A High-Speed Channel Assignment Algorithm for Dense IEEE 802.11 Systems via Coherent Ising Machine

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***Abstract*—This letter reports on an ultra-fast and accurate channel assignment approach using a coherent Ising machine (CIM) for dense wireless LAN (WLAN) systems. CIM is a laser-based high-speed hardware approach for solving Ising problems using optoelectronic features. We formulate the total-throughput maximization problem for large-scale centralized WLAN systems as a combinatorial optimization problem. Subsequently, the problem is converted into an Ising problem to be optimized via a CIM. Simulation results reveal that the CIM can improve the total throughput performance and give results in a very short time (millisecond order).**

***Index Terms*—Channel assignment, Ising problem, coherent Ising machine, combinatorial optimization, wireless LAN.**

I. INTRODUCTION

HARDWARE-BASED search algorithms such as quantum computers [1], [2] and Ising machines [2]–[8] are expected to solve various optimization problems in wireless communication systems at very high-speed. Large-scale implementation of quantum annealing, D-Wave [2], and coherent Ising machines (CIMs) [3]–[8], have enabled to solve large Ising problems. Because various combinatorial optimization problems can be formulated as an Ising problem [9], these machines enable fast optimization of large problems.

The D-Wave [2] is a well-known quantum annealing machine. However, the mutual interactions between the Ising spins are sparse, and the applicable size for the D-Wave is not large enough for problems requiring high-density coupling. In contrast, the CIM has fully coupled Ising spin networks of optical pulses generated by laser oscillators [10]. Therefore, the CIM can be applied to various problems requiring dense coupling, which include various real-world problems. Reference [11] showed that the CIM was more effective than the D-Wave for large and dense problems. In [6], the CIM with 2000 bits was implemented. The CIM has been applied to typical benchmark combinatorial optimization problems such as Max-Cut and traveling salesman problems [5]–[7], and exact solutions to these problems have been obtained in a short time (5 ms) when the problem is of a stipulated size.

Various large-scale combinatorial optimization problems in wireless communication systems need to be solved rapidly, for example, dynamic channel assignment, and resource scheduling. Another example is that of access points (APs) in dense wireless LAN (WLAN) systems that need to select appropriate communication channels in a short time to improve the total throughput in dynamic wireless environments [12]. A centralized architecture employing a channel coordinator addresses this problem [12]; however, as the number of channels and access points increases, a *combinatorial explosion* occurs. Although a simplified optimizer, such as a greedy optimizer, can solve this problem with low complexity [13], a fundamental trade-off exists between the computational complexity and optimization accuracy. In contrast, if the CIM can be applied to the channel assignment problem, the total throughput can be dramatically improved in real time.

In this letter, based on the background presented above, we propose a centralized IEEE 802.11-based system using CIM. The proposed system aims to maximize the system throughput *in real time*, optimizing the channel assignment problem via the centralized controller with the CIM. First, the throughput maximization problem is formulated as a combinatorial optimization problem. Next, we summarize how the problem can be solved by the CIM; we convert the combinatorial optimization problem into an Ising problem. The performance of the CIM was evaluated by comparing it with other optimization schemes to verify its solutions.

II. SYSTEM MODEL

We assume a dense WLAN system managed by centralized control, as summarized in Fig. 1. Each access point (AP) periodically sends the location information of the user equipment (UE) connected to it to the controller. The controller calculates the optimal channel for all APs using a CIM based on the location information data and sends the calculation results to each AP for channel assignment. Based on the above process, our system maximizes the total throughput of all UEs by

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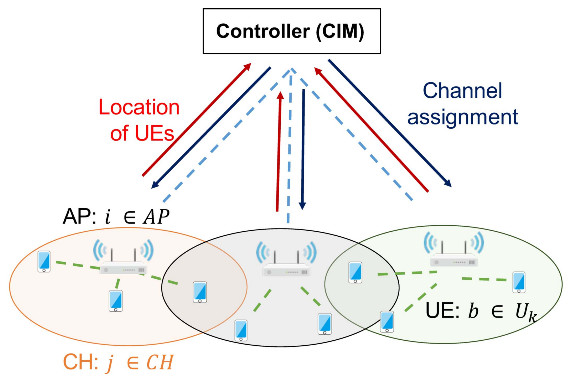

Fig. 1. System model.

selecting the best channel for each cell in real time using the CIM.

