Systematic Literature Review: Correlated Fuzzy Logic Rules for Node Behavior Detection in Wireless Sensor Network

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***Abstract*—In distributed wireless sensor network, the possibility for one or several nodes to become faulty is directly proportional upon the number of nodes within the network. Unnecessary control of the network triggers the anomaly, faulty and misbehavior in nodes which anyhow yield to degradation of network performance. Therefore, the identification of node behavior in distributed sensory system is crucially important to improve the network performance throughout the monitoring period. Though the detection schemes are several, Fuzzy logic for node behavior detection in WSN however present a more accurate incentive as it considered the uncertainties inherited in the WSN environment during the fault diagnosis period. This paper analyzes several fuzzy logic approaches for correlated node behavior detection. With six primary articles, this paper provides systematic literature review (SLR) and presents an overview of current design of research trend in this area.**

***Index Terms*—Correlated Fuzzy Logic; Node Behavior; Systematic Review; Wireless Sensor Network.**

I. INTRODUCTION

Wireless sensor network comprises of several sensor nodes which are connected via wireless networking, require low deployment and, low data usage cost and self-organizes its system [1]. Henceforth, sensor networks provide a promising approach for a variety application such as in disaster relief operation, smart building, temporary network deployment and in health care [2]. In harsh environment especially in distributed network, the node behavior indicates significant relationship towards network performance within the transmission range. The correlated events due to the distribution of node behavior towards its neighbor nodes rather having an adverse effect on network survivability [3]. On the other hand, an anomaly, faulty and misbehave node will provide poor service quality in the network. The anomaly shows data deviation pattern from normal data [4]. In a network, misbehavior nodes, often called as malicious and selfish node possibly ignites a series of misbehave nodes especially in distributed network [5]. Thus, evaluating nodes behavior in network topology is deemed as crucial. There are several methods to detect the node behavior proposed in past literatures. While the classical approaches did not consider the uncertainties inherited in the network environment. Therefore, a novel fuzzy approach introduced by [6] is used in recent studies. In fact, fuzzy logic approach in detecting node behavior is capable to blend several parameters to determine the node behavior besides providing more flexibility and simplicity for accurate representation. Anyhow, this paper analyzes several correlated fuzzy logic rules for node behavior detection in WSN to cater the potential correlated misbehavior in the network.

In this paper, a review of correlated fuzzy logic for node behavior approaches in WSN is presented according to the systematic literature review (SLR) introduced by Kitchenham [7]. Kitchenham's SLR is specifically based on the detailed discussion of relevant research questions, topic areas or even phenomena of interest. The objective of this SLR is threefold, namely 1) to critically and systematically review the correlated fuzzy logic approaches for node behavior detection in WSN, 2) to identify the correlated fuzzy logic process for node behavior detection, and 3) to reveal open issues for further development and enhancement of correlated fuzzy logic technique for node behavior detection in WSN. The organization of this paper is as follows: Section II outlines the review method, Section III discusses the result and analysis, while Section IV concludes this SLR.

II. REVIEW METHODS

This section outlined the review process along the study conducted. According to Figure. 1, the process began with formulation of research question. It is followed by search process which involves source selection and keyword search. Third, is screening of the sources according to inclusion and exclusion criteria. Here quality assessment is also measured for the primary articles selection. Then, the final step in this SLR is data extraction process where the information is extracted, collected and organized. The summary of primary articles is then presented in Section III.

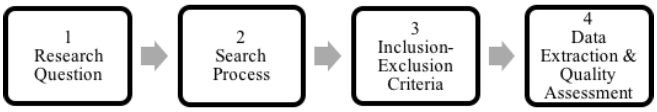

Figure 1: Steps in SLR

A. *Formulation of Research Question*

This review aims to provide answers to the following research questions (RQ), as stated in Table 1. In RQ1, the research question tends to investigate the current state and research trend on correlated fuzzy logic process for node behavior detection. For purpose of answering RQ1, journal and conferences starting from 2011 until 2016 are recognized while main topic and problem statement of correspond sources are screened for further understanding. We choose

2011 as the start date for our search is because 2011 marked the year when people starting to develop effective correlated component failures detection in real-world scenarios [5-6]. The model of fuzzy clustering in WSN is analyzed using sub-questions with respect to RQ2.Then a discussion upon limitations of current models is presented in RQ3.

