No Layovers, Only Layups - WNBA Schedule Optimization

Enhancing Logistics and Fairness for a Growing League

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Abstract

This study focuses on the creation of an optimized 40-game schedule for the WNBA 2024 season. Our primary objective is to use linear programming to minimize total travel distances. Our constraints focus on satisfying operational and fairness constraints. Specifically, we looked to balance the distribution of home and away games, ensure adequate rest periods for players, and fulfill conference play requirements. This study evaluates two primary scheduling models: the **Return Home Model**, which prioritizes teams returning home between away games, and the **City-to-City Model**, which minimizes travel by optimizing consecutive away games.

The need for this project is particularly timely given the recent surge in the WNBA's popularity. With the rise of prominent players, there has never been more eyes on the WNBA association to keep up with increased media coverage and the growing fan base. A well-designed schedule is crucial for sustaining growth of the league and enhancing overall experience for players and fans.

By leveraging mathematical programming to address real-world scheduling challenges, this study seeks to support the WNBA's mission to deliver high-quality competition, promote player well-being, and ensure logistical efficiency. The resulting schedule balances practical constraints with the league's long-term strategic goals, providing a framework that can adapt to future seasons and other professional sports contexts.

Background

Scheduling a professional sports league is a complex task that involves balancing fairness, logistical constraints, and operational efficiency. The WNBA's 2024 season requires a 40-game schedule for each team, with 20 home and 20 away games (Women's National Basketball Association). The main consideration when constructing a sporting league schedule is to minimize travel distance to reduce costs. Another important consideration when scheduling is reducing player fatigue and ensuring fairness among teams. For the 2024 season, the Indiana Fever was scheduled to play 7 games in a 12 day period, while the Las Vegas Aces were scheduled to play 4 games in the same 12 day period (Negley, 2024). Imbalances like these aren't great for the players because of player burnout or for fans, who deserve a consistent viewing schedule.

This project takes on added significance due to the recent surge in the WNBA's popularity. With the rise of notable players like Breanna Stewart, Caitlin Clark, A'ja Wilson, and Sabrina Ionescu, as well as increased media coverage and viewership, the league has reached unprecedented levels of visibility. This growth presents an opportunity for the WNBA to solidify its reputation as a major professional sports league while fostering long-term sustainability and fan engagement.

A well-structured and efficiently optimized schedule plays a crucial role in supporting this growth. By minimizing logistical burdens such as excessive travel and poorly spaced games, the league can enhance the performance and well-being of its players, ensuring higher-quality competition. Additionally, a balanced schedule improves accessibility for fans, creating consistent opportunities to watch games both in arenas and on broadcast.

Problem Statement

How can the WNBA's 2024 season be scheduled to:

1. Minimize the total travel distance for teams.
2. Satisfy constraints such as:
    a. Logistical Constraints
        i. No self-matchups
        ii. Exactly 40 games per team (20 home, 20 away).
        iii. One game per day (for each team)
        iv. At least 24 games against conference opponents.
        v. Minimum weekly games per league
    b. Fairness Constraints
        i. Maximum games per week (per team)
        ii. Adequate rest days to prevent back-to-back games.
        iii. Adequate gap between away games
        iv. Limits against games with same opponents
        v. Strength of Schedule

<u>Goal:</u> Developing an optimization model that addresses these goals while generating a practical schedule for implementation.

Data

1. Teams Data:
    a. A list of the 12 WNBA teams, their home arenas, and conference affiliations.
    b. Last 5 years of WNBA win-loss records
2. Distance Matrix:
    a. Travel distances between teams' home arenas.
3. Season Structure:
    a. 20 weeks of play.
    b. 7 days per week.
    c. An average of 2-3 games per week per team.

Model Optimization Selection:

In order to figure out how we could optimize the travel distance, there are many options to choose the objective function. When we think about travelling for a team, if the Seattle Storm were to play the Chicago Sky and then play the New York Liberty, the optimal route would be:

Seattle -> Chicago -> New York, rather than Seattle -> Chicago ->Seattle -> New York. In order to handle this we implemented two solutions (Return Home Model and City-to-City Model).

Methodology For *Return Home Model*:

Return Home Model:

This model takes the assumption that teams in the WNBA want to be able to return home in order to prepare for the next upcoming game that they have. This model adopts a strategy that is similar to that of the NFL. This is due to the fact that we will be able to put a specified gap between away games that would allow the teams to return home and prepare for. We can design our objective function to track distance specifically from the home arena to the next arena.

