An Agent-Based Approach for Optimizing Modular Vehicle Fleet Operation

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Abstract

Modularity in military vehicle designs enables on-base assembly, disassembly, and reconfiguration of vehicles, which can be beneficial in promoting fleet adaptability and life cycle cost savings. To properly manage the fleet operation and to control the resupply, demand prediction, and scheduling process, this paper illustrates an agent-based approach customized for highly modularized military vehicle fleets, and studies the feasibility and flexibility of modularity for various mission scenarios. Given deterministic field demands with operation stochasticity, we compare the performance of a modular fleet to a conventional fleet in equivalent operation strategies and also compare fleet performance driven by heuristic rules and optimization. Several indicators are selected to quantify the fleet performance, including operation costs, total resupplied resources, and fleet readiness.

When the model is implemented for military Joint Tactical Transport System (JTTS) mission, our results indicate that fleet modularity can reduce total resource supplies without significant losses in fleet readiness. The benefits of fleet modularity can also be amplified through a real time optimized operation strategy. To highlight the feasibility of fleet modularity, a parametric study is performed to show the impacts from working capacity on modular fleet performance. Finally, we provide practical suggestions of modular vehicle designs based on the analysis and other possible usage.

Keywords: Agent-based Modeling, Operation Management, Decision Support System, Fleet Modularity

1. Introduction

Military vehicles operate in a variety of environments and scenarios resulting in a diverse set of requirements from the fleet mix. To satisfy these requirements, the US Army operates a large number of diverse vehicles designed for specific operational needs. Moreover, mission requirements and the appropriate fleet mix change over time. Therefore, the introduction of new vehicles leads to resource wastage and mission delays. Thus, the application of modularity to military vehicle fleet was proposed to reduce the fleet life-cycle cost and make faster and less expensive the vehicle technology updates.

A modular architecture refers to using interchangeable components to create products in different variants (Ulrich, 1994). Architectures of modular military vehicle have been developed for many years. In the 1980s, Family of Vehicles (FOVs) were designed with modular architectures. Later, two examples of an entire FOV have been proposed, named as Armored Family of Vehicle (AFV) in the 1980s and Future Combat Systems (FCS) in the 2000s (Dasch & Gorsich, 2016). In general, previous research in military vehicle modularity proposed a range of modular vehicle architectures based on the manufacturing cost and commonality of components. Nevertheless, to evaluate the performance of the modular fleet, it is important to use a wide perspective of fleet-level performance, which includes fleet readiness and operation costs.

Our research is inspired by these challenges. In general, multiple types of modular vehicles are created by combining different variants of modules according to the physical and interface constraints. Figure 1 compares the structures of a conventional tactical vehicle and a highly modularized tactical vehicle. For the modularized vehicle, five types of modules are considered: a) cabin, b) chassis and power train, c) tires and suspension, d) payload and e) armor. Modules are assumed to be easily connected and disconnected in field by plug-in and pull-out actions to achieve vehicle assembly and disassembly. Furthermore, vehicle reconfiguration can be quickly realized also by module replacement. On-field assembly, disassembly and reconfiguration (ADR) actions enable the modular fleet to change its configuration in real time, and also to differentiate the modular fleet operation from the conventional fleet operation.

Recent studies focus on the fleet-level performance with consideration of operation management. For example, an integrated fleet operation model was built to evaluate the effectiveness and cost of operating a modular fleet (D’Souza et al., 2016). That approach integrates a functionality model, a fleet operation model, a manufacturing model, and a transportation model. Later, a mathematical model was formulated to compare the fleet performance under equivalent operation strategies designed for both the conventional fleet and the modular fleet (Bayrak et al., 2018). Their results showed that fleet modularity is beneficial in life cycle cost saving. Such prior studies compared fleet
performance with several significant assumptions, including no vehicle reconfiguration, as well as a heuristic and time-invariant operation strategy. Thus, there is a need for in-depth effort to create an adaptive operation strategy that could be updated in real time according to the latest field information.

