MULTI CRITERIA DECISION BASED RANKED DISCOVERY FRAMEWORK FOR IoT RESOURCES

Vandana C.P
Research Scholar, Visvesvaraya Technological University (VTU)
Department of Information Science Engineering
New Horizon College of Engineering, Bangalore, India
vandana.hareesh@gmail.com

Dr. Ajeet A. Chikkamannur
Professor and Head of Department, Department of Computer Science and Engineering
R. L. Jalappa Institute of Technology, Karnataka, India
ac.ajeet@gmail.com

Abstract

The growth rate of Internet of Things (IoT) ecosystem has led to an enormous pool of heterogeneous IoT resources with similar capabilities. Providing the right IoT resource at the right time is an indispensible requirement for user application performance. In this paper, we propose a framework for returning the most pertinent IoT resource based on ranking, as the user query response. Proposed Multi Criteria Decision making framework computes the weights of the various criteria based on fuzzy logic user preference and entropy based objective weight. This computed weights for the criteria are applied on approach Technique for Order Preference by Similarity to Ideal solution (TOPSIS). Effectiveness of the proposed approach is compared with current state of work. Also real time testbed experiment based study is carried out to demonstrate the effectiveness and robustness of proposed approach.

Keywords: **Discovery; Rank; MCDM; TOPSIS; IoT resource; Similarity; fuzzy logic**

1. Introduction

Internet of Things (IoT) [1] is a paradigm shift where the physical world entities can be connected to the Internet and provide services in cyber world. With the proliferation of low cost sensing devices and advancement in embedded technologies, billions of intelligent computing objects now exist in our ecosystem [2]. These “things” in IoT which are the real-world entities , now become smart with sensing, actuating and data acquisition and processing abilities with the help of RFID tags, sensors, actuators, smart phones, computers , other electronic gadgets. Various application domains like Healthcare, industrial automation, intelligent transport systems, smart factories, smart home and cities are leveraging the power of IoT platforms. In order to facilitate user application seamless integration and functionality, search and discovery of IoT resources is a challenge. With huge heterogeneity and large-scale proliferation of IoT resources, searching and retrieving the best resources matching the specific user requirement and constraints is a need. IoT resources being resource constrained, heavy search and indexing algorithms is not feasible and hence is an area of research.

A user request with quick response time, minimum service cost, low network bandwidth usage, energy usage awareness may be some of the criteria to be considered while searching the best IoT resource satisfying the user specified requirements. An IoT resource may not be available all the time due to decrease in energy, or lack of communication link. Quality of service (QOS) parameters may degrade over the time because of the resource constrained environment. So, the selection framework not only should provide the best IoT resource based on the requirement but also handle the dynamic nature and its effect by an adaptation strategy. In case the selected IoT resource becomes unavailable [3], an alternative resource with same capabilities must be retrieved and provided to the user. Even if a new better IoT resource is added later, it must be provided to the user after the initial selection is performed.

In any general selection framework, it must support an initial selection of the best IoT resource based on the user query, should consider all other dynamic attributes to reach to a final selection. Alternative selection must be available based on ranking in case if the selected resource becomes unavailable or better resource becomes available. An internal caching mechanism can facilitate the faster accessibility and reusability. User should be notified about the new IoT resources available and the current best resource available.

In this current work, IoT resource is assumed to comply with IoT resource ontology[4]. The various QOS parameters like availability, accuracy, reliability, response time, battery lifetime, remaining energy cost, response time, throughput are considered based on the servicetype provided by the IoT resource. Additional criteria like frequency, sensitivity, measurement range, precision, latency, resolution, detection rate, operating power range, security, trust factor, accessibility, robustness, configurability, user satisfaction rating can be considered. Cost can be a combination of capacity, cost of data transmission, cost of data generation, data ownership cost.

In this paper, a novel approach for IoT resource retrieval based on user requirements is proposed which matches the user query. A multi criteria decision making system is proposed where dynamic to static mapping is performed to retrieve the best IoT resource available in that context.

The contribution in this paper includes:

- An IoT resource retrieval framework is proposed which performs multi feature similarity search of IoT resources with similar capabilities.
- The proposed framework computes the weights for the various criteria based on fuzzy logic based user preference amalgamation with entropy based objective system weights.
- Ranking of the devices is computed based on Technique for Order Preference by Similarity to Ideal solution (TOPSIS). Based on ranking, the most pertinent devices from the device repository matching the user query are returned.

IoT Resource features are extracted from vendor specification as carried out in our previous work [5]. Section 2 details the literature survey carried out in this field; Section 3 discusses the proposed IoT resource discovery and ranking model with multi criteria decision making methodology. Section 4 discusses the implementation and results, followed by Section 5 describing the future work in this regard.

2. Related Work

IoT would enable humans and Things to be connected Anywhere, Anytime with Anything and Anyone, ideally using Any path and Any service, according to Vermesan et al.[6]. The challenge with IoT paradigm would be to discover the most pertinent IoT resource according to the user requirements from the abundant available repository of IoT resources with heterogeneous properties. Some of the context –aware techniques to search and select sensors are reviewed.The context-aware sensor selection framework CASSARAM[7] address the sensor selection model based on user preference and priorities using quality of service as a criteria. A weighted Euclidean distance metric is used to find the sensor matching the user preference. However, the framework does not consider the changes in sensor ontology (addition or deletion of sensors).

In Ebrahimi et al.[8], proposed a meta-heuristic approach (AntClust) to group the sensors with matching context properties. Based on user requirement, the best sensor group is selected. Sensor semantic overlay networks (SSONs) is created based on these groups for changing sensor network. However, the time complexity increases linearly as the senor count increases. Multi Criteria Decision Making (MCDM)[9] is a problem in which decision maker should choose one solution amongst the various alternatives on the basis of a either qualitative and /or quantitative analysis of a set of multiple criteria. MCDM technique Simple Additive Weight method(SAW), Analytical Hierarchy Process (AHP), Technique for the Order Preference by Similarity to Ideal Solution (TOPSIS), Vlse Kriterijumska Optimizaxija I Kompromisno Resenje (VIKOR) are compared and a quantitative analysis of their performance is conducted by comparing with Pareto optimal solution.

Elimination-Selection algorithm (E-S Algorithm) proposed by Nunes et al.[10] combines multiple-criteria decision method TOPSIS and prominent best option by using Fast Non-Dominated sort. In [11] a Cloud of Things based sensing resource discovery architecture is proposed based on virtualization in a centralized repository. The gossip algorithm is employed to select the best resources based on randomized and asynchronous distributed virtualization (RADV) algorithm. Domain based Pruning of undesired resources is performed followed by benefit metric construction locally, local assignment to find an optimal solution. A cloud agent selects the solution with maximum benefit. Khodadadi et al. [12] proposes a Thing Description Document (TDD) to describe the IoT resource properties and its services. A syntax based search is performed to find matching resource as per the user criteria. The resultant set is again searched for suitable resource according to particular task.

