SkiAgents: A Network-based Analysis Tool for Winter Resort Management

Cooper McGuire
College of Engineering
Cornell Tech
New York, New York
Email: cjm424@cornell.edu

Jacob Everly
College of Engineering
Cornell Tech
New York, New York
Email: je354@cornell.edu

***Abstract*—The use of graph analysis in transportation networks has been proven to ease congestion and aid in operational efficiency. In this paper, we propose approaches to ease the congestion that are seen at ski resorts with customers by applying transportation network theories. By implementing an agent based model utilizing our network, we are able to estimate where a ski resort has the greatest congestion and suggest infrastructure projects that can increase the flow of skiers across the resort, resulting in greater customer satisfaction.**

I. Introduction

Analysis and mitigation of congestion at a ski resort is challenging in its demands for real-time data collection. To efficiently manage a ski resort you have to manage weather conditions, terrain conditions, and large fluctuations in customer flow. All of which can be unpredictable throughout the season. Recently, the adoption of radio-frequency identification (RFID) ski passes have allowed for enhanced monitoring of on-mountain arrivals and boarding of ski lifts at base villages. Surveillance technologies such as ultra-wideband (UWB) and computer vision are being developed to better gauge the real-time count of skiers in localized areas. Both technologies face significant challenges in terms of operational feasibility, maintenance, adoption, investment, and synthesis of information. We propose an offline planning tool independent of real-time surveillance for resort-wide efficiency improvements through infrastructure alterations.

If a ski slope or lift closes it drastically changes the flow of skiers across the area which could result in major congestion and wait times at ski lifts. Large crowds where a dangerous sport is being performed leads to an exponential increase in risk of injury and accidents. Optimizing your ski resort congestion before one of these closures occurs helps management reduce the risk of over-congestion and the occurrence of unnecessary injuries.

For decades, graph theory has been applied to help solve traffic congestion in cities, railway networks, pipelines, and power lines. By using graph theory, researchers are able to realize graphically the roads and intersections of cities to identify the most congested areas. This analysis helps to identify the most efficient routes for commuters to take and the roads that need to be improved for better traffic flow.

In this paper we have implemented an agent based model of skiers that move throughout a digital twin of the Crested Butte ski resort. This digital twin is manually creating with a directed graph that has the slopes, intersections, and lifts of the resort. Generating arriving groups of skiers using distributions, we can use Monte Carlo simulations to base conclusions on how the mountain management could better ease congestion across the ski area.

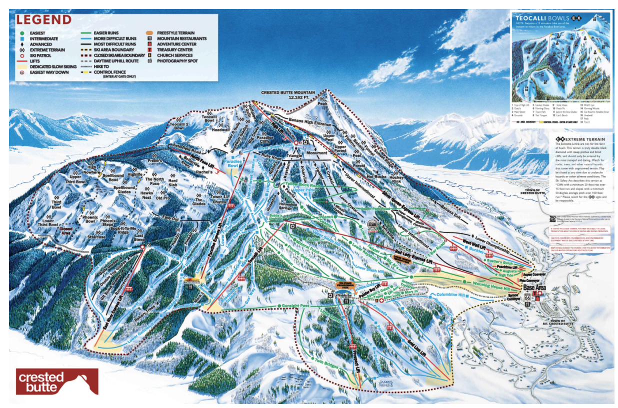


Fig. 1. Crested Butte Trail Map

A. Agent-Based Modelling

Agent-Based Models (ABMs) are a powerful tool in understanding the behavior of skiers in ski areas. ABMs use autonomous agents to simulate the individual preferences of skiers, and how they interact with each other and their environment. This simulation allows ski area managers to gain insight into how skiers move, and make more informed decisions regarding the placement of ski lifts and maintenance of ski trails. The potential of ABMs to enhance ski area operations is the focus of this research paper. The paper will explore the benefits of employing ABMs in ski area management and how they can be used to optimize operations.

II. Method

In this research, we created a directed graph that represented a ski area. The edges of the graph represent the ski slopes and have attributes of length, difficulty, and position. The ski lifts have attributes of capacity, time duration to ride, and position. This data was gathered from a handful of resort reference sources and parsed into our model.