Data and Model Setup:

Data Structures Setup:

We utilized a hashmap in order to store the pertinent data for the model to analyze:

```
'ATL': {
    'name': 'Atlanta Dream',
    'city': 'Atlanta',
    'state': 'Georgia',
    'conference': 'Eastern',
    'coordinates': (33.7490, -84.3880),
    'timezone': 'ET',
    'arena': 'Gateway Center Arena',
    'strength': 0.40
},
```

Distance Calculation:

The distance matrix created is a fundamental element of our scheduling problem for the travel distances between the home arenas. In order to be able to properly implement the calculation for the distances we utilized the Haversine Formula for latitude longitude coordinate distance.

$$d = 2r \arcsin\left(\sqrt{\sin^2\left(\frac{\phi_2 - \phi_1}{2}\right) + \cos(\phi_1)\cos(\phi_2)\sin^2\left(\frac{\lambda_2 - \lambda_1}{2}\right)}\right)$$

Using this formula we were able to pre-compute the distances for each city to city. We stored all this information in a matrix and use it to calculate our objective function:

	ATL	CHI	CON	IND	NYL	WAS	DAL	LVA	LAS	MIN	PHO	SEA
ATL	0.00	588.34	857.64	426.96	746.49	541.52	737.39	1740.88	1931.33	907.35	1587.54	2176.81
CHI	588.34	0.00	800.58	164.71	714.17	593.39	817.08	1520.10	1741.09	354.33	1450.72	1731.71
CON	857.64	800.58	0.00	745.80	111.63	316.34	1497.23	2320.12	2539.79	1088.57	2239.03	2463.56
IND	426.96	164.71	745.80	0.00	646.43	490.61	778.39	1589.85	1804.54	510.29	1495.12	1866.39
NYL	746.49	714.17	111.63	646.43	0.00	204.99	1389.13	2229.43	2447.24	1019.56	2141.51	2404.23
WAS	541.52	593.39	316.34	490.61	204.99	0.00	1198.46	2079.60	2292.58	930.94	1976.21	2320.33
DAL	737.39	817.08	1497.23	778.39	1389.13	1198.46	0.00	1051.96	1219.61	869.87	866.36	1667.89
LVA	1740.88	1520.10	2320.12	1589.85	2229.43	2079.60	1051.96	0.00	228.26	1292.60	255.93	870.94
LAS	1931.33	1741.09	2539.79	1804.54	2447.24	2292.58	1219.61	228.26	0.00	1520.36	356.58	959.54
MIN	907.35	354.33	1088.57	510.29	1019.56	930.94	869.87	1292.60	1520.36	0.00	1277.59	1390.28
PHO	1587.54	1450.72	2239.03	1495.12	2141.51	1976.21	866.36	255.93	356.58	1277.59	0.00	1113.70
SEA	2176.81	1731.71	2463.56	1866.39	2404.23	2320.33	1667.89	870.94	959.54	1390.28	1113.70	0.00

<u>Optimization Model implementation:</u>

We utilized PuLP as a linear programming package for Python in order to solve the optimization problem that we have. This framework allows us to transform the model that we have into a standardized format for our optimization solver to solve. We then defined the necessary variables, constraints and objective function so that the algorithm can find the optimal schedule.

We were able to formulate the problem as a minimization problem through using PuLP's LP problem class.

```
print("Model initialization")
prob = pulp.LpProblem("WNBA_40_Game_Schedule", pulp.LpMinimize)
```

The algorithm run through PuLP was using the CBC solver (COIN or Branch and Cut). We set a maximum time constraint and ran the branch and bound algorithm in order to find the optimal integer solution

<u>Optimization Model</u>

Through our designed distance matrix we were able to to create the objective function:

```
prob += pulp.lpSum(x[i,j,w,d] * distance_matrix.loc[i,j]
                   for i in teams
                   for j in teams
                   for w in weeks
                   for d in days)
```

This allows us to multiply every possible game variable with the distance that it would be utilizing the distance matrix. Note that we only need to track the distance for the traveling team as the home team would be 0 distance.

Objective Function:

Minimize total travel distance:

$$\text{Minimize} \sum_{i \in T} \sum_{j \in T} \sum_{w \in W} \sum_{d \in D} x_{ijwd} \cdot d_{ij}$$

Where:

x_{ijwd} : Binary variable indicating if team i plays team j on week w, day d (1=yes, 0=no). Binary variables ensure that a game is either scheduled or not.

d_{ij} : Distance between team i and team j

Constraints:

1. No self-matchups:

$$x_{iiwd} = 0 \quad \forall i, w, d$$

2. Total games (40 per team):

$$\sum_j \sum_w \sum_d (x_{ijwd} + x_{jiwd}) = 40 \quad \forall i$$

3. Home games (20 per team):

$$\sum_j \sum_w \sum_d x_{jiwd} = 20 \quad \forall i$$

4. One game per day:

$$\sum_j (x_{ijwd} + x_{jiwd}) \leq 1 \quad \forall i, w, d$$

5. Maximum games per week:

$$\sum_{j \in \text{Teams}} \sum_{d \in \text{Days}} (x_{i,j,w,d} + x_{j,i,w,d}) \leq 3, \quad \forall i, \forall w$$

6. No back-to-back games:

$$\sum_j \left(x_{ijwd} + x_{jiwd} + x_{ijw(d+1)} + x_{jiw(d+1)}\right) \leq 1$$

7. Conference play:

$$\sum_{j \in \text{Conf}(i)} \sum_w \sum_d (x_{ijwd} + x_{jiwd}) \geq 24 \quad \forall i$$

