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An Adaptive Framework for Event Detection in Wireless Sensor Network

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Abstract: ***A wireless sensor network is the new generation technology that holds the capability and it has transformed to interact with the physical environment according to the user's demands. The features of a sensor network play the major role in various application fields that fit in the broad category for tracking, monitoring, automation and detection and in that category WSN plays the predominant role in event monitoring. Event detection in sensor networks is the process of observing; evaluating an event based on multiple attributes and generates an alarm at the appropriate time. A framework was developed to detect the event in in-door environment. The proposed event detection model comprises of three phases. In the first phase the network id grouped and cluster head is determined and subsequently composite model was developed to determine the event and the final phase involves in the fuzzy rule optimization. A simulation setup has created and the experimental evaluation validates the event detection mechanism through various metrics such as cluster communication, event accuracy are measured and evaluated. The results are compared with the energy efficient HEED algorithm and connected dominating set based cluster MCDS-CCH algorithm further the composite event detection mechanism with optimization rule outperforms than the well-established J48 decision tree classification algorithm.***

Keywords **:** ***Event detection, Sensor network, event accuracy, Fuzzy model, Fuzzy genetic***

I. INTRODUCTION

The recent advancement in digital electronics, embedded microprocessor, and MEMS technology has paved the way to the rapid development in wireless communication. The networking technology supports low-cost multifunctional mode, i.e. the number of sensor nodes deployed in the experimental area depends on the application type [1]. Sensor Nodes are self-configurable and they are spatially distributed in the unattended environment in a random manner.

Nodes are battery powered device and have the capability to sense and measure the condition of their surrounding environments. Parameters monitored using sensor networks are temperature, smoke, vibration, a direction of the wind and its speed, existence of certain objects, mechanical stress level, chemical composition, crucial body functions and intensity of sound.

The sensor network uses multi-hop communication; due to limited transmission range, it depends upon on the other intermediate nodes to reach the Base Station (BS). The BS connects the wireless sensor network and the end user. To have a prolonged network lifetime, the collection of multiple sensors in a group forms a cluster and in each group, one of the nodes acts as a Cluster Head (CH). The cluster node acts as a key node and it plays the vital role for the entire communication. The network holds the inherent capability and adapts to the dynamic behavior of the environment.

The correlation of multiple attributes of the precise value of sensed data confirms the event and decides to which degree of the extent the condition is true. Fuzzy logic handles uncertainty and ambiguity that exists in the environment. The fuzzy rules expand exponentially since compositions of multiple attributes are involved in the decision process. Henceforth without affecting the detection rate, the rules are finely tuned by the bio-inspired Genetic algorithm by improving the rule set with the highest true alarm occurrence rule in the repository.

The recognizable occurrence of a phenomenon during a point of time in a specific location is defined as an event. They are classified as an atomic and composite event. Atomic event measures single attribute value for instance humidity level in an environment. The composition of multiple attributes forms the composite event. The correlation of multiple attributes of the precise value of sensed data confirms the event and decides to which degree of the extent the condition is true.

Fuzzy logic handles uncertainty and ambiguity that exists in the environment. The fuzzy rules expand exponentially since compositions of multiple attributes are involved in the decision process. Henceforth without affecting the detection rate, the rules are finely tuned by the bio-inspired Genetic algorithm by improving the rule set with the highest true alarm occurrence rule in the repository.

II. BACKGROUNDS AND RELATED WORKS

This section effectively explores the overview of state-of-the-art techniques that exist in the literature associated with the dynamic selection of CH and a range of event detection mechanisms. These techniques are critically reviewed in the perspective different evaluation parameters such as event accuracy, reduction of false alarm rate, detection rate and energy of the node. In general, all the literature work grabs the strength of the sensor network that deploys hundreds of sensors to observe and detect the event in the environment.

Clustering technique plays the vital role in extending the lifetime of the network by minimizing the energy consumption [2].

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A geographically stretched node forms the virtual group. The node either acts as a CH or member node. The member node contacts the CH through single-hop or multi-hop communication. In a group, only one node can act as CH at an instant of time. The backbone of the network is CH nodes. Several Clustering techniques [3] such as Low-Energy Adaptive Clustering Hierarchy (LEACH), Distributed Election Clustering Protocol (DECP), Hybrid Energy-Efficient Distributed clustering (HEED), Energy Efficient Clustering Scheme (EECS), The Adaptive Threshold sensitive Energy Efficient sensor Network protocol (APTEEN) have been developed to maximize the network lifetime.

