A Modified League Championship Algorithm for Numerical Function Optimization Via Artificial Modeling of the “Between Two Halves Analysis”

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Abstract— Inspired by the competition of sport teams in a sport league, the League Championship Algorithm (LCA) has been introduced recently for optimizing nonlinear continuous functions. LCA tries to metaphorically model a league championship environment wherein a number of individuals, as artificial sport teams, play in pairs in an artificial league for several weeks (iterations) based on a league schedule. Given the playing strength (fitness value) along with a team intended formation (solution) in each week, the game outcome is determined in terms of win or loss and this will serve as a basis to direct the search toward fruitful areas. At the heart of LCA is the artificial post-match analysis where, to generate a new solution, the algorithm imitates form the strengths/ weaknesses/ opportunities/ threats (SWOT) based analysis followed typically by coaches to develop a new team formation for their next week contest. In this paper we try to modify the basic algorithm via modeling a between two halves like analysis beside the post-match SWOT analysis to generate new solutions. Performance of the modified algorithm is tested with that of basic version and the improved algorithm called RLCA, performs well in terms of both final solution quality and convergence speed.

Keywords—numerical function optimization; league championship algorithm; particle swarm optimization algorithm.

I. INTRODUCTION

Inspired from the natural and social phenomena, metaheuristics have attracted many researchers from various fields of science in recent years. This interest is by far in applying the existing meta-heuristics for solving real world optimization problems in many fields such as business, industry, engineering, etc. However, beside all of these applications, occasionally a new metaheuristic is introduced that uses a novel metaphor as a guide for solving optimization problems. There are many ways to classify metaheuristic algorithms, e.g. nature inspired versus others; population based versus single point, etc. Two broad groups are evolutionary algorithms (EA) and the swarm intelligence based algorithms. EAs are inspired by nature’s capability to evolve living beings well adapted to their environment. EAs can be succinctly characterized as computational models of evolutionary processes [1]. Genetic algorithm is among the first and most popular EAs. Swarm intelligence (SI) originated from the study of colonies, or swarms of social organisms. Studies of the social behavior of organisms (individuals) in swarms prompted the design of very efficient optimization algorithms. For example, simulation studies of the graceful, but unpredictable, choreography of bird flocks led to design of the particle swarm optimization algorithm, and studies of the foraging behavior of ants resulted in ant colony optimization algorithm [2].

Proposed in 2009 by Husseinzadeh Kashan [3], the league championship algorithm (LCA) is a new algorithm for global optimization which mimics the sport league championships. Beside the nature, culture, politics, etc as the sources of inspiration behind various algorithms, the sport metaphor is used for the first time in LCA. LCA is an evolutionary algorithm in which a number of individuals making role as teams compete in an artificial league for several weeks (iterations). Based on the league schedule in each week, teams play in pairs and the outcome is determined in terms of win or loss, given the team’s playing strength (fitness value) resultant from a particular team formation (solution). Keeping track of the previous week events, each team devises the required changes in its formation/playing style (a new solution is generated) for the next week contest and the championship goes on for a number of seasons (stopping condition). The way in which a new solution associated to an LCA’s team is generated is governed via imitating the post-match analysis process followed by coaches to design a suitable arrangement for their forthcoming match. In a typical match analysis, coaches will modify their arrangement on the basis of their own game experiences and their opponent’s style of play.

Since its original introduction in 2009, LCA has been employed successfully for solving complex constrained optimization problems [4, 5] and scheduling problems [6]. In this paper we try to make LCA more realistic via an artificial
modeling of the “between two halves analysis” beside the post-
match analysis typically followed in the original LCA. With
the aid of such a modeling we will obtain a variational operator
with the aim of improving the convergence quality of the
original algorithm. The resultant algorithm which is called
RLCA (R stands for a more realistic) is compared with the
original LCA where the results indicate that RLCA is able to
reach the same quality results, a bit faster.

The remainder of the paper is organized as follows. Section
II reviews, in brief, the common terminology used in sport
leagues. Section III puts forward some idealized rules and
describes the mechanism of original LCA. In section IV we
introduce the modified version of LCA called RLCA via
artificially modeling of a “between two halves analysis”.
Section V deals with computational experiments and
comparisons. Finally section VI concludes the paper.

