Proceedings of the 2018 Winter Simulation Conference
M. Rabe, A. A. Juan, N. Mustafee, A. Skoogh, S. Jain, and B. Johansson, eds.

REDUCING POWER CONSUMPTION IN SMART CAMPUS NETWORK APPLICATIONS THROUGH SIMULATION OF HIGH-PRIORITY SERVICE, TRAFFIC BALANCING, PREDICTION AND FUZZY LOGIC

J.R. Emiliano Leite
F. R. Massaro
Paulo S. Martins
Edson L. Ursini

School of Technology
University of Campinas - Unicamp
Limeira, SP, 13484-332, BRAZIL

ABSTRACT

In this work, we tackle power consumption reduction of battery-dependent devices in a smart campus (including hospital) application. These devices are connected by networked systems which may be subject to fluctuation of the message delays that control essential equipment. We show through five case studies using discrete event simulation that power consumption may be reduced using proper prioritization and balancing of the network emergency traffic. A predictor algorithm and a fuzzy logic controller were used to indicate the level upon which the system must switch off the load in order to reduce power consumption. The analysis of a case study shows that a considerable reduction in power consumption was achieved through the reduction of message delays and also due to the fuzzy control of AC and lighting equipment.

1 INTRODUCTION

The importance of uninterrupted and durable power in a smart green campus is critical, especially in areas that include hospitals and emergency care that must cope with national disasters, severe weather storms and human error. Critical consumers of durable power supplies are mobile and usually small devices that form the communication infrastructure and carry critical information stemming from RFIDs (*Radio-Frequency IDentification*), sensor devices and mobile phones, as well as from larger equipment such as medical equipment, life support systems, air conditioning (AC), and lighting systems.

Uninterrupted and prolonged power is also growing importance and required in a campus area for the IT (*Information Technology)* infrastructure, including mobile devices and IoT (*Internet of Things)* devices, especially in emergency scenarios due to the wide spreading of mobile devices that carry critical information in the event of a catastrophe. Therefore, simulation and analysis tools that attempt to model power consumption in the data network that interconnect all these systems and their applications - are critical elements in supporting the decision making that is required for such strategic planning, as can be seen in Dahal et al. (2015), Hinton et al. (2011), and Hu et al. (2004). We are concerned with reducing the consumption of electric power by using four strategies (Table 1):

1. *Batteries from mobile devices (IoT/AdHoc network)*: These are the devices that compose the IoT and AdHoc network shown in Figure 1. They are required to operate either on normal conditions or in the event of a power outage. Their lifetime is independent on the message delays ΔT in the network. Instead, they are dependent on the *amount of traffic*, measured in Erlang, and on traffic congestion in these devices, which are directly related to the variations on the network utilization ΔU. The larger the congestion, the larger the power consumption, due to the cost of retransmission and error

978-1-5386-6572-5/18/$31.00 ©2018 IEEE

recovery mechanisms that are in place when the network is overloaded. Therefore, a network that is balanced and has lower utilization represents less battery consumption. These batteries operate in normal conditions and also in the event of a catastrophe, as long as they are charged. The goal is to increase battery lifetime as well as operation efficiency, especially in emergency cases. Through two case studies (Cases 1 for high and 2 for low traffic), we show in Section 4 how balancing the traffic leads to power/energy consumption.

2. *Batteries that supply emergency equipment* and AC systems (i.e., high consumption), which are part of a larger UPS (*Uninterruptible Power Supply*) (not shown in Figure 1) and are operational exclusively in the event of a power outage. The lifetime of these batteries is dependent on the exact time that they are switched on and off. Ideally, they should be switched on as soon as possible in the event of an emergency, to allow for a short response time. They should also be switched off as soon as possible once they are no longer needed, or (normal conditions are restored) in order to preserve energy and/or battery lifetime. Since these batteries are controlled by network control messages that are susceptible to a delay ΔT, in time units (ms or secs), the lifetime of these batteries depends on the average network delays. Through Cases 2 (for low-traffic conditions) and 3 (high-traffic conditions) it is shown that by manipulating the priority of control messages we can reduce ΔT and thus reduce energy consumption, thus extending battery life. In Case 4 we consider a high network traffic. Unlike the batteries from mobile devices, these batteries are not affected by fluctuations in the network utilization ΔU, or at least one may argue that the impact they suffer is negligible.
3. *Other equipment*, i.e., equipment supplied directly from the power network during normal conditions - and that are not necessarily emergency or high consumption components of the system. The impact of ΔU and ΔT on this class is much similar to the one on mobile devices. Therefore, the results from case studies extend to this class as well. Much like the previous category, the devices that are supplied from the network generate inefficiency if they remain in operation beyond necessary time, i.e., they are switched off late. If their message-triggered, Internet enabled controller delays, then this incurs in extra power consumption. This class of equipment may benefit from load balancing in the network, but the improvement is not as sensitive and significant as in the case of devices that are dependent on a battery with limited capacity.
4. *Applications*: Saving energy at the application level through fuzzy control. This case considers the control of devices (i.e., their operational level in percentage %) regarding power consumption. A fuzzy logic controller determines the level of operation as a function of process variables such as temperature, humidity and clarity to control AC and lighting.

Table 1: Strategies for Smart Campus energy consumption reduction.

