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Intelligent recreation agents in a virtual GIS world

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Abstract

This paper describes a method for simulating the interactions of different human recreators in a complex natural environment by integrating intelligent agents and geographic information systems (GIS). The purpose of this model is to assist recreation planners and managers to evaluate a set of alternative management scenarios that i) alter the scheduling of recreators as they enter a park; ii) increase or decrease the size or access to facilities such as roads and trails, parking lots, visitor centres or camp grounds; or iii) separate recreators onto different roads and trails. By simulating the behavior of different agents in a virtual environment as described by GIS, it is possible to manipulate the number and type of agents, and characteristics of the environment to study the dynamic relationships between the two systems. This provides park managers with an insight into the probable effects of a given management scenario on user flows and satisfaction.

1. Introduction

Outdoor recreation is on the increase world wide as people have more leisure time, greater mobility, and more disposable income. In addition there is a proliferation of new types of recreation such as mountain bike riding, snow boarding, canyoning and other emerging activities that have different environmental requirements and are often in conflict with more traditional outdoor activities. As visitor numbers increase, there is a simultaneous increase in environmental impacts, crowding, and conflicts between different recreational types and users. These circumstances make recreation management a complex problem. Managers of natural areas must accommodate increasing visitor use while at the same time, maintaining environmental quality and ensuring visitors have the high quality experience they anticipate.

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Conventional methods used in the design and planning of park management facilities have depended on user surveys and traffic counts to estimate the requirements. However, these methods fall far short of the real needs of managers who must comprehensively evaluate the cascading effects of the flow of visitors through a sequence of sites and estimate the effects of increasing visitor flows through time. In addition, managers need to know if designed capacities for parking, visitor centers, roads, camping areas, and day use facilities can accommodate projected visitor numbers. Crowding, conflicts between different recreation modes, impacts on environments and seasonal effects such as day length and weather are all factors park planners must consider in the design and location of new facilities.

There are many options available to park managers to deal with heavy visitor use. New sites can be opened up, a system of reservations can be implemented; areas can be closed so sites can recover from over use; facilities can be expanded to accommodate large numbers of visitors. Each of these strategies will have different impacts on the overall system. The complex inter-relationships between these decisions are almost impossible for a manager to predict. It is in this context that simulation of recreation behavior is of real value. This paper describes a computer simulation methodology that uses intelligent agents to simulate recreation behavior, coupled with Geographic Information Systems to represent the environment. The simulation framework has been developed in two contexts, one to simulate river trips in the Grand Canyon, and the other as a generalized simulation system for complex recreation in any setting.

2. The need for recreation simulation

Computer simulation has typically been utilized to study biophysical environmental processes (Goodchild et al., 1993) with more recent attention being focused on “human dimensions” of environmental systems. Many of these simulation modeling efforts employ a number of artificial intelligence techniques combined with Geographic Information System (GIS) functions to address human-environment interactions (e.g. Green, 1987; Slothower, 1996; Gimblett et al. 1996a, 1996b; Briggs et al. 1996). Exploratory studies by Berry et al. (1993), Gimblett et al. (1994), Saarenmaa et al. (1994) and Gimblett and Itami (1997) that have incorporated artificial intelligence techniques with GIS have shown potential for improving resource management decision-making. But emerging simulation technologies such as robotics and artificial life have been slow to embrace the advantages of using georeferenced spatial data (Tobler 1979). Others such as Tobler (1979) and Itami (1988) have suggested the use of cellular automata (CA) as a method for simulating dynamic environmental processes over large scale landscapes, and applications of this approach have been successfully demonstrated (e.g., Green et al. 1987; Manneville et al. 1989). Individual-Based Models (IBM) have recently been applied to develop spatially-explicit models of ecological phenomena. IBMs are “organisms-based models capable of modeling variation among individuals and interactions between individuals” (Slothower et al. 1996). IBMs offer potential for studying complex behavior and human/landscape interactions within a spatial framework. One form of individual-based modeling approaches, “agent-oriented programming,” facilitates representation of dynamic interactions among multiple agents that coexist in an environment. Included in this approach is the study of complex adaptive systems, where tools and techniques are being developed to study emergent behavior, for example Swarm (Hiebeler, 1994, Langton et al. 1995); Echo (Forrest et al. 1994), and GENSIM (Anderson and Evans 1995). The combination of spatially-explicit IBMs, reactive agents, artificial intelligence (AI) and GIS offers a powerful alternative to previous modeling techniques for exploring emergent, complex, evolutionary processes. This paper describes the use of agent-based systems coupled with GIS to simulate human recreation behavior in natural landscapes.

