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► To cite this version:

Xiaocui Li, Zhangbing Zhou, Junqi Guo, Shangguang Wang, Junsheng Zhang. Aggregated multi-attribute query processing in edge computing for industrial IoT applications. *Computer Networks*, 2019, 151, pp.114 - 123. 10.1016/j.comnet.2019.01.022 . hal-03486380

HAL Id: hal-03486380

<https://hal.science/hal-03486380>

Submitted on 20 Dec 2021

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Aggregated Multi-Attribute Query Processing in Edge Computing for Industrial IoT Applications

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Abstract

The popularity of smart things constructs sensing networks for the Internet of Things (IoT), and promotes intelligent decision-makings to support industrial IoT applications, where multi-attribute query processing is an essential ingredient. Considering the huge number of smart things and large-scale of the network, traditional query processing mechanisms may not be applicable, since they mostly depend on a centralized index tree structure. To remedy this issue, this article proposes a multi-attribute aggregation query mechanism in the context of edge computing, where an energy-aware IR-tree is constructed to process

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query processing in single edge networks, while an edge node routing graph is established to facilitate query processing for marginal smart things contained in contiguous edge networks. This decentralized and localized strategy has shown its efficiency and applicability of query processing in IoT sensing networks. [Experimental](#) evaluation results demonstrate that this technique performs better than the rivals in reducing the traffic and energy consumption of the network.

Keywords: Multi-attribute aggregation query, Energy-aware IR-tree, Edge node routing graph, Edge computing.

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1. Introduction

With the popularity of smart things being ubiquitously deployed, adopting smart things to facilitate industrial applications becomes a reality nowadays. Intuitively, smart things in the Internet of Things (IoT) include sensors, actuators, and smart embedded devices [1], and they can provide sensory data to promote the validity and applicability of a proper decision-making. Due to the fact that smart things are [mostly](#) scarce in their computational, communication, and energy resources, aggregating sensory data of certain IoT smart things, and functional combination and collaboration [3], requires to reduce the amount/size of data packets to be transmitted in the network, and thus, to decrease the energy consumption. With the swift growth of the number of smart things being deployed in tremendous fields, traditional centralized sensory data gathering mechanisms through constructing routing trees may not be an appropriate strategy, when sensory data of smart things located within a certain sub-region are interested. Instead, sensory data should be gathered, and processed [whenever](#) possible, in a localized fashion, while only the result should be aggregated and routed to the centre for further exploration. We argue that this strategy is proper, especially when sensory data, like multimedia data, are large in volume. Due to this concern, edge computing [2, 4] has been proposed in recent years as the complement of cloud computing [32], where industrial IoT applications should be processed in a distributed and localized fashion as

much as possible [5]. It is worth noting that sensory data query processing is an essential ingredient of typical industrial IoT applications [6]. Considering the functional diversity of smart things and the complexity of potential events to be studied, this article aims to explore the query processing, where various kinds of smart things contained in a certain sub-region in an IoT sensing network [7] are necessary to [cooperate and](#) collaborate for environment monitoring and potential event detection. Taking the assumption that the kind of smart things corresponds to a certain sensing attribute [into consideration](#), an aggregated multi-attribute query processing mechanism is essential to support industrial IoT applications, where edge computing is applied to promote sensory data processing and aggregation at the network edge.

Traditional techniques have been developed to study the multi-attribute query processing. Generally, an index tree, like an R-tree, is built to manage [smart things](#) distributed in a network. Queries are processed leveraging this index tree, where the result can be (i) a single object, which can satisfy certain spatial and multi-attribute constraints [8, 9, 10, 11, 12], or (ii) a set of contiguous objects, which can collectively satisfy certain constraints [13, 14, 15]. Since objects may be unevenly distributed in the network, authors adopt proper mechanisms for handling objects contained in dense and sparse sub-regions. Objects in dense sub-regions should be prone to be recommended, since they can have more counterparts to be replaced when found improper [16]. Note that objects in certain directions may be more appropriate in certain settings, and thus, a direction-aware spatial keyword query method is proposed to satisfy direction-aware requirements [17]. Generally, these techniques construct a single index tree to support the query of spatial objects, where a single or multiple attribute(s) is/are to be examined. This centralized query processing strategy may not be appropriate when an IoT sensing network is large in scale, and things are huge in quantity. Besides, the network greenness requires to reduce the traffic and energy consumption of the network. Consequently, sensory data should be processed in a localized and distributed fashion when possible. In recent years, techniques have been developed to enable the search of IoT things,

53 where a single thing is mostly interested [18, 19]. Other techniques explore the
 54 network communication topology [20], an effective collection [21], management
 55 [22], and aggregation [23] of sensory data, a load-balancing routing [24], and
 56 the prolonging of network lifetime [25, 26]. To the best of our knowledge, a dis-
 57 tributed and localized mechanism has not been explored extensively to support
 58 the multi-attribute query processing in IoT sensing networks.

59 To address this challenge, this article proposes a *Multi-attribute Aggregation*
 60 *Query (MAQ)* processing technique in edge computing. In this context, the net-
 61 work is divided into sub-regions, where these sub-regions, corresponding to the
 62 regions of edge networks, are regulated by respective edge nodes. Generally,
 63 an edge network can have one edge node. Queries are processed firstly at the
 64 network edge by edge nodes, and the results are aggregated and routed to the
 65 centre afterwards. It is worth emphasising that smart things regulated by con-
 66 tiguous edge nodes may satisfy the requirement in a collective fashion, which
 67 requires the examination of sensory data provided by marginal smart things
 68 contained in contiguous edge networks. Major contributions of this article are
 69 summarized as follows:

- 70 • *Query processing in single edge networks.* An *Energy IR-tree* (i.e., *EIR-*
 71 *tree*) is constructed to facilitate the query processing of smart things con-
 72 tained in a single edge network. Besides the inverted files specified upon
 73 the R-tree for indexing attributes of smart things, an energy factor is
 74 adopted to estimate the amount of energy consumption with respect to
 75 the number and density of smart things in certain sub-regions.
- 76 • *Query processing for marginal smart things in contiguous edge networks.*
 77 Considering the amount of sensory data generated by smart things in the
 78 marginal sub-region of contiguous edge networks, a packet transmission
 79 graph is constructed upon edge nodes, in order to decrease the network
 80 traffic. Sensory data packets are transmitted between edge nodes, only
 81 when these sensory data are examined highly possible to benefit the query
 82 answering. The results with respect to independent and marginal edge

83 networks are assembled and aggregated for processing this query.