We define the optimization problem by carefully formulating the throughput model of the UE. First, we define the set of APs, UEs, and available channels as *AP*, U_i, and *CH*, where U_i is the set of UEs connected to AP $i \in AP$. The objective of our problem definition is to maximize the throughput by minimizing both the interference among multiple UEs and APs in the PHY layer and the backoff time, which causes transmission latency in the MAC layer. When the AP i and k use the same channel, and if the distance between the UE $a \in U_i$ in these cells and the UE $b \in U_k$, d_{iakb}, is larger than the carrier sense range R_{CS}, $d_{iakb} > R_{\text{CS}}$, the UE a and UE b interfere with each other in the PHY layer. In contrast, if $d_{iakb} \leq R_{\text{CS}}$, no PHY layer interference occurs due to career sense on the MAC layer; however, the throughput decreases as the backoff time increases. Especially in a large and dense environment such as a stadium, the increase in the backoff cannot be ignored. Thus, we formulated the throughput of the UEs as Eq. (1), considering both the MAC layer [14] and the PHY layer capacity:

$$S_{ijkla} = R_{\text{payload}} \frac{T_{\text{success}}(n_{ijkla})}{T_{\text{success}}(n_{ijkla}) + T_{\text{fail}}(n_{ijkla})} r, \quad (1)$$

$$r = B \log_2\left(1 + \frac{P_{\text{S},ia}}{P_{\text{I},ijkla} + P_{\text{Noise}}}\right), \quad (2)$$

where S_{ijkla} is the throughput of the UE $a \in U_i$ when APs i and j use channels k and l, respectively. S_{ijkla} consists of the MAC layer part corresponding to the increase in transmission latency caused by the backoff time in Eq. (1) and the PHY layer part corresponding to the channel capacity, which depends on the interference in Eq. (2).

We describe the MAC layer part in Eq. (1): R_{payload} as the ratio of the payload size to the total packet length, which is given by

$$R_{\text{payload}} = \frac{(\text{Payload length})}{(\text{PHY header}) + (\text{MAC header}) + (\text{Payload length})}, \quad (3)$$

where (PHY header) and (MAC header) are the lengths of the header on the PHY layer and the MAC layer, respectively, and (Payload length) is the length of the payload in one MAC frame. $\frac{T_{\text{success}}(n_{ijkla})}{T_{\text{success}}(n_{ijkla})+T_{\text{fail}}(n_{ijkla})}$ is the ratio of the time required for transmission for the UE a, where $T_{\text{success}}(n)$ is the channel occupation time for successful transmission, and $T_{\text{fail}}(n)$ is the channel occupation time when the transmission failure occurs, when the number of devices in the carrier sense range R_{CS} is n. $T_{\text{success}}(n)$ and $T_{\text{fail}}(n)$ are expressed as follows:

$$T_{\text{success}}(n) = p_{\text{s}}(n) p_{\text{tr}}(n) T_{\text{s}}, \quad (4)$$

$$T_{\text{fail}}(n) = (1 - p_{\text{tr}}(n))(\text{slot length}) + p_{\text{tr}}(n)(1 - p_{\text{s}}(n)) T_{\text{c}}, \quad (5)$$

where (slot length) corresponds to the time length of one slot. T_{s} is the time consumption associated with a successful transmission, and T_{c} is the time consumption due to collision when more than two UEs compete for one transmission opportunity, which are expressed as follows:

