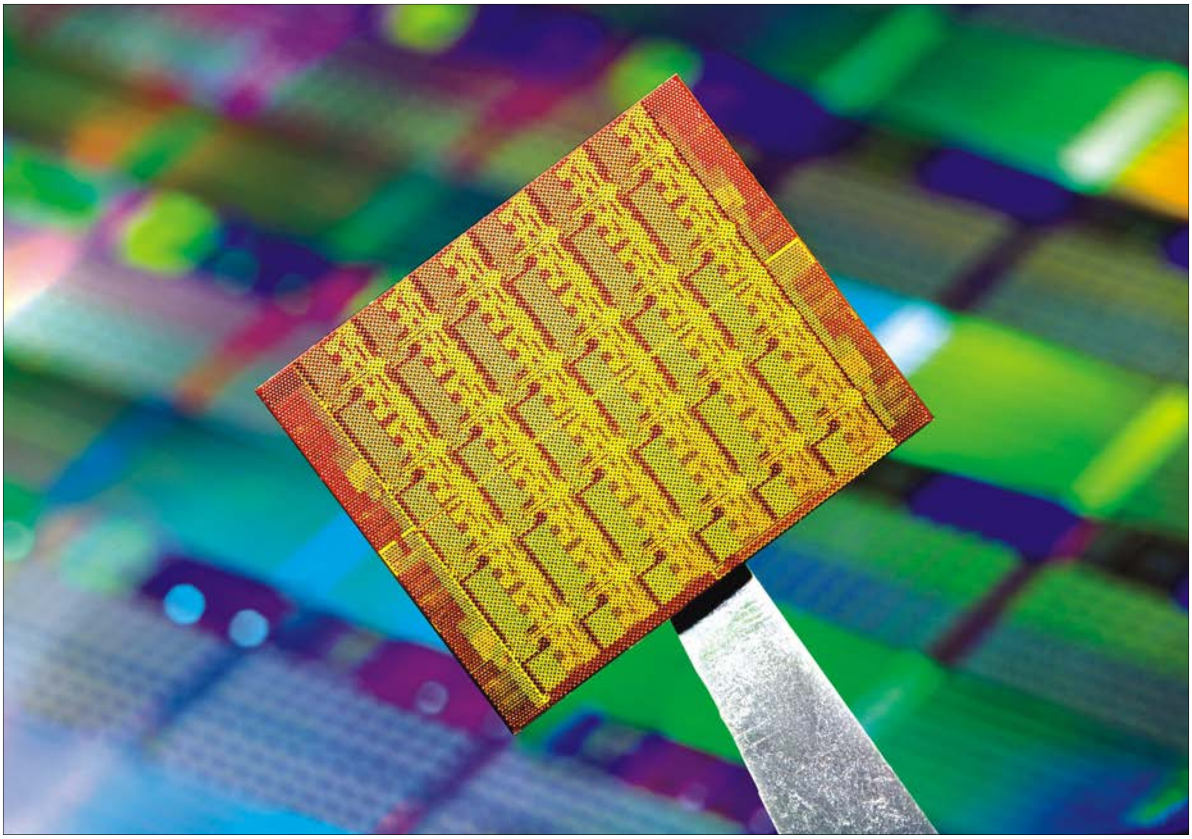

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Research Article
Modeling Delay and Energy Consumption for Wireless Sensor Networks with High Coefficient of Variability

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Abstract

Background and Objective: Previous attempts to estimate the delay and energy consumption in wireless sensor networks employed an M/M/1 queue model. In the M/M/1 queue model, the packet length is assumed to have low variability in packet sizes and therefore, service time is best modeled by the exponential distribution. The objective of this study was to estimate the delay and energy consumption for wireless sensor networks with high coefficient of variability. **Methodology:** To overcome the weaknesses of M/M/1 queue model, this study proposed to model delay and energy consumption under heavy-tail distribution where packet sizes was highly variable as depicted in the Internet using M/G/1 queue model. The service time of packets in the M/G/1 queue was modeled using Bounded Pareto, Lognormal and Weibull distributions. Bounded Pareto, Lognormal and Weibull distributions that depict the heavy-tailed distributions. The coefficient of variation represents the ratio of the standard deviation to the mean and it is a useful statistic for comparing the degree of variation. **Results:** The numerical results obtained from the derived models show that the average waiting time and energy consumption is higher under the M/G/1 (where G represents Bounded Pareto and Weibull distributions) than under M/M/1 queue model. However, the average waiting time and energy consumption was lower under M/Lognormal/1 than under M/M/1 queue model. It was also observed that increase in the coefficient of variability leads to increase in average waiting time and energy consumption. **Conclusion:** The M/M/1 queue model under estimates delay and energy consumption for wireless sensor networks with high coefficient of variability.

Key words: Average waiting time, coefficient of variability, energy consumption, heavy-tailed distribution, network life, wireless sensor networks

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Data Availability: All relevant data are within the paper and its supporting information files.

INTRODUCTION

Wireless sensor networks (WSNs) have recently received more and more attention due to their potential in civil and military applications as well as the advances in micro-electromechanical systems technology[1]. Wireless sensor networks can be deployed in extremely hostile environments, such as battle field target areas, earthquake disaster scenarios and inaccessible spaces inside nuclear facility to monitor environmental changes or other required information.

Wireless sensor networks normally feature dynamic topology, limited energy, nodes with limited resources and non-reliability of data transmission. Hence, they need real-time, energy conservation and coordination in above aspects to improve the network performance of WSNs and satisfy the performance requirements of the task scheduling system[2].

A typical sensor network consists of a large number of sensor nodes deployed either inside the phenomenon of interest or close to it. The primary purpose of sensor networks is to provide users access to the information gathered by the spatially distributed sensors, rather than enabling end-to-end communication between pairs of nodes as in other large-scale networks such as the Internet or wireless mesh networks. Due to limited transmission range of sensor nodes, the sensory data are delivered to a processing center, called sink node, via multi-hop communication implying that each sensor node plays the dual role of being a data originator and a data router. This information is then processed to obtain useful data, which is then sent to the user[3]. Mean delay experienced by the packets in a sensor node is defined as the average waiting time of the packets in the queue[4,5].

A critical issue in wireless sensor networks is the limited availability of energy within the network and hence optimizing energy is critical[6]. Communication is the most energy consuming function among sensor nodes and thus, all network communication protocols designed for sensor networks must be energy efficient in order to optimize network life time[7]. Therefore, energy saving in wireless sensor networks is quite important. Furthermore, network life time in wireless sensor networks is usually estimated by estimating the energy consumption of nodes.

It is expected that in 10-15 years that the world will be covered with wireless sensor networks with access to them via the internet[8]. The workloads observed in the Internet constitute around 99% of short jobs and the 1% which are the largest jobs account for more than 50% of the total amount of workload[9]. This property has also been referred to as heavy-tail property[10,11], but it is not restricted to heavy-tail distributions[12]. The internet traffic model is not necessarily heavy-tailed[12], rather it fits many distributions that have high coefficient of variation (CoV>1). Coefficient of variation is defined as the ratio of the standard deviation to the mean of a distribution and it is a common metric to measure the variability of a distribution, the higher the CoV value of a distribution the higher the variability of the distribution. Typical examples of CoV observed in the Internet traffic range between 5-20[11,13].

