Delay and Deployment Cost Optimization of Edge Computing based on C-RAN in Intelligent Plant

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***Abstract*—In order to minimize the deployment cost of network equipment and delay for data offloading of intelligent services in intelligent plants, this paper proposes a new edge computing architecture based on the cloud radio access network(C-RAN). In this architecture, we consider a computing offload mode which allows one sensing device (SD) to offload computing tasks to more than one access point. The problem of joint optimizing deployment cost and delay is solved based on the immune algorithm and Lagrange multiplier algorithm. The simulation result shows the significantly decrease of delay for data offloading in single-SD multi-access point mode.**

Keywords—Deployment cost, low delay, C-RAN, edge computing, intelligent plant.

I. INTRODUCTION

With the rapid development of information technology in the 21st century, achieving intellectualization has increasingly become the key to the survival and development of enterprises. In the era of industrial 4.0, intelligent factories are usually built with the help of the Internet of Things (IoT), cloud computing, network physical systems, and cognitive computing [1], while the IoT follows a cloud-centric internet architecture. However, due to the upgrading of carrier networks, the intelligent plant has a requirement for cost-effective deployment of the network devices, and the industrial services have a requirement for delay sensitivity. Therefore, the network planning faces new challenges.

Meanwhile, centralized cloud computing cannot support the real-time computation applications from large-scale IoT devices in actual factories. Some studies tried to make centralized cloud computing more geographically dispersed, in which computing resources, network resources, and communication resources can be distributed closer to data access points. In this case, the edge computing is proposed. For the performance requirements of reliability and real-time accessibility [2], the authors have realized the application of edge computing in intelligent maintenance management and efficient manufacturing detection system [3][4]. In order to realize the low-cost deployment of an intelligent logistics center network computing system, Chun-Cheng Lin *et al.* in [5] proposed a new network architecture that combined fog equipment and edge equipment. Edge computing has many different applications. Some works focus on deploying network framework in intelligent factories [6]. Besides, the authors in [7][8] also consider the optimization of offloading latency.

However, traditional access networks cannot be able to realize flexible edge computing at the edge of the network [9]. To adapt to the 5G era, a new green network framework of cloud radio access network (C-RAN) is proposed in [10]. In [6], Xin Wang *et al.* studied the deployment planning of cloud wireless access network components, where the central unit (CU) and the distributed unit (DU) are integrated into the same station of the access node. Yijin Pan *et al.* in [7] proposed a cloud wireless access network, in which CU and DU are divided into two layers.

Motived by the above discussion, this paper mainly studies the optimal deployment of C-RAN based edge computing architecture in the intelligent factory, considering the delay for data offloading and deployment cost. Assuming that the position of sensing devices (SDs) is known, the problem solved in this paper is to select the optimal deployment position of CU devices, DU devices, and radio unit (RU) devices, and reasonably divide the data for the SD. Under the constraints of the maximum coverage and the maximum equipment access capacity, the total deployment cost and the delay for data offloading are jointly minimized. It is time-consuming to search for the optimal solution in a large number of feasible deployment solutions. Therefore, we apply the immune algorithm and Lagrange multiplier algorithm, which can effectively reduce the solution space and obtain the optimal solution. In summary, the main contributions of this paper are as follows:

- In this paper, we consider an edge computing framework based on C-RAN in the intelligent plant environment. The combination of C-RAN and edge computing enables extensive deployment of edge computing in large-scale intelligent factories. Based on this framework, data can be offloaded to multi-RU devices.
- Immune programming and Lagrange multiplier

