Improving Volunteer Productivity and Retention during Humanitarian Relief Efforts

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***Abstract*— In the aftermath of a disaster, humanitarian organizations quickly assemble a workforce that can immediately serve a community's needs. However, these needs change over time, and the volunteer base (and their skill sets) also changes over time. In this paper, a mathematical programming model is formulated to solve a volunteer assignment problem in which beneficiaries' needs are addressed based on how many volunteers are assigned to each of the levels of needs. In addition, we also examine the changes in these volunteer assignments based on several key cost parameters, need likelihood scenarios, and volunteer training opportunities. Under various demand scenarios, the optimum decision is to begin training some unskilled volunteers early in the response period even when the short-term, unskilled task demands are still high, in preparation for the more skilled, long-term task demands that are yet to come. Humanitarian relief organization managers who generally feel as though a peak of long-term/skilled volunteer task demands will come at some point during the disaster response should strongly consider allowing volunteer training assignments.**

***Keywords*—** *Volunteer management, optimization, humanitarian aid, resource assignment, training*

1. Introduction

Disasters are generally classified into two kinds, namely natural disasters such as floods, earthquakes, or hurricanes; and manmade disasters such as hazardous materials spills, terrorist activities, and wars. These disasters can cause a significant degree of damage when they occur. According to Van Wassenhove [20], on average, 500 large-scale disasters, natural and human-made, kill about 75,000 people and affect a population of 200 million every year. Humanitarian organizations have to quickly respond by preparing and managing relief activities. A key resource for each organization is the volunteer base. One important aspect of successful volunteer management is appropriately assigning volunteers, according to their desired tasks or skill levels, to best help the affected population. According to Falasca et al. [7], in order to successfully retain their volunteers, humanitarian organizations should appropriately and efficiently manage them. Because of limited resources and highly variable demands in affected areas, the number of volunteers assigned to a certain task may be too few or too many in any given time period. The humanitarian organizations may need to train volunteers in order to reassign them to different tasks, which may pose more problems due to variable task demands for subsequent time periods.

In this paper, a volunteer management model (VMM) is proposed to help relief managers deal with assigning and training volunteers in order to satisfy the humanitarian needs, with the goal of minimizing the total cost of assigning volunteers, leaving needs unsatisfied, and incurring volunteer task mismatches (i.e. assigning a nurse by trade to search and rescue). This is one of the first models developed for assigning, training, and transferring volunteers to accomplish different tasks over a time horizon. To the best of our knowledge, no models have been developed that specifically include volunteer training capabilities.

The organization of the paper is as follows. We briefly introduce literature related to humanitarian logistics, both in general and specifically addressing volunteer management. In Section 2, we introduce the VMM model. Sections 3 and 4 contain findings generated from the modeling approach. In Section 5, we consider a special case in which all work must be completed by a specified deadline. Finally, we provide conclusions and future work in Section 6.

2. Literature Review

While quantitative research that addresses volunteers in the field is quite limited, there are many other application areas where researchers have contributed to humanitarian crisis management during the response and recovery phases. We mention a few of these areas in particular, and then turn the focus specifically to volunteer management.

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2.1 Other humanitarian crisis management area

Evacuation is considered a challenging issue in humanitarian relief operations. Moving people from affected areas to a safe place, giving the uncertainty in the weather or the infrastructure situation, is not an easy action to be accomplished. Optimization models have been developed to handle some of these evacuation issues. For instance, Cova and Johnson [5] introduced a network flow model to identify optimal lane-based evacuation routing plans in a complex road network. They used a mixed integer programming approach to find optimal evacuation routing plans for a sample network. In another study, Yi and Özdamar [21] proposed a mixed integer multi-commodity network flow model for evacuation and support in disaster response activities. An earthquake scenario based on Istanbul’s risk grid, as well as larger size hypothetical disaster scenarios, were used to illustrate the model. In addition, there are many studies considering evacuation planning for disasters, (e.g. [6, 12, 15, 17-19]).

When evacuation is not an option and residents must shelter-in-place, we turn our attention to providing aid to the disaster-stricken area. *Last mile distribution* refers to the delivery of relief supplies from distribution centers to people in the affected areas. Many studies have focused on this area. Barbarosogu and Arda [2] developed a scenario-based stochastic programming model to represent a multi-commodity, multi-modal network flow problem. The main goal was to minimize the loss of life and maximize the efficiency of search and rescue operations. Balcik et al. [1] proposed a mixed integer programming model to optimize resource allocation and routing decisions from a number of local distribution centers to a number of demand locations, with the goal of minimizing the transportation costs and maximizing the recipients’ benefits, keeping into account vehicle capacity and delivery time restrictions. The best allocation can be easily found, however, only for problems with small numbers of nodes and routes. Hentenryck et al. [11] proposed a multi-stage stochastic hybrid optimization algorithm for the single commodity allocation problem (SCAP) for disaster recovery. The objective was to minimize the amount of unsatisfied demands, the time it took to satisfy the demand, and the storing costs of the commodity. To validate the algorithm, it was used in hurricane disaster scenarios generated by Los Alamos National Laboratory. For more examples in literature, see e.g., [10,13].

