An Optimal 5G MEC System Deployment Approach for Smart Construction Sites

Shi-Yu Zhang[1], Zhen-Yin Annie Chen[1], Chun-Cheng Lin[1,*]
[1]*Department of Industrial Engineering and Management*, *National Yang Ming Chiao Tung University,* Hsinchu 300, Taiwan
zsysafw569.mg12@nycu.edu.tw, zhenyin.mg12@nycu.edu.tw, cclin321@nycu.edu.tw

***Abstract*—With the rapid development of smart construction, the proliferation of sensors and smart devices on construction sites has introduced significant challenges in data processing and communication. Conventional cloud computing struggles to handle the real-time demands of construction data, and existing MEC deployment methods often neglect energy efficiency and the complexities of multi-story sites. This work proposes a mathematical model for 5G MEC deployment, addressing installation, connectivity, and energy consumption, and solves it using a hybrid algorithm combining simplified harmony search (SHS) and variable neighborhood search (VNS). By leveraging SHS for global exploration and VNS for efficient local optimization, the approach effectively tackles the NP-hard problem of 5G MEC server and base station placement. Experimental results on real-world construction scenarios validate its superiority in computational efficiency, energy savings, and cost reduction, establishing it as a viable solution for optimizing 5G MEC deployment in smart construction sites.**

Keywords—*Smart construction, edge computing, MEC deployment, 5G mobile communication network, metaheuristic algorithm*

I. Introduction

Conventional construction site management often relies on manual methods, leading to inefficiencies, quality issues, cost overruns, and safety risks. Labor shortages and stagnant productivity further underscore the need for technological solutions. Smart construction integrates advanced technologies like robotics, sensors, machine learning, and 5G to create intelligent, efficient frameworks that enhance safety and operations. Task-specific robots for bricklaying, welding, bolting, and demolition improve productivity and reduce hazards. The growing use of sensors and smart devices generates vast data, surpassing traditional cloud processing limits. 5G and multi-access edge computing (MEC) address this by enabling real-time data analysis at the network edge, reducing cloud dependency, and ensuring low-latency communication. These advancements support applications like unmanned aerial vehicle (UAV) operations, equipment monitoring, and environmental sensing, optimizing construction in complex environments [1].

This work is motivated by three main factors. First, existing research on MEC server deployment has predominantly focused on energy savings, total costs, and access delay optimization, often neglecting the energy consumption of MEC servers themselves. Task offloading to edge nodes shifts energy demands to these nodes, making it critical to minimize their energy consumption while maintaining an optimal balance between connection quality and operational costs. Furthermore, conventional energy-saving strategies designed for cloud data centers [2] are not directly applicable to MEC systems. Second, multi-story construction sites introduce significant complexity to 5G and MEC deployments, necessitating solutions that effectively address equipment mobility and real-time data processing requirements. Finally, while 5G technology holds considerable promise for enhancing monitoring and automation in construction, limited research exists on deploying 5G and MEC in complex, multi-layered construction environments. Although 5G deployment has been studied in other domains, including smart cities and IoT applications (e.g., green planning in smart cities [3], high-density 5G algorithms [4], and device layouts in fog computing [5]), comprehensive optimization of multidimensional 5G MEC systems for construction sites remains largely unexplored.

This work proposes an optimization framework that integrates the simplified harmony search (SHS) algorithm [6] with the variable neighborhood search (VNS) algorithm for the efficient deployment of 5G MEC systems in smart construction sites. The framework considers key factors such as installation, connectivity, and energy consumption. Similar to previous studies on server deployment, the task of deploying 5G edge computing servers and small cells in construction sites has been proven to be NP-hard [7]. In the proposed approach, SHS functions as the primary optimization method, while VNS enhances its local search capabilities, improving the efficiency of regional solution exploration [8]. SHS stands out for its straightforward application to various engineering optimization problems by tuning parameters like memory size, iteration count, harmonic memory consideration rate (C_h), and pitch adjustment rate (C_p), making it experimentally feasible. Although SHS is effective in solving complex optimization problems, its regional search capabilities are significantly enhanced through the integration of VNS. The VNS algorithm improves SHS's efficiency in obtaining region-optimal solutions by leveraging varied neighborhood structures [9]. The algorithm is evaluated through experiments, demonstrating its effectiveness in real-world MEC deployment scenarios on construction sites.