Mk means algorithm [4] select a set of three nodes as a Cluster Head and as a rotational basis, these selected nodes balances the load in the network. The drawback exists in these techniques is the initiation of re-clustering loads the transmission cost. The improved nodes such as SNs and CHs follows the strategy that executes the detection cum evaluation within the network in a distributed fashion or the BS centrally makes the decision about the event. Handling event detection varies in different perspectives approach one such elementary idea is a threshold based evaluation that assigns a threshold value and generates an alarm upon the reading goes beyond or lesser than the pre-defined limit [5, 6].

In the hierarchical classification, the tree generates different level of height based on the collaboration of multiple sensor values [7, 8] events are identified. The fuzzy technique improves the decision making, shrinks the resource consumption and it holds the capability to handle uncertainty data. In [9] the area divided into the region, each sub-region holds a CH.

The sensor node takes the local decision and forwards the decision result data to the fusion center, which takes the final decision of the event occurrence. In [10] handles the event in a distributed form which focuses on a single event, composite event and maintains the received event as a stream.CH takes the major responsibility, the stream is frequently scanned and the BS will not receive the redundant event.

The author [11] detected fire for burning mattress and chair through the local event detection scheme and tried to capture data from the multiple sensor nodes to improve the accuracy. Rule base structure was developed with space and timing constraint. This model has evaluated the detection delay and accuracy of the event. According to [12] fuzzy-decision based Composite event detection algorithm forms the topology with the dominating set. The dominant point will act as a decision node and based on fuzzy rule space and time correlation determines the faulty node.

The grid-based distributed algorithm [13] model comprised of two phases they are initialization phase and data collection. The nodes which are not active are put in the sleep mode. Neighbor nodes exchange the information in a random way to determine the event. The authors [14] collaborates with different types of the sensor node and form the event boundary and construct triangulation to achieve event tracking. Numerous bio-inspired optimization techniques are deployed in event detection that works in a centralized approach. In general, considerable research has been devoted to event detection rather less attention has been paid to develop an independent model that generates fuzzy rule along with an optimization mechanism.

III. RESEARCH OBJECTIVE

The main objectives of the proposed work are as follows:

- To develop a cluster head selection algorithm using fuzzy association rule.
- To design a composite event detection module to detect the occurrence of the event in the midst of high confidence by consideration the spatial and temporal semantics.
- To generate true alarm occurrences rule set by reducing the exponentially raised fuzzy rule through a genetic algorithm.
- To design and evaluate a collaborative framework which improves the event accuracy and their real- time performance metrics are compared with J48 decision tree.

IV. METHODOLOGY

The implementation of composite event detection comprises of three phases. In Phase 1 determination of CH selection algorithm. The next phase deals with a novel algorithm with the composition of the mathematical model along with a fuzzy system that detects the event in the environment and finally reducing the rule set through the fitness function that tries to maximize the true alarm occurrence in the rule set. The following assumptions are considered in the composite event detection model.

1. Sensor nodes are heterogeneous (supports with different sensing capability).
2. Sensor nodes are prone to failure and nodes have equal energy without any discrimination.
3. The mobility of sensor nodes is static in the event detection model.
4. Each sensor node holds the unique node id and radio Links are symmetric.

A. Association Rule-Based Cluster Head Selection Mechanism

The main objective of this model is to obtain the minimized rule set by applying the association rule to the fuzzy rule and forming a bin with rules that is larger than the threshold (Ɪ). The support and confidence generate the classification rule. The naïve approach produces the strong rules and eliminates the irrelevant weak rules. Weight (w) varies from 0 to 1 for the fuzzy item. For all input parameters residual energy, node centrality, reachability, and reliability the fuzzy linguistic variable holds the weights. Considering 512 random samples with Ɪ = 80% of weight, the Equation (1) calculates Fuzzy Weighted Confidence (FWC) that holds the linguistic values of potential (CH) are Weak (W), Rather Weak (RW), Medium (M), Strong (S), Rather Strong (RS), Very Strong (VS).

$$FWS(A \Rightarrow B) = \frac{|A \cup B|}{n} \qquad (1)$$

B. Composite Event Detection Mechanism

This Proposed CED model comprises of two different modules (1) Reading of neighborhood sensed nodes and evaluates the confidence level of the sensor node (2) Deals with the fuzzy decision system to confirm the composite event in the determined indoor environment.

