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Original article

Harnessing the Power of Quantum Computing to Build an Ideal Team and Line-Up for the Euroleague Fantasy Challenge

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Abstract

Quantum computing (QC) is a computational science that provides efficient results for solving optimization problems. Quantum annealing (QA) is a form of QC and leverages superposition and quantum tunneling, which are phenomena of quantum mechanics. QA is used to solve real-life problems thanks to its superior properties. Therefore, studying QA with a specific focus on fantasy sports based on realistic scenarios offers a relatively under-explored, but promising approach, which represents the primary motivation of this study. Thus, this study presents a mathematical model for the Euroleague Fantasy Challenge (EFC) by Euroleague based on binary integer programming (BIP) to build the ideal team by selecting 10 players and one head coach among 288 players and 18 head coaches, in such a way that some team-building criteria set by the EFC are met and the PTM (Avg points) is maximized. To achieve it, this study uses the open-source Python library PyQUBO to express this model in the quadratic unconstrained binary optimization (QUBO) form and solves this model in the QUBO form through the D-Wave's Leap Hybrid (quantum-classical) Solver to identify the ideal basketball team and head coach. Accordingly, a mathematical model based on BIP is presented to find the team formation with the highest PTM (Avg points) value, considering various potential team formations for the chosen team. It then converts this model into the QUBO form in the PyQUBO library and solves it on both the D-Wave's Advantage 4.1 and Hybrid Solver. Both solvers suggest the same line-up (1 guard, 3 forwards, 1 center) as the ideal line-up. This study will hopefully contribute to the relevant field by encouraging further studies to leverage QC to guide complex decision-making processes in all team sports.

Keywords: Quantum Annealing, Fantasy Basketball, Euroleague Fantasy Challenge, Quantum Optimization, QUBO, Pyqubo, D-Wave's.

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INTRODUCTION

Quantum computing (QC) offers efficient solutions to challenging optimization problems through the gate-based model or the quantum annealing (QA) (Apolloni, Carvalho, & De Falco, 1989; Kadowaki & Nishimori, 1998; Hauke, Katzgraber, Lechner, Nishimori, & Oliver, 2020; Rajak, Suzuki, Dutta, & Chakrabarti, 2022) method. The QA method represents a heuristic method inspired by the simulated annealing (SA) (Kirkpatrick, Gelatt & Vecchi, 1983) method and seeks to find the optimal energy by drawing on phenomena such as superposition and quantum tunneling provided by quantum mechanics. This method formulates the problem to be solved as an energy problem and finds the ground state corresponding to the lowest energy. To do so, the problem must be expressed mathematically in the form of quadratic unconstrained binary optimization (QUBO) or Ising Model. Many real-world problems have been mathematically modeled in the QUBO or Ising model and addressed through the QA method (Neukart et al., 2017; Salehi, Glos & Miszczak, 2022; Domino, Kundu, Salehi & Krawiec, 2022; Ikeda, Nakamura & Humble, 2019).

Basketball, like many different sports, has a complex nature as it involves many choices. For example, choices that may affect the outcome of the match and the success of the team in the long term, such as head coach selection, player selection, lineup of selected players, need to be made by taking into account many and different elements (game strategy, budget, opposing team, etc.) and these choices are actually realities. It represents the problem of life. Scenarios that change instantly in a basketball match show how close the choices made are to real-life problems. Thanks to the superior features of QC and the currently available quantum technologies, the ability to solve such a problem based on a real scenario promises hope for solving problems based on more complex real scenarios in the future.

Fantasy sports allow individuals to build virtual teams based on real scenarios, participate in paid or free tournaments and win prizes in digital platforms. Being a branch of fantasy sports, fantasy basketball offers many leagues (National Basketball Association (NBA), Euroleague, and so on) in which individuals can compete against each other. The Euroleague Fantasy Challenge (EFC) (Euroleague Fantasy Challenge, n.d.) is one of such platforms that has two different fantasy basketball leagues: Euroleague and Eurocup. This platform has two game modes: Classic mode and draft mode. Each player and each head coach have a credit value; to create a team of 10 players (four guards, four forwards, two centers) and one head coach, you must either click the “random team” button (which allows the system to assign a random team) or pick the players and coach of your own choice within a specific credit budget (Euroleague Fantasy Challenge Rules, n.d.).

