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On the Performance, Availability and Energy Consumption Modelling of Clustered IoT Systems

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Abstract Wireless Sensor Networks (WSNs) form a large part of the ecosystem of the Internet of Things (IoT), hence they have numerous application domains with varying performance and availability requirements. Limited resources that include processing capability, queue capacity, and available energy in addition to frequent node and link failures degrade the performance and availability of these networks. In an attempt to efficiently utilise the limited resources and to maintain the reliable network with efficient data transmission; it is common to select a clustering approach, where a cluster head is selected among the diverse IoT devices. This study presents the stochastic performance as well as the energy evaluation model for WSNs that have both node and link failures. The model developed considers an integrated performance and availability approach. Various duty cycling schemes within the medium-access control of the WSNs are also considered to incorporate the impact of sleeping/idle states that are presented using analytical modeling. The results presented using the proposed analytical models show the effects of factors such as failures, various queue capacities and system scalability. The analytical results presented are in very good agreement with simulation results and also present an important fact that the proposed models are very useful for identification of thresholds between WSN system characteristics.

Keywords WSNs · IoT · Energy Consumption · Stochastic Models · Performability · Clustering

1 Introduction

The Internet connected systems of physical devices where lightweight communication protocols are employed for interconnecting computing devices, digital and mechanical instruments, animals, people or other objects are called Internet of Things (IoT) [5], [19], [35]. With these capabilities, it is possible for the IoT users to have close interaction with the physical world based on the activity of the sensor nodes [4]. As the main source of sensor node activities, wireless sensor networks (WSNs) are an integral part of IoT [1], [17]. WSNs can be considered as the key technology for IoT, since they provide the main infrastructure which consists of numerous sensors working collaboratively to monitor event occurrences in a given habitat. The

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sensor nodes are equipped with limited resources in terms of power supply and the queue capacity; in which network packets are stored. Because of power supply limitations, the processor units as well as the communication technology should also be selected carefully; such that, the capabilities of the nodes in terms of processing and radio communication are not inherently restricted. However, as long as the sensor nodes are alive, they can work unattended and transmit their observed values to sink node of the network directly or via multiple hops through other relay sensor nodes in the network. There are many IoT applications that require WSNs with varying Quality of Service (QoS) demands such as low delay, high bandwidth, and minimal energy utilisation; influenced by the complexities of the deployed environments. These can be listed as target tracking, industrial automation, smart city transport systems, smart agriculture, disaster monitoring, assisted living, and many others [5], [9], [17], [42]. The emergence of IoT has been a significant enhancement for the use of WSNs deployment in nearly all areas requiring any form of monitoring.

1.1 Quality of Service for IoT Applications

The diversity of IoT application environments that demand different QoS, makes the performance and availability evaluation of WSNs a very challenging task considering that majority of such network scenarios depend on battery-powered nodes with limited energy resources [10], [44]. Furthermore, sensor node and communication links are prone to failures, just like other communication networks that may lead to degradation in the availability and the performance of such networks. Moreover, for data intensive applications, limited queue capacity may result in increased packet loss rate, further degrading the network performance. In view of these factors, WSN designers ought to consider factors such as fault tolerance, operating environment, scalability, network topology, and energy efficiency. Recent studies such as [14], [28], and [40], consider OPNET, MATLAB, NS-2, and TOSSIM based simulations as well as real system implementations (testbeds) for the evaluation of new algorithms to improve the battery lifetime and QoS values under variable traffic load conditions.

Increasing the lifespan of WSNs is a well investigated research topic [9] - [44]. One of the most widely used energy saving technique is to use medium-access control (MAC) layer protocols to put idle nodes into sleep mode[10], [42]. The sleep state guarantees reduced power consumption by switching off most device components like microprocessor, memory and Radio Frequency module (RF). However, even though significant energy saving may be achieved; there exists a trade-off between the node energy savings and the network performance in terms of throughput and data delivery delay. [10]. The studies on performance and energy efficiency evaluation of WSN based technologies, should consider potential thresholds between these measures.

1.2 Motivation and Contribution

Performance, availability, and energy efficiency related factors such as queue capacity, the number of available channels, the channel failure rate, average energy consumption per transmission and the response time are very important for efficient and reliable configurations of clustered WSN systems. To the best of our knowledge, in the literature, there are no analytical modelling attempts in which these factors have been considered all together. The pure performance models in the literature are well known for their overestimation of the ability of the system to perform. This is mainly caused by the arbitrary assumption of avoiding all system and environmental level failures. Pure availability models on the other hand; tend to be conservative since different levels of performance are not taken into account. In other words, the outcome of availability models would allow us to analyse the probabilities of being in a certain state, but the effect of this probability on the overall QoS of the system would not be considered. Therefore, a composite measure for performance and availability (performability)[37] is necessary for realistic evaluation and optimization of WSNs. Considering the limitations of existing analytical modelling attempts, the contributions of this study can be listed as follows:

- A methodology is presented for modelling and evaluation of sensor networks which are widely used for IoT applications by integrating performance and availability/reliability studies in the presence of node and link failures.
- The impact of replacement and restoration of the failing nodes are considered unlike the existing analytical modelling and simulation studies.

– Apart from performability evaluation, a stochastic modelling approach is also presented for energy evaluation that considers the challenges resulting from resources constraints and different operative states of the systems.
– Unlike the existing studies, the performability models that are developed, incorporate additional system dynamics such as sleep schedule schemes implemented in the MAC layer, impact of limited queue capacities, and challenges posed by channel and node failures and restoration.
– Explicit analytical expressions are used for the evaluation of desired performance measures and energy consumption in various states.

Numerical results obtained from analytical models and the comparison with simulation results show that the approaches perform well in terms of accuracy. To the best of our knowledge, this is the first study that integrates the performance and availability characteristics of sensor networks considering the aforementioned additional system dynamics.

The remainder of the paper is organized as follows: Section 2 provides a detailed overview of the related work, while section 3 presents a detailed description of the system together with a summary of the assumptions considered. Section 3.3 presents the two-dimensional Markov system model and section 4 presents the solution approaches employed for the models. In Section 5, the performability results obtained from the proposed model are presented and discussed. In Section 6, the energy model for the clustered WSN system is presented. Furthermore, the results achieved by the proposed energy consumption model are presented and analysed in terms of system performance. Finally, Section 7 concludes the work on the proposed model and discussions of future work is disseminated.

2 Related Work

There is a wealth of information related to attempts on improving WSNs in terms of energy efficiency, performance, availability, and reliability [9] - [44]. Since WSNs form an essential part of IoT applications, the improvement of WSNs through new standards in physical layer, more efficient MAC mechanisms/ sleep cycles, and network layer routing and clustering attracts interest of researchers and engineers working in this field. Analytical modelling, simulation, and bench-marking are widely used for performance evaluation of new designs [6]. In this section, modelling, and simulation works on WSNs' pure performance, availability/reliability and energy efficiency. Benchmarking studies similar to [14] come with important limitations such as the cost of the infrastructure, scale of the system to be considered as well as the difficulties usually encountered to extrapolate the results obtained for a specific scenario [6]. Therefore, simulation and analytical modelling studies are quite commonly utilised for studying WSNs. To the best of our knowledge, there are no studies which consider performance, availability and energy efficiency aspects together using analytical modelling approaches.

Considering pure performance, Nguyen et. al. address requirements for energy efficiency and QoS provisioning in an integrated manner for IEEE802.15.4-based WSNs [28]. OPNET and MATLAB simulation packages are utilised to show the performance of the newly introduced adaptive energy-efficient algorithm which can adapt the MAC level parameters of IEEE802.15.4 sensor nodes according to the queue occupancy level of sensor nodes and the offered traffic load levels.

In [27], a hybrid PUSH-PULL traffic model is proposed for efficient data exchange in IoT applications using different types of inter-arrival times within a simulation environment. A relay network used for IoT connectivity in LTE/LTE-A systems is considered in [22]. Similar to our study, a queuing model of a two-hop wireless relay network is considered particularly in order to compute the end-to-end packet delay. Exponentially distributed inter-arrival times (Poisson packet arrival process) are considered together with the IEEE802.11 distributed coordination function where each node is modelled as a single-server queuing system. The resulting one dimensional continuous time Markov chain is solved for state probabilities using a product form solution. Since the availability of the existing resources are not considered, the two dimensional representation of the system is not needed which in turn makes the product form solutions possible.

In [11], queuing theory and analytical models are considered to study and analyse the performance of fog (or edge) computing systems where, fog nodes are placed in close proximity to IoT devices with responsibilities such as local aggregation, processing and analysis of IoT workload. The authors state the potential of significant performance and response improvements and analyse the minimum numbers of fog nodes needed to be able to cope with the IoT workload. The arrival process of incoming messages are considered to follow a Poisson process, and the superposition of all incoming streams is presented with an aggregate arrival rate λ similar to our study. The processing times of the edge computing nodes and virtual machines are considered to be independent and identically distributed with exponential random variables. M/M/1/K, M/M/1, and M/M/n/K queuing models are utilised to model the Edges Computing, Cloud Gateway, and Physical Servers respectively. Since the system considered does not have the transitions which expose the feedback property (forwarding the incoming requests back to the systems they were originated), and since the potential server failures are ignored; product form solutions (even Jackson networks solution) can be used for solving these models for steady state probabilities. Similar to our approach, the authors used simulation results for justification of analytical models and employed analytical solutions to specify key parameters which are essential for efficient working conditions such as the number of edge computing nodes needed for a specific configuration.

