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An Approach for Managing Operating Assets for Humanitarian Development Programs

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Every year, humanitarian organizations assign a sizable portion of their limited financial resources to procure, operate and maintain operating assets, without which service delivery would be nearly impossible. In this study, using vehicles to represent operating assets, we identify policies for sizing and allocating operational capacity to minimize the expected deprivation costs in a humanitarian development context. First, we develop a stochastic dynamic programming model, and then an efficient heuristic policy that considers the interaction of asset purchasing and operating decisions when the budget is uncertain. Based on a dataset provided by a large international organization, we estimate the parameters of our model to run numerical experiments. Results demonstrate the following: (i) Although budget uncertainty increases the expected deprivation costs and decreases capacity utilization, the negative impact of budget uncertainty is mitigated if budget savings between periods is allowed; (ii) a policy for minimizing the expected deprivation costs over time may avoid using all available assets in all periods; (iii) in situations in which the variation in the criticality of missions is large, both the expected deprivation costs and fleet utilization decrease; and (iv) in most conditions, a centralized asset procurement model outperforms a decentralized model, not only in terms of logistic costs but also in minimizing the expected deprivation costs.

Key words: asset procurement; fleet management; humanitarian development programs; simultaneous allocation optimization; stochastic dynamic programming
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1. Introduction

Although humanitarian organizations (HOs) need to maintain an adequate level of relief items (such as blankets, medicines and vaccines) to satisfy their beneficiaries' primary needs, these organizations require sufficient operating assets (such as vehicles and medical facilities) to deliver services. Operating assets are the support equipment used to deliver aid to regions in urgent need. Typically, these assets are durable items that supply services over multiple periods, are often expensive to acquire and require costly regular maintenance. However, a shortage of these assets poses critical challenges for effective service delivery in poor countries (McCoy and Lee 2014). Therefore, HOs assign a sizable portion of their limited financial resources to procure, operate and maintain operating assets. For instance, during 2016, the acquisition, repair, maintenance and depreciation of equipment and operating assets cost World Vision International a few millions of dollars.[1] Due to the amount spent relative to other expenses and due to its essential role in service delivery, asset management is arguably the most significant determinant of how effectively an HO delivers on its mandate. Yet, to our knowledge, even a change in the management team of a country office may lead to a significant alteration in the number of operating assets while there is no instrument to evaluate the value of the new policy. Indeed, the idiosyncratic characteristics of humanitarian development programs make decisions to acquire and use operating assets a serious challenge. In this study, taking some of these characteristics into account, we analyze the impact of operating capacity on the deprivation cost (i.e., beneficiaries' suffering due to insufficient humanitarian service delivery) and propose policies for purchasing and allocating operating assets.

To develop our model, we focus on *vehicles* as representatives of long-life operating assets, which are the centerpiece of humanitarian aid delivery (Eftekhar and Van Wassenhove 2016). Vehicle procurement has characteristics similar to the acquisition of many other types of assets, such as power generators and water-purification systems (Besiou et al. 2014), which makes this practice a suitable choice for the present study. Finally, vehicle fleet management is often cited as a major challenge for humanitarian operations (de la Torre et al. 2012); a well-managed fleet saves HOs millions of dollars every year (Eftekhar and Van Wassenhove 2016).[2]

By and large, vehicle procurement in humanitarian settings is subject to many limitations. First, security problems, the lack of reliable roads and poor infrastructure depreciate vehicles less predictably than under normal conditions and increase the chance of accidents (Eftekhar and Van Wassenhove 2016). Therefore, instead of following a preset policy based on age or mileage to dispose used vehicles, field offices might get rid of used vehicles much later or earlier than planned (Gu et al. 2018). Second, due to the lack of funding for maintenance and fuel, the available vehicles may not always be usable (McCoy and Lee 2014). Third, a vehicle is a multiple-use asset assigned to transportation missions with different levels of criticality (e.g., staff transportation and material distribution). Finally, unpredictability in funding (Eftekhar et al. 2018, Natarajan and Swaminathan 2014) and earmarked funding (Besiou et al. 2014) add additional limitations. These challenges are common in managing most operating assets at the field. Considering all these aspects, we analyze the impact of vehicle fleet management on society's overall expected deprivation costs. Furthermore, we propose a heuristic to determine how many vehicles to buy and how many to operate in each period to minimize the expected deprivation and logistics costs over multiple periods.

