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Sports Competition System Arrangement Based on an Improved Multi-Objective Optimization Algorithm

Feng Wang
Guangdong Ocean University, China

Zhengchang Li
https://orcid.org/0009-0003-7440-6601
Guangdong Ocean University, China
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ABSTRACT

This research suggests a flexible scheduling method for professional athletic events that hybridizes the tabu search with the genetic algorithms, resulting in a significant improvement in the efficiency of traditional game scheduling game-match planning outcomes. This project aims to lower the travel expenses for all participating teams. As a starting point for the experiment, data from well-known sports leagues (such as Major League Baseball and the National Basketball Association) has been utilized. The new strategy more effectively identifies superior outcomes than previous methods. Apart from devising a workable plan that satisfies all scheduling constraints, the challenge tackled in this paper is further complicated by the need to minimize travel expenses and ensure that each club plays an equal number of home games. To overcome the difficult challenge, the authors describe the issue of scheduling as a matter of optimization and use the idea of evolutionary strategy, taking into account sequential occurrences in a socially connected environment.

KEYWORDS

Sports Scheduling, Multi-Objective Optimization, Competition, Schedule Optimization

INTRODUCTION

The organization of sporting activities, especially in professional leagues such as the National Basketball Association (NBA), Major League Baseball (MLB), and the National Hockey League (NHL), is an essential organizational problem for the multi-billion-dollar industries. The process of scheduling implies trade-offs across various elements, which can be the equitable allocation of venues, transportation costs, player exhaustion, and unexpected elements such as weather delays. All these issues are not purely mathematical; they also affect team performance, operational budgeting, and league competitiveness. Therefore, scheduling is a vital concern, both as a matter of policy and as a technical question. The factors that serve as this research's primary motivations are:

- Professional sports leagues are widespread and well established (for example, the Premier League, the NBA, MLB, and the NHL).
- The expense of travel is rising.

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- Consideration must be given to the athletes' energy.
- The stadiums' locations and the teams' rotations must be taken into account.
- The use of Google Maps is growing in popularity.

The initial factor is the widespread popularity of professional sports leagues. The sports business has a lot to offer diverse partners in the entertainment, marketing, and advertising sectors. For instance, the National Football League's advertising allotment has grown every year due to the audience's preference for thrilling and visually appealing games. Elite professional sports leagues usually view their players as valuable assets, even when it comes to travel expenses. Every time they relocate, they must take a flight or road trip, but the cost of oil (and therefore the cost of travel) has increased rapidly over the past decade. The athlete's spirit is an additional aspect. After a few consecutive matches without adequate recovery, athletes often expend all their energy. Therefore, it is essential to establish a fair timetable that benefits all clubs and individuals.

Professional sports are businesses (Liang et al., 2021). Many business-related events may occur, including trading players, selling the entire club, or relocating the headquarters. For instance, the Montreal Expos, an MLB club, relocated to Washington, DC, in 2005 and changed their name to the Washington Nationals. MLB moved the Houston Astros from the National League to the American League in 2012. The 82 games per team of the 2011–2012 NBA season were condensed into 66 games due to a lockout caused by a labor dispute. The considerations above suggest that establishing a fair and ideal timetable for any league is crucial (Szymanski & Winfree, 2018). A minor occurrence might cause significant changes to the seasonal timeframe.

Last, the Google Maps program is quite popular. Extracting geographic information from this renowned technology is useful. Using geographical data, we can compute the actual distance between teams. It is a good interface to use in developing our system. Major athletic events athletic events are infamously hard to schedule (Zhang, 2022) because of the complexity of every activity involved in these events and the many, even conflicting, factors that must be taken into account, including distance traveled (Ilarri et al., 2018), equity, and revenue. This process has, in the past, been very costly in terms of finances and time. It is occasionally addressed as a satisficing problem, i.e., a problem in which any solution that satisfies the limitations of the problem is chosen, as opposed to being an optimization problem because of the extensive solution space.

The problem of scheduling in professional sports leagues is an intricate organizational decision issue where the concerns of fair competition, efficiency, and the welfare of the players need to be balanced. The global expansion of leagues and the growth in competition schedules are providing administrators with growing challenges in reducing the travel distance, dealing with fixture congestion, and ensuring equity in teams. These are not merely logistical but also managerial, involving the budget, the performance of the athletes, and the sustainability of the organization. Even though optimization algorithms are available, the current methods tend to run independently of business data systems and managerial processes. To fill this gap, the current research will create a hybrid web-based decision-support system that is based on smart optimization and real-world data integration with the help of the SQL Server and Google Maps APIs. The system is intended to enable league administrators to create viable, just, and cost-efficient schedules and offer clear visualization and testing of the scenario.

An adaptable algorithm and a web-based organizing system have been proposed in previous studies (Gaudenzi, 2019; Ilarri et al., 2018; Zhang, 2022) to address the scheduling challenges faced by professional athletic leagues such as the NBA.. The NBA must schedule 1,230 games over 170 days while balancing travel costs, player welfare, and arena availability. This paper presents a case study of an information technology (IT) system designed to support this multi-billion-dollar scheduling challenge. These motivations can be integrated into a discussion of organizational drivers, such as rising operational costs, the strategic importance of player health, and league-wide fairness..

The primary contribution of this paper is a case analysis of a prototype web-based scheduling system, evaluating its technical performance, its potential for cost savings and improved fairness, and the managerial lessons learned from its design. The process could present the sports league managers with statistical data and relieve the planner of the burden of work. The study should be viewed as a prototype case study rather than an actual deployment. The web-based scheduling system was implemented and tested using real data from the NBA (2012–2013) and MLB (2009–2011). These datasets will be presented as replication cases, which will enable us to test the system in a real-world situation, as professional sports organizations do. Even though the leagues were not formally supporting the system, its design and assessment could provide helpful information on how to incorporate such a tool into the league activities, who would be using it, and what sort of organizational effects it may have. This way of framing the study makes it possible to extend the contribution beyond discussing the performance of the algorithm only and mentioning lessons when it comes to the design of IT systems, their adoption, and the lessons they impart to managers.

RELATED WORK

Schedule optimization–related concerns are addressed in this section. Generally speaking, scheduling issues aim to match the components of multiple sets as ideally as possible. A famous operational research issue is the two-dimensional assignment challenge, whose Hungarian solution approach relies heavily on mathematical concepts developed nearly 15 years before linear programming was invented (Sadeghi Moghadam et al., 2021). Recently, researchers have looked at expanding the fundamental allocation issue to three or more dimensions. Costa (1995) used genetic algorithms (GA) and tabu search (TS), two heuristic techniques, to determine the best pathway for the NHL scheduling problem.. He developed a novel heuristic method for use in NHL timeline planning. The newly developed approach can fulfill the rules efficiently and obtain a suitable timetable. The most significant benefit is that it can save on expenses when sports teams play away from home and the travel distance exceeds 128,700 kilometers .

While the three-dimensional problem receives much attention in research on the multivariate assignment challenge, many findings are readily transferable to higher-dimensional challenges. Lagrangian relaxation is used in numerous branch-and-bound approaches designed to determine the best solution to this issue (Anuradha et al., 2019; Balas & Saltzman, 1991; Khalili-Fard et al., 2024). These processes identify firm limits. Although multidimensional allocation issues are generally NP-hard, polynomial solution techniques have been developed for some scenarios. Additionally, current research has explored the development of heuristic solution approaches due to the complexity of the problem. A TS technique, utilizing a Latin-square design as the foundation for the move-generating process, is applied after assessing heuristic analogous approaches to obtain a preliminary solution to the transportation issue.

According to the perspective of Durán et al. (2019), an autonomous sports club should choose the travel route with the lowest cost. They use the Multiple Traveling Salesman Problem to determine the NBA scheduling solution. A sports team can play another team up to five times in one trip. In other words, a sports team can visit no more than five places in the same trip.. The timetable is used to confirm whether the minimal expense satisfies the applicable NBA restriction after it has been determined. They repeatedly went through this mathematical procedure until they arrived at a sensible timeline. This scheduling approach was applied in the NBA's regular seasons during 1980–1981 and 1981–1982, demonstrating its effectiveness in reducing travel-related expenses by approximately 20%..