Table 1
Research Question in SLR

RQ#	Research Question Details	
RQ1	What is the current state of knowledge on correlated Fuzzy logic rules in node behavior detection?	
RQ2	How fuzzy logic function in node behavior detection?	
	RQ2.1	What are the state of behavior of sensor nodes in WSN?
	RQ2.2	How was the correlated fuzzy is modeled in previous work?
RQ3	What are the limitation of current correlated fuzzy rule for node behavior detection in WSN?	

B. Search Processes

One of many strengths of performing SLR includes how it can offer to select the best articles as the sources for the research conducted. The following are the list of digital databases used in our searches:

i. ScienceDirect
ii. Emerald Insight
iii. IEEE Digital Library
iv. Google Scholar

The outline of the research process is detailed out in Figure 2.

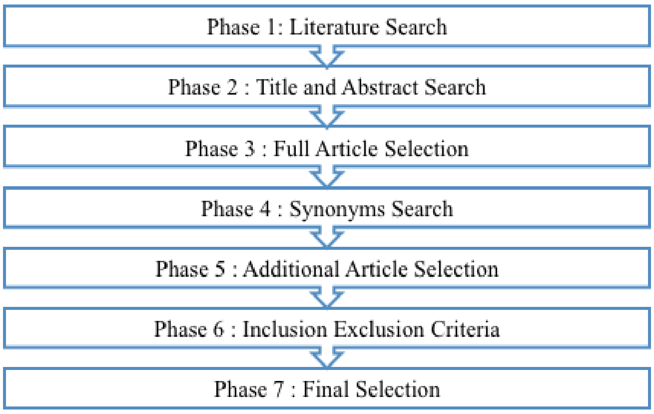

Figure 2: Search Process in SLR

The initial search was using the following keyword: "*Correlated*" "*Fuzzy Logic in Sensor Network*" OR "*Anomaly detection*" OR "*Intrusion*" OR "*misbehavior node*". The selection of articles conducted based on the relevant titles and abstracts which then downloaded in Phase 2. Here the collection of relevant articles analyze the process in regards to correlated fuzzy logic for node behavior detection in WSN. In order to have more relevant support articles, alteration of keyword search is used in Phase 4. Since there are merely a number of articles based on correlated fuzzy logic rule in WSN, a specific keyword for WSN is chosen in Phase 5, such as "*anomaly detection*", "*intrusion detection*" and "*misbehaved node in WSN*".

C. Inclusion-Exclusion Criteria

Inclusion and exclusion criteria are used to scope down the selected articles. The collection of relevant articles is screened against the inclusion and exclusion requirement, before they are considered as primary articles. For final review, those articles should fulfill inclusion criteria in Table 2 else articles are excluded, those satisfied exclusion criteria in Table 3.

Table 2
Inclusion Criteria

INCL#	Inclusion Criteria
INCL1	Correlated fuzzy logic rules for node behavior detection in WSN must be the major topic of publication

Table 3
Exclusion Criteria

EXCL#	Exclusion Criteria
EXCL1	Articles did not focus on correlated fuzzy logic rules for node behavior detection in WSN
EXCL2	Article did not focus on correlated fuzzy logic model.
EXCL3	White papers, unreferreed web articles, short papers, workshop papers less than two pages, research proposals and articles not written in English are excluded.

D. Data Extraction and Quality Assessment

The process of data extraction aimed to accurately reflect information reported in the publication to perform systematic analysis in coherent presentation to be able address the review questions. Table 4 outlined the criteria for grading the quality of the selected articles according quality assessment criteria for SLR used in [10]. The ratio scales denote Yes=1 point, No=0 point and Partially = 0.5 point.