However, ADR actions enabled by fleet modularity also introduces an additional layer in fleet operation, which dramatically raises the complexity and difficulty in military mission scenario, especially when diverse range of vehicle types and field events are involved. It is hard to formulate the problem with all details by using a centralized management strategy. Even if the model is established, it is often intractable to solve because of computation complexity \cite{Li2017}. In order to address this issue, increasing attention has been focused on the multi-agent systems (MAS), where the decisions are made by multiple autonomous or semi autonomous problem-solving agents \cite{Adhau2013,BoehlIng2011}. Compared to other simulation modeling techniques, i.e., system dynamic \cite{LinShe2018}, and discrete event \cite{Sharda2012}, ABM is more active in reacting to the changes in the environment \cite{Maidstone2012}, which can truly reflect the situation in military mission environment. Furthermore the interaction between agents can also represent the information dynamics among commanders. In this study, we customize multiple types of agents for modular fleet to autonomously yield operation decisions with consideration of main characters in military operations.

Although literature on managing a modular fleet operation through MAS is insignificant, attention has been received in other areas such as manufacturing operations \cite{Ready2006,Anosike2009,He2014} and supply chain management \cite{Julk2011,Giann2011,Meng2017}. According to the relationship among agents, the frameworks of MAS can be broadly classified into three categories: hierarchical/master/slav relationships \cite{Jones1986}, heterarchical cooperation \cite{DufF1994,McLe2001} and hybrid framework \cite{Ryu2003}. In 2009, an agent-based \cite{Anosike2009} is applied to the dynamically integrated manufacturing systems (DIMS), which consists of a modeling and planning layer, a process flow layer and a simulation layer, to make planning and machine control decisions together with system reconfiguration and restructure. In 1998, Swaminathan \cite{Swaminathan1998} presented a high fidelity model representing supply chain dynamics with implementation of ABM. The agents are classified into structural elements and control elements. Structural elements contain production agents to manage the inventory; transportation agents to relocate the product from one agent to another. The control elements are used to manage inventory stocks, forecast demands, control material and information flow. Previous studies show the capacity of ABM in decision making, especially in the complex and time-varying system.

Compared to the existing operation problems, the military operation has two special characteristics. One is the highly uncertain and transient demands, which requires the decision maker’s rapid reaction; another is the high probability of damage during operation, which requires the timely repair and maintenance to ensure resource utility rate. Combining the additional flexibility from fleet modularity, management of this complex operation system in a hostile environment remains an unresolved problem.

In this study, we go beyond the existing literature, and propose an agent-based model that integrates vehicle dispatch, assembly, disassembly and resource resupply decision making processes in a mathematical model, which is customized for the military mission scenario where the damage/maintenance are non-negligible. Operation decisions are optimized through collaboration among agents to reduce operational costs and supplied resources. We also perform parametric analyses to evaluate robustness of our model and benefits from fleet modularity.

2. JTTS Mission Scenario

Our mission scenario is created based on the Joint Tactical Transport System (JTTS) which is a vehicle demonstrator program in US Army Tank Automotive Research, Development and Engineering Center (TARDEC). Vehicle fleet operations is at a certain area, named as field. A field contains a main base and \(N\) camps. An example of field layout is shown in Fig. \ref{fig:field_layout}. Main base provides the space to receive and store the resources (vehicles and modules) supplied from global manufacturer. For modular fleet operation, base also provides the equipment for ADR actions. Camps are close to the battle field, which are the places to receive the demands.

In reacting to the demands, a convoy, which is a group of vehicles, is required to be customized and dispatched to camps to satisfy the demands. Operation actions also vary according to the type of fleets. For a conventional fleet, the operation actions to be determined include

1. vehicle resupply
2. vehicle relocation between different locations
3. vehicle convoy composition.

Once fleet modularity is considered, modules are the only resources required for operating a modular fleet. The actions to be determined include

1. module resupply
2. vehicle relocation between different locations
3. ADR actions
4. vehicle convoy composition.

Compared to conventional fleet, modular fleet needs to achieve transition from modules at supplier to vehicles at camps, which increases the difficulty in fleet operation. This process can be analogized as a completely dynamic supply chain, as shown in Fig. 3.

Although the similarity between the modular fleet operation and civilian applications is significant, there are marked differences between operating a military fleet and a commercial fleet. For example, the enemy's actions are the main source of damage to the military fleet. The critical damage of modules/parts incur the loss of the resources. The uncritical damage also leads to vehicle repair or maintenance, which increases the uncertainty of vehicle usage. The stochasticity of damage creates additional complexity in management of a military fleet. Taking the modular fleet operation as an example, we summarized the operation process in Fig. 4.