In an attempt to reduce delay, maximize through put and conserve energy consumption in channel access, Sikandar and Kumar[14], developed a model based on M/M/1 queue, where arrival follows Poisson distribution and service time is exponentially distributed. The expression for the average waiting time for an M/M/1 queue system is given as[14]:

$$W_Q = \frac{\lambda \overline{X^2}}{2(1-\rho)} \quad (1)$$

where, $\overline{X^2}$ is the second moment of the distribution and ρ is the load in the system.

ρ is the load in the system, λ is the average arrival rate of requests in the system, W_Q is the average waiting time.

Based on M/M/1 queueing model, the mean number of packets in the sensor N is determined as:

$$N = \frac{\rho}{(1-\rho)}$$

Where,

$$\rho = \frac{\lambda}{\mu}$$

and the probability that the sensor is in idle state is determined as $P_o = (1\text{-}\rho)$. Energy required for sending a data packet can be determined as:

$$E_{TX} = \frac{\text{Packet size}}{\text{Band width}} \chi \text{Transmission power} \quad (2)$$

The average energy consumption of a sensor can be expressed as[15]:

$$P_W = NE_{TX} + (1\text{-}\rho)E_{idle} \quad (3)$$

Where, N is the mean number of packets in the sensor, μ is the average service rate of packets in the system. P_o is the probability that the sensor is in idle state. E_{TX} is the energy required for sending a data packet, P_W is the average energy consumption of a sensor, E_{idle} is the energy consumed by sensor while in idle state.

In the M/M/1 queue model, the packet length was assumed to have low variability and therefore, modeled by the exponential distribution. However, recent internet traffic measurements have revealed that the internet traffic exhibits a high variability property, many flows are short web transfers and about 1% of the largest flows carry more than 50% of all bytes[16,17]. Motivated by the fact that this traffic characteristic cannot be represented by M/M/1 queueing system, this study proposed to model delay and energy consumption under heavy-tailed distribution where packet sizes are highly variable as depicted in the Internet.

The main objective of this study was to estimate delay and energy consumption for wireless sensor networks with heavy-tailed packet size distribution. This has been achieved as the model for delay and energy consumption based on heavy-tailed distribution where packet sizes are highly variable has been derived and implemented to compare performance with the M/M/1 queue model.

MATERIALS AND METHODS

This study employed the use of analytical models and MATLAB tool to study the performance of wireless sensor networks in terms of average queue delay and energy consumption. An analytical model is a set of formulae or computational algorithms used to analyze systems. Analytical models provide a faster and more computationally efficient methods of obtaining performance measures. In particular, queueing theory was used to model arrival and service rate of requests in the system. Queueing models are suitable in a variety of environments ranging from common daily life scenarios to complex service and business processes, operations research problems, or computer and communication systems[18]. Given certain customer arrival patterns and service requirements, the order of service is the most important point affecting the performance of a service management facility.

The basic queuing system can be illustrated as customers arriving for service, waiting for service if the server was busy and leaving the system after completing service. The basic queuing model can be identified by some basic elements of the system as[19]:

- **Input process:** Input process represents either the number of arrivals during a time interval or the time interval between successive arrivals. Furthermore, the distribution can also be used to determine the arrival of customers to the system. If the arrival of customers and the services being offered match then a queue may not build up. However, if customer arrivals exceed the system capacity then a queue builds up.
- **Service mechanism:** It involves the number of servers, the number of customers being served at any time and the duration of service. The processing time was represented by appropriate distribution functions
- **Queuing:** The number of customers waiting for service is an important point of consideration. The waiting room or queue length can be considered infinite. The realization of such queue is hard in real network such as telecommunication networks
- **Queue discipline:** This involves the way in which customers are serviced or removed from the queue

System model: Consider a WSN that consists of large number of sensors that are uniformly distributed and a sink node at the center of the field that collects data from other nodes. In this WSN model, the following assumptions are made:

- All sensors in the WSN are identical, that is, sensors are assumed to be homogeneous
- The arrival of data packets to sensors is assumed to follow a Poisson process with mean arrival rate (λ) per node. Poisson distribution models random arrivals to systems
- Service time of sensor node follow Bounded Pareto distribution, Lognormal and Weibull distributions
- Buffer capacity is infinite

Let the network consist of N contending sensor nodes. The channel can be in busy or idle state. If channel becomes busy it means that there was on-going transmission in the channel otherwise the channel was in the idle state. A channel may switch from busy to idle state or vice-versa in active time. Switching from one state to another state was termed transitions.

Mathematical background: In this section mathematical expressions for the average queue delay and energy consumption are derived for heavy tailed distributions. The performance metric considered here was the average queue delay and energy consumption. Average queue delay was the time taken by a packet in the queue, while energy consumption was the amount of energy consumed by nodes. The lower the average queue delay the better is the performance of the system and the higher the average queue delay the worse the performance of the system. Similarly, the lower the energy consumption, the better was the efficiency and the longer the network life time. On the other hand, the higher the energy consumption, the worse the efficiency and the shorter the network life time.

Specifically the M/G/1 queue model was used, where M represents Poisson arrival with mean arrival rate (λ) per node with exponentially distributed inter arrival times. Poisson distribution best models random arrivals into systems. G represents general service time, which in this case shall be Bounded Pareto, Lognormal and Weibull distributions. One server was assumed in all cases. Poisson probability distribution is given as[17]:

$$P(x) = \frac{\lambda^{x} e^{-\lambda}}{x!} \quad x = 0,1,2,... \tag{4}$$

Where,

x = number of arrivals in a specific period of time.

λ = average, or expected number of arrivals for the specific period of time, e = 2.71828.

The probability density function of a Bounded Pareto distribution BP (k, P, α), where k and P are the minimum and the maximum job sizes and α is the exponent of the power law and is given by:

$$f(x) = \frac{\alpha k^{\alpha}}{1-\left(\frac{k}{P}\right)^{\alpha}} x^{-\alpha-1} \quad k \le x \le P, \ 0 \le \alpha \le 2 \tag{5}$$

The cumulative distribution function F(x) and the nth moment m_n of the BP(k,P,α) distribution are respectively:

$$f(x) = \frac{\alpha k^{\alpha}}{1-(k/P)^{\alpha}} \left[1-(k/x)^{\alpha} \right] \quad k \le x \le P, \ 0 \le \alpha \le 2 \tag{6}$$

$$m_n = \frac{\alpha}{(n-\alpha)(P^{\alpha}-k^{\alpha})} (P^n k^{\alpha} - P^{\alpha} k^n) \tag{7}$$

From Eq. 5, the mean of the Pareto distribution is given as:

$$E(x) = \frac{k^{\alpha}}{\left(1-\left(\frac{k}{P}\right)^{\alpha}\right)} \left(\frac{\alpha}{\alpha-1}\right) \left(\frac{1}{k^{\alpha-1}} - \frac{1}{P^{\alpha-1}}\right) \tag{8}$$

The Pareto distributions that emerge in computer system applications typically have α ∊ (0.9, 1.3)[17]. In the implementation considered in this study, the mean equals 72.7. Similar mean has been used by Bansal[10], BP (10, 5 10^5, 1.1) have highly varying job sizes with about 99% of the jobs being small and less than 1% of the largest jobs constituting more than 50% of the total load[17]. In this study the BP job size distribution BP (10, 5 10^5, 1.1) with C = 5 is used as an example of the BP distribution that exhibits the high variability property. This distribution was also used to analyze the unfairness of shortest remaining processing time (SRPT)[10].