8. Gap between away games:

$$\sum_{j \in teams} (x_{i,j,w,d} + x_{i,j,w,d+1} + x_{i,j,w,d+2} + x_{i,j,w,d+3} + x_{i,j,w,d+4}) \leq 1$$

9. Weekly games:

$$\sum_i \sum_j \sum_d x_{ijwd} \geq 6 \quad \forall w$$

10. Limit games against same opponents

$$\sum_{w \in \mathcal{W}} \sum_{d \in \mathcal{D}} x_{i,j,w,d} \leq \begin{cases} 3 & \text{for same conference teams} \\ 2 & \text{for different conference teams} \end{cases}$$

11.

For each $i \in$ teams :

$$\text{Let } B = \frac{\sum_{t \in \text{teams}} \text{strength}_t}{|\text{teams}|} \cdot \text{games\_per\_team}$$

$$\sum_{j \in \text{teams}} \sum_{w \in \text{weeks}} \sum_{d \in \text{days}} (x_{i,j,w,d} \cdot \text{strength}_j + x_{j,i,w,d} \cdot \text{strength}_j) \geq B - 5$$

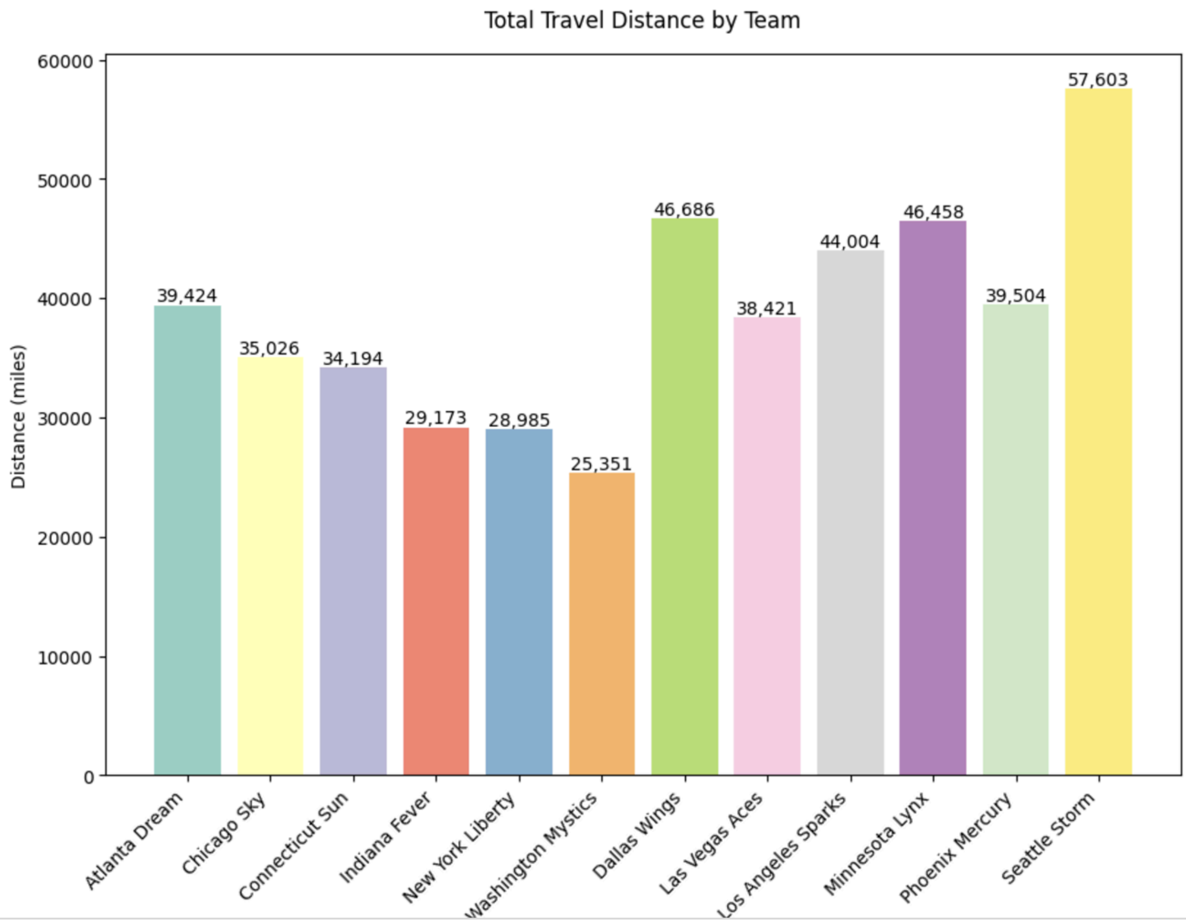
$$\sum_{j \in \text{teams}} \sum_{w \in \text{weeks}} \sum_{d \in \text{days}} (x_{i,j,w,d} \cdot \text{strength}_j + x_{j,i,w,d} \cdot \text{strength}_j) \leq B + 5$$