The inventory management in humanitarian logistics has received some attention from the optimization modeling perspective. Beamon and Kotleba [3] developed a stochastic inventory control model that determines optimal order quantities and reorder points for a long-term emergency relief response. In another study, Ozbay and Ozguven [14] developed a stochastic inventory control model for disaster planning. The goal was to determine the optimal amount of initial stock to prevent disruption during the delivery and consumption process. In a third study, Blecken et al. [4] formulated an inventory relocation model that relocated the optimal stock under demand uncertainty in risk-prone post-disaster scenarios. It was shown that the overall inventory cost could be significantly reduced when considering demand uncertainty in post-disaster scenarios. As policies are created to support humanitarian relief distribution, we require resources in the field to provide delivery, support, and other functions. In other words, we cannot look at these important issues without considering how the role of the volunteer worker impacts humanitarian aid policies.

2.2 Volunteer Management

In volunteer management and scheduling, not much work has been done compared to traditional labor management. In one study, Gordon and Erkut [9] developed a spreadsheet-based decision support tool to generate shift times and schedule volunteers for the Edmonton folk music festival. They used integer programing formulation to handle the task preferences, with the goal of minimizing the number of surplus volunteers. In contrast, the cost of volunteer shortages was not clearly considered. Sampson [16] demonstrated how volunteer labor assignment (VLA) problems are quite different from traditional labor assignment (TLA) problems. He considered the volunteer as a laborer with no cost; then he incorporated this difference into a goal programming model. In VLA, the goal was to minimize the total cost of assigning too few or too many volunteers, volunteer assignments, and unsatisfied task demand. Falasca et al. [7] developed a multi-criteria optimization model to help in assigning volunteers to tasks. As with Sampson [16], they reviewed the differences between a volunteer labor assignment and a traditional labor assignment. In another study, Falasca et al. [8] discussed the creation of a spreadsheet multi-criteria volunteer scheduling model for helping a small development organization in a developing south American country. The goal of the model was to reduce the number of unfilled shifts, minimize the total scheduling costs, and minimize undesired assignments. This study is different from Sampson [16] in that it considers that the volunteer labor cost is not negligible, such as travel expenses.

What research has been done in volunteer management assignment motivates us to explore more in this area. This topic has been lightly studied to date, yet it is one of the key components to any relief organization’s efforts. In the model described below, we expand on the topics covered by similar models such as VLA, but also explore new ideas, such as volunteer training for different tasks and volunteer attrition due to volunteer task assignment mismatching.

3. Humanitarian Volunteer Management Model

This model is designed to help humanitarian organization managers effectively and efficiently manage volunteer resources in the aftermath of a disaster. The consequences of poor volunteer resource allocation can directly affect the ability of the organization to meet the short-term and long-term needs of the community. For example, little elaboration is necessary to imagine the impacts of not having enough skilled volunteers available for a search-and-rescue effort immediately following an earthquake. However, assigning too many volunteers to certain tasks at the expense of other tasks can also cause serious problems in the long term as well. For example, if too few volunteers are assigned to preventative cholera outbreak measures due to seemingly more pressing immediate tasks, then a cholera epidemic could break out that perhaps was avoidable. This model serves to help prevent these types of issues from occurring, via a mathematical approach to volunteer resource management.

The objective is to minimize the cost of volunteer transportation/living expenses, unmet task demand costs (in terms of time delays, relief aid shortages, etc.), and volunteer retention costs (the costs of losing volunteer(s) due to mismatched volunteer assignment preferences). The latter cost seeks to identify the impact of unnecessarily assigning volunteers to tasks for which they did not request, (e.g., an electrician working in triage or an unskilled volunteer working as a carpenter). In particular, we want to measure the negative impact on volunteer goodwill and the likelihood of their remaining on-site during the crisis. Initial data that is required by the model includes periodic task demands (deterministic or stochastic), available resource pool and their skill levels, and the costs associated with volunteer training, unmet task demand, etc. Overall, the constraints (1) limit the number of available volunteers within each group, (2) account for period(s) when volunteers being trained are able to assist in their new task at a limited efficiency as they undergo on-the-job training, and (3) account for changing future task demands based on current task progress by the volunteers.