The foundation of the evolutionary approach is biological evolution through natural selection (Balas & Saltzman, 1991; Mirjalili, 2019), a theory initially put forth by Bueno (2014). The concept states that if the overall population density does not increase exponentially, selection will become unavoidable due to the limited number of individuals that may live in the setting and their innate desire to reproduce. The process of natural selection favors individuals who have adjusted best to their surroundings or who compete for the available resources the most successfully (Mirjalili, 2019). The theory of survival of the fittest is another term for this. Darwin acknowledged the existence of minute, seemingly random, and unscheduled differences in phenotypes alongside choice (Balas & Saltzman, 1991; Mirjalili, 2019). Evolutionary methods are a key aspect of computational algorithms that work with populations; the core ideas of evolutionary computation include generations, fitness, variations, and selection. All evolutionary computing models use the same procedure: initially, a preliminary result set is produced; thereafter, the fitness of the solutions is assessed and the solutions with the highest likelihood of reproducing via crossing and/or mutations are chosen. Then, in a competition with the current answers, these new potential solutions try to figure out who survives and procreates and who doesn't (Mirjalili, 2019). We will now discuss these ideas in the context of how evolutionary algorithms employ them.

Evolutionary techniques have been used in numerous contexts, including sports management. Utilizing an evolutionary method, Yang et al. (2020) generated satisfactory outcomes for the MLB schedule and reported a considerable improvement over previous solutions. Barone et al, 2006 employed the polygon construction approach in an evolutionary strategy to generate efficient game plans for the Australian Football League (AFL; Goossens, 2018).. With teams from five states, the AFL is Australia's top sports league. It is impossible to conduct a thorough search for a solution to the competition's scheduling issue within an acceptable timeframe. One crucial factor to consider when tackling these issues is the limited number of workable answers within the potential search field. The AFL aims to balance the predicted revenue for the league with the fairness of the competition for teams, among other trade-offs. Sports scheduling problems have seen the successful application of single-purpose evolutionary algorithms. There has been no prior use of multi-objective evolutionary algorithms in sports scheduling.. One of its advantages is that it can offer a dependable set of answers that may be assessed by weighing the compromises between the objectives.

PROPOSED SCHEDULING METHOD

Framework Design

The suggested scheduling structure is a multilevel process that integrates the definition of constraints, data integration, optimization, and assessment within a web-based system. It aims to create viable and economical routines that professional sports associations can adopt to meet their organizational and logistical needs. The framework operates in the following stages:

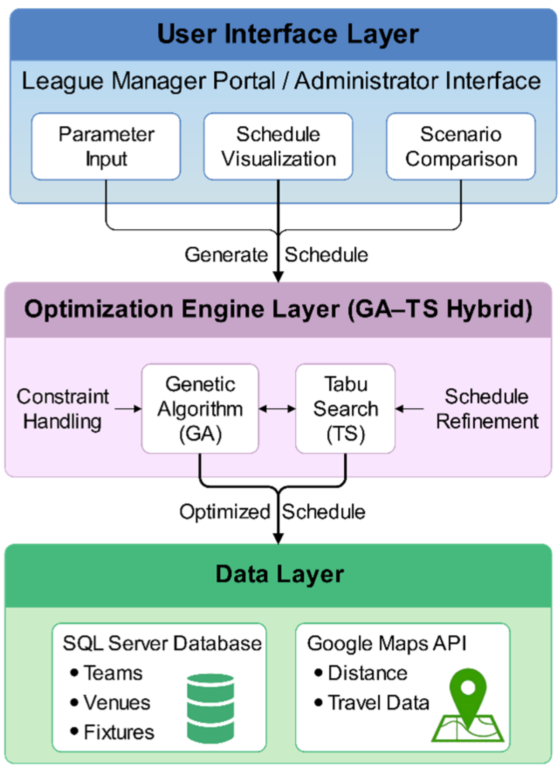
1. Constraint specification and input: league administrators or IT personnel determine the most critical parameters of the season, including the number of teams, divisions, and games as well as the season's opening and closing dates. Additionally, they establish league-specific parameters, such as commemorative matches or blackout dates. At this stage, hard, soft, and travel constraints are added to the database (see the Constraints Definition section).
2. Data preparation: the geographic distance between stadiums is calculated using the Google Maps API and stored in SQL Server, along with data about the team and scheduling restrictions. This creates a centralized data source from which the optimization engine receives inputs.
3. Preliminary schedule generation: the system generates the initial population of schedules using a constructive heuristic method. These are schedules that meet minimum feasibility requirements but have not yet been optimized for cost or fairness. Each schedule is characterized as a chromosome, and the single games are the genes.
4. Optimization through hybrid GA–TS engine: the optimization engine refines the initial schedules through an iterative development process. A GA utilizes a combination of crossover and mutation to explore the solution space, whereas TS is employed to refine the search within promising

solutions. The individual schedules of each candidate are optimized based on the objective criterion of minimizing total travel distance, even at the expense of constraint breaking.

5. Evaluation and constraint checking: schedules generated are checked against hard, soft, and travel constraints. Any infeasible schedules are either fixed or deleted. New values of fitness are then recalculated, and the process is repeated until convergence is achieved.
6. Output and managerial review: the optimal schedules are available as text or a spreadsheet and presented in the system's web interface. League planners and decision-makers can evaluate this approach and implement policy-based changes before its adoption.

The system architecture shown in Fig. 1 presents a high-level overview of the complete IT artifact. It starts with the data management layer, where the team locations, venue availability, and previous season information are kept and updated in the SQL Server database. The inputs will be dynamically connected to the optimization engine that incorporates the modules of GA and TS to create viable and efficient schedules. The decision-support layer also offers visualization and performance analytics, allowing managers to assess the scenarios by travel distance, fairness, and sustainability indicators. Last, the web interface allows the administrators to make changes on a real-time basis, compare options on scheduling, and make informed decisions.

Figure 1. Conceptual Architecture of the Proposed Web-Based Scheduling Decision-Support System



Note. API = application programming interface.

Organizational Context and Stakeholder Requirements

The web-based scheduling system was explicitly designed in direct relation to operational issues of professional sports leagues, aiming at finding a balance between efficiency in travel, equality, and the welfare of players. Feedback from league managers, schedulers, and IT personnel highlighted ongoing challenges in legacy scheduling processes, including the need for extensive manual validation and limited capacity to test alternative what-if scenarios on a unified platform.. These insights from stakeholders informed the technical design of the system, which ensured that each computational element had a well-defined organizational requirement.

From a managerial perspective, the administrators of the leagues focused on fulfilling four interconnected goals: minimizing the total travel distance to minimize transportation and accommodation expenses; increasing the level of fairness by reducing the difference between back-to-back games and travel load; ensuring the well-being of the players by carefully scheduling fixtures; and contributing to the environmental sustainability as per corporate social-responsibility guidelines. They, in turn, were transformed into the literal model constraints and weighted performance metrics in the engine of optimization. As a practical usability measure, the system will also be combined with an intuitive web interface that will enable nontechnical decision-makers to visualize the schedules, then alter the parameters and immediately evaluate the effects. Real-time data synchronization with the SQL Server and Google Maps APIs was used to keep the distance calculations and venue logistics accurate. The development team worked in liaison with the operational staff in the process of prototype evaluation based on the NBA and MLB datasets to test the scalability, accessibility by users, and responsiveness of the system. In their feedback, they indicated the value of transparency, auditability, and quickness of schedule modification needs, which steered improvements of the algorithmic and interface layer. This paper presents the scheduling platform not merely as an algorithmic contribution but as a holistic IT artifact that facilitates evidence-based, fair, and sustainable sports management operations by grounding system design in stakeholder engagement and real-world decision contexts..

Constraints Definition

To resolve the schedule issues, we revised the gene method (Alami Merrouni et al., 2020; Wang et al., 2017) and the TS method (Samorani et al., 2019). To identify the most efficient system of arranging professional games globally, certain restrictions should be outlined and defined. Three types of constraints are distinguished, including hard constraints, soft constraints, and travel constraints, to make schedules produced by the system feasible and relevant to the organization. Such constraints are used during the optimization to distinguish between the requirements that must be followed and mere preferences.

Hard constraints refers to the scheduling needs of the league that cannot be compromised. Some of them are division, season format, and calendar restrictions:

- Season format: every team must play the number of games set, both at home and away.
- Division rules: each team must play the other teams in divisional matches the designated number of times.
- Calendar limitations: games cannot be played on blackout dates that are either public holidays or league events.

In the event of violating any hard constraint, the schedule is considered infeasible and is either repaired or discarded during the optimization process.

Soft constraints are ideal conditions that enhance fairness and organizational balance but can occasionally be compromised when necessary. Examples include:

- Even pairings: avoiding imbalance in the frequency of the same two teams' encounters.

- Rematching: ensuring that there is sufficient time between repeat games by a team against the same opponent.
- Special events: playing celebratory games or season openers at a particular time.

