2} + \alpha\, \overline{T_t}\, P_{S_3} + C_P \alpha + C_R \alpha \tag{5}$$

$$T_e = \overline{T_a} + \alpha\overline{T_p} + \alpha\overline{T_t} \tag{6}$$

$$LT_e = \frac{E_{resource}}{\bar{P}_e} \tag{7}$$

3.3 Fuzzy Controller

The high speed, real-time Fuzzy controller controls the change detection probability and thus the power consumption of sensor node. It is a fuzzy inference system (FIS) with two inputs (i.e. temperature threshold and arrival rate). The "Sugeno" model of fuzzy inference process is used for computing the constant change detection probability (α) as the required output function. The number of membership functions for temperature threshold, arrival rate and output are 3 each; see figure 2. The Sugeno type FIS architecture consists of three steps: fuzzify inputs, apply fuzzy operation, apply implication and defuzzification.

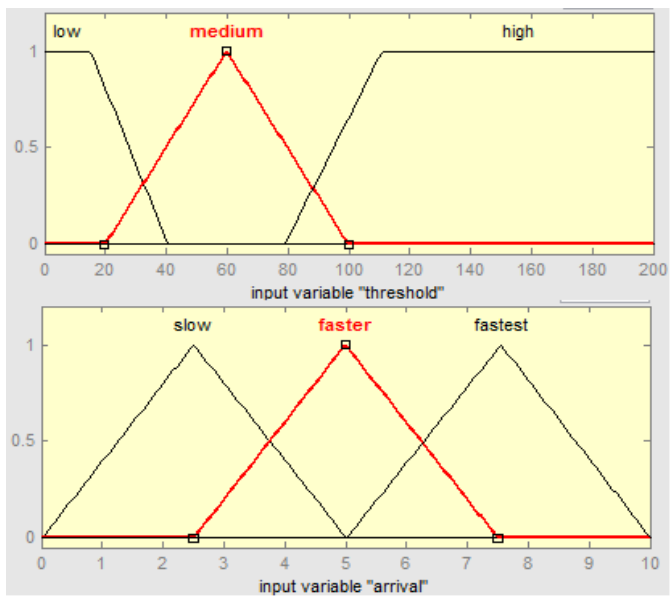

Fig. 2. Shape and range of Membership functions for input variables (temperature threshold and event arrival rate)

In step 1, the crisp input values are converted to fuzzy values by their membership functions. Step 2 involves IF, and THEN rules. Defuzzification is done using weighted average (wtaver) method. The value of temperature threshold represented by "x", ranges from 0-200 with three membership functions ($\mu_{(Low)}$, $\mu_{(Medium)}$ and $\mu_{(High)}$), equations (8-10). The input event arrival rate represented by "λ" is taken from 0 to 10 events per hour with three membership functions as $\mu_{(Slow)}$, $\mu_{(Faster)}$ and $\mu_{(Fastest)}$, equations (11-13).

$$\mu_{(Low)}(x) = \begin{cases} 1, & 0 \le x \le 20 \\ \frac{40-x}{20}, & 20 \le x \le 40 \\ 0, & 40 \le x \le 200 \end{cases} \tag{8}$$

$$\mu_{(Medium)}(x) = \begin{cases} 0, & 0 \le x \le 20 \ \ and \ \ 100 \le x \le 200 \\ \frac{x-20}{40}, & 20 \le x \le 60 \\ \frac{100-x}{40}, & 60 \le x \le 100 \end{cases} \tag{9}$$

$$\mu_{(High)}(x) = \begin{cases} 0, & 0 \le x \le 80 \\ \frac{x-80}{30}, & 80 \le x \le 110 \\ 1, & 110 \le x \le 200 \end{cases} \tag{10}$$

$$\mu_{(Slow)}(\lambda) = \begin{cases} \frac{\lambda}{2.5}, & 0 \le \lambda \le 2.5 \\ \frac{5-\lambda}{2.5}, & 2.5 \le \lambda \le 5 \\ 0, & 5 \le \lambda \le 10 \end{cases} \tag{11}$$

$$\mu_{(Faster)}(\lambda) = \begin{cases} 0, & \le \lambda \le 2.5 \ and \ 7.5 \le \lambda \le 10 \\ \frac{\lambda-2.5}{2.5}, & 2.5 \le \lambda \le 5 \\ \frac{7.5-\lambda}{2.5}, & 5 \le \lambda \le 7.5 \end{cases} \tag{12}$$

$$\mu_{(Fastest)}(\lambda) = \begin{cases} 0, & 0 \le \lambda \le 5 \\ \frac{\lambda-5}{2.5}, & 5 \le \lambda \le 7.5 \\ \frac{10-\lambda}{2.5}, & 7.5 \le \lambda \le 10 \end{cases} \tag{13}$$