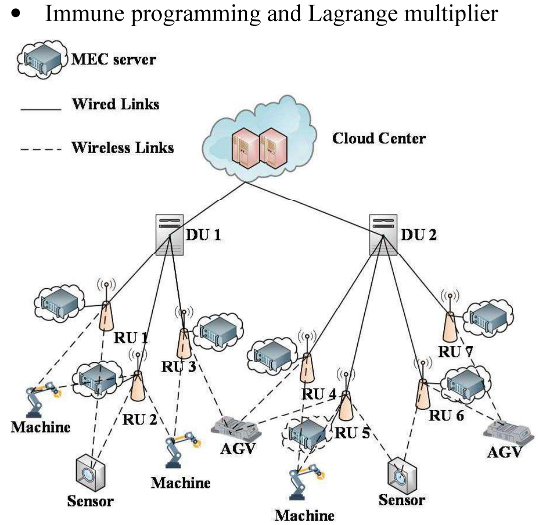


Fig. 1. Smart factory edge computing architecture based on C-RAN

$$\min_{\omega,l,x} \underbrace{\lambda(C_{\mathrm{CU}}\sum_{a\in P_{\mathrm{CU}}}\omega_a + C_{\mathrm{DU}}\sum_{b\in P_{\mathrm{DU}}}\omega_b + C_{\mathrm{RM}}\sum_{c\in P_{\mathrm{RM}}}\omega_c}_{1} + \underbrace{C_{\mathrm{F}}\sum_{m\in P_{\mathrm{CU}}\cup P_{\mathrm{DU}},n\in P_{\mathrm{DU}}\cup P_{\mathrm{RM}}} l_{mn}d_{mn})}_{2} +$$

$$\gamma\max_{c\in P_{\mathrm{RM}}} \underbrace{[\sum_{g\in\mathrm{O}} x_{gc}\frac{\beta_c}{B_{\mathrm{uplink}}\log_2(1+\frac{P_{\mathrm{TX}}h_{\mathrm{uplink}}}{\sigma^2})} + \sum_{g\in\mathrm{O}} x_{gc}\frac{\omega_g}{f_c} + \sum_{g\in\mathrm{O}} x_{gc}\frac{\beta_c'}{B_{\mathrm{downlink}}\log_2(1+\frac{P_{\mathrm{RU}}h_{\mathrm{downlink}}}{\sigma^2})})]}_{3} \tag{2}$$

algorithm are applied to obtain the optimal solution of the deployment cost and delay optimization problem.

The rest of this paper is organized as follows. In section II, the architecture of an edge computing network based on C-RAN is given, and a nonlinear programming formula is given for the joint optimization of deployment cost and delay. Section III proposes an optimization algorithm based on the heuristic algorithm and nonlinear programming. Section IV is the simulation analysis part of this study. Section V elaborates on the conclusions of this paper.

II. System Model and Problem Formulation

A. Network Model

As shown in Fig. 1, an edge computing architecture deployed in a smart factory consists of cloud centers, DU devices, RU devices, and SDs following a top-down approach. Each RU device is connected to an edge computing server. SDs, like RFID sensing door, are used to sense goods and store goods' information in factories. When a data packet needs to be processed by the SD, the RU device provides the required data for task processing and processes the data using the computing function of edge server. And then it sends the calculation results back to the SD. Finally, the cloud center will play a role in the long-term storage of data and overall analysis of historical data through the link from RU devices to DU devices, DU devices to CU. As shown in Fig. 1, the wire links between cloud center and DU devices and the wire links between DU devices and RU devices are connected by optical fibers, while the connection between RU devices and SDs are wireless.

In a smart factory, SD is bound to the fixed production equipment so that the network deployment is based on the fixed location of SDs. Therefore, the position decision problem will be simplified to the determination of the position of RU equipment based on the position of SDs that satisfies the constraint conditions. Similarly, from bottom to top, the positions of DU devices are determined by the positions of RU devices, and the location of the cloud center in the uppermost layer is determined by the locations of the DU devices. Significantly, low layer equipment usually connects with upper layer equipment based on the shortest distance priority principle.