Results:

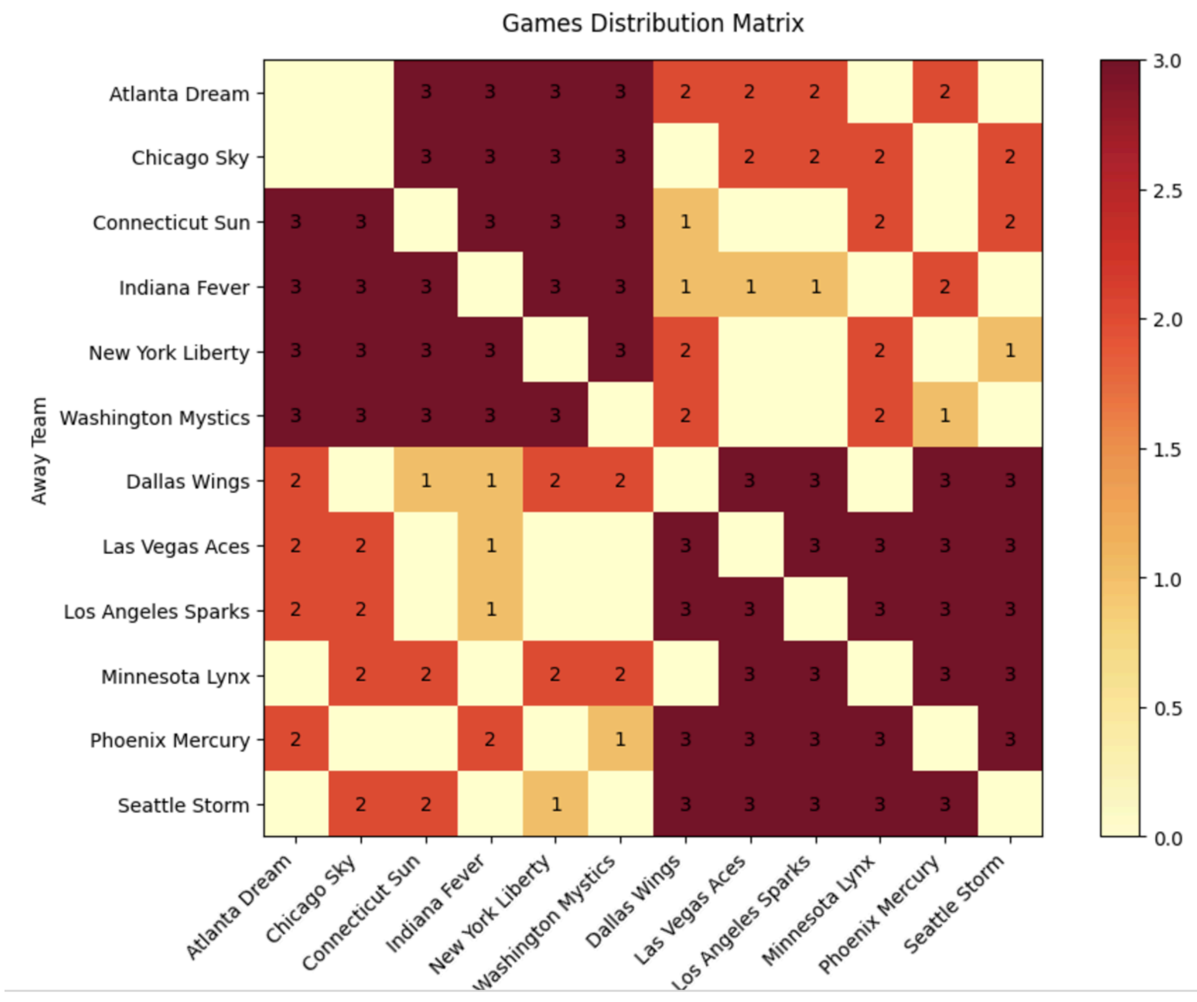
The model generated a complete 2024 WNBA schedule, which adheres to all constraints. The schedule highlights include:

1. A total of 168 conference games and 72 non-conference games.
2. Each team plays exactly 40 games (20 home, 20 away).
3. The schedule ensures at least 6 games per week across the league.
4. Conference play requirements are met, with each team playing at least 24 games within their conference.