II. A REVIEW ON THE SPORTS LEAGUE KEYWORDS

A sports league is an organization that exists to provide a
regulated competition for a number of people to compete in a
specific sport. League is generally used to refer to competitions
involving team sports, not individual sports. A league
championship may be contested in a number of ways. Each
team may play every other team a certain number of times. In
such a set-up, the team with the best record becomes
champion, based on either a strict win-loss-tie system or on a
points system where a certain number of points are awarded for
a win, loss, or tie, while bonus points might also be added for
teams meeting various criteria [7].

Generally each team has a playing style which is realized
during the game via team formation. A Formation is a method
of positioning players on the pitch to allow a team to play
according to its pre-set tactics. For example, the most common
formations in soccer are variations of 4-4-2, 4-3-3, 3-2-3-2, 5-
3-2 and 4-5-1 [8]. Usually each team follows a best formation
which is often related to the type of players available to the
teach.

It is vital for a sport team to devise for suitable game plans
and formations for each of its match. After each match,
coaches follow a post-match analysis to analyze their game
and their opponent’s game to plan on how they can develop a
style of play to improve on their weaknesses or obtain more on
their strengths. Likewise, a coach analyzing opposition
performance will use data to try to counter opposing strengths
(threats) and exploit weaknesses (opportunities). Such kind of
analysis is typically known as strengths/weaknesses/
opportunities/threats (SWOT) analysis, which explicitly links
internal (strengths and weaknesses) and external factors
(opportunities and threats). The SWOT analysis provides a
structured approach to conduct the gap analysis. A gap is
sometimes spoken of as “the space between where we are and
where we want to be”. When the process of identifying gaps
includes a deep analysis of the factors that have created the
current state of the team, the groundwork has been laid for
improvement planning. The gap analysis process can be used to
ensure that the improvement process does not jump from
identification of problem areas to propose solutions without
understanding the conditions that created the current state of
the team.

III. THE LEAGUE CHAMPIONSHIP ALGORITHM (LCA)

LCA is a population based algorithmic framework for
global optimization over a continuous search space. A common
feature among all population based algorithms like LCA is that
they attempt to move a population of possible solutions to
promising areas of the search space, in terms of the problem’s
objective, during seeking the optimum.

The keywords that were presented in previous section can
be matched to the most commonly used evolutionary terms as
follows: “league” stands for the “population of solutions”;
“week” stands for “iteration”; “team” stands for the “i-th
member of the population” and a particular “formation” for
team i at week t is matched to the i-th “solution” of the
population in iteration t; “playing strength” stands for the
“function or fitness value”. In the remainder of the paper we
use both terminologies, alternately. The algorithm terminates
after a certain number of “weeks” (S) in which each season
comprises L−1 weeks (iterations) yielding S×(L−1) weeks of
contests (L is the population size which is an even integer).

Before giving details of LCA, we first put forward several
idealized rules which constitute the rationale of LCA.

rule 1. It is more likely that a team with better playing strength
wins the game. The term “playing strength” refers to
ability of one team to beat another team.

rule 2. The outcome of a game is not predictable given known
the teams’ playing strength perfectly. In other words, it
is not unlikely that the world leading soccer team FC
Barcelona loses the game to “Zorrat Karane Pars Abade
Moghan” from Iranian 3rd soccer division.

rule 3. The probability that team i beats team j is assumed equal
from both teams point of view.

rule 4. The outcome of the game is only win or loss; there is no
tie in the basic version of LCA.

rule 5. When team i beats team j, any strength helped team i to
win has a dual weakness caused team j to lose. In other
words, any weakness is a lack of a particular strength.

rule 6. Teams only focus on their upcoming match without
regards of the other future matches. Given the previous
week results, new formations are set based on the
analysis of the teams’ current best formation.

Fig 1 shows the schematic flowchart of LCA for
optimizing an unconstrained numerical function. Like many
other evolutionary algorithms, LCA works with a population
of solutions. Each member of the population at iteration i is a
potential solution that is related to one of the teams and is
interpreted as the team formation at week t. Given a function f
of n variables, each solution such as i can be represented with a
vector of n real numbers. We can see each variable as one of
the players where a change in the value of a variable may
reflect a change in the job of the relevant player. We use
\( X_i = (x_{i1}, x_{i2}, ..., x_{in}) \) to address the formation of team i at
week t. By \( f(X_i) \) we address the function value relevant to
formation \( X_i \) (recall that \( f: \mathbb{R}^n \rightarrow \mathbb{R} \) and we are seeking the
global minimum of \( f) \). This value is called the playing strength along
with formation \( X_i \). By \( B_i = (b_{i1}, b_{i2}, ..., b_{in}) \) we address the best
formation for team \( i \), realized till week \( t \). This is the best solution that has been obtained so far for the \( i \)th member. To determine \( B'_t \), a greedy selection is done between \( f(X'_t) \) and \( f(B^-_t) \). If \( f(X'_t) \) is better than \( f(B^-_t) \), then \( B'_t \leftarrow X'_t \); otherwise \( B'_t \leftarrow B^-_t \).