To derive general insights from the characteristics of our proposed policies under various operational conditions, we formulate the problem as an infinite-horizon Markov decision process (MDP). Inspired by Holguin-Veras et al. (2013) and Vanajakumari et al. (2016), we set minimizing the expected deprivation costs as the objective function. Although different from the usual settings (e.g., a linear cost function that minimizes the response time or maximizes the demand coverage), we believe this objective function fits HOs' ultimate goal more realistically. In addition to the common cost functions that are vehicle acquisition costs, operating and fixed costs, and residual value (Vemuganti et al. 1989), we take four essential factors inherent to humanitarian settings into account: (i) the randomness of individual vehicle disposal, (ii) the unpredictability of budget availability, (iii) the restricted budget to be spent during a certain time window, and (iv) the variation in criticality of transportation missions. Because obtaining the optimal policy is analytically and numerically complex, we develop an efficient heuristic policy, which has only an average of 0.33% optimality gap (for the dataset that we used), and derive managerial insights, based on our numerical experiments. As the input for our numerical experiments, we use field data to estimate the model parameters empirically. Our dataset contains information on 1074 Toyota Land Cruisers that a large international humanitarian organization (hereafter, LIHO, due to confidentiality reasons) owned from 2000 to 2015 in five countries of operations. We applied Bayesian analysis method to obtain point estimation for the variables of interest.

Our analysis shows that an increase in budget uncertainty increases the expected deprivation costs and decreases capacity utilization. However, we find that the opportunity to budget savings between periods neutralizes the negative effect of budget uncertainty on the expected deprivation costs. In addition, the deprivation costs increase in harsh environments where the probability of vehicle disposal is high. Although field managers usually prefer to assign their full operating capacity to upcoming demands (Pedraza Martinez et al. 2014), our results suggest that an optimal policy that minimizes the expected deprivation costs over time avoids operating *all* vehicles in *all* periods. This policy is mainly due to the uncertainty in the budget and random vehicle disposal that influences a forward-looking HO to adopt frugality. Furthermore, results demonstrate that when the most critical transportation missions are much more important than the least critical ones, the expected deprivation costs are lower than when the variations in the criticality of the organization's missions are small. In other words, the average deprivation costs surges if there is less variation in the criticality of the transportation missions. Likewise, we observe that in situations where variations in mission criticality decrease, fleet utilization grows. Finally, our numerical results indicate that a centralized vehicle procurement model (with a longer procurement lead time but a cheaper purchase price) outperforms a decentralized model (with a shorter lead time but a more expensive purchase price) in minimizing the expected deprivation costs over time.

Literature Review—Given the importance of asset procurement and utilization in the commercial sector, they have been the subject of significant research (Rust 1985). Because we chose vehicles to represent operating assets, we focused on references that concentrate on vehicle fleet management. The OM/MS community has paid substantial attention to fleet management—due to its pivotal role in order fulfillment and cost magnitude (Turnquist and Jordan

1986)—to find the optimal level of transportation capacity under different circumstances. Attention has been paid to vehicle replacement policies (Brosh et al. 1975), fleet sizing with deterministic demand but stochastic travel time (Turnquist and Jordan 1986), fleet sizing with stochastic demand (Papier and Thonemann 2008, Slaugh et al. 2016) and optimal fleet capacity allocation policies (Papier and Thonemann 2010, Savin et al. 2005). Scholars in this stream of literature study a variety of novel problems. Yet, the results are not tailored to a humanitarian setting.

In a humanitarian context, fleet management in relief operations has received much attention. Examples include aid distribution (Yi and Ozdamar 2007), vehicle routing (Campbell et al. 2008, Vanajakumari et al. 2016) and scheduling for victim evacuation (Barbarosoglu et al. 2002). The typical objectives of these studies are to minimize service delivery time or to maximize demand coverage. Compared to relief operations, the number of studies of fleet management problems in development programs is smaller but the topics are broader. Scholars study the vehicle supply chain (Besiou et al. 2014), replacement policy and vehicle reliability (McCoy and Lee 2014, Pedraza Martinez and Van Wassenhove 2013), field-vehicle utilization (Eftekhar and Van Wassenhove 2016, Gu et al. 2018) and the fleet-sizing question (Eftekhar et al. 2014). The paper most similar to the present study is that by Eftekhar et al. (2014) that develops a stylized quadratic control model to determine the optimal fleet size over time. The objective of their study is to minimize the sum of operating costs and the cost demand–capacity mismatch over an infinite time horizon, where demand is deterministic but varies frequently and all transportation missions are equally critical. In addition to the vehicle replacement policy, their model takes a deterministic budget limitation into account and generates simple but practical insights into fleet sizing in this context. Yet, it does not take budget uncertainty, random disposal of vehicles, procurement lead time, and differences in mission criticality, inherent to a humanitarian setting, into consideration. In this study, we take one step forward and analyze a more advanced setting. In addition, the objective function of our model is to minimize human suffering due to a deficit in fleet capacity, and it determines the right quantities of vehicles to acquire and to operate. To the best of our knowledge, such a setting has not been previously studied.

