Optimal Resource Allocation& SchedulingDuring Adversity Recovery Plan

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Abstract

The optimal Resource Allocation and Scheduling during Adversity Recovery (RASAR) is associated with the mobilization/execution of required resources of personnel/material within the affected area of relief operation. This is comprised of various facilities, equipment, methods, utilities to deploy, distribute, install and control between heterogeneous inflows and distribution to the victimand damaged location in the disaster area. An ICT driven system that can coordinate and collaborate multi-Resource mobilization to immediately improve the drastic conditions at all the levels has been identified as an utmost priority and need for the Society.

This work demonstrates both conceptual framework and the ICT implementation of an optimal generalized methodology. This methodology assesses and triggers the routing and scheduling of diverse resourcesat the defined operational area to efficiently and effectively target the damage control.

Index Terms—Resource allocation, routing, scheduling, recovery plans, heuristic search, disaster management.

1. Introduction

In the last decade, serious shortcomings during adversity management operations such as earth quake, tsunami explicitly illustrated the need for mobilization process improvement[1]. As a result, the development of amethodology that integrates diverseresources to more efficiently andeffectively plan and execute logistics support within a disaster area has become the utmostpriority and immediate need for the entire society.

Achieving betterresource allocation efficiency mandates that we have to discard theconventional “just –in-case” approach and move to a rapid and reliableroutingprocess that provides time definitedeployment of resources to victims[2]. Responding to thisrequirement, various agencies initiated the development of Geo-ICT[3] basedautomated Disaster Management Systemwhich enables operators/planners to react to frequently occurring contingency situations.

Theyare also trying to develop a scalable modelthat meets the largefataladversity management requirements. Resource distribution is the flow of personnel, materiel and services within disaster area to overcome the damaged caused.TheRecovery Plan[4] is comprised of facilities, utilities, manpower, installations andprocedures designed to assess, collaborate, receive, store, maintain, distribute and allocate the flow of resources between heterogeneous inflows and distribution to the victim and damaged location in the disaster area.Such a recovery system may beefficiently represented by a networkwhere the associated physical entities arecategorized as nodes, modes and routes.

This paper describes animprovised methodology that provides allocating, routing and scheduling of heterogeneous resources at the specified demand areato provide efficient time definite deployment of facilities to victims for generalized adversity situations. The model developed has been found to be robust, flexible, and capable of solving typical disaster problems(post disaster recovery plans).

Mathematical optimization[5] search was the underlying framework utilized in the developmentof this methodology and several other significant concepts were taken into account during the associated research.

2. Problem Statement

A Resource Allocation and Scheduling during Adversity Recovery (RASAR) methodology should provide adversity management planners with a system thatsupport efficient resource routing and scheduling plans that achieve time constraint deploymentof required facilities to victimized area. As explained below, modelingrequirements for the RASAR extend well beyond those of the conventional resource management[6] in disasters.

During a typical adversity, there are multi-facetresource requirements with differingcharacteristics such as medical services/ambulances, transportation (air, ground, and water), fire services, shelter homes, communication systems, food supplies.Resourceallocation requirementsinclude the ability to make multiple deployments during the planning horizon, the ability toperform direct services from outside the disaster area and the ability to retain at damage prone locations. Scheduling considerations include resource availability, service times, loadtimes, and unload times. All resources operate from their control centre or a hub.

Resource distribution network nodes are control centers, hubs and victim/victimized locations.Control centers are the supply nodes. The hubs or support areas in the vicinity of disaster area are intermittent nodes, which coordinate, collaborate and regulate resources. Victims are sink nodes that receives the facilities. All nodes have time critical constraints, sequencing and location constraints. Hubshave resource storage constraints and victims have time definite facility demands.

A RASAR has three types of time slot constraints: early time allocation (ETA), timely allocation(TA) and multiple time windows (MTW) for non allocationand non deployment. An ETA stringently defines a victim service starting time but does not constrain resourceallocation or deployment times. A TA defines when a victim service must be complete but does not constrain serviceoccurrence, or resource allocation and deployment times.MTWs restrict resource allocation and deployment at a node but do not stipulate when facilities are loaded or offloaded.There are two types of location constraints. A working location limits the number of resources that can simultaneously service a victim. Aparking location limits the number of resourcesplaced at a victimized location.