Duty cycling at the MAC layer is a common method used to reduce the energy consumption caused by idle listening in WSNs. Most studies on WSN protocols define a common duty cycle value throughout the network to achieve synchronisation among the nodes. In [10], authors presented an analytical model for WSNs with sleeping nodes and used it to evaluate the system performance in terms of average network capacity, data delivery delay and mean energy consumption. An evaluation method for packet buffer/queue capacity using queuing theory was proposed in [33]. Holding nodes which store the packets that did not receive timely services are used successfully for the evaluation of congestion in the queues. In another study [42], authors presented a stochastic model of WSNs capturing the behaviour of sensor nodes as they switch between sleep and active states. Furthermore, the model is used to evaluate energy consumed in various operative states. In a more recent study [9], authors proposed a novel framework enabling an adaptive duty cycling scheme for sensor networks that take into account the operating duty cycle of the node, and application-level QoS requirements. Using the Continuous Time Markov Chain (CTMC) model developed, they derived key QoS metrics including the loss probability, latency and average energy consumption; all of them as a function of the duty cycle. All these studies evaluating the systems from a pure performance point of view use a very strong assumption of perfect systems avoiding the availability and reliability concerns which in turn can cause serious overestimation.

Pure availability and reliability evaluation of WSNs have also remained as a hot research area in the past two decades. In order to improve dependability of WSN systems with high reliability requirements in failure prone environments, a Markov model for a fault-tolerant network is proposed in [25] and used to characterise WSN reliability and Mean Time to Failure (MTTF) for facilitation of application-specific designs. In another study [34], authors proposed a methodology based on automatic generation of fault tree for evaluating reliability and availability of WSNs for industrial applications when permanent faults occur on network devices. In [21], authors proposed a reliability model for analysing border effects and assurance of network connectivity in the presence of node failures and used it to analyse the trade-off between the number of sensors against communication distance in a network with high reliability requirement. A similar study on reliability and network lifetime based on MAC protocols and sleep/active scheduling mechanisms is proposed in [38]. As an advancement to the fault-tolerance presented in [25], authors in [26] incorporated models of fault detection and used the models to analyse both fault detection and fault tolerance in WSNs. In these studies which focus purely on availability, different levels of performance, and delays which are caused by various states in terms of availability are not considered.

In our previous studies, performability analysis of WSNs have been considered [30], [31]. However, the models presented are simpler than the extended models presented in this study. In [30], only the failed state and the fully active state of the system are considered, while in [31], node and channel failures are considered separately. In this work, these models are extended for analysing various options to switch into the sleeping mode in detail. Furthermore, unlike the existing studies, in this work, energy consumption behaviour is analysed together with the performability related measures; thus providing a complete behaviour analysis of a clustered WSN system.

In WSN based systems which are commonly used for IoT applications, the phenomena characterises the application interests in a manner that allows the applications to be oblivious to the underlying sensor network infrastructure and protocols. Considering the models that govern the generation of the application traffic, it is possible to classify sensor networks in terms of the data delivery required by the application of interest. These include continuous, event-driven, query-driven and hybrid data delivery models [20], [36]. Mixed opinions are presented in the literature on the appropriate packet inter-arrival distribution times for WSNs. Recent studies show that it is possible to use Poisson distribution for tractability reasons [10], [33], [36], [43], [44]. However other probabilistic distributions like Bernoulli, Log-normal and Gamma have also been mentioned in some areas. In [39], a comparison is presented for measured inter-arrival times and theoretical exponential distribution, and the results confirm that the exponential distribution closely model inter-arrival times except in low periodic traffic conditions.

The last part of this section considers the analytical modelling attempts for energy efficiency of WSN based systems. With regard to WSN energy conservation, three main approaches which aims at saving the limited sensor node energy are identified in the literature [3]. These include implementation of duty cycle sleep scheduling mechanisms in the MAC layer and routing protocols [2], data driven approaches that eliminate redundant information transmission thus reducing energy wastage, and lastly, the use of mobility approaches for collecting data from static nodes. Alteration of sleep/active operation has widely been used as indicated earlier. However, this brought with it many operating conditions, which in some areas has negatively affected the WSN performance. Energy saving in WSNs is therefore a trade-off to network performance, hence, modelling such networks require consideration of the desired application performance levels.

In order to address energy concerns in WSNs, the model presented in [10] is used to evaluate the trade-off between average delivery delay and average energy consumption for the network as a function of sleep/active transition rates. The main transition energy components are considered as transmitting, receiving, and wake-up. In a similar study presented in [42], a detailed stochastic model for evaluating node energy consumption in WSNs was presented. Using the model, explicit expressions are obtained for the stationery distribution of the number of data packets in various operative states. Average power consumed is considered for operations such as transmission in full and reduces active phases; transition from active to reduced mode; and from sleep to active state and vice versa. However, this study neither considers the power consumed while receiving data packets nor the power consumption in sleep mode. It is further indicated that their model fails to provide a standard stochastic renewal process given that the probabilities of being in sleep and active states are not satisfied by the proposed transition rates. Similar to other studies, the possibility of node failure and replacement/restoration are not taken into account in [42] as well. In a more recent study [9], a mechanism enabling sensor nodes to achieve energy neutrality at every node in a WSN by balancing energy supply and demands with the main objective of enabling network designers to trade-off between QoS requirements and the operating duty cycle is proposed. Conspicuously missing out in their energy evaluation is the average power consumed when receiving data packets, in addition to the analysis of effects caused by sleep scheduling schemes. Moreover, despite channel degradation being considered, there is no account for complete failures of both channel and sensor nodes during operations. In order to provide a realistic energy evaluation model for WSNs, there is a need to incorporate more detailed possible operating conditions for sensing nodes in addition to performance and availability requirements that may significantly influence energy expenditure for the sensing nodes and that of the overall sensing network. The following table summarises the studies considered on evaluation of IoT and WSN based infrastructures and shows the contribution of our approach.

Table 1: Comparison of the related work

	Evaluation Approach		**Evaluation Criteria**			
	Simulation	Analytical Modelling	Pure Performance	Pure Availability	Performability	Energy Modelling
[11], [14], [27], [33]	✓	X	✓	X	X	X
[28], [40]	✓	X	✓	X	X	✓
[22]	X	✓	✓	X	X	X
[10]	✓	X	X	X	X	✓
[42]	X	✓	✓	X	X	✓
[25], [26], [34]	X	✓	X	✓	X	X
[21]	✓	X	X	✓	X	X
[38]	X	✓	X	✓	X	✓
[9]	✓	✓	✓	X	X	✓
This study	✓	✓	✓	✓	✓	✓

3 System Description and Assumptions

3.1 System Description

In this study, the sensor network consists of M stationary, identical sensor nodes that are uniformly distributed over a unit radius and further grouped into K clusters each with a single coordinator defined as the cluster head (CH). In each cluster, the CH is assumed to be centrally located and directly reachable by all cluster nodes (member nodes) based on the IEEE802.15.4/ZigBee standards. All the nodes are assumed to be equipped with omni-directional antennas with the same communication radius (d). Apart from sleep schedules, the nodes are capable of choosing arbitrary transmission power levels within the available radius, d in order to conserve their limited energy. After waking up, nodes use CSMA/CA MAC protocol to contend for the available communication channel. On the other hand, the CH is the central link for communication between the member nodes and the sink either directly or through other intermediary CHs. In order to enhance reliability and availability of the network, the CH operation is rotated periodically among strategically deployed Full Function Nodes (FFN) which are deployed to establish disjoint paths between every sensor and/or relay node pair. The rotation takes place based on their energy levels and other metrics deemed appropriate [26]. We also assume the deployment of redundant sensor nodes that remain inactive until the need to replace a failing node arises [25]. In this study, we consider a cluster-tree network topology such that for every cluster, there is at least one connecting route to the sink. Depending on the application area, the data collected can be used as input to the larger ecosystem of the IoT. A network topology of the system under consideration in given in Figure 1.

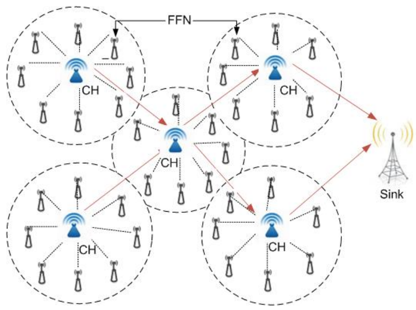


Fig. 1: Network topology of the reference system scenario

Information sensed and aggregated at the nodes is forwarded to the CH, which finalises the cluster data aggregation. The CHs may also generate data packets based on their observations. In order to contend with data streams, the CH is equipped with a finite length buffer modelled as a centralised First in First out (FIFO) queue. CH is responsible for forwarding the total information to the sink as explained earlier. Like other communication networks, this system is subject to channel and node failures resulting from errors in software configurations, system vulnerability attacks, hardware, and link degradation. We assume that renewable power sources (Solar Cells, Vibration approaches, and Thermoelectric generators) which are commonly used to recharge the batteries are employed to minimise failures caused by power depletion [24].

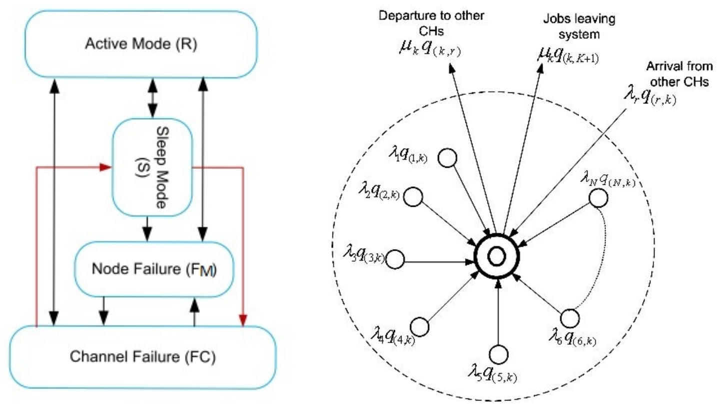
3.2 Sensor Node Behaviour

Sleep and active operations are widely used to conserve the limited energy resources in WSNs [3], [10], [26], [42]. The techniques used for the implementation of sleep scheduling in WSNs further complicates the operating conditions of the sensor nodes and the overall network. The two main sleep scheduling approaches used include adaptive duty-cycling schemes implemented at the MAC layer to adjust the sleep wake-up periods based upon the observed operating conditions [2], [3], [41]; and the on-demand wake-up scheduling implemented using a second low-power radio transceiver [18], [29]. The second low power transceiver is used to monitor the channel for packet arrivals when the main radio transceiver is switched off or in sleep mode.

