Optimization of Player-Combinations in Multiplayer Games

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***Abstract*—There are many games in which a large number of players form groups, and each group plays against the other on the Internet. When separating players from a set of players into groups of the same number with players, a combinatorial explosion may occur. When trying to find the best grouping, the search consumes a considerable amount of time. Especially, in an environment where players are gathered randomly and groups are formed and disbanded one after another, as is often the case in online games over the Internet, it is necessary to find the optimal combination of players in a short period. Such grouping optimization is performed as an application on the network and focuses on the interaction of players. To cope with this combinatorial optimization problem, this study uses quantum annealing, a computational technique that has attracted much attention in recent years. In this paper, we describe the setting of the multiplayer game, define the optimal grouping requirements, and show the conversion of those requirements into Hamiltonians. The novelty is to use quantum annealing for optimization in an environment where the elements to be grouped are randomly collected, e.g., elements on a large network, where fast and accurate grouping is required. This study also presents the implementation results using Fixstars Amplify and discusses future directions.**

Keywords*—*Ising machine, Quantum annealing, grouping optimization, multiplayer game

I. INTRODUCTION

There are many games in which a large number of players form groups, and each group plays against each other. Examples include soccer and baseball in sports. When considering the optimal grouping of a large number of players, a combinatorial explosion may occur. Especially in an environment where players are gathered randomly and groups are formed and disbanded one after another, as is often the case in online games over the Internet, it is necessary to find the optimal combination of players in a short period. Such grouping optimization is performed as an application on the network and focuses on the interaction of players. Typically, we use the grouping algorithm based on rating of players, indicators of player strength, role, geographic location, and so on. In an effort to reduce the time required for grouping, the best grouping may be given up. However, if grouping is completed with only a small amount of information of players, their satisfaction may not be achieved.

Quantum Annealing (QA) was proposed by Kadowaki and Nishimori in 1998 [1], and has attracted attention as a computation technique specialized for combinatorial optimization problems. A combinatorial optimization problem is a problem of searching for an alternative that satisfies given constraints and minimizes an evaluation function out of a huge number of ones.

In this paper, to ensure optimal matching between groups, we perform grouping taking into account the rating and role of players, using quantum annealing. We define the optimal grouping requirements and convert it to a Hamiltonian, and evaluate by comparing execution times and accuracy with other methods. The novelty is to use QA for optimization in an environment where the elements to be grouped are randomly collected, e.g., elements on a large network, where fast and accurate grouping is required.

The rest of the paper is as follows. Section 2 explains technique used in this study and multiplayer game. Section 3 describes the details about formulation. Section 4 shows an experiment result and Section 5 concludes this paper.

II. RELATED WORK

A. Quantum Annealing

Optimization methods based on quantum annealing are a rapidly growing field in recent years. This technique is a very promising approach to solving combinatorial optimization problems using the principles of quantum mechanics. Compared to classical annealing methods, quantum annealing has high parallelism and exponential efficiency [2], and is expected to be applied to large-scale optimization problems. Traditionally, annealing has been limited to theoretical approaches and mathematical modeling, but advances in quantum hardware have made it possible to generate these quantum states on real physical devices. Several platforms, including the quantum annealer of D-Wave System and Qiskit Aqua of IBM, are developed, and experiments have been being conducted by the research community [3, 4]. In addition, various applications of quantum annealing are being explored. Problems have been attempted in such diverse areas as graph theory, clustering, and machine learning [5, 6, 7]. QA has shown promising results for severe NP-hard problems, as the traveling salesman problem and the maximum cut problem [8, 9], opening up new possibilities for solving problems that are difficult to solve using classical methods.

