Estimating Force Structure Manpower and MHE Capabilities

■ By Mustafa Rawat and Michael Pipkin

The Army Armaments Research, Development and Engineering Center's Logistics Research and Engineering Directorate (LRED) at Picatinny Arsenal, New Jersey, builds discrete event simulation (DES) process models to answer questions related to manpower and materials-handling equipment (MHE) capabilities. For more than 10 years, LRED has developed models for organizations such as the Combined Arms Support Command (CASCOM), the Army Sustainment Command, and the Army Field Support Battalion–Kuwait.

Decision-makers have successfully gained a thorough understanding of system bottlenecks for baseline operations by using the approach of developing a model based on subject matter expert (SME)-defined workflows, including process times and resource inputs, and then validating it against known use cases. This method offers the flexibility to analyze the effect on doctrine, organization, training, materiel, leadership and education, personnel, facilities, and policy caused by changes in the baseline process and to recommend improvements to the overall distribution system.

Developing Models

LRED developed models for CASCOM's Force Development Directorate to estimate the manpower and MHE capabilities at a corps storage area, an ammunition transfer and holding point, and a supply support activity. It developed similar models for the Army Sustainment Command in order to recommend the adequate level of manpower needed to support installation supply support activity operations in the continental United States. The outcome of this analysis was critical in helping the command assess and balance contractual manpower needs across seven pilot sites.

For the Army Field Support Battalion–Kuwait, LRED developed a model for the battalion to document and formalize the business processes associated with an armored brigade combat team deployment and to estimate the capacity of the government and contractor workforce.

The model also helped establish a baseline process, identify resource bottlenecks, and enable continuous process improvement. LRED also made recommendations to the battalion commander on how to optimally allocate personnel and equipment.

Transaction-Based Models

The models that LRED developed were transaction-based models. The workload forcing function that drives these models is transactional data obtained from an enterprise business system like the Standard Army Ammunition System–Modernization or the Standard Army Retail Supply System. Figure 1 lays out the approach used to build these process models. The process steps are not complex and can be replicated easily for most DES models.

One of the biggest challenges with this approach is the significant amount of time spent by the modeler to understand the business process being modeled. LRED has developed a customized Microsoft Visio stencil called VisioSim that allows modelers to capture SME knowledge of the business process and build workflows using DES modeling process blocks. The stencil used by LRED is designed to correspond to the Arena DES modeling environment.

VisioSim significantly saves time for both the SME and the modeler. Once the process workflows have been developed, the modeler, with help from SMEs, populates individual process steps with the time and resources (personnel and equipment) required to complete that process step. If available, empirical data is used for the process times. If unavailable, SME input based on a probability distribution is used.

User Test Cases

In order to validate the model, user test cases are jointly developed by the stakeholder SMEs and a modeler. Once the process workflow and test cases are finalized, the modeler preprocesses the input data that will be used as the forcing function for this transaction-based model.

This step usually takes a significant amount of time because the modeler also addresses issues related to missing data and data quality. In this stage of the process, the SMEs and the modeler may also have to make some assumptions if the input data cannot support the business rules developed during the process workflow mapping stage.

Once preprocessing the input data is complete, the modeler builds the model in the preferred DES modeling environment. Any errors found are debugged and eliminated. This baseline model is then validated against previously defined test cases.

Multiple simulations of the model are usually carried out, followed by postprocessing the output data by tabulating or plotting it. The output data is then analyzed to identify process inefficiencies, system bottlenecks, and throughput.

After inefficiencies have been identified, the modeler and SMEs conduct a what-if analysis. During this stage, the modeler can modify the process, provide additional resources, or introduce equipment with new capabilities.

All of these possibilities are then simulated and the output is reanalyzed against the baseline process to quantify the potential efficiencies that could be realized by implementing one or more of the suggested improvements identified during the what-if analysis. As suggested improvements are implemented by the stakeholder over time, a new baseline is established and the analysis process is repeated.

Using Transactional Data

Transactional data from the Standard Army Ammunition System–Modernization and the Standard Army Retail Supply System has been used extensively to build transaction-based models. This approach has successfully captured personnel and equipment utilization at nodal levels, such as ammunition supply points and supply support activities.