In low traffic application areas, on-demand sleep scheduling scheme is preferred because of its ability to switch the node ON when a new packet arrives and allow the node to enter sleep mode automatically after servicing the last packet.

Based upon on-demand scheme and operation states highlighted, a system model is developed in this study for evaluating the system performability and mean energy consumption in various operative states. The model developed consider four main operative states: active, sleep, node failure, and channel failure. Figure 2a represents a block diagram illustrating the possible operative states and transitions between the states that a node would go through during its operations. While in sleep state, the node does not interact with the external world. It consumes the lowest power just to keep its circuitry in the wake-up mode. During this period, the low power radio transceiver will continue to monitor the channel for arriving data packets. The node is only woken up by the transceiver if the arriving packet is destined for it. Once woken up on arrival of a new packet, the node will continue to receive and serve incoming packets and only return to sleep state when there are no more packets in the system. Packet inter-arrival times at the CH and service times are assumed to be exponentially distributed with mean rates of $1/\mu$ and $1/\lambda$. The service discipline is $(FCFS)$. Since sensor nodes have finite queue capacity, any data packets arriving when the buffer is full are dropped.

During operation in either active or sleep state, the node or channel may fail as shown in Figure 2a. When a node fails, it is considered for repair/replacement immediately. As soon as repair/replacement is complete, the node is restored to normal operative conditions. In the case of a CH failure, the nodes re-enter the system as FFNs and will have to contend as fresh FFNs for future CH responsibilities. In case of channel failures, sensor nodes do not transmit or receive packets until normal channel operation resumes. Channel and node inter failure times are assumed to be exponentially distributed with rates $1/\zeta$ and $1/\xi$ respectively. When fault tolerant WSN models are considered, the time required for repairing the nodes, dealing with channel failures, or replacing a node with redundant ones in the field should be incorporated to the repair time similar to the studies in [21], [25], [26], [34]. The node and channel repair/restoration times are assumed to follow exponential distribution with means $1/\eta$ and $1/\theta$ respectively. The interruption policy is to resume service at the point of interruption or repeat with re-sample.



(a) CH phase transition diagram (b) Single CH Queueing Model

Fig. 2: Modelling abstractions for the system

In clustered WSNs, the total data arriving at the CH originate from within the cluster (internal sources) and externally from other CHs (external sources) forwarding their data to the sink. In this study, a maximum of 36 nodes inclusive of the CH are considered per cluster as recommended in the IEEE802.15.4/ Zigbee standards. Given the total arrival at the CH constitutes a relatively large number of independent Poisson streams, the resulting superposition of all the arriving data from both internal and external sources follow Poisson distribution [8] with rate λ_k, where k stands for the CH (node k). The following section discusses the system model including the WSN CH queuing model and further representation using two dimensional Markov model for the CH queue.

3.3 WSN Cluster Head Queuing Model

Figure 2b represents the proposed queuing model for a single CH. The queuing system considered has a single server with various operative states and limited queuing capacity (L). In a cluster, the CH is assumed to be directly connected to N sensing nodes within its communication radius (d). Each sensor node independently monitors its area and contends for channel availability to relay the packets to the CH. Since the CH has limited queue capacity, the packets arriving when the queue is full are dropped and assumed lost. Once processed at the CH, the packets leave the queuing system and are forwarded to the sink directly or through an intermediary CH (node r). At node r, the procedure is the same until the packet reach the sink.

From Figure 2b, letting k represent the CH, jobs leaving node k are rerouted to node r with probability $q_{k,r}$ for service at node r. If jobs are not routed $q_{k,r} = 0$. It is assumed without loss of generality that as far as the queue length distributions are concerned $q_{k,k} = 0, (k = 1, 2, \ldots, K)$. Also, the exit probability from the system after a job is serviced at node k is $1 - \sum_{r=1}^{K} q_{k,r}$. The exit probability is assumed to be non-zero for at least one value of k. Q is the routing probability matrix of size $K \times K$, such that, $Q_{k,r} = q_{k,r}; (1 \leq k, r \leq K)$. To analyse the performability of this system, steady state conditions are considered. The total arrival rate (λ_k) at CH node k can be computed as the sum of external and internal traffic rates.

$$\lambda_k = \sum_{n=0}^{N} \lambda_n q_{n,k} + \sum_{r=1}^{K} \lambda_r q_{r,k}; \qquad k = 1, 2, \ldots, K \tag{1}$$

The first term of the summation (let's say σ_k) represents the sum of all internal arrivals within the cluster while the second term is for the sum of arrivals from other cluster heads. In order to define the total arrival rates for each node, the row vectors $\lambda = (\lambda_0, \lambda_1, \lambda_2, \ldots, \lambda_N)$ and $\sigma = (\sigma_0, \sigma_1, \sigma_2, \ldots, \sigma_N)$ can be used. For steady state analysis of these systems, we need to make sure that $\hat{\mu}_k > \lambda_{k,e}, k = 0, 1, 2, \ldots K$ where $\hat{\mu}_k$, and $\lambda_{k,e}$, are the effective service and arrival rates respectively.

3.4 Two Dimensional Markov Representation of the Cluster Head Queue Model

Figure 3 presents the proposed performability model capturing various operative states of the CH. The vertical dimension (j) represents the number of requests in the system and the horizontal dimension (i) represent the system's operative states. Sleep (S_{LP}), active (R), node failure (F_M), and channel failure (F_C) are the different operative states considered for the proposed system model. Sleep state (S_{LP}) can only be entered at the end of service for the last job in the system with rate μ or when the system is restored from either node or channel failures with rates η and θ respectively. During normal operation in active state (R), the duration for which a sensor node can stay in sleep state is assumed to be exponentially distributed with a mean of $1/\lambda$. Data packets can be received and serviced as illustrated in Figure 3. Packet arrivals are assumed to follow Poisson distribution with rate λ, while packet service times are assumed to be distributed exponentially with rate μ.

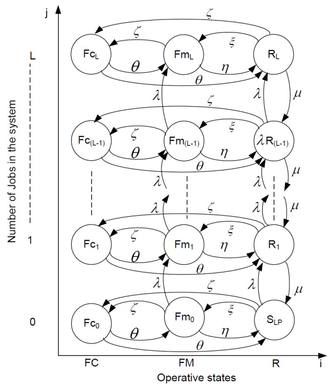


Fig. 3: Performability model

In either active or sleep state, a sensor node may fail. The time between sensor node failures is distributed exponentially with rate $1/\xi$. Channel failures may occur either when operating in phase R, or when the node is down. The time between channel failures is assumed to be exponentially distributed with rate $1/\zeta$. The duration taken to restore a channel after failure is assumed exponentially distributed with a mean of $1/\theta$. From the diagram, the system may reach either state F_{c_L}, F_{m_L} or R_L when the CH buffer is full. As highlighted earlier, data packets will continue to arrive in phase F_M as long as there is some space in the buffer.

Using a pair of integer valued random variables $I(t)$ and $J(t)$ to specify CH operative states and the number of packets in the system respectively, it is possible to describe the system state at time t. In this case, $I(t)$ represents operative states including active, node failure, and channel failure determined by lateral transitions in the lattice strip. On the other hand, $J(t)$ is determined by vertical transitions resulting from arrival or departure of packets. The irreducible Markov process on a lattice strip (a Quasi Birth Death (QBD) process) that models the system can therefore be described by $X = [I(t), J(t); t \geq 0]$. The state space of this process is (0, 1, . . . , N) × (0, 1, . . . , L). The steady state probabilities of this Markov process can be defined as $P_{i,j}$ with i and j representing the system operative state and the number of packets in the system including the one in service. From Figure 3, the possible transitions in the process X are defined in terms of λ, μ, η, ξ, θ and ζ. The next section discusses the two possible solution approaches employed and calculate the steady-state probabilities of this system.

4 Solution Approaches for the Proposed Model

It is essential to numerically analyse the proposed system model and thus, two solution approaches namely, Spectral Expansion and System of Simultaneous Linear Equations are used in order to calculate the steady state probabilities of the system model presented in figure 3. The results obtained are further validated by an event-driven simulation program written in `C++`.

4.1 Spectral Expansion Solution Approach

Spectral Expansion is a well-known exact solution method for steady state analysis of two-dimensional Markov processes in semi-infinite or finite lattice strips. It has successfully been used to solve performance and dependability problems arising in computing and communication systems [8], [13], [37]. A detailed study of spectral expansion technique can be found in [7], [13]. In this approach, transition matrices A, A_j, B, B_j, C, and C_j are derived from the performability model presented in figure 3 and used to solve the two-dimensional Markov process X which evolves with the following transitions:

A_j: Purely lateral transition rates, from state (i, j) to state (k, j), $(i \neq k;)$, caused by a change in the operative state (i.e., a change in random variable $I(t)$ reflecting a change in operative states).

Note that ξ and ζ are used here to indicate transition rates resulting from node and channel failures respectively. Similarly, θ and η represent channel restoration and node repair rates respectively.

B_j: One-step upward transition rates, from state (i, j) to state $(k, j + 1)$, caused by packet arrival in the queue.

C_j: One-step downward transition rate, from state (i, j) to state $(k, j - 1)$, caused by a departure of a serviced job, in this case, jobs forwarded from the CH to the sink.Hence,

$$A = A_j = \begin{bmatrix} 0 & \theta_1 & \theta \\ \zeta & 0 & \eta \\ \zeta & \xi & 0 \end{bmatrix}, \; B = B_j = \begin{bmatrix} 0 & 0 & 0 \\ 0 & \lambda & 0 \\ 0 & 0 & \lambda \end{bmatrix}, \text{ and } C = C_j = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & \mu \end{bmatrix}$$

For all A_j, B_j and C_j, the range for i, j and k are $(i = 0, 1, \ldots, N; \quad k = 0, 1, \ldots, N;$ and $j = 0, 1, \ldots, L)$. The transition rate matrices do not depend on j for $j \geq M$, where M is a threshold having an integer value [7], [8]. For the system considered here, M is the number of servers available in the CH which is one. The matrices A, B and C above are of size 3×3. A_j, B_j and C_j matrices represent system state when $j < M$. With state transition matrices established, spectral expansion solution technique is used to derive steady state probabilities for the system using equation 2.

$$P_{i,j} = \lim_{t \to \infty} P(I(t) = i, \quad J(t) = j); \quad 0 \leq i \leq N, \quad 0 \leq j \leq L \tag{2}$$

where N and L represent the number of operative states and a finite queue capacity respectively.

