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Fuzzy Rough Set Theory Based MAC Model for Wireless Body Area Networks

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Abstract:
The health care system with Wireless body sensor networks is functioning in irreconcilable circumstances. All packet transmissions are served for the particular application by satisfying the quality of service parameters without distressing battery life time of body sensors. To fulfill the requirements, distributed queuing body area networks (DQBAN) scheme is come into existence as substitute enrichment protocol to 802.15.4 MAC. Instead of fuzzy logic scheduling scheme, rough set theory and a novel cross layer fuzzy rough set theory (FRST) is introduced. FRST is the integration of fuzzy and rough set theories, and it is used to greatly reduce data redundancy. Experimental results show that fuzzy-rough set scheduling is more powerful than the conventional rough set based approach. The proposed scheme achieves considerable low power utilization and suitablefor coexisting scenarios. Simulation is carried out using MATLAB.

Keywords: *Distributed queuing body area networks, Fuzzy rough set theory, Wireless body sensor networks*

I INTRODUCTION

Human body monitoring using a WSN may be achieved by attaching sensors to the body's surface as well as implanting them into tissues for a more accurate clinical practice. The realization that proprietary designed WSNs are not ideally suited to monitoring the human body and its internal environment has led to the development of wireless Body Sensor Networks (BSNs) [1]. In healthcare systems, the scale of demand for human body monitoring can only be appreciated once the magnitude of patient early diagnosis and treatment is considered. Several examples illustrate this need, but none as dramatically as chronic cardiovascular related illnesses. In this context, regular patient monitoring using electrocardiography (ECG) is required, along with other investigations, to aid diagnosis so that prompt treatment can be initiated to prevent long-term related complications. Apart from ECG, patient monitoring is normally in the form of further vital sign measurements (blood pressure, heart rate, respiratory rate, temperature). In hospitals, where a large number of patients are treated every year, BSNs offer a special benefit. Patients receive monitoring of various levels of intensity, ranging from intermittent (four to six times a day), to intensive (every hour), and to continuous invasive or non-invasive monitoring, such as that seen in the intensive care unit. Aside from being restrictive and "wired", ward-based patient monitoring systems tend to be very labor intensive, requiring manual measurement and are prone to human error. Automation of this process, along with the ability to pervasively monitor patients wherever they are in the hospital (not just at their bedside), is desirable not only to the healthcare provider, but also to the patient [1]. Most archetypal hospital care scenarios conform to a centralized infrastructure with heterogeneous traffic as for instance the one portrayed in Fig. 1.

Fig. 1 represents an example where the vital signs data of several hospitalized real-time monitoring patients (wearing different on-body sensors on bed or walking) and doctors' notes (working on a PDAs or Laptops) are transmitted to ahospital Care Unit for controlling. In a hospital environment, a centralized architecture is appropriate as the Body Area Network (BAN) coordinator (e.g. the Care Unit in Fig. 1)is superior to the rest of the body sensors (e.g. ECGs, Respiratory-rate, Blood Pressure, Oxygen Saturation (*SpO*2)) in terms of processing memory and power resources. Note that if the traffic load (or number of sensors) in the BAN notably increases beyond saturation limits, a cluster-tree architecture with several BAN coordinators can be adopted, as also allowed in 802.15.4 [2]. This article analyses the DQBAN behavioralbounds within a star-based BAN with a single coordinator close to saturation limits. Although the challenges faced by BSNs in healthcare environments are in a certain way similar to those already existing in WSN applications, there are intrinsic differences, which require special attention.