$$T_{\text{s}} = \frac{(\text{PHY header}) + (\text{MAC header}) + (\text{Payload length})}{r} + \text{SIFS} + \text{DIFS} + \text{ACK} + 2\Delta, \quad (6)$$

$$T_{\text{c}} = \frac{(\text{PHY header}) + (\text{MAC header}) + (\text{Payload length})}{r} + \text{DIFS} + \Delta, \quad (7)$$

where r is the PHY layer bit rate, DIFS is the length of the DCF inter-frame space, SIFS is the length of the short inter-frame space, ACK is the length of the acknowledgment message, and Δ is the propagation delay. $p_{\text{tr}}(n)$ is the probability that at least one UE transmits packets, and $p_{\text{s}}(n)$ is the transmission success probability of each UE, which are expressed as follows:

$$p_{\text{tr}}(n) = 1 - (1 - \tau)^n, \quad (8)$$

$$p_{\text{s}}(n) = \frac{n\tau(1-\tau)^{n-1}}{p_{\text{tr}}} = \frac{n\tau(1-\tau)^{n-1}}{1-(1-\tau)^n}, \quad (9)$$

where τ is the transmission probability, and n is the number of wireless devices in the carrier sense range. τ is given by

$$\tau = \frac{2(1-2p)}{(1-2p)(W_{\min}+1) + pW_{\min}(1-(2p)^m)}, \quad (10)$$

$$p = 1 - (1-\tau)^{n-1}, \quad (11)$$

where p, $W_{\min}$, and m denote the collision probability, minimum contention window, and backoff stage, respectively.

n_{ijkla} in Eq. (1) is the number of UEs that satisfy the following two conditions: the UE that uses the same channel as the UE a, and the distance between the UE and a is less than or equal to R_{CS}. n_{ijkla} is given by $n_{ijkla} = |U_i| + \delta_{jl}|C_{iak,1}|$, $C_{iak,1} = \{b \in U_k | d_{iakb} \leq R_{\text{CS}}\}$, where δ_{jl} represents the Kronecker delta. $\delta_{jl}|C_{iak,1}|$ determines the increase in the number of UEs in the carrier sense range using the same channel. The larger n_{ijkla} reduces throughput S_{ijkla}.

Next, we explain the PHY layer part modeled in Eq. (2). B is the bandwidth, and P_{Noise} is the noise power. $P_{\text{S},ia}$ is the received power of the desired signed for UE a in AP i, while $P_{\text{I},ijkla}$ is the interference power. These terms are expressed as follows:

$$P_{\text{S},ia} = P_{\text{tra}} L(d_{ia}), \quad (12)$$

$$P_{\text{I},ijkla} = \frac{1}{|C_{b,2}|} \sum_{b=1}^{C_{b,2}} P_{\text{tra}} L(d_{ikb}) \delta_{jl}, \quad (13)$$

where P_{tra} is the transmission power, d_{ia} is the distance between AP *i* and UE *a*, and d_{ikb} is the distance between AP *i* and UE *b*. $L(d)$ is the path loss function,

$$L(d) = -148 + 10\alpha \log(d) + 20 \log(f), \tag{14}$$

where α is the path loss exponent, and f is the considered frequency. $C_{b,2}$ is the set of UE b interfering with UE a,

$$C_{b,2} = \{b \in U_k | d_{iakb} > R_{\text{CS}}\}. \tag{15}$$

The interference $P_{\text{I},ijkla}$ in Eq. (13) is averaged out as they do not occur simultaneously because of carrier sense.

By using the throughput model S_{ijkla} formulated as above, we define the channel assignment problem to maximize the total throughput using the binary variable v_{ij} ($\in \{0,1\}$), which can be expressed by the following equation:

$$\underset{\boldsymbol{v}}{\text{maximize}} \; \sum_{i=1}^{|AP|} \sum_{j=1}^{|CH|} \sum_{\substack{k=1 \\ k \neq i}}^{|AP|} \sum_{l=1}^{|CH|} \sum_{a=1}^{|U_i|} S_{ijkla} v_{ij} v_{kl}, \tag{16}$$

$$\text{subject to} \; \sum_{j=1}^{|CH|} v_{ij} = 1, \tag{17}$$

where Eq. (17) denotes that each AP can use only one channel.