The contribution of this study to the existing literature has three components. First, it extends the existing literature by conceding the limitations of and characteristics specific to humanitarian operations, such as demand variation, differences in mission criticality, budget uncertainty and random vehicle disposal. Second, it considers the joint decisions regarding purchasing and operating vehicles, and explicitly analyzes the interaction of the two decisions. We show that these decisions are highly interdependent when transportation missions have different levels of criticality and the budget is uncertain. Finally, we construct a model that retains the dynamics enforced by these limitations and determine a heuristic policy that achieves close to minimal expected deprivation costs over time, and that is flexible enough to be adapted to a variety of settings.

2. Model Description

In this section, we describe a model for vehicle fleet sizing and allocation at the national (or field) office level with the objective of minimizing the expected deprivation costs. Therefore, we consider a case in which, at the beginning of each period, the decision-maker makes two decisions: (i) how many vehicles to acquire, and (ii) how many vehicles to operate. These decisions are made once she knows the total budget available and the existing fleet size, given the demand for transportation missions in the period. The term "transportation mission" refers to a group of related duties (e.g., distributing foods to remote communities, or administration tasks) that require vehicles to serve a particular program in a certain period. Next, we describe each component of our model.

2.1. Demand and Deprivation Cost

Similar to Eftekhar et al. (2014), we assume that the office periodically predicts the demand for transportation services assigned to different missions, and provides estimates of the demand (i.e., the number of required vehicles to fulfill all the projected missions). Demand in humanitarian development programs is usually predictable (Pedraza Martinez and Van Wassenhove 2013), though it may vary over time (Eftekhar et al. 2014). Accordingly, we allow for any seasonal demand pattern with D_t as the demand in period t, n as the number of demand phases in a seasonal cycle, and D_m as the average demand. Let us denote the demand phase of period t in the seasonal cycle by ω_t. For example, the demand function can take a sinusoidal form, as in Eftekhar et al. (2014).

If the office provides larger capacity (i.e., more vehicles) than D_t, it causes additional operating and fixed costs, and if it provides smaller capacity than D_t, it fails to fulfill some transportation missions, resulting in deprivation cost. Deprivation cost is "valued as changes in human well-being" and measures beneficiaries' suffering from not receiving humanitarian aid (Holguin-Veras et al. 2013). Although HOs' ultimate goal is to alleviate the deprivation costs by maximizing demand coverage, all transportation missions are not equally important; the impact of some missions to alleviate human suffering might be greater than others, which we consider as *more critical* missions. Due to the resource limitation, prioritizing the missions is inevitable (Gralla et al. 2014, Holguin-Veras et al. 2013, Wang et al. 2017), and thereby the office prioritizes its demands and assigns vehicles to the most critical transportation missions (i.e., it assigns the first available vehicle to serve the transportation mission that has the largest potential to reduce deprivation cost, the second available vehicle to serve the second most important transportation mission, and so forth). This prioritization leads to convex behavior of the deprivation cost in the number of vehicles assigned.

To prioritize missions, the office first has to estimate the deprivation cost that can be avoided if a transportation mission is fulfilled. One way to estimate it is to use Stated Preference techniques, where an expert or a group of experts are asked to value all transportation missions in terms of their impact and importance (see, e.g., Holguín-Veras et al. 2016, Wang et al. 2017). Then, from a predicted set of transportation missions, and their respective deprivation cost, the decision-maker can estimate the *differences in mission criticality* (i.e., the difference between the deprivation costs of the most critical mission and the least critical mission).