3. Multi-agent simulation of outdoor recreation

We have developed two recreation simulation systems with two independent development teams. The Grand Canyon River Trip Simulator (GCRTS) was developed using GIS and intelligent agent modeling techniques to simulate rafting trips down the Colorado River through Grand Canyon National Park. It is a single purpose simulation model built specifically for simulating river trips in the Grand Canyon. The modeling system employs statistical analyses and mathematical models based on existing river trip itinerary data as well as new data collected from river trip reports. GCRTS provides the natural resource manager with advanced visualization of individual trip progress, as well as interactions among trips during specified time periods. Locational information includes specified river reaches, camps and attraction sites, exchange points, and restricted areas. The agent-based modeling system provides managers (and other potential users) with an effective decision support tool for representing and evaluating the distribution and volume of use along the river (Gimblett et al 2000).

RBSim 2 (Recreation Behavior Simulation) (Gimblett & Itami, 1997; Gimblett, 1998; 1998a; Gimblett et al. 1999; Itami et al., 1999) is a computer simulation tool, integrated with a GIS that is designed to be used as a general management evaluation tool for any park. This capability is achieved by providing a simple user interface that will import park information required for the simulation from a GIS. Once the geographic data is imported into RBSim 2, the park manager can change a number of variables including the number and kind of vehicles, the number of visitors, and facilities such as the number of parking spaces, road and trail widths and the total capacity of facilities.

RBSim 2 and GCRTS use the same fundamental principles for simulating recreation behavior. However, they were developed by independent development teams with different objectives. RBSim 2 is more advanced since it is designed as a generic simulation tool. Discussion in this paper will therefore focus on the RBSim 2 architecture.

RBSim 2 allows park management to explore the consequences of change to one or more variables so that the quality of visitor experience is maintained or improved. Statistical measures of visitor experience are generated by the simulation model to document the performance of any given management scenario. Management scenarios are saved in a database so they can be reviewed and revised. In addition, the results of a simulation are stored in a database for further statistical analysis. The software provides tables and graphs from the simulation data so park managers can identify points of over crowding, bottle necks in circulation systems, and conflicts between different user groups.

Specifically RBSim 2 uses concepts from recreation research and AI and combines them in a GIS to produce an integrated system for exploring the complex interactions between humans and the environment (Gimblett et al. 1996a; Gimblett et al. 1996b, Gimblett 1997a, Gimblett and Itami, 1997, Itami et al., 1999). RBSim 2 joins two computer technologies:

- GIS to represent the environment
- Autonomous human agents to simulate human behavior within geographic space.

RBSim 2 uses autonomous agents to simulate recreator behavior. An autonomous agent is a computer simulation that is based on concepts from Artificial Life research. Agent simulations are built using object oriented programming technology. The agents are autonomous because once they are programmed they can move about their environment, gathering information and using it to make decisions and alter their behavior according to specific environmental circumstances generated by the simulation. Each individual agent has its own physical mobility, sensory, and cognitive capabilities. This results in actions that echo the behavior of real animals (in this case, human) in the environment.

The process of building an agent is iterative and combines knowledge derived from empirical data with the intuition of the programmer. By continuing to program knowledge and rules into the agent, watching the behavior resulting from these rules and comparing it to what is known about actual behavior, a rich and complex set of behaviors emerges. What is compelling about this type of simulation is that it is impossible to predict the behavior of any single agent in the simulation and by observing the interactions between agents it is possible to draw conclusions that are impossible using any other analytical process.