III. Applying CIM to the Channel Assginment

The CIM [5], [6] can solve a combinatorial optimization problem formulated as an Ising problem, by searching the state of Ising spins, $\boldsymbol{\sigma} (= [\sigma_1, \sigma_2, \ldots, \sigma_N])$, corresponding to the minimum of the Ising Hamiltonian:

$$H_{\text{Ising}}(\boldsymbol{\sigma}) = -\frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} J_{ij} \sigma_i \sigma_j + \sum_{i=1}^{N} \lambda_i \sigma_i, \tag{18}$$

where σ_i is the state of the *i*th Ising spin, $\sigma_i \in \{-1, 1\}$, J_{ij} is the mutual interaction between the *i*th and *j*th Ising spins, λ_i is the external magnetic field of the *i*th Ising spin, and *N* is the number of Ising spins.

Although a well-known quantum annealer [2] does not usually have densely connected mutual interactions, J_{ij}, among the spins, the CIMs developed in [5], [6] have fully connected mutual interactions among all *N* Ising spins [11]. Therefore, these CIMs are applicable to most general optimization problems, which require dense or arbitrary mutual interactions in their Ising Hamiltonian. The CIMs with full mutual interactions have been realized using optical pulses on a long optical fiber as the Ising spins. The mutual interactions among all pulses are calculated at an FPGA, by measuring the phase of each pulse and adding the feedback to the corresponding pulse in the fiber.

To solve a combinatorial optimization problem using the CIM, we need to formulate both the objective function and constraints in the form of Eq. (18) by deriving J_{ij} and λ_i. By setting appropriate J_{ij} and λ_i, the CIM can search the state of the Ising spins σ corresponding to the solution of the problem. To derive these parameters, we use a mutually connected neural network [15], in which each neuron takes 0 or 1, because it is easier to formulate by $\{0, 1\}$ than by $\{-1, 1\}$. We formulate the channel assignment problem using $\{0, 1\}$ and convert it to $\{-1, 1\}$ to derive J_{ij} and λ_i. The energy function of the mutually connected neural network is given by

$$E_{\text{NN}}(\boldsymbol{X}) = -\frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij} X_i X_j + \sum_{i=1}^{N} \theta_i X_i, \tag{19}$$

where X_i is the state of the *i*th neuron, $X_i \in \{0, 1\}$, w_{ij} is the connection weight between the *i*th and the *j*th neurons, θ_i is the threshold of the *i*th neuron, and *N* is the number of neurons. By updating neurons X_i based on the inputs for each, $\sum_{j=1}^{N} w_{ij} X_j$, the energy function E_{NN} always decreases when the following conditions are satisfied: no self-feedback ($w_{ii} = 0$), and connections are symmetric ($w_{ij} = w_{ji}$) for all *i* and *j*. Optimization algorithms based on a mutually connected neural network solve the problem by its autonomous dynamics, minimizing the energy function. This method has been applied to various combinatorial optimization problems [7], [15]. In this letter, we apply it to the channel assignment problem. In [7], a CIM has been formulated to solve a simple channel assignment problem to maximize the channel capacity. In this study, we have formulated the total throughput of the IEEE802.11 system based on not only the channel capacity in the PHY layer but also the CSMA/CA protocol in the MAC layer.