84 Extensive experiments are conducted to evaluate the efficiency and applica-
85 bility of our technique. The results demonstrate that this technique performs
86 better than the rivals in reducing the network traffic and energy consumption
87 of smart things.

88 The rest of this article is organized as follows. Section 2 introduces rele-
89 vant concepts and the energy model, which are used in our query. Section 3
90 introduces the query processing which is applied to single edge networks. Sec-
91 tion 4 presents sensory data routing mechanism in edge nodes and the query
92 mechanism in marginal edge networks. Section 5 shows the implementation and
93 evaluates the approach developed in this article. Section 6 reviews and discusses
94 related techniques. Finally, Section 7 concludes this work.

95 2. Preliminaries: Concepts and Energy Model

96 This section presents relevant concepts and the energy consumption model.

97 2.1. Concept Definition

98 In edge computing, a network region can be represented by disjoint edge
99 networks, where an edge node is responsible for managing smart things in the
100 respective edge network. Edge nodes can be (i) a *super* smart thing, which can
101 have more computational, communication, and energy resources than *ordinary*
102 smart things, or (ii) an ordinary smart thing. In this setting, smart things
103 should take the role of edge nodes in a rotation manner for instance, to ensure
104 the overall energy consumption of smart things as balanced somehow at the
105 network level as possible. A marginal edge network of sensory data routing for
106 contiguous edge nodes is defined as follows:

107

108 **Def. 1. Edge Node Data Routing Network.** An edge node data routing
109 network is defined as a tuple $g = (Dgn, Rlt, Cst)$, where:

- 110 • Dgn is the set of edge nodes contained in marginal edge [networks](#).
- 111 • Rlt is the set of sensory data routing relationships between contiguous
- 112 edge nodes.
- 113 • Cst is the set of sensory data routing cost for contiguous edge nodes,
- 114 corresponding to the weights specified on the edges in Rlt .

115 In marginal edge [networks](#), by means of edge computing, $g.Dgn$ is respon-
 116 sible for data interaction transmission, which is only the result of localization
 117 processing. An edge node data routing network is represented in terms of a
 118 weighted directed graph, where the vertexes are edge nodes and the weights on
 119 the directed edges represent sensory data routing cost for contiguous edge n-
 120 odes. The edge node routing graph is stored in the form of an adjacency matrix,
 121 which specifies the sensory data forwarding strategy between edge nodes.

122 Considering the diversity of smart things and the complexity of applications
 123 to be supported, various kinds of attributes are sensed by smart things. Without
 124 loss of generality and for simplicity, in this article we assume that a smart thing
 125 is relevant to a single kind of attribute. A query can be defined as follows:

126 **Def. 2. Multi-Attribute Aggregation Query.** A multi-attribute aggrega-
 127 tion query is defined as a tuple $q = (Rgn, Kd, Cst)$, where:

- 128 • $Rgn = (x, y, wdt, hgt)$ is a regular region of q , such that x and y are the
- 129 top-left x - or y -coordinate, and wdt and hgt are the width and height of
- 130 query region.
- 131 • $Kd = \{k_1, k_2, \dots, k_m\}$ is a set of attributes that are interested by q .
- 132 • Cst is a set of constraints defined upon Kd to specify the conditions that
- 133 should be satisfied by neighboring smart things in a collective fashion.

134 Generally, $q.Rgn$ is a rectangle and smart things are deployed in a two-
 135 dimensional network space. $q.Rgn$ may be contained by an edge network, or
 136 by multiple contiguous edge networks. [A sample multi-attribute aggregation](#)

137 query network is presented as follows to illustrate the relationship between a
 138 multi-attribute aggregation query and the edge node data routing network:

Figure 1: A sample multi-attribute aggregation query network.

139 A multi-attribute aggregation query q is specified in terms of three attributes
 140 hmt , tmp and prs , representing humidity, temperature and pressure, respec-
 141 tively. In Figure 1-(a), four edge networks (e.g., Rgn_0 , Rgn_1 , Rgn_2 , Rgn_3)
 142 is displayed and $q.Rgn$ are determined. Besides, the boundary range of data
 143 communication between edge networks is identified. In Figure 1-(b), edge net-
 144 works are represented in terms of a graph, where vertexes are edge nodes
 145 in the corresponding edge networks (e.g., v_0 , v_1 , v_2 , v_3). Note that edge nodes
 146 are responsible for the propagation and localization of the query. Prior to data
 147 transmission, neighboring edge nodes send control packets to determine whether
 148 sensory data exchanges in-between are necessary or not. This strategy should
 149 decrease sensory data packets forwarding between neighboring edge nodes and
 150 thus, it can reduce the energy consumption of the query upon marginal edge
 151 networks. Subsequently, the edge node data routing network is built and repre-

Table 1: Parameters in the energy model.

<i>Name</i>	<i>Description</i>
E_{elec}	Energy consumption constant of the transmit and receiver electronics.
ϵ_{amp}	Energy consumption constant of the transmit amplifier.
k	The number of bits in one packet.
d	The distance of transmission.
n	The attenuation index of transmission.
$E_{Tx}(k, d)$	The energy consumption to transmit a k bit packet with a distance d .
$E_{Rx}(k)$	The energy consumption to receive a k bit packet.
$E_{ij}(k)$	Energy consumption for transmitting a k bit packet from a smart thing SmT_i to a neighboring smart thing SmT_j .