4. Simulation object model

RBSim 2 uses object oriented software technology to model components of the overall simulation system. These software objects include:

- Network Object Model - contains network topology for roads, trails and other linear features organised as a forward star network with associated attributes and methods for calculating travel time and distances across the network.
- Terrain Model - contains elevation data represented as a regular grid of elevations.
- Graphics Engine - provides visualisation of the park as a map showing current location of recreation agents.
- Simulation Engine - controls the scheduling of agents, controls simulation events such as weather, road opening and closure, seasonal events and other user defined events.
- Output Object - stores run-time states for agents and the network.
- Agent Object - represents the recreator’s personality, mobility characteristics, and reasoning system.

It is beyond the scope of this paper to describe the entire simulation system. Instead we will focus on the Agent object model, where most of the complexity is encapsulated.

5. Agent object model

The agents are cast as **Intentional Agents**, they are capable of higher cognitive processes such as goal-directed behavior using planning, and adaptive reasoning.

Very broadly, the agents can be thought of as being assembled from a number of components:

- **Physiology** which governs the basic physical functioning of the agent.
- **Reasoning system** for processing information about the environment, internal states and the impact of other agents.
- **Actions** that the agent performs within the world.

The nature of each of the components governs the type of agent that is specified.

5.1 Agent physiology

Physiology refers to the physical aspects of an agent that allow it to function in the world. Physiology enables the agent to:

- Maintain a “homeostatic” internal state necessary for the continued existence of the agent (physiological state)
- Move in the environment (locomotion)
- Sense the environment (perception)

5.1.1 Energetics

The **energetics** of an agent are those aspects that govern the consumption and production of energy by the agent and, consequently, its mobility. For animals, some of the variables that govern energetics include their mass, height and stored energy. For (combustion-driven) vehicles the stored energy corresponds to the amount of fuel present. RBSim 2 models the energetics of pedestrian agents by assigning each agent a nominal fitness level. The fitness level determines the length of time an agent can continue moving along a given slope without resting.

5.1.2 Locomotion

Agents are **mobile**. The basic constraint that will be maintained during agent movement will be the maximum speed. Agent locomotion in RBSim 2 is defined by:

- Travel mode. Including car, bus, helicopter, foot and other means of locomotion
- Travel speed. The speed associated with each travel mode is bounded between a minimum and maximum speed. This speed may be altered by congestion on the network or travel impedance defined in the network for turning, stop signs, or road condition.
- Location on a network. Agents may be restricted to specific segments of the network for a given travel mode (eg. helicopters) or agents may share a network with agents in alternative travel modes (cars and buses).
- Travel direction. Travel direction is relative to the agent’s trip plan. The node list in the trip plan determines the direction of travel. If the trip plan is altered, the travel direction may change. Travel direction is constrained by network topology (eg. where there is one-way travel between nodes).

5.2 Perception

Perception of the world. Agents are able to determine the number and type of agents that are visible within a given radius. Intervisibility between agents is constrained by topographic relief and screening effects of vegetation or other surface obstructions defined by a GIS grid overlay. In addition, agents are able to detect network attributes such as road width, design speed, facilities such as park lots and picnic grounds, and environmental states such as the time of day, weather and the presence of other agents.

5.3 Agent reasoning

Agents are *goal oriented.* **Goals** are achieved by a *Travel plan.* A **Travel Plan** is a list of primary destinations defined as a "*locale*" in a network. A **locale** is a collection of one or more *attraction nodes* with associated facilities that have a shared identity and can be grouped based on proximity to each other or common access. **An attraction node** is a node along a network where the agent may stop. Examples are: a toilet block, a viewing platform, an information sign, or a visitor's centre.