Assuming that data g with H bytes from a SD needs to be processed, the data can be divided into independent data of any size. Each of these data can be offloaded to any edge server for computation. Define the data migrated to RU c as β_c, and the set of data segmentation migrations as O ={1,…,O}. If data g is migrated to RU c, $x_{gc}=1$. For SDs, B_{uplink} is the uplink bandwidth allocated by RU to the SD. P_{TX} is the transmitting power of the SD. h_{uplink} is the uplink channel gain. σ^2 is the white noise power. Therefore, the uplink rate between the SD and RU c is $R_c^{\mathrm{ul}} = B_{\mathrm{uplink}}\, log_2\,(1+P_{\mathrm{TX}}h_{\mathrm{uplink}}/\sigma^2)$. Similarly, the downlink rate can be expressed as $R_c^{\mathrm{dl}} = B_{\mathrm{downlink}}\, log_2(1+P_{\mathrm{RU}}h_{\mathrm{downlink}}/\sigma^2)$. In this article, it is assumed that all RU associated with the same SD will start processing at the same time after receiving all data. At this time, the data execution delay of the SD includes the calculation delay and the sum of the delay for data offloading of uplink and downlink.

$$T_c = T_{\mathrm{comp}} + T_{\mathrm{uplink}} + T_{\mathrm{downlink}} = \sum_{g\in\mathrm{O}} x_{gc}\left(\frac{\beta_c}{R_c^{\mathrm{ul}}} + \frac{\omega_g}{f_c} + \frac{\beta_c'}{R_c^{\mathrm{dl}}}\right) \tag{1}$$

where β_c is the uplink transmission data size (in bytes). β_c' is the downlink transmission data size (in bytes). ω_g is the total amount of data when computing a task. f_c is the fixed service rate (cycles/second) provided by the edge server of each RU device for the SD.

B. Problems Modeling

Specifically, the network planning problem in this article is to provide the optimal deployment and path scheme from SDs to the cloud center in the smart factory. Based on bottom-up order, SDs, RU devices, and DU devices are connected to RU devices, DU devices, and CU devices respectively such that: 1) the deployment cost of edge computing architecture reduces, and 2) delay for data offloading reduces. The total deployment cost is minimized under constraints of the maximum coverage of RU devices and the maximum equipment access capacity of CU devices, DU devices, and RU devices.

Firstly, the network parameters and variables used in the model are defined, as shown in Table 1. The formulas of the objective function (2) and constraint conditions are given. Constraint conditions are（2a）-（2o）.

$$j = \sum_{c\in P_{\mathrm{RM}}} l_{ce},\quad \forall e\in P_{\mathrm{SD}} \tag{2a}$$

$$\omega_c \le \sum_{e\in P_{\mathrm{SD}}} l_{ce},\quad \forall c\in P_{\mathrm{RM}} \tag{2b}$$

$$l_{ce} \le \omega_c,\quad \forall c\in P_{\mathrm{RM}},\ e\in P_{\mathrm{SD}} \tag{2c}$$

$$\sum_{b\in P_{\mathrm{DU}}} l_{bc} = \omega_c,\quad \forall c\in P_{\mathrm{RM}} \tag{2d}$$

$$\omega_b \le \sum_{c\in P_{\mathrm{RM}}} l_{bc},\quad \forall b\in P_{\mathrm{DU}} \tag{2e}$$

$$l_{bc} \le \omega_b,\quad \forall c\in P_{\mathrm{RM}},\ \forall b\in P_{\mathrm{DU}} \tag{2f}$$

$$l_{ab} = \omega_b,\quad \forall b\in P_{\mathrm{DU}} \tag{2g}$$

$$l_{ce}d_{ce} \le R_{\max},\ \forall c \in P_{\mathrm{RM}},\ e \in P_{\mathrm{SD}} \tag{2h}$$

$$\sum_{e \in P_{\mathrm{SD}}} l_{ce} \le D_{\mathrm{RM}},\ \forall c \in P_{\mathrm{RM}} \tag{2i}$$

$$\sum_{c \in P_{\mathrm{RM}}} l_{bc} \le D_{\mathrm{DU}},\ \forall b \in P_{\mathrm{DU}} \tag{2j}$$

$$\omega_b, \omega_c, l_{mn} \in \{0,1\} \tag{2k}$$

$$\sum_{g \in \mathrm{O}} \beta_g = H \tag{2l}$$

$$\beta_g \ge 0,\ \forall g \tag{2m}$$

$$\sum_{c \in P_{\mathrm{RU}}} x_{gc} = 1,\ \forall g \in \mathrm{O} \tag{2n}$$

$$x_{gc} \in \{0,1\} \tag{2o}$$

In the above objective function, the three parts in (2-1) are respectively the costs of installing the cloud center, DU devices, and RU devices. (2-2) represents the costs of laying optical fiber links between cloud center and DU devices, and between DU devices and RU devices. The expression (2-3) respectively indicate uplink delay, computed delay, and downlink delay of data offloading, where λ , $\gamma \in [0,1]$ represent scalar weights to balance the importance of deployment cost or data offloading latency in joint cost of deployment cost and delay.