Let us define certain diagonal matrices D_J^A, D_J^B, D_J^C, D^A, D^B, and D^C of size $(N + 1) \times (N + 1)$ as follows:

$$D_J^A(i,i) = \sum_{k=0}^{N} A_j(i,k); \quad D^A(i,i) = \sum_{k=0}^{N} A(i,k);$$

$$D_J^B(i,i) = \sum_{k=0}^{N} B_j(i,k); \quad D^B(i,i) = \sum_{k=0}^{N} B(i,k);$$

$$D_J^C(i,i) = \sum_{k=0}^{N} C_j(i,k); \quad D^C(i,i) = \sum_{k=0}^{N} C(i,k);$$

and also introduce new matrices Q_0, Q_1 and Q_2 as: $Q_0 = B, Q_1 = A - D^A - D^B - D^C$, and $Q_2 = C$. From the Markov process X, all the state probabilities in a row can be defined using equation 3 from where the balance equations [4 - 7] are obtained.

$$v_j = (P_{0,j}, P_{1,j}, \ldots, P_{N,j}); \quad 0 \le j \le L \tag{3}$$

$$v_0[D_0^A + D_0^B] = v_0 A_0 + v_1 C_1 \tag{4}$$

$$v_j[D_j^A + D_j^B + D_j^C] = v_{j-1}B_{j-1} + v_j A_j + v_{j+1}C_{j+1}; \quad 1 \le j \le M-1 \tag{5}$$

$$v_j[D^A + D^B + D^C] = v_{j-1}B + v_j A + v_{j+1}C; \quad M \le j \le L \tag{6}$$

$$v_L[D^A + D^C] = v_{L-1}B + v_L A \tag{7}$$

The normalisation equation is given as:

$$\sum_{j=0}^{L} v_j e = \sum_{j=0}^{L}\sum_{i=0}^{N} P_{i,j} = 1 \tag{8}$$

where e is the column vector of L elements each of which sums up to 1. From Equation 6 we obtain equation 9 as:

$$v_j Q_0 + v_{j+1}Q_1 + v_{j+2}Q_2 = 0; \quad (M-1) \le (L-2) \tag{9}$$

and the characteristic matrix polynomials [7], [13] can be expressed as given in Equation 10.

$$Q(\lambda) = Q_0 + Q_1\lambda + Q_2\lambda^2; \quad \bar{Q}(\beta) = Q_2 + Q_1\beta + Q_0\beta^2 \tag{10}$$

where: $\psi Q(\lambda) = 0; \quad |Q(\lambda)| = 0; \quad \phi\bar{Q}(\beta) = 0; \quad |\bar{Q}(\beta)| = 0$; Here (λ, ψ) is the eigenvalue, left-eigenvector pair of $Q(\lambda)$, (β, ϕ) is the eigenvalue, left-eigenvector pair of $\bar{Q}(\beta)$ respectively. Furthermore,

$$v_j = \sum_{k=0}^{N}(a_k\psi_k\lambda_k^{j-M+1} + b_k\phi_k\beta_k^{L-j}); \quad M-1 \le j \le L \tag{11}$$

In state probability form equation 11 becomes:

$$P_{i,j} = \sum_{k=0}^{N}(a_k\psi_k\lambda_k^{j-M+1} + b_k\phi_k\beta_k^{L-j}); \quad M-1 \le j \le L \tag{12}$$

Here $\lambda_k(k = 0, 1, \ldots, N)$ and $\beta_k(k = 0, 1, \ldots, N)$ are $N+1$ eigenvalues each, that are strictly inside the unit circle [7], [13], and $a_k(k = 0, 1, 2, \ldots, N)$ and $b_k(k = 0, 1, 2, \ldots, N)$ are arbitrary constants which can be scalar or complex conjugate. v_j vectors can be obtained using the process explained in [7]. From the state probabilities $(P_{i,j})$, desired steady state performance, availability, and performability measures can be computed.

Table 2: Transition Matrix A

$$\begin{array}{c}
\begin{array}{ccccccccccccc}
F_{c0} & F_{m0} & R_0 & F_{c1} & F_{m1} & R_1 & \dots & F_{c(L-1)} & F_{m(L-1)} & R_{(L-1)} & F_{cL} & F_{mL} & R_L
\end{array} \\
\begin{pmatrix}
(\theta_1+\theta) & -\zeta & -\zeta & 0 & 0 & 0 & \dots & 0 & 0 & 0 & 0 & 0 & 0 \\
-\theta_1 & (\zeta+\eta+\lambda) & -\xi & 0 & 0 & 0 & \dots & 0 & 0 & 0 & 0 & 0 & 0 \\
-\theta & -\eta & (\eta+\xi+\lambda) & 0 & 0 & -\mu & \dots & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & (\theta_1+\theta) & -\zeta & -\zeta & \dots & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & -\lambda & 0 & -\theta_1 & (\zeta+\eta+\lambda) & -\xi & \dots & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & -\lambda & -\theta & -\eta & (\zeta+\xi+\lambda+\mu) & \dots & 0 & 0 & 0 & 0 & 0 & 0 \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \vdots \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \dots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots \\
0 & 0 & 0 & 0 & 0 & 0 & \dots & (\theta_1+\theta) & -\zeta & -\zeta & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & \dots & -\theta_1 & (\zeta+\eta+\lambda) & -\xi & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & \dots & -\theta & -\eta & (\zeta+\xi+\lambda+\mu) & 0 & 0 & -\mu \\
0 & & 0 & 0 & 0 & 0 & \dots & 0 & 0 & 0 & (\theta_1+\theta) & -\zeta & -\zeta \\
0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 & -\lambda & 0 & -\theta_1 & (\zeta+\eta) & -\xi \\
0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 & 0 & -\lambda & -\theta & -\eta & (\zeta+\xi+\mu) \\
1 & 1 & 1 & 1 & 1 & 1 & \dots & 1 & 1 & 1 & 1 & 1 & 1
\end{pmatrix}
\end{array}$$

Vector "b" is an ((L+1) x 1) given by: $b = (0, 0, 0, 0, 0, 0, \dots, 0, 0, 0, 0, 0, 0, 1)$ and Vector "x" for the unknowns is a (3L x 1) and is given by:
$x = (F_{co}, F_{Fm}, R_0, F_{c1}, F_{Fm1}, R_1, F_{c2}, F_{Fm2}, R_2, \dots, F_{c(L-2)}, F_{Fm(L-2)}, R_{(L-2)}, F_{c(L-1)}, F_{Fm(L-1)}, R_{(L-1)}, F_{cL}, F_{FmL}, R_L)$

4.2 System of Simultaneous Linear Equations

A set of Kolmogorov linear equations are derived at steady state using Equation 13. Assuming the system is in state (i), then events causing transition into state j occur with rate $g_{i,j}$.

$$P_i \sum_{i \neq j} g_{i,j} = \sum_{i \neq j} P_j g_{j,i}; \quad i, j \epsilon S \tag{13}$$

Letting G be the generator matrix of a continuous-time Markov chain with state space S, the steady-state probabilities can be defined in terms of G and the state probability vector $P = lim_{t \to \infty} P_{i,j}(t)$ [23]. As $t \longrightarrow \infty$, the Kolmogorov forward equation becomes $PG = 0$. When steady state analysis is performed where the behaviour of the process does not change in time, in stochastic systems, the probabilities that various states will be repeated will remain constant. The steady state probabilities can then be defined as; $P = (P_0, P_1, \dots, P_N)$.

Taking a visual balance equation from the performability model of Figure 3, a set of equations are obtained and used to determine the elements of the state transition rate matrix G and the unknown state probability vector P for the system model [23]. The resulting mathematical expressions take the form of standard linear simultaneous equations "$Ax = b$" where A becomes the state transition rate matrix G, x is the unknown probability vector P and vector b is the resulting product of matrix G and vector P. The elements of A, x, and b are given in Table 2. In order to obtain limiting state probabilities, the resulting set of equations together with the normalisation equation $\sum_{i \epsilon S} P_i = 1$, are solved with the aid of `MATLAB` routines for computing large sparse finite-element matrices.

Similar to the spectral solution approach, the obtained state probabilities $P_{i,j}$ can be used to compute the desired steady state measures like availability, reliability, and performance.

4.3 Computation of Performability Measures

Using state probabilities obtained, it is possible to compute various performability measures.

It is possible to formulate analytical expressions for computing blocking probability P_B, effective arrival rate λ_{ke}, and the rate at which jobs are lost λ_{kl} due to blocking as presented in Equations 14, 15, and 16.

$$P_B = \sum_{i=0}^{N} P_{i,L} \tag{14}$$

$$\lambda_{ke} = \lambda_k (1 - P_B) \tag{15}$$

$$\lambda_{kl} = \lambda_k P_B \tag{16}$$

The Mean Queue Length (MQL) can be expressed as:

$$MQL = \sum_{j=0}^{L} j \sum_{i=0}^{N} P_{i,j}; \quad i \leq 0; \quad j = 0, 1, 2, \dots, L. \tag{17}$$

$$\gamma = \mu \sum_{j=1}^{L} P_{i,j}; \quad i = 2; \quad j = 0, 1, 2, \dots, L. \tag{18}$$

Considering that service is only possible when the system is in the active state, throughput (γ) can be expressed using Equation 18. Here, the computation holds only when the system is operating in state R of Figure 3 represented by $i = 2$. Once the MQL and throughput are established, the system response time R_T and utilisation u can be computed using Equations 19 and 20 respectively.

$$R_T = MQL/\gamma \tag{19}$$

$$u = 1 - \sum_{i=0}^{N} P_{i,0} \tag{20}$$

Here $P_{i,0}$ is the probability of having no jobs in any of the system's operative state.

