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Research Article

Parameter Improvement of the Soccer League Competition Algorithm by Introducing Stubborn Players: Application to Water Distribution Network

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A modified soccer league algorithm is presented in this paper. The effect of stubborn fixed players is investigated and the algorithm is implemented to three benchmark water distribution networks. The modified algorithm is compared to several algorithms. The results show that the modified algorithm performs better than the soccer league competition algorithm, in particular, on the average number of evaluations required to find the optimal cost. Computational results show that the utility benefit of both the individual player and team is essential. The algorithm becomes more reliable when utility benefits are high and as the number of fixed players increases.

1. Introduction

Optimization techniques have been in recent years regarded as important in line with technological advancement. The reliability of these optimization techniques is essential in real world applications [1–4]. Some techniques have been introduced to improve system reliability such as the techniques that increase reliability of system components and using redundancy components in many different subsystems [5]. Several hybrid algorithms have been introduced to improve performance of heuristics such as genetic algorithms [6], simulated annealing [7], ant colony optimization system [8], and particle swarm optimization [9].

Metaheuristic algorithms have been in recent years used to solve water distribution systems such as Max-Min Ant System [10], soccer league competition (SLC) [11], harmony search optimization approach [12], and shuffled frog leaping algorithm [13]. This research is motivated by the success of the soccer league competition algorithm of Moosavian [11] to solve water distribution network problems.

The remainder of the paper is organised as follows. In Section 2, a review and modification of SLC algorithm is presented. Implementation of the modified SLC algorithm is done in Section 3 and conclusions are drawn in Section 4.

2. Review and Modification of Soccer League Competition (SLC) Algorithm

The successful implementation of the Soccer League Competition algorithm of Moosavian [11] to solve water distribution network motivates this research. The soccer league algorithm's ideas are based on the soccer league and competition among players and teams and is relatively new but its promising results have motivated this research to explore the possibilities of expansion of the algorithm. The soccer league algorithm has the following steps.

Step 1. Initialisation of the problem and algorithm parameters: this involves defining the objective function and decision variables. The number of seasons, teams in the league, fixed players, and substitutes are determined in this step.

Step 2. Samples generation is carried out in this step of the algorithm. The total number of players in the league is calculated.

Step 3. Teams assessment is done by first arranging players according to their power. The power of each team is equal to the summation of power of each fixed player in the team.

Step 4. The league starts and competitions are initialised between all possible pairs of the teams that are in the league. Winners and losers in each match are determined. Imitation operator is introduced to fixed players in the winning team. The solution vector related to the fixed players in the team is regarded as moving toward the best solution vector of the league. A new fixed player is generated based on the solution vector of the winner team's fixed players. Provocation operator is introduced to screen the substitutes. The substitutes need to prove that they are better than the fixed player in the winner team. A new solution vector of substitutes in the winner team moves toward the solution direction of the fixed players. If the new solution vector generated is better than the older solution vector, the old solution vector is replaced (see Moosavian [11] for details).

Step 5. League update is done after every season. The players are arranged taking into account their updated power. Best players are allocated to best teams, average performers to average performing teams, and weakest players to bottom teams in the league table.

Step 6. Steps 3, 4, and 5 are repeated until the number of seasons required is achieved. Relegation of weakest teams and promotion of better performing teams take place.

The third step of the SLC algorithm is modified in order to achieve a better assessment of the teams in the league. Since power of fixed players in the team is used to determine the power of the teams, an attempt to incorporate stubbornness among the fixed players is carried out. It is a fact that most super star players become stubborn due to praises and they are usually assured of their fixed player status in most teams. It is therefore imperative to include this fact in the metaheuristic so as to improve its performance. Definitions of terms that are used are presented in "Definitions of Terms" section.

The team power is basically defined as the average power of its fixed players. The algorithm of Moosavian [11] did not incorporate the possibility of stubborn players. Stubborn players have an effect on the power of team which is an important aspect of the SLC algorithm. Team power is the most important part of winning the game. The power of player, as defined in the SLC algorithm, $P_{i,j}$, is

$$P_{i,j} = \frac{1}{F_{i,j}}, \quad i \in T, \; j \in J. \tag{1}$$

Incorporating the proposed effect of the stubborn players into (1) is presented as follows. We start by looking at the utility function of the team, T, which is given as follows:

$$U_i = B_m - C_m + b. \tag{2}$$

The team's performance can be affected by bribes given to either the couch or player or both. The utility function of the individual player is presented by (3) taking note of the effect of bribe. Bribes cannot be neglected when we are talking of soccer games:

$$U_j = \alpha\pi + H - \beta W_m - b. \tag{3}$$

Using (1) to (3), the power of an individual player can be formulated as in (4) since performance of an individual player is affected by the behavior of the couch toward each game:

$$P_{i,j} = \frac{1}{F_{i,j} \times \gamma \left[U_i + U_j\right]}. \tag{4}$$

The total team power is based on the power of each fixed player. It is therefore important to find the probability that the stubborn player secures the fixed position in the team. The probability that a stubborn player secures a fixed position in the team can be calculated as follows:

$$\begin{aligned} \epsilon(j) = {} & \tilde{\eta}(\sigma)\,\delta(x_j)\,R + \left(1 - \delta(x_j)\right) Q \\ & + \left[1 - \tilde{\eta}(\sigma)\right] x_j E - Q. \end{aligned} \tag{5}$$

Now, the total team power can be calculated by the following:

$$Y_i = \frac{1}{N_i} \sum_{j=1}^{N_i} \epsilon(j)\, P_{i,j}. \tag{6}$$

Figure 1 shows the flow chart of the modified soccer league algorithm.

3. Numerical Examples

Implementation of the modified soccer league algorithm is carried out in this section. Formalisation of steps required for comparing metaheuristics is important. In Chiarandini et al. [30], two main models were introduced and these are the univariate and multivariate models taking into account the solution cost and run time. There are good practices required to fairly compare metaheuristics. It is important to use benchmark problems [31]. It is also vital to present results in a way that allows fair comparisons of metaheuristics. These include showing execution time and the mean number of iterations to obtain the best result. The execution time and quality of solution are regarded as the main performance measures of primary interest. McGeoch [32] presents a detailed explanation of experimental analysis of algorithms.

In this paper, these best practices are implemented for a fair and effective comparison of the proposed modified heuristic with the other heuristics available in the literature. Three benchmark problems, that is, the two-loop, Hanoi,

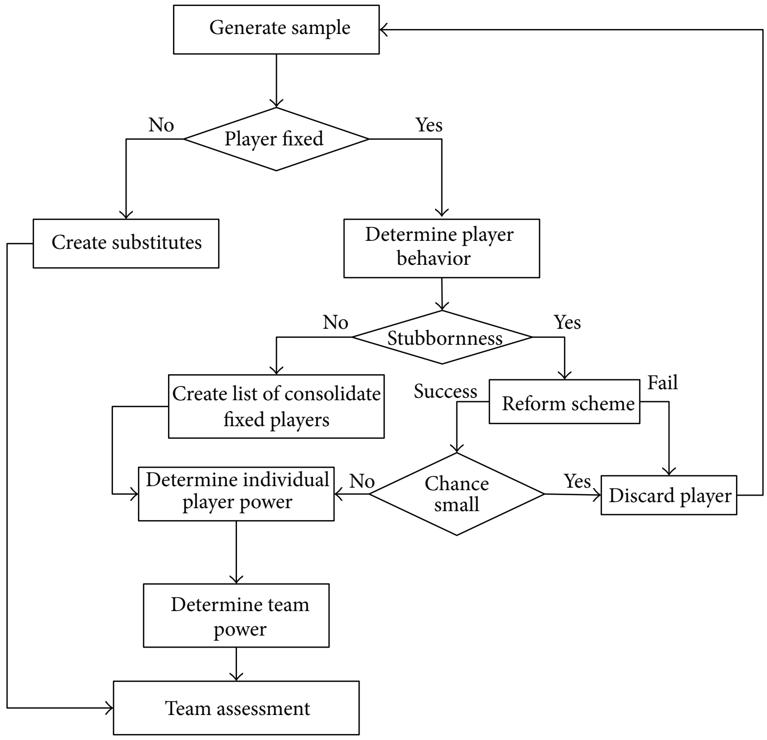

Figure 1: Modified soccer league algorithm flow chart.

Table 1: Control parameters choice and average values.

Parameter	Initial/manual value	Average computational value
γ	0.1	0.821
β	30% of b	51% of b
α	2%	45.9%

and New York Tunnels water networks, are used to test the performance of the modified heuristic. Computations are executed in MATLAB environment on a PC with AMD E-300 APU with RadeonTM @1.30 GHz and 4.00 GB RAM. A total of 100 runs are performed for each problem recording the number of evaluations and the optimal cost.