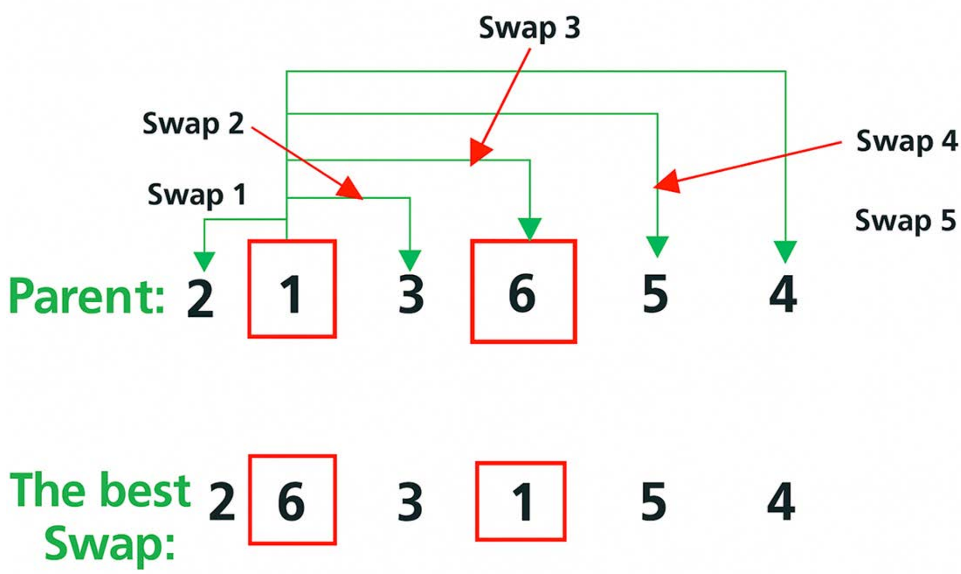
Soft constraints are tolerated but penalized by the objective function; therefore, they are not encouraged except when necessary to maintain feasibility.

The travel constraints are primarily geographic. The system utilizes the Google Maps API to calculate the straight-line distance between the home stadium of one team and the away stadium of its opponent.. All these distances are factored into the objective to reduce travel throughout the season. For example, the system is aware that New York is 354 km away from Boston and will prefer schedules that minimize the overall travel load on all teams.

Updated GA Mutation

It is important to verify that the modified schedule satisfies the complex restrictions after the game calendars have been updated. Another mutation can happen, provided the hard restrictions are satisfied. Since the mutating frequency is often set around 0.1 and 0.05, most mutations should be eliminated, and the likelihood of a mutation is relatively low. The revision of the mutation technique expedites the scheduling process. The system determines which mutation is most appropriate by computing all the possible mutations for each gene and comparing their fitness (X). This system uses a post-modification order-oriented mutation technique. The selective crossing of genes, as opposed to random crossover, is the key distinction between this approach and the previous one. Gene 4 is randomly selected for mutation by the population, as illustrated in Fig. 2. The potential alterations, which span from Swap 1 to Swap 5, are confirmed by the mutation of Gene 4. Once the fitness is verified, the ideal mutation population, Swap 2, is chosen. Using this strategy, we treat every day of the timetable as a gene, so the total number of genes (N) is equal to the number of days. Genes are chosen at random from the whole population, and $N - 1$ ways exist for exchanging genes. Start the process of transitioning from the ($N - 1$)th gene to the principal gene. Make a note of every trip expenditure that each switching approach generates, and then choose the timetable that results in the lowest overall travel expenses.

Figure 2. Demonstration of the Swap Procedure



Objective Function

The objective function aims to determine the total travel expenses incurred by every club in a league. The penalty algorithm is used to steer the optimization procedure in the direction of workable, nearly perfect solutions. Because effective solutions often arise from the cross-pollination of feasible and infeasible solutions, it is crucial to allow infeasible solutions into the population. The function for fitness may be found using Equation 1.

$$F(s) = w \times \left(RT_1 + RT_2 + \ldots + RT_K\right) + TD \tag{1}$$

In Equation 1, *TD* is the cumulative travel distance, *w* is the weight, and RT_K is the number of breaches of the constraint.. The direct route is the primary focus of this study, with the overall distance estimated using the Google Map API. The adaptive mutation mechanism is accomplished through the use of this subsequent technique. The best matching set is obtained by integrating the swarm intelligence. A sports league's scheduling issue is suggested to be resolved using the Professional Sports Game Scheduling approach. The Professional Sports Game Scheduling algorithm (Algorithm 1) establishes a starting population as the first step.. For that, a constructive heuristic might be applied. Next, a local search is performed for every individual to get an estimate of the local minimum. Mutation operators are employed in the main loop to select individuals at random for a specified duration. The additional individuals produced by the mutation operator are added to the population after going through the local search process to maintain local optimality. To maintain a certain population level or to ensure the next generation is raised, specific individuals are selected for survival. Maintaining the population's variety while keeping the search focused on specific goals is the primary objective of a suitable selection technique.

Algorithm 1. Professional Sports Game Scheduling

Input: P; // population of sports game
Output: CandidatePathSelection(P); // sets of candidate paths
Initialize population P;
for each individual $i \in P$ do $i := TabuSearch(i)$;
Repeat
for $i = 1$ to number of mutation **do**
select one individual $i_m \in P$,
$i_m := Mutation(i_m)$;
$i_m := TabuSearch(i_m)$;
add individual i_m to P;
end for;
$P := CandidatePathSelection(P)$;
Until converged;
End;

TS Featuring Communal Events

We propose the home–away operator, which is a straightforward modification operator. Our technique uses the home–away operator during the TS phase. The two sides' game plans are to be swapped by the operator. The operator is tasked with swapping the two matches between the teams presented in Algorithm 1. Subsequently, the operator continues to fulfill the restrictions. Using this operator can result in either a poorer or a better schedule. The local search is an essential step in increasing our algorithm's effectiveness.

Soft Constraints and Swapping of Schedules

Using this procedure, the algorithm verifies whether the game schedule produced after the crossover or mutation operation complies with the established guidelines. If the schedule passes verification, the algorithm continues searching for improved event plans; otherwise, the schedule is discarded.. It compares the total cost of travel and the instances of soft constraint violations using data from both the current and previous generations. Substitute the prior generations with the younger generations if the periods of soft restriction violation occur and the new generation's total travel expenses are less than those of the previous generation. If not, do not change anything. The algorithm assesses the timing of soft constraint violations to determine which schedules should be penalized if their performance metrics fall below those of the previous generation.. The punishment parameter is the product of all infraction times multiplied by 0.1% of the entire travel distance. The scenarios are displayed in Table 1.

Table 1. Rule-Based Scenarios Showing Travel Constraint Violations and Swap Conditions

Parent: A Child: B	Travel distance	Instances of violation	Penalized value + covering distance	Swap
Scenario 1	B < P	B < P		Yes
Scenario 2	B < P	B > P		No
Scenario 3	B < P	B > P	B < P	Yes
Scenario 4	B > P	B > P	B > P	No
Scenario 5	B > P	B < P	B < P	Yes
Scenario 6	B > P	B < P	B > P	No

Note: "Parent (P)" and "Child (B)" refer to two consecutive generations of scheduling solutions in the evolutionary algorithm. "B < P" indicates that the child schedule (B) performs better than the parent (P) for that metric.

An Illustration

In this section, we provide a real-world example of the suggested approach in operation, taking restrictions into account. Six well-known MLB leagues are chosen: Arizona Diamondbacks (X), Atlanta Braves (A), Seattle Mariners (W), Minnesota Twins (Z), Toronto Blue Jays (B), and Colorado Rockies (Y). We'll assume for this instance that the hard limits are set and also that no further soft limitations are taken into account. To minimize transportation costs, the Google API can be utilized to calculate the shortest possible distance between teams, as shown in Table 2. This technique is executed using the distances as inputs. The initial computational outcomes are shown in Table 3.

Table 2. Summary of Direct Inter-Team Distances (in Kilometers) Used for Optimization Between Six Participating Teams

	W	X	Y	Z	A	B
W		1,793	1,639	2,240	3,507	3,326
X	1,793		943	2,058	2,556	3,035
Y	1,639	943		1,124	1,949	2,160
Z	2,240	2,058	1,124		1,462	1,112
A	3,507	2,556	1,949	1,462		1,183
B	3,326	3,035	2,160	1,112	1,183	

Note. *X = Arizona Diamondbacks; A = Atlanta Braves; W = Seattle Mariners; Z = Minnesota Twins; B = Toronto Blue Jays; Y = Colorado Rockies.*

Table 3. Example of the first computational output showing team match pairings for the initial schedule.

