Natural disasters have caused severe damage to mankind throughout history. In recent years, natural disasters have struck many areas, and many people have lost lives or property. In Hurricane Katrina, at least 1,836 people died. In the Wenchuan earthquake on 12 May 2008 in China, 69,185 people died and 18,403 people went missing.

Relief operations require logistics systems to successfully transport the injured and deliver medical personnel, machinery, food, water, and other supplies. For example, in the Wenchuan earthquake, in one day, 19 helicopters and six cargo-transport planes were sent to the area. Approximately 5,800 soldiers from medical and rescue units and 150 tons of supplies were delivered to the affected area. Logistics became the lifeline in Wenchuan and the surrounding area.

However, the massively destroyed road network and frequent thunderstorms have severely hindered logistics activities. In cases such as this, emergency-logistics planning becomes an extremely difficult problem that can affect the entire rescue and recovery situation.

To help government and disaster relief organizations prepare for and manage such disasters, we're developing the Artificial Emergency-Logistics-Planning System (AELPS). AELPS, which is based on artificial-society theory (for more on this, see the “Related Work in Logistics Planning” sidebar), uses agent modeling to describe the behavior of basic elements in an emergency-logistics system. AELPS can form the basis of a complex computational platform that generates logistics phenomena during disaster relief and gives intuitive results that can be used in emergency-logistics planning.

Emergency-logistics planning for severe natural disasters
In normal situations, state-of-the-art decision support systems can effectively support emergency-logistics planning. However, when facing severe natural disasters, they might not properly handle the additional complications. Such disasters pose three unique problems for emergency-logistics planning.

First, each logistics request comes from a different working unit—such as the medical unit, the construction unit, the rescue unit, or the hazardous-material and pollution control unit. These units share a single transportation network with limited capacity. If the logistics-planning system considers each unit’s logistics demands separately and simply models them as individual inputs, it won’t identify the relative importance of each type of demand. To solve this problem, the system should use multiobjective optimization.

Second, for a traditional transportation network model, especially a multicommodity network flow problem, each link in the network usually has a fixed capacity. However, in severe natural disasters, each link’s capacity might dynamically change in each period of the planning horizon. This is because subsidiary disasters such as mud slides or residual earthquakes could easily destroy roads and bridges at any time. Meanwhile, rescue units could reconstruct these structures at any time. So, the decision support system should be able to adapt to a constantly changing transportation network.

Third, logistics planning should cooperate with the planning of rescues, healthcare supply delivery, pollution control, epidemic control, and so on. For example, if the logistics planning doesn’t consider each scenario for each different demand, the plan could transport people or supplies to an unfavorable location in the event of subsidiary disasters. Furthermore, because people can sometimes rescue themselves, their independent movement and relocation can significantly complicate planning.

So, we can see that emergency-logistics planning for severe natural disasters must consider different types of requests simultaneously and manage the formation of coalitions of different working units.

The AELPS framework
AELPS (see Figure 1 on page 88) will employ seven components:

- The Emergency-Logistics-Planning System (ELPS) is the core planning engine; it solves logistics-planning problems interactively with all the subsystems.
- The pollution subsystem monitors and controls any hazardous materials that might pollute underground water systems.
Related Work in Logistics Planning

Recently, emergency-logistics planning has come under extensive study. Most researchers focus on developing effective decision support systems and optimization models. Gerald Brown and Antonios Vassiliou introduced a decision support system that deconstructs operational assignments of units into tasks and deconstructs the tactical allocation of units into task requirements.1 Fernando Tovia developed an emergency response model that disaster relief organizations can use to evaluate their response capabilities, assess the logistics challenges in the event of a natural disaster, and perform what-if analysis of weather disturbances.2 Linet Özdamar, Ediz Ekinci, and Beste Küçükyazıcı developed a natural-disaster-logistics decision support system that incorporates requests for supplies and transportation that arise during a new planning-time horizon.3 This system can generate optimal mixed-pickup-and-delivery schedules for vehicles within that horizon, which solves a dynamic time-dependent transportation problem.