Trip plans are generated from a *Trip Matrix*. A **trip matrix** is a table of locales showing the number of trips from locale to locale. The trip matrix is derived either from traffic count data, or programmatically from user specified inputs in the scenario designer. The simulation engine to schedule and initialize agents uses the trip matrix.

When an agent arrives at a locale, the agent uses its internal reasoning system to decide which nodes to visit and in what order. The mode of travel, the personality profile, time constraints and proximity of different attraction nodes to the point of arrival determine these decisions.

5.4 Agent personality

People have different reasons for participating in outdoor recreation. These include nature appreciation, physical fitness, cultural awareness, aesthetics, social interaction and education. The relevant personality characteristics that are modelled in this version of RBSim 2 are divided into two classes: Constraints and Motivations.

5.4.1 Constraints

Constraints are factors related to the agent itself which constrain participation in an environmental recreation opportunity.

- Energetics as defined under physiological state.
- Locomotion as defined under physiological state.
- Time available. Each agent has time constraints. If time is highly constrained, stops may be abbreviated or skipped completely. Other factors influencing time available can be based on length of daylight or time of day in relationship to hours of daylight left.
- Follows trails. All agents stay on defined roads and trails. No attempt is made in this version of RBSim 2 to simulate travel across open country with undefined trails.

5.4.2 Motivations or intentions

Motivations are interests people have in different physical aspects of the environment that represent a set of values. Any person engaging in a recreational activity will have a set of motivations or intentions that he or she wishes to satisfy. Motivations include:

- Human needs, such as physiological needs, are satisfied by facilities such as toilets and picnic grounds. Likewise safety needs are provided for by facilities such as access ramps or paved trails.
- Viewing platforms and scenic walks satisfy scenic/aesthetic interests.

- Ecological interests are provided for by locating trails near areas of diverse vegetation communities, bird viewing areas, interesting geological formations or other environmental features.
- Historic, archaeological or other sites where important historical events have occurred satisfy historical/cultural interests.
- Social motivations Many people are primarily interested in interaction with other people. For these people the landscape merely provides a backdrop for these social interactions to take place.

RBSim 2 allows the user to define other personality characteristics. The key requirement is that each personality characteristic has a corresponding attribute in the network database so motivations or intentions and constraints can be measured against environmental characteristics as described in the next section.

6. Reasoning during the execution of a plan

All agents follow a plan as described earlier, however these plans may change during the execution depending on events that occur during the journey. For instance, if there is a bottleneck in the system during which agents lose time, shortening the available time for the journey, then the plan may need to be altered. Any alterations to the original plan need to be recorded because this is a measure of satisfaction in terms of meeting the agent's expectations.

In order to be able to adjust the plan during the journey, agents must have a reasoning system. Agents reason to achieve a plan according to motivations and constraints. Reasoning results in a decision. Decisions are based on selecting the highest priority options. Options are alternative attraction nodes that are ranked according to weighted criteria. Criteria are of three classes:

- Environmental including trail characteristics, length of day, ranking of the site according to motivations and intentions (see above)
- Internal state includes energy levels, personality profile, anything memorized by the agent (past experience).
- Number of other agents at each node.

6.1 Fuzzy Decision Making

An example of the application of environmental reasoning might be at a fork in the trail where a decision should be made as to which route to take. Such a decision might be based on the following criteria:

- Destination – if two trails ultimately lead to the same destination, then the following factors may come into play.
- Distance – the recreator may wish to take the shortest distance, or on the other hand, if a longer walk is intended the longer distance may be preferable.
- Steepness – if one fork of the trail is steeper than the other, the agent may opt for the easier trail.
- Views – if one trail looks like it leads to better views, this trail may be selected over the other.
- Environmental diversity – the most interesting or diverse route may be more desirable.

How does the agent decide which trail to take if both trails ultimately lead to the same destination? The answer may differ from one agent to the next depending on the goals, intentions, and physical condition of the agent, as well as energy levels, time to complete the journey and other factors. In other words the decision is based on a complex hierarchy of factors that may be changing as the agent continues its journey.