The constraints are described below from bottom to top of the link. Constraint (2a) stipulates that each SD e can be associated with j RU devices ($j \ge 1, j \in \mathbf{N}_+$). Constraints (2b) and (2c) indicate that the connection between SD e and RU device c determines whether the RU device is deployed in the corresponding location. Constraint (2d) forces that each DU device must link to a RU device. Constraints (2e) and (2f) determine whether to deploy DU devices. Constraint (2g) ensures that the association between cloud center and DU equipment is determined by whether DU equipment is deployed. For the wireless link between the SD and the RU device, the constraint (2h) limits the coverage of the RU device, that is, the distance between the SD and the RU device. For each RU device and DU device, the maximum capacity of the access device is given in the constraint (2i) -(2j). Constraint (2k) indicates that the variable is a binary 0-1 variable. Constraint (2l) guarantees that the sum of data bytes unloaded to each RU device is the total amount of data to be calculated. Constraint (2m) limits the amount of migrated data allocated to each RU device to be nonnegative. Finally, constraint (2n) and (2o) ensure that each independent data after segmentation can be migrated to only one RU device, and the variable value is 0 or 1.

III. Optimization Algorithm

Obviously, the problem in (2) is a nonlinear programming problem that is difficult to solve directly. Therefore, the problem can be decomposed into two uncoupled subproblem, one is cost optimization and the other one is delay optimization.

TABLE I. Definition of notation

Notation	Description
P_{CU}	Potential point set of cloud center(CU) equipment
P_{DU}	Potential point set of DU equipment
P_{RM}	Potential point set of RU devices connected to edge servers
P_{SD}	Point set of sensing devices
C_{F}	The price of fiber per unit length
C_{CU}	The price of installing the cloud center
C_{DU}	The price of installing DU equipment
C_{RM}	The price of installing RU equipment and edge servers
d_{mn}	Distance between node m and n (m)
β_c	Uplink transmission data size (byte)
β_c'	Downlink transmission data size (byte)
ω_g	The total amount of data when computing a task (byte)
B_{uplink}	Uplink bandwidth (MHz)
B_{downlink}	Downlink bandwidth (MHz)
P_{TX}	Transmitting power of sensing equipment (w)
P_{RU}	Transmitting power of RU equipment (w)
h_{uplink}	Uplink channel gain
h_{downlink}	Downlink channel gain
σ^2	White noise power level
f_C	Fixed service rate of edge server of RU equipment(cycles/sec)
O	Data segmentation migration set

For cost optimization, this is modeled as a mixed-integer linear programming problem (3) under the constraints (2a) - (2k). In this article, the immune algorithm is proposed to solve the cost optimization problem, and the diversity generation and maintenance mechanism of the immune system is used to maintain the diversity of the group. It overcomes the "premature" problem which is difficult to be dealt with in the general optimization process, especially in the optimization process of multi-peak function. Finally, the global optimal solution is obtained.

$$\begin{aligned}\min_{\omega,l}\ \ & \lambda(C_{\mathrm{CU}} \sum_{a \in P_{\mathrm{CU}}} \omega_a + C_{\mathrm{DU}} \sum_{b \in P_{\mathrm{DU}}} \omega_b + C_{\mathrm{RM}} \sum_{c \in P_{\mathrm{RM}}} \omega_c \\ & + C_{\mathrm{F}} \sum_{m \in P_{\mathrm{CU}} \cup P_{\mathrm{DU}},\, n \in P_{\mathrm{DU}} \cup P_{\mathrm{RM}}} l_{mn} d_{mn})\end{aligned} \tag{3}$$