4.4 Operative State Analysis

Using appropriate solution approaches for steady state probabilities, studies such as [11], [12] consider complex communication systems for the analysis of performance and availability measures. In the case of WSNs, use of state probabilities is significant in establishing the time the systems spend in various states for performance optimisation and energy conservation. In addition, the approach may also be used to evaluate the performance of various WSN protocols in terms of performance and energy saving. In comparison to similar studies for WSNs, our work provides a more detailed analysis of steady state probabilities thereby enabling a detailed evaluation and analysis of desired system performance and energy saving. Table 3 presents a detailed summary of the system state probabilities considered.

Table 3: Summary of operative state probabilities

State Probability	Measurable Process
Blocking Probability (P_B)	Ratio of jobs lost during operation, Depends on queue capacity & traffic load hence a measure of system performance
Sleeping Probability (P_{SLP})	Measure of time period the system stays in sleep mode to save power
Node Failure Probability (P_{FM})	Measure of Node down time, Has direct effect on system performance and availability
Channel Failure Probability -(P_{FC})	Measure of channel down time, Has direct effect on system performance and availability
Probability of being in any state without jobs ($P_{i,0}$)	Measure of time the system stays empty in either active or any of the failed states, Forms a component of wasted energy
Probability node failing when system empty ($P_{FM,0}$)	Measure of node failure period when system is empty
Probability of the channel failing when system empty-($P_{FC,0}$)s	Measure of channel failure period when system is empty

The probability of the system being in the sleep state (P_{SLP}) is computed using Equation 21.

$$P_{SLP} = 1 - (\sum_{j=1}^{L}\sum_{i=0}^{N} P_{i,j} + P_{FM,0} + P_{FC,0}) \tag{21}$$

Here, $P_{FM,0}$ and $P_{FC,0}$ represent the probability of the CH and channel failures when the system is empty respectively. Since the CH may fail in any state during operations, Equations 22 - 24 are used to compute CH failure in various states.

$$P_{FM} = \sum_{j=0}^{L} P_{i,j}; \quad i = 1; \quad j = 0, 1, 2, \dots, L. \tag{22}$$

$$P_{FM,j} = \sum_{j=1}^{L} P_{i,j}; \quad i = 1; \quad j = 1, 2, \dots, L. \tag{23}$$

Since the CH is in failed state FM represented for $i = 1$.

$$P_{FM,0} = 1 - (\sum_{j=1}^{L}\sum_{i=0}^{N} P_{i,j} + P_{SLP0} + P_{FC0}); \quad 0 \le i \le N; \quad 1 \le j \le L. \tag{24}$$

$P_{FM,0}, P_{FC,0}$, and P_{FM} remain as introduced in the previous sections. $P_{FM,j}$ and $P_{SLP,0}$ represent the probabilities of the node failing with jobs in the system and the node being in sleep state respectively. Similarly, the probability of channel failure during operation may be given using Equations 25 - 27.

$$P_{FC} = \sum_{j=0}^{L} P_{i,j}; \quad i = 0; \quad j = 0, 1, 2, \dots, L. \tag{25}$$

$$P_{FC,j} = \sum_{j=1}^{L} P_{i,j}; \quad i = 0; \; j = 1, 2, \ldots, L. \tag{26}$$

Equations 25 and 26 will hold only during channel failure state FC represented by $i = 0$.

$$P_{FC,0} = 1 - (\sum_{j=1}^{L}\sum_{i=0}^{N} P_{i,j} + P_{SLP0} + P_{FM0}); \; 0 \le i \le N; \quad 1 \le j \le L. \tag{27}$$

In Equation 27, $P_{FC,j}$ is the probability of channel failure for the cases where there are jobs in the system.

5 Performance Evaluation of the Proposed Model

In this section, we present numerical results for the proposed niche performability model. The numerical results comparison is achieved using two solution approaches - Spectral Expansion Exact Solution Technique and the System of Simultaneous Linear Equations as discussed in Section 4. The results obtained through the analytical models are further compared with the results obtained from discrete-event simulation similar to the studies in [6], [8], [11], and [12]. The discrete event simulation framework used is similar to the ones described in [8], [12], [30] and [32]. It is observed that the numerical and simulation results are in good agreement with a discrepancy of less than 0.1%.

5.1 Key Parameters

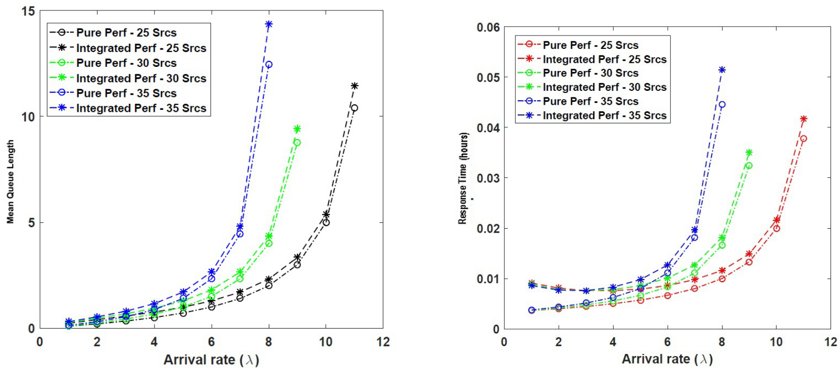
For optimal CH operations, 25 to 35 nodes were used for the experiments, just below the maximum 36 recommended by IEEE802.15.4/ZigBee standard. Arrival rates ranging from 1 packet/second to 20 packets/hour have been considered as in [9], [33], [44]. In order to choose the packet arrival rate at say k^{th} CH, we consider N source nodes including the members of the k^{th} cluster, the CH itself and other CHs; all together with a maximum of 36 nodes from within a cluster and a small number of other CHs. Each node contributes a packet at a mean rate of λ ranging from $1 - 20$ packets/hour. With N source nodes (cluster members and CHs of some other clusters) transmitting, the total arrival rate at the CH of the k^{th} cluster can be calculated using the equation 1. Assuming an event-driven arrival process, alongside various values of λ the service rate of the k^{th} CH, μ_k is chosen to have a value for stability even at large queuing capacities. In order to identify optimum operation, we used queue capacities of $L = 10, 30, 50$ and 100.

In this study, all sensors are assumed to use the CC2420 radio transceiver and are attached with a $2 \times AA$ batteries of $2.7 - 3.3$ volts capable of continuous operations for 3.25 days. In addition, good availability mechanisms like use of backup CHs and solar charging systems [25] are assumed, hence failures resulting from battery depletion are not considered. A failure rate of $\xi = 0.001$ per hour, and a repair rate of $\eta = 0.5$ per hour are considered. The chosen value is consistent with repair rates of $0.04 - 0.1$ used in previous studies [34].

Unwanted electromagnetic signals like noise and interference are common to communication channels and have a random nature. Physical obstructions may also give rise to the corruption of signals, which may be reduced by good planning during deployment. However, the main contributor remains environmental factors which depend heavily on the deployment location of the sensor networks. All these may occasionally cause channel failures. In consideration of channel failures and recovery, $\zeta = 0.001$ and $\theta = 0.6$ are used for failure and recovery rates respectively. The parameter values given in this section are maintained in the analysis except where stated otherwise.

5.2 Results and Discussions

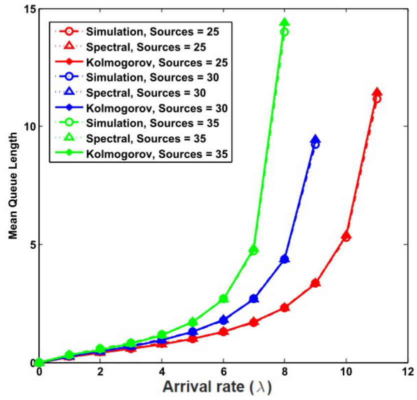
The results presented in this section are for various number of nodes and transmitting at different arrival rates. The number of sources in each cluster represents the number of nodes contributing to the traffic with arrival rate λ. In other words, the system becomes more congested as number of sources and/or λ increases. Since it is desirable to present results in comparison to pure performance, the number of sources are pushed as much as possible to ensure that the system is in steady state (total amount of arrival should be less than effective number of services). Following this, since we are expecting large volume of arrivals from these sources, the queue capacity is taken as $L = 100$. Please note that the models presented are flexible and can incorporate various parameter values. Results presented in Figures 4a and 4b show that, differences between the pure performance and performability models are greater for lower arrival rates exceeding 60% for $\lambda = 1$ while it is less than 8% for $\lambda = 10$. This is mainly due to the fact that for highly congested systems the queuing capacity becomes the main limiting factor rather than the service capacity. Since in most WSN environments event occurrences are characterised by low arrival rates, pure performance models can cause serious overestimations. In the Figures 4a and 4b, the legend "Pure Perf", stands for systems considering pure performance while "Integrated Perf" is for systems with combined performance and availability.