Determining confidence factor

The confidence factor evaluated from the sensed environment reads the spatial and temporal semantics. The node records the measurement value and saves temporarily the sensed value in its memory location. Upon raising an alarm, the model constructs the detection window of size DRMIN and DRMAX. The node that falls in the detection range is identified as neighborhood nodes. The vector of measured reading Snr = [Si1, Si2,..., Sin] collected for the time period of K as represented in Equation (2).

$$K = E_{ai}(t) - 5epochs \quad (2)$$

Eai (t): indicates the event raised at the node i at the time t, the recent 5 slot is the assumed time periods fixed in this model. The measures in each set Sij are independent and calculated as per Equation (3).

$$s_{ij} = \mu + \tau j + \varepsilon ij \quad (3)$$

In the first stage, it calculates the descriptive analysis of measurement. The Second stage performs the hypothesis testing with analysis of variance and it statistically analyzed Tukey test. C.F Parameter setting is performed based on the below-specified algorithm.

Initially, all the nodes in the deployed environment hold the parameter Confident factor. The default value 1 is assigned to the parameter. The measurement analyses read within each sensor node and across the neighborhood nodes that exist in the coverage of detection window are analyzed and evaluated. To improve the conclusion and to reduce Type I error, the null hypothesis states that no fluctuation exists in the sensor measurement. Hence it states that there is no significant mean difference in the sensor for the last epochs for the probability α =0.5. As a consequence, C.F retains the same value.

Fuzzy assisted decision system

The relationship between the input and output variable represents the relationship in the form of If….then rule as similar to the human reasoning that is expressed through fuzzy rules. Degree of Membership (DOM) value of the linguistic set lies between the values of zero to one. The input parameters are temperature t, change in temperature ¨t, smoke s, change in smoke ¨s , C.F is set to linguistic term Low (L), Medium (M), High (H) and follows the Triangular membership function. As an instance, the Fuzzy rules are framed .The Figure 1 represents the Hypotheses based semantic algorithm

C. Optimization of fuzzy rule

The increase in no of variables generates exponentially raised the large volume of fuzzy rules that occupies a considerable amount of memory space in the node. As the rule traversal time gradually increases in turn that affects the event detection time. Hence identification of optimized rule set obtained by stating the fitness function that tries to maximize the true alarm through the genetic algorithm as stated in Equation (4) and the rules are encoded as a chromosome.

$$F(x) = \frac{\sum_{x=1}^{a} Cta - \sum_{y=1}^{b} Ctb}{\sum_{z=1}^{c} Tocc} \quad (4)$$

for $\forall N_n \in D_n$ do
$T_{Loc} \leftarrow$ collect data for k periods
// Calculate the variance of the sensor reading
for each epoch k do
$$\overline{x_i^*} = \frac{1}{k}(S_{i1} + S_{i2} + \cdots + S_{ik})$$
end for
// Calculate the grand mean of sensor reading that exist in the detection window DR_{min} and DR_{max}
$$\bar{x} = \frac{1}{|k*n|}\left(\sum_{i=1}^{n}\sum_{j=1}^{k} S_{ij}\right)$$
end for
The parameters are evaluated using Tukey test by using Eqs. (3.8) – (3.12)
$T \leftarrow$ d.f. (SS_{among}, SS_{within})
if F > T then
// Variation in sensor's measurement reading
Accept the (H_a) alternative hypothesis
C.F. ← C.F. – 0.1
else
// No variation in sensors measurement reading
Accept the (H_0) null hypothesis
C.F ← C.F.
end if

Fig. 1. Hypotheses based on Spatial-Temporal Semantics

V. RESULTS AND DISCUSSION

The experiment was carried out in the indoor environment; four differently sized network layouts were deployed. The set up of nodes varies from 10- 50. These nodes are deployed in the area of 100 *100 m. Three gateway nodes form a cluster size with a maximum of 12 end sensor device. Sensor nodes are Xbee S2 modules that provide endpoint connectivity. By making the use of XCTU software one of the nodes was configured as the coordinator node which was placed in the center position.