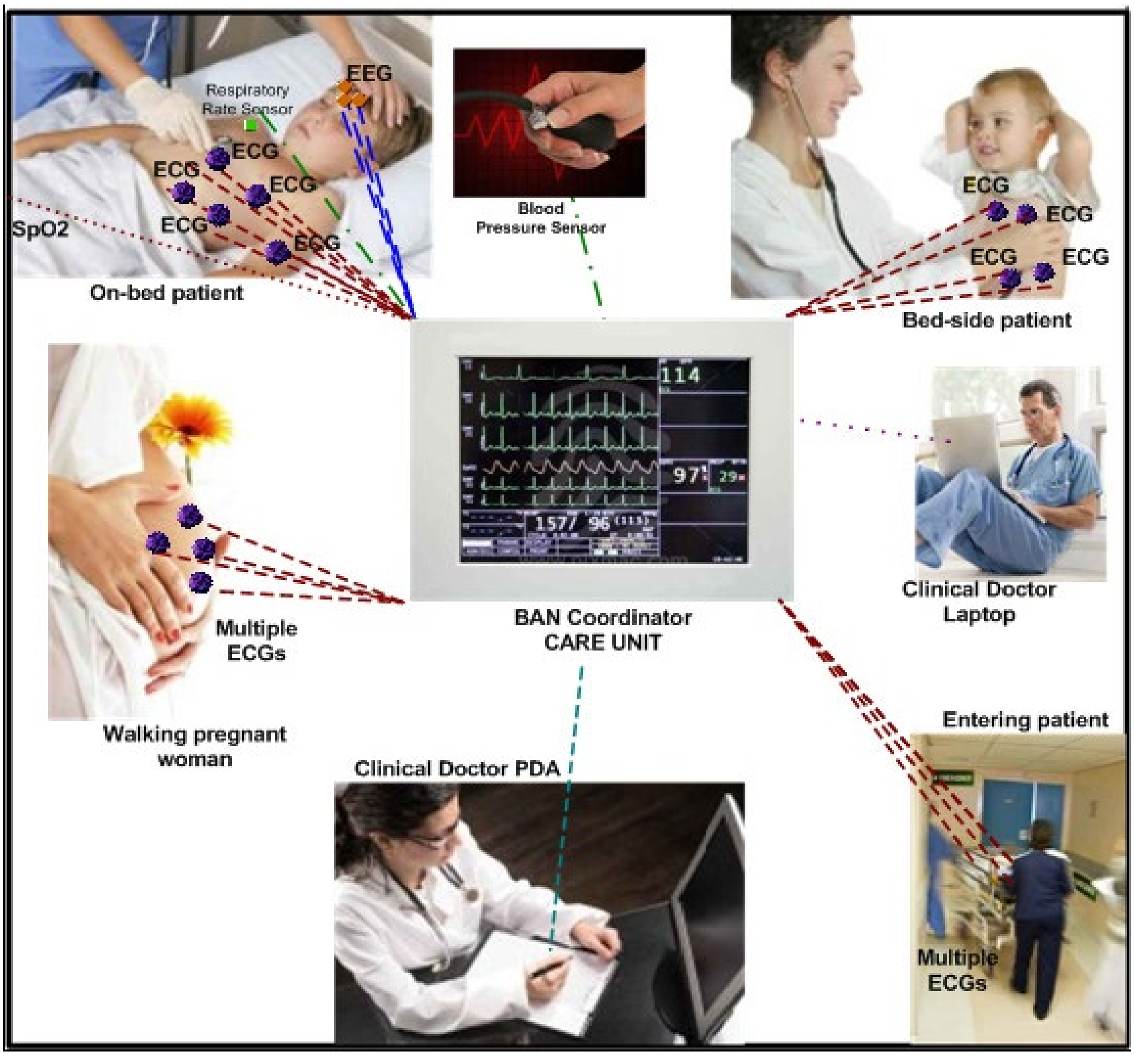

Figure 1. A star-based BAN in a hospital scenario

The purpose of Section 2 is to provide a brief description of these special requirements that characterize BSNs, while analyzing the standard de facto for WSNs, the low-rate IEEE 802.15.4 MAC/PHY standard (802.15.4) [2],[19]. Section 3 introduces a new Medium Access Control (MAC) protocol model with an energy-aware radio activation policy that pursues the idea to satisfy these specific medical requirements under BSNs in realistic hospital care scenarios. For that purpose, a novel cross-layer fuzzy-based scheduling algorithm and fuzzy rough set theory based scheduling algorithm is also presented in Section 4. Section 5 shows the simulation results used to evaluate the whole system performance under specific hospital settings. The last section concludes the paper.

II PROBLEM STATEMENT

The MAC layer is responsible for coordinating channel accesses, by avoiding collisions and scheduling data transmissions, to maximize throughput efficiency at an acceptable packet delay and minimal energy consumption. The 802.15.4MAC [2] is intended to serve a set of applications with very low power consumption and cost requirements, though with relaxed demands for data rate and Quality of Service (QoS). In the literature, it is already possible to find some publications in relation to wireless BSNs in healthcare systems, such as[3], [4], where the authors performed an evaluation analysis of 802.15.4 [2] under medical settings. It was pointed out that the scalability of 802.15.4 is not a given feature, since the current 802.15.4 MAC design does not support a high sensor density area and its use is extremely restricted under interference scenarios. Simulation results in [5] confirm that the 802.15.4 MAC is energy efficient in controlled environments,(i.e. without interference), but it fails in supporting QoS in co-existing scenarios, which is a serious issue fo r medical applications. Human monitoring BSNs must support high degrees of reliability under specific message latency requirements, without endangering sensor power consumption to avoid frequent battery replacements. The fact that the 802.15.4MAC does not fully satisfy BSN requirements highlights the need for the design of new scalable MAC solutions. These guarantee low-power consumption to all different sorts of body sensors while ensuring rigorous QoS under co-existent scenarios in healthcare systems.