The control parameters are α, γ, and β. Sequential Parameter Optimization (SPO) introduced by Bartz-Beielstein et al. [27] is used to tune the parameters. The algorithm is allowed to perform a total of 1000 tests and is repeated 50 times. An initial population of 100 is used. Table 1 presents the initial values of the parameters used to perform the tests and the average values that are then used in the computational experiments. It is noticed that there is an inverse relationship between b and β; that is, as $b \to \infty$, then $\beta \to 0$.

3.1. Two-Loop Water Network. A two-loop network problem of Alperovits and Shamir [28] is considered. The problem has 1 reservoir, 7 nodes, and 8 pipes. Figure 2 is the diagrammatic presentation of the network. The pipes in the network, all of them, are 1000 m long. Table 3 shows the cost data of available pipe diameters in both inches and millimeters.

Table 2: Two-loop network node information.

Nodes	Demand (m^3/h)	Elevation (m)
1	−1120	210
2	100	150
3	100	160
4	120	155
5	270	150
6	330	165
7	200	160

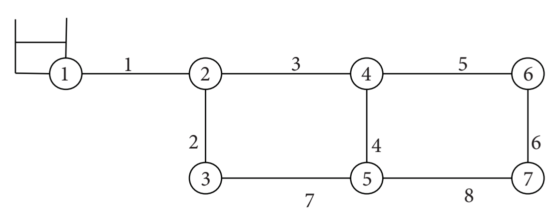

Figure 2: Two-loop water network.

Table 2 shows the node information of the network. The results are compared to those of genetic algorithm (GA) [14], simulated annealing algorithm (SA) [15], shuffled leapfrog algorithm (SLA) [13], shuffled complex algorithm (SCA) [16], modified genetic algorithm [17], particle swarm optimization (PSO) [18], differential evolution (DE) [19], harmony search (HS) [12], scatter search (SS) [21], PSO + DE [18], particle swarm harmony search (PSHS) [20], and SLC [11].

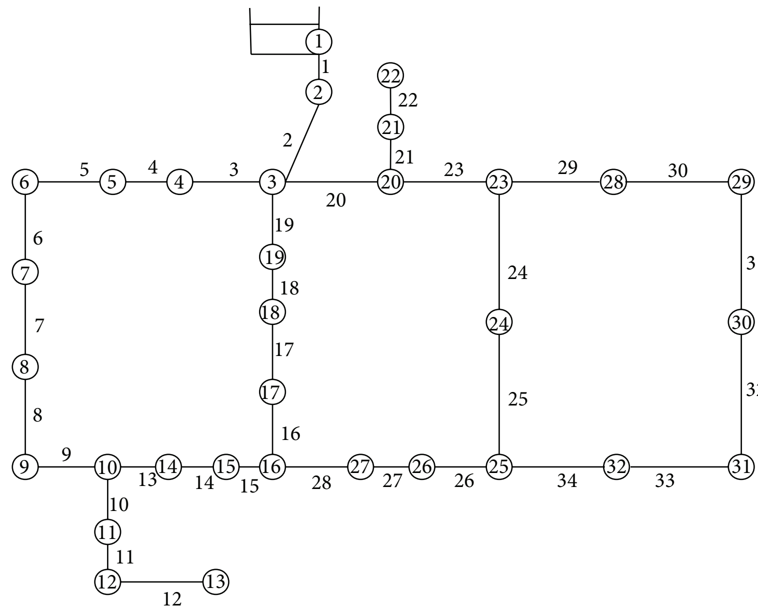

Figure 3: Hanoi water networkt.

Table 3: Cost and diameter information for the two-loop water network.

Diameter (in)	Diameter (mm)	Cost ($/m)
1	25.4	2
2	50.8	5
3	76.2	8
4	101.6	11
6	152.4	16
8	203.2	23
10	254	32
12	304.8	50
14	355.6	60
16	406.4	90
18	457.2	130
20	508	170
22	558.8	300
24	609.6	550

Table 4: Results obtained by different metaheuristics for two-loop network.

Algorithm	Mean evaluations	Cost ($)
GA [14]	65 000	419 000
SA [15]	25 000	419 000
SLA [13]	11 155	419 000
SCA [16]	11 019	419 000
Modified genetic algorithm [17]	2440	419 000
PSO [18]	5138	419 000
DE [19]	4750	419 000
HS [20]	2891	419 000
SS [21]	3215	419 000
PSO + DE [18]	3080	419 000
PSHS [20]	233	419 000
SLC [11]	2051	419 000
Modified soccer league algorithm	1031	419 000

The computational results of the two-loop network are shown in Table 4. The modified soccer league algorithm that uses stubborn players performs better in terms of average number of evaluations (1031) as compared to other heuristics, especially, the soccer league competition algorithm. As reported in Moosavian [11], the optimal costs ($419 000) are exactly the same for all the algorithms.