Author [13] proposed framework accepts the user query in the form of natural language, then convert the query into a binary encoded format understood by the sensor. Grouping of the sensors is performed based on energy level and distance. In [14], based on user preference IoT spatial-temporal attributes are rated. Further IoT service selection is performed based on absolute dominance relationship. Dominance relationship among services follows that a n-dimensional point x is said to dominate another point y if it is better than or equal to y in all dimensions and better than y in at least one. However, absolute dominance may not be reliable mechanism in case of conflicting multiple same values for the IoT service attributes. Work carried out in [15], suggests clustering of IoT web services based on functionality. This step is followed by spatial indexing is applied on it. Time slots based on temporal specification is assigned. Cluster composition, tree construction and multiple level searching for indexing IoT web services have performance constraints. Skyline services [16], which are the subset of candidate services that are not dominated by other services, are selected. A refinement of absolute dominance relationship between physical services is proposed as an extension. The research work [17], shows the amalgamation of Analytical Hierarchy Process and TOPSIS to choose IoT resource based on quality of Service (QOS) criteria. AHP technique is employed for weight computation followed by TOPSIS for ranking the resources based on the QOS features.

3. Proposed IoT Resource Discovery and Ranking model

The proposed model for finding the most pertennet IoT resources is based on fuzzy logic [18] based user preference computation, objective weight computation technique based on entropy approach, multicriteria decision making techniques TOPSIS. As per the IoTResource model , each IoT device which offer multiple services have spatial, temporal, QOS attributes associated with it which needs to be monitored (telemetric). Inorder to rank the IoT resources, the prefernces from the users can be taken and amalgamated with the objective weight computed from the periodic monotoring of the values of the IoT resource telemetric attributes as shown in fig1.

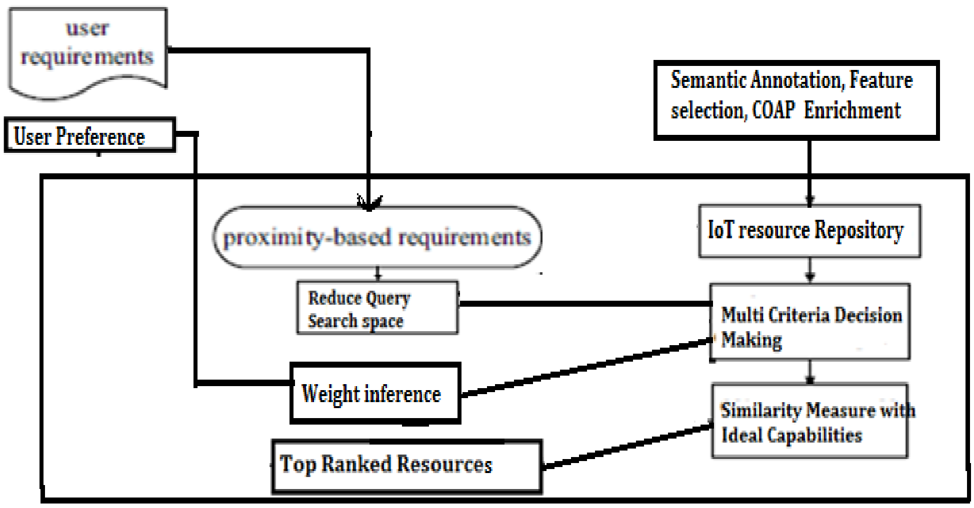


Fig. 1 IoT Resource Discovery and ranking framework

A user query comprises of the required discriminating and service relevant attributes. The retrieval of the most pertinent resource coagulates to a multi criteria decision making (MCDM) problem as shown in Eq. (1), where the number of similar IoT resource candidates range from i = 1,2..m and QOS attributes range from j=1,2,..n.

$$F = \begin{bmatrix} r_{11} & r_{12} & r_{13} & & r_{1n-1} & r_{1n} \\ r_{21} & r_{22} & r_{23} & & r_{2n-1} & r_{2n} \\ r_{31} & r_{32} & r_{33} & & r_{3n-1} & r_{3n} \\ . & . & . & & . & . \\ . & . & . & \dots & . & . \\ . & . & . & & . & . \\ r_{m-1\,1} & r_{m-1\,2} & r_{m-1\,3} & & r_{m-1\,n-1} & r_{m-1\,n} \\ r_{m1} & r_{m2} & r_{m3} & & r_{mn-1} & r_{mn} \end{bmatrix} \quad (1)$$

During the initial discovery phase, the proposed model would try to return the most ranked resources. In case ranking does not exist, the framework would retrieve the most semantically matching IoT resources based on the default preference model computed by the objective weight function. For these retrieved resources, the rank based on user preference is computed based on combination of user preference and default preference model augmented by fuzzy logic.

3.1 Fuzzy logic based User Preference Computation

In real world problems, measuring and providing solutions in terms of binary value (crisp logic) may not be feasible. The uncertainty dealing with decision making based on binary values (0,1) can be resolved by applying Fuzzy logic. Fuzzy Logic is an effective approach which is multi-valued and emphasis on approximation instead of accuracy. It enables the usage of measurements in terms of numerical values and its linguistic mapping which represents the human cognitive ability.

Fuzzy logic based weight inference engine is proposed which would accept the preferences on the attributes from end users in terms of linguistic terms (close to human thinking ability). The engine would map it to the quantitative terms and would return the weights associated with the features. The application of fuzzy logic in retrieving the most pertinent IoT resource matching the user requirements can provide the most comprehensive solution. A fuzzy set P in a universe of discourse U is given by the membership function **μ**P(i) that maps each element i to a real number in interval[0,1].The closer the value of the membership function **μ**P(i) to 0, the more is its relevance. We apply triangular fuzzy system to design a membership function to derive fuzzy boundaries of preferences as shown in Eq. (2):

$$\boldsymbol{\mu}\mathrm{P(i)} = \begin{cases} 0 & \mathrm{i} < l \\ \frac{i-l}{m-l}, & l \le i \le m \\ \frac{u-i}{u-m}, & m \le i \le u \\ 0, & i > u \end{cases} \tag{2}$$

where l,m,u represent the lowest boundary, middle and upper boundary values respectively which are crisp values. A triangular fuzzy set is represented by this triplet value (l,m,u).The user preferences is accepted in linguistic form as shown in table Table1

Table 1 User Preference and associated values

User Preference	Associated Values
Very High Requirement (VHR)	(0.8,1.0,1.0)
Highly Required (HR)	(0.6,0.8,1.0)
Medium Requirement (MR)	(0.4,0.6,0.8)
Low Requirement(LR)	(0.2,0.4,0.6)
Very Low Requirement (VLR)	(0.0,0.2,0.4)

3.2 Entropy based Objective Weight Computation

Based on the periodic monitoring of the attribute values of similar IoT resources, the object weight is computed by applying the Entropy concept [19]. Entropy measures the uncertainty in information contained in the decision matrix and is used to generate the weights. Some of the IoT resource attributes would have maximization criteria like resolution rate, brightness, while certain attributes would have minimization criteria like battery usage, storage. The decision matrix (1) is normalized as per Eq. (3) and Eq. (4) depending upon maximization attribute or minimization attribute respectively.

$$x_{ij} = \frac{r_{ij}}{\sum_{i=1}^{m} r_{ij}} \tag{3}$$

$$x_{ij} = \frac{1/r_{ij}}{\sum_{i=1}^{m} 1/r_{ij}} \tag{4}$$

As per the Eq. (5), the entropy for each attribute is computed, where the constant k = -1/ln m, for j=1,2..n computes the entropy in the interval [0,1]

$$e_j = -k \sum_{i=1}^{m} \mathrm{x_{ij}} \ln x_{ij} \tag{5}$$

The amount of divergence for each attribute is normalized to generate the objective weight given by Eq. (6) in the range[0,1]

$$ow_j = \frac{1-\mathrm{e_j}}{\mathrm{n}-\sum_{\mathrm{j}=1}^{\mathrm{n}} \mathrm{e_j}} \tag{6}$$

The higher the value of the entropy, the more is the disorder and more important is the attribute. The fuzzy rule applied is shown in Table 2 to map to system opinions. Table 3 shows the corresponding values mapped to system generated opinions.