Data stored in these systems is assigned a specific transaction code. This code represents the arrival of inbound commodities that need to be stored or the outbound movement of stored commodities to customers or other nodes in the supply chain. In the model, these transactions are modeled as entities.

Each entity can have a number of user-defined attributes, such as the transaction code, a transaction date and time stamp, a unique commodity identifier, and physical characteristics such as weight and dimensions.

When a transaction entity is introduced into the model, the model logic routes the entity through the appropriate workflow based on its transaction code. As it traverses the workflow, this entity is delayed by processes, seizes and releases resources, waits in queues, and affects (or is affected by) the value of global variables defined in other parts of the model logic. Throughout its life cycle, internal statistics are collected at the entity level and then aggregated to generate system-level metrics.

Common metrics, such as resource utilizations, the number of entities waiting, wait times in queues, and other user-defined statistics, are recorded by the modeling environment. These transaction-based models, while being fairly detailed and accurate, are also very tedious to develop. They require a significant amount of time for data preprocessing, but most importantly, they are highly dependent on the availability and accuracy of the data. The question is, how do we build nontransaction-based models to estimate manpower and equipment allocations for force structure right-sizing experiments?

Proposed Solution

To simplify the process of building DES models when transactional data is unavailable, LRED designed a model with two approaches to addressing the resource capacity. This could be carried out by assigning an almost infinite resource capacity or by not defining any resources at all. This solution proposes building an unconstrained resource capacity model that does not define any resources.

A nontransactional workload based on a probability distribution could represent transportation platforms or pallets (entities) that are continuously presented to the model. The model then processes this workload based on the business rules defined in the underlying workflows and keeps track of the total labor and MHE hours required. However, since the model does not have any resources, and therefore no queues, inefficiencies like system bottlenecks cannot be identified.

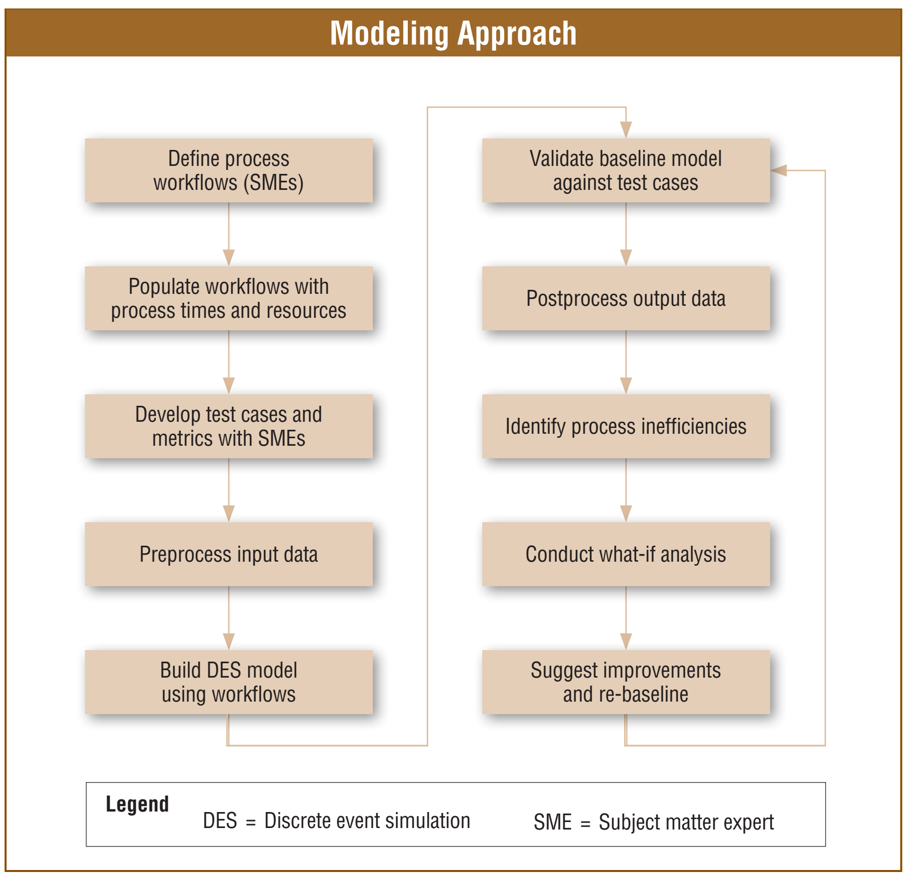

Figure 1. This chart shows the approach to building process models using simple steps that can be easily replicated for most DES models.