The main contribution of this work is to develop a cost-effective 5G MEC deployment framework for multi-story construction sites, combining integer programming and a hybrid SHS-VNS algorithm to optimize server and small cell placement while addressing the unique spatial complexities and constraints of such environments.

[*] Corresponding author. E-mail: cclin321@nycu.edu.tw

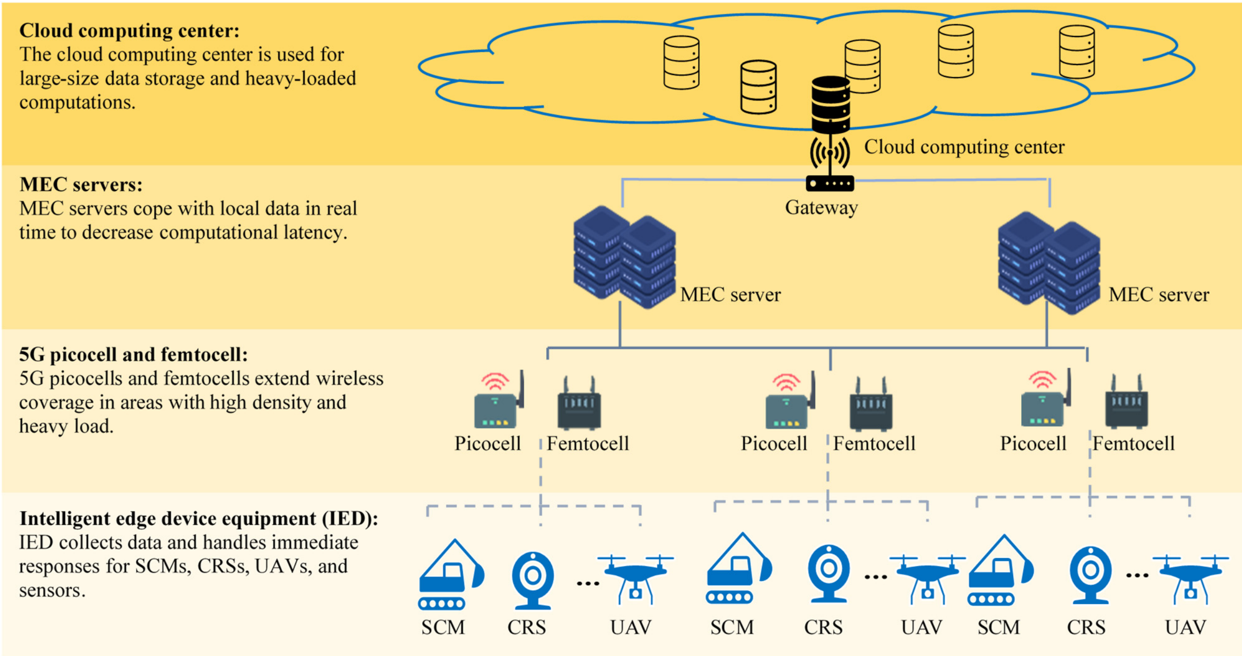

Fig. 1. The architecture of a 5G MEC system for a smart construction site.

II. vSYSTEM ARCHITECTURE

This work considers the placement of a 5G MEC system for a multi-story smart construction site, which consists of the following main components: private cloud computing center, gateway, MEC server, 5G picocells and femtocells, and intelligent edge device and equipment (IED) (Fig. 1). IEDs in this work refer to electronic terminal equipment integrated with sensors, such as smart construction machines (SCMs), UAVs, and construction site sensors (CRSs). IEDs can promptly address issues, filter collected data, standardize formats, and integrate data into a software system before transmitting it to the MEC server for temporary storage and processing. When the MEC server's capacity is exceeded or long-term storage is needed, data is relayed to the cloud computing center through a gateway for processing and historical analysis.

III. PROBLEM SETTING

This work investigates the deployment of 5G MEC systems in smart construction sites, with the goal of establishing an optimization model that minimizes the total cost of equipment deployment and operation while satisfying practical application requirements. The smart construction site is represented as an $m \times n$ grid coordinate system, where the positions and quantities of intelligent edge devices (IEDs) are fixed and predetermined. These IEDs comprise smart construction machines (SCMs), unmanned aerial vehicles (UAVs), and construction site sensors (CRSs). For these fixed-location IEDs, the work focuses on optimizing the deployment locations of MEC servers, Picocells, and Femtocells, as well as ensuring efficient network connectivity among the devices.