Table 4
Quality Assessment Checklist

Item	Answer
QA1: Was the article refereed?	Yes/No
QA2: Was there a clear statement of the objective of the research?	Yes/No/Partially
QA3: Was there an adequate description of the context in which the research was carried out? For example, clearly stated the problems that leads to the research, descriptions on research methodology used etc.	Yes/No/Partially
QA4: Was the data collection done very well?	Yes/No/Partially
QA5: Was the simulation results rigorously analyzed?	Yes/No/Partially

III. RESULTS AND DISCUSSION

In this section, we will present the selected studies and describe the answers to RQ1 and RQ2.

A. Selected Studies

From the keyword search, the outcome shows about 51 articles with different categories such as journals, conference proceeding, thesis and part of chapters from e-book. Then selectively filtered until the only relevant articles regarding correlated fuzzy in WSN and showed a number of three relevant articles. From synonym keyword search, there are additional three articles which result in just six articles for further review purposes. The list of selected articles is stated in Table 5.

Table 5
Quality Assessment Score for Primary Articles

Author and Year	Title	Sources	Quality Score
Salahshoor et al. 2011 [11]	Simulation Modelling Practice and Theory Fault detection and diagnosis of an industrial steam turbine using a distributed configuration of adaptive neuro-fuzzy inference systems	Science Direct	5
Khan et al. 2012 [12]	Application of fuzzy inference systems to detection of faults in wireless sensor networks	Science Direct	5
Grigoras, Gheorghe Cartina, Gheorghe 2013 [13]	The fuzzy correlation approach in operation of electrical distribution systems	Emerald Insight	4.5
Shamshirband et al 2014 [14]	Co-FAIS: Cooperative fuzzy artificial immune system for detecting intrusion in wireless sensor networks	Science Direct	4.5
Shao, Hang, et al. 2014 [15]	Vessel track correlation and association using fuzzy logic and echo state networks	IEEE Digital Library	5
Nisha et al. 2015 [16]	Improving Data Accuracy Using Proactive Correlated Fuzzy System in Wireless Sensor Networks	Google Scholar	5

B. Correlated Fuzzy Logic Rules in WSN

RQ1: What are the current state of knowledge on correlated fuzzy logic rule for node behavior detection in WSN?

Historically, correlated fuzzy logic approaches appear in various research area. The study for nodes behavior detection in WSN shows an attractive topic using the fuzzy logic. From 51 articles found, there are several research papers have proposed scheme for node behavior detection but mainly concerned individual node behavior. Meanwhile for this SLR paper, only selective articles are considered based on five quality assessment criteria conducted (refer to Table 4). Thus, Table 5 present the primary articles selected whereby according the research publication distribution, over the five years back, there are continuous studies in this network management area. Within the year 2011 till 2015, on overall there is one research conducted in yearly basis. The demanded and updated of this area of research have provide better fundamental for high quality of service (QoS) of wireless sensor network in general.

C. Fuzzy Logic Model for Correlated Node Behavior

RQ2: How fuzzy logic function in node behavior detection process?

To answer RQ2, two sub-question are derived to explain the method lies in this study as stated earlier. The first sub question, RQ2.1: What are the state of behavior of sensor nodes in WSN?

From overall selected studies, there are four states of node behavior in network which give different impact towards network performance: cooperative state, selfish state, malicious state and fail state. The following describes each state in details:

1) Cooperative state

Wireless sensor node is self-organized and has to cooperate to form a working communication network. Communication is only work if nodes participate and forward other node's packets. Meanwhile the limited resources is an issues. In [17] stated that a node in network will behave properly in the energy level at least at 80%. In addition, in this state the node is properly connected with its peer nodes in order to functioning as data forwarding to base station. Thus, for efficient network performance, nodes are motivated to behave according to possible energy level and forward a fair amount of other node's packet as needed [18].

2) Selfish state

Nodes that refuse to forward other's packets defined as selfish nodes [19]. It thus maximizing their benefit at the expense of others. They are acted cooperatively and cheat only if it gives them an advantage. In addition, this kind of selfish node can accelerate the average end to end delay in which whenever the number of nodes become selfish increased, less feasible route will be available and results to longer delays. Average end to end delay increases by 60% if 50% of the nodes become selfish [20].