Fig. 2. Directed Resort Graph

A. Arrival and Exit Models

Next, we determined an arrival function for our skier groups as a Poisson distribution with a dynamic rate of $r(t) = (-\frac{1}{8000} * (t - 390) * (t - 840))^{+}$ on weekends $r(t) = (-\frac{1}{20000} * (t - 390) * (t - 840))^{+}$ on weekdays, where t is the time from midnight in minutes. For reference, arrivals begin at 6:15am and end at 2:00pm, peaking at 10:15am. Exit times are generated upon group initialization and follow a bounded normal distribution of $Normal(870, 40)$. Skiing groups begin to exit the resort at 12:30pm, with the last groups beginning their descents at 4:45pm; the expected exit time is 2:30pm. By adding and removing groups from the graph, we were able to see how the ski area would change when more or fewer people arrived or left. Further, we simulate traffic on both weekdays (2000 skiers) and weekends (5000 skiers). This model was a useful tool to help us better understand how the ski area changes throughout the day. A unique trait to Crested Butte is that all skiers must enter and leave from the base village area which is node one of our network.

B. Group Attributes

Generation of agents was driven by the different ski levels of the skiers on the mountain. We divided the skiers into three categories: beginner, intermediate and expert. We then assigned relative size of each group based on likelihood and the speed at which each group skied. We used this data to determine the destination preferences of each group and the

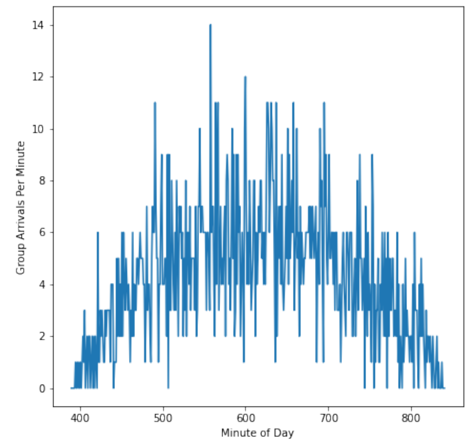


Fig. 3. Arrival Distribution

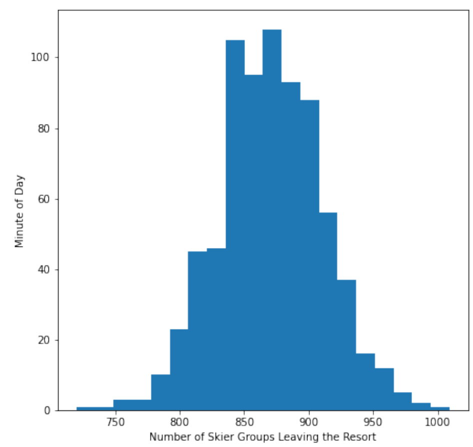


Fig. 4. Exit Distribution

amount of time it would take for each group to complete a run.

TABLE I
SKIER SKILL AND PREFERENCE DISTRIBUTIONS

	Beginner	Intermediate	Expert
Speed (km/h)	23.3	37.7	50.0
Destination Preference [GR,BL,BK]	[1,0,0]	[0.3,0.7,0]	[0.05,0.45,0.5]
Portion of Total Skiers	0.40	0.35	0.25

C. Agent Based Model and Graph Traversal Algorithm

We then developed a program that can onboard agents to the directed graph. The program takes the attributes of the agent group and the ski area into account when deciding their ski level, ski speed and group size. Agents are onboarded and removed based on the distributions established earlier in this paper. The program then moves the agents through the graph using a random walk algorithm that accounts for the group's ski level and which ski runs they can access. With these program we are able to calculate the average wait time and general congestion in the ski area.

We first created network subgraphs for each skier level based on what runs they would be comfortable skiing down. For example, a green skier would not transit black runs to get to their preferred slope. Next, we sampled this subgraph for edge destinations to assign where the group wants to ski. Finally, we used Dijsktra's shortest path algortihm to traverse the corresponding subgraph until reaching the destination. When the skier arrives at the destination, a new destination and path is generated. If the agent reaches a lift, they are added to the respective queue. At each time step, a maximum number of agents are allowed to enter the lift based on the lift's capacity. Once an agent's predetermined time to exit has arrived, it will change its destination to be the node at which it entered the network.