B. Multiplayer Games

Games exist in many forms, one of which is the multiplayer game. This is a game in which multiple people play against or cooperate with each other. In this study, we assume that the players are grouped from a randomly collected set of players and that the groups compete with each other. Such multiplayer games often adopt a rating system to quantify player strength [10, 11, 12]. If there is an imbalance in competence within the group, players feel uncomfortable. Weak teams and players feel tremendous frustration when they are overwhelmed in a game [13]. If each players have a role within the group, the results showed that in virtual groups, such as those found in online games, the role variety is associated with higher performance of group, but the ability disparity is associated with lower performance [14]. To prevent this, a grouping should be made in such a way that increases the role variety within groups and eliminates the ability disparities between and within groups. However, the number of grouping combinations is enormous, and finding the best grouping among them is not an easy task [15]. A long waiting time imposes a psychological burden on the players [16]. Therefore, spending a long time for finding the optimal grouping is not effective. Saito et al. evaluated grouping optimization for compatibility among members using quantum annealing [17]. In this study, grouping optimization is performed using parameters that depend only on the players themselves, not on the compatibility between players.

III. PROBLEM DEFINITION AND FORMULATION

In this section, we explain the Ising model and QUBO, the evaluation function used in QA, and the problem definition in this study.

A. Ising Model and QUBO

The search of QA is performed by finding the ground state of the Hamiltonian as follows, which is called the Ising model.

$$H(\sigma) = -\sum_{i<j} J_{ij}\sigma_i\sigma_j - \sum_{i=1} h_i\sigma_i \tag{1}$$

Here, $\sigma_i, h_i, and\ J_{ij}$ are the state of the ith qubit which can take values ±1, the bias on each of the qubits, and interaction between two qubits, respectively. First, the state of each spin is made quantum mechanically indeterminate. The spins are initially set to take on two states at the same time in the quantum mechanical sense, in the absence of being determined whether the value of the spins is either $+1$ or -1. Then, as the quantum mechanical effects, or quantum fluctuation, are gradually reduced, the interaction between the spins and the influence of the local magnetic field are strengthened, so that each spin autonomously chooses a state that is determined to be either ±1 toward the ground state of the Hamiltonian (1) of the Ising model. In solving optimization problems, instead of Ising variables, we sometimes formulate them using binary variables whose values are 0 or 1. By converting the binary variable q_i to the Ising variable σ_i as in (2), the problem can be formulated as a quadratic polynomial in binary variables, which can also be solved by a quantum annealing machine.

$$q_i = \frac{\sigma_i + 1}{2} \tag{2}$$

This quadratic polynomial by binary variables is called Quadratic Unconstrained Binary Optimization (QUBO). As the name suggests, QUBO is unconstrained. Therefore, depending on the problem, it may be necessary to add constraints as penalty terms in the objective function.

B. Problem Definition

We consider optimal grouping of random players in multiplayer games. The game has an element called a role, and players are assigned to one of several roles. As parameters, players have a rating, which represents their general strength, and an expertise, which is how good they are at each role. The rating is a numerical representation of a players' ability or skill in the multiplayer game. It indicates how good a player is in the game, similar to a ranking or rating in sports. For example, just as a soccer player is rated based on specific skills and accomplishments, the players' strength is rated based on their performance and achievements. The role refer to the players' role in the multiplayer game and the tasks for that they are responsible. This is similar to positions in sports or teamwork. For example, just as a goalkeeper in soccer plays a defensive role, a player in a game engages in a specific role. There are offensive and defensive roles, and their combination in a group contributes to the team's overall victory.

TABLE I. Example of Ratings and expertise with 4 players and 2 roles

Player	Rating	expertise of Role 1	expertise of Role 2
1	1.1	5	2
2	1.8	3	4
3	1.9	5	4
4	1.2	1	3

Under these assumptions, we define the requirements for optimal grouping as follows.

1. Minimizing the variance of strength within a group.
2. Avoiding overlapping roles of players in each group.
3. Assigning each player the role the player performs the best with.

In addition to these, we add three additional constraints.