The output variable ranges from 0 to 1 with three power states membership functions as μ_{active}, μ_{sleep} and $\mu_{deep\text{-}sleep}$. They have constant values as output MFs μ_{active}=1, μ_{sleep}=0.5 and $\mu_{deep\text{-}sleep}$=0 respectively. The possible number of rules between inputs and output are 9 (3*3= 9), as represented in table 2. The performance and accuracy of the system is tested and validated with the adaptive neuro-fuzzy inference system (ANFIS). This "Sugeno type" fuzzy inference system is trained and tested for minimum error at output. Input parameters are optimized using the least square (LSQ) method. Here, 30 data sets have been used for training and FIS is tested and validated by random input variables. The average error values are computed below 0.013 within 10 epochs, as shown in figure 3.

Table 2 Rule base for change detection probability (α)

		"IF" Temperature threshold		
		$\mu_{(Low)}$	$\mu_{(Medium)}$	$\mu_{(High)}$
"AND" Arrival Rate	$\mu_{(Slow)}$	$\mu_{deep\text{-}sleep}$	μ_{sleep}	μ_{active}
	$\mu_{(Faster)}$	$\mu_{deep\text{-}sleep}$	μ_{sleep}	μ_{active}
	$\mu_{(Fastest)}$	μ_{active}	μ_{active}	μ_{active}

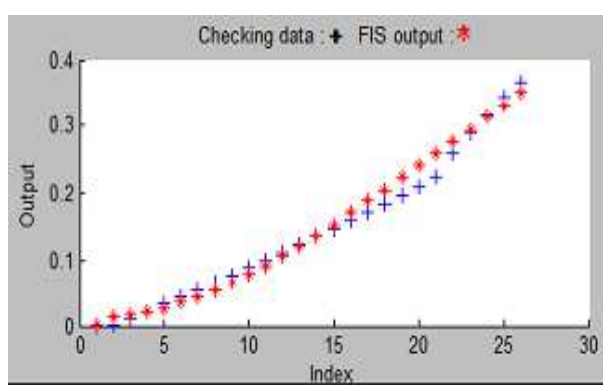

Fig. 3. Computed error between training and testing data sets

For wireless sensor network applications, dynamic decision-making based on the above model follows algorithm 1 & 2:

Algorithm 1: Event flow for dynamic decision-making

1. **Initialize:** timer value= 't_1', sensor state= 'ON', expected event time='X'.
2. **Input:** time-based, Poisson distributed, random events, event temperature value, service time, arrival rate
3. Start timer to log time
4. For events with FIFO queue discipline of capacity N and single server, compute:
   4.1 Number of events departed from queue
   4.2 Number of events in the queue at a given time
   4.3 Average wait time of events for schedule out from FIFO queue
   4.4 Number of events departed from the server
   4.5 Average wait time in server
   4.6 Server utilization
   4.7 Number of processed events from server
5. Stop and read timer value t_2
6. Compute elapsed time (t) i.e. $t=t_2 - t_1$
7. Calculate queuing delay (D) for events as- D= X-t
8. End

Algorithm 2: Greedy approach for power management

1. Initialize pre-processor for filtering temperature sensor values for fire detection
2. Detect anomaly/fire as an event from the pre-processor
3. Compare present filtered value with its immediate previous value in the analyser unit
4. Detect the change in the current filtered value from the previous value obtained.
5. Compute the change detection probability 'α' (0 to 1) for every detected event
6. Compute the event arrival rate 'λ' as inputs of the power manager unit
7. Compute energy and time for power consumption calculation, equations (5& 6).
8. Compute power consumption and lifetime of sensor node, equations (4&7), respectively.
9. End

Algorithm 3: Fuzzy control for power management

1. Select the initial FIS structure: temperature threshold value 'T' and event arrival rate 'λ' as inputs in fuzzy inference system (FIS)
2. Initialize the membership function shapes and values
3. Define input/output rules as shown in table 2.
4. Compute the change detection probability (0 to 1) by FIS
5. Evaluate the performance of FIS by computing learning error between actual and targeted output using least mean square error method
6. Compute energy and time for power consumption calculation, equations (5& 6).
7. Compute power consumption and lifetime of sensor node, equations (4&7), respectively.
8. End

4. PERFORMANCE EVALUATION

The model is simulated on SimEvents/Matlab, where the random event arrival and servicing follow $M/M/1/K_i$ model. The proposed model consists of FIFO queue to sequence the arrived events, single server for processing, power manager for FCDPM and delay analyser, figure 1. Simulation parameters of sensor node are shown in table 3; refer notations in table 1. The daily weather forecast data for temperature is taken from [37]

with slight modifications to meet the requirement of forest fire. Before applying to the system, the data is cleaned and aggregated to get the normal cyclic behavior. The performance is evaluated with power consumption, delay and processor utilization matrices. The overall power consumption and lifetime depend on the change detection probability at sensor node input. The change detection probability is modeled with fuzzy controller with two input variables (arrival rate and threshold) and one output (change detection probability).