WZ	XW	WY	WB	YW	BW	WX	WA	ZW	AW	WA	WZ	XW	ZW	WY	WB	YW	AW	BW	WX
XA	YZ	AX	AY	XZ	XY	YB	BX	XB	YX	YZ	XA	AY	BX	XZ	XY	AX	YB	YX	ZY
BY	BA	ZB	ZX	AB	ZA	AZ	ZY	YA	BZ	XB	BY	ZB	YA	BA	ZA	BZ	ZX	AZ	AB
W: 355 X: 316 Y: 303 Z: 289 A: 283 B: 332 Total: 1,878 km																			

Note. *X = Arizona Diamondbacks; A = Atlanta Braves; W = Seattle Mariners; Z = Minnesota Twins; B = Toronto Blue Jays; Y = Colorado Rockies.*

In the computational output, the home team is represented by the first letter in each pair, and the away team by the second. Each block corresponds to one round of scheduled matches. By using the computation, the journey distance can be decreased. When we optimized Team B against the original feed (the official timetable), we minimized the distance by at least 141 km.

System Architecture and Integration

Although the main principle of our strategy is an improved optimization algorithm, the contribution of this study extends further, as the design of a web-based scheduling system enables league administrators and IT managers to apply these algorithms in practice. The system is developed as a prototype, and it has several layers: a data management layer, an optimization engine, and a user interaction layer.

The system is built on the data management layer that relies on SQL Server 2003. Information concerning the teams, the location of the stadiums, season rules, and previous schedules is found in this layer. The distance matrices delivered by the Google Maps API are also used in it, and calculations of the path to a location can be dynamically recalculated. The system allows effective querying of the constraints using a relational database. Also, it will enable the addition of league-specific parameters, such as special commemorative games or restrictions based on public holidays.

The core components of the system are the hybrid scheduling engine, a combination of GAs and TS, which is stored in the optimization layer.. This engine is in direct contact with the database, where the team and distance information is retrieved and the schedules of the candidates are formed. The findings are also entered back into the system to be evaluated. The system does not give the raw output of the algorithm; it rearranges the results in a form more digestible to a manager, it signals the percentage of criteria met by the system, and it indicates any violation of restrictions.

The user interaction interface is a web-based interface, which is lightweight and can be used to ensure that the operation of the system enables the involvement of the schedulers and decision-makers without the necessity of having technical skills. The season parameters are manually entered, and the user sets the weight parameters to achieve a balance between fairness and travel cost. Then the optimization is run and each schedule option is exported in a spreadsheet or in text format. There is also a simple visualization tool that enables administrators to compare various schedules with each other as well.

The structure of the system can be incorporated into the workflow of the existing leagues with ease. Testing has revealed that several major issues should be addressed in a live implementation. At the beginning, the geographic data needs to be synchronized with the external sources continuously to confirm that the information is accurate and timely. Second, the issue of scalability should be looked at because leagues may have different sizes, structures, and rules and a system must be capable of supporting this diversity without needing a significant redesign. Third, usability is necessary. League schedulers might not be technically trained, which is why the interface should be easy to use. Organized change management and training would also have to support adoption.

This structure is why this research is not only limited to the algorithm but also presents a prototype information system that uses real-world data, optimization techniques, and organizational decision-making processes.. In defining the system in this way, the study emphasizes the technical and managerial parts of implementing IT in the process of scheduling professional sports.

EXPERIMENTAL SETUP AND RESULTS

This section evaluates the performance and organizational impact of the proposed scheduling system using real-world datasets from the NBA and MLB. The experiments are structured into four components: datasets and limitations, experimental setup, results, and managerial interpretation. Together, these findings show that the system is not only a technically effective optimization tool but also a practically valuable decision-support system for professional sports leagues.

Case Context and Organizational Problem

The NBA and MLB are professional sports associations that are complex ecologies of scheduling and need to find equilibrium between monetary efficacy, competitive equity, and player health. In each season, the NBA must organize a total of more than 1,230 games within a period of 170 days, as opposed to MLB, which has to organize a total of more than 2,400 games with widespread intercity travel. Such timing requirements pose tremendous operational pressure in the form of fatigue during travel, the availability of the venues, and budgeting. The leagues in this research are modeled as client organizations, reflecting the real-world context in which the proposed decision-support system would be implemented.. The system solves prominent organizational sore spots such as increased travel expenses, inefficiencies in the logistics, and inequity in the distribution of matches by means of an integrated IT structure, which incorporates optimization intelligence with managerial decision-support functionalities.

Performance Outcomes

The research utilizes the regular season schedules of the NBA (2012–2013) and MLB (2009–2011). These leagues were chosen due to their complexity: the NBA needs 1,230 games in 170 days and MLB needs 2,430 games in 162 days. Scheduling in both instances must consider fairness, cost-effectiveness, and logistical viability. Some aspects were not included in the analysis, such as unforeseen circumstances (e.g., weather disturbances), previous competitions, and the players' circumstances. Although they are essential in practice, they are highly contextual and cannot be easily quantified for use in computation. The major priorities were reducing the total travel distance, minimizing back-to-back games, and sustaining obedience to hard constraints.

Information was collected chronologically across multiple leagues to demonstrate that our method is applicable in all scenarios and can be easily modified with minimal changes to the conditions. The official league sites and Google Maps services provided the training data, including team data and travel distances. The internal links to the SQL Server 2003 database were used to store and retrieve all of the data. Please note that, since no further computations were made during our testing, we have excluded the bandwidth. Four percentage coefficients, 1%, 0.5%, 0.1%, and 0.05%, were selected for the initial assessment of mutation likelihood in both MLB and the NBA. To summarize the tests, our technique reached the target value using 300,000 optimization computations. The proposed approach demonstrates that, compared with the brute-force method (which considers all possible match combinations across the days in a season and requires 2,000,000 computations), our technique achieved significantly higher computational efficiency. The detailed experimental results for each league are presented in Tables A1 and Table A2 (Appendix A).This system was implemented on SQL Server 2003 to manage data, utilized the Google Maps API to calculate geographic distances, and employed a hybrid GA–TS optimization engine to generate schedules. The experiments were conducted on a standard workstation equipped with 16GB of RAM and an Intel Core i7 processor. Mutation rates of 0.01 through 0.5 were used to test the rate of convergence and quality of the solution. Although in the case of the NBA, data convergence was often achieved after 50,000 iterations, for MLB, data convergence was achieved after approximately 30,000 iterations. The schedules were compared with the official league schedules on overall travel distance, equity (the even distribution of travel among teams), and the frequency of back-to-back games.

The system recorded some improvements to official schedules. In the case of MLB, the optimized schedules reduced the travel distance by up to 9.7%, equivalent to approximately 133,000–154,000 km per season. Optimized schedules in the NBA case resulted in a 315,000-km reduction in travel distance compared to the actual 2012–2013 schedule. Additionally, the number of back-to-back games decreased by 96 cases, resulting in an enhanced possibility of player recovery. Fairness was also improved. The gap between the shortest and the longest team travel distances in MLB was narrowed by 210% to 174 km, thereby minimizing the inequities between teams. The NBA reported that several teams had unfair scheduling patterns, with some teams overloaded with travel.. Last, using existing carbon conversion emissions factors, we estimated that these travel cuts would save approximately 237,873 kg of CO_2 per season, equivalent to the carbon uptake of about 782 fir trees in 30 years.

Managerial Interpretation

The results of the experiment yield several managerial implications. To begin with, the system indicates that there can be significant cost reductions, as a direct connection exists between travel cost reduction and operating cost reduction. Although the exact amount of financial savings that will be achieved is determined by the travel arrangements specific to the leagues, a 9% decrease in travel can result in millions of dollars of annual savings to leagues of the size of MLB.

Second, the minimization of back-to-back matches has direct effects on the welfare of players, including better performance, a lower risk of injuries, and a positive reputation for the league as fair. Third, the enhancements in equity and fairness between teams mitigate any potential conflict among stakeholders over competitive balance. Finally, the environmental advantages align with the growing trend of sports organizations to become sustainable, which has both reputational and public relations value.

MLB League Experiment

To prepare the material for calculation, we first converted the official information from the source data websites into acronyms. The mutation rate, typically between 0.1% and 0.05%, was selected for the experiment. We used rates of 0.05%, 0.06%, 0.09%, 0.1%, 0.11%, and 1% to achieve the best results. The data shows that the shortest traveled distance, 1,438,818 km, occurred at a probability coefficient of 0.10%, and 30,000 mutations must occur to reach the convergent point, as shown in Table 4 and Table 5.