Strategies →	Priorization	Network load balancing		Traffic	Fuzzy	mode
Energy reduction in	Delay reduction (ΔT)	Delay reduction (ΔT)	Utilization reduction (ΔU)	load	control logic	of operation
IoT/AdHoc network (on battery) (Figure 1)	✗	✗	✓Case 1 ✓ Case 2	high low	✗	normal, power out.
emergency equip. (on UPS battery)	✓ Case 4 ⊖ Case 3	✓ Case 1 ⊖ Case 2	✗	high low	Case 5 ✓	power outage
other equipment (power network)	✗	✗	✓	high low	✗	normal
Application power saving	⊖	⊖	⊖	⊖	Case 5 ✓	normal power off

✗= ineffective , ✓= effective, ⊖ = negligible

The goal of this paper is to understand the impact of prioritization of messages on the power consumption in a system. The operation of the complete system relies upon a heterogeneous and multi-service communication network. There is an application for emergency, AC, light, that is active in the event of power outage. The activation is via control messages that traverse the network from sensors until a controller element.

Traffic is related to power consumption through priorities. By increasing the priority of messages, their average response time becomes shorter. This means that control emergency equipment is activated earlier. This improves the responsiveness of the system. This also means that control equipment is switched off earlier, resulting in battery saving.

Priorities are important because they are related to the power consumption so that sensors that are related to large power consumption must be serviced and notified in shorter time. A predictor algorithm and a fuzzy logic controller were used to indicate the level upon which the system must regulate the load (%) in order to reduce power consumption (Case 5).

The contribution of this paper lies in: 1) It offers an analytically validated network discrete event simulation model, which includes IoT and AdHoc networks combined; 2) The model can be used or applied to reason about energy saving as a function of priority and traffic congestion; and 3) The study also provides case studies that showcase the approach. On the other hand, the use of this type of approach (simulation + priorization + fuzzy control) allows a quick way to obtain qualitative results on the reduction of energy consumption, which does not need to be necessarily considered in excessive detail. The model also enables the evaluation of the mobility (RWP) of the AdHoc network and the effectiveness of the fuzzy control. It also allows its validation by analytical models (in our case this was carried out with the Jackson network). Considering its structure, the model can be used for both planning/dimensioning and for real-time (dynamic) performance. To the best of our knowledge (and as discussed in Section 2), we have not found in the literature review work that approaches this topic with such combined features.

2 RELATED WORK

In the work by Lukovic et al. (2016), UPSs require an increase of reliability by means of proactive actions. The authors provide a concept called SmartUPS including online failure prediction of components. Our work also employs an IoT network, but it studies the impact of prioritizing the network traffic and network congestion on energy saving. Unlike Lukovic et al. (2016), we add a fuzzy logic controller to better support power management.

Measurements show the existence of a direct relationship between base station traffic load and power consumption. According to this relationship, the paper by Lorincz et al. (2012) developed a linear power consumption (Watt X Erlang) model for base stations of GSM *(Global System for Mobile Communications)* and UMTS *(Universal Mobile Telecommunications System)*.

Mobile communications consume significant amount of energy. In the work by Dahal et al. (2015), more than 50% of the total energy is consumed by the radio access, and within this fraction - 50-80% is used by the power amplifier. The results revealed a linear relationship between the power consumption and traffic loads, and the authors provided suggestions for energy-efficient wireless communication. The paper by Hinton et al. (2011) presents a network-based model of power consumption for the Internet infrastructure. The access network dominates the Internet's power consumption. As access speeds grow, the core network routers dominate power consumption. Several strategies were created to improve the energy efficiency of the Internet. The paper also proposes to make cellular networks more energy-efficient. Their approach does not compare to the one in our paper, as our focus is on the network dimensioning, priority setting and fuzzy control.

Hu et al. (2004) measured results of power consumption and cost in a large hospital in Taiwan. Air-conditioning (A/C) is the major component of power consumption and it accounts for more than 50% of the total building energy use. Some approaches to shift peak load are proposed. Unlike the work by Hu et al. (2004), our work includes a fuzzy logic module to control A/C and lighting.

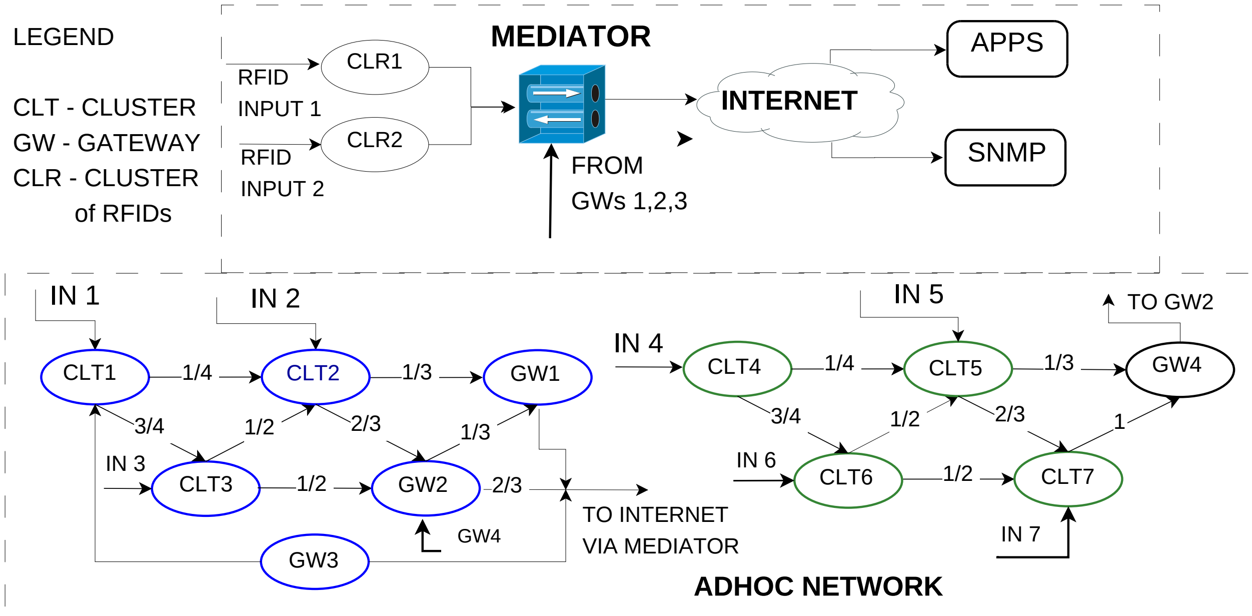

Figure 1: IOT network model.