III DISTRIBUTED QUEUING MAC FOR BSNS

3.1DQBAN LOGIC SYSTEM MODEL

Like DQRAP, DQBAN utilizes the two common logical distributed queues CRQ and DTQ, for serving access requests via the “access mini slots” and data packets via the “data slot” respectively. However, instead of keeping a first-come first- served discipline in DTQ, a cross-layer fuzzy-rule based scheduler is introduced in the DQBAN logic system model as depicted in Fig.2

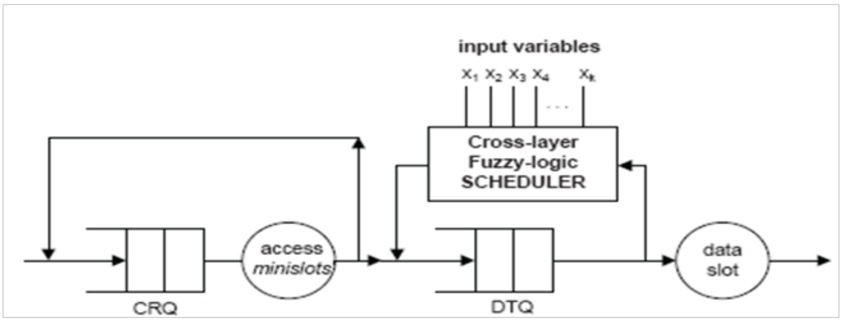

Figure 2. DQBAN logic system model

3.2NEED FOR SCHEDULAR

Scheduler permits a body Sensor, though not occupying the first position in DTQ, to transmit its data in the next frame collision-free “data slot” in order to achieve a far more reliable system performance. This is obtained by integrating a fuzzy logic system in each body sensor in the

March- April 2020
ISSN: 0193-4120 Page No. 3330 - 3342

BSN. Fuzzy-logic approach allows each particular body sensor to individually deal with multiple cross-layer inputs of diverse nature (i.e. $x1$, $x2$, to xkin Fig. 3.2) and react accordingly to demand or refuse the next frame "data slot"[20].

3.3DQBAN SCHEDULING MINISLOTS

Those body sensors occupying the n first positions in DTQ, with the exemption of the one transmitting in the "data slot" of the current super frame may send a warning in the assigned scheduling minislot to demand or refuse the next "data slot" in case of danger. This situation can happen

- if a non-transmitting body sensor requires urgently to send its packet sooner as indicated in its current position in DTQ (for example due to excessive packet system delay or not enough residual battery lifetime), or
- Whenever a body sensor occupying the second position in DTQ does not find it convenient to transmit in the next frame may be due to interferences.

3.4 DQBAN SYNCHRONIZATION PREAMBLE

Apart from the transmit and receive modes, each body sensor supports two further states shutdown, when the clock is switched off and the chip is completely deactivated waiting for a start-up strobe; and idle, when the clock is turned on and the chip can receive commands (for example, to turn on the radio circuitry). In the DQBAN context, every body sensor in idle mode synchronizes to the BSN through a preamble sequence of duration Tpre. Thereafter, it receives all related information of the state of the queues CRQ and DTQ via the FBP. Each body sensor in the BAN uses energy-aware radio activation policies in order to maximize its battery lifetime and minimize its overall energy consumption.

IV CROSS-LAYER FUZZY-LOGIC SCHEDULINGALGORITHM

4.1FUZZY LOGIC SYSTEM

In general, a Fuzzy Logic System (FLS) is a nonlinear mapping of an input data vector into a scalar output. Fig .3 contains four components: fuzzifier, fuzzzy rules, inference engine, and defuzzifier.

The FLS is fulfilled with three sensor dependant time-variant input variables from diverse nature:

- Signal-to-Noise Ratio (SNR(i,t) derived at the reception of a feedback frame
- Waiting Time in the system (WT(i,t)) calculated from an inherent clock
- Residual Battery Life (BL(i,t)) derived from an inner hardware memory.