Building a team for both real sports and fantasy sports is a complex undertaking. Similarly, determining the most ideal game strategy and players based on the performance data of the players who will play in the game represents another important problem. In the relevant literature, Mahrudinda et al. (Mahrudinda, Supian & Chaerani, 2020), modeled 11 players from a sample of 17 players to form the line-up for the Liverpool F.C in the 2020-2021 season considering the rating values of the players in binary integer programming (BIP) format for two different formations; they, then, solved the model through the R programming language and found the game formation and line-up that yielded the most optimal solution. Following that, Iturrospe (Iturrospe, 2021) stated the model by Mahrudinda et al. (Mahrudinda et al., 2020) in the BIP format as a Binary Quadratic Model (BQM) and solved it on the D-Wave's Hybrid Solver. The researcher compared the results and revealed that a small improvement in the game formation and line-up can be obtained. Gurobi Optimizier by Gurobi Optimization presented two solution examples for fantasy basketball that predict players' fantasy points by means of machine learning using the historical data of NBA players (Combining machine learning and optimization modeling in fantasy basketball, 2023). In the first example, they predicted future fantasy points of players and identified the optimal line-up of five players considering the budget and position eligibility constraints. In the second example, they also demonstrated a predictive model to forecast fantasy points of players and further extended the optimization model in the first example to fulfill the requirements of the "DraftKings" contest for the optimal line-up of players.

To date, team formation or selection of the best players in team sports other than football and basketball has been investigated by several optimization studies drawing on classical methods (Das, Mukherjee, Patel & Pauli, 2023; Robel, Khan, Ahammad, Alam & Hasan, 2024; Jha, Kar & Gupta, 2023). However, as far as we know, there is no study in the literature that both builds a team and finds the best line-up considering the PTM values using QC for the EFC in European basketball. This study aims to show that the superior features of quantum computing allow to solve difficult problems encountered in real life. The motivation of this study is to form a team in EFC and to determine the most optimal formation, both of which represent a real-life scenario. To achieve this, this study draws on the real statistics recorded at the end of the first 13 weeks of the 2023-2024 season for the classical mode of the Turkish Airlines Basketball League in the EFC, and presents a mathematical model with an objective function to select 10 basketball players (four guards, four forwards, two centers) and one head coach with the highest PTM values among a total of 288 players (110 guards, 113 forwards, 65 centers) and 18 head coaches to form a team in such a way that the credit limit increasing every week is not exceeded. Here, it is significant to note that this study does not intend to meet the limit in the number of players that can be selected from one team during the season or play-offs phase in the EFC[1], as this would not reflect a real-life scenario.

This model is mathematically converted in the QUBO format through PyQUBO, an open-source Python library. The penalty coefficients in the QUBO format are determined by the SA method and the problem is solved through the D-Wave's Hybrid (quantum-classical) Solver to identify the 10 most ideal

[1] Although this study originally did not account for this criterion on the number of players that can be selected from one team, the results obtained in this study and presented in Table 2 fulfill this criterion.

players and one head coach (see Table 1). Then, the best line-up of 5 players by different game strategies (see Table 2) is determined through both the quantum annealing and hybrid methods. This article is structured as follows: Materials and Methods presents the QA, the Binary Quadratic Model (BQM), the QUBO model, the Ising model, the PyQUBO and the Quantum Annealers. Results and Discussion offers the BIP model for the team formation problem and presents the solution for the best line-up and thoroughly examines the solution processes using the D-Wave's Advantage 4.1 and Hybrid Solver. The last section is devoted to the conclusion.

MATERIALS and METHODS

Preliminaries

This section informs on the concepts prerequisite for the conduct of this study and for solving optimization problems with the quantum annealing method in general, provide the mathematical definitions of these concepts, and describes the Python library used for the solution process and the quantum annealers used.