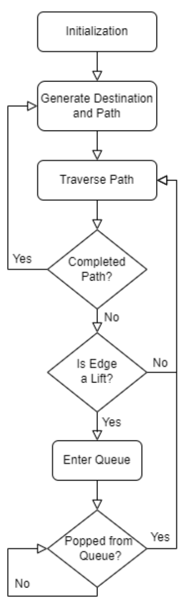


Fig. 5. Agent Logic Diagram

D. Visualization Dictionary

Next we developed a master dictionary to visualize the location of the groups and the amount of time they are waiting. This dictionary is created by mapping each agent to a ski run and the average wait time for that particular ski run. By mapping each ski run to the average wait time, it is easier to see where the groups are located and how long they are waiting. This dictionary allows us to analyze the ski area and make adjustments to the ski runs and ski lifts accordingly.

E. Ski Lift Queuing

This model is built using the queuing function in Python. The queuing function is a tool for simulating real-world queuing systems, like our ski lift lines. The model indexes as our agents arrived and tracks the amount of time each agent is spending waiting to get on a ski lift. The flow rates of the ski lifts is being taken from when we created the graph. Here each ski lift was given a capacity of people and a passenger ride time. This model makes sure the ski lifts are filled to maximum capacity just as the ski management does. Through this model we can get average wait times for skiing groups and the ski lifts.

III. Results

When simulating the ski area operating throughout the day, we tested two different situations that would impact congestion. This being that the amount of people skiing on the weekday and weekend. These values vary greatly. So we wanted to test both volumes of people and see how congestion on the mountain would be impacted. We visualized the amount of time waiting vs skiing and the average wait time at each lift throughout the day.

A. Wait Time vs Skiing Time

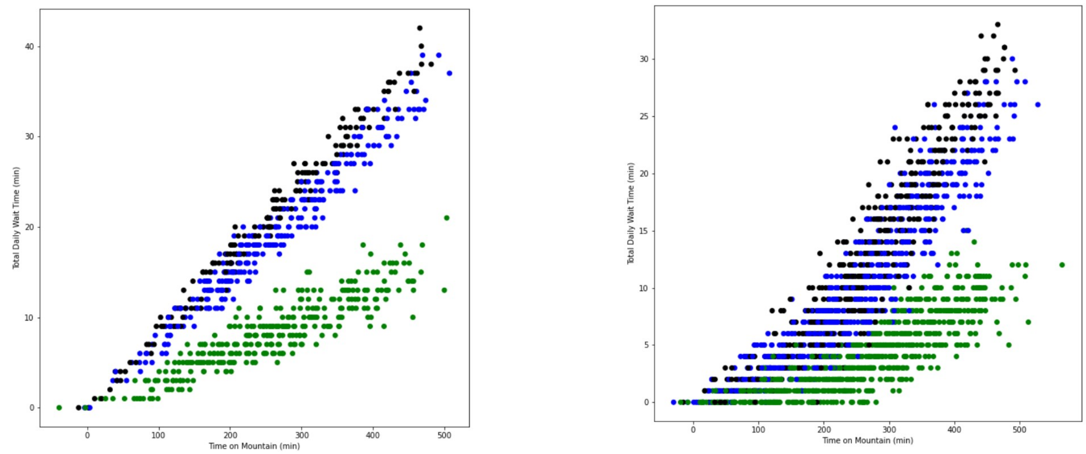
We see from Figure 6 that on a weekday your wait time vs skiing time is dependent on your ski level. This makes sense as the lines will be shorter so higher level skiers will spend less time in the line, but since they can ski faster there time proportionally on a ski lift will go up. On the weekends this correlation drops partially, this would be caused by the increase in average wait time. Since everyone would be spending more time waiting in line.

B. Ski Lift Wait Times

Figure 7 shows the graphs for the running average wait times for all nine lifts on the mountain. The graphs reveal that the average wait times on the weekends will be exponentially longer due to the increased traffic. Here we see how wait times evolve for certain lifts throughout the day as well. During the weekdays in lighter congestion wait times are mostly consistent throughout the day. We see from these two graphs that we have two outliers in wait times. On the weekends Silver Queen and Painter Boy have the largest wait times, peaking around 1:30 in the afternoon. These coincide with their centrality rankings. We can conclude that centrality directly correlates to ski lift wait times.