4. Players having only one role.
5. Players belonging to only one group.
6. The number of people per group being fixed.

If the number of people per group is equal to the number of roles, overlapping of roles can be avoided completely, but if the number of roles is smaller, overlapping must be allowed. An example with 4 players, 2 roles, and 2 groups is shown in Table I. This is an example where overlapping roles can be perfectly avoided. From requirements 3 above, players 1, 2, 3 and 4 should ideally be assigned to roles 1, 2, 1 and 2, respectively. Here, the strength of a player for a given role is calculated as the product of players' rating and expertise, i.e., Player 1 with Role 1, Player 2 with role 2, Player 3 with Role 1, and Player 4 with Role 2 are 5.5, 7.2, 9.5, and 3.6, respectively. If we try to minimize the variance of strength within a group from requirements 1, players 1 and 4, and players 2 and 3 will be in the same group. Since the roles of the two players in the group are different, requirement 2 is satisfied.

C. Mathematical Models

A QUBO model of the grouping optimization considering role of players is formulated as follows.

Let us define $p \in P$, $g \in G$, $r \in R$, and N as a player, a group, a role, and the number of players per group, respectively. In addition, let $e_{p,r}$ and s_p denote the expertise of player p in role r and the rating of player p, respectively. We define the binary variables needed to construct the objective function as follows.

$$q_{p,g,r} \tag{3}$$

where q is 1 if player p belongs to group g and is assigned to role r, and 0 otherwise. In the search for the optimal grouping, we use the variance of strength per group, V_g, which we define here.

$$V_g = \frac{\sum_{p\in P}\sum_{r\in R}\left(s_p e_{p,r} q_{p,g,r}\right)^2}{N} - \left(\frac{\sum_{p\in P}\sum_{r\in R} s_p e_{p,r} q_{p,g,r}}{N}\right)^2 \quad (4)$$

In the first term, the average of the squares of the players' strength in a particular group g is computed. In the second term, the squares of average of the players' strength in g.

From the (3) and (4), we compose Hamiltonians that express each requirement and constraint.

1. Minimizing the variance of strength within a group.

$$min \sum_{g\in G} V_g \quad (5)$$

Equation (5) means that the variance of strength of player per group should be minimized so that players of the same strength are grouped together as much as possible.

2. Avoiding overlapping roles of players in each group.

$$min \sum_{g\in G}\sum_{r\in R}\sum_{\substack{a,b\in P\\ a\neq b}} q_{a,g,r} q_{b,g,r} \quad (6)$$

Equation (6) means that avoiding overlapping roles of players in each group by minimizing the sum of the products of binary variables for the same role of different players belonging to the same group.

3. Assigning each player the role the player performs the best with.

$$min \; -\sum_{g\in G}\sum_{r\in R}\sum_{p\in P} e_{p,r} q_{p,g,r} \quad (7)$$

Equation (7) means that maximizing the sum of the strengths for the roles assigned to a player, so that assigning each player the role the player performs the best with.

4. Players having only one role.

   and

5. Players belonging to only one group.

$$\forall p \in P, \sum_{g\in G}\sum_{r\in R} q_{p,g,r} = 1 \quad (8)$$

For each dimension p of the binary variable $q_{p,g,r}$, there is only one qubit with the values 1, the others are 0.

6. The number of people per group being fixed.

$$\forall g \in G, \sum_{p\in P}\sum_{r\in R} q_{p,g,r} = N \quad (9)$$

For each dimension g of the binary variable $q_{p,g,r}$, the total number of elements with value 1 is N.

D. Hamiltonian

Based on the definitions in 3.C, the Hamiltonian to be minimized is as follows.

1. Minimizing the variance of strength within a group.

$$H_1 = \sum_{g\in G} V_g \quad (10)$$

2. Avoiding overlapping roles of players in each group.

$$H_2 = \sum_{g\in G}\sum_{r\in R}\sum_{\substack{a,b\in P\\ a\neq b}} q_{a,g,r} q_{b,g,r} \quad (11)$$

3. Assigning each player the role the player performs the best with.

$$H_3 = -\sum_{g\in G}\sum_{r\in R}\sum_{p\in P} e_{p,r} q_{p,g,r} \quad (12)$$

4. Players having only one role.

   and

5. Players belonging to only one group.

$$H_4 = \sum_{p\in P}\left(\sum_{r\in R}\sum_{g\in G} q_{p,g,r} - 1\right)^2 \quad (13)$$