Table2 Object weight ow_j and associated values

Object Weight ow_j	Associated System Opinion
$0.8 \le ow_j \le 1$	Very High Requirement (VHR)
$0.6 \le ow_j < 0.8$	Highly Required (HR)
$0.4 \le ow_j < 0.6$	Medium Requirement (MR)
$0.2 \le ow_j < 0.4$	Low Requirement(LR)
$0 \le ow_j < 0.2$	Very Low Requirement (VLR)

Table 3 System generated opinion values mapping

Objective weight based System Opinion	Associated Values
Very High Requirement (VHR)	(0.8,1.0,1.0)
Highly Required (HR)	(0.6,0.8,1.0)
Medium Requirement (MR)	(0.4,0.6,0.8)
Low Requirement(LR)	(0.2,0.4,0.6)
Very Low Requirement (VLR)	(0.0,0.2,0.4)

3.3 Overall Attribute Weight Inference Methodology

The user preference in terms of linguistic terms and objective weight converted in terms of linguistic terms as discussed in previous sections is amalgamated to compute the final overall weight of the various attributes. Fuzzy mean value between the user preference and system generated opinion is computed and defuzzification based on average is computed.

Table 4. Overall Attribute weight computation

Attribute	User Preference	System generated opinion	Fuzzy Average	Defuzzified
Accuracy	VHR (0.8,1.0,1.0)	VLR (0.0,0.2,0.4)	0.8,1.2,1.4	1.133
Sensitivity	HR (0.6,0.8,1.0)	VLR (0.0,0.2,0.4)	0.6,1,1.4	1
Operating Temperature Range	LR (0.2,0.4,0.6)	HR *(0.6,0.8,1.0)*	0.8,1.2,1.6	1.2
Power Consumption	VLR (0.0,0.2,0.4)	VHR (0.8,1.0,1.0)	0.8,1.2,1.4	1.133
Calibration	HR *(0.6,0.8,1.0)*	VHR (0.8,1.0,1.0)	1.4,1.8,2.0	1.73

3.4 Ranking based on modified TOPSIS

The values of all the features must be converted to consistent units. Hence the normalization is performed using the Eq.(7).

$$r^1_{ij} = \frac{r_{ij}}{\sqrt{\sum_{i=1}^{n}\sum_{j=1}^{m} r_{ij}{}^2}} \tag{7}$$

The weight vector as shown in Eq. (8) is inferred by the Overall Attribute Weight Inference Methodology discussed previously. Based on weight vector 8, Eq.(9) is derived.

$$W=[w_1, w_2, w_3, \ldots, w_n] \tag{8}$$

$$F = \begin{bmatrix} w_1 r_{11}^1 & w_2 r_{12}^1 & w_3 r_{13}^1 & & w_n r_{1n}^1 \\ w_1 r_{21}^1 & w_2 r_{22}^1 & w_3 r_{23}^1 & & w_n r_{2n}^1 \\ w_1 r_{31}^1 & w_2 r_{32}^1 & w_3 r_{33}^1 & & w_n r_{3n}^1 \\ . & . & . & \ldots & . \\ . & . & . & & . \\ . & . & . & & . \\ w_1 r_{m-1\,1}^1 & w_2 r_{m-1\,2}^1 & w_3 r_{m-1\,3}^1 & & w_n r_{m-1\,n}^1 \\ w_1 r_{m1}^1 & w_2 r_{m2}^1 & w_3 r_{m3}^1 & & w_n r_{mn}^1 \end{bmatrix} \tag{9}$$

Decision matrix represented by Eq. (9), can be normalized and transformed to Eq. (11) by applying Eq.(10), where i=1,2,..n and j = 1,2,3...m

$$f_{ij} = \frac{w_i}{\sum_{i=1}^{n} w_i} \; r_{ij}^1 \tag{10}$$

$$F = \begin{bmatrix} f_{11} & f_{12} & & f_{1n} \\ f_{21} & f_{22} & & f_{2n} \\ . & . & & . \\ . & . & \dots & . \\ . & . & & . \\ . & . & & . \\ . & . & & . \\ f_{m1} & f_{m2} & & f_{mn} \end{bmatrix} \tag{11}$$

Depending upon maximization/minimization criteria, attribute values with most ideal behavior can be determined. The most maximization ideal attribute value can be found by finding the maximum value amongst all values of a particular attribute. Correspondingly, minimization ideal attribute value can be found by finding the minimum value amongst all values of a particular attribute.

Ideal Maximization Feature (IF^+) is given by Eq.(12) and Eq. (13)

$$IF_i^+ = \max\{f_{1i}, f_{2i}, .., f_{mi}\} \tag{12}$$

$$IF^+ = \{IF_1^+, IF_2^+, IF_3^+ .., IF_n^+\} \tag{13}$$

Ideal Minimization Feature (IF^-) is given by Eq.(14) and Eq.(15)

$$IF_i^- = \min\{f_{1i}, f_{2i}, .., f_{mi}\} \tag{14}$$

$$IF^- = \{IF_1^-, IF_2^-, IF_3^-, .., IF_n^-\} \tag{15}$$

The relative distance between Ideal minimization feature and feature vectors is given in equation 16. Distance measure with respect to Ideal maximization feature is given by Eq.(17).

$$Dist_i^+ = \sqrt{\sum_{i,j=1}^{n} (IF_i^+ - f_{ij})^2} \tag{16}$$

$$Dist_i^- = \sqrt{\sum_{i,j=1}^{n} (f_{ij} - IF_i^-)^2} \tag{17}$$

The Correlation based distance computes the similarity or dissimilarity relation between the various criteria is given by Eq. (18) and Eq. (19) respectively.

$$Corr\_Dist_i^+ = 1 - \frac{\sum_{i=1}^{m} (f_i - \sum_{i=1}^{m} f_i)(IF_i^+ - \sum IF^+)}{\sqrt{\sum_{i=1}^{m} (f_i - \sum_{i=1}^{m} f_i)^2 \sum_{i=1}^{m} (IF_i^+ - \sum IF^+)^2}} \tag{18}$$

$$Corr\_Dist_i^- = 1 - \frac{\sum_{i=1}^{m} (f_i - \sum_{i=1}^{m} f_i)(IF_i^- - \sum IF^-)}{\sqrt{\sum_{i=1}^{m} (f_i - \sum_{i=1}^{m} f_i)^2 \sum_{i=1}^{m} (IF_i^- - \sum IF^-)^2}} \tag{19}$$

$$P_i^+ = \sqrt{Dist_i^+ \quad Corr\_Dist_i^+} \tag{20}$$

$$P_i^- = \sqrt{Dist_i^- \ Corr\_Dist_i^-} \tag{21}$$

The relative closeness of each criteria to the ideal solution is computed and given by Eq. (20) and Eq.(21). The ranking index R, given by Eq. (22), is used the arrange IoT resources in decreasing order as per their rank

$$R = \frac{P_i^-}{P_i^- + P_i^+} \tag{22}$$

The proposed framework of IoT resource retrieval and ranking follows the steps:

1. Construct the multi criteria decision matrix
2. Calculate the weights for the criteria

3. Compute the weights for user preference based on fuzzy logic. Compute the entropy based objective weight.
4. Defuzzification to get amalgamated criteria weights.
5. Compute Ideal solution Maximization and Minimization Ideal values. Compute the rank index.
6. Rank IoT resources based on decreasing order of rank index value.