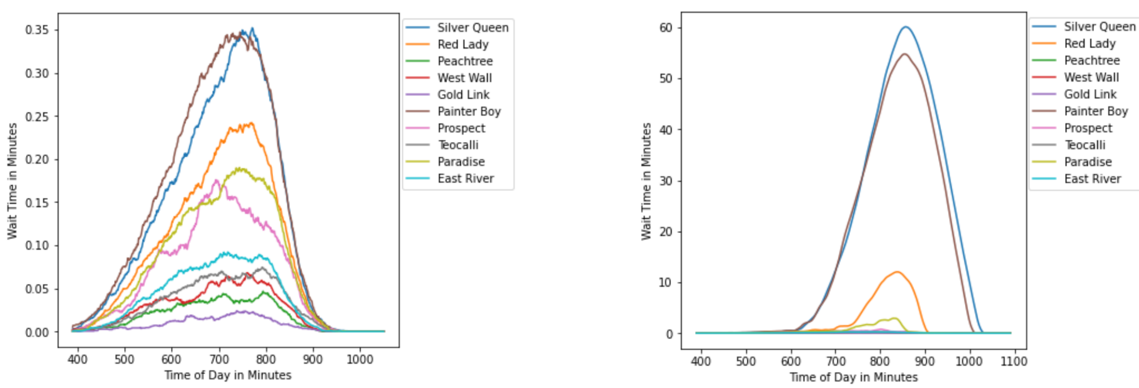
C. Centrality Metrics

As an aside to the ABM modelling, the construction of a transportation network to reflect the mountain layout allows for insights to be draw from centrality metrics of out intersection nodes. For instance, degree centrality is used to determine critical intersections that should have yield or caution signs to reduce collisions between cross-trafficking skiers. Further, betweenness centrality is useful in determining the best



(a) Weekday Traffic (b) Weekend Traffic

Fig. 6. Wait Time vs. Skiing Time Per Level



(a) Weekday Traffic (b) Weekend Traffic

Fig. 7. Wait Time (min) By Lift Throughout Day

placement of on-mountain amenities such as restaurants and bars. Since betweenness centrality measures the portion of shortest paths in the network that transit through a node, it is particularly useful in determining points which are heavily trafficked by all levels of skiers. Below we show the top nodes found using each of our metrics.

TABLE II
TOP CENTRALITY NODES BY METRIC

Degree Centrality	12,7,45,1,2,5
Betweenness Centrality	1,7,44,45,42,12

Considering the current placements of restaurants and bars in reality are $\{1,12,24,50\}$, our model captures a portion of established reasoning while also placing amenities at the tops of the Red Lady, Silver Queen, and Teocalli lifts. Our network also suggests the top of Painter Boy and Gold Link as a central location for amenities.

D. Operations Improvements

Grooming ski slopes provides skiers with a smoother and more consistent surface to ski on. When a ski slope is groomed, the snow is packed down, creating a more consistent surface that gives better control over your skis and provides more grip for turning. This allows for increased speeds along with more confidence. Additionally, grooming the ski slopes removes any potential obstacles that may slow skiers down, such as bumps and ruts. All of these factors combined contribute to a 1.7 km/h mean increase in speed across all skier levels[1].

TABLE III
EFFECTS OF GROOMING ON MAXIMUM LIFT WAIT TIMES (MIN)

	Baseline	All Slopes Groomed
Weekday	0.68	0.69
Weekend	60.19	66.50

Contrary to prior beliefs, our model shows grooming only increases the maximum wait time seen by skiers. Intuitively, the faster a skier is, the more frequently they will finish their runs and visit a lift. Thus, we believe the reasoning selective grooming helps congestion is due to preference changes in destinations. Putting groomed trails in sections of the resort with little traffic may balance out the wait times better.

Another option for improving wait times at the bottom of lifts is to increase the capacity of the lift itself to more quickly process the queue. Our model assumes all lifts are being operated at capacity, thus the only method of increasing lift capacity is an infrastructure improvement to replace lifts. As seen in Figure 7, the lifts Silver Queen and Painter Boy see the highest wait times throughout the day, especially on weekends where their efficiency is substantially below their counterparts. We analyzed the return on investment of constructing a 6 seat chairlift with a hourly capacity of 3000 skiers, an industry leading lift used at various resorts[3]. We measured success in terms of the average maximum wait times seen by skiers through 10 full-day trials. This was run for both weekday and weekend traffic.