3.2. Hanoi Water Network. The Hanoi network layout is shown by Figure 3. The network has 34 pipes, 32 nodes, of which one is a reservoir, and 3 loops. Table 5 presents the node and pipe data and Table 6 presents the cost information as described by Fujiwara and Khang [29]. There are 2.87×10^{26} possible designs and 6 commercially available diameters. The modified soccer league algorithm is compared to Max-Min Ant System (MMAS) [22], PSO [18], hybrid discrete dynamically dimensioned search (HD-DDS) [23], genetic algorithm pipe network optimization model (GENOME) [24], genetic heritage evolution by stochastic transmission (GHEST) [25], SS [21], DE [19], self-adaptive differential evolution (SADE) [26], and SLC [11].

The computational results are shown in Table 7. The results show that the optimal cost is the same for all algorithms. The average evaluations required by the modified algorithm to find the optimal solution are 65 443, fewer than that of MMAS, HD-DDS, and SLC. It is important to note that the modified algorithm has a success rate of 100% for the 100 runs. The algorithm performs better than the SLC algorithm in particular.

Table 5: The Hanoi network pipe and node data.

Pipe	Length (m)	Pipe	Length (m)	Node	Demand (m^3/h)	Node	Demand (m^3/h)
1	100	18	800	1	−19940	18	1345
2	1350	19	400	2	890	19	60
3	900	20	2200	3	850	20	1275
4	1150	21	1500	4	130	21	930
5	1450	22	500	5	725	22	485
6	450	23	2650	6	1005	23	1045
7	850	24	1230	7	1350	24	820
8	850	25	1300	8	550	25	170
9	800	26	850	9	525	26	900
10	950	27	300	10	525	27	370
11	1200	28	750	11	500	28	290
12	3500	29	1500	12	560	29	360
13	800	30	2000	13	940	30	360
14	500	31	1600	14	615	31	105
15	550	32	150	15	280	32	805
16	2730	33	860	16	310	—	—
17	1750	34	950	17	865	—	—

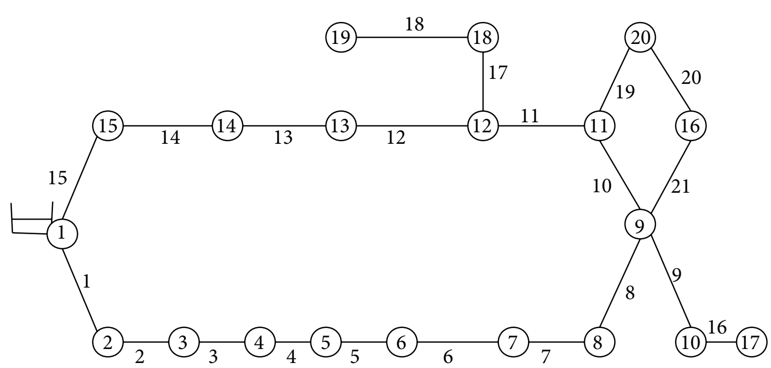

Figure 4: New York Tunnels water network.

Table 6: The cost data of the Hanoi network.

Diameter (inches)	Cost per unit length (unit)
12	45.726
16	70.400
20	98.387
24	129.333
30	180.748
40	278.280

3.3. New York Tunnels Network. The New York Tunnels city network was first presented by Neelakantan and Suribabu [17]. The network consists of 1 loop, 21 pipes, and 20 nodes as shown in Figure 4. It is fed by gravity from a reservoir. Table 8 presents the pipe length and node data of the network. The search space of this optimization problem has $16^{21} = 1.93 \times 10^{25}$ possible designs [33]. Available commercial diameters of the network and the respective costs are shown in Table 9.

The results are shown in Table 10 and 15 311 average evaluations, lower than those of SLC, SS, and HD-DDS, produced the optimal cost of $38.64 million. The best cost is found by the modified soccer league algorithm with an average success probability of 100% of 100 runs. A significant reduction in the mean evaluations from 15764 of SLC to 15 311 is worth noting.