Quantum Annealing (QA)

QA is a meta-heuristic method to solve optimization problems based on Adiabatic Quantum Computing (AQC) (Farhi, Goldstone, Gutmann & Sipser, 2000). The working principle of this method is presented below:

$$H(t) = \left(1 - \frac{t}{\tau}\right) H_{initial} + \frac{t}{\tau} H_{final} \tag{1}$$

where $t \in [0, \tau]$; $H_{initial}$ is the initial Hamiltonian state; H_{final} is the final Hamiltonian state, the system is only in the initial state $H_{initial}$ at the moment $t = 0$, and then evolves into the state H_{final} at the moment $t = \tau$, which gives the desired solution (Farhi et al., 2001).

Binary Quadratic Model (BQM)

BQM has a structure that includes both the Ising and the QUBO models through the D-Wave's system (D-Wave, Ocean-Dimod-Models: BQM, CQM, QM, others, n.d.). Below is the mathematical definition of the BQM model:

$$E(v) = \sum_{i=1} a_i v_i + \sum_{i<j} b_{i,j} v_i v_j + c \tag{2}$$

where $v_i \in \{-1, +1\}$ or $\{0,1\}$. If $v_i \in \{-1, +1\}$ represents the Ising model, $v_i \in \{0,1\}$ represents the QUBO model.

Quadratic Unconstrained Binary Optimization (QUBO)

QUBO has variables in the form of $\{0,1\}$ $(x_i = x_i^2)$ and called binary. Below is the most general form of the QUBO model:

$$\min/\max\ y = x^T.Q.x \tag{3}$$

where x represents a binary vector; x^T is the transpose of x; Q represents an upper triangular square matrix with real coefficient (Glover, Kochenberger & Du, 2019).

Ising Model

The variables of the Ising model are in the state $s_i \in \{-1, +1\}$ based on statistical mechanics and expressed as spin (down ↓, up ↑); many optimization problems are modeled in this form (Lucas, 2014). The most general form of the Ising model is provided below:

$$H(s) = \sum_i h_i s_i + \sum_{i<j} J_{i,j} s_i s_j \tag{4}$$

where J is the interactions between the neighbouring spins; h represents the impact of an external magnetic field.

PyQUBO

PyQUBO is an open-source Python library that can convert the objective functions and constraints that form optimization problems into the QUBO format (Zaman, Tanahashi & Tanaka, 2021). Once these problems are converted into the QUBO format, they can be solved through quantum annealers.

D-Wave's Advantage and D-Wave's Hybrid (Quantum-Classical) Solver

D-Wave's is a commercial QC company that seeks to solve optimization problems through QA and Hybrid (quantum-classical) Solvers using various quantum annealers (D-Wave's 2000Q, D-Wave's Advantage). Each annealer, such as D-Wave's 2000Q (Chimera), D-Wave's Advantage (Pegasus), has its own unique number of qubits and graph architecture. This study uses the D-Wave's Advantage 4.1 (McGeoch, & Farre, 2021). version with the Pegasus topology for the pure quantum annealing. In this Pegasus topology, where not all qubits are connected to each other through couplers. This entails matching of logical variables to physical variables on the machine. Therefore, this study used Minor Embedding provided by D-Wave's Advantage QPU to facilitate the process. To connect logical qubits and physical qubits to each other, it is prerequisite to use a parameter expressed by chain strength. The optimization problem may be overridden when the chain strength is set as too high; a too low chain strength value, on the other hand, may result in chain breaks in the sample set. For this reason, the first good guess for tuning this parameter is to set the chain strength equal to a value close to the largest absolute value in the QUBO of the problem (D-Wave, 2020). Yet, given that tuning of the chain strength parameter is beyond the scope of this study, this parameter is used as default in this study. As for hybrid (quantum-classical) computing, it utilizes hybrid_binary_quadratic_model_version2 (McGeoch, Farre & Bernoudy, 2020) which can perform calculations on up to 20,000 fully connected and 1,000,000 sparsely connected variables through the D-Wave's Leap Hybrid Solver. This version benefits from the Pegasus topology for Quantum Unit Process (QPU).