To enhance modeling scientific and reduce problem complexity, this work based on the system architecture described in references [10] with extensions and improvements. Potential deployment locations for MEC servers, Picocells, and Femtocells are predefined, and optimization algorithms are employed to decide whether to deploy devices at these locations. The optimization process considers a series of practical system constraints, including connectivity, capacity, latency, distance, and connection constraints.

In terms of connectivity, the model stipulates that IEDs must connect to at least one Picocell or Femtocell located on the same floor, and these small cells must establish connections with at least one MEC server. Additionally, MEC servers are required to maintain reliable connectivity with cloud computing centers. Regarding capacity, the transmission demand from IEDs to base stations must not exceed the base stations' maximum transmission capabilities, and the transmission demand from base stations to MEC servers must remain within the computational capacities of the servers. For latency, both wireless connections (IEDs to base stations) and wired connections (base stations to MEC servers) must satisfy the maximum allowable latency between IEDs and MEC servers. Distance constraints ensure that wireless connections between IEDs and base stations do not exceed the coverage range of the base stations, while wired connections between MEC servers and base stations must remain within permissible distances. Furthermore, the number of connections for each base station and MEC server must not exceed their capacity constraints, and all deployment and connection decision variables are binary.

The objective of this optimization is to minimize the overall deployment and operational costs of the 5G MEC network by strategically selecting device deployment locations and network connection paths under the specified constraints. The cost model comprehensively considers the procurement, deployment, and operational costs of devices, as well as the expenses of connection paths such as fiber optic cabling.

IV. Proposed Algorithm

A. Solution encoding

During the improvisation process, the best harmony solutions found so far are stored in harmony memory (*HM*), which is composed of *hms* harmonies denoted as $\{X_1, X_2, \ldots, X_q, \ldots, X_{hms}\}$. Each harmony X_q represents a solution consisting of the decision variables for deployment of the three types of devices, encoded as $X_q = (\chi_{q1}, \chi_{q2}, \ldots, \chi_{q\mu}) \rightarrow (\alpha_1, \alpha_2, \ldots, \alpha_{|M|} \mid \beta_1, \beta_2, \ldots, \beta_{|P|} \mid \gamma_1, \gamma_2, \ldots, \gamma_{|F|})$, in which note χ_{qh} is a number within range [0, 1] for each $h \in \{1, 2, \ldots, \mu\}$; $\mu = |M| + |P| + |F|$; each note χ_{qh} corresponds to one of the binary decision variables α_m, β_n, and γ_f for deploying an MEC server, a picocell, and a femtocell are deployed at locations m, n, and l, respectively (i.e., if $\chi_{qh} < 0.5$, the corresponding decision variable is one; otherwise, zero).

B. Cost evaluation

Given a harmony $X_q = (\chi_{q1}, \chi_{q2}, \ldots, \chi_{q\mu}) = (\alpha_1, \alpha_2, \ldots, \alpha_{|M|} \mid \beta_1, \beta_2, \ldots, \beta_{|P|} \mid \gamma_1, \gamma_2, \ldots, \gamma_{|F|})$, the deployment of three types of devices can be determined; and simultaneously, the decision variable x_{ij} determines the connectivity between each pair of devices i and j. Then, the cost of this harmony is evaluated as the objective function in Equation (1), in addition to the cost associated with penalizing violations of constraints below:

$$c_{link} + c_{vertical\,link} + c_{install} + c_{energy} + \Omega \cdot (\eta_{link} + \eta_{capacity} + \eta_{latency} + \eta_{workload} + \eta_{cover} + \eta_{connection}) \tag{1}$$

where Ω serves as the penalty cost for violations, which is a significantly large value; η_{link}, η_{capacity}, η_{latency}, η_{workload}, η_{over}, and $\eta_{\text{connection}}$ denote the number of violating constraints for device connection, device computation and transmission capacity , maximum delay time , coverage range, and maximum connections respectively. Through this penalty scheme, the proposed SHSVNS can obtain feasible solutions without penalty costs after a large number of iterations.

C. Proposed SHSVNS

The classical HS algorithm employs a two-stage process to determine new solutions based on the judgement of two random numbers with two parameters. Unlike the HS algorithm, the SHS algorithm utilizes a one-stage process based on a single random number falling within three ranges divided by two parameters C_h and C_p for greater simplicity and efficiency. To enhance the local search capabilities, this work further integrates the SHS algorithm with VNS, which systematically explores the neighborhood structure by alternating between various neighborhoods of the current solution. This proposed SHSVNS is outlined in Algorithm 1.