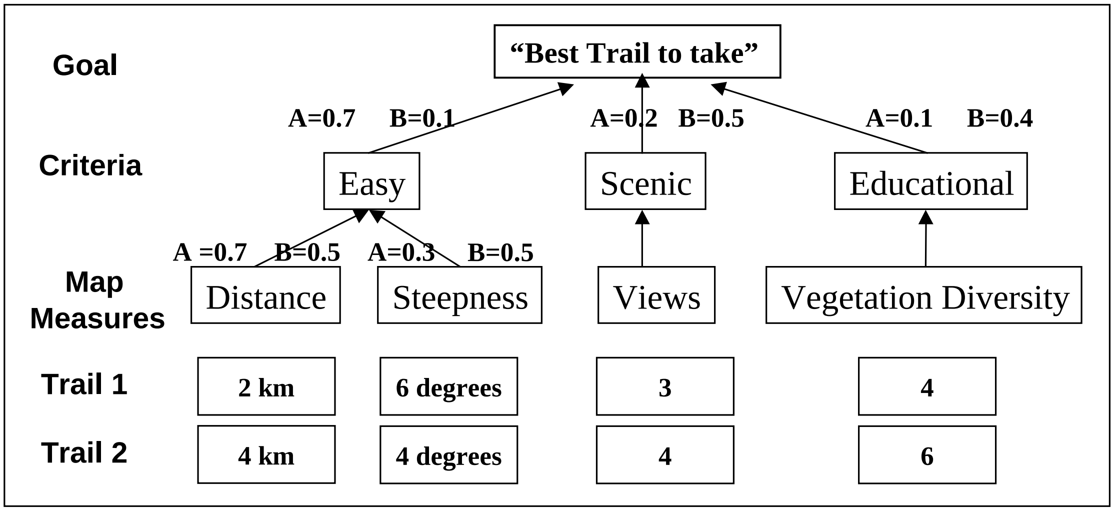

Figure 1. An example of a decision hierarchy that could be constructed to integrate environmental measures from maps into criteria for trail selection. In this context, the structure of the decision hierarchy would be identical for each class of recreation agent, however the weightings on the criteria could be different between agents, resulting in different choices.

This type of decision making falls nicely in the class of fuzzy decisions. Yet any given decision must marry a range of environmental factors against a set of decision criteria (motivations and constraints). An approach to dealing with this problem is to prioritize criteria and then measure the performance of environmental factors that contribute to each criterion. The Analytical Hierarchy Process (AHP) (Saaty, 1995) provides a framework to do this. In AHP decision criteria are defined and weights are derived from a method of pairwise comparison. If the criteria can be measured from environmental factors, it is possible to make decisions incrementally based on local environmental conditions or globally based on measurements of entire environments.

Table 1 shows an example of a decision hierarchy for the above factors and how the decision criteria for selecting a trail can be measured using GIS operators on a map database. Note that the structure of the decision hierarchy would be the same between agents, but the weightings of the criteria could be different say between a 25 year old backpacker and a family walking with small children. The figure shows two trails with the measurements for each of the map measures. Weights for the criteria can be generated for two different groups A) a family with young children and B) nature loving young hikers. Note that the weights vary for the two groups. The choice of trail to take can be calculated as in Tables 1 and 2.

Table 1. Criteria weights and trail ratings. Criteria weights for two different recreation groups. Group A prefers easy walks; Group B prefers interesting walks with good views (weights for each group sum to 1). Normalized ratings for each trail are calculated by dividing each value by the sum of all values for each criterion. Distance and Steepness are subtracted from one since the criterion is easiness and the scale must be reversed to measure easiness in the positive direction. The normalized ratings for trail 1 and trail 2 sum to 1 for each criterion.