3 SYSTEM MODEL

An IP packet is modeled as an entity that arrives to the system and crosses several internal queues in a cluster before its departure (i.e., before it is consumed by an application). The network model is a hierarchy consisting of clusters which contain nodes, which in turn have multiple CPUs, thus allowing several parallel connections. Inherent to each queue is the waiting delay before a packet can be processed by a server. Clearly, both queueing and processing times are subject to statistical distributions. Therefore, a network cluster may be regarded as a set of internal queues (each one associated with an outbound link). The left part of Figure 1 consists of network components such as the mediator MD, two clusters ($CLR1$, $CLR2$), which perform the acquisition of RFID tags; gateway and the Internet. The end points can be RFID and sensors for different applications. There are two applications: 1) smart and green building including the control of actuators, and 2) SNMP (*Simple Network Management Protocol).*

The lower part of Figure 1 is an AdHoc Network that generates data traffic which is aggregated by the IoT mediator. It consists of the following elements: 7 clusters ($CLT1....CLT7$); 4 gateways or Internet nodes ($GW1....GW4$); 7 Inputs: model data packets generated by IoT sensors; 3 Internet outputs from gateways GW1, GW2 and GW3: they model the flow of IP packets outbound; Input variables: data arrival and service time distributions in a node; Control variables: probability of node connectivity inside a cluster. This probability is provided by the Random Waypoint (RWP) algorithm; Output variables: mean queue time and mean CPU utilization on each cluster for a given position of the nodes within the cluster (Leite et al. 2017).

Each node receives packets at the input link and forwards them to one of the outbound links using UDP over IP (Datagram). Since the arrival of requests for the RFID and AdHoc networks can be modeled as a Poisson process, the traffic volume of each individual node can be extended to the traffic volume of a cluster by the simple sum of the rates of Poissonian arrivals. Thus, we sum the rates of each node to form a cluster of ten nodes. Table 2 shows the probabilities of transmission for each link as well as the related cluster-head CPU(s). CPUs 25 to 34 are used only at the application level. CPUs 1 to 24 are used at the network level (the exceptions are CPUs 19 and 23, which are also used by the application level). Table 3 partially shows the routing probability associated to each link (Figure 1) but in a matrix form (Leite et al.

Table 2: Network configuration.

F	Prob.	CPU	F	Prob.	CPU	F	Prob.	CPU	F	Prob.	CPU
$GA1$	1	25	$GA2$	1	28	$GA3$	1	29,33	$GA4$	1	19,34
AdHoc	1,1,1,1	30,31,32,33	$CLR1$	1	21	$CLR2$	1	22	MD	1/2, 1/2	24, disc
GWI	1/3,1/3,1/3	23, 26, 27	$GW1$	1	5	$GW2$	1/3, 2/3	11,6	$GW3$	1	14
$GW4$	1	17	$CLT1$	1/4, 3/4	1,2,20*	$CLT2$	1/3, 2/3	3,4	$CLT3$	1/2, 1/2	7,8
$CLT4$	1/4, 3/4	12,15	$CLT5$	1/3, 2/3	16,13	$CLT6$	1/2, 1/2	9,10	$CLT7$	1	18

GA=application gateway, F=function, Prob.=probability. * output-CPU 20 to $GW3$ is used only in an emergency. disc=discard

2018; E. L. Ursini and P. S. Martins 2018). The full table may be formed by examining Figure 1 and the probabilities between each pair of nodes (e.g., GW, CLT, CLR, MD) in the network.

To simulate the performance of the network, the adopted mobility model was the Random Waypoint (RWP) (Leite et al. 2017). To evaluate each node independently, a MATLAB routine generates random positions for the ten nodes within each cluster every one second. Nevertheless, this is not the focal point of this paper. All cases used the model shown in Figure 1, where internal nodes have limited mobility. Lastly, the proposed model is general and it can be instantiated for specific applications. For example, the probabilities of transmission for outgoing links can be measured in a real application and replaced in the model. The arrival and service distributions considered may also be replaced by actual measurements and/or other types distributions.

Table 3: R Matrix (partial): probability of transmission per output link.

——	CLT1	CLT2	CLT3	CLT4	CLT5	CLT6	CLT7	GW1	GW2	GW3	GW4	CLR1	CLR2	MD
CLT1	0	1/4	3/4	0	0	0	0	0	0	0	0	0	0	0
CLT2	0	0	0	0	0	0	0	1/3	2/3	0	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
GW1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
CLR2	0	0	0	0	0	0	0	0	0	0	0	0	0	1
MD	0	0	0	0	0	0	0	0	0	0	0	0	0	0

CLT - cluster, GW - gateway, CLR - Cluster RFID, MD - mediator

4 CASE STUDIES

The five cases attempt to show the impact of message prioritization, traffic balancing, and fuzzy logic control on the reduction of power consumption. The first four cases address the network in connection with message priorities and traffic balancing (network decongestion). The last case deals with power reduction when a fuzzy logic control is added after the network (application). Tables 4 and 5 show the traffic arrival rates and the traffic calculation for overloaded and balanced networks. Table 5 shows the traffic in Erlangs and uses λ_i/μ_i for each CPU. The results for case studies 1-4 are presented in Table 6.