Now we put forward greater details on the main steps of LCA; especially the manner of generating the league schedule, winner/loser recognition and setting up a new team formation.

A. Generating the league schedule

Since LCA mimics the championship process in a sport league, it becomes required to schedule matches of the artificial league. A single round-robin schedule is utilized where each team plays every other participant once in each season. For a league of size \( L \), single round robin tournament requires \( L(L-1)/2 \) matches, because in each of \((L-1)\) rounds (weeks), \( L/2 \) matches will be run in parallel (if \( L \) is odd, there will be \( L \) rounds with \((L-1)/2 \) matches, and one team have no game in that round).

The scheduling algorithm is simple and we illustrate it using a league of 8 teams \((L = 8)\). Let assign each team a number and pair them off in the first week (Fig. 2a). Fig. 2a implies that team 1 plays 8, 2 plays 7 and so on. For the second week, fix one team, say team 1, and rotate the others clockwise (Fig. 2b). In this week, 1 plays 7, 8 plays 6 and so on. For the third week, once again rotate the order clockwise. So, 1 plays 6, 7 plays 5 and so on (Fig. 2c). We continue this process until getting the initial state. The last week (week 7) schedule can be obtained from Fig. 2d. If \( L \) is odd, a dummy team is added. In each week, the opponent of the dummy team gets rest.

\[
\begin{array}{cccccccc}
1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 \\
2 & 3 & 4 & 5 & 6 & 7 & 8 & 1 \\
3 & 4 & 5 & 6 & 7 & 8 & 1 & 2 \\
4 & 5 & 6 & 7 & 8 & 1 & 2 & 3 \\
5 & 6 & 7 & 8 & 1 & 2 & 3 & 4 \\
6 & 7 & 8 & 1 & 2 & 3 & 4 & 5 \\
7 & 8 & 1 & 2 & 3 & 4 & 5 & 6 \\
8 & 1 & 2 & 3 & 4 & 5 & 6 & 7 \\
\end{array}
\]

It is worth to mention that the round-robin tournament can be modelled as an edge-coloring problem in a diagraph [9].

In LCA, championship continues for \( S \) successive seasons where the league schedule for each season is a single round robin schedule, yielding \( S \times (L-1) \) weeks of contests. It is worth to indicate that in our implementation of RLCA we use the same schedule for all of the \( S \) seasons.

B. Winner/loser recognition

In a regular league system, teams compete on weekends and the outcome in terms of win, loss or tie is determined for each team. Based on this, each team is scored by 3 points for win, 0 for loss and 1 for tie. Disregarding the occasional crisis which may entrap even excellent teams in a continuum of abortive results, it is more likely that a more powerful team having a better playing strength beats the weaker one (idealized rule 1). We can assume a linear relationship between the playing strength of a team and the outcome of its game. Therefore, proportional to its playing strength, each team may have a chance to win the game (idealized rule 2).

Using the playing strength criterion, the winner/loser in LCA is recognized in a stochastic manner with this condition that the chance of win for a team is proportional to its degree of fit (recall that in the basic version of LCA there is no tie). The degree of fit is proportional to the team’s playing strength and is measured by means of the distance with an ideal reference point. Let us consider opponents \( i \) and \( j \) which will fight at week \( t \), having their formation strategy \( X'_t \) and \( X'_t \), and playing strength \( f(X'_t) \) and \( f(X'_t) \), respectively. Let \( p'_t \) be the chance of team \( i \) to beat team \( j \) at week \( t \). \( p'_t \) can be defined accordingly. Let also \( \hat{f} \) be an ideal value (e.g., a lower bound on the optimal value). Based on the idealized rule 1 we have:

\[
\frac{f(X'_t) - \hat{f}}{f(X'_t) - f} = \frac{p'_t}{F'}
\]
Based on the idealized rule 3 we can also write:

\[ p'_i + p'_j = 1. \]  
(2)

From (1) and (2) we thus get:

\[ p'_i = (f(X'_i) - \tilde{f})/\int f(X'_i) + f(X'_j) - 2\tilde{f}. \]  
(3)

To determine the winner or loser, a random number in [0,1] is generated and if it is less than or equal to \( p'_i \), team \( i \) wins and team \( j \) loses; otherwise \( j \) wins and \( i \) loses.