A key component of this model is its ability to incorporate a variety of task demand scenarios to represent changing short-term and long-term community needs. It is logical to assume that task demand for a crisis response would not be known with certainty. In an attempt to factor in uncertain task demands, multiple task demand scenarios with respective probabilities can be introduced into the model, which in turn allows the model to best place volunteers based on the expected task demands for each period. Next, we provide the details of the model formulation, including all decision variables and parameters specified within the formulation.

3.1 Decision variables

$v_{ijt\alpha}$: Volunteers with skill i, assigned to task requiring skill j, for time period t, with α training periods remaining

V_{it} : "Pool" of volunteers with skill i in period t

w_{jst} : Volunteer hours for task requiring skill j, under scenario s, for time period t

$\hat{d}_{jst}$: Additional task demand (time units) caused by previous unfulfilled task demands, for task requiring skill j, under scenario s, for time period t

Note that the model will provide the optimal volunteer assignments $v_{ijt\alpha}$ based on all possible task demand scenarios and their respective probabilities (or likelihood of occurrence). Only one course of action can actually be chosen, thus $v_{ijt\alpha}$ is not specified for each demand scenario. The initial volunteer set for all skill levels (V_{i1}) are defined. The following is a list of the other parameters under consideration for the volunteer management model

3.2 Parameters

$\bar{d}_{jst}$: Task demand (time units) requiring volunteers with skill *j*, under scenario *s*, for period *t*

K_j : Penalty factor for unmet volunteer task (with skill *j*) demand, $K_j \geq 1$

z_j : Time required to train a volunteer for skill *j* (in periods)

e_j : Volunteer efficiency factor for assignment with skill *j* (mismatched volunteers only)

h_j : Volunteer work-hours multiplier per assignment *j*

P_s : Probability that demand scenario *s* will occur

A_{ij} : Assignment preference mismatch factor for volunteer with skill *i* assigned to task requiring skill *j* (in terms of # of volunteers)

C^A_i : Volunteer with skill *i* attrition cost

C^E_j : Unmet volunteer task requiring skill *j* demand cost, final period only

C^M_i : Per-period volunteer with skill *i* assignment mismatch cost

C^U_j : Per-period cost of unmet volunteer task (with skill *j*) demand

C^V_i : Per-period volunteer with skill i costs (transportation, living, others)

I : Number of different skill/task levels

S : Number of total task demand scenarios

T : Number of periods

3.3 Formulation

To summarize, our desire is to determine a least-cost assignment of volunteer resources to task demands per period. Using a formulation based on the likelihood of various task demand scenarios occurring, along with the decision variables and parameters previously introduced, we can now present the formulation of the Volunteer Management Model (VMM).

$\mathbf{MIN}\left(\sum_{j=1}^{I}\sum_{s=1}^{S}\sum_{t=1}^{T-1} P_s \times C_j^U \times \hat{d}_{jst}\right) + \left(\sum_{j=1}^{I}\sum_{s=1}^{S} P_s \times\right.$ *CjE×djsT+i=1ICiVj=1It=1Tα=0 zjvijtα+i=1ICiA(Vi1−ViT)+i=1ICiMj≠i t=1Tα=0 zjvijtα* (1)

Subject to

$$\hat{d}_{jst} = \left(\bar{d}_{jst} + \hat{d}_{js(t-1)} - w_{jst}\right)K_j \ \ \forall\, j, s, 0 < t \qquad (2)$$

$$w_{jst} \left[\sum_{i \geq j} v_{ijt0} + \left(\sum_{i<j}\sum_{\alpha>0} v_{ijt\alpha}\right) e_j\right] h_j \ \ \forall\, j, s, t > 0 \qquad (3)$$

$$V_{it} \leq V_{i(t-1)} - \sum_{j>i, \alpha>1} A_{ij} v_{ij(t-1)\alpha} - \sum_{j<i} A_{ij} v_{ij(t-1)0} - \sum_{j>i} v_{ij(t-1)1} + \sum_{m<i} (1 - A_{mi}) v_{mi(t-1)1} + 0.5 \ \ \forall i, t > 1 \qquad (4)$$

$$v_{ijt(\alpha-1)} \leq v_{ij(t-1)\alpha}\left(1 - A_{ij}\right) + 0.5 \quad \forall i < j, t > 1, \alpha \geq 1 \qquad (5)$$

$$\sum_{j=1}^{I}\sum_{\alpha=0}^{z_j} v_{ijt\alpha} \leq V_{it} \quad \forall\, i, t > 0 \qquad (6)$$

$$\hat{d}_{jst} = 0 \quad \forall j, s, t = 0 \qquad (7)$$

$$v_{ijt\alpha} = 0 \quad \forall i \geq j, \alpha \neq 0, t > 0 \qquad (8)$$

$$v_{ijt\alpha} = 0 \quad \forall i < j, 0 < t \leq z_j, \alpha \leq \left(z_j - t\right) \qquad (9)$$

$$v_{ijt\alpha} = 0 \quad \forall i < j, t > 0, \alpha > z_j \qquad (10)$$

$$v_{ijt\alpha}, V_{it}, w_{jst}, \hat{d}_{jst} \geq 0 \quad \forall\, i, j, s, t, \alpha \qquad (11)$$

$$v_{ijt\alpha}, V_{it} \quad integer \quad \forall\, i, j, t, \alpha \qquad (12)$$