4.1 Case 1 - Congested Network Without Priority

Figures 2(a) and 2(b) illustrate the results for Case 1. In Case 1 (Table 6, column 2) messages have no priority. It uses an arrival rate of EXPO (0.4) (= 2.5 packets/sec) for a congested network.

Table 6 shows the total average message delay times (in seconds). The delays are obtained from the input to the mediator output. The delays depend on the path taken by the packets in the routing scheme. The first column shows the type of messages, which are 1) SNMP with high and low priority; 2) Sensor 1 measures current and voltage for an air conditioning (AC); 3) Sensor 2 indicates level of illumination; 4) Sensor 3 reads current and voltage battery values (UPS), and 5) RFID tag. Note that some message delays are abnormally large due to the fact that the network lies in an overloaded condition. Therefore, it

Table 4: Cases 1 & 2 - Overloaded (γ_o and λ_o) and balanced (γ_b and λ_b) traffic arrival rates in packets/sec.

—	CLT1	CLT2	CLT3	CLT4	CLT5	CLT6	CLT7	GW1	GW2	GW3	GW4	CLR1	CLR2	MD
γ_o	2.5	2.5	2.5	2.5	2.5	2.5	2.5	0	0	0	0	1.67	1.67	5.0
λ_o	2.5	5.31	4.38	2.5	5.31	4.38	8.23	7.01	15.7	0	10.0	1.67	1.67	25.8
γ_b	1.67	1.67	1.67	1.67	1.67	1.67	1.67	0	0	0	0	1.67	1.67	5.0
λ_b	1.67	3.54	2.92	1.67	3.54	2.92	5.49	4.68	10.49	0	6.67	1.67	1.67	20

Table 5: Cases 1 & 2 - Overloaded and balanced traffic in each CPU (Erlang).

CPU	1	2	3	4	5	6	7	8	9	10	11	12
Traffic$_o$	0.125	0.125	0.267	0.267	0.71	0.587	0.219	0.219	0.219	0.219	0.587	0.125
Traffic$_b$	0.084	0.084	0.177	0.177	0.468	0.525	0.146	0.146	0.146	0.146	0.525	0.084
CPU	13	14	15	16	17	18	19	20	21	22	23	24
Traffic$_o$	0.267	0	—	0.267	1.00	0.823	–	–	0.167	0.167	–	0.258
Traffic$_b$	0.177	0	0	0.177	0.667	0.549	0	–	0.167	0.167	–	0.20

CPU 20: Emergency, CPU 19,23: Application, Total$_o$ = 6.734 E, Total$_b$ = 4.896 E

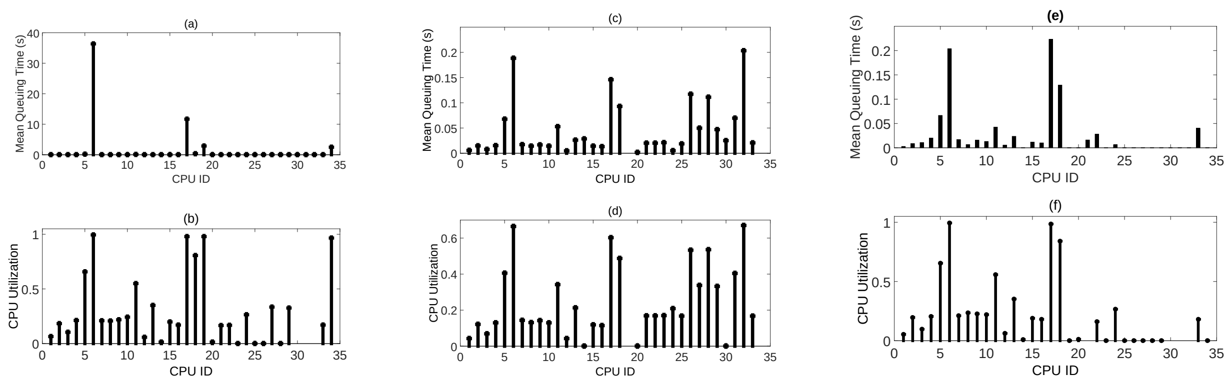

Figure 2: CPU mean queuing time and utilization: Case 1 (a,b), Case 2 (c,d) and Case 4 (e,f).

is expected that some messages may 'starve' in a buffer causing undesirable results for some applications. The purpose of balancing the network is to remove such abnormal conditions. In addition, Table 6 shows the priorities chosen for each type of message, where 0 is the highest priority. Tables 4 and 5 are related to this case, i.e., the evaluation of traffic under overload. The γ values refer to the packet generation rate in each cluster, according to Table 4 (overloaded and balanced traffic). From the values of γ and Matrix R, we may calculate the λ values that correspond to a Jackson network (Jackson 1957). Further details of this calculation are shown in the following subsection.

In Figures 2(a) and 2(b), we observe that some CPUs are overloaded (i.e., high CPU utilization), and the overloading of a single node can be propagated to other nodes to the point of compromising the whole network (in the event of a worst-case scenario). This congestion leads to higher CPU utilization in each node, since congestion triggers the error detection and correction as well as retransmission of lost packets. It is only in the following case, i.e., Case 2, that we balance the network and the difference in the utilization is related to the reduction in power consumption for the batteries of the mobile devices. By figuring out this relationship, we become able to estimate the actual gain in power consumption.

4.2 Case 2 - Balanced Network Without Priority

Case 2 (Table 6, column 3) shows the simulation results (Figs 2(c) and 2(d)), where the messages have no priority, and the arrival rate is set to an EXPO (0.6) (= 1.67 packets/sec) for a stable (non-congested) network. Tables 4 and 5 are related to Cases 1 and 2. The evaluation of traffic under balanced load.