Although transaction-based models are extremely useful in identifying system-level inefficiencies or the resource augmentation needed for a dynamic workload (periods of surge and lull in demand), nontransaction-based models can be used to estimate labor and MHE hours-per-ton processing rates for relatively steady state workloads.

Simulation

This approach replicates most of the process steps shown in figure 1. However, it significantly reduces the time spent on preprocessing transactional input data.

To explain this concept further, let us attempt to estimate the optimal manpower and MHE allocation to handle the workload at a generic ammunition support activity (ASA). This ASA supports the four major ammunition supply processes: receive and store, issue, ship, and turn-in. LRED builds a DES model using the VisioSim workflows developed from an earlier study for an ammunition transfer and holding point located in Afghanistan.

Once a working baseline model has been developed, entities are created (in this case, pallets) and presented to the ASA model. The model processes these entities based on their type (receipt, issue, shipping, and turn-in). If available, the modeler can leverage data from earlier studies or rely on SME input to make decisions on the proportion of inbound and outbound pallets that follow ground (versus air) modes of distribution.

The modeler or the SME also estimates the distribution of full depot pallets (versus mixed or partial pallets) that have to be banded. This is especially critical in the issue process. This model is then simulated for a period of one year over multiple replications.

Throughout the simulation run, the modeler collects a number of metrics that are then averaged over multiple replications. For this study, the most relevant metrics are the labor hours and MHE hours required to process one ton of supplies for receipt, issue, shipment, or turn-in.

Since no resources are defined in the model, the assumption is that personnel and MHE are always available when needed and are therefore 100 percent used performing some task. This assumption is not realistic because of the inherent downtimes in the process, causing the recorded capability to be higher. However, for the purposes of this discussion, we can address this issue by adding a utilization factor to the model output.

Figure 2 shows notional labor and MHE rates for processing a ton of ammunition along with the distribution of tonnage by workflow processed at the ASA. In this case, receipt accounts for 40 percent of the total tonnage handled by the ASA.

Next we normalize these rates, so even though receipt is 40 percent of the tonnage processed by the ASA, we do not allocate 40 percent of the labor and MHE hours to that process. This is because some processes, such as issue and turn-in, are more labor intensive and require proportionally more hours. Similarly, figure 3 shows the normalized percentages for labor and MHE hours.

If we assume the availability of 30 personnel and five MHE, the example in figure 3 shows the allocation of these resources based on the normalized percentages calculated in figure 3. From figure 4, you can see that even though the issue process is 30 percent of the daily tonnage it should get 48 percent and 57 percent of the available personnel and MHE respectively.

Extending the Results

Based on the explanation provided above, you can see that these runs can be easily extrapolated to cover different "blends" of receipt, issue, shipment, and turn-in processes. Furthermore, we can also develop linear plots for these blends based on a ratio of personnel to MHE. In other words, using the 30 personnel and five MHE example, we can say that we

Process	Labor Hours/Ton	MHE Hours/Ton	Percent of Tonnage
Receipt	2	0.5	40
Issue	5	2	30
Shipping	2	0.75	20
Turn-In	4	1	10

Figure 2. This chart shows notional labor and materials-handling equipment (MHE) rates for the distribution of ammunition.

Process	Percent of Tonnage	Normalized Percent Tonnage (Labor)	Normalized Percentage (materials handling equipment)
Receipt	40	26[2]	19
Issue	30	48	57
Shipping	20	13	14
Turn-in	10	13	10

$$\frac{40\% \times 2}{(40\% \times 2 + 30\% \times 5 + 20\% \times 2 + 10\% \times 4)} = 0.26$$

Figure 3. This chart shows a representation of normalized percentages for labor and materials-handling equipment. The equation shows how the normalized percentage for labor was calculated. The percent comes from the percent of tonnage on this chart and the number it is multiplied by comes from the labor hours per ton in figure 2.