IoT resource semantically annotated attributes comprise of both static and dynamic attributes. These attributes are either capable of discriminating the resource or service relevant attributes [21]. These attributes are extracted from the device specification and can be categorized to static and dynamic attributes. Static attributes values wont change over the time. Dynamic attributes must be under constant monitoring and its value change over the time.

Discovery of most pertinent resource based on static and dynamic attributes.

1. Classification of the IoT resource (R) attributes based on their values as Static and Dynamic Attributes. S={s1,s2,s3,..,sn} D={d1,d2,d3,…dm}
2. Given a User request (Q) comprising of requested IoT resource attributes Q= q1,q2,..qi {qi ∈ {S,D}+}
3. Both R and Q are consistent with respect to a common ontology T
4. Initialize search criteria with initial Dynamic Attribute based on user request Q
5. If matching value of Dynamic Attribute for IoT resource found in search space, then
   5.1 Map Dynamic Attributes to corresponding Static Attribute , {d1d2..dn}→s1
   5.2 Return the discovered IoT resource R
6. Else
   6.1 Include the next Dynamic Attribute 'di' in the search criteria and perform the search.
7. Repeat until corresponding Static Attribute is found, IoT resource is discovered.

Table 5. Notation used in Algorithm

O	Ontology consists of respective IoT resource description and its property values. For eg SSN ontology for sensor descriptions and details
Q	Client Query consist of features of interest
S	Set of static attributes of the IoT resource whose value dont change over the time
D	Set of static attributes of the IoT resource whose value change over the time
S1	The result of the query which is the unique static attribute identifying the best selected IoT resource. It can be either the unique identifier (ID) or the URL of the resource.
RS	Result set based on search of static attributes of the query (EXACT _MATCH)
NRS	New Resultant Set based on search of dynamic attributes of the query (NEAR_MATCH)
FRS	Final Result Set based on query on remaining dynamic attributes and multicriteria decision making (Dynamic-Static-Match)

Pre-Requisites:
Static Attributes of the IoT Resource $S=\{s_1, s_2, s_3, \ldots s_n\}$
Dynamic Attributes of IoT Resource $D=\{ d_1, d_2, d_3 \ldots D_m \}$
where, n+m = total number of features of an IoT Resource present in the repository

Algorithm: IoT RESOURCE SELECTION

INPUT: $Q = \{ q_1, q_2, q_3 \ldots q_p \}$, $q_i \in \{ S \text{ or } D\}$
OUTPUT: Ranked S_1 [value], S_2 [value], S_3 [value].. S_n [value]
Begin

1. Select all static attributes , si ∈Q , perform
   RS ← EXACT_MATCH(si)
2. If di∈Q = {} and │RS│==1 then
   return RS[s1[value]]
3. Else
   for each di∈Q, for all rsi ∈RS
      NRS ← NEAR_MATCH(di,RS)
4. If │NRS│==1, then

Return NRS[s1[value]]
Else
Drem<-Remaining di of the feature set F of the NRS
FRS<-Dynamic_Static_Match(Drem,NRS)
5. If │FRS│==1, then
Return FRS[s1[value]]
Else
Return the Desc_rankorder_list(FRS[s1[value]])
End

Algorithm: EXACT_MATCH

INPUT: Static Attributes of query { $q_1, q_2, q_3\ldots q_p$ } , $q_i \in Q$
Static Attributes in Datasource S={$s_1, s_2, s_3, \ldots. s_n$}
Ontology referred O
OUTPUT: RS
1. For each $q_i \in S$ do
q_1[value]==s_2[value] ∩ q_2[value]==s_3[value] ∩ q_3[value]==s_4[value] ∩ ….∩q_3[value]==s_4[value] ∩q_p[value]==s_p[value]=> RS { $rs_1, rs_2, rs_{3,..} rs_k$ }
2. Return RS

Algorithm: NEAR_MATCH

IN: Dynamic Attributes of query { $d_1, d_2, d_3\ldots d_p$ } , $d_i \in Q$
Dynamic Attributes of RS={$dr_1, dr_2, dr_3, \ldots. dr_n$}
OUTPUT: NRS
1. For each $q_i \in S$ do
P=Proximity_Measure(d1[value],dr1[value])
NRS { $nrs_1, nrs_2, nrs_{3,..,}nrs_k$ }← min(p|pi∈P)
2. Return NRS

Algorithm: Dynamic_Static_Match(D_{rem}, NRS)

IN: Remaining Dynamic Attributes of Drem{ $d_1, d_2, d_3, \ldots, d_n$} , $d_i \in D$
Final Result Set, FRS
Weight set W={$w_1,w_2,w_3..w_n$} of corresponding dynamic attributes as in equation 8
OUTPUT: FRS
1. MCDM(Drem,NRS,W) as equation 22
2. Return FRS

Step1 all the static attributes from the incoming query are taken to perform an EXACT_MATCH. Here the values of the static attributes defined in the query are matched with the values of the static attributes present in the datasource, the resultant set of data entries form the RS. Incase if the exact value of static attribute is not present in the data source, then proximity computation is done in NEAR_MATCH. If the number of entries in resultant set is more, then MCDM based on modified TOPSIS is performed to return the ranked result set. Highest ordered entry is returned to user query. **Best case**: If the RS has exactly one entry, if there are no further dynamic attributes in the incoming queries, then S1 attribute of the resultant tuple is chosen and its value is return to the query.

4. Implementation and Result Discussion

The effectiveness of the proposed resource retrieval model based on ranking is evaluated based on data set computed from our previous work [19] which is also available for download for research community. The data set comprises of the attributes of the 7 Light sensors derived by semantic annotation and extraction from sensor specifications provided by manufacturer as shown in Table 6. Table 7 represents the matrix for decision making.

Table 6 Attributes of IoT Light Sensors

Device ID	Device Model	Accuracy	Measuring Range	Current consumption	Power	Operating Temperature
L1	BH1750	+/-20%	1-65535lx	0.12mA	2.4V-3.6V	-30° c to 70° c
L2	VEML6035	+/-10%	6710lx	0.5mA	1.7V-3.6V	-20° c to 75° c
L3	LT-1PA01	+/-20%	2000lx	0.8mA	2.7V-3.6V	-30° c to 70° c
L4	NS060	+/-20%	65535	0.66mA	5V	-30° c to 80° c
L5	Opt3001	+/-15%	8300lx	1.8mA	1.6V-3.6V	-20° c to 70° c
L6	MAX44009	+/-10%	188000lx	0.65mA	1.7V -3.6V	-40 °c to +85° c
L7	ISL29147	+/-20%	40000lx	0.2mA	2.25-3.634V	-30° c to 70° c

Table 7 Decision matrix for IoT Light sensors

Device ID	Accuracy	Measuring Range	Current consumption	Power	Operating Temperature	Location
L1	0.0198	155535	0.12mA	2.78	33 ° c	12.9280058, 77.6902479
L2	0.050	6610	0.5mA	2.55	36° c	12.9280058, 77.6902479
L3	0.02	1900	0.8mA	3.41	40° c	12.9280058, 77.6902479
L4	0.030	63535	0.66mA	4.22	35° c	12.9280058, 77.6902479
L5	0.011	7300	1.8mA	3.12	39° c	12.9280058, 77.6902479
L6	0.002	178000	0.65mA	3.12	42° c	12.9280058, 77.6902479
L7	0.016	38000	0.2mA	2.22	47° c	12.9280058, 77.6902479