After using the Markov model to balance the network, we adjusted the values of the simulation. The Jackson's network model showed that the dimensioning of the network and elimination of bottlenecks. The model also was useful for validation. Once the model was validated, we can use other distributions, that the Jackson model does not cover (Jackson 1957).

Since the initial simulation model has both exponential arrival and service distributions, it may be validated against Jackson's open queueing network model. The solution is obtained from a Markov chain. The packet arrival rate is 1/0.6 = 1.67 packets/sec. The first seven arrivals, each generated by a cluster (gateways do not generate traffic), yield 1.67 packets/sec (the remaining four are gateway inputs), therefore: γ = [1.67, 1.67, 1.67, 1.67, 1.67, 1.67, 1.67, 0, 0, 0, 0, 1.67, 1.67,5.0]. We also need the 14 *times* 14 matrix R (Table 3), which describes the probabilities shown in Figure 1 . The total arrival rates in each cluster or gateway is given by the vector: $\lambda = \gamma\, [I-R]^{-1}$, λ = [1.67, 3.54, 2.92, 1.67, 3.54, 2.92, 5.49, 4.68, 10.49, 0, 6.67, 1.67,1.67,20]. From the rates obtained from Table 4, it is possible to calculate the waiting time for each CPU (W_i, [i=1....24]) by means of the equation (1). This equation gives the delay in an M/M/1 queue for overloaded and balanced traffic:

$$W_i = \frac{\lambda_i/\mu_i}{\mu_i - \lambda_i}, \qquad \mu_i = \frac{1}{0.1} = 10 \tag{1}$$

packets/sec, where λ_i and μ_i are the rates for each CPU. Since all the delay values obtained from the simulation model matched the ones from the analytical model, the simulation model may be deemed validated (Ursini and Martins 2018). This validation is a crucial step since it allows further extensions to this model, i.e., the inclusion of other model features such as new types of distributions. Due to the high utilization of the mediator (output CPU 24), its service rate was increased 5 times (i.e., from 10 to 50 packets/sec).

The initial distribution adopted for the arrival and service rate was the exponential. This distribution is suitable since 1) it allows for validating of the model with an analytical model, and 2) it is the one that stresses the network (the worst case when there is no bursts). If the exponential distribution does not match the reality, it is possible to combine exponential distributions to form Erlang(k) distributions, which may better reflect the actual traffic model in the network. The infinite summation of Erlang(k) distributions leads to a constant distribution. Otherwise, if there are bursts in the network, the Pareto or Hyper-exponential distributions may be employed, depending upon the application. Once the model is validated by incremental evolution other types of extensions may be studied.

4.3 Case 3 - Balanced Network With Priority

Case 3 (Table 6, columns 4,5,6,7) shows the simulation results where the message are assigned a priority, and the traffic arrival rate is an EXPO (0.6) (= 1.67 packets/sec) for a uncongested network. As it can be seen in Table 6, the reduction in the average delay time was not significant, and it may be due to stochastic variations of this variable.

Case 3 has two variants, (a) and (b). In sub-case (a) the sensors are assigned a priority within 3 priority classes (low, medium and high). Furthermore, most sensors were assigned a priority within class 1. In Case 3(b), we reduced the number of priority levels to only two levels (high and low), so that half of the inputs were allocated to one group and the other half to another. The goal of this case was to better observe the impact of prioritization of packets on the timing performance (i.e., average delays), which ultimately maps onto power saving. It is possible to notice that, when the network utilization is low, these changes in priority assignments had a negligible impact on the average packet delays and network utilization.

4.4 Case 4 - Congested Network With Priority

Figs 2(e) and 2(f) shows the results for Case 4. In this case we study the effect of applying a high priority to emergency traffic when the networks is congested. The results are shown in Table 6 (columns 8,9). As we can see, the average delay time for the messages from sensors 1 and 2 was substantially reduced, and it increased sensors 3 accordingly. Messages with high priority can effectively traverse the network under congested traffic. The remaining traffic (SNMP and RFID) showed no substantial changes. This case is compared against Case 1 which has the same conditions, except that the traffic has no priority. This reduction in the average delay ΔT may be translated to an energy saving for UPS equipment, as discussed in the following section.

Table 6: Network message delay time (secs) for case studies 1-4 (prio=priority).

Message source type	Case 1	Case 2	Case 3				Case 4	
	congested	balanced	balanced		balanced		congested	
	no-prio	no-prio	(a) with 3 prio		(b) with 2 prio		with prio	
	delays	delays	delays	prio	delays	prio	delays	prio
SNMP (high)	0.093	0.085	0.085	0	——	0	0.09	0
sensor 1 AC			2.091	**1**	2.090	**1**	2.27	1
sensor 2 light	28.04	2.28	3.730	**2**	3.728	**1,2**	4.45	2
sensor 3 battery			3.127	**3**	3.127	**2**	84.76	3
RFID	2.170	2.145	2.145	4	2.144	4	2.15	4
SNMP (low)	—–	—–	—–	5	0.086	5	—-	5

4.5 Case 5 - Air Conditioning, Lighting and UPS Control

Considering that the system adopted in this work includes actuators, this section covers the mechanisms that provide support for such actuators. These mechanisms were subdivided into two groups: 1) support for lighting and AC control, and 2) mechanisms to signal the need for UPS battery replacement. For the conditions set by the application, the temperature range is from 19 to 32 degrees Celsius. Humidity varies between 10 and 80%, whereas the amount of light varies from 70 to 800 lumens.