The RASAR has tiered distribution architecture. The first order tier containsthe control centers and hubs/victims served by the control centers. Middle tiers consist of hubs thatservice hubs/victims. The last order tier consists of victim served by a hub.Each tier is a self-contained distribution network. However, they are not independent ofeach other.Lower ordered tiers are dependent on higher ordered tiers. For example, thehubs in a lower ordered tier receive facilities as victim within a higher ordered tier.Once a hub receives its resource supply, it can then distribute these to its victim.

Fig. 1 presents an example of a RASAR. There are four Tiers within thisnetwork: Tier 0 is the HQ with victim (1, 2, Agency); Tier 1 is the Agency hub withvictim (Dept.1, Dept.2, 3); Tier 2 is the Dept.2 hub with victim (Actor3, Actor4, and5); and Tier 3 is the Dept.1 hub with victim (Actor1, Actor2, and 4).

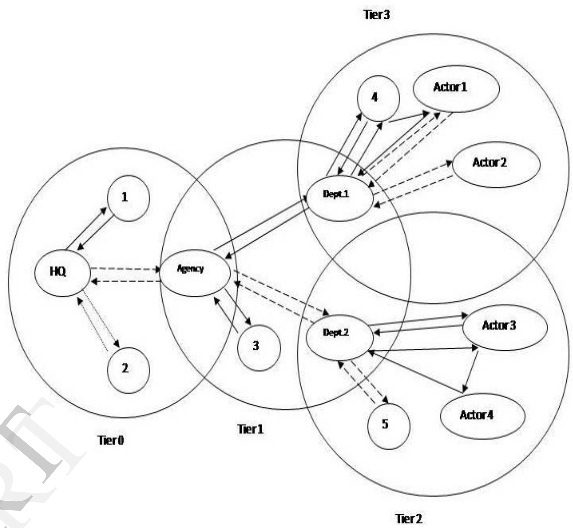

Fig 1: Example of RASAR

Note that unlike aconventional network hierarchy, both Tiers 2 and 3 derive from Tier 1.Hubs distribute resource after it is received and executed. Resource, characterized bythe facility delivered and time of delivery, is allocated and prepared for execution to itsnext victim. Resource is either supplied directly or kept for laterdelivery.

The RASAR primary objectives are to minimize unmet victim demand(demand shortfall), late supplies (shortfall), resource utilization costs and resource mobilization costs. Late supply times are weighted by the amount of facilities delivered late.

3. RASARMethodology

Heuristic Search Optimization (HSO)has been used successfully to attack several difficult combinatorialoptimization problems[7]. Based on previous results we are sure that itwill provide an efficient and effective means to find quality RASARsolutions. Fig. 2 provides foundations and description of how theRASAR is represented in the

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HSO framework and a description of the HSOmethodology employed.

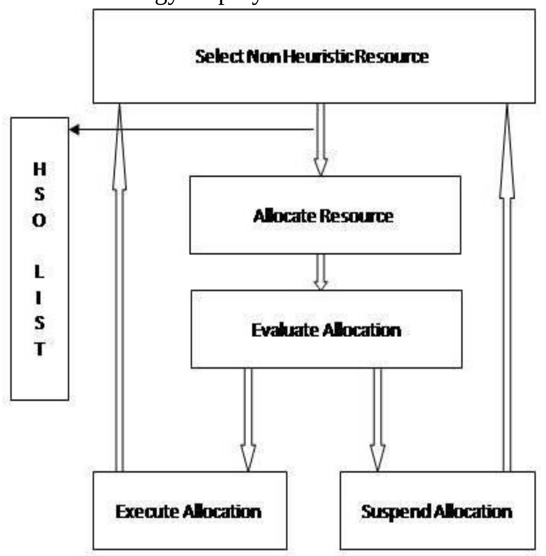

Fig 2: Heuristic Search Framework

3.1 Modelling Assumptions

It is a recognized fact that no "real-world" problem's inherent complexities can becaptured in a usable model of manageable size. For this reason, while preserving themethodology's capability for practical planning purposes, number of assumptions hasto be incorporated into the HSO representation of the RASAR e.g. sufficient supplies of required resources are available at time 0 at head quarter or control locations, resource utilization and forwarding are independent of victim and localconditions etc.

3.2 Overview Of HSO

In this section, the HSO architecture used to solve the RASAR ispresented. Fig.3 graphically depicts this architecture which is partitioned into a Pre-HSphase and the HS phase. Figure 3 pictures an overview of the HSO for the RASAR with all the major components of each procedurewithin each phase.