152 sent as an adjacency matrix, as shown in Figure 1-(c), and 1-(d), respectively,
 153 where the value is either 0 or 1. Note that 0 represents no data packets to be
 154 sent between edge nodes, 1 represents data packet to be sent between edge n-
 155 odes. A query is typically injected into the network from an edge node, and this
 156 query should be processed by a single edge node, or through the collaboration
 157 of multiple edge nodes to achieve the multi-attribute aggregation in single edge
 158 network and marginal edge network.

159 2.2. Energy Model

160 This article applies the first-order radio model [27], which has been widely
 161 adopted in wireless sensor networks (WSNs), to calculate the energy consump-
 162 tion between smart things, since sensor nodes in WSNs are indeed a typical kind
 163 of smart things, and WSNs can be regarded as a special type of IoT sensing
 164 networks. Parameters of this energy model are presented in Table 1.

165 Specifically, the energy consumption to transmit a k bit data packet with a
 166 distance d are denoted as $E_{Tx}(k, d)$, and the energy consumption to receive a
 167 k bit data packet are denoted as $E_{Rx}(k)$, which can be calculated as follows:

$$E_{Tx}(k, d) = E_{elec} \times k + \epsilon_{amp} \times k \times d^n \quad (1)$$

$$E_{Rx}(k) = E_{elec} \times k \quad (2)$$

168 Note that E_{elec} is the constant of energy consumption for transmission and
 169 receiver electronics, and ϵ_{amp} is the constant of transmission amplifier. In the
 170 course of transmitting a packet of k bits from one thing to another, the energy
 171 consumption $E_{ij}(k)$ is calculated as follows:

$$E_{ij}(k) = E_{Tx}(k, d) + E_{Rx}(k) \quad (3)$$

172 where the parameter d represents the distance between one smart thing nd_i
 173 and another nd_j . $E_{ij}(k)$ is assumed the same as $E_{ji}(k)$ for smart things and
 174 edge nodes. The parameter n of the attenuation index for packet transmission
 175 depends on the surrounding environment. Generally, when smart things are
 176 barrier-free for forwarding data packets, n is set to 2. Otherwise, n is set to a
 177 value between 3 to 5.

178 3. Single Edge Network Query Processing

179 Leveraging an IR-tree [10], this section constructs an *Energy IR-tree* (*EIR-*
 180 *tree*) to support the multi-attribute query processing in a single edge network.

181 3.1. *EIR-Tree Construction*

182 Before presenting the construction of our *EIR-tree*, we briefly introduce the
 183 IR-tree as the background. Generally, a node in an IR-tree can be represented
 184 as a tuple (id, mbr, O) , where (i) id is an identifier of this node, (ii) mbr is the
 185 *Minimum Boundary Region (MBR)* covered by this node, and (iii) O refers to
 186 the set of objects contained in mbr . A node has a pointer to an inverted file, and
 187 attributes sensed by objects in O are recorded in this inverted file. Leveraging
 188 the IR-tree structure, an *EIR-tree* is constructed as presented by Algorithm
 189 1, where the energy consumed for sensory data packets transmission between
 190 smart things and edge nodes is considered.

191 As presented by Algorithm 1, based on the IR-tree structure, we obtain the
 192 mbr collection that covers smart things. These smart things in this collection
 193 serve as the leaf nodes of our *EIR-tree* (line 1). For instance, in Figure 2-(a),
 194 for a single edge network, ten smart things (e.g., $o_1, o_2, \dots, o_{10}$) are displayed.

Table 2: Sample inverted file for the *EIR*-tree as shown in Figure 2.

<i>IF_Node</i>	k_1	k_2	k_3
<i>R1</i>	(1, o_1)	null	(1, o_2)
<i>R2</i>	(1, o_3)	(1, o_5)	(1, o_4)
<i>R3</i>	(1, o_7)	(1, o_6)	(1, o_8)
<i>R4</i>	null	(1, o_{10})	(1, o_9)
<i>R5</i>	(2, <i>R1</i> , <i>R2</i>)	(1, <i>R2</i>)	(2, <i>R1</i> , <i>R2</i>)
<i>R6</i>	(1, <i>R3</i>)	(2, <i>R3</i> , <i>R4</i>)	(2, <i>R3</i> , <i>R4</i>)
<i>Root</i>	(3, <i>R5</i> , <i>R6</i>)	(3, <i>R5</i> , <i>R6</i>)	(4, <i>R5</i> , <i>R6</i>)

Algorithm 1 EIRTreeConstruction

Require:

- MBR_{set} : the set of leaf nodes in an IR-tree

Ensure:

- tr : the root node of constructed *EIR*-tree

```

1: leaf nodes  $\leftarrow$  nodes in  $MBR_{set}$ 
2:  $num \leftarrow$  the number of nodes in  $MBR_{set}$ 
3: while  $num > 1$  do
4:   for  $nd_i \in MBR_{set}$  do
5:      $E(k) \leftarrow$  calculated by Eqn. 3
6:   end for
7:    $tn \leftarrow nd_1$  and  $nd_2$  with the biggest  $E(k)$  in the  $MBR_{set}$ 
8:    $tn.mbr \leftarrow$  covered by  $nd_1$  and  $nd_2$ 
9:    $tn.O \leftarrow$  contained by  $nd_1.O$  and  $nd_2.O$ 
10:   $MBR_{set} \leftarrow MBR_{set} - \{nd_1, nd_2\}$ 
11:   $MBR_{set} \leftarrow MBR_{set} \cup \{tn\}$ 
12:   $num \leftarrow$  the number of nodes in  $MBR_{set}$ 
13: end while
14:  $tr \leftarrow MBR_{set}$ 

```

---

195 Meanwhile, according to the spatial division of [10], leaf nodes (e.g., R_1 , R_2 ,
196 R_3 and R_4) are identified. In addition, we deploy three attributes denoted as
197 k_1 , k_2 and k_3 , which are represented in terms of triangle, square and circular,
198 respectively. An inverted file is appended to represent the attributes sensed by
199 tree nodes (leaf nodes and non-leaf nodes) (denoted k), the frequency of k , and
200 the list of tree nodes or smart things which have the attribute k , where each

tree node containing smart things as an item in the inverted file are is described by Table 2 (e.g., R_1 , R_2 , R_3 and R_4).