Since \( \tilde{f} \) may not be known in advance, we use from the best function value found so far (i.e., \( \tilde{f} = \min \{ f(B'_i) \} \)).

It is worthy of note that the above win/loss simulation is consistent with idealized rules 2 and 4.

C. Setting up a new team formation

Before any strategy or intervention is applied, it is important for a coach to evaluate the strengths and weaknesses of the individual members and the team as a whole. This will serve as a guide as to how to approach them and the kind of professional relationship that should be developed, which area to focus on, and how to teach the required game skills to enhance their performance. The analysis also includes the evaluation of opportunities and threats that comes along with the unique dynamics of the team. Strengths and weaknesses are often internal, while opportunities and threats often relate to external factors. This analysis is typically known as SWOT analysis and can be used when a desired objective is defined.

Considering the goal of beating the opponent, technical staffs analyze their own game and the opponent’s previous game. Such analysis is called post-match analysis. The points sensed from the analysis of the team’s previous game (at week \( t \)) are considered as internal factors (strengths/weaknesses) and those perceived from analyzing opponent’s previous game can be regarded as external factors (opportunities/threats).

Such an analysis is also used in LCA, artificially. In an artificial post-match analysis followed by team \( i \), if it had won (lost) the game from (to) team \( j \) at week \( t \), we assume that the success (loss) was directly due to the strengths (weaknesses) of team \( i \) or based on the idealized rule 5 of section 3, it was directly resulted by the weaknesses (strengths) of team \( j \). Now, based on the league schedule at week \( t+1 \), assume that the next match of team \( i \) is with team \( l \). If team \( l \) had won (lost) the game from (to) team \( k \) at week \( t \), then that success (loss) and the team formation behind it may be a direct threat (opportunity) for team \( i \). Apparently, such a success (loss) has been achieved by means of some strengths (weaknesses). Focusing on the strengths (weaknesses) of team \( l \), gives us an intuitive way to retreat from the possible threats (to receive benefits from the possible opportunities). Referring to idealized rule 5, we can focus on the weaknesses (strengths) of team \( k \) instead. Let us introduce the following indices:

\[ l = \text{Index of the team that will play with team } i \text{ at week } t+1 \text{ based on the league schedule.} \]

\[ j = \text{Index of the team that has played with team } i \text{ at week } t \text{ based on the league schedule.} \]

\[ k = \text{Index of the team that has played with team } l \text{ at week } t \text{ based on the league schedule.} \]

Based on the previous week events (idealized rule 6 of section 3), the possible actions for team \( i \) derived from the artificial post-match analysis can be summarized in Fig. 3. For example, if team \( i \) had won and team \( l \) had lost, then it is reasonable that team \( i \) focuses on the strengths which made it capable to win. At the same time it should focus on the weaknesses that brought the loss for team \( l \). These weaknesses may open opportunities for team \( i \).

![Figure 3. Actions suitable for team i when devising its formation for the next match (based on the previous week win/loss statuses).](image)

Adopting a suitable focus strategy from Fig. 3, based on the previous week events, now teams should try to fill their gaps. Assume that team \( i \) has lost the game to team \( j \) and during match analysis it has been revealed that the reason was for the weakness in a man to man defence (which allowed counter attacks by team \( j \)). Therefore, there is a gap between the current penetrable defensive state and the state which ensures a man to man defence. Let us assume that \( B'_i \), \( B'_j \), and \( B'_k \) are the best team formations associated to teams \( i, j \) and \( k \) till week \( t \), respectively. By “\( B'_i - B'_j \)” we address the gap between the playing style of team \( i \) and team \( k \), sensed via “focusing on the weaknesses of team \( k \)”. In this situation, team \( k \) has won the game from team \( l \) and to beat \( l \), it is reasonable that team \( i \) devises for a playing style almost similar to that was adopted by team \( k \) at week \( t \) (for example playing counter attacking or high pressure defence). In a similar way we can interpret “\( B'_i - B'_j \)” when “focusing on the weaknesses of team \( k \)”. Here, it may be sensible to avoid from a playing style rather similar to that was adopted by team \( k \) (for example avoid from playing counter attacking or high pressure defence). We may interpret “\( B'_i - B'_j \)” or “\( B'_i - B'_j \)” similarly.