3.3. The Pre-Heuristic Search Phase

The Pre-HS phase achieves the following:

(i) Sets parameter values and assimilates a filecontaining the victims and resource specifications for the current problem to be solved.
(ii) Generates the group neighbourhoods and
(iii) Creates and evaluates an initial solution.A greedy assignment heuristic [8] creates the initial solution by assigning prioritized victims to resources that best meet their demands.

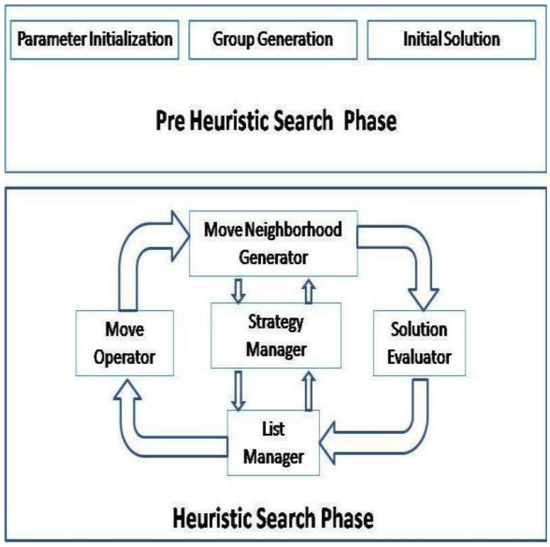

Fig. 3: Heuristic Search Optimization Architecture

Victims are assigned priorityratings using thefollowing equation:

VictimPriorityRating=

$$\frac{victDist}{avgDist} * \sum_{i=1}^{n} [victDemandi * (periodLength/TDDi)(n-i)]$$

where
i = TDD (Time Definite Delivery) requirement index per victim
n = number of TDD requirements per victim
TDDi= victim TDD requirement for index *i*
victDist= distance of victim to nearest depot/hub
avgDist= average distance of all vicims to their nearest depot
victDemandi= victim demand
periodLength= total model time period

Resources are ordered based on the ratio of their capacity and average delivery time.
*ResCapPerAvgDeliveryTime= resCap/(2*avgDist/speed+loadTime+unloadTime+rebuildTime)*
where
resCap= resource capacity
speed= resource shifting speed
loadTime= time to initiate a resource
unloadTime= time to unload a resource at victim site
rebuildTime= time to rebuild a resource

Once created, the initial solution, or first incumbent solution, is evaluatedaccording to an objective function that assesses the demand filled shortfall, TDDshortfall, fixed costs, variable costs and other penalties

3.4 The Heuristic Search Phase

Running until a termination criterion is satisfied[9], each iteration of the HS phasepasses through five major components; *move neighborhood generator, solutionevaluator*, *strategy manager*, *listmanager*, and *move operator*. Aniteration begins by generating and applying a moveneighborhood to the incumbentsolution and ends when the *move operator* creates a new incumbent solution.

The *move neighborhood generator* creates and applies move neighborhoods to theincumbent solution. Move neighborhoods are generated and employed based on solutionattributes and data collection. This neighborhood extracts victim letters fromcycles in order to reduce fixed and variable costs. It is specifically called when excessvictim letters reside in cycles and when the *strategy manager* dictatesimplementing super diversification measures.

Working closely with the *list manager*, the *solution evaluator* determines theobjective function value for each neighbor. The goal of this process is to find the best non-Heuristicobjective function to replace theincumbent solution.

The *list manager* uses the *orbit* and *move* lists to interact with the *solutionevaluator* to prevent cycling within the HS process. The orbit list tracks traversed orbitsand the move list tracks recent diversification moves. Both lists allow an element’s heuristicstatus to be determined and changed.

The *strategy manager* determines whether to continue with normal HSprocesses, to intensify or to diversify the search. Decisions are based on collected searchdata and search parameters.

4 Concluding Remarks

The development of an automated solution methodology to the RASAR problemhas been characterized as a major priority and immediate need for the society.

This paper documents groundbreaking new conceptual outcome based in a flexibleheuristic search optimization (HSO) framework and presents a plausible implementation of this. This combination of theory and application will result in arobust, efficient, and effective generalized resource allocation and scheduling methodology. This methodology evaluates and suggests the routing and scheduling of multi-modal resourceassets to provide economicallyefficient time definite delivery of these to victims of the disaster.Many programs are available that “perform” resource allocation and scheduling. However they do not prescribe highly effective, near optimal routes and schedules forall resources. Therefore, this model is the unique of its kind to offer thisfunctionality.

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