3.4 Constraint explanations

The objective function serves to minimize costs to the relief organization, measured in terms of the expected cost of unmet task demand, the expected cost of not completing the total volunteer task demand by the final time period, cost per volunteer per time period (for travel, living expenses, etc.), cost for volunteer attrition (lost volunteers from assignable causes), and the cost of mismatching volunteer tasks with their respective skill levels. If the cost of leaving task demand unmet is not significant, then C^E can be set equal to C^U, thus leaving C^U as the sole cost driver. It is logical that $C^E \geq C^U$ for all tasks j. Constraint (2) defines the amount of additional task demand ($\hat{d}$) created per time period, based on the difference between task demands (or needs) and the actual work accomplished. This difference is then multiplied by a penalty factor K_j, implying that the unmet task demands may increase needs in future periods.

Constraint (3) confines the volunteer work completed on a task in a certain period to be no more than what can be done by the assigned volunteers that are already trained for the task, plus the untrained volunteers currently going through training for that task. Volunteers initially assigned to a task for which they were not already skilled go through a training period of length z_j, during which they are only a factor amount e_j as efficient before they are fully trained. The number of periods left in training is tracked by the index α. Notice the volunteer hours multiplier h_j.

Constraint (4) defines the number of available volunteers in the next time period for each skill level i to be equal to the current number of available volunteers in skill level i. The constraint also accounts for the number of volunteers who leave due to the mismatching of assignments and preferences or who are moving from one skill level to another skill level upon the completion of training. The constant 0.5 is included to cause the volunteers available to round to the nearest integer, without losing linearity in the model via rounding or truncating functions. Constraint (5) tracks the progress of the volunteers in training, by updating their remaining training periods value α. Volunteers lost due to assignment preference mismatches are accounted for as well. The constant 0.5 is included to cause rounding to the nearest integer, as in constraint (4). Constraint (6) limits the number of assigned volunteers to be less than or equal to the number of available volunteers at the beginning of the period, for each skill level.

Constraints (7), (8), (9), and (10) prohibit invalid decision variables. Constraint (8) prohibits additional task demand prior to the model's first time period, period 0 (necessary due to subscript definitions). Constraints (8), (9), and (10) prohibits invalid volunteer assignment variables, i.e. v_{1210} (if some training is required of a volunteer of skill level one assigned to a task requiring skill level two, thus the training periods remaining must be greater than zero in the first period). Constraints (11) and (12) satisfy non-negativity and integer constraints for the decision variables.

Please note that skill levels are numerically hierarchical. That is, volunteers of skill level one are less skilled than volunteers of skill level two, two are less than three, and so on. Thus, training only occurs for volunteer assignments to tasks above their skill level.

4. Model Behavior and Volunteer Assignments – An Example

4.1 Base conditions and methodology

As stated earlier, a key component of this model analyzed is the task demand variability component, represented through each task demand scenario *s*. Variability in the amount of relief needed is endemic to humanitarian crisis response, given the volatile and ever-changing nature of disaster situations. This is accounted for by allowing multiple different possible demand scenarios, and respective probabilities, to be inputted into the model, which then subsequently generates volunteer assignments based on the lowest expected cost. For the sake of analysis, it is assumed that the parameters C^V_i (per-period volunteer costs), C^A_i (volunteer attrition cost), and C^M_i (per-period volunteer assignment mismatch cost) are constant, as these values can be estimated by the relief organization.

The following example is modeled off a potentially real humanitarian disaster situation. After a disaster, there are immediate short-term task demands (food, water, shelter) as well as long-term recovery task demands (primarily reconstruction). For this example, two task demands are considered, broadly characterized as short term (task/skill type 1) and long term (task/skill type 2). These require unskilled and skilled volunteers respectively, since long-term needs generally involve tasks such as reconstruction of homes and infrastructure. Unskilled volunteers can still be assigned to long-term recovery tasks, but at a lower efficiency as previously described. Four potential task demand scenarios are considered due to the uncertain task demands that may be encountered by a humanitarian relief organization; they are displayed in Figures 1-4. There are 100 volunteers in each skill level, and the collective volunteer pool can satisfy a maximum of 7000 units of demand and 5600 units of demand for unskilled and skilled tasks, respectively. For each task demand scenario, the general idea is high short-term response needs initially, with varying patterns for long-term recovery needs. The peaks of each task demands are purposefully higher than the stated maximums in order to encourage variable volunteer assignments over time.