Process	Percent of Tonnage	Percent Personnel Allocation (Normalized)	Personnel Allocation	Percent MHE Allocation (Normalized)	MHE Allocation
Receipt	40	26	7.74	19	0.95
Issue	30	48	14.52	57	2.86
Shipping	20	13	3.87	14	0.71
Turn-in	10	13	3.87	10	0.48

Figure 4. This chart compares the percentage of personnel and materials-handling equipment allocated based on process output, which is represented as percent of tonnage.

have a 6-to-1 ratio for personnel to MHE. So, for every additional MHE that is added to the force structure, six personnel should be added.

Figure 5 shows a notional family of plots that are generated by extrapolating the data. From this graph we can determine the capability of an ammunition unit based on a certain blend of receipt, issue, shipping, and turn-in processes. Blend 1 has a 6-to-1 ratio for personnel to MHE compared to blend 3, which has a 4-to-1 ratio.

In order to achieve a 100-ton-per-day capability at an ASA whose distribution of tonnage by process closely resembles blend 1, we would require 20 personnel and three or four pieces of MHE. To achieve the same level of daily tonnage processing capability for blend 2, we would require 30 personnel and the number of MHE would be somewhere between four and five.

An association between a blend and phase of operation can easily be made. By following this approach we can adjust the capability for any unit based on the business processes and the class of supply it supports (derived through the workflows) and the phase of the operation, such as offensive, defensive, and stability, in which it is currently deployed.

The method presented here represents an entirely new approach to both developing base tables of organization and equipment and estimating the required manpower and MHE necessary to provide logistics support during each of the operational phases of combat.

Rather than depend on an outdated tons-based approach to build Army force structure and estimating the number and composition of logistics units required to provide sufficient distribution support, force developers and theater planners can use approved tables similar to the ones shown in this article to ensure both tables of organization and equipment and deployed sustainment units are adequate to support our combat forces.

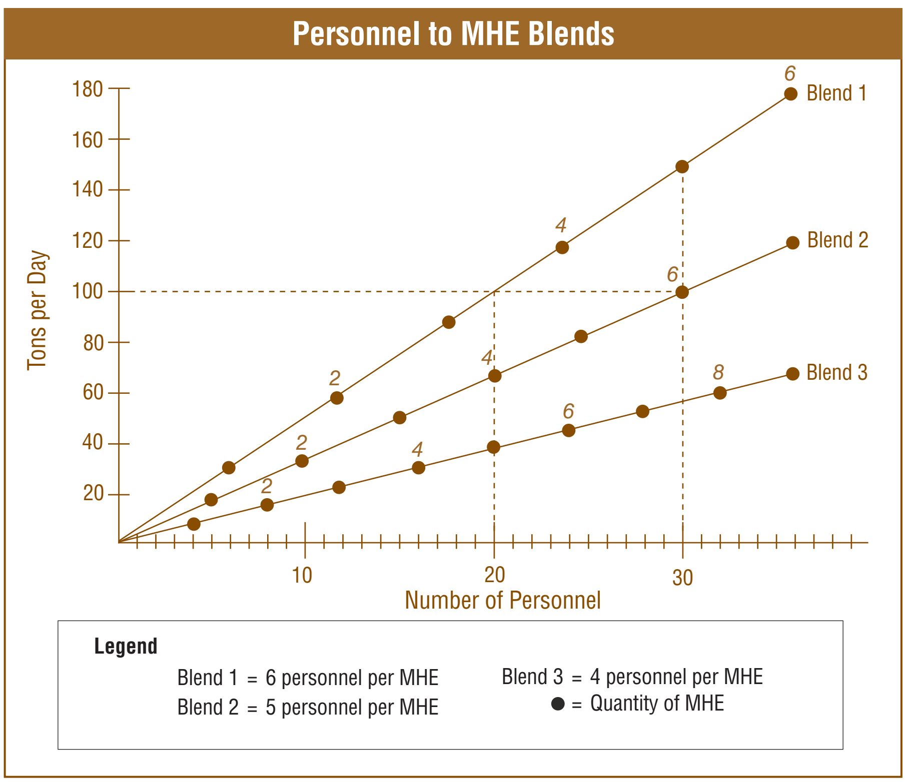

Figure 5. This chart shows how the receipt, issue, shipping, and turn-in processes affect output based on the number of personnel available per piece of materials-handling equipment (MHE).

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