First, the problem should be formulated in the form of Eq. (19). In this regard, it is necessary to define the relationship between the solutions and the state of the neuron $\boldsymbol{X}$. We defined neuron X_{ij} as follows:

$$X_{ij} = \begin{cases} 1 & \text{if the AP } i \text{ uses the channel } j, \\ 0 & \text{otherwise}. \end{cases} \tag{20}$$

To solve the problem defined in Eq. (16), the function of X_{ij} is given as follows to solve it using a neural network:

$$E_1(\boldsymbol{X}) = \sum_{i=1}^{|AP|} \sum_{j=1}^{|CH|} \sum_{\substack{k=1 \\ k \neq i}}^{|AP|} \sum_{l=1}^{|CH|} \sum_{a=1}^{|U_i|} \sum_{b=1}^{|U_k|} - (S_{ijkla} + S_{ijklb}) X_{ij} X_{kl}. \tag{21}$$

Since Eq. (16) is a maximization problem, we replace the problem with minimization by multiplying -1 to Eq. (21) to apply the minimization dynamics of the CIM and the neural network. Moreover, S_{ijklb} is added because w_{ij} must be symmetric ($w_{ij} = w_{ji}$). To satisfy the constraint of the problem that AP can use only one channel at a time, the following function should also be minimized:

$$E_2(\boldsymbol{X}) = \sum_{i=1}^{|AP|} \left(\sum_{j=1}^{|CH|} X_{ij} - 1 \right)^2. \tag{22}$$

From Eqs. (21) and (22), the energy function of this problem is given by: $E_{\text{WLAN}}(\boldsymbol{X}) = V_1 E_1(\boldsymbol{X}) + V_2 E_2(\boldsymbol{X})$, where V_1 and V_2 are the scaling parameters for each term. By comparing the coefficients of $E_{\text{NN}}(\boldsymbol{X})$ and $E_{\text{WLAN}}(\boldsymbol{X})$, the weights w_{ijkl} and threshold θ_{ij} to minimize $E_{\text{WLAN}}(\boldsymbol{X})$ by the mutually connected neural network can be derived as follows:

$$w_{ijkl} = -2\Big(V_2\delta_{ik}(1-\delta_{jl}) - V_1(1-\delta_{ik})\sum_{a=1}^{|U_i|}\sum_{b=1}^{|U_k|}(S_{ijkla}+S_{ijklb})\Big), \quad (23)$$

$$\theta_{ij} = -V_2. \quad (24)$$

To solve the problem using the CIM whose outputs are $\{-1, 1\}$, it is necessary to obtain J_{ijkl} and λ_{ij} from w_{ijkl} and θ_{ij} [7]. We use the conversion equations proposed in [7], which are expressed as

$$J_{ijkl} = \frac{w_{ijkl}}{2}. \quad (25)$$

$$\lambda_{ij} = \theta_{ij} - \sum_{k=1}^{N}\sum_{l=1}^{N}\frac{w_{ijkl}}{2}. \quad (26)$$

Using Eqs. (25) and (26), J_{ijkl} and λ_{ij} for the CIM to solve Eq. (16) are derived as follows:

$$J_{ijkl} = \frac{1}{2}\left\{-2\left(V_2\delta_{ik}(1-\delta_{jl}) - V_1(1-\delta_{ik})\sum_{a=1}^{|U_i|}\sum_{b=1}^{|U_k|}(S_{ijkla}+S_{ijklb})\right)\right\}, \quad (27)$$

$$\lambda_{ij} = -V_2 - \sum_{k=1}^{N}\sum_{l=1}^{N}\frac{1}{2}\left\{-2\left(V_2\delta_{ik}(1-\delta_{jl}) - V_1(1-\delta_{ik})\sum_{a=1}^{|U_i|}\sum_{b=1}^{|U_k|}(S_{ijkla}+S_{ijklb})\right)\right\}. \quad (28)$$

By using the obtained J_{ijkl} and λ_{ij}, the CIM converges to the state corresponding to the solution of the channel assignment problem in a short time [17].