The probability density function of lognormal distribution is given as[20]:

$$f(x, \mu, \delta) = \frac{1}{x\delta\sqrt{2\pi}} \exp\left\{\frac{-(\ln x-\mu)^2}{2\delta^2}\right\}, \ x>0 \tag{9}$$

where, the variable x>0 and the parameters μ and δ are real numbers. The expectation of the lognormal distribution is given by:

$$E(x) = e^{\mu+\frac{\delta^2}{2}}$$

where, k>0 is the shape parameter and λ>0 is the scale parameter of the distribution and x is a "time-to-failure." The Weibull distribution is often used in the field of data analysis due to its flexibility. Depending on parameters, the Weibull can behave as a normal distribution, an exponential distribution, or a heavy-tailed distribution. The Weibull distribution has recently emerged as a good model of empirical distribution in many computer applications[21]. A Weibull distribution is summarized by two parameters: A shape parameter, α and a scale parameter, λ. The pdf of the Weibull distribution is given as[21].

$$f(x) = \frac{\alpha x^{\alpha-1}}{\lambda^{\alpha}} e^{-\left(\frac{x}{\lambda}\right)^{\alpha}}$$

The cumulative distribution function of a Weibull distribution is given as:

$$\bar{F} = e^{-\left(\frac{x}{\lambda}\right)^{\alpha}}$$

The ith moment of the Weibull distribution is given as:

$$E(x^i) = \lambda^i \Gamma\left(1+\frac{i}{\alpha}\right)$$

where,

$$\Gamma(\alpha)=\int_0^{\infty}x^{\alpha-1}e^{-x}dx$$

and can be thought of as a continuous version of the factorial function.

In particular, Γ(n)=(n – 1)! for any positive integer n. The mean of the Weibull distribution is given as:

$$E(x)=\lambda\Gamma\left(1+\frac{1}{\alpha}\right)$$

On the other hand the squared co efficient of variation for Weibull distribution is given by:

$$C_x^2=\frac{\Gamma\left(1+\frac{2}{\alpha}\right)}{\left\{\left(1+\frac{1}{\alpha}\right)\right\}}-1 \quad (10)$$

Typical observed values for α in computer applications range between 1/3 and 2/3 which correspond to CoV values in the range of 3-19[21].

Expression for delay using M/G/1 queue system: Under the M/G/1 queue system, the arrival rate of requests into the system follows a Poisson distribution. The service time was assumed to follow a general distribution. In this case, the service time was assumed to follow BP, lognormal and Weibull distributions. One server and infinite capacity buffer were assumed.

Assume a system was in state j if there are a total of j requests in the queue. The system goes from state j to state j+1 if another request comes into the system. If the system was in state j and a request was served, it goes to state j – 1.

Assume that once a sensor gets the channel, it sends all the data it collected while in the waiting state. Therefore, the average delay for the sensors in the queue can be derived as follows:

If the rate of generation of packets per sensor was λ then the average delay W_Q for any queue system is given as[21]:

$$W_Q=\frac{\lambda\overline{X^2}}{2(1-\rho)} \quad (11)$$

Where, $\overline{X^2}$ the second moment of the distribution and ρ is the load in the system. However, under the heavy tail distribution, the average waiting time was affected by the variability property. The variability property was captured by a metric called coefficient of variability. The coefficient of variation CoV which is defined as the ratio of the standard deviation to the mean,

$$CoV=\frac{\sqrt{V(X)}}{E(X)}$$

where, V(X) and E(X) is the variance and mean of a distribution.

$$E(X^2)=V(X)+E(X)^2$$

$$E(X^2)=CoV^2E(X)^2+E(X)^2$$

$$E(X^2)=(1+CoV^2)E(X)^2$$

Hence,

$$W_Q=\frac{\lambda\left(1+CoV^2\right)E\left(X\right)^2}{2\left(1-\rho\right)}$$

$$=\frac{\lambda\left(1+CoV^2\right)E\left(X\right).\frac{1}{\mu}}{2\left(1-\rho\right)}$$

$$=\frac{\left(1+CoV^2\right)\lambda E\left(X\right)}{2\left(\mu-\lambda\right)}$$

Therefore, the general expression for the average waiting time is given as:

$$W_Q=\frac{\left(1+CoV^2\right)\lambda E\left(X\right)}{2\left(\mu-\lambda\right)} \quad (12)$$

For the BP distribution, the expression for the average delay simplifies to:

$$W_Q=\frac{\left(1+CoV^2\right)\lambda\frac{k^{\alpha}}{\left(1-\left(\frac{k}{P}\right)^{\alpha}\right)}\left(\frac{\alpha}{\alpha-1}\right)\left(\frac{1}{k^{\alpha-1}}-\frac{1}{P^{\alpha-1}}\right)}{2\left(\mu-\lambda\right)} \quad (13)$$

For the lognormal distribution, the expression for the average delay simplifies to:

$$W_Q=\frac{\left(1+CoV^2\right)\lambda e^{\mu+\frac{\delta^2}{2}}}{2\left(\mu-\lambda\right)} \quad (14)$$

For the Weibull distribution, the expression for the average delay simplifies to:

$$W_Q = \frac{\left(1+CoV^2\right)\lambda^2\Gamma\left(1+\frac{1}{\alpha}\right)}{2\left(\mu-\lambda\right)} \tag{15}$$

Expression for energy consumption using M/G/1 queue system: Based on M/G/1 queueing models, the mean number of packets in the sensor (N) is determined as:

$$N = \frac{\lambda\left(1+CoV^2\right)\lambda E\left(x\right)}{2\left(\mu-\lambda\right)} \tag{16}$$

Using Little's law, $N = \lambda W_Q$. And the probability that the sensor is in idle state is determined as: $P_o(1-\rho)$, where, $\rho = \lambda/\mu$. From Eq. 3, the average energy consumption is:

$$P_W = NE_{TX}+(1-\rho)E_{idle} \tag{17}$$

For the BP distribution, the expression for the average energy consumption simplifies to:

$$P_W = \left(\frac{\left(1+CoV^2\right)\lambda^2\frac{k^\alpha}{\left(1-\left(\frac{k}{P}\right)^\alpha\right)}\left(\frac{\alpha}{\alpha-1}\right)\left(\frac{1}{k^{\alpha-1}}-\frac{1}{P^{\alpha-1}}\right)}{2\left(\mu-\lambda\right)}\right).E_{TX}+(1-\rho).E_{idle} \tag{18}$$

where, E_{TX} is a s shown in Eq. 2.

For the lognormal distribution, the expression for the average energy consumption simplifies to:

$$W_Q = \left(\frac{\left(1+CoV^2\right)\lambda^2 e^{\mu+\frac{\delta^2}{2}}}{2\left(\mu-\lambda\right)}\right).E_{TX}+(1-\rho).E_{idle} \tag{19}$$

For the Weibull distribution, the expression for the average energy consumption simplifies to:

$$W_Q = \left(\frac{\left(1+CoV^2\right)\lambda^3\Gamma\left(1+\frac{1}{\alpha}\right)}{2\left(\mu-\lambda\right)}\right).E_{TX}+(1-\rho).E_{idle} \tag{20}$$

Next, the derived models of average delay and energy consumption under heavy tailed distribution are used to evaluate the performance while comparing it with models under the exponential distribution.