The matrix is normalized to fall in the range from 0 to 1.As shown in Table 9, the overall weight is computed followed by proximity to ideal case in Table 11. Finally the IoT Light sensors are ranked based on the computed rank index score as shown in Table 12

Table 8 Normalized matrix

Accuracy	Measuring Range	Current consumption	Power	Operating Temperature
0.29279421	0.8966483	0.21001511	0.336964 1	0.31896341
0.7393722	0.0381023	0.33602441	0.30908162	0.34796012
0.2957513	0.0109514	0.33602413	0.4133269	0.38662233
0.4436278	0.36627498	0.27722042	0.51150726	0.33829454
0.16266353	0.04208401	0.75605563	0.37817598	0.37695678
0.02957519	0.1026158	0.27302009	0.37817598	0.40595345
0.23660149	0.21906743	0.08400618	0.26908676	0.45428125

Table 9 Overall Weight Inference for attributes

Feature	Object based weight		User Preference	Final weight
	Entropy	System generated opinion		
Accuracy	0.4225	MR (0.4,0.6,0.8)	MR (0.4,0.6,0.8)	1.2
Measuring Range	0.7143	HR (0.6,0.8,1.0)	HR (0.6,0.8,1.0)	1.6
Current consumption	0.4225	MR (0.4,0.6,0.8)	VHR (0.8,1.0,1.0)	1.533
Power	0.4325	MR (0.4,0.6,0.8)	MR (0.4,0.6,0.8)	1.2
Operating Temperature	0.375	LR (0.2,0.4,0.6)	VLR (0.0,0.2,0.4)	0.6

Final weights computed W={ 1.2,1.6,1.533,1.2,0.6}

Table 10 Weighted Decision matrix

Accuracy	Measuring Range	Current consumption	Power	Operating Temperature
0.05805446	0.23316073	0.05232467	0.06571711	0.03110321
0.14660218	0.00990898	0.08371947	0.06028009	0.03393078
0.05864087	0.00284827	0.08371947	0.08060984	0.03770086
0.08796131	0.09524459	0.06906856	0.09975763	0.03298825
0.03225248	0.01094335	0.18836881	0.07375446	0.03675834
0.00586409	0.02668378	0.06802207	0.07375446	0.0395859
0.0469127	0.05696536	0.02092987	0.05247913	0.04429851

$IF^{+}=$ [0.00586409 0.00284827 0.18836881 0.09975763 0.03110321]

$IF^{-}=$ [0.14660218 0.23316073 0.02092987 0.05247913 0.04429851]

Table 11 Light Sensors proximity measure to Ideal case

Device ID	P_i^-	$P_i^{\mp}$
L1	0.25858175	0.74141825
L2	0.56349433	0.43650567
L3	0.68281054	0.31718946
L4	0.48952377	0.51047623
L5	0.88723462	0.11276538
L6	0.67000763	0.32999237
L7	0.51950575	0.48049425

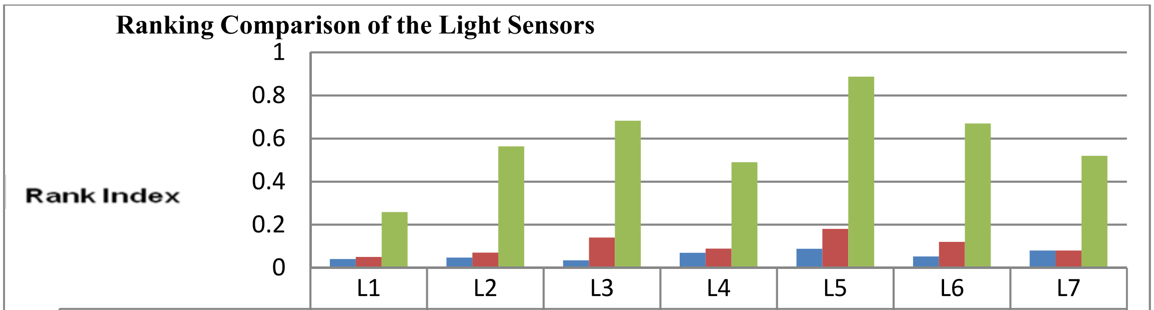
Table 12 Ranked IoT Light Sensors

Device ID	Rank Index Score	Rank Order
L1	0.25858175	7
L2	0.56349433	4
L3	0.68281054	2
L4	0.48952377	6
L5	0.88723462	1
L6	0.67000763	3
L7	0.51950575	5

The proposed approach is compared with basic AHP-AHP and AHP-TOPSIS approach[18] for ranking. As shown in fig. 2, the rank index scores are compared. All the cases depicts that L5 has the highest rank. Spearman's Rank Correlation coefficient was employed to find the correlation coefficient value amongst the various approaches which was observed to be 0.91. The correlation values depicts that the ranking obtained are highly associated with each other, hence ranking generated by both approaches is same.

$$Coefficient = 1 - \frac{6\sum_{i=1}^{n} rd_i^2}{n(n^2-1)} \tag{23}$$

Where rd_i is the rank difference of the ith IoT resource using the approaches and n represents the total IoT resources considered for comparison.



	L1	L2	L3	L4	L5	L6	L7
AHP-AHP	0.04	0.047	0.034	0.069	0.088	0.052	0.08
AHP-TOPSIS	0.05	0.07	0.14	0.089	0.18	0.12	0.08
Proposed Approach	0.258582	0.563494	0.682811	0.489524	0.887235	0.670008	0.519506

Fig. 2. Rank value comparison

As shown in fig. 3 and fig. 4, the amount of time taken to compute the rank of the IoT resources. It is observed that AHP-AHP model grows linearly as the number of devices and number of features increase. The approach AHP-TOPSIS[17], performs the weight computation using AHP technique and hence employs pairwise comparison which increases as the number of resources and features are increased. Our proposed approach does not employ any pairwise comparison, rather depends on Entropy based objective weight computation. Also amalgamation of the user preference is used for weight computation. From the result it is evident that even if the number of IoT resource attributes and devices are increased, the proposed approach increases by 9%.