Table 3 Simulation parameters

Parameter	Value	Parameter	Value
P_{S_0}	2.3 mW	$E_{resource}$	1.863 kJ
P_{S_1}	25.3761 mW	T_a	0.5sec
P_{S_2}	237.712 mW	T_p	2sec
P_{S_3}	315 mW	T_t	0.175sec
C_R	0.0066 mJ	C_P	2.2064 mJ

Figure 4 shows surface view for output of FIS and variation of change detection probability (alfa) with threshold and event arrival rate. This represents that the high temperature and higher event arrival rate are the major cause of consumption. In the traditional model, the power consumption increases with the increase in event arrival, but the intelligent decision-making on fuzzy-based model switches the node power at different levels and saves a significant amount of power consumption.

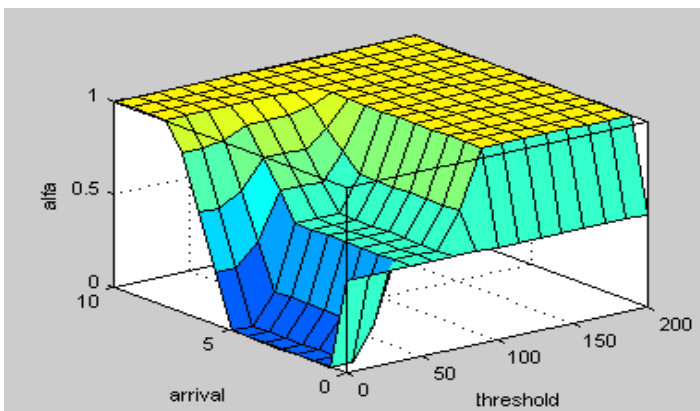

Fig. 4. Surface view for varying change detection probability (alfa)

Figure 5 (a) depicts the comparative analysis for power consumption between previous DPM model [35] and proposed FCDPM model. This saves more than 50% of the node power by reducing the wasteful processing and communication for event arrival. In order to decrease the power consumption, we increase the event inter-arrival time. This decreases the duty cycle (ON time of sensor node). A very careful selection of duty cycle is required to minimize the number of missed events during node is OFF. This model handles the stochastic events intelligently and commands the components for suitable operation. The effect of event's inter-arrival time also influences the power saving as depicted in figure 5 (b). The larger inter-arrival time between upcoming events makes the system more energy efficient. The switching of components between different power

levels and the ON/OFF cycle of sensor node obviously introduces delay between event arrival and transmission time. This latency should not be that much large to miss the deadline of an event. If this delay increases gradually with arrived events, the missed-events rate increases and thus the behavior of WSN for that particular application changes. Our FCDPM model guarantees the timely event processing and communication within marginal delay at output end as shown in figure 6 (a). The maximum delay is found below 13ms even at a very fast event occurrence rate (i.e. 5 min and 10 min inter-arrival time) and this does not show gradual increasing behavior with input change.

One more interesting fact that came out by in-depth evaluation of this model is that the model represents dynamic voltage scaling effect without applying any voltage scaling technique as depicted in figure 6 (b). The processor utilization here is dependent on the event arrival rate. The maximum utilization goes around 99%, 80% and 45% at 2min, 5min and 10min inter-arrival time of events respectively. Therefore, the processor utilization can be interpreted as the operating voltage levels in voltage scaling techniques. As event arrival varies the processor dynamically changes its operating voltage but makes the system slower for lower event arrival rate.

After comparing the greedy/existed model [35] with our proposed FCDPM model, we have observed that more power can be saved with fuzzy controller based dynamic power management model. The simulation results are validated by performing two valued sample t-test on the samples of power consumption variable at two different events arrival rate. Here, the input arrival is stochastic in nature and we have taken the samples after conduction 100 different experiments on each arrival rate.