To operate a highly modularized vehicle fleet in the complicated military mission scenario, we need to make real-time decisions on vehicle dispatch, ADR action scheduling and module resupplies. A mathematical model is required to be formulated to analyze field situations and provide suggestions on operation decisions based on the current inventory status and camp demands. By realizing operation decisions into a military mission simulation model, we can capture fleet performance by using the indices including fleet readiness, operation cost, and total supplied resources.

3. Model Formation

To satisfy these requirements, we customized an ABM, which can be used for demand forecasting and operation decisions making. With consideration of computational efficiency and restriction of communication on the field, we created multiple types of agents to represent decision makers with different functionalities, in terms of camp agent, base agent, and supply agent. Each of them can communicate with adjacent agents and make decisions in a centralized manner. According to the priority in perceiving the combat information, we formulated a hierarchical framework to connect a number of agents structured in a master-slave relationship. The control decision is gener-
ated from agent and sent downward to their subordinates. Correspondingly, status reports flow bottom-up to a higher level supervisory agents. Fig. 5 demonstrates the information flow among agents.

3.1. Camp agent

As the upstream agent of the framework, camp agent needs to determine the dispatch order in reacting to the received demands assuming that all the orders are achievable by the downstream agents. Demands from military mission scenario are classified into two aspects, which are convoy requirements $a_c$ and vehicle requirements $a_v$. Convoy requirements specify the requirement for overall convoy, which are generally additive attributes carried by vehicles, e.g., personnel/material capacity, firepower, etc. In contrast, vehicle requirements are mainly from environmental constraints, e.g., vehicle weight, tire type, threat level, and terrain capacity.

Taking camp $n$ as an example, we denote the formed convoy to camp $n$ as $d^c_n(t)$, and the received convoy attribute requirements as a vector $a$, where

$$d^c_n(t) = \left[ d_{v1}^c(t), d_{v2}^c(t), \ldots, d_{vNv}^c(t) \right]^T$$

$$a = [a_{c1}, a_{c2}, \ldots, a_{cn}, a_{v1}, a_{v2}, \ldots, a_{vn}]^T$$

To avoid the myopic decisions, the camp agent usually makes decisions not only for the current time, but also for the short future. The objective of convoy formation is to optimize fuel economy, demand fulfillment, acquisition cost, convoy weight, etc. The convoy dispatch problem can be generalized as an optimization problem:

$$\text{minimize } \sum_n w_{c_n} d^c_n(t),$$

subject to

$$(a) f^\alpha (d^c_n(t)) \geq a_{cn}, \forall \alpha$$

$$(b) f^\beta (d^c_n(t)) \geq a_{vn}, \forall \beta,$$

where $t_p$ is the planning horizon. $w_{c_n}$ is a vector represent the interests costs for all types of vehicles. $f^\alpha$ is a scalar function to evaluate the convoy attributes of type $\alpha$. $f^\beta$ is a scalar function to evaluate the vehicle attributes of type $\beta$. Constraints (a)(b) ensure that both convoy and vehicle of the convoy satisfy the requirements. In this study, we follow the objective used in previous research [Bayrak et al. 2018], and consider the objective as fuel economy and constrained by order fulfillment and terrain condition.

3.2. Base agent

Given convoy dispatch schedule, $d^c_n(t)$ and the associated operation period $t^o(t)$ to satisfy the demands, we can denote the expected number of vehicles operating in the battle field $D^c_n(t)$ as our demand, as shown in Eqn. [4]

$$D^c_n(t) = \sum_t d^c_n(t), \forall t \in t^o(t).$$

Base agent aims to plan ADR actions to ensure all the dispatch decisions can be achieved. However, vehicle damage and maintenance commonly exist during operation, which require additional time to reuse the damaged vehicles. In other words, the time of vehicle recovery...
can be seen as an extension of field operation. And its stochastic occurrence raises the difficulties in estimating vehicle demands. Based on the fact that vehicle damage and maintenance only occur during convoy operation, additional vehicle usage highly dependent on the vehicle dispatch schedule. In this study, we forecast the demands through Auto-regressive Exogenous (ARX) model [Pandit et al., 1983]. Take the vehicle in type \( k \) as an example, the expression of ARX model is