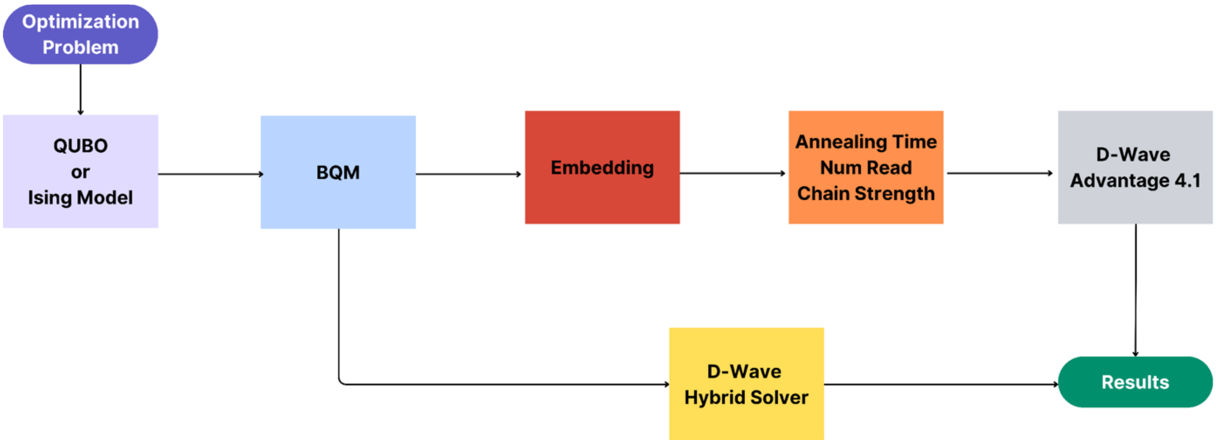

Figure 1. Workflow of Computing Process (Goodrich, Sullivan, & Humble, 2018; Fang, & Warburton, 2020; Yarkoni, Raponi, Bäck, & Schmitt, 2022)

Figure 1 includes the workflow that we created inspired by similar research in the relevant literature (Goodrich, Sullivan, & Humble, 2018; Fang, & Warburton, 2020; Yarkoni, Raponi, Bäck, & Schmitt, 2022).

RESULTS and DISCUSSION

Binary Integer Programming for the Selection of 10 Players and One Head Coach for the Euroleague Fantasy Challenge

Building an ideal basketball team is a challenging problem for both modern basketball and fantasy basketball. This study, first, proposes a mathematical model to create a better team for the EFC that meets the EFC criteria and has an additional objective function, which can replace a team generated randomly. This model is then solved through QC (D-Wave's Hybrid (quantum-classical) Solver). Below is this model in the BIP format that fulfills the Euroleague Fantasy Challenge criteria and can also maximize the PTM value.

$$\max \sum_{i=0}^{N-1} ptm_i x_i \tag{5}$$

$$\text{subject to: } \sum_{i=0}^{N-1} credit_i x_i \leq 100 + 0.3(tt - 1) \tag{6}$$

$$\sum_{i=0}^{N-1} x_i = 11 \tag{7}$$

$$\sum_{i=0}^{c-1} x_i = 1 \tag{8}$$

$$\sum_{i=c}^{g-1} x_i = 4 \tag{9}$$

$$\sum_{i=g}^{f-1} x_i = 4 \tag{10}$$

$$\sum_{i=f}^{N-1} x_i = 2 \tag{11}$$

$$x_i \in \{0,1\} \tag{12}$$

where N is the total number of players and head coaches, c = total number of head coaches, g = total number of guards, f = total number of forwards and tt is the parameter for the next round. Accordingly, Eq. (5) suggests that maximum number of players must be selected considering the PTM value; Eq. (6) implies that the sum of the coaches and players to be selected must not exceed the credit limit of 103.9; Eq. (7) shows the total number of the coaches and players to be selected; Eq. (8) suggests that only one head coach must be selected; Eq. (9) shows the number of the guards to be selected; Eq. (10) shows the number of the forwards to be selected, and Eq. (11) indicates the number of the centers to be selected. Eq. (12) represents the decision variable that equals to 1 when a player or a coach is selected and 0 if not. Also, as EFC increases the total credits at the end of each week by 0.3, which is a constraint for the selection of a player and head coach, an additional formula to increase the credit limit is added to Eq. (6). Here, it is important to note that to express the total credit of 103.9 recorded at the end of the first 13 weeks in integer format, this credit value is rounded to the nearest lower integer, that is, to 103. This study further uses the LogEncInteger encoding method provided by PyQUBO (Zaman et al., 2021) to convert Eq. (6) into the QUBO format (Lucas, 2014). The detail information that shows how the PTM values of the players and head coaches are calculated is presented in the EFC website (Euroleague Fantasy Challenge Rules, n.d.).