In the immune algorithm, variable ω and l are initialized firstly. In this case, the initial antibody group is randomly generated in the feasible solution space and the initial antibody population consists of a memory pool and a reserved population. Fitness function and expected reproduction probability are used to evaluate antibody. Using the elite retention strategy, several individuals with the highest antigen affinity are stored in the memory pool at each update, and then the excellent individuals in the remaining population are stored in the memory pool according to the expected reproduction probability. After the formation of the parent population, the antibody population will be selected, be crossed, and be mutated to get a new population, and then the

Algorithm 1 Joint Optimization of Deployment Cost and Delay Algorithm

Input: P_{CU} , P_{DU} , P_{RM} .

1. **while** true **do**
2. **for** $c \in P_{\mathrm{RM}}$ **do**
3. When constraint (2a) -(2c), (2h) -(2i), and (2k) are satisfied, connect sensing devices with RU devices based on the shortest distance first principle; Use immune algorithm from section III to solve cost optimization;
4. **end for**
5. obtain the optimal connecting set and calculate the deployment cost $Cost_{\mathrm{RM}}$ according to (2);
6. **for** $b \in P_{\mathrm{DU}}$, $m \in P_{\mathrm{DU}}$, $n \in P_{\mathrm{RM}}$ do
7. When constraint (2d) -(2f), (2j), and (2k) are satisfied, connect RU devices with DU devices based on the shortest distance first principle; Use immune algorithm from section III to solve cost optimization;
8. **end for**
9. Obtain the optimal connecting set and calculate the deployment cost $Cost_{\mathrm{DU}} + Cost_{\mathrm{F}}^{\mathrm{DU}}$ according to (2);
10. **for** a$\in P_{\mathrm{CU}}$, $m \in P_{\mathrm{CU}}$, $n \in P_{\mathrm{DU}}$ **do**
11. When constraint (2g) is satisfied, connect DU devices with the cloud center based on the shortest distance first principle; Use immune algorithm from section III to solve cost optimization;
12. **end for**
13. Obtain the optimal connecting set and calculate the deployment cost $Cost_{\mathrm{CU}} + Cost_{\mathrm{F}}^{\mathrm{CU}}$ according to (2);
14. Obtain the deployment cost C and total connection topology;
15. s=s+1
16. **if** s=maxIteration
17. **break**
18. **end if**
19. **end while**
20. Based the optimal deployment and connection topology from step 14, solve the latency optimization with Lagrange multiplier algorithm from section III to minimize the maximum transmission latency T_c.

Output: Optimal deployment and connection topology, joint cost of deployment and transmission latency

memory individuals will be extracted from the memory pool to form a new generation of the population. Finally, this algorithm gets the optimal antibody with the lowest fitness score when the termination condition is satisfied.

For task migration of mobile edge computing, the collaboration between multi-edge servers is beneficial to shorten the computing delay and save the computing resources between sensing and RU device, the min-max fairness principle is adopted and a min-max problem is proposed. For delay optimization, Lagrange multiplier method is used to solve the mixed-integer nonlinear programming problem (4) under the constraints (2l) - (2o). The algorithm has good convergence speed and numerical stability.

$$\min_{x} \quad \max_{c \in P_{\mathrm{RM}}} \gamma T_c \tag{4}$$

The problem minimizes the maximum delay between the SD and the RU device. It also improves the fairness of the collaboration. In this work, the Lagrange multiplier method is used to solve the delay sub-problem. To obtain the optimal solution of the delay sub-problem, a new variable k is introduced firstly, and then the objective function of the problem transforms into formula (5). Then formula (5a) should be added to the constraint set. Besides, formula (2o) is transformed into formula (5b). Thus, the min-max problem is transformed into the minimize problem of data offloading latency.

$$\min_{k} \quad \gamma k \tag{5}$$

$$\sum_{g \in \mathrm{O}} x_{gc} \left(\frac{\beta_c}{R_c^{\mathrm{ul}}} + \frac{\omega_g}{f_c} + \frac{\beta_c'}{R_c^{\mathrm{dl}}} \right) \le k, \forall c \in P_{\mathrm{RM}} \tag{5a}$$