IV. Numerical Results

In this section, the computer simulation results are presented to evaluate the performance of the proposed method. Based on [8], [16], we use the simulation model of a CIM, defined as

$$\frac{dc_{ij}}{dt} = (-1+p-c_{ij}^2-s_{ij}^2)c_{ij} + \sum_{k=1}^{N}\sum_{l=1}^{N}J_{ijkl}c_{ij} - \lambda_{ij}, \quad (29)$$

$$\frac{ds_{ij}}{dt} = (-1-p-c_{ij}^2-s_{ij}^2)s_{ij} + \sum_{k=1}^{N}\sum_{l=1}^{N}J_{ijkl}s_{ij} - \lambda_{ij}, \quad (30)$$

where c_{ij} and s_{ij} are the in-phase and quadrature-phase components of the ijth optical pulse amplitude. The Ising spin σ_{ij} is implemented in c_{ij}. If $c_{ij} \geq 0$, then $\sigma_{ij} = 1$. If $c_{ij} < 0$, then $\sigma_{ij} = -1$. p is the power of the pump pulses, which is used to amplify c_{ij}. The value of c_{ij} starts out small, close to 0. With Eq. (29) and (30), c_{ij} becomes larger, and the values eventually converge. The final state of c_{ij} indicates the solution of the combinatorial optimization problem.

In the simulations, we have used the following system parameters: B is 20 MHz, P_{tra} is 20 dBm, P_{Noise} is -174 dBm/Hz, $\alpha = 3.0$, the carrier sense threshold is -75 dBm, $W_{\min} = 32$, $m = 4$, (PHY header) = 128, (MAC header) = 272, (payload length) = 8184, (slot length) is 5 μs, DIFS is 28 μs, and SIFS is 128 μs.

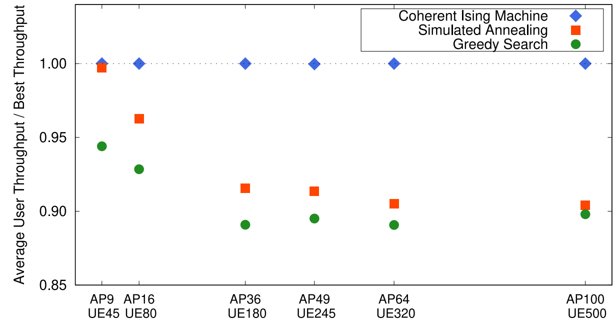

Fig. 2. Comparison of the solutions of the algorithms: CIM, SA and greedy algorithms, which are applied to maximization of the objective function in Eq. (16).

A. Performance Verification of CIM

To evaluate the performance of the proposed method, we compared the proposed algorithm with other optimization algorithms. Specifically, the solutions of the proposed method are verified by comparing them with those of other typical algorithms for solving combinatorial optimization problems, such as simulated annealing (SA) [17] and greedy algorithms. These algorithms can solve large-scale combinatorial optimization problems with reasonable computational complexity.

The simulation flow is as follows: first, we prepare problem instances with the locations of the APs and UEs. Second, we ran CIM simulations using Eqs. (29) and (30) with the derived J_{ijkl} and λ_{ij} in Eqs. (27) and (28), respectively. Third, we evaluated the obtained solution by the objective function Eq. (16), and calculated the average throughput per UE.

We have used 6 problem instances: AP9UE45, AP16UE80, AP36UE180, AP49UE245, AP64UE320, and AP100UE500; the numbers after AP and UE indicate the number of APs and UEs deployed in 150m $\times$ 150m area for each instance. The available channel is $|CH| = 4$ in all simulations, and five UEs are connected to each AP, and each position is fixed. In AP100UE500, 400 ($= |AP| \times |CH|$) Ising spins are required for the calculation.

The simulation results are shown in Fig. 2. These results represent the average user throughput of 10 runs divided by the best solution for each problem instance; the value of 1 implies that the optimizer can always find the optimal channel assignment. The results show that the channel selected by the CIM has the best performance. The results obtained by the CIM are almost the same as the best solution shown in dotted line of Fig. 2. The results demonstrate the superiority of the proposed method for larger problems.