\[
e_k(t) = a_1e_k(t-1) + \ldots + a_ne_k(t-na) + b_0\sum_n d_k^e(t) + \ldots + b_nb\sum_n d_k^n(t-na)\]

\[(5)\]

where, \( e_k(t) \) is the extra vehicle usage from repair and maintenance at hour \( t \). \( a_i \) and \( b_j \) are the parameters to be determined by fitting the historical data. \( na \) and \( nb \) specify the review horizon of historical data in additional usage and dispatch order. With continuously training by using latest field information, agent can real-timely adjust the model in reacting to the time-varying scenario and enemy’s actions. To guarantee the robustness of production planning [Ouelhadj & Petrovic, 2009], we compile the predicted hourly demands into the daily demands. The goal is to manage the inventory stocks to ensure the sufficiency of vehicles for the demand in the next day.

Thus, an effective management strategy is required to efficiently operate the fleet and rapidly respond to the stochasticity. In this study, we propose two methods to achieve real-time inventory management. Two strategies are named as Empiricist which is driven by heuristic rules and Optimizer which is based on the mathematical optimization. We also compare the results from these management strategies to show their impacts on the overall fleet performance.

3.2.1. Empiricist

Empiricist represents a rule-based approach. No firm schedule is generated in advance and all the decisions are made to the unfulfilled field demands and inventory status. Specifically, at the beginning of each day, Empiricist creates a set of spare vehicles \( s^+ \) based on the vector \( v^+ = (s_v - d_v)^+ \), and a remaining demand set \( s^- \) based on the vector \( v^- = (d_v - s_v)^- \). Additional two sets are also defined for decision making: \( s^-_a \) for the demands to be satisfied by assembly, \( s^-_r \) for the demands to be satisfied by reconfiguration.

According to the popular sequencing rules used by the industry [Nahmias & Cheng, 1993], military operation [Bayrak et al., 2018] and suggestions from military experts, we created a rule-based strategy as a mixture of First-come, first-served (FCFS), Shortest processing time (SPT) and Earliest due date (EDD). The algorithm is demonstrated in Fig. 6.

3.2.2. Optimizer

Optimizer represents an optimization-based approach. The objective is to maximize fleet readiness with minimized operation costs, in terms of inventory holding cost, insufficiency cost, and ADR action cost. The actions to be determined are

1. Number of vehicles of type \( k \) to be assembled, \( o_{ak} \)
2. Number of vehicles of type \( k \) to be disassembled, \( o_{dk} \)
3. Number of vehicles of type \( k \) to be reconfigured into type \( k' \), \( o_{kk'} \)
4. Number of vehicles of type \( k \) to be dispatched from main base to camp \( n \), \( o_{kn} \).

We assume that all the actions require less than 24 hours to finish and can be accomplished in one day. Thus, by selecting the module/vehicle stocks as states, e.g., \( s_{vk} (t) \), system dynamics is dominated by Eqn. 6.

\[
s_{vk}(t) = s_{vk}(t-1) + o_{ak}(t) - o_{dk}(t) - \sum_{k\neq k'} o_{kk'}(t) - \sum_{k\neq k'} o_{k'k}(t).
\]

\[(6)\]

Thus, the fleet operation problem can be formulated by a
linear programming model to optimize operation actions in the planning horizon \( t_p \).

\[
\min \sum_{o} \left[ \sum_{k} c_{ak} a_{ok}(t) + c_{ak} d_{ok}(t) \right] \\
+ \sum_{k' \neq k} o_{kk'}(t) + \sum_{k} c_{nk}[s_v(t) - \sum_{n} o_{kn}^n(t)] \\
+ \sum_{k} \sum_{n} \epsilon_k^n(D_k^n - \epsilon_k^n(t)) \right] \\
\text{s.t.} \ (a) \left\{ \sum_{k} t_{ak} a_{ok}(t) + t_{dk} d_{ok}(t) \right\} \leq p_{\text{max}}, \forall k, t \\
(b) \left\{ \sum_{n} o_{kn}^n(t) \right\} \leq s_k(t), \forall k, n, t \\
(c) o_{kn}^n(t) \leq \epsilon_k^n(t), \forall k, n, t \\
(d) a_{ok}(t), d_{ok}(t), a_{kk'}(t), o_{kn}^n(t) \geq 0, \forall k, t,
\]

where, \( c_{kn} \) corresponds to the hold cost of vehicle of type \( k \). \( \epsilon_k^n \) is the sufficiency cost of a vehicle of type \( k \) at camp \( n \). Insufficiency cost may also vary among camps to reflect different tactical importance. \( t_{ak}, t_{dk} \) and \( t_{kk'} \) are the time required to finish ADR actions, which is evaluated according to the complexity of actions. Constraint (a) claims that ADR actions should be scheduled under capacity threshold; (b) ensures the operation actions are strictly constrained by current stocks; (c) guarantees that the number of dispatched vehicles cannot exceed the dispatch order; (d) ensures all the decision variables are non-negative.