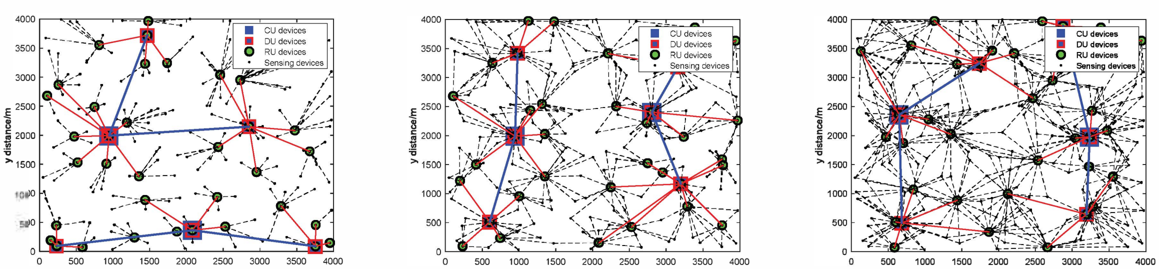
$$0 \le x_{gc} \le 1 \tag{5b}$$

In the Lagrange multiplier algorithm, variable k, x, β are initialized. After that, the augmented Lagrange function $F(k, x, \beta)$ of the sub-problem is constructed so that the solution of unconstrained optimization problem can be solved. If the termination condition is satisfied, the optimal solution $k^*, x^*, \beta^* = k^q, x^q, \beta^q$ is obtained. Stop the calculation.

Combined with the above description, an algorithm called "joint Optimized Deployment Cost and Delay algorithm" is finally proposed. The detailed process is shown in Algorithm 1.

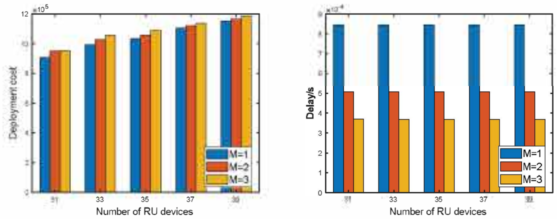
IV. Numerical Results

This section uses MATLAB to implement the "Joint Optimization of Deployment Cost and Delay Algorithm" proposed in the previous section. Our simulation runs on a PC equipped with an Intel Core i5-8250 CPU and 8.0 GB memory. This study sets the simulation parameters based on [6][11]. The specific values are as follows: the area of the smart factory is 4000m×4000m; the number of CU devices, DU devices, RU devices, and sensing devices are set to 2, 6,



(a) M=1 (b) M=2 (c) M=3

Fig. 2. Optimal architecture deployment diagrams



(a) (b)

Fig. 3. a) Deployment cost and b) delay as number of RU devices increases

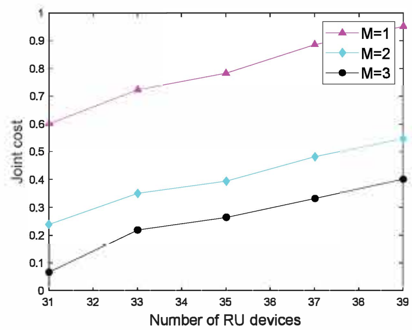
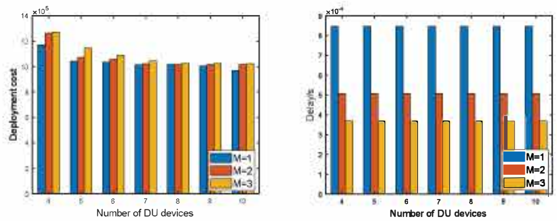


Fig. 4. Joint cost of deployment and delay as number of RU devices increases



(a) (b)