3) Malicious state

In general, malicious node defined as node which active in both data discovery and launching attacks. Malicious event in somehow highly correlated in the anomaly event occurrence whereby intruder make the sensors to get the false reading [21]. In distributed network, the false reading yields to retransmission of packet data in alternate path hence energy is exhausted in large amount. In[16], study found that anomaly event is highly correlated to malicious behavior. While in paper [14] stated DDoS was commonly due to malicious event. Therefore several previous work recently study the identification and the impact of malicious node which consequently aims to increase data accuracy and penalized anomaly event in the network.

4) Fail state

Node is said to be failed if there is no participation in route discovery. The main reasons for the faulty node is due to energy exhaustion which is below 50% of energy level, misconfiguration and thus change either to selfish state, malicious state or failure state [18].

D. Modeling Process for Correlated Node Behavior

The second sub-question, RQ2.2 investigates on how was the correlated fuzzy is modelled in previous works.

In general, fuzzy logic involves three main stages which are fuzzification, inference engine and defuzzification process [13]. The fuzzification phase is where the crisp variable mapped to linguistic value which represent the degree of membership function. In inference engine, the IF-THEN rules is activated using variables in both condition and conclusion rules. Consequently, defuzzifier determined the crisp output value. Figure. 3 illustrates the overview analysis of this SLR. Fuzzy Inference System, FIS involves two types which are Mamdani-type and Sugeno-type FIS. According to the past literature Mamdani-type FIS had been modeled quantitative and qualitatively. Whereby Sugeno-type FIS only modeled quantitatively.

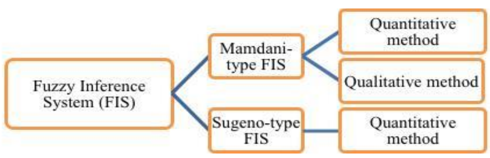

Figure 3: Overview of the SLR Analysis

1) Quantitative fuzzy logic with Sugeno-type FIS

Paper [12], adopted Sugeno-type FIS in fault detection for wireless sensor networks. The fuzzy process namely fuzzification, inference engine and defuzzification phases adopted in this paper is summarizing as follows:

a) Fuzzification

In this phase sensor measurement of a node is approximated by a function of peer nodes measurement, **x**=$(x_{1,}x_{2,\dots,}x_{n,})^T$ whereby **x** is the input matrix in fuzzification process which consist of peer nodes. The measurement is physically quantity basis such as temperature of the node and so forth.

b) Defuzzification

In this phase, the crisp output value is calculated which is the abscissa under the center of gravity of the fuzzy set. The author also defined the output of fuzzy system as $y = \frac{\sum_{i=1}^{n} \propto_i y^i}{\sum_{i=1}^{n} \propto_i}$ where $\propto_i$ denotes the overall truth value of the premise of the *i*th implication and is computed as $\propto_i = \prod_{l=1}^{M} A_l^i(x_i)$

c) Inference engine

The method for fuzzy inference is on the basis of Takagi-Sugeno-Kang (TSK) method. Several variables both in the condition and the conclusion of the rules are utilized in fuzzy rule base. In this fuzzy inference engine, the corresponding rules are activated and all the activations are accumulated using max-min operations. A fuzzy IF-THEN rule can be written as the following statement:

R^l: IF x_1 is B_1^l and x_2 is B_2^l and … x_n is B_n^l THEN y is y^l

whereR^l (l=1,2,…,M) the *l*th implication. x_j(j=1,2,….,n) are input variables of FLS, y^l is output B_n^l is the fuzzy membership function which can represent the uncertainty in the reasoning.