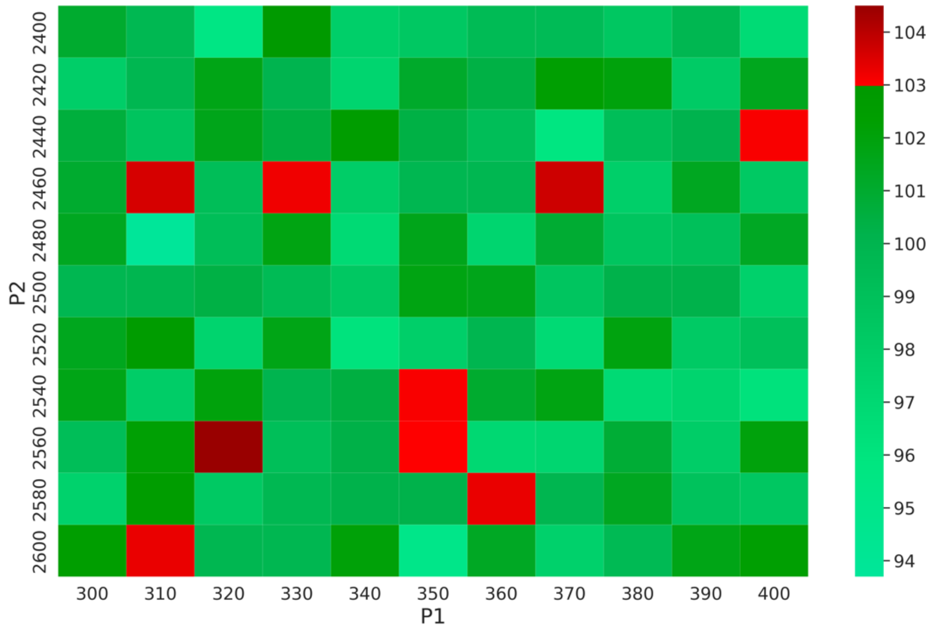

Figure 2. Parameter tuning for finding the ideal penalty coefficients

Where P1 is the penalty coefficient selected after converting Eq. (6) into the QUBO format and P2 is the penalty coefficient selected after converting Eq. (7,8,9,10,11) into the QUBO format, Figure 2 presents the data about the selection of the most ideal P1 and P2 penalty coefficients to meet all the constraints for different values. To determine these penalty coefficients, this study uses the SA method and sets the num_reads and sweeps parameters to 1000. Further, to prevent any possible error caused by the decimal point of the PTM values, each PTM value is multiplied by 100 before any calculation is performed. Thus, P1 is set to 400 and P2 is set to 2600 to solve the research problem on the Hybrid Solver.

The quantum annealer and D-Wave Hybrid Solver does not guarantee to yield the optimal solution (Ayanzadeh, Halem, & Finin, 2020; Malcolm et al., 2024). For this reason, it is important to run it more than once. Since situations where all constraints are met are expressed as feasible solutions, in this study, solutions that meet all constraints and correspond to the lowest energy provided by existing Hybrid (quantum-classical) hardware systems are considered as the optimal solution.

Table 2. The results of 10 runs on the D-Wave's Hybrid Solver.

Run	H. Coach	Guard	Forward	Center	T. Credit	Max. PTM	QPU
1.	1	4	4	2	102.4	132.69	00:277s
2.	1	4	4	2	102.9	130.9	00:314s
3.	1	4	4	2	101.4	124.35	00:270s
4.	1	4	4	2	103	128.66	00:244s
5.	1	4	4	2	101.8	132.39	00:239s
6.	1	4	4	2	99.5	128.5	00:239s
7.	1	4	4	2	99.6	126.95	00:268s
8.	1	4	4	2	103.2	124.36	00:200s
9.	1	4	4	2	102.4	131.31	00:311s
10.	1	4	4	2	102.1	134.71	00:279s