Given the fact that usually teams play based on their current best formation (obtained it suitable over the time) while preserve the required changes recommended by the post-match analysis (see idealized rule 6), the new formation \( X^{t+1} = (X^{t+1}_i, X^{t+1}_j, \ldots, X^{t+1}_n) \) for team \( i (i=1, \ldots, L) \) at week \( t+1 \) can be set up by one of the following equations.

If \( i \) had won and \( l \) had won too, then

\[ x^{t+1}_i = b'_i + \gamma'_i(\psi_i(b'_i - b'_d) + \psi_i(b'_i - b'_d)) \forall d = 1, \ldots, n \]  
(4)

Else if \( i \) had won and \( l \) had lost, then

\[ x^{t+1}_i = b'_i + \gamma'_i(\psi_i(b'_i - b'_d) + \psi_i(b'_i - b'_d)) \forall d = 1, \ldots, n \]  
(5)

Else if \( i \) had lost and \( l \) had won, then
\[ x_{id}^{t+1} = b_d^{t'} + y_{id}^{t'} (\psi_r(b_d^{t'} - b_{d0}^{t'}) + \psi_r(b_d^{t'} - b_{d0}^{t'})) \quad \forall d = 1,...,n \] (6)

Else if \( i \) had lost and \( l \) had lost too, then
\[ x_{id}^{t+1} = b_d^{t'} + y_{id}^{t'} (\psi_r(b_d^{t'} - b_{d0}^{t'}) + \psi_r(b_d^{t'} - b_{d0}^{t'})) \quad \forall d = 1,...,n \] (7)

End if

In the above formulas, \( d = 1,...,n \) is the dimension index and \( r_1, r_2 \sim u(0,1) \). \( \psi_r \) and \( \psi_{r2} \) are constant coefficients used to scale the contribution of “retreat” or “approach” components, respectively. Note that the sign in parenthesis results in acceleration toward winner or retreat from loser. \( y_{id}^{t'} \) is a binary change variable which indicates whether the \( d \)-th element in the current best formation will change or not. The value of 1 for \( y_{id}^{t'} \) allows making a change in the value of \( b_d^{t'} \).

Let us define \( Y_i = (y_{id}^{t'}, y_{id}^{t'},..., y_{id}^{t'}) \) as the binary change array with number of ones equal to \( q_{id}^{t'} \). It is not usual that coaches do changes in all or many aspects of their team. Generally the number of changes is relatively low. By analogy, it may seem suitable that the number of ones in \( Y_i \) be small. To simulate the rate of changes ( \( q_{id}^{t'} \) ), we use a truncated geometric distribution [10]. Using a truncated geometric distribution, we can set the rate of changes dynamically, with more emphasis given to the smaller/larger rate of changes. The following formula gives the random number of changes made in \( B_i^{t'} \) to get the new team formation \( X_i^{t+1} \):

\[ q_{id}^{t'} = \left\lfloor \frac{\ln(1 - (1 - p_c) r)}{\ln(1 - p_c)} \right\rfloor : q_{id}^{t'} \in \{1,2,...,n\} \] (8)

Where \( r \sim u(0,1) \) and \( p_c < 1, p_c \neq 0 \) is an input parameter. The greater positive (negative) value of \( p_c \), the smaller (greater) number of changes is recommended. After simulating the number of changes by (8), \( q_{id}^{t'} \) elements are selected randomly from \( B_i^{t'} \) and their value changes according to one of equations (4) to (7) (i.e., their corresponding \( y_{id}^{t'} \) gets 1). If \( x_{id}^{t+1} \) lies outside of the feasible range it is retrieved into allowable range by assign it a random value within the range.

IV. THE MODIFIED LEAGUE CHAMPIONSHIP ALGORITHM VIA MODELING ARTIFICIAL “BETWEEN TWO HALVES ANALYSIS”

Match analysis data can be used to guide team preparation and performance at various stages within the coaching process. The key stages are before the game, during the match and, finally, afterwards. Simple match statistics can be collected during a game and used to help make tactical decisions. The advantage for the coach is that he/she has objective data upon which to base the half- or full-time ‘team talk’ or to make various tactical changes and/or substitutions.