RESULTS AND DISCUSSION

The performance of the derived models was evaluated using Matlab and the results were then presented. In many applications, particularly computer science applications, it was frequently the case that empirical job size distributions exhibit very high variability and are best modeled by a Pareto distribution, or a Log Normal distribution with high coefficient of variation. Some examples include UNIX process CPU requirements[22] (where CoV values of 5-7 have been measured), sizes of files transferred through the Web[11], durations of FTP transfers in the internet[23] and Central Processor Unit requirements for supercomputing jobs[24].

Using the formula for squared coefficient of variation for Weibull Distribution and values for α in computer applications ranging between 1/3 and 2/3[21], the CoV values was found to be in the range of 3-19. The coefficient of distribution for the exponential distribution was one[17].

The arrival rate of 0-4 packets sec^{-1} and service rate of 5 packets sec^{-1} were chosen to study the behaviour of the sensor nodes at maximum utilization of 90% (utilization=arrival rate/service rate). Similar values of arrival rates and service rates were also depicted in[14,25]. In the evaluation of different network performance, a load or utilization of 0.9 was taken as high load and the maximum load was taken to be one[17].

Table 1 shows the evaluation parameters used in the analysis which was consistent with parameters used in literature[14].

Evaluation of performance in terms of average waiting time: In this section the performance of the derived models in terms of average waiting were evaluated while comparing with M/M/1 queue model.

Table 1: Evaluation parameters

Parameters	Values
Arrival rate, λ	0-4 packets sec^{-1}
Service rate, μ[14,25]	5 packets sec^{-1}
Load[17]	0-0.9
Mean of Bounded Pareto[17]	72.7
Mean of Lognormal[20]	$e^{1/2}$
Coefficient of variation for BP	5 and 6[11,13]
Coefficient of variation for Lognormal	5 and 6[11,13]
Coefficient of variation for Weibull[21]	3 and 4

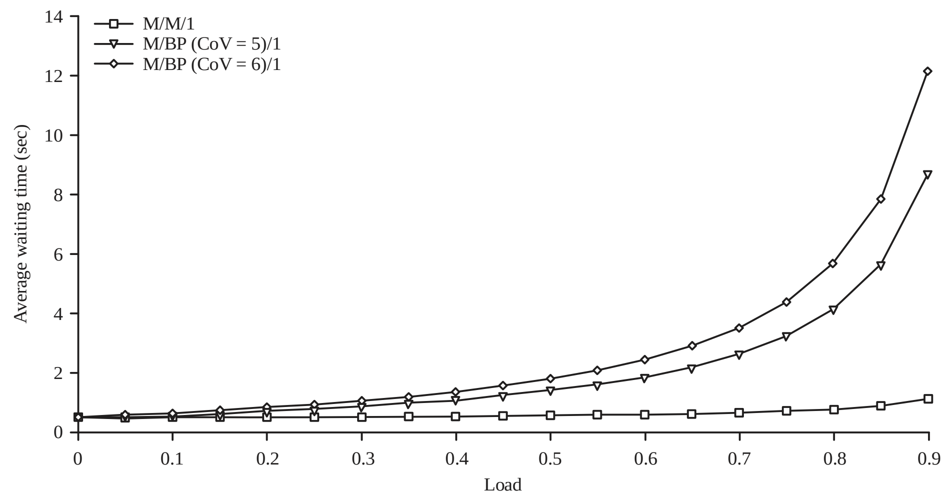

Fig. 1: Average waiting time versus load for BP (CoV=5), BP (CoV=6) and M/M/1

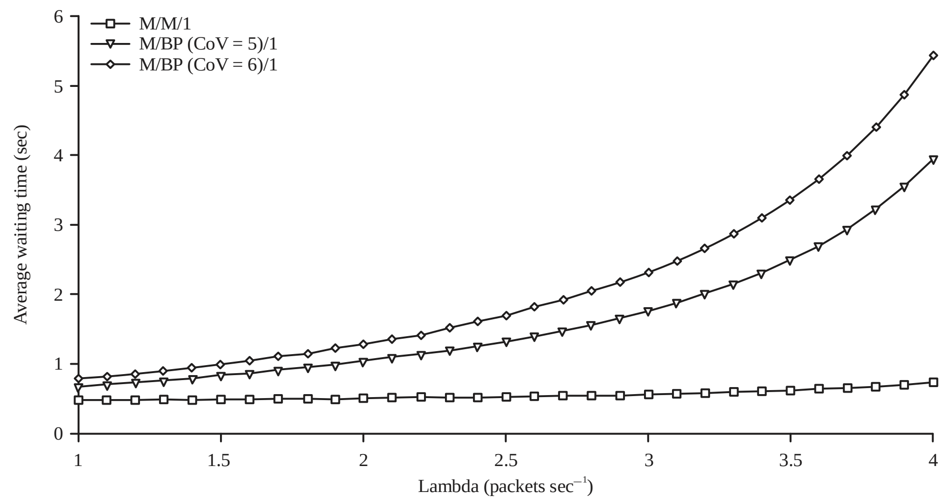

Fig. 2: Average waiting time versus arrival rate for BP (CoV=5), BP (CoV=6) and M/M/1

Comparison of M/M/1 and M/Bounded Pareto/1: In this section the performance of M/M/1 and M/Bounded Pareto/1 are compared. In doing this equations 1 and 12 were used to plot graphs 1 and 2. The mean for both distributions are fixed to 72.7 as shown in Table 1.

Figure 1 shows a graph of average waiting time against load for a Bounded Pareto distribution with CoV=5, Bounded Pareto distribution with CoV=6 and M/M/1 queue system with CoV=1. It was observed that average waiting time increases with increase in load regardless of the distribution. It was further observed that initially the average waiting time of packets under the two distributions were the same, however as the load increases the average waiting time under the BP distribution was higher than under the M/M/1 distribution. This can be explained by the fact that under the BP distribution, there was a higher variation in the size of requests unlike under the M/M/1 queue system where the service time of requests are similar. It can also be observed that as the CoV increases, the average waiting time also increases. In other words, increase in variability of packet sizes lead to increase in average waiting time.