3.3. Supply agent

Given the schedule of operation actions, resupplies in proper schedules are important to ensure that fleets can operate smoothly without delays. Two inventory control strategies are commonly used in practice, which are optimal (Q,R) policy \( \text{[Nahmias & Cheng, 1993]} \) and order-up-to-level policy \( \text{[Silver et al., 2009]} \). In optimal (Q,R) policy, the inventory status is assumed to be reviewed continuously, once stocks reach to the reorder point \( s \), an optimized resupply order \( Q \) is placed, which is calculated to minimize the expected cost of holding, setup and shortages. In the order-up-to-level policy, the inventory status is periodically reviewed which is closer to JTTS mission scenario. Once stocks are below the reorder point \( s \), the resupply order is calculated as

\[
o = S - IP,
\]

where, \( IP \) is the inventory position, which is the sum of on-hand stocks and on-order stocks minus back-orders. \( S \) is the order-up-to-level, which is calculated by Eqn. \( 9 \)

\[
S = E(X) + k\sigma_X + (n - E(\tau))\mu,
\]

where, \( \tau \) records the length of time that the inventory position drops below the reorder point until the next review instant. \( \mu \) is the demand rate during the review interval. \( R \) is the total demands over the lead time \( \tau + L \), with mean and standard deviation as \( E(X) \) and \( \sigma_X \) respectively. \( n \) denotes the desired period to reorder. \( k \) is the factor that determines the safety level, which is evaluated according to the target fill rate.

Previous methods require the estimation of \( \mu \) in resupply order calculation. However, in this study, module damage heavily depends on the vehicle dispatch schedule, which leads to a dramatic change in \( \mu \) among different review intervals. Given dispatch schedule and module usage history, we can forecast the module demands \( D_{m_i}(t+1, t+n) \) in the next review interval and use it as a substitution of \( \mu \) in order-up-to-level calculation.

\[
S(t) = E(X) + k\sigma_X + D_{m_i}(t + 1, t + n - E(\tau)). \quad \text{(10)}
\]

The module usage consists of two parts, ADR actions and repair/maintenance. Modules for ADR actions usage \( D_{m_{ADR}} \) can be estimated according to the output from base agent. Taking modules in type \( i \) as an example, its usage can be estimated by

\[
d_{m_{i}}^{ADR}(t) = \sum_{k} M_{v_{i}m_{i}}(a_{rk}(t) - o_{rk}(t)) + \\
\sum_{k' \neq k} (M_{v_{i}k'} - M_{v_{i}m_{i}})(o_{kk'} - o_{kk'}). \quad \text{(11)}
\]

where, \( M_{v_{i}m_{i}} \) indicates the number of module of type \( i \) carried by vehicle of type \( k \). The predictions on the modules usage for repair and maintenance is similar as the approach for the extra vehicle unavailability. However, as a module might be used in multiple types of vehicles, the damage probability also varies for different vehicles. We consider this fact in module usage forecasting. Denote the set of vehicle types that contains modules in type \( i \) as \( \phi_i \), and the total number of vehicle types that contain module in type \( i \) as \( n_i \), the forecasting of module usage of type \( i \) can be expressed as

\[
d_{m_{i}}^{E}(t) = p_1 d_{m_{i}}^{E}(t-1) + ... + p_{np} d_{m_{i}}^{E}(t-np) + \\
\sum_{\gamma \in \phi_i} \left[ q_{\gamma i} \sum_{n} d_{m_{i}}^{E}(t) + ... + q_{nq} \sum_{n} d_{m_{i}}^{E}(t-nq) \right], \quad \text{(12)}
\]

where, \( p_i \) and \( q_j \) are the parameters to be evaluated based on the historical data. \( np, nq \) are the corresponding review horizons. The total module usage can be calculated.