4.5.1 Lighting and AC Control

Two functions were created using fuzzy logic, one for lighting and another for air conditioning control. In order to support fuzzy functions in the simulation process, it was necessary to integrate the DES simulation with the MATLAB software through the use of the VBA (Visual Basic for Applications) module, which allows the exchange of information between the two software components in a transparent way. Both fuzzy functions receive as input parameters the current temperature, the brightness factor and the relative humidity percentage. For each parameter, functions were assigned for subdivision into three groups: low (L), medium (M) and high (H) (Table 7).

Figures 3a, 3b and 3c show the input variables for lighting and AC fuzzy control. For the functions of temperature shown in Figure 3a, three triangular functions were used with parameters [19.01 20.3 21.58], [19.9 23.5 27.1] [24.4 28 31.6] respectively. For humidity, (Figure 3.b), three triangular functions were also used: [0.1 0.15 0.2], [0.15 0.2 0.4] and [0.35 0.5 0.8]. For clarity (Figure 3c), three gaussian functions were used: [70.7 157], [107 400] and [135.9 800].

Figure 3d illustrates the output functions for AC lighting control, which represents the value for calibration of the air-conditioning / lighting system in the range of 0 to 1. The output values were subdivided into three groups: low, medium and high, represented by triangular functions with the following

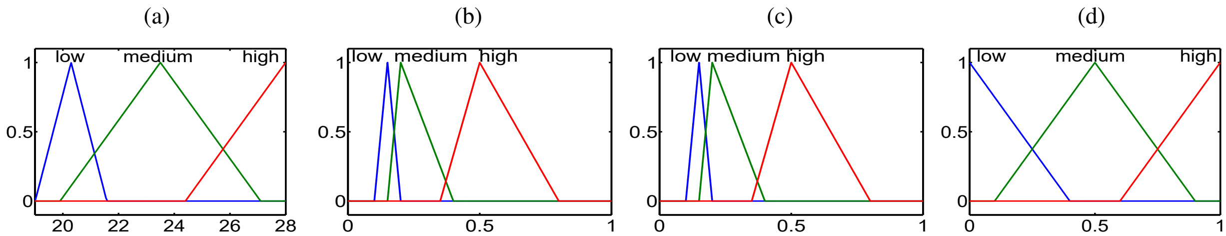

Figure 3: Input (a,b,c) and output (d) fuzzy variables for air conditioning and lighting.

Table 7: Example of fuzzy rules using conjunction (AND).

Input Variables			Output Variables	
Temperature	**Humidity**	**Clarity**	**AC Level**	**Lighting Level**
L	L	L	L	H
M	L	L	M	H
H	L	L	H	H
...	...	...	...	...
M	H	H	H	L
H	H	H	H	L

e.g., RULE 1: IF TEMP=L AND HUM=L AND CLARITY=L THEN AC LEVEL=LOW

parameters: [0 0 0.4], [0.1 0.5 0.9] and [0.6 1 1]. Thus, the result of defuzzification will be used by the air-conditioning actuator to regulate ambient temperature and illumination.

Although the input and output functions are the same for both actuators (air conditioning and lighting), what will differentiate the actuation form are the fuzzy rules defined for each actuator. Thus, it was necessary to create 27 fuzzy rules for each actuator. Table 7 presents the fuzzy rules created for both the air-conditioning and the lighting actuators. Each rule determines the level of the air-conditioning temperature (low, medium or high) according to the input variables (temperature, humidity and clarity) which reflect the characteristics of the environment. Similarly, rules for the lighting level are also specified in the same table. Figure 4a summarizes the data on AC and lighting power reduction in a boxplot chart, showing that the AC has a more symmetric behavior regarding power consumption whereas lighting does not. Figures 4b and 4c present the results obtained regarding the energy saving indices of the air conditioning and lighting systems provided from the implementation of the proposed approach. These results indicate that the average saving was 48.35% in air conditioning and 46.58% in lighting.

4.5.2 UPS - Battery Replacement Control

In hospital environments, the UPS system is extremely important when there is a power outage, as it provides support to the electro / electronic equipment until the power supply is reestablished. To ensure the effective operation of this system, continuous monitoring of the current and voltage of the batteries is necessary. Thus, this work proposes the use of prediction for the current and voltage variables, for the proactive monitoring of the UPS system and the application of fuzzy logic to the decision making on the exchange of the batteries. In this work, a predictor based on the Kalman Filter (Welch and Bishop 1995) was used to predict the current and voltage variables of the batteries, which are input parameters to the fuzzy logic that determines the need to exchange the UPS battery pack. Figures 5a and 5b represent the input functions for each of the variables. For the current functions shown in Figure 5a triangular functions with the following parameters were used: [0 30 35], [32 40 48] and [45 60 80]. Figure 5c shows the output functions indicating whether or not to replace the battery. The current and voltage variables of the battery are predicted in an individualized way by the predictor, whose results are submitted to the defuzzification process that determines if the battery should be replaced or not.

Therefore, the fuzzy function responsible for the battery replacement indication receives as input the predicted value of the current and the battery voltage, which are subdivided into 3 groups: low, medium and

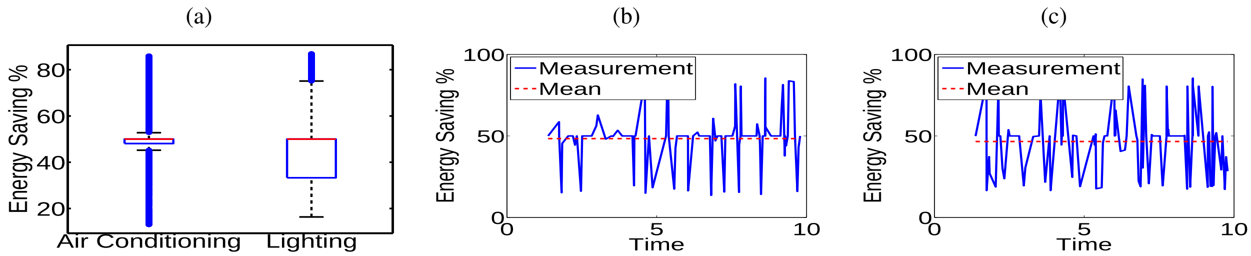

Figure 4: Power reduction in air conditioning and lighting.