Researchers have studied coalition management as part of military logistics. One such AI-based logistics planning and scheduling system is DART (Dynamic Analysis and Replanning Tool).4 Following the system’s success during Operation Desert Shield and Operation Desert Storm, the new generation of DART will focus on coalition management while considering cultural differences, military rules of engagement, and so on.

The concept of artificial societies originated in the 1980s; it combines artificial life and a simulated society. In an artificial society, agents interact and generate macroscopic patterns by emergence, thus growing a “society.” Artificial-society theory has long been applied to support urban development or logistics planning in complex environments. For example, Fei-Yue Wang and Shuming Tang used an artificial society for integrated, sustainable development of metropolitan systems.5 Additionally, social computing, which integrates psychology and organizational development with computer technology advances, can be employed.6

References


Potential applications

AELPS supports emergency-logistics planning in three ways. First, it can help evaluate disaster relief logistics plans. Because AELPS contains many subsystems, it can capture every aspect of possible scenarios, a unique advantage over traditional what-if analysis.

Second, it can help train logistics planners. Disasters occur at random places and times; to help planners be better prepared, AELPS can simulate disasters. The planners can then use AELPS to test a proposed plan.

Third, it can work in parallel with the actual disaster relief system, learning from it. With this parallel structure, AELPS can work as a decision support system that generates logistics plans to execute in the real system.

The successful implementation of AELPS

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• The medical and rescue subsystem generates rescue plans based on population information and determines medical-resource allocation.
• The geology subsystem forecasts geological subsidiary disasters on the basis of geological spatial information.
• The weather subsystem provides weather forecasts to guide rescue actions and support forecasting geological subsidiary disasters.
• The epidemiology subsystem forecasts disease epidemics after disasters and thus helps determine the allocation of vaccines and sanitation materials.
• The transportation subsystem tracks the changing transportation network and provides connection and capacity information to the ELPS.

These components will enable AELPS to handle simultaneous requests and manage coalition formation.

An earthquake scenario

Figure 2 shows a possible scenario for AELPS. The bottom map shows the spatial characteristics of an area that has suffered a severe earthquake. The top three maps are called layers in a geographic information system.

The top layer, derived from the weather subsystem, demonstrates the current or forecasted weather for the area. During bad weather conditions such as a thunderstorm, sending helicopters into the area is impossible. Thunderstorms also mean a higher chance of mud slides. So, results from examining the weather subsystem can be correlated with secondary geological disasters.

The second layer is a geological layer generated using information from the geology subsystem. The red areas indicate potential mud slides at the foot of the mountains. So, rescue forces or vehicles should avoid these areas.

The third layer is the pollution layer, generated using information from the pollution subsystem. Assuming a factory will leak some amount of hazardous materials, pollutants will seep into nearby rivers at a certain rate, threatening the quality of drinking water downstream.

On the basis of this information, the logistics plan can guarantee that rescue units and pollution control units choose the best route to the factory.

To consider more factors, additional layers can represent other subsystems. AELPS can then generate logistics plans that consider each subsystem’s dynamics.

could support emergency-logistics decisions for severe disasters. However, many issues still require further exploration. For example, how to model the knowledge from different subsystems is critical for logistics decisions. Identifying the related knowledge and modeling it into a uniform structure will be the key to building AELPS. Also, solving the large-scale logistics-planning problem remains extremely challenging; its scale is large, it’s dynamic, and it involves many elements from different subsystems.

Developing the system will involve six steps. First, we’ll identify the knowledge that can represent the subsystems. Second, we’ll identify the knowledge that’s related to AELPS. Third, we’ll model all the knowledge into a uniform structure. Fourth, we’ll build a prototype system that includes the ELPS and one or two subsystems. Fifth, we’ll build a computational platform based on the AELPS prototype. Finally, we’ll expand the system with all the AELPS subsystems.

Acknowledgments

This work was supported partly by Ministry of Science and Technology grants 2006CB705500 and 2007AA11Z217, National Natural Science Foundation of China grant 60621001, Chinese Academy of Sciences grants 2F05N01 and 2F07N04, and the Shandong Province Taishan Chair Professor Fund. Thanks to Fei-Yue Wang and Jin Yuan Li for their invaluable discussions and support for this article.

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