Second paper under Sugeno-type FIS [13], the author introduced adaptive neuro-fuzzy inference system (ANFIS) in order to diagnose distributed faults in steam turbine. This model anyhow provides a mechanism to interpret the combinatory nature of data. Furthermore, ANFIS possibly able to handle high degree of interaction in systems consisting multiple inputs and outputs. In general, a sequence of fault detection in ANFIS divided into two adaptive layers for instance layer 1 and 4. The first layer considered premise parameter consist of modifiable parameters while layer 4 includes three modifiable parameters pertaining the first-order polynomial, called consequent parameters. The by layer process for correlated fuzzy model is summarized as follows:

a) First layer

Nodes in first layer act as adaptive and the membership function is: OL1=$\mu_{A_i}(x1)$

b) Second layer

Nodes are fixed and each node measure the firing strength (w_i) of a rule, whereby it is the multiplication of the incoming signal: OL2$_i$= w_i=$\mu_{A_i}(x1) \times \mu_{B_i}(xn)$

c) Third layer

Nodes are fixed and each node estimates the ratio (w_i) of the ith rule's firing strength to sum of the firing strength of all rules j. Here the normalization of firing strength from the previous layer is sustained. While the output represented by: OL3$_i$=$w_i = \frac{w_i}{\sum_{j=1}^{i} w_i}$

d) Fourth layer

Nodes are adaptive and the output of each node is the product of the previous relative firing strength of the *i*th rule and denoted by: OL4$_i$=$w_i(p_i X1 + q_i Xn + r_i)$

e) Fifth layer

Only a node and perform the function of simple summer which computes the overall output as the summation of all incoming signal from layer 4: OL5$_i$=$\sum_{i=1}^{f} w_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$

In ANFIS, the IF_THEN rules can be constructed based on the following structure which operated in inference engine stage.

If X1=A_i and Xn=B_i then $f_i = (p_i X1 + q_i Xn + r_i)$ where p_i, q_i, r_i are the parameters to be determined during the training stages.

While the third paper under Sugeno-type FIS is a study by Shao et al. [15]. This study performed vessel track correlation using Fuzzy k-Nearest Neighbor (Fuzzy k-NN). Here data sample **X** = $\{x_1, x_2, \dots, x_n\}$ and corresponding labels u_{ij} = {0,1}, where u_{ij}=1 denoted that data vector x_j belongs to class *i* and u_{ij}=1 denoted that it does not belong to class *i*. while the membership of a test vector z being assigned to class i can be calculated by:

$$u_i(z) = \frac{\sum_{j=1}^{k} u_{ij} \left(\left\|z - x_j\right\|^{-2/(m-1)}\right)}{\sum_{j=1}^{k} \left\|z - x_j\right\|^{-2/(m-1)}} \quad (1)$$

Therefore, in fuzzy k-NN, the data points that are more similar to the test sample are then more likely to affect the final classification.

2) Quantitative fuzzy logic with Mamdani-type FIS

The implementation of quantitative Mamdani-type FIS found in [11]. Whereby the application of correlated fuzzy model proposed in the operation of electrical distribution system. This paper employed fuzzy logic based on the correlation theory. The fuzzy correlation model is used to improve the prediction accuracy for size of load in power flow system. In this study, the input variables are The fuzzy and correlation technique algorithm is presented as below:
The correlation coefficients:

$$k_{P_r P_i} = \rho p_r p_i * \frac{\sigma p_i}{\sigma p_r} \; ; \; k_{P_r Q_i} = \rho p_r Q_i * \frac{\sigma_{Q_i}}{\sigma p_r} \quad (2)$$

$$\rho p_r p_i = \frac{\sum_{j=1}^{h} (P_{rj} - \bar{P}_r)(P_{ij} - \bar{P}_i)}{n * \sigma_{P_r} \sigma_{P_i}} \quad (3)$$

$$\rho p_r Q_i = \frac{\sum_{j=1}^{h} (P_{rj} - \bar{P}_r)(Q_{ij} - \bar{Q}_i)}{n * \sigma_{P_r} \sigma_{Q_i}} \quad (4)$$

$$\sigma_{P_r} = \sqrt{\frac{\sum_{j=1}^{h} (P_{rj} - \bar{P}_r)^2}{n}} \quad (5)$$

$$\sigma_{P_i} = \sqrt{\frac{\sum_{j=1}^{h} (P_{ij} - \bar{P}_i)^2}{n}} \quad (6)$$