The nodes are battery powered using 1.5V AA batteries operates at 2.4 GHz with a bandwidth of 1 Mbps. The most occurred rule set is pruned and placed in the intermediate table that comprises the population size of ù=128 samples. The probability of crossover and mutation is set as Pc=.8 Pm =0.1 respectively. The sensors are continuously monitored and on the occurrence of the event and alarm signals are reported to the Base station.

In this proposed work, the analysis was performed in terms of the energy of the node after deploying the fuzzy decision unit and the false alarm rate was evaluated. The evaluated value is compared with a J48 decision tree. By considering the reading of the neighborhood nodes the confident level is evaluated, the hypothesis works well as the no of neighborhood nodes increases the decision of the CED shows the slight improvement in the result the indices such as event accuracy, error rate, false positive rate performs well and it also proves that the proposed model with the hypothesized decision of neighborhood perform better than the J48 decision tree. The Table 1 represents the parameter for network. The energy consumption is represented in Figure 2.

Table- I: Parameters of Network Topology

Parameter	Value
Network Topology	
Network Size	100m x 100 m
No of Nodes	10 ~ 100
BS Location	50m x 50 m
Node distribution	Fixed
PHY/MAC Layer	IEEE 802.15.4
Radio Model	
Energy Model	Battery
Operating Channel	2.4 GHz
Baud rate (BD) bps	115,200 bps
Data bits	8
Bandwidth	1 Mbps
Energy	
E_{elec}	50 nJ/bit 0.0013 pJ/bit/m4
ε_{fs}	10 nJ/bit/m2
ε_{amp}	0.0013 pJ/bit/m4
E_{DA}	5 nJ/bit/Message

. The external index silhouette index measures the intra clustering similarity and the internal indices such as rand index and jaccard index that evaluates the inter cluster similarity. According to the theoretical representation, the rand index should be nearer to the integer value 1. The index value which was nearer to 1 represents a well-formed comparable cluster set in the network. The significance of the Rand index was analyzed in Figure 3. Clusters are formed that vary from the size in the range of 2, 4, 6, 8, and 10 virtual groups comprised of a maximum of 100 sensor nodes. Approximately maximum of nodes nearly 10 - 12 form the cluster group of size 10.

Table-I I: Qualitative measures of Internal and External Indices

No of Clusters	Jaccard Index			Rand Index			Silhouette Index		
	HEED	MCDS -CCH	FACH	HEED	MCDS -CCH	FACH	HEED	MCDS -CCH	FACH
2	0.55	0.43	0.6	0.7	0.65	0.75	0.6	0.5	0.4
4	0.78	0.5	0.75	0.78	0.75	0.81	0.57	0.45	0.38
6	0.68	0.76	0.83	0.85	0.8	0.88	0.5	0.4	0.35
8	0.8	0.8	0.92	0.89	0.85	0.92	0.45	0.39	0.3
10	0.88	0.84	1	0.92	0.89	0.98	0.3	0.35	0.29

The above Table 2 represents the Qualitative measures of internal and external Indexes with respect to number of cluster. Figure 4 demonstrates the graph of Jaccard index value and the index varies linearly starting from 0.6 values to 0.9 across the different set of cluster group. The 0-1 is the standard theoretical value for Jaccard index. A high value for this index indicates the better cluster legitimacy. FACH results in the highest value for this index on compared to other techniques.