In this article, high energy consumption means that the intensity of data packets exchange is relatively strong. When constructing an index tree, energy consumption is considered as an essential factor, and a fusion strategy of energy consumption is adopted. Specifically, given a set of tree nodes, we calculate the energy consumption of each tree node in the collection MBR_{set} (lines 4-6). Here, the $E(k)$ represents the energy consumption of collecting sensory data in each tree node, which is calculated by Eqn. 3 (line 5).

For instance, the weight of the tree node R_1 , is computed as follows:

$$W_{R1}(k) = 2 \times E_{elec} \times k + \epsilon_{amp} \times k \times d_{o1,o2}^n \quad (4)$$

Note that a certain tree node in MBR_{set} has a relatively high energy consumption, which means that the intensity of sensory data exchange is large. Such tree nodes are selected as a merged new tree node according to their energy consumption. At each merging step, two tree nodes with the biggest weight are selected to be merged (lines 7-11). The *EIR*-tree is constructed through merging tree nodes from bottom to top, until the root node has been established (line 14). An example of constructed *EIR*-tree is shown in Figure 2-(b).

3.2. Query Processing in Single Edge Networks

In general, the single edge network query processing is performed by traversing *EIR*-tree, and the inverted file is used to check whether there is an attribute of interest in the edge network. By eliminating smart things that are not in the scope of interest for the query as early and prompt as possible, the query can avoid processing non-target things.

Leveraging the *EIR*-tree, Algorithm 2 presents the procedure of querying smart things with a set of attributes. In the similar fashion, the query q in each single edge network is executed. Moreover, the relevant definition of the involved parameters in the query is presented in Section 2.1. In general, the query starts at the root node of *EIR*-tree (line 2). When the inverted file of one

---

Algorithm 2 IndexQuery

Require:

- q : the tuple (Rgn, Kd, Cst)
- tn : the tree node to launch the query, and initially set to the root node of *EIR*-tree

Ensure:

- Rst_{set} : a set of collections, where each collection is associated with an attribute

```
1:  $O_{set} \leftarrow \emptyset$ 
2: if  $tn \neq NULL$  then
3:   if  $\exists$  attribute  $k_i \in Kd$  in  $tn.inverted$  file then
4:     if  $tn.hasChild()$  then
5:       IndexQuery( $q, tn.leftChild$ )
6:       IndexQuery( $q, tn.rightChild$ )
7:     else
8:        $O_{set} \leftarrow tn.getFilterObject(Cst)$ 
9:        $Rst_{set} \leftarrow Rst_{set} \cup O_{set}$ 
10:    end if
11:  end if
12: end if
```

---

229 tree node tn contains certain attribute, the query is propagated to the tree node
230 tn 's children (lines 3-7). This procedure iterates until (i) the inverted file of a
231 non-leaf node does not contain any attribute, or (ii) the leaf node is reached.
232 So far, we obtain a set that consists of collections, where each collection is
233 associated with an attribute (lines 8-9). Consequently, via iteration, the result
234 set that satisfies the query specification is **constructed** (lines 1-12).

Figure 2: Query processing of the attribute k_2 upon the *EIR*-tree.

For instance, smart things with the attribute of k_2 are to be retrieved. Based on the example of *EIR*-tree as shown in Figure 2-(b), the root node contains the attribute k_2 from Table 2, and the child nodes R_5 and R_6 contain k_2 as well. Therefore, the query is propagated to the non-leaf node R_5 and R_6 . We also note that R_2 , a child of R_5 , contains k_2 , while another child R_1 does not. At the same time, R_3 and R_4 , the children of R_6 , contain k_2 . As the result, the query is propagated to the leaf nodes R_2 , R_3 , and R_4 . Specifically, from Table 2, o_5 , o_6 and o_{10} correspond to the smart things for R_2 , R_3 and R_4 , respectively, contain attribute k_2 .

4. Marginal Edge Network Query Processing

To facilitate query processing leveraging smart things located in the marginal sub-regions of contiguous edge networks, this section constructs a packet transmission graph for specifying the sensory data forwarding strategy between edge nodes, and sensory data are gathered and routed along the paths in this graph for examining the fact that whether queries can be answered by these smart things in marginal edge networks or not.

4.1. Sensory Data Routing Cost Calculation for Contiguous Edge Nodes

A parameter is used to denote the percentage of boundary distance λ , which represents a range about the ratio of the distance between a smart thing and corresponding edge node to the length of the current region, to specify the number of smart things which require to transmit sensory data transmission. Generally, given the coordinates of a smart thing $P_0 (x_0, y_0)$ and an edge node $P_1 (x_1, y_1)$, they have the following relationship:

$$JS = \sqrt{(x_0 - x_1)^2 + (y_0 - y_1)^2} \div rSide \quad (5)$$

where $rSide$ refers to the size of the region in which the edge node is located. JS is used to judge the spatial scope of transmitted data. If the value JS is not more than the specified standard parameter λ , this means that the smart thing P_0 is within the scope of interactive data.

Algorithm 3 CostCalculation

Require:

- λ : a parameter of percentage for boundary distance
- num : the number of edge nodes
- Rst_{sets} : sets consists of the result set in each edge node's region

Ensure:

- wgt_{mtx} : a weighted adjacency matrix, whose values represent the cost of sensory data communication energy between contiguous edge nodes

```
1:  $gnData_{mtx} \leftarrow \emptyset$ 
2: for  $i = 0; i < num; i++$  do
3:   for  $j = 0; j < num; j++$  do
4:     if  $i \neq j$  and  $gn_i$  and  $gn_j$  are contiguous then
5:        $gnRst_{set} \leftarrow \emptyset$ 
6:       while each  $Rst_{setj} \subset Rst_{sets} \neq NULL$  do
7:          $Temp_{set} \leftarrow$  get one attribute set from  $Rst_{setj}$ 
8:          $O_{set} \leftarrow \emptyset$ 
9:         while  $Temp_{set} \neq NULL$  do
10:          if  $JS \leq \lambda$  then
11:             $O_{set} \leftarrow O_{set} \cup \{o\}$ 
12:          end if
13:        end while
14:         $gnRst_{set} \leftarrow gnRst_{set} \cup O_{set}$ 
15:      end while
16:       $gnData_{mtx}[i][j] \leftarrow gnRst_{set}$ 
17:       $k \leftarrow$  Calculate the transmission data of  $gnRst_{set}$ 
18:       $d \leftarrow$  Euclidean distance of  $gn_i$  and  $gn_j$ 
19:       $E_{ij}(k) \leftarrow$  calculated by Eqn. 3
20:       $wgt_{mtx}[i][j] \leftarrow E_{ij}(k)$ 
21:    end if
22:  end for
23: end for
```

---

262   The presentation of Eqn. 5 is to specify the number of smart things that
263   need to transmit their sensory data. Defining boundary data transmission regu-
264   lations, we can obtain the transmission data at the boundary which is delivered
265   to the corresponding edge node. Edge nodes are responsible for sensory data
266   transmission. Thereafter, we can use Eqn. 3 to calculate the communication

267 cost between edge nodes.

268 Algorithm 3 presents the cost calculation procedure for transmitting sen-
 269 sory data packets between edge nodes. Based on query results of single edge
 270 networks, we calculate the energy consumption of communication between edge
 271 nodes. For each single edge network, we obtain the result set of its region by
 272 Algorithm 2. When a result set in a certain single edge network exists, the
 273 boundary data of this region is performed (lines 4-15). Based on this result set,
 274 we acquire the negotiated transmission smart thing data from an edge node to
 275 its neighbors within the specified parameter of percentage of boundary distance
 276 λ and JS (lines 10-12). The amount of data transmission between edge nodes is
 277 identified by localization processing, which consists of collections of data smart
 278 thing identified by each attribute (line 14). The distance between two edge n-
 279 odes gn_i and gn_j is defined as a 2-d Euclidean distance (line 18). Finally, the
 280 cost of sensory data transmission between edge nodes is calculated by Eqn. 3
 281 (line 19), and the result of sensory data routing cost for contiguous edge nodes
 282 is stored in the form of an adjacency matrix (line 20).

283 4.2. Edge Node Routing Graph Construction

284 Considering the amount of sensory data generated by smart things in the
 285 marginal sub-region, a packet transmission graph is constructed upon edge n-
 286 odes, in order to decrease the network traffic. The edge node data routing
 287 can be modeled as an optimization problem, where the energy consumption is
 288 considered as the decision factor:

$$Z = \sum_{i=1}^n \sum_{j=1}^n w_{ij} \times c_{ij} \quad (6)$$

289 where:

$$c_{ij} = \begin{cases} 0 & \text{otherwise} \\ 1 & (w_{ji} \neq 0 \text{ and } w_{ij} \leq w_{ji}) \end{cases} \quad (7)$$

290 where w_{ij} (non-zero value) represents the energy consumption of an edge
 291 node to another edge node, and c_{ij} is calculated depending on the comparison

of the energy values between two edge nodes. By objective function, we can achieve a minimum of energy consumption for data communication within a reasonably acceptable range.

Based on this function, a two-step strategy for graph construction is presented as follows: (i) the filter step is to filter out sensory data packets that do not contribute to the query results. Some edges are filtered by heuristic greedy algorithm. According to the results of Algorithm 3, by traversing neighbor edge nodes in turn, we reserve the directed edge with the smallest energy value, so that the total transmitted energy is minimized in the edge node routing graph construction. For example, the energy consumption from an edge node gn_i to a contiguous edge node gn_j is w_1 , and the energy consumption from gn_j to gn_i is w_2 ($w_1 \leq w_2$). We naturally reserve the edge from gn_i to gn_j , and remove the edge from gn_j to gn_i . After this step of filtering, we have preserved the one-way transmission edge between the edge nodes. Considering the situation that a loop exists in the process of sensory data transmission, we propose (ii) the refinement step is to avoid the repeated transmission of data packets. It is worth noting that the graph we built is used to integrate the results of the query between the regions, the ring is not allowed to exist. However, in the filter step, we consider that there may be one ring in the filtered graph. Hence, we adopt a strategy as a refinement step during the construction of the edge node routing graph, which detects whether there is a ring in current graph. If there is a ring, we change the flow of data between the newly added edges. Ultimately, a unidirectional acyclic routing graph is constructed accordingly to represent edge node routing graph.

4.3. Marginal Edge Network Query Mechanism

Sensory data packets are transmitted between edge nodes, when these data are examined highly possible to benefit query answering. A pruning method is adopted to accelerate the query data transmission progress.

As presented by Algorithm 4, we achieve the decrease of energy consumption. We adopt control package pruning strategy which is designed as reducing

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Algorithm 4 MarginalRegionQuery

Require:

- $drgh_{mtx}$: an edge node routing graph

Ensure:

- $CrsRst_{set}$: a set of numerous groups, where each group on the whole satisfies the query

```
1:  $Z \leftarrow 0$ ;  $num \leftarrow drgh_{mtx}.row$ 
2: for  $i = 0$ ;  $i < num$ ;  $i++$  do
3:   for  $j = 0$ ;  $j < num$ ;  $j++$  do
4:     if  $drgh_{mtx}[i][j] \neq 0$  then
5:        $flag \leftarrow$  check the data demand of neighbor node  $gn_j$ 
6:       if  $flag$  then
7:          $gn_i$  transmit data to  $gn_j$ 
8:          $Z \leftarrow$  calculated by Eqn. 6
9:          $CrsRst_{set} \leftarrow$  get enumeration groups
10:      end if
11:    end if
12:  end for
13: end for
```

---

322 packet transmission. As the input for an edge node routing graph, we send a
323 control packet to determine whether gn_i needs to send data to gn_j (line 5). If
324 the neighbor edge node needs the data, current edge node sends data (line 7).
325 Otherwise, the procedure will detect the next edge node (lines 2-13). Based
326 on this pruning strategy, we can calculate the optimized energy consumption Z
327 (line 8) by Eqn. 6, which is greatly beneficial to improve the processing perfor-
328 mance. Note that the enumeration [procedure](#) applies [only](#) to some situations
329 where the number of possible solutions is not too large. Given the limited
330 number of query attributes, we can take an enumeration strategy to get an enu-
331 merated set of query between regions (line 9). Meanwhile, the time complexity
332 of the enumeration algorithm depends on the number of loop nesting, which is
333 the number of query attribute keywords.