Table 1 shows the results of 10 runs on the D-Wave's Hybrid Solver, where the time limit is set to 10 seconds and the last column shows the QPU time used for each run. The reason why the problem was run for 10 times is to understand whether the penalty coefficients obtained by simulated annealing violate the existing constraints while solving the problem with Hybrid Solver, and to find the lowest energy that satisfies all constraints by running it more than once against any potential problems related to decoherence and noise in existing quantum devices. Indeed, as seen in Table 1, all constraints regarding the selection of players by position, head coach selection and credit limit are met in 9 out of 10 runs, except for the 8th run. The 8th run meets the criteria for the selection of players and head coach, however exceeds the total credit limit by 0.2 points. This implies that the Hybrid Solver has been able to yield 9 feasible solutions and one unfeasible solution in 10 runs for this problem.

Drawing on Table 1, this study further finds that the 10th run meets all the criteria and also yields the highest PTM value. Therefore, the 10th run (as shown in Table 2) represents the ideal team to be used in this study. Here, it is worth noting that the Hybrid Solver is expected to select those with the highest PTM values when deciding between players with equal credits and head coaches with equal credits. However, upon scrutinizing the 10th run, it becomes evident that this is not the case for only one player, as when deciding between Luka Mitrovic (16.12 PTM) and Tadas Sedekerskis (18.92 PTM), both of who worth the same credits, the Hybrid Solver favors Luka Mitrovic with the lower PTM value. In other words, the Hybrid Solver achieves to select the player or the head coach, among others with equal credits, with the higher PTM value for 6 out of 7 cases in the 10th run (as for the selection of the remaining 4 players, there was no player with equal credits in the 10th run, therefore, no further discussion on the selection of these 4 players is needed). As the Leap Hybrid is a probabilistic solver, it does not guarantee to yield the optimal solution (Malcolm et al., 2024). Therefore, we refrained from intervening this result and decided to proceed the study with the team in the 10th run as part of our purpose to showcase the capabilities of the Hybrid Solver.

Table 2. The list of 10 players and the head coach with the highest PTM value as found in the 10th run.

H. Coach	Credit	PTM	Guard	Credit	PTM	Forward	Credit	PTM	Center	Credit	PTM
Dusko I.	7.1	8.33	Nicolas L.	13.5	17.59	Alec P.	12.9	19.15	Damien I.	8.8	9.42
			Marco G.	11.0	12.6	Dinos M.	12.1	19.63	Alen S.	8.3	10.72
			Aleksa A.	6.1	7.19	Luka M.	11.6	16.12			
			Stefano T.	5.4	5.83	Tarık B.	5.3	8.13			

Table 2 includes the list of 10 players and the head coach with the highest PTM value, as found in the 10th run.

Team Formation through Binary Integer Programming

Team formation is of critical importance for the success of any sports team, as it is one of the factors that affect the match outcome in modern basketball as well as fantasy basketball. So much so that a team formation that does not allow players to individually realize their potential may change the course of the game or even lead the team to lose the game. This section is intended to determine the most ideal team formation using the player list formed based on the model that this study proposes for the EFC and ensuring a maximum PTM value. The mathematical expression to be used for this purpose is given below in the BIP format. Then, this expression in the BIP format is converted to the QUBO format via the PyQUBO, an open-source Python library. Following that, different team formations are solved both on the pure quantum annealer and Hybrid Solver to determine the optimal value and the list of the players corresponding to this value. The BIP model used to determine the line-up is as follows:

$$\max \sum_{i=0}^{9} ptm_i z_i \tag{13}$$

$$\text{s.t.} \sum_{i=0}^{9} z_i = p$$

$$\sum_{i=0}^{3} z_i = gs$$

$$\sum_{i=4}^{7} z_i = fs \tag{14}$$

$$\sum_{i=8}^{9} z_i = cs$$

$$z_i \in \{0,1\}$$

where p is the number of the players to be selected; gs is the number of the guard/s to be selected; fs is the number of the forwards to be selected; and cs is the number of the center/s to be selected. Eq. (13) suggests that the players to be selected must have the maximum PTM value; Eq. (14) represents the constraint related to the total number of players to be selected, that is, the constraint for selecting two guards, two forwards and one center; and the last constraint is the decision variable that equals to 1 if a player or a head coach is selected and 0 if not. The mathematical expression of Eq. (13) and Eq. (14) in the QUBO format is given below in Eq. (15), which is converted into a minimization through multiplication by -1 since the objective function represents a maximization function:

$$-\min \sum_{i=0}^{9} ptm_i z_i + \lambda \left[\left(\sum_{i=0}^{9} z_i - p \right)^2 + \left(\sum_{i=0}^{3} z_i - gs \right)^2 + \left(\sum_{i=4}^{7} z_i - fs \right)^2 + \left(\sum_{i=8}^{9} z_i - cs \right)^2 \right] \quad (15)$$

where λ is the penalty coefficient. This coefficient value must be chosen sufficiently large.

Table 3. The solutions of different team formations on the pure Quantum Annealear and Hybrid Solver.

Guard	Forward	Center	Min. E. for QA	Min. E. for Hybrid
2	2	1	-79.69	-79.69
2	1	2	-69.96	-69.96
1	2	2	-76.51	-76.51
1	3	1	-83.21	-83.21
3	1	1	-67.23	-67.23

Table 3 presents the results obtained from the solutions of different team formations on the pure quantum annealer and Hybrid Solver. Prior to moving forward with the discussion of these results, it is necessary to note that it is plausible for small-sized problems that the pure quantum annealer and Hybrid Solver yield the same or similar results; as expected, these results of this study obtained on the pure quantum annealer and Hybrid Solver are the same. Indeed, this simply means that the selected penalty coefficients meet the constraints and that both devices achieve to find the lowest energy. Now, these results demonstrate that the ideal team formation is found to be 1-3-1 for the selected list of 10 players both in the quantum and Hybrid Solver. The players in this team formation are, respectively, as follows: Nicolas Laprovittola, Alec Peters, Dinos Mitoglou, Luka Mitrovic and Alen Smailagic.

In the QA method implemented on the D- Wave's Advantage 4.1, the annealing time is set to the default value, which is 20 µs, num_reads = 1000, and the chain_strength is set to the default too. For the team formation of the Hybrid Solver, time limit is set to the default value of 3 s. The QPU used by each run for the Hybrid Solver, respectively, is 00.115 s, 00.116 s, 00.016 s, 00.066 s, and 00.033 s. Also, the penalty coefficient used in both methods is λ = 23.

Conclusion

Quantum annealing is a meta-heuristic method that offers more and more efficient solutions to optimization problems with the rapid progress of quantum technologies. This study presents a mathematical model in the BIP format that builds an ideal team of 10 players and one head coach in such a way that some EFC criteria are met and the highest PTM values are selected. Then, this model in the BIP format is converted into the QUBO format. The given constraints are translated into penalties, as required by the QUBO format. Following that, the penalty coefficients are calculated through the SA method. Then, this problem of the selection of the ideal team is solved on the Hybrid (quantum-classical) Solver to determine the list of 10 players and one head coach that corresponds to the minimum energy. Based on this list, this study presents a mathematical model in the BIP format for different team formations. Likewise, this mathematical model is converted into the QUBO format through PyQUBO, and once the penalty coefficients required are determined, this problem of the team formation is solved on the pure quantum annealer (D-Wave's Advantage 4.1) as well as the Hybrid (quantum-classical) Solver. The results of the best team formation and line-up obtained in both methods are compared. Strikingly, this study finds that both methods suggest the same team formation and line-up as the ideal team formation and line-up.

This study solves the problem of building a team with 10 players and one head coach and selecting a line-up of five players in fantasy basketball, which entails a complex decision-making process for all team sports, through a Hybrid (quantum-classical) Solver. In doing so, it follows certain team-building criteria set by the EFC and seeks to maximize the PTM values. Thus, it shows that the power of QC can be leveraged also in different disciplines with real-life scenarios. This study further concludes that the currently available pure quantum technologies are able to yield efficient ways to build player line-ups in sports. Future studies may focus on team sports other than basketball, which are characterized by complex real-time choices that have the potential to harness the power of QC.

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Conflict of Interest

The authors declare no conflict of interest.

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