Algorithm 1 SHSVNS()

Input: Candidate positions of MEC servers, Picocells, and Femtocells in the smart agricultural park.
Output: Deployment of MEC servers, Picocells, and Femtocells.

Initialize the *HM* consisting of *hms* harmonies $X_1, X_2, \ldots, X_{hms}$.
Evaluate costs of all harmonies $f(X_1), f(X_2), \ldots, f(X_{hms})$.
for $iter = 1$ to $iter_{\max}$ **do**
  Consider $X_{\text{new}} = (\chi_{\text{new},1}, \chi_{\text{new},2}, \ldots, \chi_{\text{new},\mu})$
  for $h = 1$ to μ **do**
    Generate a random value $rand_1$
    if $rand_1 < C_h$ **then**
      $\chi_{\text{new},h}$ = a random value from range [0, 1]
    else if $rand_1 < C_p$ **then**
      $\chi_{\text{new},h} = \chi_{q,h}$ where q is a random number from $\{1, 2, \ldots, hms\}$
    else
      $\chi_{\text{new},h} = \chi_{q,h}$ where q is a random number from $\{1, 2, \ldots, hms\}$
      $\chi_{\text{new},h} = \chi_{\text{new},h} + U(-bw, bw)$ where U denotes uniform distribution
    end if
  end for
  Call Algorithm 2 to conduct VNS() on X_{new}
  The worst harmony in the *HM* is replaced by X_{new} if X_{new} is better
end for
Output the best harmony in the *HM* as the final solution

Algorithm 2 VNS()

Input: Harmony X_{new}.
Return: A local optimum of harmony X_{new}.

Set $k = 1$
while $k \le k_{\max}$ **do**
  Use the neighboring structure N_k to shake harmony X_{new} to generate X'_{new}
  for $i = 1$ to $I_{\max}$ **do**
    $X''_{\text{new}} = X'_{\text{new}}$
    Use the neighboring structure N_k on X''_{new} to generate a neighboring solution X'''_{new}
    if $f(X'''_{\text{new}}) < f(X''_{\text{new}})$ **then**
      $X''_{\text{new}} = X'''_{\text{new}}$
    end if
  end for
  if $f(X''_{\text{new}}) < f(X_{\text{new}})$ **then**
    $X_{\text{new}} = X''_{\text{new}}$
    $k = 1$
  else
    $k = k + 1$
  end if
end while
Return X_{new}

V. Simulation Results and Analysis

A. Experimental setup and settings

The simulation targets a medium-sized construction site in the interim construction phase with an area, and was used to validate the effectiveness of SHSVNS in a diverse and dynamic construction environment. The parameters of the simulation are set below. The site internally contains 15 MEC server locations, 30 picocell locations and 70 femtocell locations. To measure the system cost, we introduce the concept of generic cost unit (gcu), where the fiber unit cost $c_f = 50$. The deployment costs of an MEC server, a picocell and a femtocell are $c_M = 800$, $c_P = 600$, and $c_F = 100$, respectively. The penalty unit cost Ω is set to 10^6. The data transmission rate (bps) is set to $s_{kn} = s_{kf} = 1000$, $s_{nm} = 1000$, $s_{fm} = 5000$. The coverage areas of MEC server, picocell and femtocell are $R_{\text{M}} = 70$m, $R_{\text{P}} = 100$m, $R_{\text{F}} = 10$m, respectively. The upper constraints of data processing capacity of MEC server, picocell, and femtocell are $H_m^M = 10^5$, $H_n^P = 3 \times 10^4$, and $H_f^F = 10^4$, respectively. The maximum delay time (ms) is set as $D_{\text{P,M}} = D_{\text{P,M}} = D_{\text{F,M}} = 50$, $D_{\text{E,P}} = D_{\text{E,F}} = 80$. The highest number of devices that can be supported by MEC servers, picocells, and femtocells in the site are set to $N_{\text{M}} = 2$, $N_{\text{P}} = 20$, $N_{\text{F}} = 30$, respectively; and the maximum data transfer requirement for each IED is $\omega_k = 2000$.

To verify the performance of SHSVNS, this work compares it with the classical genetic algorithm (GA) and the SHS. The parameters of the three algorithms are tested in several experiments and adjusted to the optimal settings: $hms = 20$, $C_h = 0.3$, $C_p = 0.7$, $bw = 0.5$, $I_{max} = 16$ for SHSVNS, $hms = 50$, $C_h = 0.8$, $C_p = 0.8$, $bw = 0.5$ for SHS, and GA is set as follows:50 chromosomes, single-point crossover rate = 0.7, mutation rate = 0.1. Experiments show that after 1000 iterations, all three algorithms have converged significantly, and the solution quality shows not significant improvement, so the maximum number of iterations is set to 1000.