Table 4. Team B's Particular Setup (Team B, Third Iteration of Optimization Results)

Round	*Match 1*	*Match 2*	*Match 3*	*Match 4*	*Match 5*	*Match 6*	*Match 7*	*Match 8*	*Match 9*	*Match 10*	*Match 11*	*Match 12*
1	***WZ***	***XW***	***WY***	***WB***	***YW***	***BW***	***WX***	***WA***	***ZW***	***AW***	***BW***	***WX***
2	***XA***	***YZ***	***AX***	***AY***	***XZ***	***XY***	***YB***	***BX***	***YB***	***YX***	***ZY***	—
3	***BY***	***BA***	***ZB***	***ZX***	***AB***	***ZA***	***AZ***	***ZY***	***YA***	***BZ***	***XB***	—
4	***BA***	—	—	—	—	—	—	—	—	—	—	—
5	*W:* ***355*** *X:* ***316*** *Y:* ***303*** *Z:* ***276*** → ***277*** *A:* ***283*** *B:* ***325*** → ***303***											*Total:* ***1,837 km***

Table 5. Team Final Particular Setup

Round	*Match 1*	*Match 2*	*Match 3*	*Match 4*	*Match 5*	*Match 6*	*Match 7*	*Match 8*	*Match 9*	*Match 10*	*Match 11*	*Match 12*
1	***WX***	***ZW***	***WY***	***XW***	***WZ***	***WA***	***YW***	***WB***	***BW***	***AW***	***WY***	***BW***
2	***WB***	***WA***	***YZ***	***XY***	***XA***	***ZA***	***BX***	***YX***	***AZ***	***AX***	***XZ***	***ZX***
3	***ZY***	***XA***	***AZ***	***XB***	***XY***	***ZA***	***XA***	***ZX***	***XZ***	***BA***	***AB***	***ZB***

continued on following page

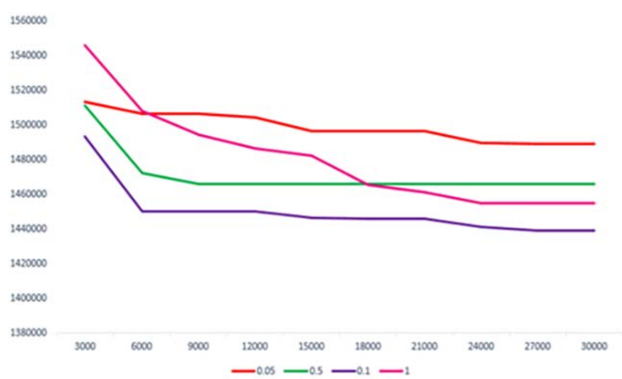
Table 5. Continued

Round	*Match 1*	*Match 2*	*Match 3*	*Match 4*	*Match 5*	*Match 6*	*Match 7*	*Match 8*	*Match 9*	*Match 10*	*Match 11*	*Match 12*
4	***BY***	***YA***	***BZ***	***XB***	***ZY***	***AY***	***YB***	***AB***	***BZ***	***YB***	***AY***	***ZB***
—	***W: 334 X: 345 Y: 273 Z: 269 A: 219 B: 293***											***Total: 1,733 km***

The results clearly show a reduction in travel lengths to 1,465,691 km and 1,489,638 km at mutation rates of 0.50% and 0.05%, respectively. However, the objective value is locked at 1% and cannot be altered by additional mutations. The outcome at 1% reaches the convergence level earlier than the result at 0.1% because of the high mutation rate of the matrix. The updated incidence of the outcome at 0.05% produces the longest travel length when compared to all the other outcomes due to the damaged genes in the matrix. Time investment may be necessary, even if the outcome at 0.05% results in a shorter trip distance than the outcome at 0.10%.

Fig. 3 displays the comparison with the mutation rate. Mutations' update frequency happens throughout the initial 8,000 times during startup. Due to the minimal mutation rate, the cryptic outcomes are displayed in the initial 10,000 iterations at 0.05%, resulting in a minimal update rate of the desired value. The goal values of 1% and 0.5% yield favorable outcomes in the initial 18,000 mutations; however, they also result in low update frequency and convergence at the midpoint of the curve. According to the experimental data, the ideal mutation rate is 0.10%.

Figure 3. An Analysis of the Rate of Mutation



It is also important to note that the amount, 1,565,510 km, was lower than the official total travel distance at the time, 1,592,819 km. ABB in Table 6 refers to the teams' names and locations, which have been abbreviated using two or three uppercase letters. The league that a team belongs to is indicated by the abbreviation LEA. The National League (NL) and American League (AL) are the two conferences in MLB. The precise location of a team is then identified by the word DIVI. A league is divided into three divisions: the East (E) Division, West (W), Division, and Central (C) Division.

Table 7 presents the outcomes of the mutations. The mutation rate, typically between 0.1% and 0.05%, will probably be selected for the experiment. The season spans from April 5, 2011, to October 16, 2011, during which the simulation is running, as shown in Table 6 and Table 7.

Table 6. Major League Baseball (MLB) Relationship and Team Abbreviations

ABB	DIVI	LEA	ABB	DIVI	LEA
BAL	E	AL	FLA	E	NL
NYY	E	AL	PHI	E	NL
BOS	E	AL	WSH	E	NL
TOR	E	AL	NYM	E	NL
TB	E	AL	CHC	C	NL
CWS	C	AL	CIN	C	NL
CLE	C	AL	HOU	C	NL
DET	C	AL	MIL	C	NL
KC	C	AL	PIT	C	NL
MIN	C	AL	STL	C	NL
LAA	W	AL	ARI	W	NL
OAK	W	AL	COL	W	NL
SEA	W	AL	LAD	W	NL
TEX	W	AL	SD	W	NL
ATL	E	NL	SF	W	NL

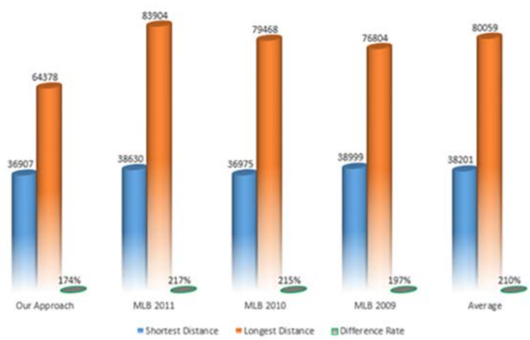
Table 7. Mutations Output for Four Distinct Possibilities Coefficients

Times	0.05%	0.50%	0.10%	1%
3,000	1,513,367	1,510,951	1,493,251	1,545,911
6,000	1,506,380	1,472,180	1,449,796	1,507,705
9,000	1,506,380	1,465,691	1,449,796	1,494,396
12,000	1,504,154	1,465,691	1,449,796	1,486,385
15,000	1,496,407	1,465,691	1,446,223	1,482,090
18,000	1,496,407	1,465,691	1,445,744	1,465,116
21,000	1,496,232	1,465,691	1,445,744	1,461,078
24,000	1,489,638	1,465,691	1,440,910	1,455,046
27,000	1,489,257	1,465,691	1,438,897	1,455,046
30,000	1,488,861	1,465,691	1,438,818	1,455,046

We use abbreviations to calculate official data obtained from websites. Table 6 uses ABB to indicate abbreviations of team names and locations. DIVI indicates the Central (C), West (W), and East (E) divisions. LEA indicates the American League (AL) and the National League (NL).

Officially recognized MLB games played between 2009 and 2011 are used as complex data for the comparison. Fig. 4 displays the noteworthy findings, which reduce the number of trips to a range of 133,000 to 154,000 km. The percentage has decreased by one degree, standing at around 9.6% in 2011, 9.7% in 2010, and 8.5% in 2009. The detailed experimental data are available in the appendix (optimized scheduled results). It is noteworthy that 23 MLB teams have shorter travel distances, with an improvement rate of almost 77%. A further concern about equity arises from the disparity in travel distances between teams, such as the longest and shortest ones, as shown in Algorithm 1. There is a twofold discrepancy when comparing the average trip distance in MLB between the shortest and longest routes, which amounts to 210%. In this study, the rate is reduced to 174%. Even with some remaining imbalance, the disparity has decreased by 36%..

Figure 4. Comparison Between Different Years



Note. MLB = Major League Baseball.

The NBA League Experiment

A similar technique was used to perform the test in the NBA. We use abbreviations to calculate official data obtained from websites. Table 8 uses ABB to indicate abbreviations of team names and locations. CNF refers to the conference to which the teams belong. The Western (W) and Eastern (E) leagues are the only ones. The word DIVI indicates the divisions. To facilitate calculation, we used a total of six divisions over two conferences. 1 represents the Atlantic division, 2 the Central division, and 3 the Southeast division in the Eastern Conference. 4 represents the Northwest division, 5 the Pacific division, and 6 the Southwest division in the Western Conference. The schedules from the NBA's 2012–2013 typical season are compared in this experiment. As a result, the start and end dates (October 31, 2013, for the first match and April 18, 2013, for the last match) were set within the same season. Of the 170 days, 7 were devoid of any gaming sessions. As a result, the training could only last 163 days.