\[
D_{m_i}(t + 1, t + n - E(\tau)) = \\
\max_{t + 1 \leq \tau \leq t + n - E(\tau)} d_{m_{i}}^{ADR}(\tau) + \\
\sum_{t + 1} d_{m_{i}}^{E}(t). \quad \text{(13)}
\]

As the resupply lead-time is assumed to be significantly shorter than review interval, thus, all resupply orders are
the resupply order can be calculated as received at reorder point. Combining with Eqn. 8, 9, 13, the resupply order can be calculated as
\[ o_{m_i}(t) = D_{m_i}(t+1, t+n - E(\tau)) + k\sigma_X - s_{m_i}(t) + s_{am_i}(t). \] (14)

ABMs are created for decision making of both fleets, where camp agent and supply agent perform in a similar way. The main difference locates at the bases agent. Conventional fleet has no choice in executing ADR actions to achieve fleet reconfiguration. In other word, conventional fleet can be regarded as a special type of modular fleet which has 0 available working time. The model is built in MATLAB, which has over 20 parameters and over 30 sub-functions, it owns a high flexibility to change the scenarios and vehicle designs.

4. Case Study

In our application, mission is provided as transporting required supply materials from a main base to several camps following the battlefield requirements. Based on the supply requirements, we select 12 types of existing military trucks to accomplish transportation missions, where 16 type of modules are created by disintegrating the conventional vehicles. According to the functionality and interface of modules, 18 types of modular vehicles are designed as substitutes of conventional vehicles.

4.1. JTTS scenario

Based on the suggestions from experts of Army, the virtual costs and time constants are \( c_{bh} = 0.5, c_{bh}^c = 100, \forall n, k \) and \( c_{am_i} = 1, c_{dm_i} = 0.5, t_{am_i} = 1, t_{dm_i} = 0.5, \forall i \). The settings of the operation system are \( \rho = 60, k = 3 \) and \( n = 30 \). We assign \( na = np = 3, nb = nq = 24 \) according to the time requirement of operation actions. After 100 realizations, we first compare the mean value of total operation cost between modular fleet and conventional fleet in Tab. 1

|                | Cost | Conv. Fleet (Empiricist) | Mod. Fleet (Empiricist) | Mod. Fleet (Optimizer) |
|----------------|------|--------------------------|-------------------------|------------------------|
| Holding        | 42289| 26402                    | 29695                   |
| Backorder      | 233  | 114110                   | 1766                    |
| Assembly       | N/A  | 7633                     | 13766                   |
| Disassembly    | N/A  | 2433                     | 4670                    |
| Reconf.        | N/A  | 46                       | 2370                    |
| Total          | 42522| 150624                   | 52267                   |

According to the plot, modular fleet managed by different approaches exhibits total distinct performances: the fleet controlled by heuristic rules even requires more resupplies than the conventional fleet; the fleet controlled by optimization shows a much lower needs in resources. Similar results exist in fleet readiness comparison which is shown in Fig. 7. Dramatically high backorders occur in the operation managed by Empiricist, in term of both mean value space by ADR actions. However, these additional operation actions incur a higher cost in backorders, especially for empiricist. Compared to Empiricist, Optimizer can yield a better schedule to significantly reduce backorders and total operational costs.

The total amount of supplies is also of interest, since there is no existing modular military fleet that can be used as a reference for cost evaluation. We also disintegrate the conventional vehicles into 18 types of ‘conventional modules’ to make fair comparison. Thus, the metric used is the sum of back-ordered modules and supplied modules. Fig. 7 compares the total supplies ordered from both fleets.

According to the plot, fleet modularity leads to around 40 percentage reduction in resupplied resources of armor (type 16 - type 18), tire and suspension (type 8 - type 10). One reason is the ease of repairing and maintaining modular vehicles, which significantly reduces unavailability periods of vehicles. Furthermore, the savings can also be interpreted as the pooling effect from the component sharing. It has been proven that a higher commonality designed in the product family can lead to lower supplies in satisfying the same service level (Gerchak et al., 1998). In this study, vehicles share a large proportion of modules, which increase module utility rate through ADR actions. With time-varying demands, modular fleet can reshape itself rapidly to satisfy the demands without ordering all the necessary vehicles.