In this model, we approximate the deprivation cost by an exponential function. Using an exponential function has several advantages. First, Holguin-Veras et al. (2013) explain that deprivation cost should be "monotonic, non-linear, and convex with respect to the deprivation time," and their results suggest that an exponential function captures best this effect. Second, the exponential function's convexity properly approximates the prioritization process discussed above. Finally, an exponential function allows valuing the relative importance of transportation missions by a single parameter. Therefore, we define the per-period deprivation cost as

$$R_t(a_t) = e^{b[D_t - a_t]^+} - 1, \qquad (1)$$

where R_t is the deprivation cost in period t if the office decides to assign a_t vehicles ($a_t \geq 0$) to serve a proportion of the demand. Parameter $b > 0$ describes the deprivation cost function's convexity. It represents the level of differences in mission criticality through the level of convexity of the deprivation cost function. A high value of b implies that the deprivation cost of the most critical transportation mission is very different from the deprivation cost of the least critical mission. On the opposite, an extreme case of $b \to 0$ implies that all transportation missions have the same level of criticality, and no prioritization would be possible. Appendix A provides the table of symbols.

In order to simply interpret b, we compare it to a Pareto analysis suggested by the United States Coast Guard (USCG 2003) to prioritize missions in health-related risk management. With a Pareto analysis, a fraction v of the total deprivation cost is avoided by fulfilling the most critical $(1 - v)\%$ of all potential transportation missions. For example, a value of $v = 0.8$ implies that serving only 20% of the most critical transportation missions avoids 80% of the deprivation cost. Parameter b can be derived from v with the following expression

$$e^{bD_m} - e^{vbD_m} = v(e^{bD_m} - 1), \quad 0.5 < v < 1. \qquad (2)$$

Essentially, parameter v expresses the same concept as b, but it is more intuitive to use in practice. We therefore use v to report our numerical results but keep b in the model description and analysis. In Online Appendix OA-3, we provide an illustrative example how to estimate the differences in mission criticality from a set of transportation missions. Yet, for the purpose of illustration, we refer to Figure 1 that provides examples of deprivation cost function for two different values of v and a demand of $D = 10$ vehicles. Figure 1a shows the graph for $v = 0.6$, which corresponds to $b = 0.17$, and Figure 1b shows the value for $v = 0.7$, which corresponds to $b = 0.39$. For conciseness, we use a common parameter b for any demand phase. Note that our model and the solution can be easily extended to period-specific values of b, and to any other function which is convex and increasing in the unmet demand.

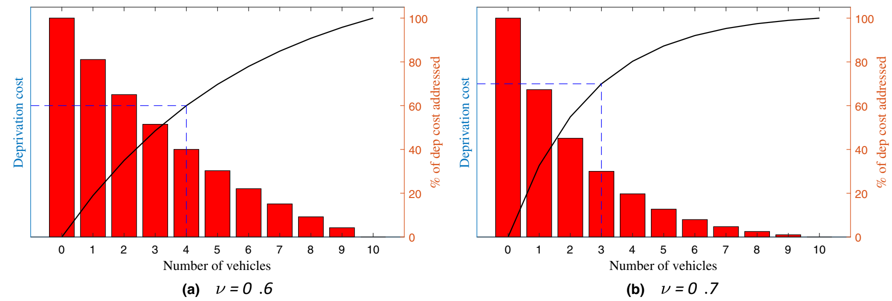
2.2. Purchasing and Operating Costs

At the beginning of period t, the management decides how many new vehicles to buy, denoted by u_t, to add to the existing fleet capacity, denoted by x_t. Each purchased vehicle costs p, and vehicles bought during period t become effectively available in period $t + 1$ (i.e., there is a procurement lead time of one period). Vehicle utilization imposes operating costs such as maintenance, fuel and the driver's salary, that are captured by $c_o > 0$ in our model. However, even maintaining an idle vehicle in the field imposes fixed costs in each period, such as a refreshing cost, workshop and office expenses, and a monthly insurance fee, denoted by $c_f \geq 0$.

2.3. Financial Resources

At the beginning of each period, there is a budget available for operating the fleet, SB_t, which consists of three components. First, the office receives a random budget, K_t, which is independent and identically distributed among periods, with a mean of μ and

Figure 1 **Deprivation Cost as a Function of Transportation Missions with Demand $D = 10$ (the solid line refers to the cumulative deprivation costs) [Color figure can be viewed at wileyonlinelibrary.com]**



standard deviation of σ. Second, the office has some (non-earmarked) budget saved from the previous periods that is available at the beginning of period t, S_{t-1}. The savings in each period depend on the initial budget, SB_t, and the amount spent during that period,