Scenario 1 is designed to represent a "classic" two-phase response, with high initial short-term task demands that gradually decrease over time, and long-term task demands that are initially low but gradually increase to a peak around the middle of the predetermined response window. As seen in Figure 1, the short-term tasks are modeled to exponentially decrease from an initial peak value, while long-term tasks generally follow a normal distribution. Scenario 2 has steadily decreasing short-term task demands, and constant long-term task demands that are approximately half of the initial short-term task demands. Scenario 3 has high short-term task demands that only begin to decrease after the 6th week, while the long-term task demands constantly increase to week 12, then decrease beginning in week 17. This could represent a crisis in which there are high immediate needs, but then some unforeseen circumstance causes a rise in long-term recovery needs weeks or months later. Scenario 4 has steady, high short-term task demands through week 6 after which they exponentially decrease; the long-term task demands begin low but increase to a high constant value beginning in week 3. This latter scenario may most accurately represent an "overwhelming" humanitarian crisis, where there are so many long-term recovery needs that they can only be represented as "high" for an indefinite horizon.

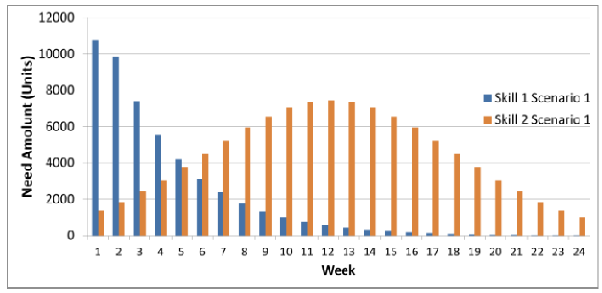

Figure 1. Task Demands Scenario 1

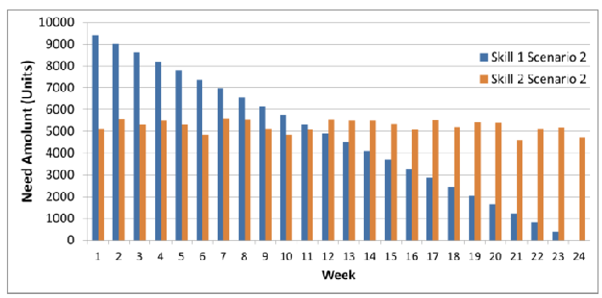

Figure 2. Task Demands Scenario 2

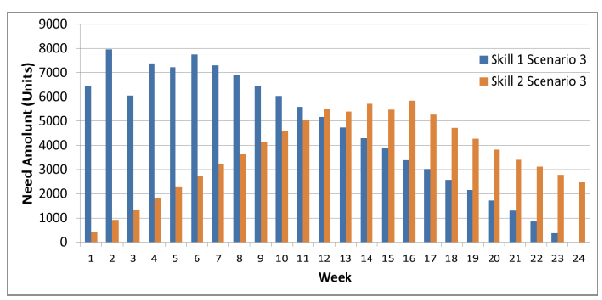

Figure 3. Task Demands Scenario 3

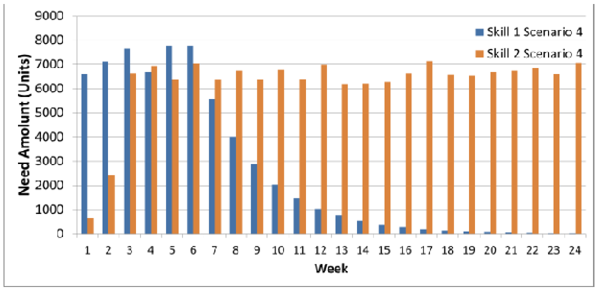

Figure 4. Task Demands Scenario 4

For the analysis that follows, these constants are used unless otherwise specified, and the unit time period is in weeks.

I=2, S=4, T=24

A_{12}=0.01, A_{21}=0.02

V_{11}=V_{21}=100

e_1=0.95, e_2=0.50

h_1=70, h_2=56

z_1 =0, z_2=6

$C^A{}_1$ =350, $C^A{}_2$ =210

$C^E{}_1$=$C^E{}_2$=10

$C^M{}_1$=3.5, $C^M{}_2$=4.2

$C^U{}_1$=$C^U{}_2$=10

$C^V{}_1$=$C^V{}_2$=350

K_1=1.5, K_2=1.1

Unskilled volunteers training and/or working in skilled (long-term recovery) tasks are assumed to satisfy task demands at only half the rate of a skilled volunteer. Short-term recovery tasks volunteers are assigned to work 70 hours/week (10 hours/day) due to the urgent nature of immediate tasks, while long-term recovery volunteers are assigned to work 56 hours/week (8 hours/day). A six week training period is defined for unskilled volunteers to become skilled. Unmet task demand costs were set at $10/hour for both task types, in the absence of realistic data. Volunteer attrition costs were set equal to the cost of the unmet task demand amount they could individually satisfy per period (C^U *h), minus the per-period volunteer costs (C^V), which are assumed to be $50/day. Volunteer mismatch costs are roughly estimated by simply taking volunteer attrition costs and multiplying it by the respective attrition probability (A_{ij}). Finally, the unmet task demand penalty factor K_j is higher for short-term recovery tasks than long-term recovery tasks, since it is assumed that short-term tasks are more urgent and thus would cause problems (in terms of additional task demands) if they are not satisfied in a timely manner.