In addition, the pooling effect also explains the different strategy for power train resupply (type 6 - 8). Modular fleet prefer to order modules of type 6; conventional fleet prefer to order modules of type 7. By checking the mapping between modular vehicles and modules, the powertrain of type 6 owns a much higher commonality than modules of type 7 among modular vehicles. This fact makes the agents prefer to use and order powertrain of type 6 to promote module utility rate and the speed of fleet reconfiguration.

Compared to conventional fleet, the standard deviations of supplies are higher during modular fleet operation, which can be explained by the extra echelon level brought by fleet modularization (Liao & Chang, 2010). According to the analogy in Fig. 3, conventional fleet operates as a single-tier supply chain, where the supplier offers all the required vehicles (products) to the base(retailer) directly. For modular fleet, workshop (manufacturer) is required to convert modules to vehicles, which makes the system become more vulnerable to the stochastic damage and maintenance.

Based on the plot, the expenditure from inventory holding for conventional fleet is markedly higher than that for modular fleet, because modular fleet can release
Figure 7: Comparison of total resupplied resources

and standard deviation. Our results show a considerable impact from operation strategy on modular fleet performance. With improper operation strategies, modular fleet may acquire more resources and suffer a much higher insufficiency.

To highlight the differences between Optimizer and Heuristics, we count the number of actions on different types of vehicles for different strategies in Fig. 9. We use the total operation time on field to represent the vehicle usage. Firstly, it can be observed that ADR actions are driven by the requirement of vehicles. Taking vehicles of type 11 as an example, we found they are mainly reconfigured from other types of vehicles rather than assembled from modules. By checking the composition of each vehicle, vehicles of type 11 are found to be easily reconfigured from other modular vehicles, but they are hard to be reconfigured to other modular vehicles.

Optimizer outputs an interesting operation strategy: the vehicle of type 11 is used as a temporary state between a more complex vehicle and modules. These transient periods are shown to be sufficient to accomplish the insignificant orders for this type of vehicle. Optimizer can properly use the field and vehicle information, and yield operation strategy which may not be easily perceived.

Compared to Empiricist, more disassembly and reconfiguration actions emerges under the management of Optimizer. Reconfiguration actions can release spare modules to guarantee the responsiveness to the stochasticity from operation. Optimizer can also timely sense the redundant vehicles, and convert them to other vehicles that can be used in the future, which promotes resource utility rate and operation effectiveness.

As a summary, the fleet managed by Empiricist performs a build-to-order manner, i.e., provides custom-built vehicles in a minimal lead time (Holweg & Jones, 2001). It is proven to be a way to restrict redundancy as the vehicles would only be assembled to the received demands (Holweg et al., 2005). However, in modular fleet operation, the key of managing whole vehicle fleet to satisfy the long-term goal of the operation, other than try the utmost to satisfy every received demands. Optimizer can successfully balance the operation actions with consideration of future impacts of current decisions, thus yield more considerate plans.

4.2. Sensitivity Analysis

It is known that sufficient production capacity gives the company the required ability to meet demands in the marketplace (Krasnikov & Jayachandran, 2008). Similarly, the ADR action capacity is essential for the modular fleet to perform in a desired way. ADR action capacity impacts on the module supplies, base infrastructure designs and personnel requirements, which is an important metric to evaluate fleet performance and budget. Because of the sophistication in the fleet operation and field demands, it is intractable to theoretically evaluate the minimal ADR actions capacity requirements (Li & Epureanu, 2017b). Therefore, taking Optimizer as an example, we conduct a parametric study on the influences from ADR actions. Based on the data from 100 realizations, Fig. 10 demonstrates the impacts from ADR capacity.

Increasing ADR capacity shrinks the mean backorders occurred during the fleet operation, which indicates a better fleet responsiveness in reacting to the demands. Once
ADR capacity reaches 60 hours, the average number of backorders become steady at 6 vehicle \cdot hours. Compared to the total operation time during the year, e.g., more than 50000 vehicle \cdot hours, these amount of backorders become unobtrusive. The remaining backorders are induced by the stochasticity in operation, which could be eliminated by setting up vehicle safety stocks base on the demand fluctuation (Nahmias & Cheng [1993]).