$$S_t(a_t, u_t) = SB_t - c_f x_t - c_o a_t - p u_t. \quad (3)$$

Third, the office earns revenue through selling used vehicles. Due to the environmental conditions, in which HOs operate vehicle disposal may not follow a preset policy of 5-year or 150,000 km whichever comes first (Gu et al. 2018; Pedraza Martinez and Van Wassenhove 2013). This is confirmed with Figure 2 showing that the age (of 5 years) and cumulative odometer (of 150,000 km) play no significant role to dismiss a vehicle. Previous research (Eftekhar and Van Wassenhove 2016), and our further data analysis indicate that many vehicles are disposed following unpredictable events, such as accidents. Accordingly, it is reasonable to assume that at the end of each period a random number of vehicles are disposed of, and an average residual value, r $(0 \leq r < p)$, for each sold vehicle is obtained. In this setting, it means that it is less predictable which vehicle(s) will be disposed next. Yet, depending on the age, accident history, and other factors, an individual vehicle may have a lower or higher chance of failure. In Appendix D, we present an extension of the model where vehicles are categorized (e.g., based on age, cumulative odometer, or other factors) into *high-* and *low-cost* status.

We use an average dismissal rate of γ that a vehicle is disposed of in a given period. This implies that the available fleet size at the beginning of a period, $L(x_t)$, follows a binomial distribution with population x_t and success probability $1 - \gamma$. We also tested this assumption with our dataset (see section 4). A kernel density estimation graphically supports our assumption that the fleet size follows a binomial distribution, and a chi-square goodness-of-fit test did not reject it at the 1% significance level. For notational simplicity, we define $c_L = c_f + c_o + \gamma(p - r)$ as the average per-period cost of a single vehicle at full utilization.

2.4. Dynamic Programming Model

Based on the above description, we define the order of events in a certain period as follows: At the beginning of period, the manager knows the allocated budget to her fleet, K_t. Given the total available budget SB_t and fleet size x_t, she decides on the number of vehicles to operate, a_t, and the number of vehicles to purchase, u_t (which will be received in the next period). Finally, she realizes the number of vehicles still available at the end of the period, $L(x_t)$, after accounting for dismissed vehicles. Therefore, the state equation for the fleet size in period $t + 1$ is

$$x_{t+1} = L(x_t) + u_t, \quad (4)$$

and the state equation for the available budget in period $t + 1$ as

$$SB_{t+1} = S_t + r(x_t - L(x_t)) + K_{t+1}. \quad (5)$$

For the numerical analysis, we limit the fleet size to a maximum of x^{max} and the budget to SB^{max}, which seems reasonable, given the typical budget limitations in the humanitarian sector. The maximum values can be set sufficiently high so as not to affect the results. We assume that the financial donations are sufficient to at least cover the fixed costs; that is, $K_t \geq c_f x^{max}$. This assumption leads us to the following model, in which the logistics costs are taken into account through the budget constraints:

$$J_0(x_0, SB_0, \omega_0) = \min \mathbb{E}\left(\lim_{N\to\infty} \frac{1}{N} \sum_{t=0}^{N} R_t(a_t)\right), \quad (6)$$

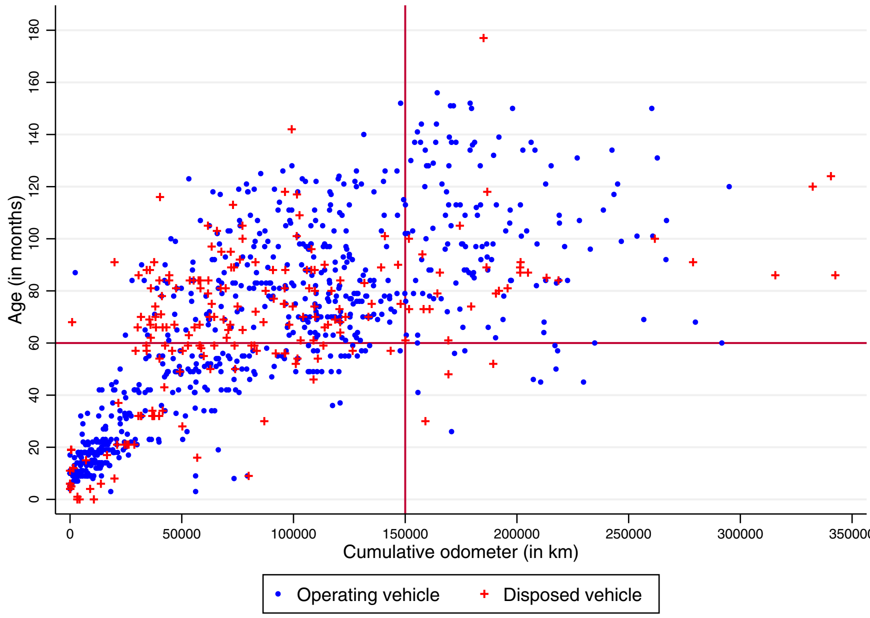
subject to

$$a_t \leq x_t, \quad (7)$$

$$S_t = SB_t - c_f x_t - c_o a_t - p u_t, \quad (8)$$

$$SB_{t+1} = \min\{S_t + r(x_t - L(x_t)) + K_{t+1}, SB^{max}\}, \quad (9)$$

Figure 2 Age and Odometer of Disposed and Active Vehicles [Color figure can be viewed at wileyonlinelibrary.com]