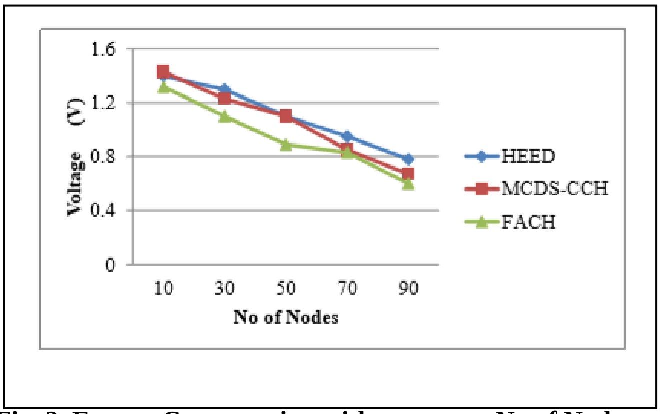

Fig. 2. Energy Consumption with respect to No of Nodes

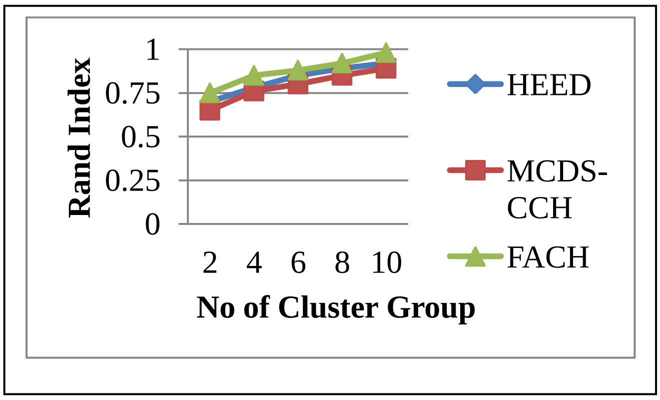

Fig. 3. Rand Index with respect to No. of Clusters

Figure 5 demonstrates the chart of silhouette index values for a different number of clusters. The index value can range from -1 and 1. A value near to 1 indicates that the data point is assigned to a very appropriate cluster. From this indirectly the selection of cluster head and its subsequent cluster formation have grouped the node with compactness.

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On an average, the HEED and FACH algorithm differ in value from 0.01 to 0.05 for each set of cluster size.

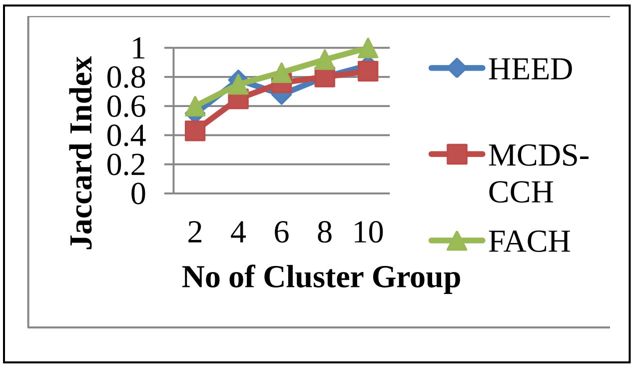

Fig 4: Jaccard Index Vs No of Cluster

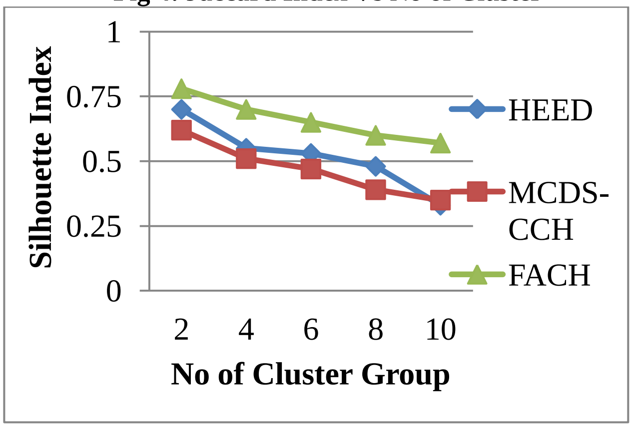

Fig 5 Silhouette Index with respect to No. of Clusters

Comparative analysis with the MCDS-CCH algorithm with FACH indicates that they vary 0.05 to 0.1 ranges. However, there was a minimal level difference that directs to the unity value exist in the FACH model. The Table 3 represents the accuracy and error rate of an event.