6. The number of people per group being fixed.

$$H_5 = \sum_{g\in G}\left(\sum_{r\in R}\sum_{g\in G} q_{p,g,r} - N\right)^2 \quad (14)$$

We also define penalty coefficients as parameters, and the sum of the products of these and each Hamiltonian is the objective function used in this study. The larger λ is, the greater the effect of that them on the Hamiltonian.

$$H = \lambda_1 H_1 + \lambda_2 H_2 + \lambda_3 H_3 + \lambda_4 H_4 + \lambda_5 H_5 \quad (15)$$

Finally, the solution is the combination of binary variables q such that the value of equation (15) is minimized.

IV. Implementation and Results

This section describes the implementation and results.

A. Implementation Environment

In this study, the implementation is done with Amplify SDK, a middleware library for Ising machines developed by Fixstars Corporation [11]. This is because it is compatible with a variety of Ising machines and solvers, including D-Wave. Ising machines specialize in solving optimization problems described by quadratic polynomials of binary variables.

B. Considerations Regarding Penalty Coefficients λ

We have a penalty coefficient λ for each term in the Hamiltonian, and depending on its value, the solution may not be obtained. Basically, the magnitude of these coefficients serves as an indicator of how important each term in the objective function is in solving the problem and how strictly the requirements must be satisfied. First, let us consider the penalty coefficients of the constraints, λ_4 *and* λ_5. These coefficients are set to 1 because the constraints must be satisfied. In this experiment, for simplicity, the number of people per group and the number of rolls are set to be equal. Therefore, for the same reason, λ_2 is also set to 1. Next, we consider λ_1. We change the value of λ_1, and adopt it that results in the smallest sum of variances in all groups. We set the number of players, roles, and players per group to 100, 5,

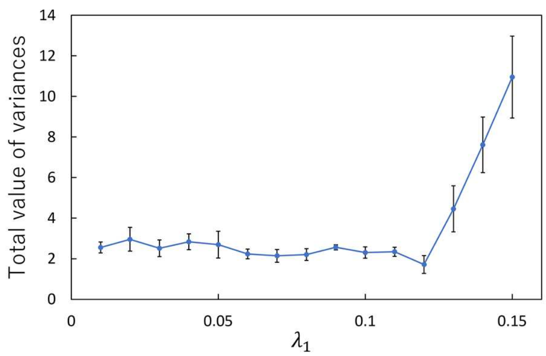

Fig 1. Total value of variances when changing λ_1

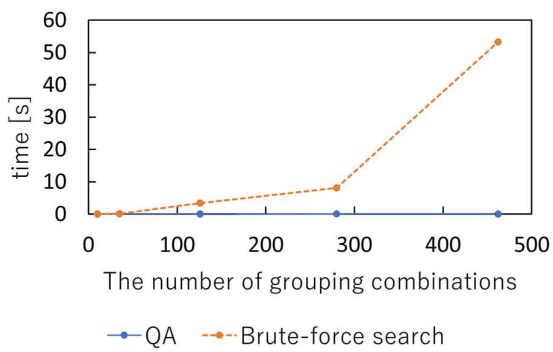

Fig 2. Comparison of time between QA and Brute-force search

TABLE II. The number of combinations of grouping for each |P| and |G|

|P|	**|G|**	**The number of combinations of grouping**
6	2	10
8	2	35
10	2	126
9	3	280
12	2	462

and 5, respectively. In addition, the rating of the players is set from 1.0 to 1.9 in increments of 0.1, and the degree of expertise is set from 1 to 5 in increments of 1. This time, we use random numbers to determine those two parameters and fixed the seed value. λ_3 is temporarily set to 0. The results are shown in Figure 1. Because of the stochastic nature of QA, the result may change with each run. In particular, this often happens with the (10) in this study. Therefore, we plot the average value of five runs on the graph. Standard deviations are also used for the error bars.