Figure 2 shows a graph of average waiting time against average arrival rate for a Bounded Pareto distribution with CoV=5, Bounded Pareto distribution with CoV=6 and M/M/1 queue system with CoV=1. It was observed that average waiting time increases with increase in arrival rate regardless of the distribution. It was further observed that for low arrival rate values, the average waiting time of packets under the two distributions were closer, however as the arrival rate increases the average waiting time under the BP distribution

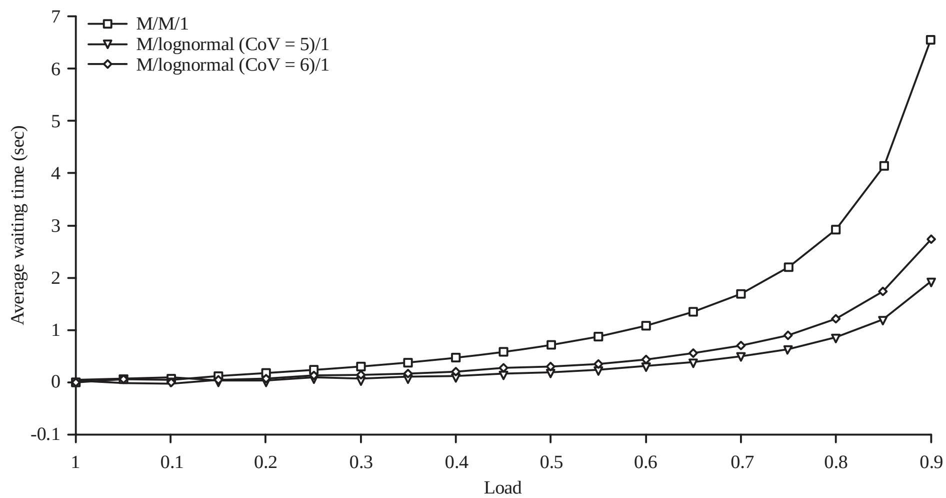

Fig. 3: Average waiting time versus load for Lognormal (CoV=5), Lognormal (CoV=6) and M/M/1

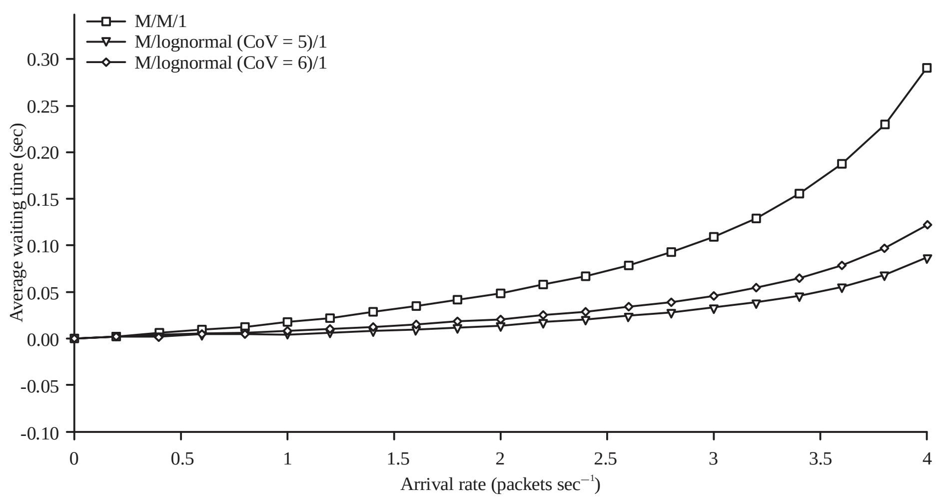

Fig. 4: Average waiting time versus arrival rate for Lognormal (CoV=5), Lognormal (CoV=6) and M/M/1

was higher than under the M/M/1 distribution. In the same vein, it can be concluded that variability in packet size has an effect on the average waiting time.

Comparison of M/M/1 and M/Lognormal/1: The performance of M/M/1 and M/Lognormal/1 was compared. In doing this equations 1 and 13 were used to plot graphs 3 and 4. The mean for lognormal distribution is fixed at $e^{0.5}$ or 1.6487 and the mean for the M/M/1 or exponential distribution is fixed at 72.7 as shown in Table 1.

Figure 3 shows a graph of average waiting time against load for lognormal distribution with CoV=5, lognormal distribution with CoV=6 and M/M/1 queue system with CoV=1. In doing this equations 1 and 13 were used to plot graph 3. The study investigates the effect of varying load on the average waiting time for Lognormal (CoV=5), Lognormal (CoV=6) and M/M/1 distributions. It can be observed that average waiting time increases with increase in load regardless of the distribution. Initially the average waiting time under the distributions were the same, however, as the load increases there is a significant difference in the average waiting time under the distributions. The average waiting times under the lognormal distribution for Lognormal (CoV=5) and Lognormal (CoV=6) were lower than under M/M/1 queue system. It was also observed that as CoV increases for Lognormal (CoV=5) to Lognormal (CoV=6), there is an increase in the average waiting time. Hence, increase in variability of packet sizes lead to increase in average waiting time.

Figure 4 shows a graph of average waiting time against arrival rate for lognormal distribution with CoV=5, lognormal

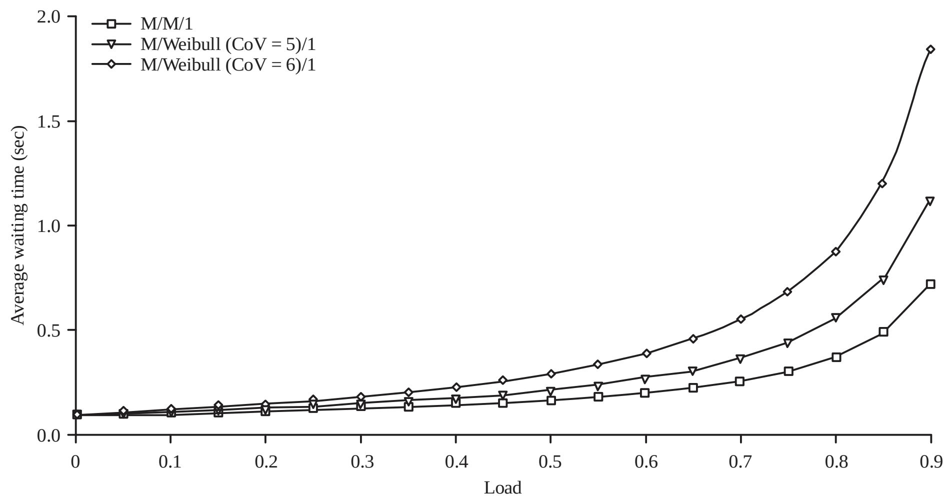

Fig. 5: Average waiting time versus load for Weibull (CoV=3), Weibull (CoV=4) and M/M/1

distribution with CoV=6 and M/M/1 queue system with CoV=1. In doing this equations 1 and 13 were used to plot graph 4. The mean for lognormal distribution is fixed at $e^{0.5}$ or 1.6487 and the mean for the M/M/1 or exponential distribution is fixed at 72.7 as shown in Table 1. This study investigates the effect of varying arrival rate on the average waiting time for Lognormal (CoV=5), Lognormal (CoV=6) and M/M/1 distributions. It was observed that average waiting time increases with increase in arrival rate regardless of the distribution. Initially the average waiting time under the distributions were the same, however, as the arrival rate increases there was a significant difference in the average waiting time under the distributions. The average waiting time of packets under the lognormal distribution is lower than under M/M/1 queue system. Therefore, as CoV increases, there is an increase in the average waiting time under the lognormal distribution.

Comparison of M/M/1 and M/Weibull/1: The performance of M/M/1 and M/Weibull/1 was compared. In doing this, Eq. 1 and 14 were used to plot graphs 5 and 6. The mean for Weibull distribution is fixed at 6 λ or 24 using the maximum value of λ of 4 requests sec^{-1} and the mean for the M/M/1 or exponential distribution is fixed at 72.7 as shown in Table 1.