	Criteria weights for group A	**Criteria weights for group B**	**Trail 1 Normalized ratings**	**Trail 2 Normalized Ratings**
Easy - Distance	0.7 * 0.7 = 0.49	0.1 * 0.5 = 0.05	1 - 2/6 = 0.67	1 - 4/6 = 0.33
Easy - Slope	0.3 * 0.7 = 0.21	0.5 * 0.1 = 0.05	1 - 6/10 = 0.4	1 - 4/10 = 0.6
Views	0.2	0.5	5/12 = 0.43	7/12 = 0.57
Vegetation Diveristy	0.1	0.4	4/10 = 0.4	6/10 = 0.6

Table 2. Weighted scores for each criterion for trails 1 and 2 for groups A and B. Multiplying the group weights by the criteria ratings for each trail derives these scores.

	Trail 1 scores for group A	**Trail 2 scores for group A**	**Trail 1 scores for group B**	**Trail 2 scores for group B**
Distance	0.33	0.16	0.03	0.02
Steepness	0.08	0.13	0.02	0.03
Views	0.09	0.11	0.21	0.29
Vegetation Diversity	0.04	0.06	0.16	0.24

Table 3. Trail preference scores for each group for Trail 1 and Trail 2. Family group A will choose Trail 1(0.54) over Trail 2(0.46) because of the shorter length. For group B (young nature loving hikers) easiness is not important so higher preference is placed on views and vegetation diversity. Trail 2 (0.57) is selected over trail 1 (0.46).

	Trail 1	**Trail 2**
Preference scores for A	0.54	0.46
Preference scores for B	0.43	0.57

Decision hierarchies are implemented by giving each agent a preference profile and linking each preference to an attribute in the environmental database. These relationships are then used by the agent in two instances: i) the development of locale trip plans and ii) the selection of behaviors from a given set of states in the network or simulation environment.

7. Example simulation run

The following is an example of how a manager would use RBSim 2 for simulating existing conditions on a peak holiday during Summer 1999 and testing alternative scenarios to reduce bottlenecks and encounters. Figure 2 provides a visualization of the simulation run where agents in cars and buses can be observed traversing Great Ocean Road in Port Campbell National Park in Victoria, Australia.

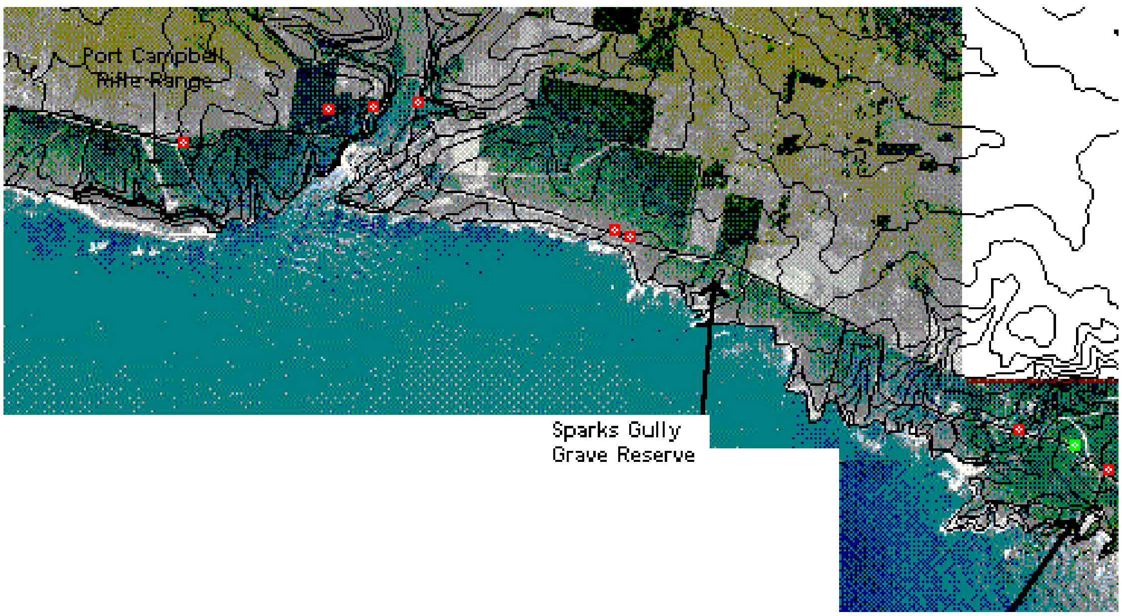

Figure 2. An example of the Visualization of the Simulation Run. Agents can be seen traversing the network