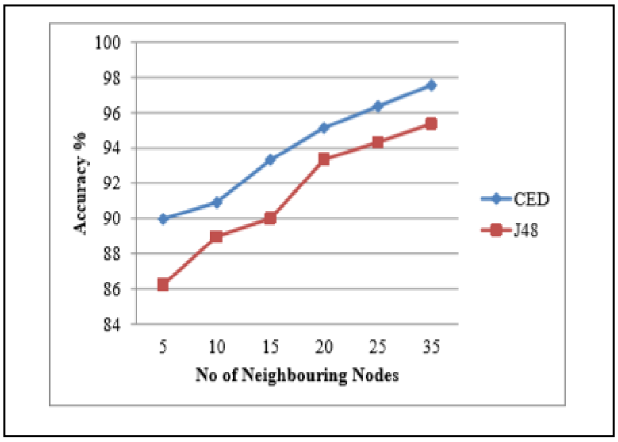

Fig. 6. Comparison of Event accuracy

Table-III: Accuracy and Event Error Rate

Neighbor nodes	Accuracy		Error rate	
	J48	CED	J48	CED
5	86.233	89.963	0.138	0.08956
10	88.967	90.90909	0.11	0.090909
15	89.999	93.33333	0.1	0.066667
20	93.3477	95.15152	0.067	0.048485
25	94.32837	96.36364	0.057	0.036364
35	95.3736	97.57576	0.046	0.024242

The Proposed CED model was analyzed in terms of sparse and dense network. With the set up of 5 neighbor nodes, the CED produces accuracy nearly to 90%, but the J48 model lacks by with the difference of 5%. The stability of the algorithm is evaluated by introducing faulty nodes that varies from 3 to 15, constantly the model outperforms better than the J48 decision tree algorithm. It is observed from Figure 6 that the no of a neighbor node increases the accuracy also increases gradually. The maximum increase of 4 % of accuracy level was achieved and from these results, it clearly depicts that the decision of neighbor node on the parameter C.F plays the vital role. The ROC curve mapped for true positive rate vs. false positive rate that also reflects the accuracy of the event. The experiment results revealed that there was a deviation in the detection rates with the fine-tuned optimized rule base.

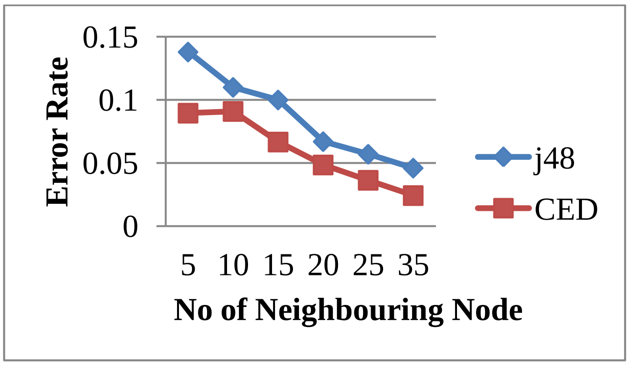

Fig 7 Plot of Error Rate

The error rate was determined in the range 0 - 1. Figure 7 depicts the graph representation of the qualitative measurement of the error rate. According to the model, the past record of the measured data was analyzed along with the C.F factor of the neighbor's reading. The analysis was estimated from the time the source node determines the event for last 5 epochs. Data are gathered and the hypotheses were determined. This comparison of reading decreased the event error rate and there was a trivial difference in the CED and J48 model. They differed in 0.01 with a maximum value of 0.04.

VI. CONCLUSION

An attempt has been made to develop an adaptive framework for event detection framework. This model was initiated and deployed with a thought of straining the network lifetime and to supply high accuracy of detection. The rate of false alarm was reduced by collaborating the reading of neighbor nodes with the trust factor. The association fuzzy weighted rule algorithm determines the CH selection. The CED unit analyses the event occurrence by reading the multiple input attributes along with the spatial and temporal properties. A hypothesis was set to determine the variance in sensor reading. Changes in the environment parameter have appropriately identified with high confidence rate in the sensor field.

The determination of the event was carried out in a short span of time via the optimized fuzzy rule with the true alarm occurrence.

The optimization process was executed in the off the shelf and the rule set was loaded on the node. In a different perspective, the framework model reduces the fault alarm reduction rate. The implemented algorithm was executed with the integration of sensor's data in the MATLAB environment.

The model has the capability to detect the event in a real-time environment and performance has been evaluated by considering the impact of event accuracy and error rate with the existence of faulty sensors, detection rate, and node's energy level. Results obtained from these analyses revealed that the inclusion of Confident Factor, rule optimization mechanism was found to yield better results compared to the J48 decision tree.

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