$$x_{t+1} = \min\{L(x_t) + u_t, x^{max}\}, \quad (10)$$

$$\omega_{t+1} = t + 1 \bmod n + 1, \quad (11)$$

$$S_t, SB_t \geq 0, \text{ and } a_t, u_t, x_t \in Z^+, \omega_t \in \{1, \ldots, n\}. \quad (12)$$

The objective function with starting state x_0, SB_0 and ω_0, $J_0(x_0, SB_0, \omega_0)$, minimizes the average deprivation costs over an infinite horizon by choosing the optimal values for purchasing, u_t, and operating vehicles, a_t, in each period. The first constraint implies that the number of vehicles to operate does not exceed the available number of vehicles. Constraints (8)–(11) represent the state equations introduced above. Constraint (12) ensures the non-negativity of the state and decision variables. We consider an infinite horizon because humanitarian development programs are typically long-term programs without a prior known ending (Polman 2011), while a finite horizon model would be affected by the length of horizon and other terminal conditions. Corollary 1 shows that the average optimal value and a stationary optimal policy exist (proof in Online Appendix OA-1).[3]

COROLLARY 1. *The limit of Equation* (6) *exists. Furthermore, there is a stationary average cost policy for the above MDP model.*

3. Heuristic Development

The optimal policy of our model does not have the typical monotone, *switching-curve* structure, because the constraints of the model do not allow the optimal value function to have the required second-order properties, such as convexity. For instance, decision variable a_t^* of the optimal policy is not always monotone in any of the state variables ω_t, x_t or SB_t, as we observed through our numerical experiments. Likewise, decision u_t^* of the optimal policy is not always monotone in ω_t. Furthermore, our optimization model has three state variables (ω_t, x_t and SB_t), two decision variables (u_t and a_t) and two stochastic elements ($L(x_t)$ and K_t), all of which render the model too complex to be solved numerically for problem instances of actual size. Consequently, due to the limitations in analytical and numerical methods, we propose a heuristic approach, the Simultaneous Allocation Optimization (SAO) heuristic, which generates *close-to-optimal* decisions within a reasonable time window. In this section, first we explain the benchmark policy, and then we describe the mechanism of our heuristic method.

3.1. Benchmark Policy

A key aspect of commercial fleet management is that serving demand directly leads to cash inflow that can be used to pay for the operating and fixed costs (e.g., Papier and Thonemann 2008). Accordingly, it is optimal to serve as many demands as possible, that is, to operate all the capacity in the current period, as long as the revenues of the marginal transportation mission exceed the operating costs. This yields a myopic policy

$$a_t^b(x_t, SB_t) = \lfloor \min\left\{x_t, \frac{SB_t - c_f x_t}{c_o}, D_t\right\}\rfloor, \tag{13}$$

where $a_t^b(x_t, SB_t)$ denotes the number of vehicles operated, which is constrained only by the fleet size, the available budget to cover the operating costs and the demand. Furthermore, in the commercial sector, as long as the average lifetime revenue from a vehicle exceeds its purchase and operating cost, it is reasonable to fulfill the demand completely. This trade-off implies an *order-up-to* purchasing policy to fill the gap between demand and capacity (i.e., the fleet size) in the next period and leads to the purchasing decision

$$u_t^b(x_t, SB_t) = \min \left\{\lfloor \frac{SB_t - c_f x_t - c_o a_t^b(x_t, SB_t)}{p}\rfloor, (D_{t+1} - \lfloor x_t(1-\gamma)\rfloor)^+\right\}, \tag{14}$$

where $u_t^b(x_t, SB_t)$ denotes the number of vehicles to be purchased in period t. The first argument in Equation (14) is the maximum number of purchases limited by the available budget, and the second argument stands for the order-up-to policy. This policy seems to correspond to the current practice in the humanitarian setting as well. Our interviews with humanitarian practitioners[4] indicate that the conventional wisdom is to completely fulfill demand whenever sufficient capacity is available. This myopic behavior also corresponds to Eftekhar et al.'s (2014) linear programming model, and so we use it as a benchmark for our heuristic.