Figure 3 provides a view of the number of agents per locale. Lochard Gorge has significantly more visitation rates than other locales and visitors are spending more time due to larger number of attractions at that locale. This results in a higher number of encounters and when compared to Figure 4 (showing the maximum waiting time at parking lots) it is likely that facilities are over capacity and visitors are experiencing crowding effects.

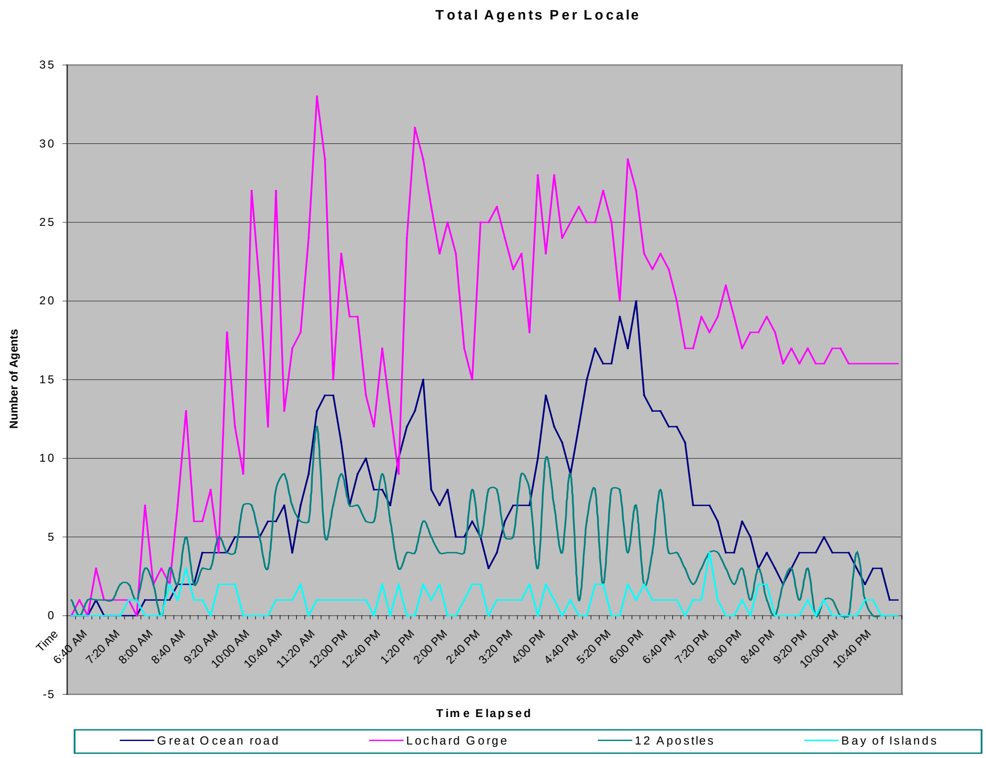

Figure 3. Summary of Number of Agent Per Locale.

As a result of this analysis, managers can now take appropriate actions such as diverting visitors to other sites or increasing the capacity of trails and parking lots. They can also test those actions by returning to the simulation environment, making changes to the network and re-running the simulation using the same visitor profiles.

Figure 4 provides an example of output from the simulation illustrating maximum waiting time for parking lots in each locale. The y-axis illustrates the maximum number of minutes that cars are waiting for parking while the x-axis shows the time step of minutes during the day. It is clear that waiting times in Lochard Gorge are significantly longer than other locales which suggests that parking facilities are undersized. Again the manager can take appropriate management actions and test those actions in a rerun of the simulation after modifying the network and using the same visitor profiles. Each of the simulation runs can be statistically compared to examine degrees of change.