Statistical analysis of the experimental results is performed in SPSS. Table 11 presents results of the Analysis of Variance (ANOVA). The results show that the results of the algorithms used are significantly different from each other. Nonparametric tests, as suggested by García et al. [34], are performed to analyse the behavior of the modified soccer league algorithm as compared to the other algorithms used in each experimental problem. Table 12 presents results of the Wilcoxon test. Best 30 results among the runs are selected and used to avoid the challenge of using high runs that may result in the statistical test to detect insignificant difference as significant. The results show that the modified algorithm outperformed all the other algorithms in all experimental problems.

An experiment has been carried out to understand the behavior of the modified algorithm as the input parameters

Table 7: Computational results of the Hanoi network.

Algorithm	Number of runs	Optimal cost ($)	Mean evaluations
MMAS [22]	20	6 134 087	85 600
PSO [18]	2000	6 081 087	NA
HD-DDS [23]	50	6 081 087	100 000
GENOME [24]	10	6 081 087	NA
GHEST [25]	60	6 081 087	50 134
SS [21]	100	6 081 087	43 149
DE [19]	300	6 081 087	48 724
SADE [26]	50	6 081 087	60 532
SLC [11]	50	6 081 087	71 789
Modified soccer league algorithm	100	6 081 087	68 443

Table 8: Node and pipe information of the New York Tunnels network.

Node	Demand (m^3)	Minimum head (ft)	Pipe	Length (ft)	Existing diameter (ft)
1	−22018	300	1	11 600	180
2	92.4	255	2	19 800	180
3	92.4	255	3	7 300	180
4	88.2	255	4	8 300	180
5	88.2	255	5	8 600	180
6	88.2	255	6	19 100	180
7	88.2	255	7	9 600	132
8	88.2	255	8	12 500	132
9	170	255	9	9 600	180
10	1	255	10	11 200	204
11	170	255	11	14 500	204
12	117.1	255	12	12 200	204
13	117.1	255	13	24 100	204
14	92.47	255	14	21 100	204
15	92.4	255	15	15 500	204
16	170	260	16	26 400	72
17	57.5	272.8	17	31 200	72
18	117.1	255	18	24 000	60
19	117.1	255	19	14 400	60
20	170	255	20	38 400	60
			21	26 400	72

Table 9: New York Tunnels commercially available pipe diameters and their respective costs.

Diameter (in)	Cost (US$/ft)
36	93.5
48	134
60	176
72	221
84	267
96	316
108	365
120	417
132	469
144	522
156	577
168	632
180	689
192	746
204	804

change. Unlike the SLC algorithm which uses the number of teams, fixed players, and substitutes as input parameters only, the modified algorithm uses the utility benefit of individual player, as a percentage, U_j, the utility function of the team, as a percentage, U_i, and the number of fixed players as additional input parameters. Table 13 shows the summary of computational results in terms of number of evaluations (Evalu), optimal cost (cost), and the computational time (run time).

It is shown that if both percentage benefits of the fixed player and team are high and the number of fixed players is high, the number of evaluations is reduced significantly. The computational time is as well reduced significantly. This might be as a result of the fact that the set of fixed players constructed by the algorithm eliminate those that are stubborn and concentrate only on players that are motivated by benefits they will get for winning the match. Fixed players that cost the team are penalised and eliminated from calculating the team power. The modified algorithm becomes more reliable and efficient by increasing the number of fixed players.

Table 10: Computational results of the New York Tunnels network.

Algorithm	Number of runs	Best cost ($)	Mean evaluations
MMAS [22]	20	38.64	30 700
PSO [18]	2000	38.64	NA
HD-DDS [23]	50	38.64	47 000
GHEST [25]	60	38.64	11 464
SS [21]	100	38.64	57 583
DE [19]	50	38.64	5 494
SADE [26]	50	38.64	6 598
SLC [11]	100	38.64	15 764
Modified soccer league algorithm	100	38.64	15 311

Table 11: ANOVA results of the three experimental problems.

Problem	Definition	Degrees of freedom	p value
Two-loop	Between group	12	0.002
	Within groups	1288	
	Total	1300	
Hanoi	Between group	9	0.037
	Within groups	991	
	Total	1000	
New York	Between group	8	0.041
	Within groups	892	
	Total	1000	

Table 12: Wilcoxon test of the experimental problems.