4.2 Model behavior and insights

The basic decision characteristics of the VMM are first analyzed via a simple sensitivity analysis. The volunteer assignments decisions created by the model are primarily influenced by the values of the parameters related to the task demands: $C^U{}_j$ (per-period cost of unmet task demand), $C^E{}_j$ (unmet volunteer task demand cost, final period only; assumed to be related to $C^U{}_j$), and K_j (penalty factor for unmet volunteer task demand). These parameters are the primary drivers behind the calculation and impact of additional task demands ($\hat{d}$), which is a key decision variable in the model. Modifying their values reveals the fundamental model behavior.

Regardless of the scenario(s) chosen, reducing the value of the unmet task demand costs ($C^U{}_j$, and corresponding $C^E{}_j$) always tended to increase the amount of unmet task demand ($\hat{d}$), when all other parameters are unchanged. This is because the VMM found it less costly to leave some or most of the task demand unmet than to assign the volunteers necessary to cover the task demand in its entirety. This is mathematically determined by the relative values of $C^V{}_i$ and $C^U{}_j$; the higher the cost is per volunteer assignment, proportionally fewer volunteers will be assigned in relation to the unmet task demands. The VMM does tend to leave some task demand unmet in the final period in most parameter configurations, due to the relative values of each and their equal weighting in the objective function. This is perhaps unrealistic in some humanitarian relief operations, and thus motivated the inclusion of the last period unmet task demand cost ($C^E{}_j$) to discourage this decision. Increasing this parameter value to be greater than the unmet task demand cost ($C^U{}_j$) tends to reduce the amount of unmet task demand at the end of the last period, if possible depending on volunteer availability.

When the penalty factor (K_j) is set to the lowest sensible value of 1.0, the unmet task demand ($\hat{d}$) is simply the cumulative sum from each period. However, as the penalty factor is increased, the amount of unmet task demand ($\hat{d}$) tended to decrease, assuming enough volunteers are available to meet the task demand and the other parameters are unchanged. This is explained by the model choosing the more cost effective option of assigning more volunteers to the relief operation, rather than the more costly option of generating excessive additional task demands by not doing so.

Another key component to this model is the training and/or assignment of volunteers to tasks which do not meet their current skill level. In a humanitarian crisis response, there will likely be times where some volunteers (i.e. carpenters) are needed to help in another field by necessity (i.e. search-and-rescue) due to personnel shortages.

4.3 An example – Combined Scenarios 1 & 3

Humanitarian relief organizations cannot be certain of their projected task demands, and thus there may be several forecast scenarios with different probabilities of occurring. In Section 4, we will provide a more comprehensive analysis of various combinations of scenarios, with equal likelihoods of each scenario included in the combination. As an example, task demand scenarios 1 and 3 were considered to be equally likely, and Figure 5 provides the resulting volunteer assignments.

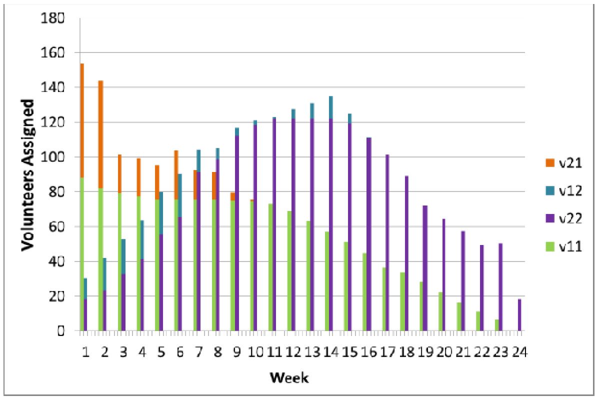

Figure 5. Scenarios 1 and 3 equally likely

In Figure 5, we have:

v21: Skilled (long-term) volunteers assigned to an unskilled (short-term) task

v12: Unskilled (short-term) volunteers assigned to a skilled (long-term) task

v22: Skilled (long-term) volunteers assigned to a skilled (long-term) task

v11: Unskilled (short-term) volunteers assigned to an unskilled (short-term) task