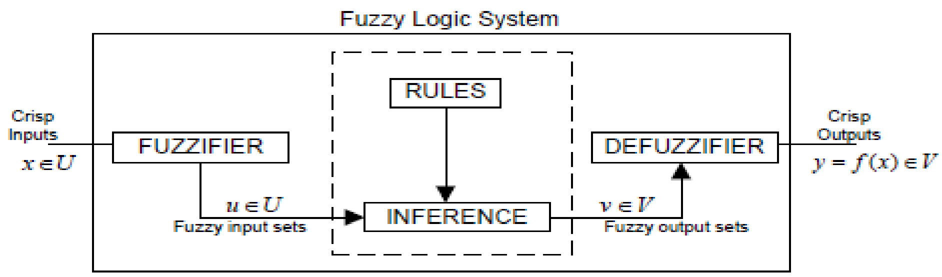

Fig .3. Fuzzy Logic System

At the entrance of the fuzzifierthere will be the following normalized input crisp variables

$$[SNR\ (i,t)] = SNR\ (i,t) - SNR_{min}(i)$$

March- April 2020
ISSN: 0193-4120 Page No. 3330 - 3342

$$[WT(i,t)] = WT(i,t) - WT_{max}(i)$$

$$[BL(i,t)] = BL(i,t) - BL_{min}(i)$$

The input normalized crisp variables in the fuzzifier are hereby identified to the fuzzy sets as following

SNR {dangerous, poor, superior};

WT {acceptable, boundary, excessive};

BL {critical, balanced, substantial};

The output fuzzy variable DTQ, at the entrance of the defuzzifier, has been associated to the fuzzy set {delay, on schedule, forward}, which form the consequents of our fuzzy rules.

Decision {delay, onschedule, forward}

A body sensor decision can be to delay its transmission to a future frame, to keep its current position in DTQ by indicating onshedule, or to ask for

a prior position in DTQ depicted by forward. We provide seven high level fuzzy rules for the output linguistic variable (Decision) with their antecedents and consequents.

4.1.1 Fuzzy Logic Rules

The first three rules indicate when data transmission requires to be delayed. Rule 1 is used to detect a bad link channel before transmitting. If there is still enough time and battery lifetime left, the aim is to defer data transmissions; otherwise it may not be possible to guarantee a particular (*BERi*) for the lowest power transmission state. Rule 2 claims to wait until batteries have been replaced, so that enough battery lifetime can be guaranteed during a packet transmission interval. In the same line, Rule 3 delays a transmission waiting for a better link channel.

Rule 3 & 4 show when a body sensor can remain in the same position in DTQ since its situation is not critical. On the contrary, the last two rules warn body sensors about a critical situation to demand the next possible collision-free “data slot” to guarantee QoS. Body sensors are allowed to send the value of its output linguistic variable Decision in the corresponding scheduling minislot[18]. A convenient way of defining all required fuzzy-logic rules, that play a role in the fuzzy inference process to determine the output linguistic values of Decision, is with a decision table as the one shown in table 1.

Table 1 Output Linguistic Values of Decision

WT		SNR		BL
	Dangerous	Poor	superior	
Acceptable	Delay	Delay	On schedule	Substantial
Acceptable	Delay	Delay	On schedule	Balanced
acceptable	Delay	Delay	Delay	Critical
boundary	Delay	On schedule	On schedule	Substantial
boundary	Delay	On schedule	On schedule	Balanced
boundary	Forward	Forward	Forward	Critical
excessive	Forward	Forward	Forward	Substantial
excessive	Forward	Forward	Forward	Balanced
excessive	Forward	Forward	Forward	Critical

To deal with complex data, Rough set theory has been adjusted. The indiscernibility relation has been substituted by tolerance relations useful in presence of many features and missing values. Rough membership functions have been parameterized to manage noisy data or extended to more approximations to deal with incomplete information.

4.2 ROUGH SET THEORY

Rough set theory can be regarded as a new mathematical tool for imperfect data analysis. The theory has found applications in many domains, such as decision support, engineering, environment, banking, medicine and others.Rough set philosophy is founded on the assumption that with every object of the universe of discourse some information (data, knowledge) is associated. Objects characterized by the same information are indiscernible (similar) in view of the available information about them. The indiscernibility relation generated in this way is the mathematical basis of rough set theory. Any set of all indiscernible objects is called an elementary set, and forms a basic granule (atom) of knowledge about the universe.