TABLE IV
EFFECTS OF UPGRADING LIFT CAPACITY ON MAXIMUM LIFT WAIT TIMES (MIN)

	Baseline	Silver Queen	Painter Boy	Both
Weekday	0.68	0.58	0.58	0.45
Weekend	60.19	60.07	58.90	30.63

When replaced independently of one another, there is little improvement to the congestion at these most central of ski lifts. However, when both are replaced we see a 49.1% decrease in the maximum wait time seen by skiers on high traffic days. Although expensive, this is the single most rewarding action the resort could make.

Adding a new downhill ski slope to a resort can help ease congestion at ski lifts in two ways. First, it will provide skiers with an additional option for where to ski, which can help distribute skiers more evenly across the resort's slopes. Second, it may provide a more direct and accessible route from one section of the resort to another, bypassing the need for riding a ski lift. Of course, geographical constraints and considerations must be adhered to. Each of the following black, blue, and green slope sets were comprised of five slopes with three intersections. Each set of slopes were comprised of the same lengths and were placed in the same place in the network–connected to the Paradise lift on the underdeveloped side of the resort. Figure 7 shows minimal wait times throughout the day in this area. Again, we measured success in terms of the average maximum wait times seen by skiers through 10 full-day trials at weekday and weekend traffic levels.

The above table displays the impact on congestion by more evenly distributing the options for beginner skiers. In fact, the distribution of destination preferences leads to 51.75% of all slopes being transited to being at the green level. Further, the layout of the resort allows for skiers to access this new area of the resort while bypassing the busiest lifts at Silver Queen and Painter Boy. This constitutes a reduction of 18.6% in maximum wait times albeit expensive to construct such an addition.

TABLE V
EFFECTS OF ADDING RUNS ON MAXIMUM LIFT WAIT TIMES (MIN)

	Baseline	Green Set	Blue Set	Black Set
Weekday	0.68	0.58	0.67	0.68
Weekend	60.19	49.02	57.08	64.39

IV. CONCLUSION

Next steps would be to add a logic branch to reflect skier's behaviors in eating lunch and their respective destination preferences. Also, a dynamic slope preference probability matrix can be constructed to reflect the greater satisfaction beginner and intermediate skiers see when on groomed runs. Lastly, validating results requires data collection on wait times, preferences, arrival times, and exit times at a prospective resort.

In its current form, the agent-based model produces defensible results as to the methods of achieving greater operational efficiencies and improve customer satisfaction on-mountain. First of which is to upgrade the Silver Queen and Painter Boy lifts to 6-seat chairs, increasing the capacities of each, lowering maximum wait times by 49%. Second, constructing a series of beginner runs on the backside of the mountain, accessed by the Paradise lift, would better balance the load seen by lifts. This would in turn lower maximum wait times by 18.6%. Further economic analysis would need to be performed to come to a final decision based on return on investment and the value of customer satisfaction.

SkiAgents Video
SkiAgents Slides

V. REFERENCES

1) Bailly, N., Abouchiche, S., Masson, C., Donnadieu, T., Arnoux, PJ. (2017). Recorded Speed on Alpine Slopes: How to Interpret Skier's Perception of Their Speed?. In: Scher, I., Greenwald, R., Petrone, N. (eds) Snow Sports Trauma and Safety. Springer, Cham. https://doi.org/10.1007/978-3-319-52755-0_13

2) "Crested Butte." Jollyturns, 8 Nov. 2021, https://jollyturns.com/resort/united-states-of-america/crested-butte-mountain-resort.

3) "Ski Lifts Crested Butte." Skiresort.Info — The Largest Ski Resort Test Portal in the World, https://www.skiresort.info/ski-resort/crested-butte/ski-lifts/. Accessed 13 Dec. 2022.

4) "In a Hurry? Fastest Crested Butte Ski Lifts." Travel Crested Butte, TravelCrestedButte, https://travelcrestedbutte.com/hurry-fastest-crested-butte-ski-lifts/. Accessed 13 Dec. 2022.