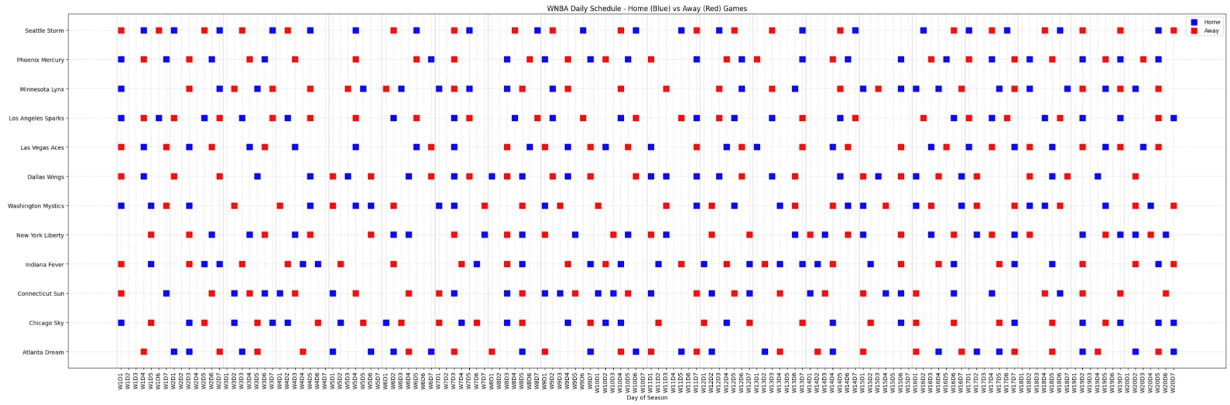
<u>Accompanying Graphics</u>



In the figure above, we can see total travel distances by team. While our model did minimize total distance traveled, there are certain disparities shown in this graph that highlight limitations in our first model based on geographic location. For example, Seattle Storm has the highest travel distance (~58,000), while the Washington Mystics (~25,000) have the lowest. This aligns with the geographic isolation of Seattle and the centralized location of Washington DC.



In the figure above, each cell represents the number of times one team plays another (home or away). For example, Atlantic Dream plays the Dallas Wings two times as the home team and two times as the away team. Higher numbers (3 matchups) are concentrated along conference rivals and we see the distribution of non-conference matchups to be pretty even. No team seems to have significantly more matchups against a single opponent, which means we reached our goal of maintaining competitive balance.



In the figure above, we see a daily schedule for the WNBA season where home games are represented in blue and away games are represented in red. We see that teams do not have excessive consecutive away games which indicates that our model adhered to the "adequate rest" constraint. A few scattered gaps in the figure indicates "bye days" for teams which align with the necessary rest that teams need for peak player performance.

Result Analysis:

From our results we can see that the travel distance is optimized to be for distances covered from the home arena with our new design for the schedule. We can see that using the away game constraint we were able to make sure that the gaps between away games was kept at above 4 game difference in order to allow teams to fly home. We decided that this was a valid schedule but we wanted to create a model that would be able to handle the transitioning from city to city. In order to do so we needed to redefine our variables and our objective function. A unique aspect of this model was the inclusion of the last 5 years team ranking data which permitted us to be able to ensure an even strength of schedule for all the teams. We were able to come up with a mean score for competition that would allow us to constrain all teams to have the same level of opponents throughout the season to ensure fairness.

Methodology For *City to City Model*:

<u>Variable Definition:</u>

We define each variable for every possible game including the home and away team in the definition:

```
x = {}
for home in teams:
    for away in teams:
        if home != away:
            for week in weeks:
                for day in days:
                    x[home, away, week, day] = pulp.LpVariable(
                        f"game_{home}_{away}_{week}_{day}",
                        cat='Binary'
                    )
```

We then define a weekly distance travel variable that is able to properly calculate the distances that each team is traveling per week. The sum of the weekly distances is the objective function we will minimize.

```
weekly_distance = {}
for team in teams:
    for week in weeks:
        weekly_distance[team, week] = pulp.LpVariable(
            f"dist_{team}_{week}",
            lowBound=0
        )
```

In order to properly account for the teams travelling path and calculating the weekly distances we need to defined two specific constraint:

```
for t in teams:
    for w in weeks:
        for day in range(6):
            for city1 in teams:
                for city2 in teams:
                    if city1 != city2 and city1 != t and city2 != t:
                        trav_dist = distance_matrix.loc[city1, city2]
                        if (city1, t, w, day) in x and (city2, t, w, day + 1) in x:
                            prob += weekly_distance[t, w] >= trav_dist * (x[city1, t, w, day]+x[city2, t, w, day + 1] - 1), f"D_A_{t}_{w}_{city1}_{city2}_{day}"
                        if (t, city2, w, day + 1) in x:
                            prob += weekly_distance[t, w] >= trav_dist * (x[t, city1, w, day] + x[t, city2, w, day + 1] - 1), f"D_H_A_{t}_{w}_{city1}_{city2}_{day}"
```

$$
\begin{aligned}
&\forall\ \text{team} \in \text{teams}, \forall\ \text{week} \in \text{weeks}, \forall\ \text{day} \in \{0,1,\ldots,5\},\\
&\forall\ \text{city}_1,\ \text{city}_2 \in \text{teams}:\ \text{city}_1 \neq \text{city}_2 \wedge \text{city}_1 \neq \text{team} \wedge \text{city}_2 \neq \text{team}:\\
&\quad \text{If } ((\text{city}_1, \text{team}, \text{week}, \text{day}) \in x \wedge (\text{city}_2, \text{team}, \text{week}, \text{day}+1) \in x):\\
&\qquad \text{weekly\_distance}_{\text{team,week}} \geq \text{distance\_matrix}_{\text{city}_1,\text{city}_2} \cdot (x_{\text{city}_1,\text{team,week,day}} + x_{\text{city}_2,\text{team,week,day}+1} - 1)\\
&\quad \text{If } ((\text{team}, \text{city}_2, \text{week}, \text{day}+1) \in x):\\
&\qquad \text{weekly\_distance}_{\text{team,week}} \geq \text{distance\_matrix}_{\text{city}_1,\text{city}_2} \cdot (x_{\text{team,city}_1,\text{week,day}} + x_{\text{team,city}_2,\text{week,day}+1} - 1)
\end{aligned}
$$