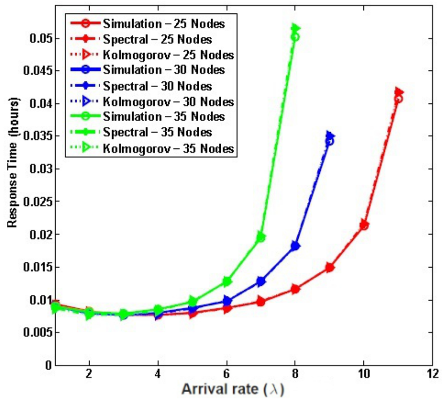
(a) Comparison of MQL (b) Comparison of response time

Fig. 4: Impact of Failures on System Performance

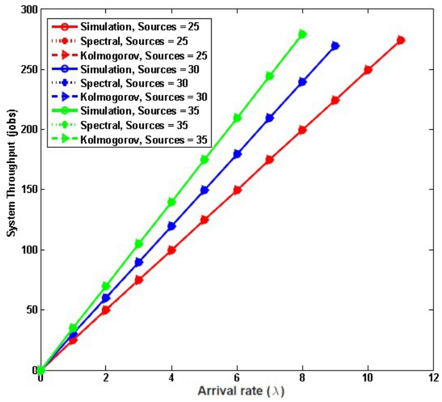
In order to evaluate the proposed WSN system model, a number of experiments are conducted for various performance measures. The first set of experiments are performed to observe how the system is affected by different mean arrival rates. For this set of experiments, arrival rates are varied from $1 - 12$ packets/hour with a fixed buffer length of $L = 100$. The system performance is measured and analysed in terms of MQL, response time and throughput. A constant number of member sensor nodes of 25, 30, or 35 are maintained throughout. The obtained results are then analysed in terms of MQL, response time and throughput as shown in Figures 5a, 5b, and 5c respectively. In these figures, results are presented using three different approaches which are systems of simultaneous equations (Kolmogorov), spectral expansion, and simulation. The system of simultaneous equations is known to suffer when the number of packets that can be accepted (vertical direction of the lattice) by the system is large, since this would increase the number of simultaneous equations and unknowns. Spectral expansion solution on the other hand, can cope with very large numbers of packets, but can suffer in case the number of operative states (horizontal direction of the lattice) are extensive. Results presented show that the two analytical approaches and simulation are all in very good agreement. When the system is lightly loaded, both MQL and response time are low as expected. However, this changes as the load is increased gradually with systems having more sources (35) becoming saturated earlier compared to those with fewer sources (25). On the contrary, throughput remains the same in all the three cases. This is because the queue capacity is large ($L = 100$), hence all packets received at the CH are processed. These set of results are significant for planning WSN coverage during deployment to ensure optimal performance. In Figure 6, minimal blocking is observed when a larger queue capacity is used as opposed to higher blocking observed at lower queue capacity. In order to obtain optimal operation levels, it is therefore necessary to compromise the traffic load against the available queue capacity. The choice of queue capacity is a compromise of the desired QoS in relation to throughput, response time and MQL.



(a) MQL vs Arrival Rate



(b) Response Time vs Arrival Rate



(c) Throughput vs Arrival Rate

Fig. 5: Impact of Arrival Rate on System Performance

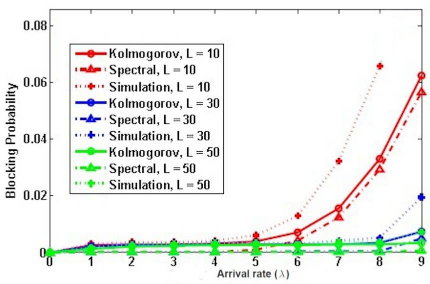
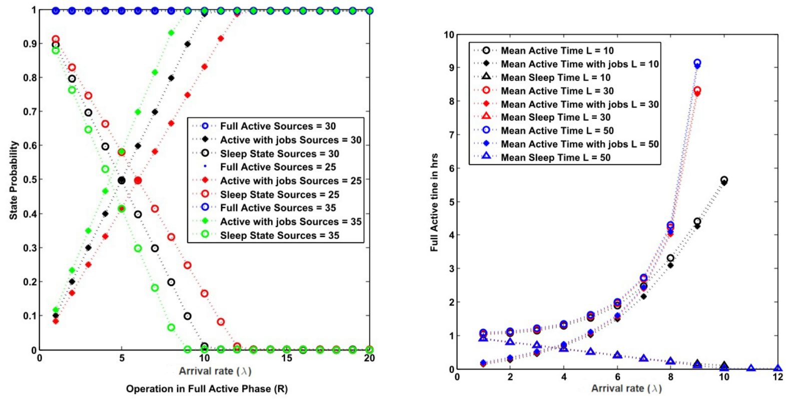


Fig. 6: Blocking Probability vs Arrival Rate

In figure 7, we analyse CH operations in full active phase R. While in this phase, the CH can either be active receiving and processing jobs or entering into sleep state whenever the system becomes empty. Figure 7a presents probabilities of operating in active states with various number of sources as the traffic load is varied. The probability of the system being in any of the possible three states; fully active, active with jobs, and sleep are observed. As expected, the node stays in sleep mode mostly when the traffic load is low. When some level of traffic load is reached, the probability of being in active state remains nearly the same at the highest value while that of sleep state remains nearly the same at the lowest value. The overall probability of being in active state is the sum of the probabilities of being active with jobs, and sleeping. Figure 7b on the other hand presents the mean times the system spends on full active, active with jobs, and sleep states. Higher traffic loads cause increases in the mean time the data packets spend in the system, thereby reducing mean sleep time and increasing energy consumption. It is also observed that larger queue sizes increase the mean time the data packets spend in the system. From the above investigation, it is possible to establish boundaries for controlling sleeping schedules in order to further conserve the limited node energy by reducing the amount of energy spent for frequent wake-up during high traffic load. In order to understand the efficacy of the proposed system model with analytical modelling, the next section discusses a case study of energy modelling and evaluation for the CH; where the proposed system model is directly applied in order to calculate the overall energy consumption of the system.



(a) Active States with Various Number of Sources

(b) Active States with Various Queue Lengths

Fig. 7: Effect of Number of Sources and Queue Lengths on the Change of Operation States at Different Traffic Loads

6 Cluster Head Energy Modelling and Evaluation

In this section, we present an analytical modelling approach for comparing the mean energy consumption in the various sensor node operative states and employ the proposed analytical models to evaluate the overall energy consumption of the CH. The analytical models presented in this study are able to work with various energy consumption models. In this study, well known models presented in [15], [16], [18] and [29] are used. In order to model energy consumption of a WSN node, the possible power consumption states are identified and defined. Please note that when a sensor is in sleep mode, the time needed for the node to be functional (i.e. connect to the network, pass the default authentication when the security aspects are considered etc.) can be easily incorporated into the energy models similar to the studies in [18] and [29]. In the energy models presented below, β is used for the time required to return from sleep to active mode. The models presented are flexible enough to use the time required according to the system dependent characteristics. We consider the Markov model for the CH presented in Figure 3. Using the model, we identify possible energy transition events from various states. In order to compute the energy spent in different operative states, steady state probabilities are considered together with the state transition energy into and out of the possible states.

6.1 Energy Consumption Modeling

In order to model the energy consumption for the system, it is essential to understand where exactly the energy is being spent within a WSN system. This section provides a breakdown of the energy consumption in different phases of the operation of a WSN.

6.1.1 Transmission Energy

Transmission energy is the energy spent when transmitting data packets from a given state $X(t) = [I(t), J(t)]$ at time t and can be calculated by the probability of being in state $(i, j) \times$ service rate (transmission) $(\mu) \times$ energy required to transmit one data packet. Letting $E_{t(i,j)} =$ Energy spent for the transition from state (i, j) to state $(i, j-1)$ caused by the transmission of one packet, then $E_{t(i,j)}$ can be computed using equation 28 where $P_{i,j}$ is the probability of being in state (i, j) at time t, μ is the data packet service rate and e_{tx} is the energy required to transmit one data packet.

$$E_{t(i,j)} = P_{i,j} \times \mu \times e_{tx} \quad \text{Joules} \tag{28}$$

The parameter e_{tx} is specified by the type of the WSN node, the communication protocol used, and the chosen connectivity. These parameters are taken from well-known studies [15] and [16]. $1/\mu$ on the other hand specifies the time needed to serve one packet. This parameter is highly dependent on the type and length of the packet (payload). Failure and repair related parameters are mainly taken from reliability related literature [21], [25], [26], [34].

In the case of a single server system, the mean energy required to transmit data packets (E_{tx}), from a state may therefore be given as in Equation 29.

$$E_{tx} = \sum P_{i,j} \times \mu \times e_{tx} \quad \text{Joules} \tag{29}$$

Assuming a multi sever system with k parallel servers, a maximum number of jobs equivalent to k can be serviced at a time if all the servers are operational. The formula for mean energy given in Equation 29 then changes to Equation 30.

$$E_{tx} = \sum min(j, k) \times P_{i,j} \times \mu \times e_{tx} \quad \text{Joules} \tag{30}$$

where k and j are the number of servers and jobs in the system respectively. Here the minimum of j and k becomes the number of jobs in service at any given time.

6.1.2 Receiving Energy

This is the energy consumed by the transceiver electronics when receiving a data packet. Since the node can only receive one data packet at a time, the energy required to receive a data packet in a given state (i, j) at time t may be given by multiplying the state probability by packet arrival rate and energy consumed receiving one data packet. Letting $E_{r(i,j)}$ be energy spent receiving data packets from (i, j) at time t, then

$$E_{r(i,j)} = P_{i,j} \times \lambda \times e_{rx} \quad \text{Joules} \tag{31}$$

where $P_{i,j}$ is the probability of being in state (i, j) at time t, λ is the packet arrival rate and e_{rx} is the energy required to receive one data packet. The mean energy required to receive data packets (E_{rx}) when in receiving state may therefore be computed using Equation 32.

$$E_{rx} = \sum P_{i,j} \times \lambda \times e_{rx} \quad \text{Joules} \tag{32}$$

Here, the energy consumption per packet received e_{rx} is also taken from [15] and [16].

6.1.3 Wake-Up Energy

This is the energy required to transit from sleep state into full active state (E_{UP}) at the arrival of a new job. This may be divided into two parts: the first part constitutes energy required to wake-up the node to be able to receive an incoming data packet and the second part constitutes the energy required to receive the first job from sleep state. The mean energy required to wake-up the sensor node and receive the first data packet may therefore be computed using equation 33. The required parameters are taken from [15], [16] and [18].

$$E_{UP} = \sum_{i=2,j=0} P_{i,j}(\lambda \times e_{rx} + e_{up}) \quad \text{Joules} \tag{33}$$

Equation 33 will hold only when the CH is operating in state R represented by $i = 2$.