The advantages of rough set theory are

- It does not need any preliminary or additional information about information about data
- It provides efficient algorithms for finding hidden patterns in data
- Rough membership functions have been parameterized to managenoisy data
- RSTextendsto more approximations to deal with incompleteinformation
- It finds minimal sets of data (data reduction)
- It evaluates significance of data
- It generates sets of decision rules from data
- It is easy to understand

4.2.1 CRISP – ROUGH SET

Any union of some elementary sets is referred to as a crisp (precise) set otherwise the set is rough (vague). Each rough set has boundary-line cases, i.e objects which cannot be with certainty classified, by employing the available knowledge, as members of the set or its complement. Obviously rough sets, in contrast to precise sets, cannot be characterized in terms of information about their elements. With any rough set a pair of precise sets, called the lower and the upper approximation of the rough set, is associated.

The lower approximation consists of all objects which surely belong to the set and the upper approximation contains all objects which possibly belong to the set. The difference between the upper and the lower approximation constitutes the boundary region of the rough set. Approximations are fundamental concepts of rough set theory.

4.2.2 DATA TABLE

Rough set based data analysis starts from a data table called a decision table. Attributes of the decision table are divided into two disjoint groups called condition and decision attributes, respectively. Each row of a decision table induces a decision rule, which specifies decision (action, results, outcome, etc.) if some conditions are satisfied.

If a decision rule uniquely determines decision in terms of conditions the decision rule is certain. Otherwise the decision rule is uncertain. Decision rules are closely connected with approximations. Roughly speaking, certain decision rules describe lower approximation of decisions in terms of conditions, whereas uncertain decision rules refer to the boundary region of decisions. With every decision rule two conditional probabilities, called the certainty and the coverage coefficient, are associated. The certainty coefficient expresses the conditional probability that an object belongs to the decision class specified by the decision rule, given it satisfies conditions of the rule. The coverage coefficient gives the conditional probability of reasons for a given decision. It turns out that the certainty and coverage coefficients satisfy Bayes' theorem. That gives a new look into the interpretation of Bayes' theorem, and offers a new method data to draw conclusions from data.

4.2.3 INDISCERNIBILITY

The starting point of rough set theory is the indiscernibility relation, which is generated by information about objects of interest. The indiscernibility relation expresses the fact that due to a lack of information we are unable to discern some objects employing available information. This means that, in general, we are unable to deal with each particular object but we have to consider granules of indiscernible objects as a fundamental basis for our theory. From a practical point of view, it is better to define basic concepts of this theory in terms of data. Therefore we will start our considerations from a data set called an information system.

An information system is a data table containing rows labeled by objects of interest, columns labeled by attributes and entries of the table are attribute values. For example, a data table can describe a set of patients in a hospital. The patients can be characterized by some attributes, like age, sex, blood pressure, body temperature, etc. With every attribute a set of its values is associated, e.g., values of the attribute age can be young, middle, and old. Attribute values can be also numerical. In data analysis the basic problem we are interested in is to find patterns in data, i.e., to find a relationship between some set of attributes, e.g., we might be interested whether blood pressure depends on age and sex.

4.2.4 APPROXIMATION

The indiscernibility relation will be further used to define basic concepts of rough set theory. Let us define now the following two operations on sets X *c* U

$$B_*(X) = \{x\ \varepsilon\ U: B(x)\ c\ X\}$$

$$B^*(X) = \{x\ \varepsilon\ U: B(x) \cap X \neq \emptyset\}$$

assigning to every subset X of the universe U two sets $B_*(X)$ and $B^*(X)$ called the B-lower and the B-upper approximation of X, respectively.

$$BN_B(X) = B^*(X) - B_*(X)$$

The above equation set will be referred to as the B-boundary region of X.

From the definition we obtain the following interpretation:

• The lower approximation of a set X with respect to B is the set of all objects, which can be for certain classified as X using B (certainly X in view of B).

• The upper approximation of a set X with respect to B is the set of all objects which can be possibly classified as X using B (are possibly X in view of B).

• The boundary region of a set X with respect to B is the set of all objects, which can be classified neither as X nor as not-X using B.

4.2.5 REDUCTION OF ATTRIBUTES

We can remove some data from a data table preserving its basic properties, when the table contains some redundant data. Let us express this idea more precisely. Let C, D *c* A, be sets of condition and decision attributes respectively. We will say that C′ *c*C is a D-reduct (reduct with respect to D) of C, if C′ is a minimal subset of C such that (C, D) = (C′, D). The intersection of all D-reducts is called a D-core (core with respect to D). Because the core is the intersection of all reducts, it is included in every reduct, i.e., each element of the core belongs to some reduct. Thus,

March- April 2020
ISSN: 0193-4120 Page No. 3330 - 3342

in a sense, the core is the most important subset of attributes, since none of its elements can be removed without affecting the classification power of attributes.