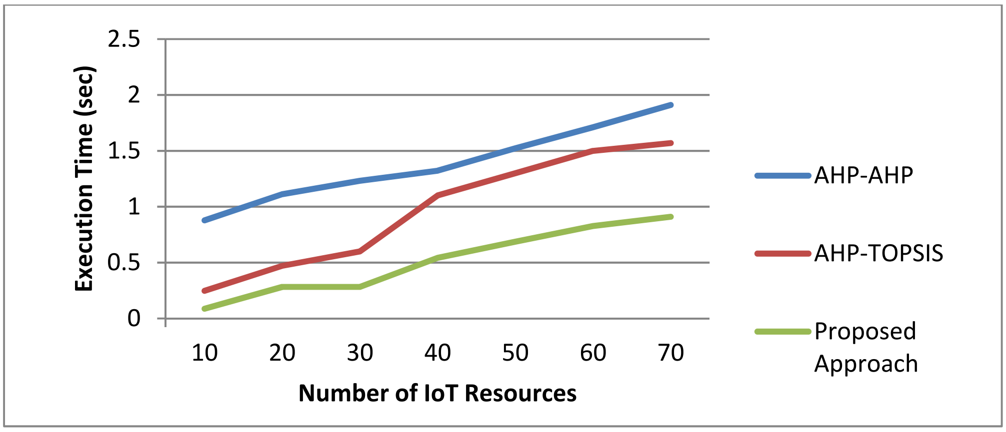


Fig.3 Ranking Time analysis in terms of Number of IoT Resources

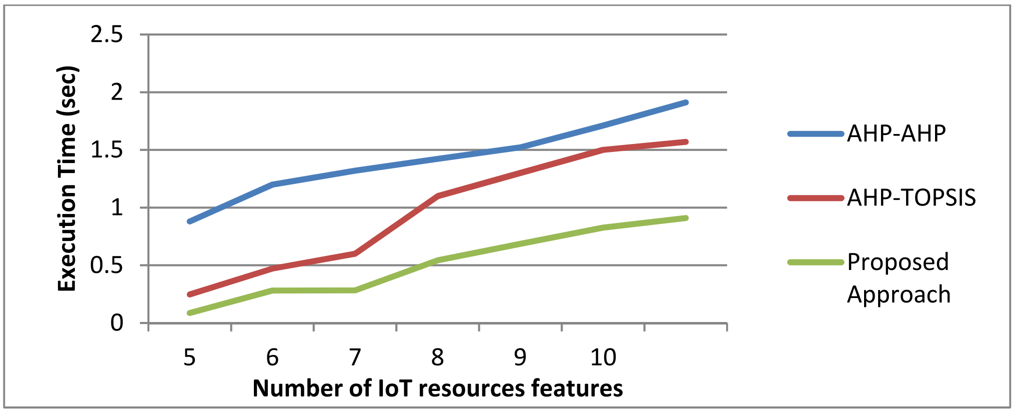


Fig. 4 Ranking Time analysis in terms of Number of IoT Resources Features

4.1 Case Study

In order to exemplify the proposed ranking model, a real time office automation case study is carried out by deploying 5 temperature sensors for IoT-based temperature monitoring system for data centre in office. It is not efficient if all the deployed temperature sensors are used for temperature monitoring. Power management by optimal usage of required temperature sensor is required in data centres. If the temperature goes below threshold then the cooling must restart else, cooling system can be controlled for better power usage. Hardware Configuration[20],[21] used to collect the data from the real sensors. Temperature Sensors DHT11, DHT22, DS18B20, ETT-10PT and LM35 are connected to 5 Arduino UNO[22] boards using I/O pins as shown in fig. 5. These microcontrollers can then connect wirelessly to the gateway via ESP8266WiFi built in Wifi module [23] as shown in Fig. 6. Real time temperature reading are collected and stored over a period of 1 week on cloud service ThingsSpeak[21]. The QOS attributes accuracy, sensitivity, power usage of the temperature sensor were updated as shown in Fig7. The semantic enriched Constrained Application Protocol (COAP) Resource directory [24] as a part of our previous work , performs the MCDM and ranks and returns the temperature sensors based on user query.

The gateway hosts the COAP server and its RD implementation. For evaluating the efficiency of the proposed model a tool based UI is created which provides COAP Client interface. The mandatory attributes comprising of discriminating and service relevant attributes derived from these temperature sensors specification is mandatory in the UI interface for SPARQL[25] query generation. Based on the usecase, the context properties (optional) can be monitored and provided by system manager which can be enriched in COAP RD. Our proposed retrieval and ranking model can also accommodate context properties based on specific use case requirements and perform the ranking.

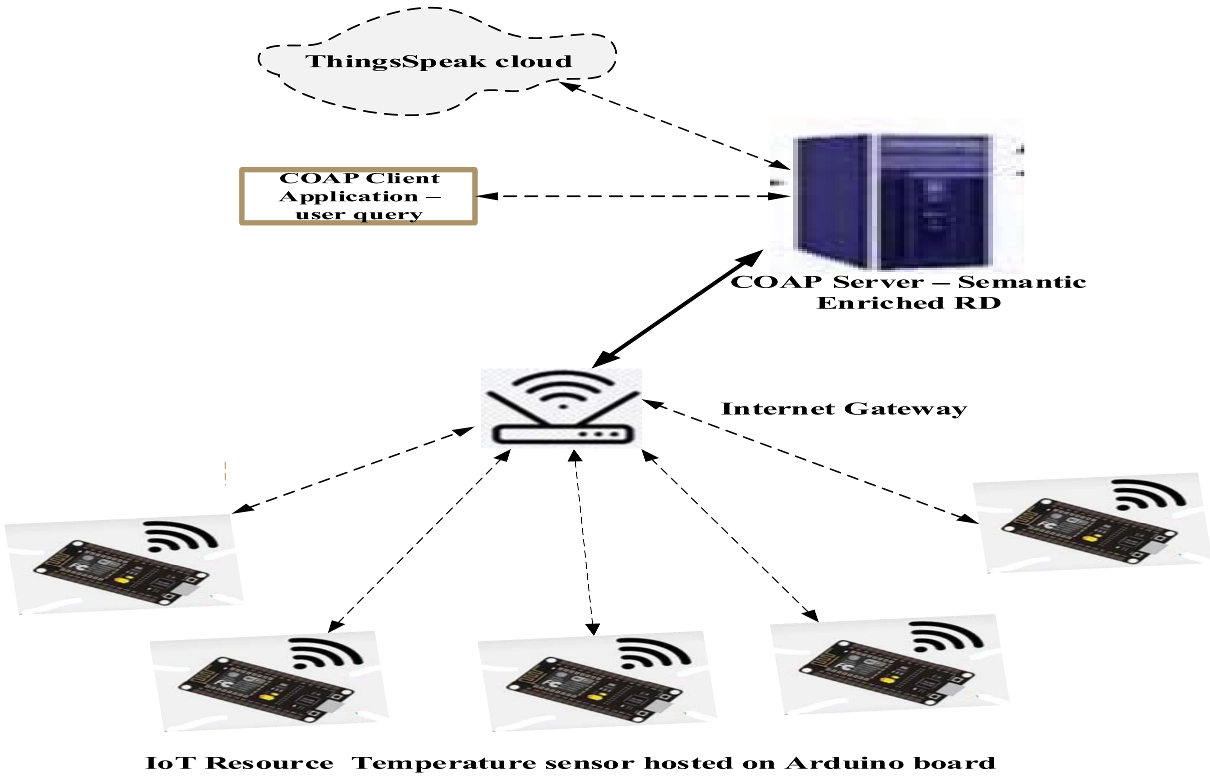


Fig 5. Real time experiment set up

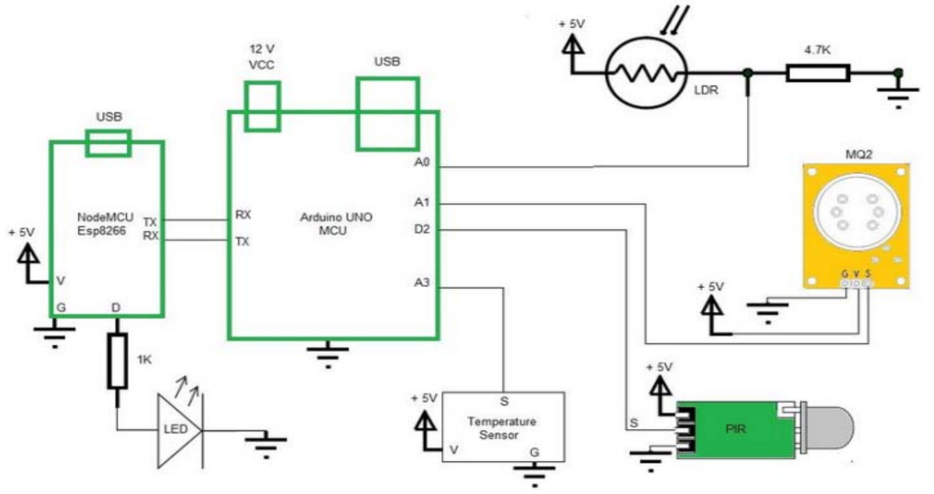


Fig 6 Circuit and Board for the real time testbed

The test bed employs 5 temperature sensors whose attribute values are shown in table 13. Fig 7 depicts the live temperature readings collected on ThingSpeak Cloud