From [18], the power required to switch the radio from sleep back to active period is computed using equation 34.

$$e_{up} = \frac{(I_{active} - I_{sleep}) \times \beta \times V}{2} \tag{34}$$

where β accounts for the time required returning to active mode and the factor 2 accounts for switching back to sleep mode from active mode. I_{active} and I_{sleep} are currents drawn in active and sleep modes respectively.

6.1.4 Sleep State Energy

While in sleep mode, several transceivers offer different energy levels [29], the transceivers differ in the number of circuitry switched off and in the associated recovery times and start-up energy. An example is the case of a complete shut down of the transceiver where the starting energy have to include initialisation and configuration of the radio as opposed to light sleep mode requiring restarting of a little circuitry since operations and configurations are maintained. The parameters used for computation of wake-up energy are taken from [15], [16] and [29]. The mean sleep energy can be computed using equation 35.

$$E_{SP} = \sum_{i=2,j=0} P_{i,j} \times e_{sl} \times t_{sl} \quad \text{Joules} \tag{35}$$

where e_{sl} and t_{sl} are consumed power and time taken in sleep state respectively. Equation 35 holds when the CH enters sleep state E_{SP} after serving all jobs. This can be represented by $i = 2$ for states and $j = 0$ for empty queue as shown in Figure 3.

6.1.5 Idle State Energy

In some cases, the nodes may be idle waiting for packet arrival in situations where sleep mechanism is not implemented or where sleep scheduling is achieved through other MAC protocols, e.g. using adaptive sleep schedule MAC protocols [44]. In such cases, the sleep state in figure 3 is replaced with idle state. The energy spent is mainly dependent on circuitry which can be found in [15] and [16]. Since idle state energy contributes to the overall energy consumption significantly relative to the time spent in the state, the mean idling energy may be computed using equation 36. This equation holds only when the system becomes empty ($j = 0$) while operating in phase R represented by $i = 2$.

$$E_{ID} = \sum_{i=2,j=0} P_{i,j} \times e_{id} \times t_{id} \quad \text{Joules} \tag{36}$$

where e_{id} and t_{id} are consumed power and time taken in idling state respectively.

6.1.6 Node Failed State Energy

In the event of node failure, the node is assumed to continue receiving data packets as long as the buffer is not full hence incurring some energy costs. In addition, restarting a node may require energy. The resulting energy spent in this state therefore comprises receiving and rebooting energy and its mean may be computed using equation 37, which holds only when the CH fails ($i = 1$).

$$E_{FM} = \sum_{i=1,j=0}^{j=L} P_{i,j}(\eta e_{nrb} + \lambda e_{Rx}) \quad \text{Joules} \tag{37}$$

where η and e_{nrb} are node repair rate and the subsequent energy spent rebooting the node after repair.

6.1.7 Channel Failed State Energy

Since no packet transfer is possible during channel failure, nodes without data packets will enter sleep mode. However, the nodes with packets will remain in the ON-state waiting to start transmission as soon as the channel becomes available. Energy is therefore consumed for maintaining the nodes in waiting state while holding the data packets in the queue until the channel is restored after which, they will resume forwarding the packets to the sink. The energy consumed is therefore same to idling energy given in equation 36.

6.2 Case-Study Model for Energy Consumption

In this section, using energy computations given in section 6.1, specific mean energy spent in the various operative states of the proposed performability model given in Figure 3 are derived. In order to evaluate the energy savings obtained by introducing sleep state, we incorporate idle state in figure 8 and compare the energy consumption in both models. The models of figures 3 and 8 are similar with a slight difference in state R. The model in figure 8 always stays in the idle mode whenever the system is empty. However, the model of figure 3 ensures the system enters sleep mode whenever the queue is empty.

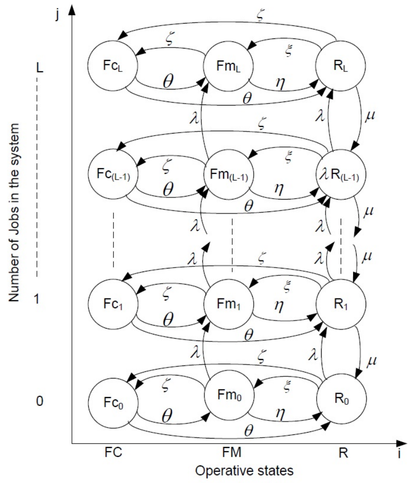


Fig. 8: Performability model with Idle Mode

6.2.1 Mean Energy Spent in Phase R

In this phase, the CH operates normally. Transitions between active/sleep modes are fully dependent upon the availability of the jobs in the system as seen in the above sections. The energy spent in this phase include the following: (a) Energy spent while receiving data packets - E_{RX}; (b) Energy spent while transmitting data packets - E_{TX}; (c) Transition energy from sleep to full operation mode - E_{UP}; (d) Energy spent restarting the CH after node failures - E_{FM}; (e) Energy spent in sleep state - E_{SP}.

Since the expected number of jobs in phase R may vary over time, the energy spent also varies accordingly. Taking into account the energy consumed when rebooting the system after node failures, the mean energy spent during CH operations can be expressed as:

$$E_{FR} = \sum_{i=2,j=0}^{j=L} (E_{TX} + E_{RX} + E_{SP} + E_{UP} + E_{FM}) \quad \text{Joules} \tag{38}$$

In the absence of failures this may reduce to:

$$E_{FR} = \sum_{i=2,j=0}^{j=L} (E_{TX} + E_{RX} + E_{SP} + E_{UP}) \quad \text{Joules} \tag{39}$$

6.2.2 Mean Energy Spent in Sleep Mode

Depending on the application area, the CH may be configured to either go into deep or light sleep or even dynamically choose between the two depending upon the state of the traffic [18]. In such cases, a significant power consumption variation in the states is eminent. Most of the available radio transceivers already have the variable power consumption for sleep states incorporated as deep and light sleep states. In order to evaluate the power levels in the proposed models, equation 35 is altered leading to equations 40 and 41.

$$E_{sp-deep} = \sum_{i=2,j=0} P_{i,j}(t_{sl}e_{sl1} + e_{up} + e_{Rx}) \quad Joules \tag{40}$$

$$E_{sp-light} = \sum_{i=2,j=0} P_{i,j}(t_{sl}e_{sl2} + e_{up} + e_{Rx}) \quad Joules \tag{41}$$

where e_{sl1} and e_{sl2} are energy spent in deep and light sleep states respectively. From the two equations, it is possible to compute a dynamically changing sleep state. For the system model depicted in figure 8, it is important to note that the distribution of idle time t_{sl} is similar to that of sleep time in the system model presented in figure 3.

6.3 Mean Energy Spent in Idle Mode

In order to account for the energy consumed while the system is operating in idling state, the computation formula is given considering energy spent while idling together with the energy used to receive the first data packet.

$$E_{ID} = \sum_{i=2,j=0} P_{i,j}(e_{id}t_{id} + \lambda e_{rx}) \quad Joules \tag{42}$$

6.3.1 Residual Energy

With all possible energy consumption in all the states known, letting the initial energy be E_{in}, then the residual energy E_{rsd} of the CH may be computed using the equation provided below:

$$E_{rsd} = E_{in} - E_{FR} \tag{43}$$

The residual energy may then be used to determine the levels necessary for CH operations as well as if CH rotation is necessary or not.

6.4 Evaluation of Energy Consumption of Cluster Head

Numerical results presented in this section show the effectiveness of the energy evaluation models developed for typical WSN CH operation based on the radio sleep schedule mechanism. The parameters used in this numerical study are mainly taken from the data sheets of the existing wireless motes with an input voltage assumed to be 3.3V. In tables 4 and 5, parameter specifications for a sample of micro-controllers, sensors and radio transceivers are presented. In this study, Telos Mote radio transceiver (CC2420) and controller (MSP430F4794) specification are used for energy consumption evaluation [15], [16]. In order to evaluate the overall CH energy consumption, this study considers energy consumed when receiving and transmitting data packets in addition to the energy consumed while moving between the above mentioned operative states.

Table 4: Micro-Controller (Processor) and Sensor Parameters Specifications

Mote	Controller	Idling ($E_{ID}W$)	Deep Sleep ($E_{SD}W$)	Running (W)	Sensor Type	E_{off}	E_{on}
Telos	MSP430F4794	0.0000039	0.000003	0.0012	DS1820	0	0.003
Mica2	Atmega128L	0.006	0.000024	0.015	DS1820	0	0.003
Imote2.0	Intel PXA271	0.1395	0.001755	0.198	TMP175	0.000003	0.001

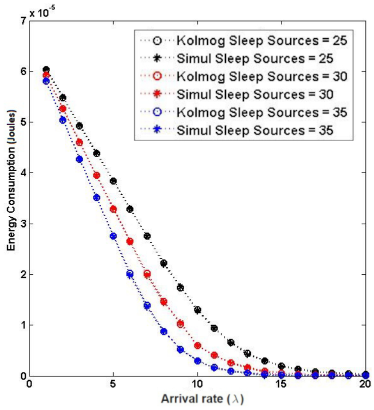
Table 5: Transceiver State Transition Power Consumption Specifications

Mote	Transceiver	Idling (E_{ID})Watts	Deep Sleep (E_{SD})Watts	Transmitting (E_{tx})Watts	Receiving (E_{rx})Watts	Full to Reduced Mode (E_{FN})Watts	Wakeup (E_{UP})Watts
Telos	CC2420	0.014058	0.000066	0.05742	0.06204	0.05742	0.0041976
Mica2	CC1000	0.0222	0.000003	0.0222	0.0312	0.0222	0.0066591
Imote2.0	CC2420	0.014058	0.000066	0.05742	0.06204	0.05742	0.0041976

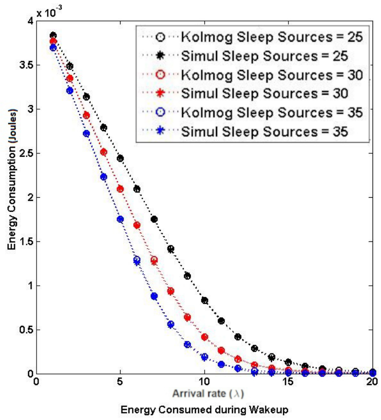
The energy evaluation is performed using the system parameters presented in Section 5. In all the cases, the queue length is chosen to be $L = 100$, while the arrival rate is varied from $\lambda = 1 - 20$ packets/hour.