334 4.4. Query Processing

335 A query, which combines the queries for single edge networks and marginal
336 edge networks, is handled. The combinations of smart things, which can satisfy

---

Algorithm 5 QueryProcessing

Require:

- q : a tuple $(Rgn, Kd, Cstr)$
- tr_{set} : a set consists of the root nodes for each region
- $drgh_{mtx}$: an edge node routing graph

Ensure:

- $queue$: a max-priority queue, where it is ranked according to Eqn. 8
- 1: $IntrGRst_{set} \leftarrow \emptyset; ExtrGRst_{set} \leftarrow \emptyset; n \leftarrow tr_{set}.size$
  - 2: **for** each $tr_i \in tr_{set}$, where $i = 0, 1, \dots, n$ **do**
  - 3: $IntrRst_{set} \leftarrow \emptyset$
  - 4: $IntrRst_{set} \leftarrow \text{IndexQuery}(q, tr_i)$
  - 5: $IntrGRst_{set} \leftarrow \text{get enumeration groups from } IntrRst_{set}$
  - 6:   **while** $IntrGRst_{set} \neq NULL$ **do**
  - 7: $g \leftarrow \text{extract certain group from } IntrGRst_{set}$
  - 8: $RC(g) \leftarrow \text{calculated by Eqn. 8}$
  - 9: $queue.Enqueue(g, RC(g))$
  - 10:   **end while**
  - 11: **end for**
  - 12: $ExtrGRst_{set} \leftarrow \text{MarginalRegionQuery}(drgh_{mtx})$
  - 13: **while** $ExtrGRst_{set} \neq NULL$ **do**
  - 14: $g \leftarrow \text{extract certain group from } ExtrGRst_{set}$
  - 15: $RC(g) \leftarrow \text{calculated by Eqn. 8}$
  - 16: $queue.Enqueue(g, RC(g))$
  - 17: **end while**
-

337 certain queries in a collective fashion, can be retrieved and evaluated. Generally,
338 the more cohesive the smart things in a collection are, the more appropriate
339 the collection of smart things is with respect to the specification of certain
340 queries. The clustering technique involving the Euclidean distance is adopted
341 for evaluating the cohesive of smart things in a collection. The objective function
342 is presented as followed:

$$RC(g) = \sum_{i=1}^K dst(g_c, o_i)^2 \quad (o_i \in g) \quad (8)$$

343

344 where K denotes the number of smart things in a collection, g_c denotes the

geographical centre of these smart things in this collection, and dst denotes the Euclidean distance between the smart thing and the geographical centre of the collection.

The procedure of query processing is presented at Algorithm 5. Query processing in single edge networks is handled as presented by Algorithm 2 (lines 2-11). Besides, an enumeration combination method is adopted for the result combination of single edge networks into collections (line 5). Furthermore, Eqn. 8 is adopted to calculate the score for each collection in all single edge network result sets (lines 6-10). In addition, the query of the marginal edge network is performed by Algorithm 4 (line 12), where the same collection scoring rules is adopted for the data processing of marginal edge network (lines 13-17). A queue is used to store global query result collections, where each collection is arranged in the descending order (lines 9,16).

5. Implementation and Evaluation

The prototype has been implemented in a Java program. Experiments are conducted upon a desktop with an Intel i5-6500 CPU at 3.20GHz, 8-GB of memory and a 64-bit Windows 10 system. In the following we introduce experiment settings and discuss evaluation results.

5.1. Experiment Settings

Table 3 presents the parameter settings of our experiments. Without loss of generality, a query is assumed to be relevant with 1 to 4 kinds of attributes, since queries are typically not very complex for the majority of domain applications. Besides, when the kinds of attributes that queries interest are large in number, queries should hardly be clearly explained and easily understood. The number of smart things ranges from 200 to 1000 with an increment of 200, and a smart thing is randomly assigned with a sensing attribute. Due to the fact that smart things may be distributed unevenly in the network, a skewness degree (denoted sd) is adopted to quantify this character. Intuitively, sd is calculated in terms

of $(dn - sn) \div N$, where (i) dn and sn refer to the number of smart things
 deployed in dense and sparse sub-regions, respectively, and (ii) N is the sum of
 dn and sn [28].

Table 3: Parameters Settings in the Experiments.

<i>Parameters Name</i>	<i>Value</i>
<i>Network query region (m^2)</i>	200×200
<i>Number of smart things</i>	200 to 1000
<i>Skewness degree</i>	10% to 50%
<i>Kinds of queried attributes</i>	1 to 4
<i>Percentage of boundary distance</i>	40% to 80%
<i>Number of bits in one pocket (k)</i>	1
<i>Attenuation index of transmission (n)</i>	2
<i>Energy consumption constants of transmit and receiver electronics (E_{elec})</i>	50 nJ/bit
<i>Energy consumption constant for transmit amplifier (ϵ_{amp})</i>	$0.1 \text{ nJ}/(\text{bit} \times m^2)$

As far as we know, this is the first technique to explore the distributed
 and localized query processing in the context of edge computing, where an IoT
 sensing network is composed by edge networks. To evaluate the efficiency of our
 technique, we have compared our technique with the *LEACH* routing protocol
 [29], where a routing tree is constructed to aggregate and forward sensory data
 packets to the sink. Note that in our experiments, the smart thing located in the
 network centre is selected to serve as the sink. Without loss of generality, the
 sink node is assumed to have unlimited energy. Therefore, the energy consumed
 for receiving data packets is specified as follows:

$$E_{ij}(k) = \begin{cases} E_{elec} \times k + \epsilon_{amp} \times k \times d^n & \text{if } j \text{ is SN} \\ 2 \times E_{elec} + \epsilon_{amp} \times k \times d^n & \text{otherwise} \end{cases} \quad (9)$$

The results of experimental evaluation are presented and compared as fol-
 lows, where various number of attributes, various skewness degrees, and different
 percentage of smart things deployed in the marginal region of edge networks are
 the factors to be considered in experiments. To reduce the randomness caused
 by the environmental configuration, experiments with a certain parameter set-
 ting is conducted ten times, and an average value is adopted as the final result

391 as shown in the following figures.