Table 8. NBA Team and Relationship Abbreviations

Team	CNF	DIVI	ABB	CNF	DIVI
PHI	E	1	ORL	E	3
DET	E	2	SAC	W	4

continued on following page

Table 8. Continued

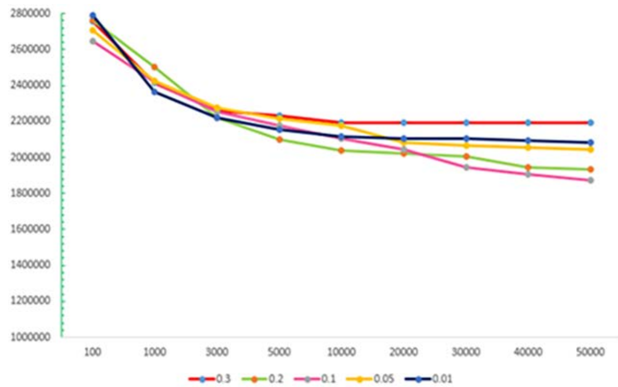
Team	CNF	DIVI	ABB	CNF	DIVI
BKN	E	1	CHA	E	3
CHI	E	2	GS	W	4
TOR	E	1	OKC	W	5
IND	E	2	LAL	W	4
BOS	E	1	HOU	W	6
CLE	E	2	UTA	W	5
NYK	E	1	NOP	W	6
MIA	E	3	MIN	W	5
MIL	E	2	DAL	W	6
WAS	E	3	POR	W	5
PHX	W	4	SAS	W	6
ATL	E	3	DEN	W	5
LAC	W	4	MEM	W	6

Following decoding, the first groups were established (see Table 8). After setup, our system calculates modifications for each gene based on distance and circumstances (hard and soft constraints) in the dataset. This leads to a learning process for evolution. After conducting numerous assessments, we found that convergence (or equivalent values) occurred at 50,000 optimization iterations, which was fewer than the number found in the MLB trial. The ideal training period was therefore determined to be 50,000. A typical setting for the crossover rate is 0.7. We evaluated efficiency at several speeds and saw no discernible differences. As a result, we set the crossover rate as a general rule at 0.7. Typically, mutation rates range from 0.01 to 0.5. However, it varies depending on the event and context. Initially, we set the mutation rate between 0.01 and 0.5. Although we achieved multiple satisfactory answers, the evolution rate started to diminish. For the remaining experiments, we used mutation rates of 0.3, 0.2, and 0.1. Table 8 and Table 9, as well as Fig. 5, provide detailed information.

Table 9. Mutation Results for Different Coefficients

Time	0.01	0.05	0.1	0.2	0.3
100	2,792,294	2,707,912	2,645,222	2,764,106	2,754,234
1,000	2,362,382	2,424,840	2,420,987	2,501,102	2,412,218
3,000	2,223,400	2,278,545	2,254,764	2,221,063	2,260,454
5,000	2,152,116	2,217,869	2,176,677	2,099,780	2,233,147
10,000	2,113,431	2,178,162	2,102,249	2,040,839	2,195,988
20,000	2,106,994	2,081,082	2,042,911	2,021,621	2,195,988
30,000	2,103,773	2,064,640	1,942,132	2,005,918	2,195,988
40,000	2,095,215	2,057,810	1,908,374	1,946,655	2,195,988
50,000	2,082,844	2,043,058	1,875,148	1,936,268	2,195,988

Figure 5. Graphical Approach for the Mutation Outcomes



The data shows that a frequency of 0.1 produced the best outcomes overall. Continuous evolution of results at rates of 0.05 or 0.01 may result in increased calculation time owing to falling mutation rates. We discovered that using a rate of 0.3 resulted in early convergence of the algorithm. The mutation ended at Generation 10,000 at a value of 2,195,988, which cannot be modified further. Setting the mutation rate to 0.1 allows us to achieve the best possible solution. We briefly examined the 0.1 mutation rate in Generation 50,000. When the mutation reaches Generation 5,000, there is a noticeable reduction in total travel distance of approximately 600,000 kilometers. Eventually, the travel distance decreases further to about 1,875,148 kilometers in Generation 50,000, which represents the most optimized and advantageous result..

We begin comparing our outcomes with the targeted objective under these parameters. Table A3 presents the calculation results of our algorithm based on actual NBA 2012–2013 season statistics. The official match setup included a home–away limitation (50% at home and 50% away), which was followed. However, one club had consecutive matches three times under these circumstances. This indicates that it deviates from the NBA's specified criteria, which is two at most. Despite this infraction, the official records of the game-match setup allow us to acquire a total journey distance of 2,190,618 km. By resolving the wrong back-to-back game-match scenario, our method enhanced performance. The outcomes are shown in Table A3 (Appendix A).

Table A4 (Appendix A) makes it clear that the timetable created by our technology complies with the NBA's rules with travel of 1,875,148 km, 315,470 km less than the authoritative setup. Table A4 displays the detailed contrasts between official data and our methodology. Even though certain teams' trip lengths rose following calculation and optimization, there was a noticeable reduction in journey distance and consecutive game-matches, which have a major impact on fairness. We eliminated at least two matches (-1 for NYK, UTA, TOR, DET, and CHI) in addition to at most 10 games (-10 for WAS) to address the back-to-back game-match issue. There was a reduction of 96 consecutive games in all, which is a significant reduction in player energy consumption and, to some extent, carbon emissions, because less distance was covered by vehicles (such as buses, trains, and airplanes).

Environmental Preservation

Besides enhancing cost-effectiveness and equity, the proposed system would help achieve broader organizational objectives in terms of sustainability. It is expected that professional sports leagues are moving toward becoming environmentally responsible to reduce operational costs and improve their image. Among the main contributors to carbon emissions in relation to league operations, travel should be regarded as one of the most essential aspects, and planning is a critical sphere of environmental impact (Field et al., 2020; Matthews et al., 2009).

The annual carbon conversion factors we used allowed us to estimate that the system could achieve savings in travel distance of approximately 237,873 km of CO_2 per season, which is comparable to the carbon absorption capacity of about 782 fir trees in 30 years. These findings demonstrate that through optimal scheduling, it is possible to achieve substantial environmental and financial benefits.

These findings can be applied in several managerial ways. First, the corporate social responsibility strategy of a league can be supported by the sustainability outcomes that help build the team's brand image among fans, sponsors, and the broader community. Second, the ability to capture carbon might allow leagues to be consistent with governmental or industry regulations on sustainability.

. Third, the generation of long-term financial value can be attained with the help of green schedules because the less a team travels, the less money they will spend on fuel, as well as other costs such as accommodation. This part demonstrated that the system's value extends beyond logistics and cost-saving, also offering strategic benefits to the organization through the inclusion of sustainability in the case analysis. In this way, the environmental contribution is not incidental but is one of the main elements of the system, especially in modern sports management.

Managerial Implications, Lessons Learned, and Organizational Impact

The proposed study represents a significant step forward in offering a more effective optimization algorithm for scheduling processes as well as demonstrating how this type of system can be applied to professional sports leagues in terms of organizational practice. The managerial implications, lessons learned, and value of the proposed approach supported by IT in general are highlighted in the following. In our case studies on the NBA (2012–2013) and MLB (2009–2011) data, we demonstrate how the league organizers can integrate the scheduling system into their activities. The system can be easily integrated with current IT structures that league scheduling departments already use by extracting geographic data using the Google Maps API and storing and retrieving data using SQL Server. The findings give practical advice to league managers and IT specialists. Our method of creating schedules has resulted in a reduction of hundreds of thousands of kilometers in overall travel distance, thereby decreasing financial and logistical costs. The reduced number of consecutive games results in a decreased level of fatigue, consequently enhancing the athletes' performance and reducing the chances of injury. The allocation of travel distribution among teams is a way of ensuring that no team is heavily disadvantaged. Sports organizations are directly aligned with the objectives of environmental responsibility, as reduced travel costs directly reduce carbon emissions.

The testing and development of the scheduling system also revealed some important lessons. In every league, there are specific rules and traditions; a systemic IT design can address limitations and implement the system in any situation. To a certain degree, reducing travel expenses can cause minor scheduling discrepancies. A multi-objective approach enables managers to trade off. Piloting on past data before the actual deployment of the program mitigates risks and instills confidence in the stakeholders.