The first constraint we defined is used to address the situation when a team is playing consecutive away games:

weekly_distance(team,week) ≥ distance_matrix($city_1$,$city_2$) · (x($city_1$,team,week,day) + x($city_2$,team,week,day+1) - 1)

In this constraint we can see that if a team is playing in two separate cities we are constraining the weekly distances if a team is playing in these two cities on two away games and only accounting for if the two cities are both being played in. That we ensure the weekly distance encompasses the amount of travel for the team.

We then define a transition for an home and away game:

weekly_distance(team,week) ≥ distance_matrix($city_1$,$city_2$) · (x(team,$city_1$,week,day) + x(team,$city_2$,week,day+1) - 1)

This is very similar to the first constraint but we just make sure to capture the home to away to transition instead.

We then kept the same constraints for the other factors.

<u>Model Execution:</u>

We executed this model and we realized that there were 300,000 constraints and the model run was taking extremely long. It was also unable to generate the solution after running it for about an hour. We decided that this method was a bit too computationally intensive and decided to relax some of the conditions in order to lower the amount of constraints and still be able to generate a valid schedule.

Methodology For City to City Model Relaxed Conditions:

The optimization model for WNBA schedule generation employs several strategic constraint relaxations to balance computational efficiency with practical scheduling requirements. This analysis examines the key relaxations and their implications for schedule optimization.

Time Window Adjustment:

In order to lower the amount of variables and constraints we need to consider a smaller window. We decided to drop the amount of weeks to choose from to 18 and the amount of days to 5. This helps decrease the model runtime significantly.

Away and Home Game Relaxation:

Instead of setting a hard limit of 20 away games and 20 home games we do a relocated version to have a range of home and away games that we could have:

$$\sum_{away \in \text{teams}, away \neq team} \sum_{week \in \text{weeks}} \sum_{day \in \text{days}} x_{team,away,week,day} \geq 15 \quad \forall \text{ team} \in \text{teams}$$

$$\sum_{away \in \text{teams}, away \neq team} \sum_{week \in \text{weeks}} \sum_{day \in \text{days}} x_{team,away,week,day} \leq 25 \quad \forall \text{ team} \in \text{teams}$$

Matchup Constraint:

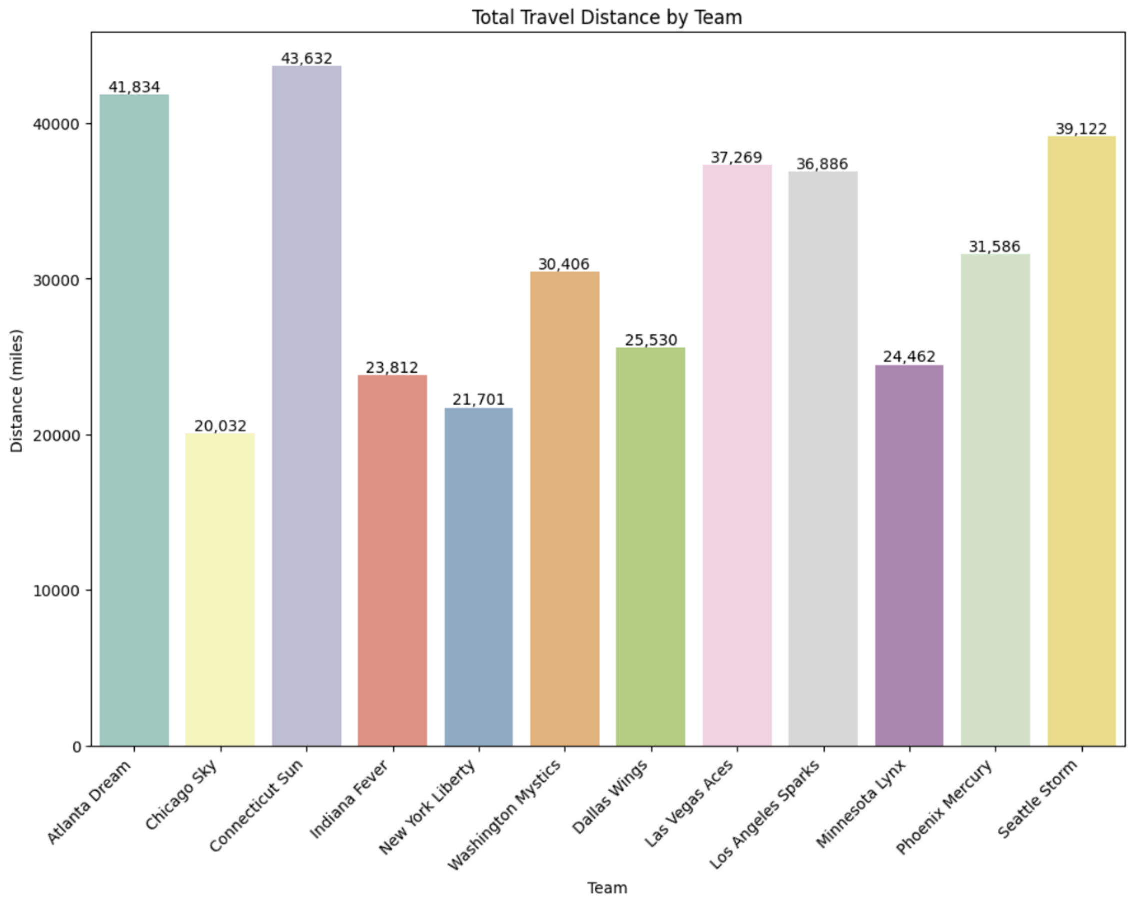
We adjusted the matchup constraint to allow up to 5 matchups against the same opponent in order to allow the optimizer to better cluster some of those games together. This is shown to be historically accurate as in WNBA seasons past, teams have played the same opponent 5 times before