4.2.6 ROUGHSET PROPERTIES

$B_*(X) \; c \; X \; c \; B^*(X)$,

$B_*(\emptyset) = B^*(\emptyset) = \emptyset$, $B_*(U) = B^*(U) = U$,

$B^*(X \cup Y) = B^*(X) \cup B^*(Y)$,

$B_*(X \cap Y) = B_*(X) \cap B_*(Y)$,

$X \; c \; Y$ implies $B_*(X) \; cB_*(Y)$ and $B^*(X) \; cB^*(Y)$,

$B_*(-X) = -B^*(X)$,

$B^*(-X) = -B_*(X)$,

$B_*(B_*(X)) = B^*(B_*(X)) = B_*(X)$,

$B^*(B^*(X)) = B_*(B^*(X)) = B^*(X)$.

If the boundary region of X is the empty set, i.e., $BN_B(X) = \emptyset$, then the set X is crisp (exact) with respect to B; in the opposite case, i.e., if $BN_B(X) \neq \emptyset$, the set X is referred to as rough (inexact) with respect to B.

4.2.7 EQUIVALENCE RELATION

The starting point of rough set theory is the idea that objects having the same description are indiscernible with respect to the available information. Consider the following table .2

Table 2 Example of information system

Patient	Headache	Muscle pain	Temperature	Flu
P1	No	Yes	High	Yes
P2	Yes	No	High	Yes
P3	Yes	Yes	Very high	Yes
P4	No	Yes	Normal	No
P5	Yes	No	High	No
P6	No	Yes	Very high	Yes

For instance, in the table 2, patient p2, p3 and p5 are indiscernible with respect to the attribute Headache, patient p3 and p6 are indiscernible with respect to the attributes Muscle-pain and Flu, and patient p2 and p5 are indiscernible with respect to the attributes Headache, Muscle-pain and Temperature.

The indiscernibility relation that may hold between the objects under investigation represents the mathematical basis for the rough set approach. Suppose an information system K = (hX, Att, val, Fi) and let A be any family of attributes.

The indiscernibility relation is intended to express the fact that dueto the lack of knowledge we are unable to discern some objects employing the available information. Apparently, IA turns out to be an equivalence relation; that is it satisfies the following conditions (for any x, y, z € X):

(Eq1) $x \; I_A x$ (reflexivity)

(Eq2) $x \; I_A y$ impliesy $I_A x$ (symmetry)

(Eq3) $x \; I_A y$ and $y \; I_A z$ imply $x \; I_A z$ (transitivity)

4.2.8 DRAWBACKS OF RST

March- April 2020
ISSN: 0193-4120 Page No. 3330 - 3342

RST have had only a partial success. Rough set theory has lot of experimental applications, but industrial use is rare. Moreover, there are no specialized journals on this topic. While other important formalisms, such as fuzzy sets, have been adopted by several researchers in different fields, RS theory is mainly used only inside its research community. Probably, the two above reasons of interest are no well suited to face real problems. In real world situations, collected data is usually uncertain and incomplete. For this reason, two approximations are not sufficient to properly describe the information hidden in data. To deal with complex data, the theory has been adjusted. The indiscernibility relation has been substituted by tolerance relations useful in presence of many features and missing values. Rough membership functions have been parameterized to manage noisy data or extended to more approximations to deal with incomplete information Hybridizations with other methods have been found, such as fuzzy sets or neural networks.

So in order to achieve good performance fuzzy rough set theory is used which has the combined features of both fuzzy and rough set theory

4.3 FUZZY ROUGH SET THEORY

The values of attributes may be both crisp and real-valued, and this is where traditional rough set theory encounters a problem. It is not possible in the theory to say whether two attribute values are similar and to what extent they are the same. For example, two close values may only differ as a result of noise, but in RST they are considered to be as different as two values of a different order of magnitude. One answer to this problem has been to discrete the dataset beforehand, producing a new dataset with crisp values. This is often still inadequate, however, as the degrees of membership of values to discrete values are not considered at all. It is, therefore, desirable to develop these techniques to provide the means of data reduction for crisp and real-value attributed datasets which utilizes the extent to which values are similar. This could be achieved through the use of fuzzy rough sets. Fuzzy-rough sets encapsulate the related but distinct concepts of vagueness and indiscernibility for rough sets), both of which occur as a result of uncertainty in knowledge.