392 5.2. Evaluation Results

393 This section presents and discusses the experimental results about the per-
394 formance of query processing.

395 5.2.1. Various Percentages of Boundary Distance and Numbers of Smart Things

Figure 3: Energy consumption for various percentages of boundary distance and numbers of smart things.

396 Figure 3 shows the comparison of energy consumption when the percentage
397 of boundary distance ranges from 40% to 80% with an increment of 10%. The
398 number of smart things varies from 200 to 1000, with the 40% skewness de-
399 gree. The number of attributes is set to 4 in query specification. Generally, the
400 percentage of boundary distance specifies the size of marginal regions in con-
401 tiguous edge networks, which determines the number of smart things involved
402 in marginal edge networks query processing. This figure shows that the energy
403 consumption increases slightly, rather than significantly, when the percentage
404 of boundary distance changes from a relatively small value to a quite large
405 one, since the energy is mostly consumed by forwarding sensory data packets
406 along the edge node routing graph for gathering and aggregating data in our

407 experiments. However, in the case when there are few sensory data packets are
 408 to be transmitted, the energy consumption should be impacted largely by the
 409 percentage of boundary distance.

410 5.2.2. Comparison for MAQ and LEACH Considering Various Numbers of S-
 411 mart Things

Figure 4: Energy consumption for *MAQ* and *LEACH* when various numbers of smart things are deployed in the network.

412 Figure 4 shows the energy consumption for our *MAQ* and *LEACH*, when
 413 the numbers of smart things is set from 200 to 10000 with an increment of 200.
 414 The percentage of boundary distance is set to 80%, and the other parameters
 415 are set to the same values as those in Figure 3, which is convenient to eliminate
 416 the influence of other factors and interference on the experimental results. This
 417 figure shows that *LEACH* requires more energy consumption than *MAQ*. In
 418 fact, *LEACH* routes sensory data of smart things with attributes specified by
 419 query specifications to the centre for centralized processing. On the other hand,
 420 *MAQ* gathers sensory data of smart things in edge networks, processes these
 421 data in a localized fashion, and routes the result of certain edge networks to the
 422 centre. Note that sensory data of marginal smart things contained in contiguous
 423 edge networks are required to be route along the routing graph. However, the

amount is much smaller than that of the packets to be transmitted in *LEACH*. This figure also shows that the increase of energy consumption for *LEACH* is much larger than that for *MAQ*. In fact, when smart things are relatively larger in number, the amount of sensory data that are processed locally by edge networks should be larger in percentage, and hence, more energy should be reduced by *MAQ* than *LEACH*. This result indicates that *MAQ* can perform better than *LEACH* in decreasing energy consumption when the network is relatively large in the number of smart things.

5.2.3. Comparison for *MAQ* and *LEACH* Considering Various Kinds of Queried Attributes

Figure 5: Energy consumption for *MAQ* and *LEACH* when various kinds of attributes are specified in query specification.

Figure 5 shows the energy consumption for *MAQ* and *LEACH*, when the number of attributes is set to 2, 3 or 4 in query specification. The number of smart things is set to 1000, and other parameters are set to the same values as those in Figure 4. This figure shows that the energy consumption is largely increased in a linear manner with respect to the increasing of the attribute number. This result is reasonable since the number of attributes is proportional to the number of smart things to be explored. On the other hand, the increasing

441 of energy consumption is much smaller in scale for our *MAQ* than *LEACH*, since
 442 the majority of the query processing task is conducted locally in edge networks,
 443 and we argue that this strategy should decrease the network traffic and energy
 444 consumption significantly.

445 5.2.4. Comparison for *MAQ* and *LEACH* Considering Various Skewness De- 446 grees

Figure 6: Energy consumption for *MAQ* and *LEACH* when smart things are distributed in the network with various skewness degrees.

447 Figure 6 shows the energy consumption for *MAQ* and *LEACH*, when the
 448 skewness degree is set from 10% to 50% with an increment of 20%. Other
 449 parameters are set to the same values as those in Figure 5. This figure shows
 450 that *LEACH* consumes much more energy than *MAQ*, due to the same reason
 451 as presented in Figure 4. Besides, the energy consumption is relatively smaller
 452 when the skewness degree is larger (i.e., 50%). In fact, head nodes in *LEACH*,
 453 as well as edge nodes in *MAQ*, are mostly chosen from sensor nodes (or smart
 454 things) which are located within dense sub-regions. When the skewness degree
 455 is large, the majority of sensory data gathering and routing tasks should be
 456 conducted in dense sub-regions, and this suggests that the transmission distance
 457 of most packets should be shorter. On the other hand, when the skewness degree

458 is small, which means that smart things are distributed in a relatively even
459 manner in the network, sensory data packets should be longer in their average
460 transmission distance. Generally, *MAQ* is more energy efficient when smart
461 things are distributed in a skewed fashion.

462 6. Related Works and Comparison

463 Along with the huge and increasing number of smart things deployed in IoT
464 sensing networks, multi-attribute query processing is considered as fundamental
465 to support domain applications. Traditional techniques have been developed to
466 support the query processing in single edge networks. In [15], authors explore
467 the problem of retrieving a group of spatial web objects. The group’s keywords
468 require to cover the query’s keywords, and the objects in the group should be
469 geographically as close as possible. A cost function is defined to evaluate the
470 merits of the results, which is composed of two kinds of semantic types. One
471 takes into account the sum of the distance between each object in the group and
472 the query location, which may fit with applications where the objects need to
473 meet at the query location, such as incident handling or the finding of project
474 partners. Another type is the maximal distance between any object in the
475 group and the query location, which may be understood as the situation where
476 tourists plan to visit several points of interest. This query for the object groups
477 inspires the research presented in this article. Note that a centralized index tree
478 is constructed to support the query of object groups. This strategy should be
479 applied to single edge networks, but may not be applicable to large-scale IoT
480 sensing networks composed of multiple edge networks.