Figure 5 shows a graph of average waiting time versus load for Weibull (CoV=3), Weibull (CoV=4) and M/M/1 queue system with CoV=1. This study investigates the effect of varying load on the average waiting time for Weibull (CoV=3), Weibull (CoV=4) and M/M/1 distributions. It was observed that average waiting time generally increases with increase in load for all the considered distributions. It was further observed that initially the average waiting time under Weibull (CoV=3), Weibull (CoV=4) and M/M/1 queue systems were the same, however as the load increases, packets experience a higher average waiting time under Weibull (CoV=3) and Weibull (CoV=4) than under M/M/1 queue system. It was also observed that average waiting time of packets under Weibull (CoV=4) is higher than under Weibull (CoV=3) implying that increase in CoV leads to increase in average waiting time.

Figure 6 shows a graph of average waiting time versus arrival rate for Weibull (CoV=3), Weibull (CoV=4) and M/M/1 queue system with CoV=1. In doing this Eq. 1 and 14 were used to plot graph 6. This study investigates the effect of varying arrival rate on the average waiting time for Weibull (CoV=3), Weibull (CoV=4) and M/M/1 distributions. It was observed that average waiting time generally increases with increase in arrival rate for all the considered distributions.

It was further observed that initially the average waiting time under Weibull (CoV=3), Weibull (CoV=4) and M/M/1 distributions were the same, however as the arrival rate increases the average waiting time of packets under Weibull (CoV=4) is higher than the average waiting time under Weibull (CoV=3) distribution which in turn is higher than the average waiting time of packets under M/M/1 queue system. It can also be observed that the average waiting time under Weibull (CoV=4) is higher than the average waiting time under Weibull (CoV=3) implying that increase in CoV leads to increase in average waiting time for a particular distribution.

Next, the performance of the system in terms of average energy consumption were analyzed.

Evaluation of performance in terms of energy consumption: The performance of the derived models was evaluated in terms of average energy consumption while comparing with M/M/1 queue model.

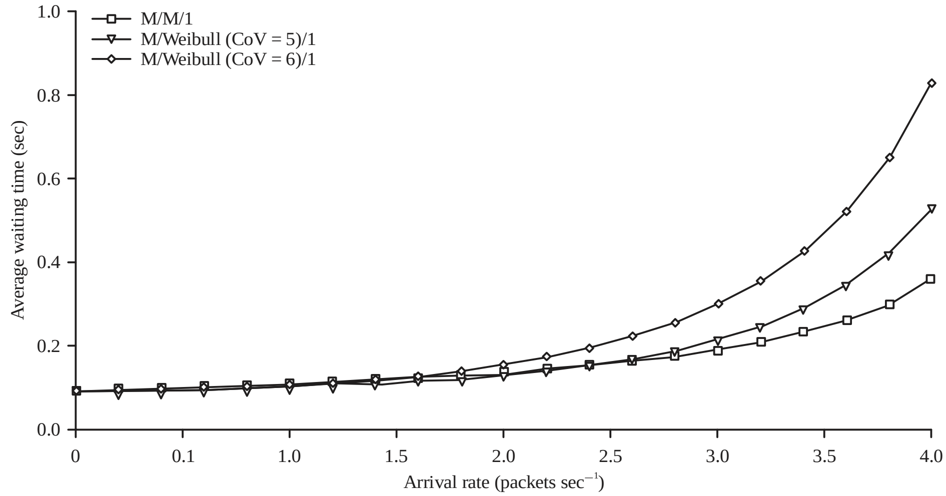

Fig. 6: Average waiting time versus arrival rate for Weibull (CoV=3), Weibull (CoV=4) and M/M/1

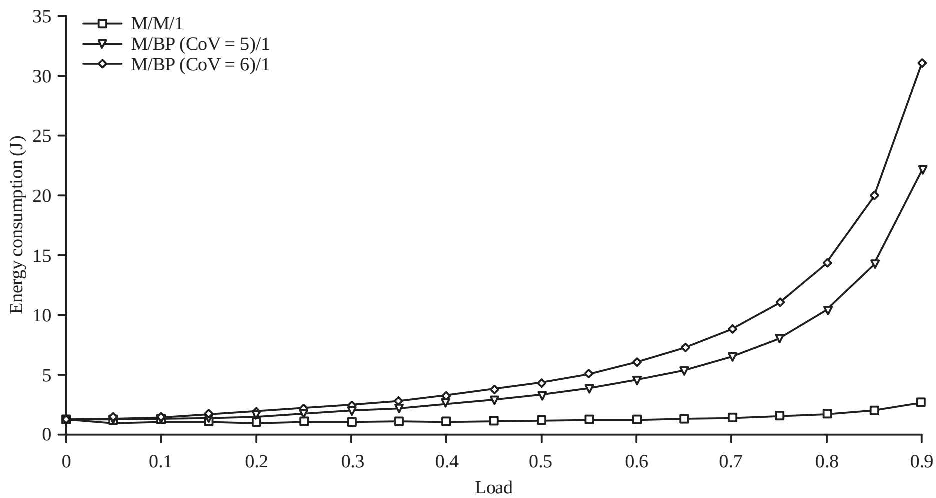

Fig. 7:Average energy consumption versus load for M/BP (CoV=5)/1, M/BP (CoV=6)/1 and M/M/1

Comparison of M/M/1 and M/Bounded Pareto/1: The performance of M/M/1 and M/BP/1 was compared in terms of average energy consumption. In doing this, equations 3 and 15 were used to plot graphs 7 and 8. The mean for both distributions are fixed to 72.7 as shown in Table 1.

Figure 7 shows a graph of average energy consumption against load for M/BP (CoV=5)/1, M/BP (CoV=6)/1 and M/M/1 with CoV=1.

This study investigates the effect of varying the load on average energy consumption for Bounded Pareto M/BP (CoV=5)/1, M/BP (CoV=6)/1 and exponential (M/M/1) distributions. It was observed that average energy consumption increases with increase in load regardless of the distribution. It was further observed that for low load values, the average energy consumption under M/BP (CoV=5)/1, M/BP (CoV=6)/1 and M/M/1 were the same, however, as the load increases in the system, the energy consumption is highest under M/BP (CoV=6)/1 followed by M/BP (CoV=5)/1 and least under M/M/1. It can also be observed that increase in coefficient of variation leads to increase in energy consumption as observed in energy consumed under M/BP (CoV=5)/1 and M/BP (CoV=6)/1.