$$\sigma_{Q_i} = \sqrt{\frac{\sum_{j=1}^{h}\left(Q_{ij}-\overline{Q_i}\right)^2}{n}} \qquad i=1,\ldots,n \qquad (7)$$

$$k_{P_i} = \sum_{j=1}^{h} \frac{(P_{ij} - k_{P_rP_r} * P_{rj})}{L_h} \qquad (8)$$

$$k_{Q_i} = \sum_{j=1}^{h} \frac{(Q_{ij} - k_{P_rQ_r} * P_{rj})}{L_h} \qquad (9)$$

where: $P_r -$ the active power from reference station r; P_i - the active power from the i substation (i= 1,2,…,n, n is the total number of the 20kV substations from the analysis system); Q_i - the reactive power from the i substation (i=1,2,….,n);$\rho p_r Q_i$,$\rho p_r Q_i$- the correlation coefficient between the active and reactive powers of the substation i and reference station r;σ_{P_i},$\sigma_{Q_{i_r}}$,σ_{P_r}-the standard deviation for $P_i(j), Q_i(j)$, and P_r(j) where j=1,2,…,h ; $\overline{P_i}, \overline{Q_i}$ and $\overline{P_r}$ are the average values of $P_i(j), Q_i(j)$, and P_r(j); L_h is window dimension analysis; h is hours number for the analysis windows.

The above correlation coefficient, $k_{P_rP_i}$, k_{P_i}, $k_{P_rQ_i}$ and k_{Q_i}used to address the correlation between two input variables (active power and reactive power) and then used in fuzzy system to determine the output which is the power flow in this study.

3) Qualitative fuzzy logic with Mamdani-type FIS

The qualitative fuzzy model for correlated event detection presented in the study by [14] and [16] both using Mamdani-type FIS method. The qualitative study whereby they merely justified the event detection by considering parameters to determine the output formation otherwise they may combine correlation acts commonly spatial, attribute and temporal act. Thus, this study illustrates the detection process as follows.

Study by [14] employed Fuzzy Misuse Detector Module (FMDM) with the objective to identify the anomaly (network packet anomalies) conditions received from the traffic.

a) Fuzzification

Several parameters such as energy usage, buffer size, time response and count is selected as the crisp value for fuzzy input. The linguistic variables for all of the parameters divided into three level which are low, medium and high with predefined range.

b) Defuzzification

While the parameters for representing output is pattern which consist of four linguistic variables namely bad, average, good and excellent with specific range.

This phase determined whether the result from defuzzification attacked inspected packets or not. The attack is assumed to occur if the crisp value of the pattern is not equal to the threshold value of the detection attack rule. While to predict the next points of anomaly attack, this paper had combined fuzzy-based Q-learning strategy with fuzzy logic controller to convert the continuous inputs into fuzzy sets. In the Q-learning algorithm, fuzzy min-max methods were employed. Correlated process Fuzzy logic process in fuzzy-based Q-learning strategy is as follow:

- Fuzzification: the input is represented by S(t)=[energy usage x time response, buffer size, count] and the
- Inference engine: if then rules formation for determined abnormality function using crisp input variables
- Defuzzification : output represented by abnormality function, C$_j$=$\sum_{j=1}^{N} \alpha_j c_j \,/ \sum_{j}^{N} \alpha_j$

Furthermore, study which conducted by [16] used correlated fuzzy logic by comparative correlation techniques namely fuzzy spatial act, fuzzy attribute act and fuzzy temporal act. The spatial act has addressed the relationship among the nearest neighbor node readings. While temporal act caters the sensor's reading time difference whereas attribute act expressed the relationship among the sensed physical phenomena of sensor nodes. Three corresponding membership functions for spatial, temporal and attribute acts namely high, medium and low level are employed. Therefore, the output of the three separate techniques are given as input to the proactive anomaly detection system. At last theanomaly assurance levels are classified as inferior nodes, doubtful nodes and superior nodes.

IV. Research Limitation and Discussion

This part providing an answer for the third research question which is RQ3: What are the limitations of current correlated fuzzy rules for node behavior detection in WSN?