Optimized away and home game calculation:

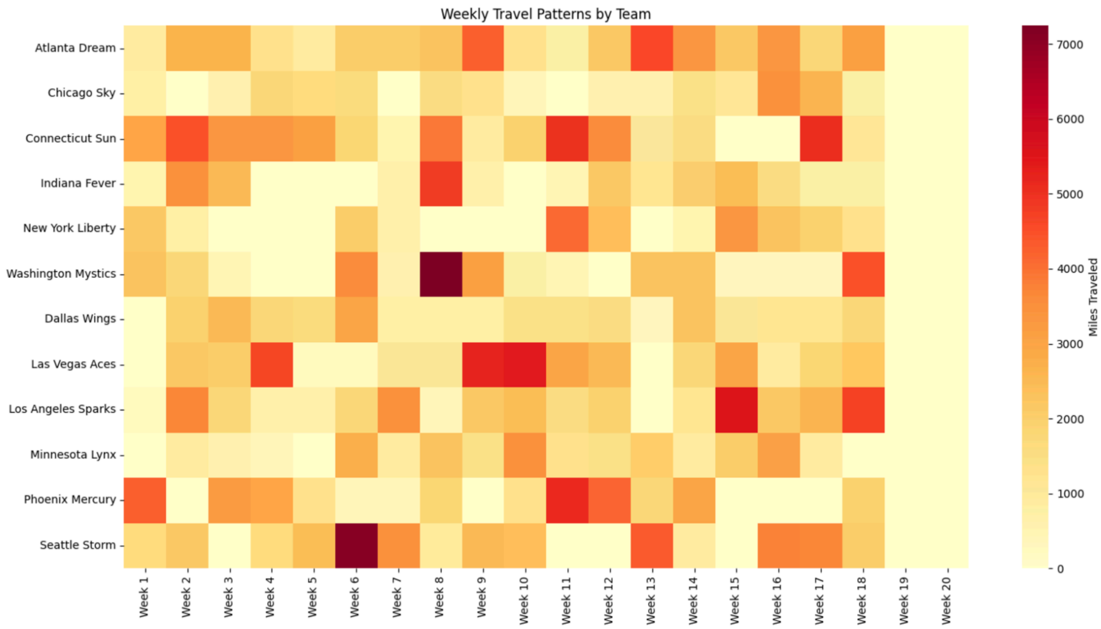
```
for t in teams:
    for w in weeks:
        for d in range(4):
            for city1 in teams:
                for city2 in teams:
                    if city1 != city2:
                        if (t, city1, w, d) in team_location and (t, city2, w, d+1) in team_location:
                            prob += weekly_distance[t, w] >= (distance_matrix.loc[city1, city2]*(team_location[t, city1, w, d]+team_location[t, city2, w, d+1] - 1))
```

We employed a new way to calculate and constrain the weekly travelling distance through using a team location tracking method. By maintaining a dictionary that has the current location for the team throughout the season, we no longer need to handle the different sequences of games played for away to away vs home to away. This allows us to have fewer conditional statements which lowers the amount of constraints. This allowed the training process to be able to reach an acceptable optimum within 1 hr.

Results:



In the figure above we see that total travel distances vary by team, with the Connecticut Sun traveling the most (~44,000) and the Chicago Sky traveling the least (~20,000). This is a substantial reduction compared to the Return-Home Model, particularly for central teams such as the Dallas Wings. Isolated teams such as the Seattle Storm still face significant travel demands but benefit from City-to-City's clustering of away games. This model achieves travel reductions for most teams compared to the Return-Home model. However, the significant gap between the least and most traveled teams highlights the omnipresent challenge of equitable travel loads.