Notice that unskilled volunteers were being trained for skilled tasks at the same time that skilled volunteers were assigned to short-term recovery tasks. This "double mismatching" in theory seems illogical, as volunteers should usually be assigned to the tasks appropriate for their skill level, and only "mismatching" uni-directionally to help fill a particular volunteer need. However, the optimum decision is to begin training some unskilled volunteers early in the response period when the short-term task demands are still high, in preparation for the upcoming long-term task demand peak around the middle of the response period. Thus, additional skilled volunteers are mismatched to cover the volunteer void created by the unskilled volunteers training for the long-term tasks. This phenomenon is interesting, as it suggests a proactive approach to volunteer management by encouraging volunteer training early, in advance of the peak task demand periods. For the specific example in Figure 5, a skilled volunteer pool of 120 people (versus the initial 100) is ready in time for the long-term task demand peak around periods 12-16. In short, if there are sufficient numbers of volunteers to cover both short and long-term task demands initially, the VMM model proposes to preemptively train unskilled volunteers in advance of a future forecasted skilled needs increase.

5. Findings – Base, Training, and Mismatching Policies

To further illustrate the benefits of the VMM to assign volunteers to tasks and training based on anticipated needs scenarios, examples are shown below comparing identical humanitarian crisis situations with different volunteer assignment rules. Each task demand scenario combination is tested, with equal scenario probabilities across each scenario in the combination. For each combination, the base case is analyzed (where volunteer training and mismatching is allowed to occur as is standard in the VMM), as well as cases where either or neither type of volunteer assignment (training and/or mismatching) are allowed. The benefits are quantified via cost analyses, unmet demand amounts, and volunteer attrition.

Parameter values from Section 3 are adopted here, with the exception of the unmet task demand penalty factor (K_j). Preliminary testing with this data set and K_j ranging from 1.1 to 1.5 led to extreme amounts of additional demands being generated due to a lack of available volunteers. This is qualitatively useful, as it can help relief managers gain insight into situations where relief needs could grow out of control. This type of "runaway" scenario instance could be roughly compared to a disease outbreak, where if a small disease problem is not able to be treated effectively by the volunteer staff, then a much larger disease outbreak could occur later. The fact that even a marginal increase in these parameters appears to have such a dramatic effect in subsequent periods is noteworthy. However, for the sake of obtaining quantitative results for comparison between the different volunteer assignment rules, no additional task demand will be generated after each period (i.e., K_j=1.0), but unmet task demand from the previous period will still be carried over to the next period.

For the purpose of these examples, 10 sets of task demands per scenario are generated, where the demands per period vary up to +/- 10% of the values given in the scenarios shown in Section 3. The model is run 10 times (once per data set), and these results are then averaged together for each volunteer assignment restriction (Base, No Training, No Mismatching, and Neither). It was observed during testing that greatly differing solutions to the VMM could occur between each data set, due to the predesigned tight numbers of idle volunteers during peak

Table 1. Training/Mismatching Averaged Performance Results

Case	Total Cost (% of Base)	Volunteer Costs (% of Base)	Cost of Unmet Task Demand (% of Base)	Volunteers Lost	Change in Unskilled Pool	Change in Skilled Pool
Base	100%	100.0%	100%	0.91	-30.0	28.4
No Training	137%	88.7%	2724%	0.06	0.0	-0.1
No Mismatching	112%	99.8%	1114%	0.50	-27.2	26.7
Neither	146%	90.4%	3547%	0.00	0.0	0.0

needs periods. Thus, an average is necessary to capture the possible diverse model results.

One general trend noticed throughout many of the examples again was the tendency for the remaining task demands in the last scenario to only be partially met, often for the skilled/long-term tasks. This is explained by the values of the volunteer assignment cost (C^V) and the last period unmet task demand cost (C^E) chosen for this series of examples; modifying the relationship between these cost parameters could affect this tendency noticeably, as discussed in Section 3.2. The full numeric results of the testing are shown in Table 1, accompanied graphically in Figure 6.

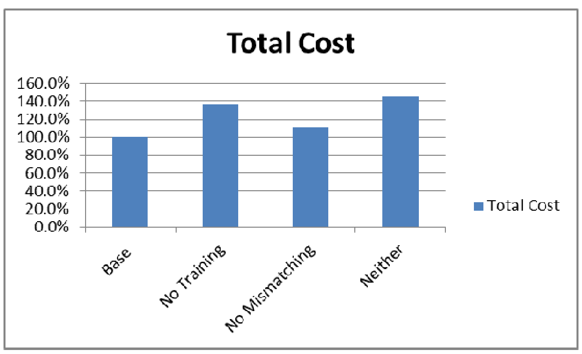

Figure 6. Average total costs across training/mismatching cases

In summary, allowing for volunteer training and mismatching (as in the base formulation of the VMM) results in the lowest total cost for all examples. Although the total costs vary widely between examples due to the different needs distributions, the important point is that the lowest cost for each example always occurred in the base case. The model has the flexibility to shift volunteers from need to need to cover as much task demand as possible. On the other end of the spectrum, preventing any volunteer training or mismatching from occurring (i.e., not allowing any shifting) always resulted in the highest cost as the organization could not make changes to address the particular needs situation.