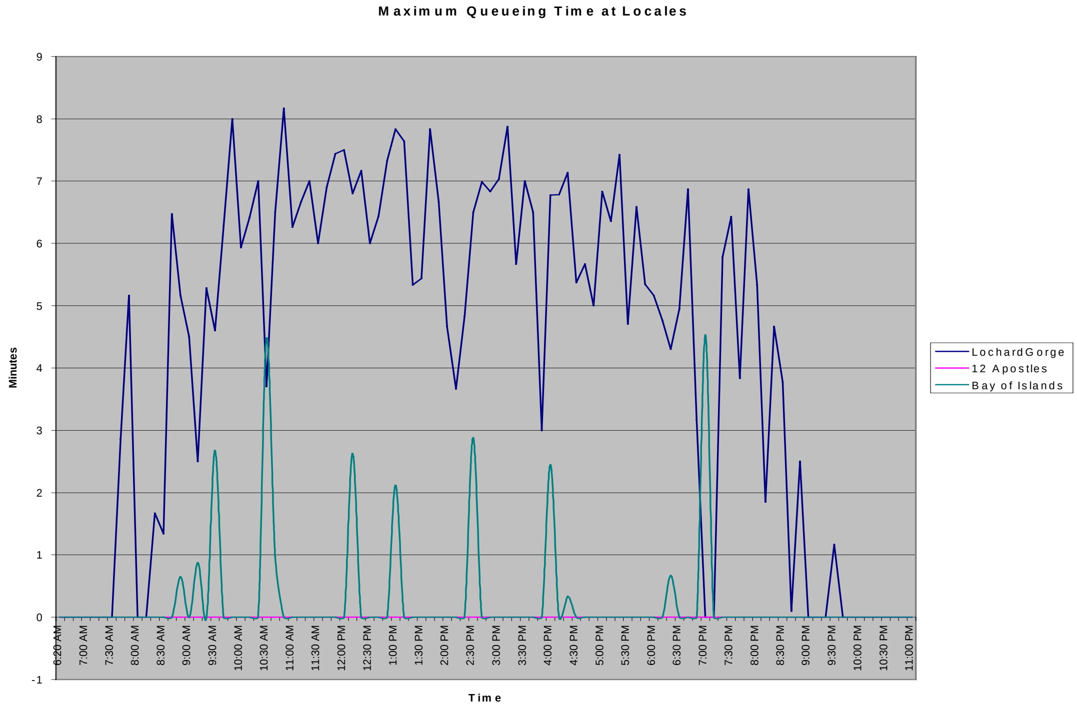

Figure 4. Maximum number of minutes waiting for parking at three locales in Port Campbell National Park.

8. Conclusion

Agent simulations are an excellent method for modeling recreator encounters and conflicts. The agent simulations provide a dynamic view of encounters between agents and identify the spatially explicit locations where they occur. The effect of these encounters on the overall recreational experience is still unknown. However, this simulation environment provides a way to test and evaluate many scenarios of recreational use.

Using a complex systems approach in the development of RBSim 2 is a significant step forward in providing practical tools for managers to aid decision making. RBSim 2 does this by making linkages between spatial data (GIS) to represent the environment, multi-agent systems (agent personality profiles) and a management scenario builder that allows the manager to impose seasonal or daily closures to different transportation modes (cars, buses, OR V's, mountain bikes etc.), and add, remove, enlarge or reduce parking lots, campgrounds etc. By generalizing the software to parameterize a simulation from existing GIS datasets, the RBSim 2 simulation platform can be used to study management alternatives in any recreation setting. The tight integration with GIS also allows ancillary models such as environmental impact models and economic models to be integrated into the simulation. Park managers can then test many different management assumptions in both qualitative and quantitative terms before committing resources to expensive construction projects.

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