The figure above is a heatmap that shows weekly travel distances for each team. Darker colors indicate weeks with higher travel distances, while lighter colors represent weeks with minimal travel. Travel seems to concentrate in specific weeks for most teams, with significant peaks around certain weeks (e.g., Week 6 for Seattle Storm). These spikes likely correspond to extended road trips. This model minimizes unnecessary return trips, which is evident from teams having sustained travel across multiple weeks rather than the frequent alternation between home and away games from the Return-Home model. This clustering of travel-heavy weeks allows for efficient scheduling but may lead to player fatigue during these periods.

```
Indiana Fever:
  Total Travel: 23,812 miles
  Average per Game: 595 miles
  Cross-Country Trips: 6
  Regional Game %: 62.5%
  Number of Road Trips: 5
  Avg Road Trip Length: 3.8 games

  Weekly Travel Pattern:
    Heaviest Travel Week: Week 8 (4,808 miles)

New York Liberty:
  Total Travel: 21,701 miles
  Average per Game: 543 miles
  Cross-Country Trips: 3
  Regional Game %: 72.5%
  Number of Road Trips: 7
  Avg Road Trip Length: 3.0 games

  Weekly Travel Pattern:
    Heaviest Travel Week: Week 11 (4,104 miles)
```

Sample Travel Distances

Analysis:

This new usage of the optimization model accounting next city constraints allows for us to better optimize the travel for no home return trips. This solution would be more fit for the current layout of the WNBA, but it does not allow for the away game back to back constraint that we constructed. In order to further optimize the model, we would need to be able to parallelize the computation in order to allow for the full model to be constructed without relaxing any constraints. Some future considerations would be to create schedules that could also design specifically harder road trips to be placed near the end in order to match up the better teams. We could generate the more anticipated matchups towards the time around the end of the season in order to give a preview to the playoffs. We could also pursue alternative solutions instead of using a scheduling program and utilize machine learning techniques to generate our schedule.

Conclusion

The Return Home and the City-to-City models each present unique strengths when it comes to optimizing the WNBA schedule. The Return Home model prioritizes logistical constraints and player-wellbeing by ensuring frequent returns to the home arena. This creates a fair balance between home and away games while adhering to rest-day constraints. However, its prioritization on this home/away constraint results in higher overall travel distances for most teams, specifically those in geographically isolated areas of the country. We created the City-to-City model to address this disparity. This model reduces total travel time by clustering away games and eliminating unnecessary return trips. However, challenges such as uneven travel distribution and fatigue during high-travel weeks arise with this model. Given these trade-offs, a hybrid approach that combines the logistical simplicity of the Return-Home model and the travel efficiencies of the City-to-City model offers a next-step in this scheduling problem. Future expansions of the project would be to incorporate regional scheduling for geographically isolated teams, balancing travel heavy weeks across the season, and integrating strategic rest-days to combat player fatigue. Another consideration would be to employ parallelization which would improve the feasibility of solving more complex scheduling problems with additional constraints.

At its core, a professional sports league thrives on its players and fans, and any schedule must prioritize fairness and player considerations to uphold the league's integrity and appeal. For the WNBA in particular, ensuring these considerations is critical to solidifying its standing in the world of professional sports. A thoughtfully optimized schedule not only supports players' physical and mental well-being but also enhances the quality of competition. This in turn, fosters deeper fan engagement and league growth. Moving forward, it is important that the WNBA continues to center player and fan experiences in its scheduling efforts to strengthen its reputation and cement its legacy in the global sports landscape.

Appendix

Output:

(Condensed) Output Schedule:

WNBA 2024 SCHEDULE

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WEEK 1

2024-05-01 (Day 1)

Las Vegas Aces @ Atlanta Dream - Gateway Center Arena

Phoenix Mercury @ Washington Mystics - Entertainment & Sports Arena

Seattle Storm @ New York Liberty - Barclays Center

2024-05-02 (Day 2)

Chicago Sky @ Minnesota Lynx - Target Center

Connecticut Sun @ Dallas Wings - College Park Center

Indiana Fever @ Los Angeles Sparks - Crypto.com Arena

2024-05-04 (Day 4)

Los Angeles Sparks @ Seattle Storm - Climate Pledge Arena

New York Liberty @ Chicago Sky - Wintrust Arena

Washington Mystics @ Atlanta Dream - Gateway Center Arena

2024-05-05 (Day 5)

Minnesota Lynx @ Las Vegas Aces - Michelob Ultra Arena

2024-05-06 (Day 6)

Dallas Wings @ Los Angeles Sparks - Crypto.com Arena

Phoenix Mercury @ Indiana Fever - Gainbridge Fieldhouse

2024-05-07 (Day 7)

Las Vegas Aces @ Minnesota Lynx - Target Center

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