B. *Experimental analysis*

The experiment conducted in this section is to deploy a 5G MEC system in the smart construction site. According to the specific needs of the construction site, the potential candidate positions of three types of IEDs are predetermined, which are represented by black, pink, and cyan dots, respectively, in Fig. 2. With the above candidate locations, the placement of the 5G MEC system in the construction site using the proposed SHSVNS is illustrated in Fig. 2, in which MEC servers, picocells, and femtocells are represented by solid red diamonds, blue pentagons, and orange pentagons, respectively, installed in the construction site. The result of this deployment consists of 7 MEC servers, 11 picocells, and 3 femtocells located on different floors, with the yellow connections denoting devices connected to the second floor and the brown connections denoting devices connected to the third floor. Therefore, the installed cost of the MEC server is 7 × 800 = 5600 gcu, the installed cost of the Picocell is 11 × 600 = 6600 gcu, and the installed cost of the Femtocell is 3 × 100 = 300 gcu. The sum of the link and energy costs is 20,120 gcu.

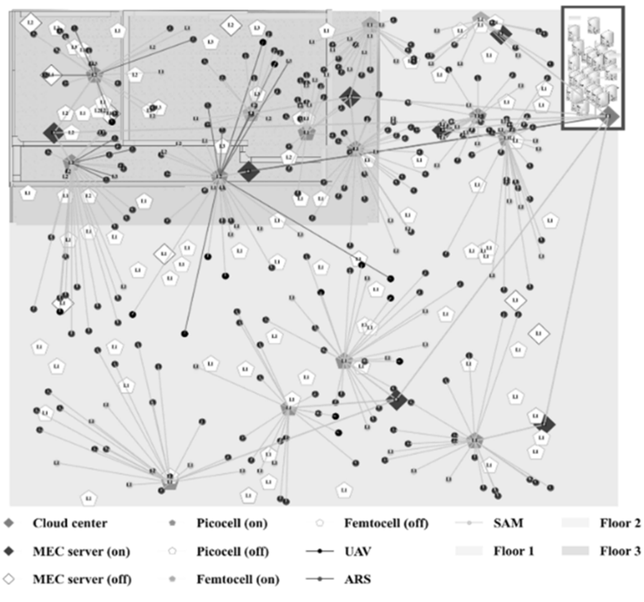

Fig. 2. Result of deploying a 5G MEC system in a smart construction site using the SHSVNS.

The total cost C_{total} and its subdivisions for the three algorithms (SHSVNS, GA, and SHS) in the 5G MEC system deployment are shown in Fig. 3, including the link and energy cost ($C_{link} + C_{energy}$), installation cost ($C_{install}$). From the results, the total cost of SHSVNS is considerably lower than the other two algorithms, suggesting that it has a significant advantage in cost optimization. SHSVNS not only controls the installation cost efficiently, but also keeps the link and energy cost at a low level. In contrast, GA has the highest total cost and all three cost components are much higher than SHSVNS and SHS. SHS has the second highest total cost, but its installation cost and link and energy costs are still higher than those of SHSVNS.

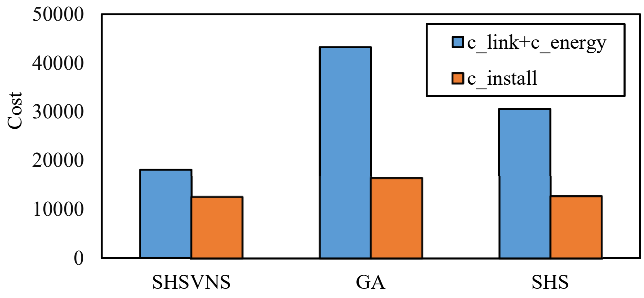

Fig. 3. Different types of costs simulated by different algorithms.

VI. Conclusion

A hybrid SHSVNS algorithm combining SHS and VNS has been proposed for 5G MEC deployment in smart multi-story construction sites. It leverages SHS's global search and VNS's local search, demonstrating advantages in efficiency, energy use, and cost reduction. Experiments highlight its effectiveness in handling multi-story deployment challenges and complex environments, with potential for broader smart city applications.

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