Table 13 Temperature Sensors deployed in real test set up

Device ID	**Model**	**Accuracy**	**Range**	**Sensitivity**	**Stability**	**Response Time**	**Time**	**Location**
T1	DHT11	0.2°C	20°C - 80°C	16 bit	0.5	10sec	2021-08-18 11:31:00.530182	12.427680, 76.451653
T2	DHT22	0.5°C	40°C - 80°C	10bit	0.5	2sec	2021-08-18 11:31:00.530182	12.427680, 76.481653
T3	DS18B20	0.5°C	*55°C - 125°C*	9-bit	1.2	1sec	2021-08-18 11:31:00.530182	12.427680, 76.491653
T4	ETT-10PT	0.1°C	-20°C - 80°C	12bit	1.133	3sec	2021-08-18 11:31:00.530182	12.427680, 76.351653
T5	LM35	0.5°C	-55°C - 150°C	10bit	0.08	5 sec	2021-08-18 11:31:00.530182	12.427680, 76.311653

e-ISSN : 0976-5166
p-ISSN : 2231-3850

Fig. 7 Temperature reading from all 5 sensors read by COAP server and stored on ThingsSpeak

The user query is posted as SPARQL as shown below to find the temperature sensor with accuracy and response time value provided. However, there are multiple temperature sensors with similar value, so based on the framework proposed, the weights are computed and ranking is performed to return the temperature sensor which is most pertinent to the user requirement.

```
SELECT ?s WHERE {
?x <info:discovery/iot_resource/accuracy> "+-0.5 °C" . ?x
<info:discovery/iot_resource/response_time> "0.001" .  ?x
<info:discovery/iot_resource/device_id> ?s }
order by asc(?accuracy) desc(?response_time) limit 5)
```

SPARQL Query to retrieve temperature sensor

Table 14 Temperature Sensor features for decision making

Device ID	**Accuracy**	**Range**	**Sensitivity**	**Stability**	**Response Time**
T1	0.2	60	16	0.5	10
T2	0.5	40	10	0.5	2
T3	0.5	180	9	1.2	10
T4	0.1	90	12	1.133	3
T5	0.5	205	10	0.08	5

Table 15 Normalized Decision matrix

Device ID	Accuracy	Range	Sensitivity	Stability	Response Time
T1	0.2236068	0.20257673	0.61312133	0.27820361	0.64820372
T2	0.55901699	0.13505116	0.38320083	0.27820361	0.12964074
T3	0.55901699	0.6077302	0.34488075	0.66768866	0.64820372
T4	0.1118034	0.3038651	0.459841	0.63040938	0.19446112
T5	0.55901699	0.69213717	0.38320083	0.04451258	0.32410186

Table 16 Overall Weight Inference for features

Feature	Object based weight		User Preference	Final weight
	Entropy	System generated opinion		
Accuracy	0.1372	LR (0.2,0.4,0.6)	MR (0.4,0.6,0.8)	1.0
Range	0.1519	LR (0.2,0.4,0.6)	VLR (0.0,0.2,0.4)	1.6
Sensitivity	0.04225	VLR (0.0,0.2,0.4)	VHR (0.8,1.0,1.0)	1.133
Stability	0.269	MR (0.4,0.6,0.8)	MR (0.4,0.6,0.8)	1.2
Response Time	0.159	LR (0.2,0.4,0.6)	HR (0.6,0.8,1.0)	1.2

Final weights computed W={ 1.0,1.6,1.133,1.2,1.2}

Table 14 depicts the decision matrix and the normalization is performed in Table 15. Based on User preference and entropy values, the overall weight is computed as shown in Table 16. Once the weights are inferred, the weighted decision matrix is computed and the proximity measures are computed as shown in Table 18.

Table 17 Weighted Decision Matrix

Accuracy	Range	Sensitivity	Stability	Response Time
0.03645961	0.05284898	0.11326699	0.0544341	0.12682936
0.09114903	0.03523265	0.07079187	0.0544341	0.02536587
0.09114903	0.15854693	0.06371268	0.13064184	0.12682936
0.01822981	0.07927346	0.08495024	0.12334767	0.03804881
0.09114903	0.18056734	0.07079187	0.00870946	0.06341468

IF^{-}= [0.01822981 0.03523265 0.06371268 0.00870946 0.12682936]

$IF^{\mp}$= [0.09114903 0.18056734 0.11326699 0.13064184 0.02536587]

Table 18 Temperature Sensors proximity measures

Device ID	P_i^-	$P_i^{\mp}$
T1	0.12940294	0.15443214
T2	0.11370562	0.18318807
T3	0.18241188	0.12390482
T4	0.05436445	0.19249052
T5	0.21108941	0.06380859

Table 19 Ranked Temperature Sensors

DeviceID	Rank Index R	Rank Order
T1	0.5440911	3
T2	0.6170157	2
T3	0.40449907	4
T4	0.77977171	1
T5	0.23211734	5

Table 19 shows the final ranking of the five temperature sensors deployed in the testbed. Temperature sensor T4 is ranked the highest and is suggested as most pertinent device for user response. The amount of time taken to execute the SPARQL query is compared with AHP-TOPSIS approach. The query is executed 20 times and the average discovery time is computed for comparison. As the number of devices increases, the discovery time increases. There is an improvement of 37% in discovery time as shown in Fig.8.

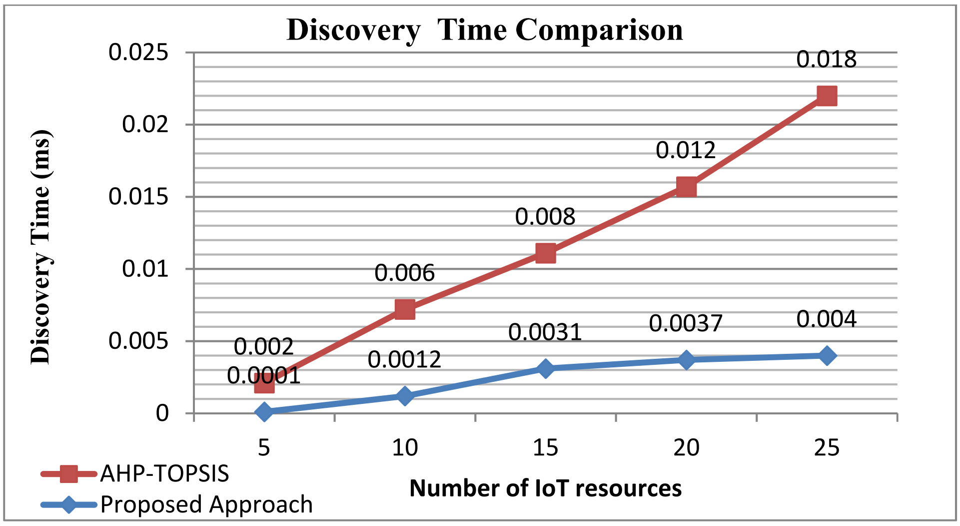


Fig. 8. Discovery time comparisons

5. Conclusion and Future work

In this paper, we presented IoT resource retrieval framework and ranking mechanism based on multi criteria decision making. The effectiveness of the proposed model is evaluated by using dataset and real time case study. Results are compared with existing state of art. In future, the framework can be extended to support distributed topology based discovery based on IoT resources social relationship amongst each other.