3.2. Development of the SAO Heuristic

The goal of our SAO heuristic is to minimize the expected deprivation cost over time. The heuristic allocates the available budget among the decisions to purchase new vehicles, to operate a fraction or all of the available vehicles and to save part of the available budget for future operations. The heuristic estimates the marginal reduction in expected deprivation costs, the *social gain*, of every possible amount of operating, purchasing and saving. Then, it applies a portfolio optimization to allocate the available budget to these three allocation options such that the estimated social gain is maximized.

Therefore, to understand the mechanism of the heuristic, it is critical to realize how the marginal value functions are estimated. At the beginning of each period, the management deducts the fixed costs from the budget and decides how many additional vehicles to buy and how many vehicles to operate. The number of vehicles that are assigned to operations has an immediate impact on the social gain in the current period. In contrast, the portion of the budget to be saved and used for the future and the number of vehicles to be operated in the next periods guarantee the continuity and persistence of operations in the future. From Equation (1), the social gain from *operating* a_t vehicles in period t is given by

$$V_t^a(a_t) = e^{bD_t} - e^{b[D_t - a_t]^+}. \tag{15}$$

Due to the uncertainty in the budget and in the number of available vehicles in future periods, as well as the limitations on the number of operating vehicles, it is difficult to calculate the marginal gain from *purchasing* one additional vehicle. Therefore, we consider the fleet's aggregated reliability during a vehicle's average operational life and use an approximation. To do so, we assume that the fleet size is affected by u_t only in period $t + 1$; for periods after $t + 1$, the fleet size is adjusted by further purchasing decisions $(u_{t+1}, u_{t+2}, \ldots)$.

In addition, due to the budget limitations, it is reasonable to assume that the HO cannot afford to own and operate a capacity (fleet of vehicles) larger than a certain threshold (i.e., an upper bound). To determine this threshold, we use a simplified version of the optimization model (6) in which all variables are continuous and all stochastic elements are replaced by their expected values (i.e., $K_{t+1} = \mu$, and $L(x_t) = (1-\gamma)x_t$). We denote the optimal number of vehicles to operate in this simplified problem by $\bar{a}_t$. Read Appendix B for the details of the deterministic formulation and for a closed-form solution of the deterministic model when demand is constant.

With this information, we can estimate the expected social gain from purchasing additional vehicles in period t, V_t^u, by considering the expected social gain in the next period, assuming that the decision-maker will not operate more than $\bar{a}_{t+1}$ vehicles. Therefore, we approximate the social gain of purchasing u_t vehicles, given the current fleet size x_t, by

$$\begin{aligned} V_t^u(u_t, x_t) &= \mathbb{E}_{L(x_t)}\left[V_{t+1}^a(\min(L(x_t) + u_t, \bar{a}_{t+1})) - V_{t+1}^a(\min(L(x_t), \bar{a}_{t+1}))\right] \\ &= \sum_{l=0}^{x_t} P(L(x_t) = l)\Big(e^{b[D_{t+1} - \min(l, \bar{a}_{t+1})]} - e^{b[D_{t+1} - \min(l+u_t, \bar{a}_{t+1})]}\Big). \end{aligned} \tag{16}$$

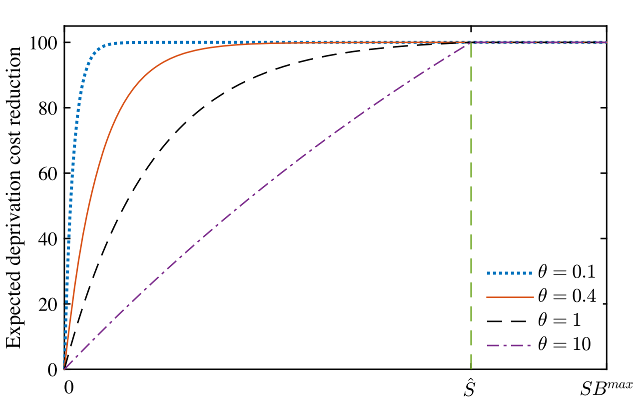
In other words, Equation (16) estimates the difference between purchasing u_t vehicles and not purchasing the vehicles. Considering the randomness of vehicle disposal at the end of the current period, this equation evaluates the expected difference in social gains in period $t + 1$ between the two options.