As described earlier, the basic LCA uses only the notion of post-match analysis to generate a new solution (team formation). In this section we try to model a “between two halves analysis” followed by coaches during the match, artificially. In terms of algorithmic features, we should modify the winner/loser recognition part of the algorithm and add a new formation (solution) generator mechanism. We assume that coaches do changes in their current formation just when they lose their game in the first half, otherwise they will retain their playing style. This means that we should first recognize the winner/loser of the first half. Let us assume that the game is being accomplished between teams \( i \) and \( j \) having formation \( X_i^{t} \) and \( X_j^{t} \), respectively. We can determine the first half winner/loser, by using the stochastic winner/loser recognition mechanism (described in section III-B). If \( i \) loses the first half to \( j \), it should devise for an alternative formation (solution), vice versa. Here, there is only an internal source of evaluation available to the coach. Let \( X_i^{t'-second half} \) denotes the new formation for team \( i \), devised during its game in week \( t \). We can define \( X_i^{t'-second half} \) accordingly. These formations may be generated as follows:

If \( i \) had won the first half from \( j \), then
\[ X_j^{t'-second half} = b_d^{t'} + y_{id}^{t'} \psi_r(x_{id}^{t'} - b_{d0}^{t'}) \quad \forall d = 1,...,n \] (9)

\[ X_j^{t'} = X_j^{t'-second half} \] (10)

Else if \( j \) had won the first half from \( i \), then
\[ X_i^{t'-second half} = b_d^{t'} + y_{id}^{t'} \psi_r(x_{id}^{t'} - b_{d0}^{t'}) \quad \forall d = 1,...,n \] (11)

\[ X_i^{t'} = X_i^{t'-second half} \] (12)

End if

In the above formulas, \( r \) is a random number in \([0,1]\). The modified winner/loser recognition part in RLCA is as Fig. 4.

![Figure 4. The winner/loser recognition part in RLCA.](image-url)
based on the mean and standard deviation of the lowest function values obtained in 10 runs of the algorithms on each problem. “Eval” also indicates the mean number of solutions generated by an algorithm before getting stopped. As can be seen from Table I, performance of RLCA is very close to LCA. On 4 out of 5 functions, both LCA and RLCA find the global optimum in each run. The only function, for which the optimum is not always obtained, is the Rosenbrock function in which the optimum lies inside a long narrow valley and this makes the convergence to the global minimum difficult. However, both LCA and RLCA approach very close to the global optimum of this function.

Comparing to PSO, both RLCA and LCA perform superior. On Rosenbrock function, PSO stops far away from optimum. On Rastrigin function which is a multimodal function with very local optima, both LCA and RLCA could escape successfully from local optima in each run. But PSO is trapped several times. Ackley’s function has also many local optima. But, the complexity of this function is fair compared to Rastrigin function. Yet, PSO needs on average to generate almost 24544 solutions to reach the optimum. This record for LCA and RLCA is 3121 and 2746. A same scenario is held on Sphere function on which the number of solutions generated by RLCA and LCA to reach optimum is almost 1/12 of PSO.

Similar to Rastrigin function, Schwefel function has many waves and many algorithms are trapped in the second best minimum of this function. Once again LCA and RLCA could reach the global minimum in each run, while PSO fails two times. The very low standard deviations signify that both LCA and RLCA are dependable and converge to the global minimum at each run. To visualize how LCA, RLCA and PSO converge to the global minimum, the evolution of the mean of best function values during the search is depicted based on logarithmic scaling of $X$ and $Y$ in Fig. 5, for different functions. It is clear that both LCA and RLCA converge to the global minimum faster than PSO. However, the difference between evolution curve of LCA and RLCA is not very significant. Though from the “Eval” column, we can find that RLCA requires generating less number of solutions to reach optimum.

VI. CONCLUSIONS

A new more realistic league championship algorithm was proposed which uses a “between two halves like analysis” beside the artificial post-match analysis to generate new solutions. From the experiments in finding the global optimum of five benchmark functions, it was revealed that the new algorithm reaches a bit faster than the original one to the optimum. For future research, there would be a great interest on testing the performance of the new algorithm on larger problems, constrained optimization problems and real world engineering problems.

REFERENCES


TABLE I. STATISTICS ON THE BEST FUNCTION VALUES OBTAINED BY LCA, RLCA AND PSO.

<table>
<thead>
<tr>
<th>Function</th>
<th>LCA</th>
<th>RLCA</th>
<th>PSO</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sphere</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Rosenbrock</td>
<td>2.92E-5</td>
<td>6.97E-5</td>
<td>8.98E-5</td>
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<tr>
<td>Rastrigin</td>
<td>0</td>
<td>0</td>
<td>0</td>
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<tr>
<td>Ackley</td>
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<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Schwefel</td>
<td>6.35E-5</td>
<td>5.39E-5</td>
<td>5.23E-5</td>
</tr>
</tbody>
</table>

Figure 5. Evolution of best function value for different functions.