481 In [14], authors present an R-tree-based indexing technique that stores com-
482 pact histograms in node entries, while preserving reasonable node fanout. Lever-
483 aging the index and histogram, a pruning strategy is implemented to prune the
484 search space and guide the search while considering the factors including group
485 diameter, distance, and relevance to the query. Generally, this histogram for
486 pruning the search space is a promising mechanism for supporting query pro-

cessing. Hence, an improved pruning strategy is proposed in [16]. Since objects may be unevenly distributed in the network, authors adopt proper mechanisms for handling objects contained in dense and sparse sub-regions. Assuming there are two sets of groups that can satisfy the query, objects in one group is in a hotspot region, and objects in the other group is in a sparse region. When the distance cost is almost the same, objects in dense sub-regions should be prone to be recommended, since they can have more counterparts to be replaced when found improper. Therefore, dealing with spatial keyword queries, the region density is also a factor to be considered. Authors propose a method to calculate the lower bound of the density cost of a node, and to prune nodes with the lower bound of density cost than the past minimum cost.

To manage objects in a network, an index tree like an R-tree is usually constructed to support spatial and multi-attribute query processing. An R-tree index is proposed in [30] to handle spatial keyword queries. In computer aided design and geo-data applications, the mechanism about the search of massive information in spatial databases is fundamental. The processing of non-zero-sized data in a multidimensional space can hardly be solved with the traditional indexing method. Therefore, authors propose an R-tree to facilitate regular access methods in relational databases. Generally, this technique considers the spatial query processing, while the text relevancy is not the focus. To remedy this issue, an index tree integrating the inverted file for text retrieval and R-tree for spatial proximity query is developed [10], such that the spatial and text relevance is considered with respect to query specification. Besides, a range region query is proposed in [31], in order to retrieve objects with keywords in a certain range. A direction-aware spatial keyword query method [17] is proposed to inherently support object query within certain directions.

Note that searching strategy for smart things is popular nowadays. In [33], the concept of multi-region attribute aggregation query over sensors in skewness distribution is presented. Authors establish an energy-efficient spatial index tree to resolve the multi-region attribute aggregation query. Generally, this technique constructs an index tree to support query in all region, which

518 is quite different from the aggregation query proposed in our technique. The
 519 processing of the multi-region attribute aggregation query inspires us to develop
 520 the marginal edge network query processing. With the popularity of big data
 521 applications [34, 35], information is no longer stored in a single region. The dis-
 522 tributed technology is increasingly used. In [36], interoperability is assumed as
 523 a challenge in implementing IoT applications. A distributed Internet-like archi-
 524 tecture for things is proposed for the process of large-scale expansion of IoT. In
 525 general, this proposed distributed architecture helps intelligent decision-making
 526 and enables automated service creation. It is worth noting that some service
 527 matching and allocation strategies [38, 39, 40] are also beneficial for searching
 528 objects. In [38], considering the explosion of Internet of things, big data and
 529 fog computing in cloud computing environment, authors explore the scheduling
 530 strategy of cloud and fog resources. This exploration has an enlightening effect
 531 on the collaboration of multiple edge nodes in the edge computing environment.
 532 Other techniques explore the network communication topology [20], an effective
 533 collection [21], management [22], and aggregation [23] of sensory data, a load-
 534 balancing routing [24], and the prolonging of network lifetime [25, 26], in the
 535 context of IoT. In [37], in order to solve the mobile environment, the data source
 536 can not be accessed due to the partition of the network. The author proposes
 537 Content Centric Networks (CCN) use in-network caching. In general, based
 538 on the reliable strategies in networks of [37], this work provides reliable data
 539 transmission and routing mechanism for us to handle queries in the marginal
 540 edge network. However, sensory data fusion in marginal edge network and the
 541 query processing mechanism in single edge networks are not explored.

542 To summarize, current techniques construct a centralized index tree to sup-
 543 port spatial and multi-attribute objects query processing. They are inspiring
 544 for us when developing our technique, however we argue that they should not
 545 be efficient when the network is large in scale. Due to this consideration, we
 546 propose a distributed and localized query processing mechanism to support
 547 multi-attribute query processing in edge computing.

548 7. Conclusions

549 With the swift growth of smart things being deployed in industrial envi-
550 ronments, sensory data gathering and aggregation is fundamental to support
551 IoT applications. Considering the large-scale of the network, the traditional
552 centralized mechanism may not be efficient and applicable when considering
553 the factors including network traffic and energy consumption, edge computing
554 is adopted to promote the distributed and localized query processing. In this
555 context, this article proposes a multi-attribute aggregation query mechanism in
556 edge computing to support large-scale industrial IoT applications. Specifically,
557 an energy-aware IR-tree is constructed to process query processing in certain
558 edge networks, and an edge node routing graph is established for aggregating
559 and forwarding sensory data packets between edge nodes, in order to facili-
560 tate query processing for marginal smart things in contiguous edge networks.
561 Extensive experiments have been conducted to evaluate the efficiency and appli-
562 cability of our technique. The results demonstrate that this technique performs
563 better than the rivals in reducing the network traffic and energy consumption.
564 This article retrieves the set of sensory data relevant to the query specification.
565 This strategy requires to examine all IoT nodes in the query sub-region. In
566 fact, when IoT nodes are densely deployed in the network, partial IoT nodes
567 may reflect the fact with certain accuracy and may satisfy the requirement of
568 domain application. Consequently, discovering partial IoT nodes in the query
569 sub-region for satisfying certain requirements is our future research challenge.

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