Figure 8 shows a graph of average energy consumption against arrival rate for M/BP (CoV=5)/1, BP (CoV=6) and M/M/1 with CoV=1. This study investigates the effect of varying the arrival rate on average energy consumption for Bounded Pareto M/BP (CoV=5)/1, M/BP (CoV=6) and exponential (M/M/1) distributions. It was observed that average energy

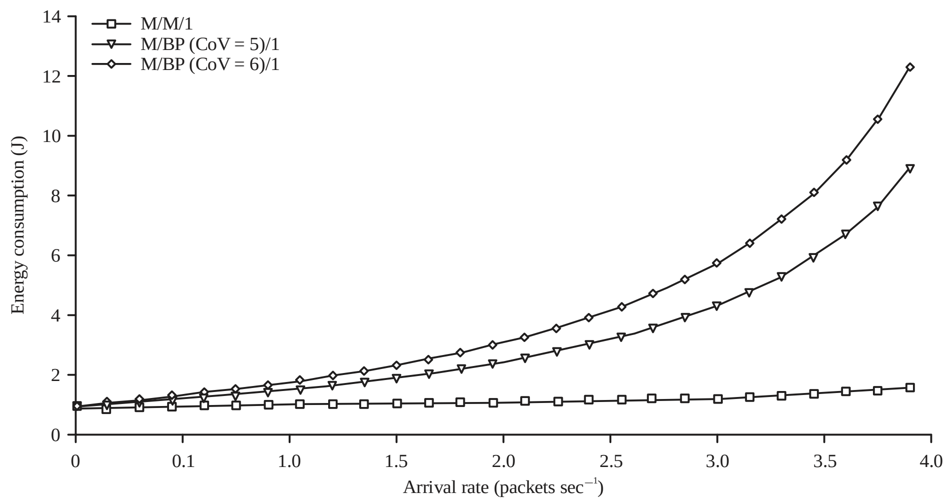

Fig. 8: Average energy consumption versus arrival rate for BP (CoV=5), BP (CoV=6) and M/M/1

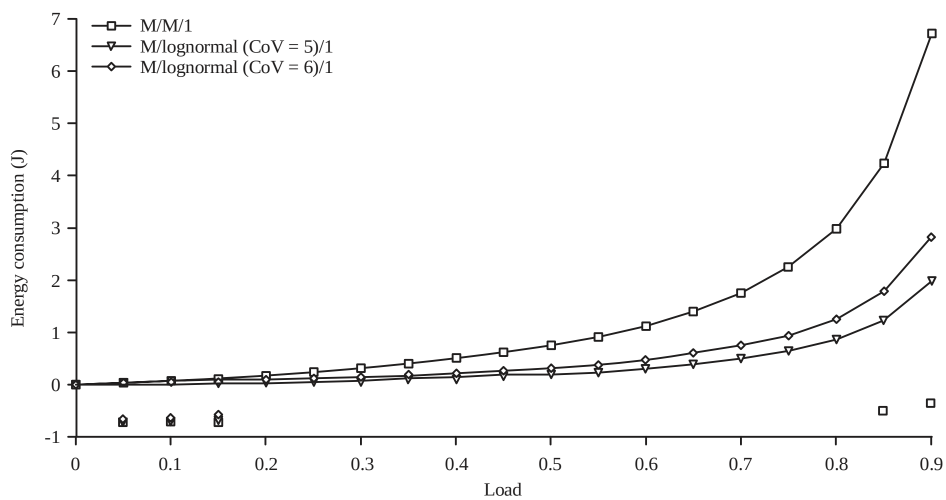

Fig. 9: Average energy consumption versus load for M/Lognormal (CoV=5)/1, M/Lognormal (CoV=6)/1 and M/M/1

consumption increases with increase in arrival rate for all the considered distributions. It was further observed that average energy consumption under M/BP (CoV=6)/1 is higher than under BP (CoV=5) which in turn is higher than under M/M/1 as the arrival rate increases. The difference in energy consumption under M/BP (CoV=5)/1, M/BP (CoV=6)/1 and M/M/1 increases as the arrival rate increases.

Comparison of M/M/1 and M/Lognormal/1: This section explores the performance of M/M/1 and M/Lognormal/1 in terms of average energy consumption. In doing this equations 3 and 16 were used to plot graphs 9-10. The mean for lognormal distribution is fixed at $e^{0.5}$ or 1.6487 and the mean for the M/M/1 or exponential distribution is fixed at 72.7 as shown in Table 1.

Figure 9 shows a graph of average energy consumption against load for M/lognormal (CoV=5)/1, M/Lognormal (CoV=6)/1 and M/M/1 with CoV=1. This study investigates the effect of varying the load on average energy consumption for M/Lognormal (CoV=5)/1, M/Lognormal (CoV=6)/1 and M/M/1 distributions. It was observed that average energy consumption increases with increase in load for all the considered distributions. It was further observed that average energy consumption under M/M/1 is higher than under M/Lognormal (CoV=6)/1, which in turn is higher than under M/Lognormal (CoV=5)/1 at higher load values. Initially the energy consumption under M/Lognormal (CoV=5)/1, M/Lognormal (CoV=6)/1 and M/M/1 were the same, however as the load increases, there is a marked difference between the energy consumption under M/Lognormal (CoV=5)/1,

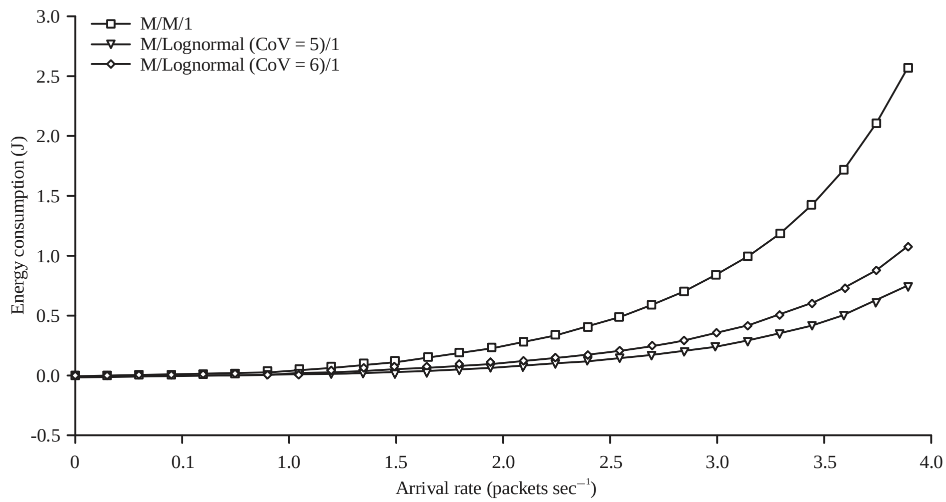

Fig. 10: Average energy consumption versus arrival rate for Lognormal (CoV=5), Lognormal (CoV=6) and M/M/1

M/Lognormal (CoV=6)/1 and M/M/1. The difference in energy consumption is even more pronounced at higher load values.

Figure 10 shows a graph of average energy consumption against arrival rate for M/lognormal (CoV=5)/1, M/Lognormal (CoV=6)/1 and M/M/1 with CoV=1.

This study investigates the effect of varying the arrival rate on average energy consumption for M/Lognormal (CoV=5)/1, M/Lognormal (CoV=6)/1 and M/M/1 distributions. It was observed that average energy consumption increases with increase in arrival rate. It was further observed that average energy consumption under M/M/1 was higher than under M/Lognormal (CoV=6)/1, which in turn is higher than under M/Lognormal (CoV=5)/1 at higher arrival rates. Initially the energy consumption under M/Lognormal (CoV=5)/1, M/Lognormal (CoV=6)/1 and M/M/1 were the same, however as the arrival rate increases, there is a marked difference between the energy consumption under M/Lognormal (CoV=5)/1, M/Lognormal (CoV=6)/1 and M/M/1. The difference in energy consumption is even more pronounced at higher arrival rates.