Two typical stages exist in the changing of average vehicle stocks, which is separated by a certain ADR action capacity (36 hours in this case). We name this capacity as separation capacity. Before it, vehicle assembly is the mainstream of on-field actions, because the agents spend most of the capacity in grouping up convoy to satisfy the demands. Thus, vehicle stocks and total resupplied resources are all at maximum once the ADR action capacity reaches the separation capacity. Once vehicle sufficiency is guaranteed, the superfluous capacity is applied to reduce the total operational cost, e.g., disassemble the vehicles to save inventory holding cost. As a sequence, stock level keeps decreasing towards the steady level.

At the separation capacity, higher amplitude fluctuation in both backorders and vehicle stocks is observed. As capacity allocation is sensitive to the stochasticity from fleet operation once the capacity is just right, a subtle change in operation may require long-term actions to re-
cover, which leads to a different fleet behavior. However, the highest amount of fluctuations in backorders exist in the lowest ADR action capacity, because the operation system does not even have the ability to satisfy the deterministic demands, let alone resist to the operation stochasticity. Once the capacity is enough, e.g., 120 hours, system always has spare capacity to deal with stochasticity from operation, which leads to a small variation of fleet performance.

5. Model Implementation

In this study, we proposed ABMs to solve operation problem of military vehicle fleets. The model can be used as a decision support tool to real-time yield operation decisions, and the model also has the capability to allow the decision makers adjust the system parameters based on different scenarios, e.g., changed terrain conditions, and tactical importance of different areas. Our model provides the platform to trade off two of the major cost drivers, acquisition costs and operation costs. It also creates operational data for design engineers to improve vehicle designs.

For example, our study shows a trade-off between major fleet performance metrics, which can be used into modular vehicle design. For example, with a higher level of vehicle modularity, the number of components are more likely to be shared by other vehicles, which amplifies the pooling effect and lead to more reductions in required resources. The burden from high fleet modularity is the reduction of responsiveness in reacting to the changes of demand. A larger number of modules usually leads to a longer time in assembly and disassembly. By using our model, designers can quantify the impacts from modularity on practical mission scenarios and improve vehicle designs accordingly.

For JTTS scenario as an example, we found that low-demand vehicles, i.e., type 11, with high commonality are formed mainly through reconfigurations, as shown in Fig. 9. However, high-demand vehicles, e.g., type 24, are mainly processed by assembly and disassembly actions. Combining with research of common component design problem (Thonemann & Brandeau, 2000), the resulted recommendations for the modular fleet design in JTTS scenario are:

1. For low-demand vehicles, high commonality is suggested to increase pooling effect and reduce resource supply.
2. For high-demand vehicles, the design needs to focus on ADR action time reduction.

Although our model was inspired by and applied to a military mission scenario, it is applicable to the scheduling of other types of scenarios, for which demand requirements are measurable. Field demands can be treated as a type of product-as-a-service (Mathieu, 2001), where, the service is accomplished by operating a vehicle convoy on field. Thus, the model can be easily generalized into the civilian applications, i.e., scheduling of reconfigurable machine system (7).

6. Conclusions and Future Work

The major aim of our work is to provide an efficient approach that would enable Army to gain competitive edge from fleet modularity, by integrating and coordinating the operation actions for improved awareness and responsiveness to the stochasticity in the fleet operation. To achieve
this aim, we formulated a multi-layer hierarchical agent-based model, and embedded it into a high fidelity simulation environment. The model is capable of automatically yielding optimal dispatching, planning, and resupply decisions in reacting to the current system status and dynamic field demands.

We implement our model in the JTTS transportation mission scenario. Results show that the total resupplied resources for operating a modularized vehicle system can be reduced by more than 40 percent. The comparison between Empiricist and Optimizer reveals the importance of operation strategy on fleet performance. We also perform a sensitivity analysis to show a close correlation between the fleet performance and available ADR action capacity.

A number of interesting branches of future research remain. In this study, field demands are highly uncertain, especially when the time is close to the deadline. The stochasticity mainly exists in the fleet operation, i.e., repair, maintenance, which can reflect the operation for a logistical mission scenario. However, unpredictability is one of the typical features of the field demands once competing against an intelligent enemy is considered. The commander always needs to make and adjust their decisions in reacting to enemy actions under time-varying combat environment [Army 2007]. To fully exploit potentials of modular fleet, one would have to formulate the competition model between the modular fleet and conventional fleet to explore the additional advantages from fleet modularity.

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