Proposed algorithm versus	Two-loop			Hanoi			New York		
	R^+	R^-	p	R^+	R^-	p	R^+	R^-	p
GA [27]	210	88	0.001	—	—	—	—	—	—
SA [28]	120	36	0.012	—	—	—	—	—	—
SLA [13]	123	37	0.033	—	—	—	—	—	—
SCA [14]	144	41	0.002	—	—	—	—	—	—
Modified genetic algorithm [15]	101	29	0.011	—	—	—	—	—	—
PSO [16]	111	33	0.012	93	24	0.002	119	89	0.003
DE [17]	213	56	0.03	117	34	0.021	144	47	0.034
HS [19]	122	37	0.041	—	—	—	—	—	—
SS [18]	144	54	0.032	127	51	0.043	154	71	0.011
PSO + DE [16]	123	77	0.037	—	—	—	—	—	—
PSHS [19]	142	56	0.000	—	—	—	—	—	—
SLC [11]	13	6	0.049	43	6	0.39	33	8	0.042
MMAS [20]	—	—	—	134	67	0.001	89	23	0.003
HD-DDS [29]	—	—	—	129	66	0.037	65	29	0.016
GENOME [22]	—	—	—	178	50	0.045	—	—	—
GHEST [23]	—	—	—	280	67	0.001	90	34	0.019
SADE [24]	—	—	—	128	44	0.029	138	79	0.022

4. Conclusion

This paper presented a modified soccer league algorithm by introducing stubborn fixed players. Each stubborn player is taken as a cost to the algorithm. Utility benefit of each individual fixed player and the team is used to calculate power of each fixed player. Probability of including a fixed player who has not reformed is also used to calculate the total team power. The algorithm is implemented to three benchmark problems and compared to the other algorithms available in the literature. The computational results show that the modified algorithm performs better than the SLC

Table 13: Sensitivity analysis of the input parameters.

Parameter			Two-loop			Hanoi			New York		
U_j (%)	U_i (%)	N_j	Evalu	Cost	Run time	Evalu	Cost	Run time	Evalu	Cost	Run time
0	0	1	1900	419 000	2.64	68500	6 081 087	4.02	15800	38.64	3.18
5	5	2	1502	419 000	2.33	68495	6 081 087	3.99	15792	38.64	3.04
10	10	3	1465	419 000	2.27	68490	6 081 087	3.56	15788	38.64	2.67
20	20	4	1392	419 000	2.12	68485	6 081 087	3.42	15781	38.64	2.55
30	30	5	1109	419 000	2.09	68480	6 081 087	3.37	15779	38.64	2.33
40	40	6	1001	419 000	1.73	68475	6 081 087	3.35	15768	38.64	2.21
50	50	7	954	419 000	1.65	68445	6 081 087	3.31	15765	38.64	2.15
60	60	8	869	419 000	1.62	68440	6 081 087	3.29	15742	38.64	2.08
70	70	9	701	419 000	1.45	68435	6 081 087	3.25	15703	38.64	2.01
80	80	10	602	419 000	1.37	68433	6 081 087	3.17	15596	38.64	2.00
90	90	11	503	419 000	1.28	68302	6 081 087	3.15	15584	38.64	1.98
100	100	12	375	419 000	1.24	68219	6 081 087	3.09	15347	38.64	1.85
Mean			1031	419 000	1.82	68433	6 081 087	3.41	15 311	38.64	2.34

algorithm in particular. It is also shown that the number of evaluations and computational time are reduced significantly as percentage benefits of both the player and team increase and the number of fixed players increases as well. It is recommended to increase the number of fixed players for the algorithm to be more reliable.

Definitions of Terms

π: Team benefit before bribe
$\delta(x_j)$: Probability of successful reform x attempt on player j
α: Fraction of the team benefits owned by the player outside the team
β: Bonus for the player for winning a match
γ: Stubbornness parameter that determines that the player's decision will be biased toward past decision
$\epsilon(j)$: The probability that the stubborn player i secures the fixed status
σ: Set of constraints
$\tilde{\eta}(\sigma)$: Updated belief of the team management based on conditionally observing σ
b: Bribe
B_m: Team benefit for winning match m
C_m: Team cost of losing the match m
E: Outcome with the opportunist reformer as fixed player status
$F_{i,j}$: Objective function
H: Season benefit of the player for winning the championship
i: Index denoting team
j: Index denoting player, $j \in J$
m: Index denoting match
N_i: Number of fixed player in a team, $i \in T$
$P_{i,j}$: Power of player
Q_j: Outcome when the player j cannot overrun the fixed player status
R: Outcome when a genuine reformer successfully secures the fixed player status
T: Team
U_i: Utility benefit of the team i, $i \in T$
U_j: Utility benefit of the individual player j
V: Genuine reformer benefit
W_m: Won match m
x_j: Maturity of reform x on player j
Y_i: Total power of team i.

Competing Interests

The authors declare that they have no competing interests.

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