4.3.1 FUZZY EQUIVALENCE CLASSES

Fuzzy equivalence classes are central to the fuzzy-rough set approach. This means that the decision values and the conditional values may all be fuzzy. The concept of crisp equivalence classes can be extended by the inclusion of a fuzzy similarity relation *S* on the universe, which determines the extent to which two elements are similar in *S* .The usual properties of reflexivity ($\mu_s(x, x) = 1$), symmetry ($\mu_s(x, y) = \mu_s(y, x)$) and transitivity ($\mu_s(x, z) \geq \mu_s(x, y) \wedge \mu_s(y, z)$) hold.

4.3.2 FUZZY APPROXIMATIONS

The fuzzy P-lower and P-upper approximations are defined as

$\mu_{PX}(Fi) = \inf_x \max\{-\mu Fi(x), \mu_X(x)\}$

$\mu^{PX}(Fi) = \sup_x \min\{-\mu Fi(x), \mu_X(x)\}$

Fi denotes a fuzzy equivalence class belonging to U / P. The reason for integrating fuzziness into the rough set model is to quantify the levels of roughness in the boundary region by using fuzzy membership values. It is necessary to allow elements in the boundary region to have membership values in the range of 0 to 1, not just the value 0.5.Hence, a fuzzy-rough set Y is defined as a membership function (x) Y μ that associates a grade of membership from the interval[0,1] with every element of U. For a rough set X and a crisp equivalence relation R:

$\mu_Y(RX) = 1$

March- April 2020
ISSN: 0193-4120 Page No. 3330 - 3342

$\mu_Y(U - RX) = 0$

$0 < \mu_Y(RX - RX) < 1$

4.3.3 FUZZY-ROUGH REDUCTION PROCESS

If the fuzzy-rough reduction process is to be useful, it must be able to deal with multiple attributes, finding the dependency between various subsets of the original attribute set. For example, it may be necessary to be able to determine the degree of dependency of the decision attribute with respect to P={a,b}.In the crisp case, U/P contains sets of objects grouped together that are indiscernible according to both attributes a and b. In the fuzzy case, objects may belong to many equivalence classes, so the cartesian product of U/IND({a}) and U/IND({b}) must be considered in determining U/P. In general,

$$U / P = \{a \in P : U / IND(\{a\})\}$$

Thus fuzzy rough set theory is explained. In the hospital, body sensors will transmit their packets to the central care unit in first come first serve discipline. Drawback in this scheme is that all body sensors have to wait in the queue until body sensor in the first position of the queue transmits its packet. So energy consumption is more and battery life time of body sensors gets reduced. When scheduling schemes like fuzzy logic, rough set theory, fuzzy rough set theory are used, energy consumption is less. Thus battery life time is increased.

V RESULTS AND DISCUSSION

Simulation is carried out using MATLAB. Fig. 4- 6 depicts the DQBAN MAC performance in a homogeneous BSN with an increasing number of 1lead ECG body sensors. Note that 20% of the ECG sensors involved in each simulation are initially charged with much less amount of battery. The idea is to evaluate the energy-saving behavior of the DQBAN system as the traffic load raises until saturation conditions.

5.1 ENERGY CONSUMPTION

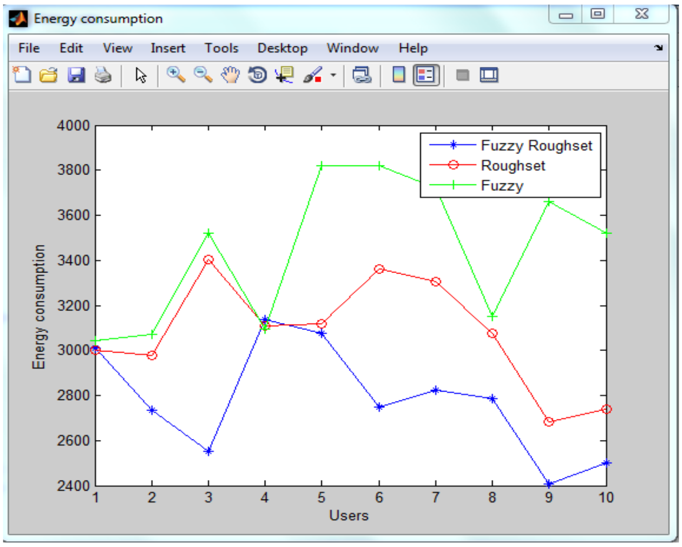

Fig .4. Energy Consumption

As the traffic load increases in the BSN, body sensors remaining longer in the system may run out of battery. As a result, the average energy-consumption per delivered information bit increases.