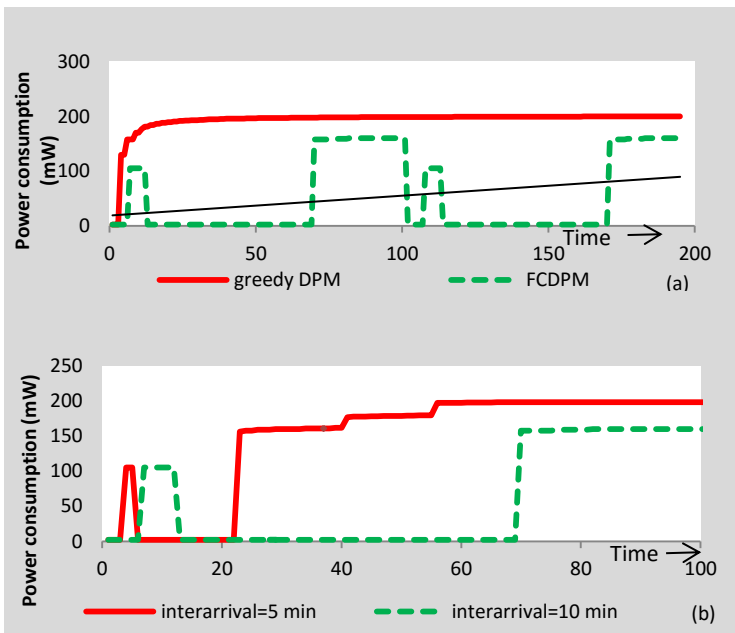

Fig. 5. Comparison of power consumption (a) between greedy DPM and fuzzy-based model, (b) fuzzy-based model (FCDPM) at different inter-arrival time i.e. 5min and 10 min

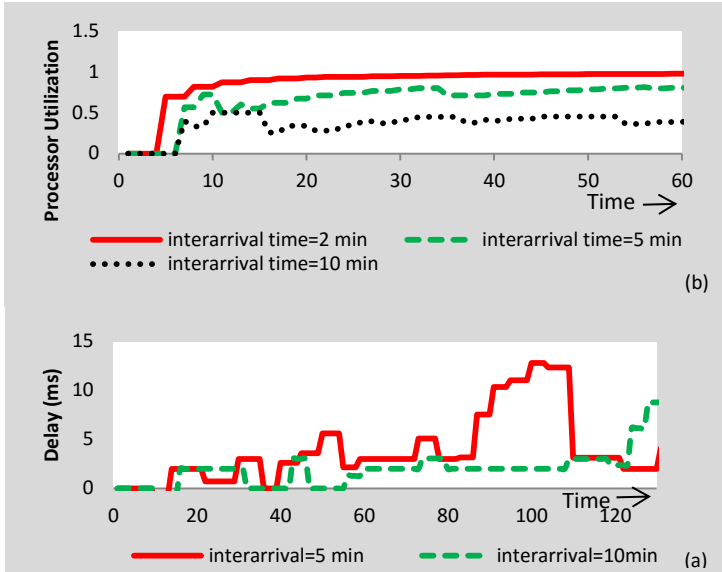

Fig. 6. Effect of inter-arrival time and threshold on (a) Delay variation (b) Processor utilization

For random inputs, the t-test directs a difference between means of two different variables. This is applicable to our roughly normal distributed data. The two-tailed hypothesis test is conducted for the *research hypothesis*: *a sensor node spends more power at slow event arrival rate than high event arrival rate.* On the other hand, the null hypothesis states: *the average difference score for two samples will be equal or less than zero*. In this test, the difference between two variables (i.e. power with arrival rate) is calculated for each value of the sample. The research hypothesis is correct when the average difference (i.e. power at slow arrival rate-power at high arrival rate) for all the values is greater than zero. Otherwise, the null hypothesis is correct. Our sampled t-test revealed that the sensor node spends more power at slow event arrival rate (mean=147.8663, standard deviation=74.90) compared to high event arrival rate (mean=58.2547, standard deviation=73.43), and t-value=10.251 at 100 degree of freedom. The correlation between power samples is found around 0.299 and the significance value, p=0.002, which is less than 0.05. Thus, we can reject the null hypothesis at 5% significance level and accept our research hypothesis. The lower confidence limit (LCL) and the upper confidence limit (UCL) are computed as 72.2687 and 106.95 respectively at 95% confidence interval of the difference.

5. CONCLUSIONS

We have presented an energy-efficient, event (forest-fire) based model for wireless sensor node. This presents the efficient use of sensor node components, their switching between high and low power states according to the stochastic event arrival. Our proposed FCDPM approach directs the processing of events at different power levels and the Markov model controls the wasteful communication due to undesired events at input. The model is experimented for forest fire input data and the results are validated using statistical tests. This simulation model will trigger the new power management aspects

when implemented on the sensor node hardware. Thus, the network lifetime can be improved by decreasing up to 40% power consumption at sensor node. In the future, we will extend this FCDPM model at network level and for other applications also.

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