Fig. 3 shows the computational time required for each method. The CPU time for the SA and greedy algorithms has been evaluated using an Intel Xeon Gold 5222 CPU @ 3.80GHz and the C language. The CIM developed in [6] can solve the Ising problem in 5 ms regardless of the problem size, which corresponds to the time that the states of all of the Ising spins in the 1 km length optical fiber are updated for

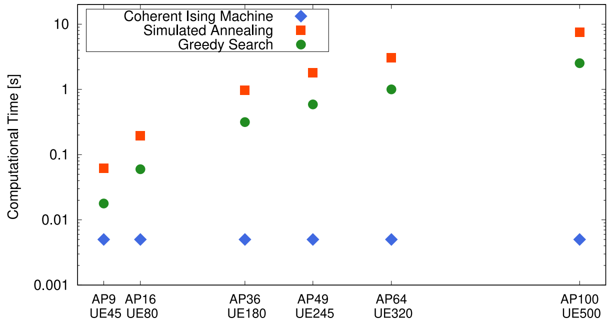

Fig. 3. Comparison of the computation times of the algorithms: CIM, SA and greedy algorithms.

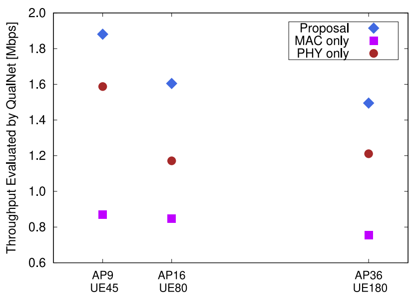

Fig. 4. Comparison of the objective function formulations, the MAC-layer-only, the PHY-layer-only, and the proposed formulation including the both PHY and MAC layers, which are optimized by the CIM, and their results are evaluated by a network simulator, QualNet.

1000 cycles. In contrast, other algorithms require more time with an increase in the problem size.

B. Comparing With Other Throughput Models

We also conducted simulation to compare the proposed method with the PHY-layer-only and MAC-layer-only throughput models. Although the proposed method considers both the PHY and MAC layers, it is compared with each one alone to verify its effectiveness. For a detailed performance evaluation of the solution, we used QualNet (version: 9.0, OS: Windows 10 x64), which is a network simulator by Scalable Network Technologies, Inc. The results in Fig. 4 show the throughput evaluated by QualNet comparing the proposed method with MAC-layer-only (MAC in Fig. 4) and PHY-layer-only (PHY in Fig. 4) throughput models.

In addition, as in the previous simulation, the throughput is the average of 10 runs using each throughput model. According to the detailed performance evaluation using the QualNet simulator, the best performance was obtained using the proposed throughput model. In AP9UE45, the proposed method improves +116% against MAC-layer-only and +18.48% against PHY-layer-only; In AP36UE180, the proposed method improves +98.39% against MAC-layer-only and +23.45% against PHY-layer-only.

V. Conclusion

In this letter, we proposed a high-speed channel assignment system using CIM. We formulated the objective function, including the MAC and PHY layers throughput models. To solve the dynamic channel assignment problem using CIM, we derived J_{ijkl} and λ_{ij} for a particular system model. The simulation results revealed that the CIM assigns channels better than the SA and greedy algorithms. Moreover, evaluation using a network simulator demonstrated that the proposed model is the best throughput model. CIM can solve combinatorial optimization problems in a short time when the problem is within a stipulated size [5], [6]. For example, a 2000-spin CIM [6] can be applied to $|AP| = 200$ and $|CH| = 10$, and the solution will be obtained in 5 ms. A larger CIM is being developed and will solve even larger-scale problems, such as a problem considering $|AP| = 10,000$ and $|CH| = 10$. These results and references show that the proposed method is the first practical application of the CIM in wireless communication systems. Further evaluation of the proposed method will be performed in future work, for a larger problem size, and other parameter settings. We will conduct more experiments on the proposed method using actual CIM.

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