The suggested system is not only technically optimizing but also directly brings value to the organization. The way this happens is that the evolutionary algorithms are confined to the geographic sources (Google Maps) and database systems (SQL Server). The benefits are in the tangible outputs: lower expenses, healthier players, equal competition, and measurable environmental gains. These outcomes are not only strategic but also reputational to the sports organizations, and this testifies to the transformational nature of IT in the management of mega sporting events. Based on the average operating costs of professional sports teams (including charter flight costs estimated at \$15–20 per kilometer, hotel costs of \$150 per night per person, and daily allowances), the elimination of 315,470 km of travel may translate into cost savings of millions of dollars in an NBA season. Even minor adjustments to team travel schedules and contractual arrangements specific to each league could result in significant financial benefits.. This shows that besides making the logistical system more efficient and more equitable, it also has an actual monetary impact on the sports organizations.

Prototype Case Study Implementation and Evaluation

The datasets included team locations, home-and-away patterns, and historical travel itineraries, all synchronized through SQL Server and the Google Maps API to ensure accurate distance computations. The system was deployed in a simulated scheduling environment where decision parameters such as fixture spacing, travel constraints, and fairness weights could be interactively modified through the web interface. This allowed league administrators and IT analysts to evaluate the algorithm’s responsiveness, transparency, and adaptability.

During implementation, several practical challenges emerged, including data synchronization delays, dynamic distance recalculations, and computational scalability as the number of teams increased. These issues were mitigated through optimized database indexing and parallelized API calls. The user interface provided visualization dashboards that enabled stakeholders to assess schedule feasibility, detect travel imbalances, and perform scenario testing in real time.

The results demonstrated tangible organizational benefits. For the MLB dataset, the system achieved an average 9.7% reduction in total travel distance, translating into direct operational cost savings. In the NBA case, the reduction of consecutive away games improved player recovery and performance consistency. Both case studies confirmed that the system could balance quantitative optimization with managerial goals such as fairness, sustainability, and player welfare.

By framing these experiments as applied case studies, this section illustrates not only the computational validity of the hybrid GA–TS model but also the real-world decision-support value of the web-based scheduling platform.

CONCLUSION

This research has been structured to provide both an algorithmic contribution and a case-style analysis of a prototype-based information system designed to assist in the scheduling of professional sports. Using the system with real NBA and MLB datasets, we have recreated the environment of real organizational applications and demonstrated the system's potential to change the practice of scheduling. This work is hence focused on the information system as an IT artifact, the organizational value that it offers, and the managerial lessons that can be learned in the process of developing and implementing the information system. The NBA and MLB are two professional sports associations that continually struggle to develop a fair, affordable, and operational approach to scheduling. This paper not only proposes a better optimization method but also provides a working IT artifact of a web-based scheduling system, which incorporates the Google Maps API, SQL Server, and a hybrid GA–TS engine. Through experimentation with the system using real NBA and MLB data, we have demonstrated how such technology can be applied to solve real organizational issues in a multi-billion-dollar industry. The findings indicate that the system will be able to reduce the travel distance, minimize the number of back-to-back games, and therefore enhance the cost-effectiveness and welfare of players.

Besides the performance of the algorithm, the system also shows how IT may be used by league administrators as a decision-support mechanism. It offers tips that work, such as reducing the expenses related to travel caused by improper scheduling, which also reduces carbon emissions. These managerial implications are obvious: lower operational costs, equal competition, better health of players, and improved ecological reputation of the leagues. More importantly, the study identifies the lessons that ought to be embraced in the future. The requirement of inclusion in organizational operations entails flexibility of system design, low-speed implementation based on past experiences, and communication of results to different parties. The decision-makers should be open to any resistance or feedback offered, and the decisions made should also be communicated in a transparent way.. Training needs to be completed in a way that guarantees that schedulers can communicate with the system with confidence. Optimally, the system should be seen not as a substitute for human judgment but, on the contrary, as a complement that supports the decision-making process. Thus, the research will help not only to justify a method of optimization but also to present a case-based examination of the process of IT system implementation in sports organizations.

The current study is a prototype validation study but not a live implementation and therefore offers a model of how to conduct studies in the future on professional leagues. It provides lessons that are transferable to other companies that have high levels of scheduling problems. The article demonstrates how IT is transformational in resolving complicated real-world issues by harmonizing technical innovation with practice within the organization.

COMPETING INTERESTS

The authors declare that there are no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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CORRESPONDING AUTHOR

Correspondence should be addressed to Dr. Zhengchang Li (lizhgengchang7719@163.com).

REFERENCES

Alami Merrouni, Z., Frikh, B., & Ouhbi, B. (2020). Automatic keyphrase extraction: A survey and trends. *Journal of Intelligent Information Systems*, *54*(2), 391–424. DOI: 10.1007/s10844-019-00558-9

Anuradha, D., Jayalakshmi, M., Kavitha, K., Sajad, B., & Raza, K. (2019). Solid assignment problem in manufacturing logistics. *International Journal of Civil Engineering and Technology*, *10*(2), 1846–1850. https://iaeme.com/MasterAdmin/Journal_uploads/IJCIET/VOLUME_10_ISSUE_2/IJCIET_10_02_181.pdf

Balas, E., & Saltzman, M. J. (1991). An algorithm for the three-index assignment problem. *Operations Research*, *39*(1), 150–161. DOI: 10.1287/opre.39.1.150

Barone, L., While, L., Hughes, P., & Hingston, P. (2006). Fixture-scheduling for the australian football league using a multi-objective evolutionary algorithm. *2006 IEEE International Conference on Evolutionary Computation*. DOI: 10.1109/CEC.2006.1688413

Bueno, E. F. (2014). *Mathematical modeling and optimization approaches for scheduling the regular-season games of the National Hockey League* [Doctoral dissertation, École Polytechnique de Montréal]. PolyPublic. https://publications.polymtl.ca/1534/

Durán, G., Durán, S., Marenco, J., Mascialino, F., & Rey, P. A. (2019). Scheduling Argentina's professional basketball leagues: A variation on the Travelling Tournament Problem. *European Journal of Operational Research*, *275*(3), 1126–1138. DOI: 10.1016/j.ejor.2018.12.018

Field, J. L., Richard, T. L., Smithwick, E. A. H., Cai, H., Laser, M. S., LeBauer, D. S., Long, S. P., Paustian, K., Qin, Z., Sheehan, J. J., Smith, P., Wang, M. Q., & Lynd, L. R. (2020). Robust paths to net greenhouse gas mitigation and negative emissions via advanced biofuels. *Proceedings of the National Academy of Sciences of the United States of America*, *117*(36), 21968–21977. DOI: 10.1073/pnas.1920877117 PMID: 32839342

Gaudenzi, F. (2019). *A framework for cloud assurance and transparency based on continuous evidence collection* [Doctoral dissertation, Univestitá degli Studi di Milano]. AIR Unimi. https://air.unimi.it/retrieve/dfa8b99c-ea11-748b-e053-3a05fe0a3a96/phd_unimi_R11308.pdf

Goossens, D. (2018). Optimization in sports league scheduling: Experiences from the Belgian Pro League soccer. In *Operations research and enterprise systems. ICORES 2017. Communications in computer and information science, vol. 884* (pp. 3–19). Springer. DOI: 10.1007/978-3-319-94767-9_1

Hung, J. C., Yen, N. Y., Jeong, H.-Y., & Chan, Y.-W. (2015). Adaptive mechanism for schedule arrangement and optimization in socially-empowered professional sports games. *Multimedia Tools and Applications*, *74*(14), 5085–5108. DOI: 10.1007/s11042-014-1852-2

Ilarri, S., Trillo-Lado, R., & Hermoso, R. (2018). Datasets for context-aware recommender systems: Current context and possible directions. In *2018 IEEE 34th International Conference on Data Engineering Workshops (ICDEW)* (pp. 25–28). IEEE. DOI: 10.1109/ICDEW.2018.00011

Kendall, G. (2018). Is evolutionary computation evolving fast enough? *IEEE Computational Intelligence Magazine*, *13*(2), 42–51. DOI: 10.1109/MCI.2018.2807019

Khalili-Fard, A., Tavakkoli-Moghaddam, R., Abdali, N., Alipour-Vaezi, M., & Bozorgi-Amiri, A. (2024). A roommate problem and room allocation in dormitories using mathematical modeling and multi-attribute decision-making techniques. *Journal of Modelling in Management*, *19*(5), 1404–1433. DOI: 10.1108/JM2-09-2023-0214

Li, M., Davari, M., & Goossens, D. (2023). Multi-league sports scheduling with different leagues sizes. *European Journal of Operational Research*, *307*(1), 313–327. DOI: 10.1016/j.ejor.2022.10.010

Liang, Y.-C., Lin, Y.-Y., Chen, A. H.-L., & Chen, W.-S. (2021). Variable neighborhood search for Major League Baseball scheduling problem. *Sustainability (Basel)*, *13*(7), 4000. DOI: 10.3390/su13074000