Table 6 shows the limitation of selected articles. From the aforementioned discussion, there are some limitation found in this study. The first limitation is that, the detection of node behavior using correlated fuzzy system has dealt specifically on either correlated failed nodes or the malicious-type nodes [11-16]. Whereas according to [22] besides failed nodes, nodes can be in the state of malicious and selfish behavior too depending on its neighboring behavior. For instance, work by Azni et al. in [3,23-24] had identified the current state of node behavior either in cooperative, malicious, selfish and failed behavior using Semi Markov process. Here the studies capable in identifying the impact of this correlated event in either selfish, malicious or failed nodes towards network resilience and survivability. However, no further research carried out to determine the different correlated node behavior using fuzzy logic system. The important of fuzzy system in correlated node behavior detection is in demanding research work as to enhance the computational complexity and accuracy detection imposed in the previous work in [3], [5]. Besides, previous works suggested that fuzzy logic has successfully implemented in many areas with good and less complex solution [25-26]. In addition, it is also important as the initial detection of misbehave node (malicious and selfish) may reduce the possibility of catastrophic failure in network operation [5].

Furthermore, fuzzy logic models in fact employed parameters for fuzzy input with number of rules for decision making. Since the process of manually extracting rules on the other hand can be time-consuming and the rules may be approximated [14]. Because these methods commonly are off-line in nature, if a very large data set is involved, it can become expensive and impractical. Thus, it may fail to detect new attacks in real-time. To overcome this problem, a hybrid soft computing method of identifying DDoS attacks is proposed for further work.

Table 6
Limitation of Selected Articles

Author and Year	Title	Strength	Weaknesses
Salahshoor et al. 2011 [11]	Simulation Modelling Practice and Theory Fault detection and diagnosis of an industrial steam turbine using a distributed configuration of adaptive neuro-fuzzy inference systems	Inter-correlation fault detection scheme to improve productivity and availability of steam turbine with low maintenance costs	Only for malicious behavior and insensitive to reasonable changes in fault time-series pattern
Khan et al. 2012 [12]	Application of fuzzy inference systems to detection of faults in wireless sensor networks	Analytical nodes behavior detection based on neighbourhood measurement	Single type of abnormal nodes behavior detection
Grigoras, Gheorghe Cartina, Gheorghe 2013 [13]	The fuzzy correlation approach in operation of electrical distribution systems	Meant for forecasting of correlated behavior with high prediction accuracy	Statistical complexity in correlation process
Shamshirband et al 2014 [14]	Co-FAIS: Cooperative fuzzy artificial immune system for detecting intrusion in wireless sensor networks	High detection accuracy for the defense against distributed of malicious behavior	Time-consuming due to multiple output combination methods
Shao, Hang, et al. 2014 [15]	Vessel track correlation and association using fuzzy logic and echo state networks	High certainty in providing correlated vessel track	Slow performance for the large dataset
Nisha et al. 2015 [16]	Improving Data Accuracy Using Proactive Correlated Fuzzy System in Wireless Sensor Networks	Correlation acts with and fuzzy logic. High detection accuracy, false alarm, sensitivity and specificity in decision making support.	General abnormal behavior detection.

V. CONCLUSION

The systematic literature review following Kitchenham guide was conducted in this paper, with motivation to grab fundamental understanding on the issues pertaining to correlated fuzzy logic modeling for node behavior in wireless sensor network. This SLR attempts to answer few research questions such as what is the state of node behavior in wireless sensor network, how fuzzy logic function in node behavior and what are the limitations of current correlated fuzzy rule for node behavior detection in WSN? The above-mentioned questions give high impact in network performance. Findings on correlated fuzzy modeling process is important to identify abnormal event in sensory system and limitation in current studies. From this SLR, we found that there is less work done related to correlated node behavior detection in wireless sensor network. As the wireless sensor applications growing recently, more challenges need to be addressed. Thus, powerful automated fault detection and diagnosis especially towards uncertainty inherited in network can be very interesting and challenging research area. This is crucial in order to prevent regular and costly equipment maintenances in WSN.

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