It can be seen that the annealer can find a solution between 0.01 and 0.12 that reduces the variances. In addition, no solution is obtained for values greater than 0.15. Finally, we consider λ_3. λ_1 is set to temporarily set to 0. We check the degree of expertise corresponding to the roles actually

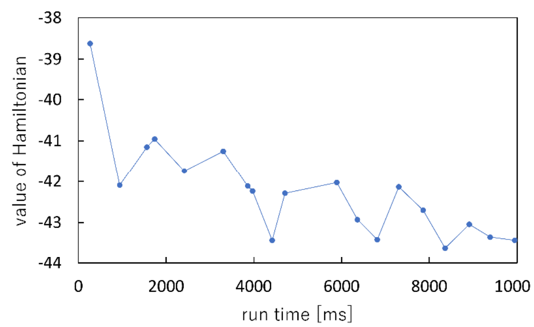

Fig 3. Transition in Hamiltonian values

assigned to the players. As a result, even if we changed λ_3 from 0.1 to 0.6, the player is assigned to the role in which he or she is most proficient without any problem. This means that if the only requirements excluding the constraints are H_2 and H_3, then the optimal solution can be found.

C. Comparison with Brute-force Search

Since there is not always a solution that minimizes H_1 and H_3 at the same time, λ_3 was set to 0, i.e., compared with the Brute-force search with the objective of minimizing the sum of variances. The Brute-force search is performed as follows. First, all grouping combinations to be made from the set of players are obtained. Next, for each grouping in each combination, all the role assignment patterns are tested, and the one with the smallest variance is adopted. Finally, the grouping with the smallest sum of variances across all groups is selected as the solution. Table II shows the combinations of the number of players and groups used in the comparison. The case where the number of players is 2 excluded because of the lack of significance in using variance. The time taken to find the optimal solutions is compared for each number of grouping combinations. The results are shown in Figure 2.

The Brute-force search diverges at a faster stage, while QA finds a solution in a time that remained almost the same even as the number of grouping combination increased. QA solves any problem size in 0.06 to 0.08 seconds.

D. Transition in Hamiltonian Values

How well the solution meets the requirements can be evaluated by the value of the Hamiltonian. In other words, the smaller it is, the closer it is to the optimal solution. We observe how the Hamiltonian value changed as the run time is increased. The number of players, rolls, and players per group are set to 100, 5, and 5, respectively. λ_1 and λ_3 are set to 0.1. The results are shown in Figure 3. Overall, the Hamiltonian values become smaller with longer execution time, but are not stable. With the player parameters used in this experiment, if we assume that all players are assigned to the role in which they are best at, the value of H_3 would be -46.0. In other words, assuming the ideal form where the sum of the variances of each group is zero and all other requirements are satisfied, the lowest value of the Hamiltonian is -46.0.

V. Conclusion and Future Prospects

There are many games in which a large number of players from groups, and each group plays against each other. When separating players from a set of players into groups of the same number of players each, a combinatorial explosion may occur. Defining the optimal grouping, the search consumes a considerable amount of time. Especially in an environment where players are gathered randomly and groups are formed and disbanded one after another, as is often the case in online games over the Internet, it is necessary to find the optimal combination of players quickly. We regard that as a combinatorial optimization problem and solve it using quantum annealing, a computational technique that has attracted much attention in recent years. In this paper, we describe the setting of the multiplayer game, define the optimal grouping requirements, and show the conversion of those requirements into Hamiltonians. Experiments show that to find a solution, it is necessary to set appropriate penalty coefficients for the value range of the data. The Brute-force search diverges at a faster stage, while QA finds a solution in a time that remained almost the same even as the number of grouping combination increased. Even with huge problem sizes of 100, 5, and 5, the number of players, roles, and players per group, respectively, QA finds solutions that satisfy the requirements perfectly or to some extent.

Future prospect is adding additional conditions and running on other annealing machines. We plan to compare it with other methods. Additionally, we make the system running on a server of a real online game and evaluate its performance.

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