Comparison of M/M/1 and M/Weibull/1: The performance of M/M/1 and M/Weibull/1 was compared in terms of average energy consumption. In doing this, Eq. 3 and 17 were used to plot graphs 11 and 12. The mean for Weibull distribution is fixed at 6 λ or 24 using the maximum value of λ of 4 requests sec^{-1} and the mean for the M/M/1 or exponential distribution is fixed at 72.7 as shown in Table 1.

Figure 11 shows average energy consumption against load for Weibull (CoV=3), Weibull (CoV=4) and M/M/1 with CoV=1. This study investigates the effect of varying the load on average energy consumption for M/Weibull (CoV=3)/1, Weibull (CoV=4) and M/M/1 distributions. It was observed that average energy consumption increases with increase in load irrespective of the distribution. It was also observed that the energy consumption under Weibull (CoV=3), Weibull (CoV=4) and M/M/1 were initially the same, however as the load increases, the energy consumption under M/Weibull (CoV=4)/1 is higher than under Weibull (CoV=3) which in turn is higher than under M/M/1. The difference in energy consumption is more pronounced at higher load values.

Figure 12 shows average energy consumption against arrival rate for Weibull (CoV=3), Weibull (CoV=4) and M/M/1 with CoV=1. This study investigates the effect of varying the arrival rate on average energy consumption for M/Weibull (CoV=3)/1, Weibull (CoV=4) and M/M/1 distributions. It was observed that average energy consumption increases with increase in arrival rate regardless of the distribution. It was further observed that the energy consumption under Weibull (CoV=3), Weibull (CoV=4) and M/M/1 were initially the same, however, as the arrival rate increases, the energy consumption under M/Weibull (CoV=4)/1 is higher than under Weibull (CoV=3) which in turn is higher than under M/M/1. The difference in energy consumption is more pronounced at higher arrival rates.

Previous attempts to estimate the delay and energy consumption in wireless sensor networks employed an M/M/1 queue model[14]. In the M/M/1 queue model, the arrival rate of packets were assumed to follow a Poisson distribution, packet length is assumed to have low variability and therefore service time is best modeled by the exponential distribution.

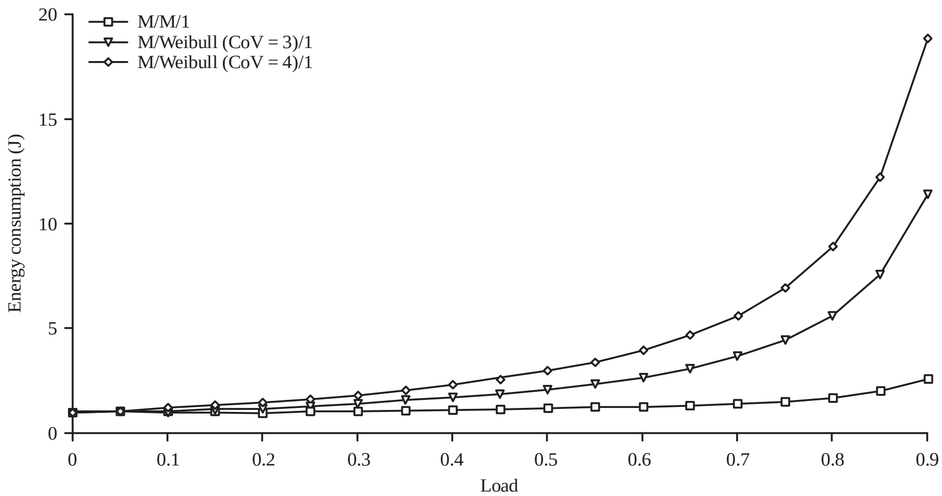

Fig. 11: Average energy consumption versus load for Weibull (CoV=3), Weibull (CoV=4) and M/M/1

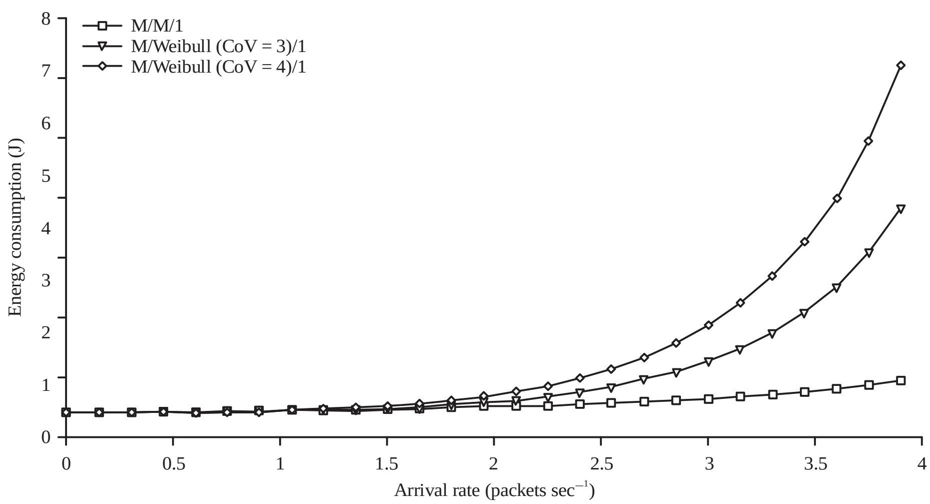

Fig. 12: Average energy consumption versus arrival rate for Weibull(CoV=3), Weibull(CoV=4) and M/M/1

In this study, the delay and energy consumption estimated using the M/G/1 queue models were found to be higher than delay and energy consumption estimated by the previous models proposed[15,16,25,26]. This was due to the fact that the M/G/1 queue model takes into consideration the high variability in packet sizes which was depicted by the type of traffic that traverses the wireless sensor network, whereas, the M/M/1 queue model assumes low variability in packets sizes and therefore underestimates the delay and energy consumption which affects the network life of a sensor network.

It was observed that the average waiting time and energy consumption was higher under the M/G/1 (where G represents Bounded Pareto and Weibull distributions) than under M/M/1 queue model. It was also observed that increase in the coefficient of variability leads to increase in average waiting time and energy consumption. Coefficient of variability was a standardized measure of dispersion of a probability distribution or frequency distribution. However, the average waiting time and energy consumption was lower under M/Lognormal/1 than under M/M/1 queue model.

CONCLUSION

An analytical model of delay and average energy consumption for WSN is presented. In this model, the packets are assumed to be highly variable and therefore, modeled using Bounded Pareto, Lognormal and Weibull distributions as opposed to the exponential distribution that models low variability in packet sizes. The model is used to compare the performance of packets under the M/BP/1, M/Lognormal/1, M/Weibull/ and M/M/1, queue models. The numerical results obtained from the derived models show that the average waiting time and energy consumption is higher under M/Bounded Pareto/1 and M/Weibull/1 than under M/M/1 queue model. However, the average waiting time and energy consumption is lower under M/Lognormal/1 than under M/M/1 queue model. It is also observed that increase in the coefficient of variability leads to increase in average waiting time and energy consumption. Therefore, the models developed can more accurately approximate the average waiting time and energy consumption when packets show high variability in packet sizes as opposed to the traditional M/M/1 queue model.

SIGNIFICANCE STATEMENTS

This study discovers the possible ways of modeling delay and energy consumption based on the M/G/1 queue model for networks that exhibit high variability in packet sizes. It is expected that this study will help researchers to uncover possible ways of modeling delay and energy consumption in wireless sensor networks with various packet sizes.

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