References

[1] Internet of Things (IoT) connected devices installed base worldwide from 2015 to 2025 (2016). https://www.statista.com/statistics/471264/iotnumber-of-connected-devices-worldwide/

[2] Global Sensors in Internet of Šings (IoT) Devices Market,Analysis & Forecast: 2016 to 2022. Technical Report,BIS Research,2017,pp187 https://www.researchandmarkets.com/research/bvgxvl/global

[3] Vandana C.P, Ajeet A. Chikkamannur, “Study of Resource Discovery trends in Internet of Things”, Int. J. Advanced Networking and Applications,Vol.08,Issue 03,ISSN: 0975-0290 pp. 3084-3089 (2016)

[4] Vandana CP, Chikkamannur AA, "Semantic ontology based IoT-resource description",Int J Adv Netw Appl. 2019;11(6):3022–3.
[5] Vandana. C. P , A. A. Chikkamannur, "Semantic Annotation of IoT Resource with ontology orchestration", 2020 Third International Conference on Advances in Electronics, Computers and Communications (ICAECC), Bengaluru, India, 2020, pp. 1-7, doi: 10.1109/ICAECC50550.2020.9339490.
[6] O. Vermesan and P. Friess, Internet of things-from research and innovation to market deployment. River Publishers Aalborg, 2014.
[7] Charith Perera, Arkady Zaslavsky, Peter Christen, Michael Compton, Dimitrios Georgakopoulos,"Context-aware Sensor Search, Selection and Ranking Model for Internet of Things Middleware",Proceedings of the IEEE 14th International Conference on Mobile Data Management (MDM), Milan, Italy, June, 2013 DOI: 10.1109/MDM.2013.46
[8] Ebrahimi, M., Shafieibavani, E., Wong, R.K., Chi, C.H.: A new meta-heuristic approach for efficient search in the Internet of Things. In: IEEE International Conference on Services Computing (2015)
[9] L. H. Nunes, J. C. Estrella, C. Perera, S. Reiff-Marganiec, and A. C. Botazzo Delbem, "Multi-criteria iot resource discovery: a comparative analysis," Software: Practice and Experience, pp. n/a–n/a, 2016,spe.2469.
[10] L. H. Nunes, J. C. Estrella, C. Perera, S. Reiff-Marganiec, and A. C. Delbem, "The elimination-selection based algorithm for efficient resource discovery in internet of things environments," in Consumer Communications & Networking Conference (CCNC), 2018 15th IEEE Annual. IEEE, 2018, pp. 1–7.
[11] S. Abdelwahab, B. Hamdaoui, M. Guizani, and T. Znati, "Cloud of things for sensing as a service: Sensing resource discovery and virtualization," in 2015 IEEE Global Communications Conference (GLOBECOM), Dec 2015, pp. 1–7.
[12] F. Khodadadi, A. V. Dastjerdi, and R. Buyya, "Simurgh: A framework for effective discovery, programming, and integration of services exposed in IoT," in 2015 International Conference on Recent Advances in Internet of Things (RIoT). Institute of Electrical & Electronics Engineers (IEEE), April 2015.
[13] Soroush Ojagh, Mohammad Reza Malek, Sara Saeedi, Steve Liang, "A location-based1 orientation-aware recommender system using IoT smart devices and Social Networks",Future Generation Computer Systems,Volume 108, July 2020, Pages 97-118
[14] Ibrahim Mashal, Osama Alsaryrah, Tein-Yaw Chung,Fong-Ching Yuan, "A multi-criteria analysis for an internet of things application recommendation system", Technology in Society ,Vol. 60, February 2020,
[15] Jin X, Chun S, Jung J, Lee K.H, "A fast and scalable approach for IoT service selection based on a physical service model", Inf.Syst. Front. 19, 1357–1372 (2017). https://doi.org/10.1007/s10796-016-9650-1
[16] Chan, C. Y., Jagadish, H. V., Tan, K. L., Tung, A. K., and Zhang, Z.,"Finding k-dominant skylines in high dimensional space," in Proc. of the ACM SIGMOD international conference on Management of data, pp.503-514, ACM, 2006
[17] Manisha Singh,Gaurav Baranwal, Anil Kumar Tripathi,"QoS-Aware Selection of IoT-Based Service",Arabian Journal for Science and Engineering, 45:10033–10050
[18] Renato Dilli, Amanda Argou, Mauricio Pilla,Ana Marilza Pernas, Renata Reiser, Adenauer Yamin,"Fuzzy logic and MCDA in IoT resources classification",SAC '18: Proceedings of the 33rd Annual ACM Symposium on Applied ComputingApril 2018 Pages 761–766 https://doi.org/10.1145/3167132.3167216
[19] Vandana C.P, Dr. Ajeet A. Chikkamannur,"An Ameliorated Ensemble Approach for IoT Resource Feature Selection Based on Discriminating and Service Relevance Criteria",International Journal of Intelligent Engineering and Systems 14 (3),March 2021, 435-446
[20] https://www.iotforall.com/using-the-internet-of-things-for-smart-office-automation
[21] https://components101.com/resistors/ldr-datasheet
[22] https://create.arduino.cc/projecthub/Cmtelesann/monitoring-temperature-remotely-with-blynk-for-dummies-aa910b
[23] Leo Louis,"Working Principle Of Arduino And Using It As A Tool For Study And Research",International Journal Of Control, Automation, Communication And Systems , Vol.1, No.2, April 2016
[24] Vandana, C.P., Chikkamannur, A.A, "S-COAP: Semantic Enrichment of COAP for Resource Discovery", SN COMPUT. SCI. 1, 88 (2020). https://doi.org/10.1007/s42979-020-0104-y
[25] SPARQL Query Language. https://www.w3.org/TR/sparql11-query/. Accessed 20 Aug 2019

Authors Profile

Vandana C.P, research scholar in department of Computer Science and Engineering in Visvesvaraya Technological University (VTU), India. She completed her MTech in Computer Network Engineering. She is working as Assistant Professor at New Horizon College of Engineering, Bangalore. She has 6 years of Industry experience in Network Management Solution (NMS) products and 8 years of academic experience. Her research areas include networking, machine learning, Internet of Things (IoT), Storage Area Network (SAN), Database Management Systems (DBMS).

Dr. Ajeet A. Chikkamannur obtained Ph.D. and M.Tech in Computer Science and Engineering from Visvesvaraya Technological University Belagavi, respectively, in 2013 and 2001. He is currently working in the Department of Computer Science and Engineering, R L Jalappa Institute of Technology, Doddaballapur, Bangalore, as Professor and Head, Computer Science and Engineering Program and Research Centre. His research domain includes Software Engineering, Reverse Engineering, Database Management Systems, Object Technology, and Internet of Things. He is an active keynote speaker in conferences, invited talks and organized several conferences. He has authored several papers in national and international journals.