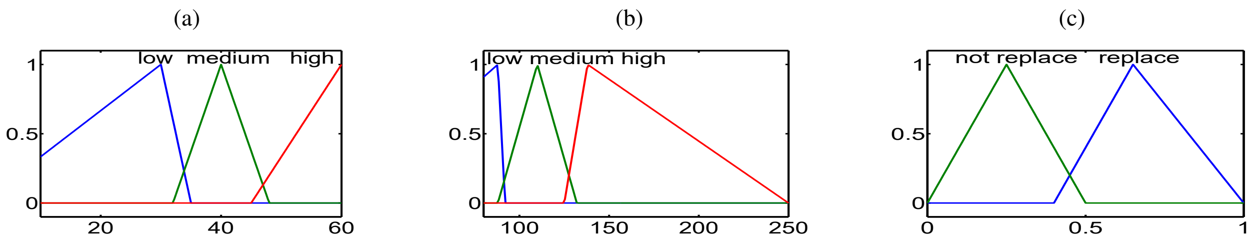

Figure 5: Input (a,b) and output (c) fuzzy for UPS control.

high. The parameters set to not replace the battery are: [0 0.25 0.5]. To replace the battery, the parameters are [0.4 0.7 1]. In order to indicate whether or not to replace the battery, we need to create nine fuzzy rules (formatted using AND). The rule that prompts for keeping the battery is if *voltage* = MEDIUM and *current* = MEDIUM then DO-NOT-REPLACE. The range for input current is [0-80] mA and for input voltage it is [0-250] volts. As shown in Figure 5b, the membership functions are triangular functions with the following parameters: [0 88 92], [88 110 132] and [125 138 250].

5 REMARKS AND DISCUSSION

Based on application of the model to the case studies, we may add the following remarks:

Network traffic: By using the Jackson Network model, we see that the first congested nodes propagated the effect of their congestion to the rest of the network (Cases 1 and 2). Thus, by applying planning and traffic engineering, it was possible to reduce network congestion. As expected, 1) the delay was strongly dependent on the network topology and priority; 2) the best gains in the allocation of priority were observed when the network was congested, and 3) the congested network substantially increased packet delays. There were small statistical fluctuations in the results that may be removed with additional replications and increased simulation time. However, these fluctuations have not sacrificed the quality of results. Since the SNMP service has the highest priority, its packets suffered the smallest jitter. Furthermore, although the RFIDs components had the lowest priorities, their message delays were not substantially affected because the topology had shorter paths to the mediator MD (Figure 1).

The numeric values that we obtained in the case studies may become more realistic if real measures on a real network are taken and used to feed the simulation model. By comparing Cases 1 and 2 (Table 5) we may see that the sensors group had the message delays significantly reduced by simply balancing the network (from 28.04 down to 2.28 s). The analysis of Cases 1 and 4 shows that by adding priority to the network when it is congested reduced the network delays from 28.04 to 2.27 and 4.45 for higher priority messages and increased the delays from 28.94 to 83.76 secs due to their low priority. The analysis of Case 3 shows that the addition of a few new priority levels does not impact the network delays.

Reduction in power consumption due to traffic balancing: In the work by Dahal et al. (2015), power consumption for base stations in ten consecutive days (including weekends), and for 864000 samples collected from a 3G system - is given by Y = a + bX, where a is given in Watt and b in Watt/E. Under high traffic, y = 1.274 + 1.713x, and the regression has a coefficient of determination that is large, i.e., $r^2 > 0.765$. For low traffic, y = 1.22677 + 0.00057x, and the coefficient of determination is low ($r^2 < 0.31$). If our simulation model had a 3G implementation such as the one by Madhu et al (Dahal, Khadka, Shrestha, and Shakya 2015), and considering that the values we obtained are for high (or peak) traffic, we would estimate a daily reduction in power consumption of 4.42 Watts (i.e., 1.274 + 1.713 (6.734-4.896) = 4.422 W). For the highest traffic load between 8-11 am to 6-8 pm, this figure would roughly translate into a monthly savings of up to 450 Watts $\cdot$ h/month, which could - in turn - represent a substantial extension of battery life.

Reduction in power consumption due to traffic prioritization: The saving in energy results mostly from the network balancing. For example, from Table 6, Cases 1 and 2, the delay reduced from 28.04 to 2.28 seconds, approximately 1000 % . On the other hand, changing the priority had not significantly changed the delay for a balanced traffic. For example, the delay reduced from 2.28 (Case 2 - without priority) to only 2.09 (Case 3 - with priority), which represents a gain of approximately 10 % . If a packet that controls UPS has a delay reduced by 26 secs, it would imply that it is switched OFF 26 secs earlier. Assuming 1000 switches in one year, it would yield 1000 x 26 secs = 7 hours approx. of consumption. Assuming a small campus with 200 ACs drawing 5000 Watts each, this would amount a total energy saving of 35 kWh. This value is enough to supply energy for roughly 6 households for one month. Clearly, in larger campuses these values could easily escalate to larger figures.