Matthews, H. D., Gillett, N. P., Stott, P. A., & Zickfeld, K. (2009). The proportionality of global warming to cumulative carbon emissions. *Nature*, *459*(7248), 829–832. DOI: 10.1038/nature08047 PMID: 19516338

Mirjalili, S. (2019). *Evolutionary algorithms and neural networks: Theory and applications. Studies in computational intelligence* (*Vol. 780*). Springer. DOI: 10.1007/978-3-319-93025-1

Sadeghi Moghadam, M. R., Safari, H., & Yousefi, N. (2021). Clustering quality management models and methods: Systematic literature review and text-mining analysis approach. *Total Quality Management & Business Excellence*, *32*(3–4), 241–264. DOI: 10.1080/14783363.2018.1540927

Samorani, M., Wang, Y., Wang, Y., Lv, Z., & Glover, F. (2019). Clustering-driven evolutionary algorithms: An application of path relinking to the quadratic unconstrained binary optimization problem. *Journal of Heuristics*, *25*(4-5), 629–642. DOI: 10.1007/s10732-018-9403-z

Szymanski, S., & Winfree, J. (2018). On the optimal realignment of a contest: The case of college football. *Economic Inquiry*, *56*(1), 483–496. DOI: 10.1111/ecin.12493

Wang, R., Zhu, Y., Tan, J., & Zhou, B. (2017). Detection of malicious web pages based on hybrid analysis. *Journal of Information Security and Applications*, *35*, 68–74. DOI: 10.1016/j.jisa.2017.05.008

Yi, X., & Goossens, D. (2023). Strategies for dealing with uncertainty in time-relaxed sports timetabling. *Annals of Operations Research*, *320*(1), 473–492. DOI: 10.1007/s10479-022-04957-0 PMID: 36120422

Zhang, S. (2022). Application of a depth model of precise matching between people and posts based on ability perception. *Computational Intelligence and Neuroscience*, *2022*, 9040349. Advance online publication. DOI: 10.1155/2022/9040349 PMID: 36188699

APPENDIX. OPTIMIZED SCHEDULE RESULTS

As illustrated in Table A1, Team B-1's optimized schedule demonstrates a balanced distribution of home and away games, achieving a total travel distance of 1,871 km after optimization. Similarly, Table A2 presents Team B-2's refined configuration, where the total distance decreases to 1,858 km, reflecting improved spatial efficiency. Together, Tables A1 and Table A2 confirm that the proposed scheduling framework effectively minimizes redundant travel while preserving fairness and competitive symmetry across teams.

Table A1. Team B-1's Particular Setup

Round	Match 1	Match 2	Match 3	Match 4	Match 5	Match 6	Match 7	Match 8	Match 9	Match 10	Match 11	Match 12
1	WX	ZW	WY	XW	WZ	WA	YW	WB	BW	AW	WY	BW
2	WB	WA	YZ	XY	XA	ZA	BX	YX	AZ	AX	XZ	ZX
3	ZY	XA	AZ	XB	XY	ZA	XA	ZX	XZ	BA	AB	ZB
4	BY	YA	BZ	XB	ZY	AY	YB	AB	BZ	YB	AY	ZB
Totals	**W: 334**	**X: 345**	**Y: 273**	**Z: 269**	**A: 219**	**B: 293**						**Total Distance: 1,733 km**

Table A2 .Team B-2's Particular Setup

Round	Match 1	Match 2	Match 3	Match 4	Match 5	Match 6	Match 7	Match 8	Match 9	Match 10	Match 11	Match 12	Match 13	Match 14	Match 15	Match 16	Match 17	Match 18	Match 19	Match 20
1	WZ	XW	WY	WB	YW	BW	WX	WA	ZW	AW	WA	WZ	XW	ZW	WY	WB	YW	AW	BW	WX
2	XA	YZ	AX	AY	XZ	XY	YB	BX	XB	YX	YZ	XA	AY	BX	XZ	XY	AX	YB	YX	ZY
3	BY	BA	ZB	ZX	AB	ZA	AZ	ZY	YA	BZ	XB	BY	ZB	YA	—	ZA	BZ	ZX	AZ	AB
4	BA	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	ZB	—	—	—
Totals	**W: 355**	**X: 316**	**Y: 303**	**Z: 276**	**A: 283**	**B: 325**														**Total**

As shown in Table A3, the optimized scheduling framework demonstrates clear improvements in both total travel distance and the reduction of consecutive games across all NBA teams in the 2012–2013 season. The refined schedules achieve fewer back-to-back fixtures while maintaining competitive balance. Correspondingly, Table A4 compares the proposed system with the official league schedule, revealing a cumulative travel reduction of 315,470 km and a decrease of 96 consecutive games overall. Together, Tables A3 and Table A4 validate the effectiveness of the web-based scheduling system in minimizing logistical load, improving player welfare, and promoting fairness, thereby substantiating the managerial and operational advantages of the proposed IT artifact.

Table A3. National Basketball Association (NBA) 2012–2013 Schedule of Games and Optimum Constructive Matches

NBA 2012–2013 match schedule						Improvement in consecutive matches	
Distance traveled	**Away**	**Home**	**Games**	**Consecutive games**	**Sum of consecutive games**	**Distance traveled**	**Sum of consecutive games**
30,869	41	41	82	2	22	30,396	16
40,213	41	41	82	2	23	34,572	18
36,281	41	41	82	2	19	35,689	20
40,153	41	41	82	2	22	33,526	18
41,053	41	41	82	2	18	47,378	18
68,993	41	41	82	2	19	44,172	18
46,730	41	41	82	2	22	46,688	17
47,125	41	41	82	2	19	48,206	18
57,048	41	41	82	3	23	37,117	18
67,603	41	41	82	2	22	58,803	17
61,359	41	41	82	2	22	46,037	19
60,681	41	41	82	2	22	49,114	15
57,648	41	41	82	2	16	87,959	16
65,331	41	41	82	2	13	67,821	22
38,448	41	41	82	2	21	41,184	11
110,938	41	41	82	2	20	84,872	15
111,981	41	41	82	2	21	83,097	13
105,003	41	41	82	2	16	92,693	18
113,467	41	41	82	2	19	77,111	10
106,352	41	41	82	2	17	104,571	13
104,908	41	41	82	2	17	76,638	19
74,292	41	41	82	2	22	59,049	15
89,028	41	41	82	2	15	65,518	18
105,104	41	41	82	2	17	114,487	19
113,076	41	41	82	2	17	82,106	19
77,222	41	41	82	2	16	69,428	15
79,471	41	41	82	2	21	72,306	16
81,815	41	41	82	2	18	64,296	10
73,071	41	41	82	2	19	64,715	13
85,355	41	41	82	2	17	55,599	15

Table A4. Comparing the Official Technique and Our Technique

Team	Distance traveled (our scenario)	Distance traveled (official scenario)	Difference in distance traveled	Consecutive games (our scenario)	Consecutive games (official scenario)	Consecutive games difference
BKN	34,572	40,213	-5,641	17	23	-6
TOR	47,378	41,053	6,325	17	18	-1
BOS	30,396	30,869	-473	16	22	-6
MIL	58,803	67,603	-8,800	17	22	-5
CHI	44,172	68,993	-24,821	18	19	-1
NYK	35,689	36,281	-592	18	19	-1
CLE	46,688	46,730	-42	16	22	-6
PHI	33,526	40,153	-6,627	17	22	-5
MIA	87,959	57,648	30,311	16	16	0
IND	37,117	57,048	-19,931	18	23	-5
DET	48,206	47,125	1,081	18	19	-1
ORL	67,821	65,331	2,490	21	13	8
SAS	55,599	85,355	-29,756	15	17	-2
WAS	41,184	38,448	2,736	11	21	-10
SAC	104,571	106,352	-1,781	13	17	-4
CHA	49,114	60,681	-11,567	15	22	-7
PHX	77,111	113,467	-36,356	10	19	-9
DAL	69,428	77,222	-7,794	15	16	-1
DEN	76,638	104,908	-28,270	18	17	1
UTA	82,106	113,076	-30,970	19	17	2
NOP	64,715	73,071	-8,356	12	19	-7
LAL	92,693	105,003	-12,310	18	16	2
POR	114,487	105,104	9,383	18	17	1
MEM	64,296	81,815	-17,519	10	18	-8
OKC	65,518	89,028	-23,510	18	15	3
HOU	72,306	79,471	-7,165	16	21	-5
ATL	46,037	61,359	-15,322	19	22	-3
LAC	83,097	111,981	-28,884	13	21	-8
MIN	59,049	74,292	-15,243	15	22	-7
GS	84,872	110,938	-26,066	15	20	-5
Total 1,875,148 2,190,618 -315,470 479 575 -96						