From the models of figures 3 and 8, transmission energy is only consumed while operating in state R. However, energy consumed for receiving packets can be realised in both states R and F_M. When the CH enters sleep state, it consumes minimal power to maintain its circuitry ready for wake-up in the event of packet arrival. In addition, the CH spends energy while waking up from sleep state. Figures 9a and 9b illustrate mean sleep and wake-up energy consumption respectively. It is seen that higher energy is consumed at low arrival rates. As the arrival rate increases, the CH becomes busy hence the amount of time spent in sleep state is reduced. Sleep time eventually becomes negligible at higher data arrivals rates. Consequently, both sleep and wake-up energies fall as illustrated in both figures. It is also observed that energy consumed for wake-up transition is much higher than energy spent in sleep state.

The models presented in figures 3 and 8 are further used to evaluate the potential contribution of introducing sleep state. In other words, we are able to analyse whether or not it is worth going into sleep state. To the best of our knowledge, this study is the first one to present an analytical approach which is capable of doing this analysis. The differences in energy cost are determined by comparing consumption in idle and sleep states. Figures 10a and 10b show the mean consumption in these states respectively. In both cases, high consumption is realised at low traffic load which confirms the fact that the data packets spend more time in the queue, thus consuming more energy. However the consumption level reduces proportionately with increasing traffic load. Minimal consumption is finally observed at higher traffic load. Under all traffic loads, idle state energy is observed higher as seen in figure 10a. A similar trend for more energy saving is observed at low traffic load as compared to negligible savings at higher traffic load.

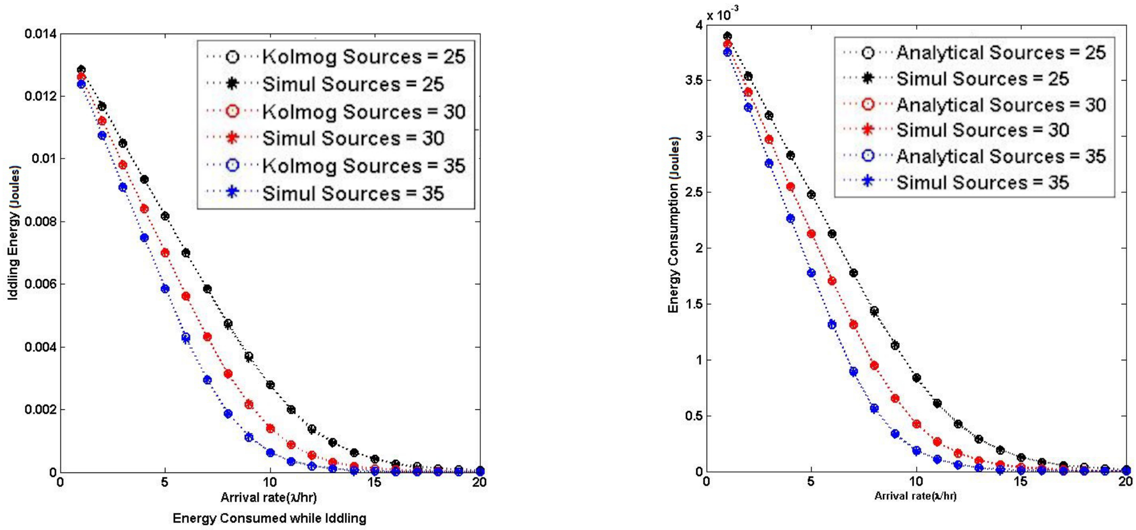


(a) Energy Consumed in Sleep State



(b) Energy Consumed during Wake-up

Fig. 9: Energy Consumed in Sleep State and During Wakeup



(a) Energy Consumption in Idle state

(b) Overall Sleep State Energy

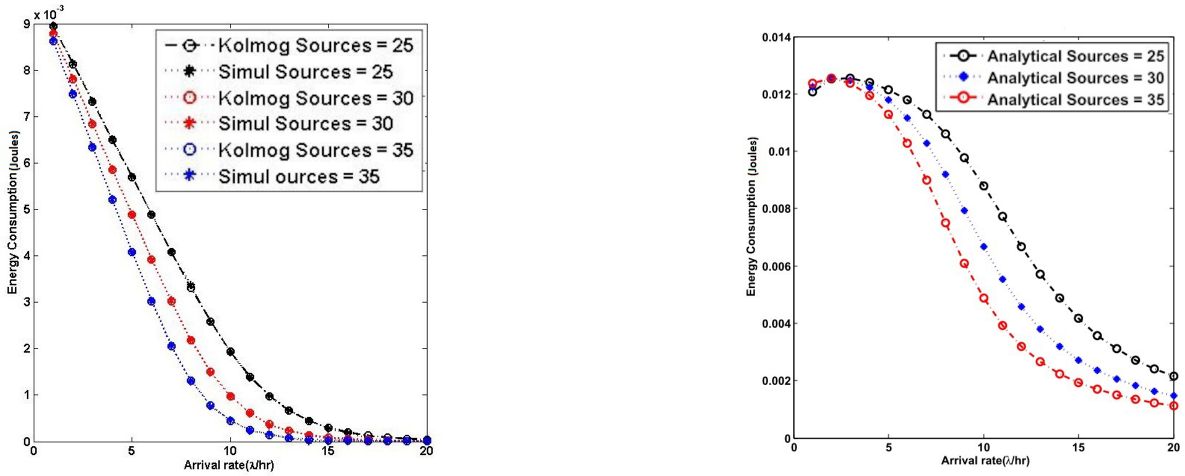
Fig. 10: Idle State and Overall Sleep State Energy

The overall energy saving graph resulting from incorporating sleep state is presented in Figure 11a. It shows the difference in power consumption obtained between idle and sleep states illustrated in figures 10a and 10b respectively. From the results, energy saving of up to 70% was realised by incorporating sleep state in the model. This illustrates the effectiveness of the proposed performability model not only on improved performance and availability but also in prolonging WSN lifespan.

Finally, Figure 11b illustrates the energy consumption for receiving data packets in node failed state. Here, more energy is consumed in receiving packets at low traffic load since the buffer is always empty hence more data packets can be stored awaiting repair completion. As arrival rates increase, increased numbers of data packets are stored during operations hence limiting the number of packets that can be accepted during node failure. In other words, plenty of incoming requests are blocked instead of being admitted. The trend continues as the arrival rate increases and finally energy consumption becomes very small since the buffer is almost always full.

The results show that increased numbers of sources lead the CH to consume higher amount of energy compared to fewer sources thereby depleting its energy faster. This becomes a trade-off when configuring network coverage and may be significant in planning network deployment and optimising WSN performance.

In the model of Figure 3, we note that frequent CH wake-up may result into higher energy consumption thus negating the purpose of sleep mode. A mechanism of controlling when to enter sleep state is therefore necessary. In order to determine control levels, we consider operations in phase R as given in Figures 7a and 7b. During low traffic loads, the CH stays idle most of the time. Therefore, this becomes a perfect time for the system to enter sleep state at the end of service of the last data packet, waking up only when a new job arrival occurs. As soon as the mean active time with jobs become greater than mean sleep time due to increased traffic intensity, the system's mean active time with jobs quickly gets high, hence higher energy consumption are observed as arrival rates are further increased. In all the observations made with buffer capacities of $L = 10, 50$ and 100, if 30 nodes are deployed, then operations below arrival rates of $4-5$ packets/hr is preferable. Above arrival rates of 6 packets/hr, the overall saving is very small and at times there is increased consumption instead, hence the system should be kept in the idle state. Table 6 gives a summary of proposed operation levels beyond which the CH should not enter sleep mode based on service of last data packet.



(a) Total Energy Saving in Sleep State (b) Energy Consumed in Node Failed state

Fig. 11: Total Energy Saving in Sleep State and Energy Consumed in Node Failed states

Considering the main objective of conserving WSN energy using on-demand sleep scheduling, this study identifies the need for setting operation levels that minimise wastage of the limited energy. The proposed model can further be used by designers to develop planning, deployment, and optimisation tools by considering performability findings given above.

Table 6: Proposed range for Optimal Sleep Operations

Sources	Proposed Arrival Rate (λ)		Proposed MQL	
	Normal	Upper Limit	Normal	Upper Limit
25	6	8	1.2885	2.3177
30	5	7	1.2885	2.6585
35	4.2	6	1.70215	2.6585

7 Conclusion and Future Directions

In this study, we present analytical models for IoT applications which utilise clustering mechanism for WSNs. The new modelling approach integrates WSN performance and availability/reliability in the presence of both node and channel failures. The models developed also consider limitations of the node queue capacity and sleep/active operating conditions. Furthermore, with the models presented; it is also possible to evaluate the systems considered for energy conservation. The results are obtained using two different solution approaches; Spectral expansion solution method and system of simultaneous linear equations. Discrete event simulations are also used as the third method for the verification of the accuracy. The results obtained using the two analytical solution approaches are in good agreement with simulation results with maximum discrepancy less than 0.1%. Moreover, with the models developed, it is shown that using on-demand sleep scheduling scheme, it is possible to save up to 70% of the energy consumption in idle state. From the investigation on the results, it is possible to determine optimal sleep operation ranges suitable for on-demand sleep schedule technique based on traffic load. The quick computational nature of analytical models allows us to study various system related thresholds. For example, when the system is heavily loaded, energy consumed in sleep state becomes greater than energy consumed in idle state. Therefore it may be a better idea to employ hybrid approach incorporating both sleep and idle states in order to overcome the higher energy consumption that may result from frequent wake-ups during high traffic load.

This paper provides a comprehensive analytical study of the performability of WSNs within the IoT framework, including energy conservation mechanisms. It is possible to extend this study to consider other sleep scheduling techniques independently or integrated together based on the WSN application areas.

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