Fig. 5. a) Deployment cost and b) delay as number of DU devices increases

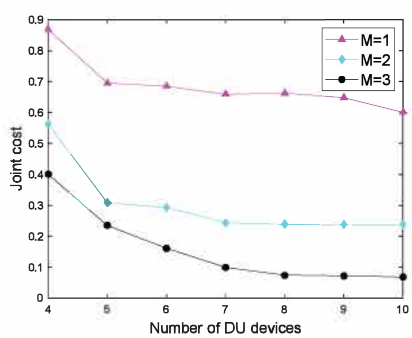


Fig. 6. Joint cost of deployment and delay as number of DU devices increases

35, and 200 respectively. Meanwhile, the cost of CU devices, DU devices, and RU devices are set to 100, 50, 150, the cost of laying fiber optic cable is 50, and the unit of cost is set to general cost unit [12]; Besides, $R_{\max} = 2000$m, $D_{RM} = 25$, $D_{DU} = 20$. The distribution of SDs follows Poisson distribution and the parameters of the immune algorithm are set as follows: the crossover probability is 0.5, the mutation probability is 0.4, and the diversity evaluation parameter is 0.95. Referring to the parameter settings of [13] [14], the parameters of the Lagrange multiplier method in this study are set as follows, assuming that the transmission data size that each SD needs to upload is $H = 0.5$MB, and $\beta_c^{'} = 0.2\beta_c$, $\omega_g = 33\beta_c$, $f_c = 2 \times 10^8$ cycles/sec. Meanwhile, uplink and downlink transmission bandwidth are set to 40MHz, and the transmitting power of the SD and RU devices are set to 1.3W and 1.1W respectively. For the convenience of research, this article assumes that the uplink channel gain is equal to the downlink channel gain. The channel gain between the RU device and the SD is $h_c = \sqrt{10^{-PaLo_c/10}\varpi\xi_c g_c}$, where $PaLo_c$ is the path loss of the distance d, and the 3GPP LTE standard is used to predict the channel, $PaLo_c$=148.1+37.6log$_{10}d$, ϖ is transmit antenna gain, while ϖ = 9dBi; noise power spectral density $\sigma^2 = -174$ dbm/Hz; ξ_c is the log-normal shadow fading coefficient, ξ_c=8dB, and g_c is the small-scale fading coefficient, followed $\mathcal{CN}(0,1)$.

To make sure that deployment cost and delay of objective functions are comparable, the cost data and delay data need to be pre-processed because the two sets of data are of different orders of magnitude. λ is set to 0.4.

Fig. 2a to Fig. 2c show the optimal architecture deployment diagrams, while the number of associated RU devices M is set to 1, 2, and 3. To further analyze the proposed algorithm, Fig. 3 and Fig. 5 show the performance of different numbers of RU devices and DU devices in terms of deployment cost and delay of data offloading respectively. Firstly, when the number of RU devices or DU devices is constant, the deployment cost increases and the delay decreases with the increase of M. When the number of RU devices increases, total deployment cost shows an increasing trend. On the contrary, total deployment cost decreases when the number of DU devices vary from 4 to 10. Besides, the increase in the number of RU devices and DU devices have no effect on delay for data offloading.

We also compare the joint cost of deployment and delay. Fig. 4 and Fig. 6 indicate that applying single-SD multi-access point mode can decrease the joint cost of deployment and delay. Hence, the algorithm proposed in this work performs well in optimizing the joint cost of delay and deployment cost in an intelligent plant.

V. CONCLUSION

This work proposes a four-tier edge computing architecture based on C-RAN. With this network framework, a nonlinear mathematical programming problem is established under the constraints of the maximum coverage and the maximum equipment capacity. To solve this problem, the "Joint Optimization of Deployment and Delay Algorithm" is proposed. Firstly, the cost optimization sub-problem is solved with the immune algorithm. After getting the optimal architecture deployment diagrams, this research adopts a Lagrange multiplier algorithm to minimize wireless transmission latency. Our simulation result shows that the proposed algorithm can effectively reduce the joint cost of radio access latency with the mode of single-sensor associating with multi-RU devices. This research assumes that SDs are fixed on industrial installation, which usually can move in actual intelligent plants, such as automated guided vehicles (AGVs), smart robots, and so on. Therefore, the mobility of SD will be a potential research direction in the future.

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