Fuzzy rough set scheduling greatly reduce energy consumption when compared to both fuzzy and rough set theory.

March- April 2020
ISSN: 0193-4120 Page No. 3330 - 3342

5.2 DELAY RATIO

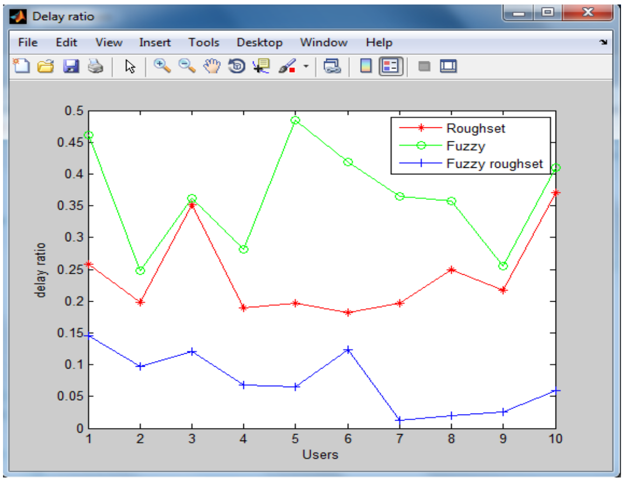

Figure .5. Delay Ratio

Delay is the measurement of the time for a signal to reach its destination. Delay ratio is more in fuzzy logic scheduling and rough set theory has less delay when compared to fuzzy. Delay is very much reduced in fuzzy rough set scheduling and hence performance is increased.

5.3 DELIVERY RATIO

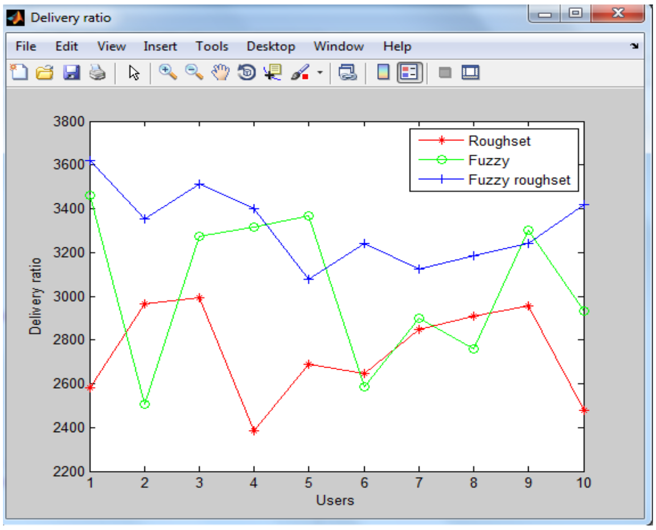

Figure 6. Delivery Ratio

The Delivery Ratio proves that the fact of scheduling data packets taking cross-layer constraints into account outperforms the fuzzy logic scheduling by guaranteeing the QoS requirements of high reliability, right message latency and enough battery lifetime to all body sensors transmissions in the BSN. The use of

DQBAN with the proposed cross-layer fuzzy-rough set theory base scheduling algorithm reaches more than 95% of transmission successes, even though 20% of the ECG sensors have critical battery constraints. Fuzzy rough set theory has good delivery ratio when compared with both fuzzy and rough set theory.

VI CONCLUSION

The new Distributed Queuing Body Area Network (DQBAN) MAC protocol commitment is to guarantee that all packet transmissions are

March- April 2020
ISSN: 0193-4120 Page No. 3330 - 3342

served with their particular application-dependant quality of service (QoS) requirements, without endangering body sensors battery lifetime in Body Sensor Networks (BSNs). Body sensors able to demand or deny the next “collision-free” time slot according to their own limits. For that purpose, instead of keeping fuzzy logic scheduling, rough set theory, fuzzy rough set theory is used. This scheduling mechanism allows a body sensor, though not occupying the first position in the new MAC queuing model, to send its packet in the next frame in order to achieve a far more reliable system performance. Experiment results shows that fuzzy rough set theory scheduling minimizes energy consumption when compared to both fuzzy logic and rough set theory. Performance evaluation is done in homogeneous environment. Future scope is that we can estimate the performance in heterogeneous environment and also can increase the number of linguistic terms and thus can improve the performance.

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