Reduction in power consumption due to fuzzy logic control: The use of fuzzy logic in the application caused a reduction of 50 % in AC and lighting power. Furthermore, the use of a Kalman-based predictor allows the replacement of batteries in advance, thus avoiding blackouts, as shown in Figure 4.

6 CONCLUSION

In this work, we addressed IP packet priorities, the reduction of network congestion, and fuzzy logic control as strategies to reduce power consumption. To illustrate the approach, we built a discrete event simulation model that includes an AdHoc network, a mediator, a set of applications and a set of inputs (RFID, sensors). This model was analytically validated using Jackson networks.

The reduction in message delays has at least two components: 1) the reduction in delays by assigning higher priorities to specific traffic, and 2) the reduction in delay by removing network congestion and overloading. In this work we attempted to reduce power consumption by tackling both forms. The increase of the priority of the emergency traffic effectively reduced the delays for these messages, which may allow the emergency UPS to be ON and OFF earlier than usual. The results showed that the model may provide estimates of the reduction in time, which may be converted to energy savings through simple formulas.

Assuming that the number of mobile devices outnumber the number of UPS devices, we may argue that balancing network traffic has a larger impact in terms of the number of devices affected, but not much power reduction in terms of kW $\cdot$ h. On the contrary, increasing the priority of emergency and control traffic has a larger gain in terms of power, but the number of devices affected are smaller, though more critical. In any case, both strategies are useful and may be used in combination, as shown in this paper.

Priority and congestion have traditionally been associated to quality of service in multimedia and improvement of worst-case response times in real time systems. This article showed another face of priority and congestion - its impact on energy consumption. In addition to improving the QoS and the emergency response to critical alarms, it has a large impact on energy saving. Therefore, they should be given a more prominent role in the design of computational systems. The use of fuzzy logic resulted in an estimated 50% reduction in relation to the power consumption without any control. For future work, we consider that the reduction in the average message delays may be better explored by having an additional fuzzy logic dedicated to traffic control.

ACKNOWLEDGEMENTS

The authors would like to acknowledge grant #2018/20715-8, São Paulo Research Foundation (FAPESP). The opinions, hypotheses and conclusions or recommendations expressed in this material are the responsibility of the author(s) and do not necessarily reflect the views of FAPESP.

REFERENCES

Dahal, M. S., S. K. Khadka, J. N. Shrestha, and S. R. Shakya. 2015. "A Regression Analysis for Base Station Power Consumption under Real Traffic Loads - A Case of Nepal". *American Journal of Engineering Research (AJER)* 4(12):85–90.

Hinton, K., J. Baliga, M. Feng, R. Ayre, and R. S. Tucker. 2011, March. "Power consumption and energy efficiency in the internet". *IEEE Network* 25(2):6–12.

Hu, S., J. Chen, and Y. Chuah. 2004. "Energy Cost and Consumption in a large acute Hospital". *International Journal on Architectural Science* 5(1):11–19.

Jackson, J. R. 1957. "Networks of Waiting Lines". *Operations Research* 5(4):518–521.

Leite, J., E. L. Ursini, and P. S. Martins. 2018, July. "Performance Analysis of IoT Networks with Mobility via Modeling and Simulation". In *The International Symposium on Performance Evaluation of Computer and Telecommunication Systems*.

Leite, J. R. E., E. L. Ursini, and P. S. Martins. 2017, September. "Simulation of AdHoc Networks Including Clustering and Mobility". In *16th International Conference on Ad Hoc Networks and Wireless (AdHocNow-2017)*, 199–209.

Lorincz, J., T. Garma, and G. Petrovic. 2012. "Measurements and Modelling of Base Station Power Consumption under Real Traffic Loads". *Sensors* 12(4):4281–4310.

Lukovic, S., I. Kaitovic, G. Lecuona, and M. Malek. 2016, Oct. "A Methodology for Proactive Maintenance of Uninterruptible Power Supplies". In *2016 Seventh Latin-American Symposium on Dependable Computing (LADC)*, 183–186.

E. L. Ursini and P. S. Martins 2018, July. "Validation of a Discrete-Event IoT Simulation Model". https://www.researchgate.net/publication/326410652_validation_of_a_discrete_event_IOT_simulation_model.

Welch, G., and G. Bishop. 1995. "An Introduction to the Kalman Filter". Technical report, NC, USA.

AUTHOR BIOGRAPHIES

JOSE R. EMILIANO LEITE is a doctoral candidate at the School of Technology, Unicamp. He works with wireless sensor networks, Internet of Things, RFID, TCP/IP, and discrete event simulation. He has Project Management (PMP / PMI) certification (USA). His email is joserobertoemilianoleite@gmail.com.

FLAVIO R. MASSARO JR. is a doctoral candidate at the School of Technology, Unicamp. He holds an MSc degree in Technology from Unicamp. He works with real time systems' analysis, discrete event simulation and fuzzy logic systems. He has experience with Oracle SQL. His email is frmasssaro@gmail.com.

EDSON L. URSINI is an Assistant Professor at School of Technology, Unicamp with a doctoral degree in Electrical Engineering (electronics and communications) from Campinas State University. He works with data networks, stochastic processes, queuing models, teletraffic and data traffic, discrete event simulation, continuous simulation, fuzzy logic systems, and performance analysis. His email is ursini@ft.unicamp.br.

PAULO S. MARTINS is an Associate Professor at the University of Campinas and holds a DPhil degree in Computer Science from The University of York, UK. He works with network design and analysis, real-time systems and software engineering. He has worked in both academia (USA, Brazil) and industry (USA, UK) including automotive and military projects with the US Air Force. His email is paulo@ft.unicamp.br.