Comparing the “no training” and “no mismatching” restrictions is more complicated. For all examples, the total costs for both cases lie between the base case and the “neither” case. Thus, the prudent comparison was to look at the relative costs for each type of single restriction. The “no training” cases had higher total costs relative to their “no mismatching” cases in the following scenario combinations:

- 1, 4, 1&3, 1&4, 2&4, 3&4, 1&2&4, 2&3&4, 1&2&3&4

While the “no mismatching” cases had higher total costs in scenario combinations:

- 2, 3, 1&2, 1&2&3, 2&3

Studying the task demands scenario graphs (Figures 1-4), it is clear that the sustained high needs for skilled volunteers in scenario 4 is significant. In those examples, their base case had substantial amounts of volunteers trained by the VMM in order to cover the skilled/long-term task demands. Restricting training results in much higher unmet task demand costs and thus total cost. Due to the presence of attrition parameters (A_p), training large numbers of volunteers does result in some volunteer attrition and corresponding volunteer attrition costs (C^A), but they are outweighed by the unmet task demand costs that newly trained volunteers help to prevent. However, this does mean that these examples with “no training” do have lower volunteer attrition. In short, humanitarian relief organization managers who generally feel as though a peak of long-term/skilled volunteer task demands will come at some point during the disaster response should strongly consider allowing volunteer training assignments.

Another way of representing the benefits of allowing volunteer training in a humanitarian relief response is shown in Table 2 below. This table computes the ratio of the total cost difference and training cost difference between the examples’ base cases and “no training” cases. This quantifies the total cost savings per dollar spent on volunteer training costs. In most cases, the VMM suggests that the training investment is well worth it, given the parameters used in this series of tests.

Place illustrations (figures, tables, drawings, and photographs) throughout the paper at the places where they are first discussed in the text, rather than at the end of the paper. Number illustrations sequentially (but number tables separately). Place the illustration numbers and caption under the illustration in 10 pt font. Do not allow illustrations to extend into the margins. If your figure has two parts, include the labels "(a)" and "(b)".

Table 2. Training value

Case	Value (Total cost reduction) per $1 training investment
Scenario 1	$1121.81
Scenario 2	$31.47
Scenario 3	$133.04
Scenario 4	$1958.09
Scenarios 1 & 2	$3.83
Scenarios 1 & 3	$545.02
Scenarios 1 & 4	$1166.97
Scenarios 2 & 3	$73.33
Scenarios 2 & 4	$483.66
Scenarios 3 & 4	$643.66
Scenarios 1 & 2 & 3	$225.84
Scenarios 1 & 2 & 4	$521.44
Scenarios 2 & 3 & 4	$282.25
Scenarios 1 & 2 & 3 & 4	$354.65

6. Conclusion and Future Work

The formulation of the Volunteer Management Model (VMM) was presented. The objective function and constraints were explained, along with the assumptions made by the model. A series of practical examples with short and long-term task demands was presented. The various features displayed by the model were discussed in the corresponding sensitivity analysis; complex parameter interactions on the objective function were observed, as well as preemptive training assignments in certain task demand scenarios. Much more analysis will be necessary to understand the true nature of these interactions. Possible additions to the model were described as well, some of which may be incorporated in future versions of the VMM pending discussions with interested parties.

This model is a good start to determining volunteer assignments for a humanitarian organization responding to a crisis. Several useful features are included, such as volunteer skill levels and training, scenario-based costing, and additional task demand generated by unmet task demand from prior periods. However, several assumptions are made as well which limit the capability of the model to a degree, such as not tracking volunteers with partial training completions or assuming that all of the requested cost parameters are known with relative accuracy. Placing these aside, the VMM has plenty of useful insight yet to be analyzed, and is currently capable enough for field testing.

Currently, the model only accounts for volunteers lost due to assignment preference mismatches, where there may be many other reasons that control volunteer availability (e.g., time available, fatigue, or injury). The model also does not have a parameter to control scheduled volunteer arrivals and departures, or a penalty cost for idle volunteers, which sometimes is a more common problem for humanitarian relief organizations than volunteer shortages. It would be interesting to consider the ability to reassign tasks/demands to other organizations, along with any costs of doing so. This could prevent any unmet demands from multiplying and overwhelming the original humanitarian organization. As discussed earlier, a practical example of this would be disease control and prevention, where falling behind on preventive health measures could be very costly later.

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