Next, we need to estimate the expected social gain from *saving* some of the budget for future periods. Estimating the impact of saving on future social gain is also challenging because the saved budget can be allocated either to operating or to purchasing at any time period in the future. We fit a parametric function to estimate the value of saving, $V^s(s|\theta)$, and adjust the degree of concavity between these points with an independent parameter. As the deprivation cost function itself consists of exponential functions, we define $V^s(s|\theta)$ accordingly and propose

$$V^s(s|\theta) = \begin{cases} e^{b'\theta\hat{S}} - e^{b'(\theta\hat{S}-s)} & \text{if } s < \hat{S}, \\ e^{bD_m} & \text{otherwise,} \end{cases} \tag{17}$$

where $\hat{S} = SB^{max} - r\gamma\mu/c_L - \mu$ is the upper threshold for the savings, μ/c_L is an estimation of the fleet size, and b' is a coefficient of function V^s that can be determined from the model parameters, and θ is a parameter that determines the degree of concavity of the savings function. Figure 3 shows the behavior of $V^s(s|\theta)$ under different values of the heuristic parameter θ. We observe that larger values for θ put a higher marginal value on savings and lead to a forward-looking behavior, whereas smaller values of θ favor more myopic strategies (i.e., undervaluing future risks). Therefore, as a rule of thumb, larger values of θ that tend to save more of the budget are suitable for situations with high uncertainty and larger variation in mission criticality (i.e., high values for b). Each value of θ results in a different SAO policy, because a different savings function V^s is used. To numerically determine the optimal value for θ, θ^*, we use simulation to obtain the average performance, that is, the average deprivation cost under different values of θ and select the value for θ^* that minimizes the average deprivation cost. For searching the value, we use the Quadratic Interpolation method (Bertsekas 1999). A numerical procedure for approximating $V^s(s|\theta)$ and for determining b' is explained in detail in Appendix C.

Figure 3 Estimated Social Gain from Saving ($V^s(s|\theta)$) for Different Values of θ [Color figure can be viewed at wileyonlinelibrary.com]



After estimating V_t^a, V_t^u and V^s, we have to solve the following allocation model to determine the decisions of the SAO heuristic:

$$\max_{u_t^h, a_t^h} \left(V_t^a(a_t^h) + V_t^u(u_t^h, x_t) + V^s\left(SB_t - c_f x_t - c_o a_t^h - p u_t^h | \theta\right)\right), \tag{18}$$

subject to

$$c_f x_t + c_o a_t^h + p u_t^h \leq SB_t, \tag{19}$$

$$a_t^h \leq x_t \text{ and} \tag{20}$$

$$a_t^h, u_t^h \in \mathbb{Z}^+. \tag{21}$$

With the optimal value θ^*, we find the heuristic decisions for the number of operating and purchasing vehicles, which we denote by $a_t^h(x_t, SB_t, \theta^*)$ and $u_t^h(x_t, SB_t, \theta^*)$, respectively. The following proposition establishes the second-order properties of the optimization model (18), which can be used to design an efficient algorithm to solve the problem within a short time in an *online* fashion (i.e., in every time period in which the model is used). The proofs are shown in Online Appendix OA-1.

Proposition 1. *The maximization function in the optimization model* (18) *is* (*non-strictly*) *concave in* a_t^h *and in* u_t^h *and* (*non-strictly*) *sub-modular in* a_t^h *and* u_t^h.

Proposition 1 implies that a_t^h and u_t^h are nondecreasing in the available budget SB_t, which we can use to further restrict the search space of the solution to Equation (18). Finally, the computation of the three functions V_t^a, V_t^u and V^s and the optimal parameter θ^* can be done once in the beginning and stored in memory.

3.3. Sensitivity Analysis

In this subsection, we discuss how the decisions of the SAO heuristic depend on the model parameters. Proposition 2 unveils limits on the average fleet size, the operating level and the expected deprivation costs (proof in Online Appendix OA-1).

Proposition 2. *For the situation in which the average donations are less than the average cost to fulfill the demand completely* (*i.e.*, $\mu \leq c_L D_m$), *and the limits* x^{max} *and* SB^{max} *are sufficiently high, we have the following results for any fleet management policy:*

1. *It holds that* $\mu = (c_f + \gamma(p - r))\mathbb{E}(x_t) + c_o\mathbb{E}(a_t)$.
2. *The expression* μ/c_L *is a lower limit for the average fleet size,* $\mathbb{E}(x_t)$*, and an upper limit for the average operating level,* $\mathbb{E}(a_t)$.
3. *The expected deprivation costs are bounded below by*

$$\mathbb{E}(R_t) \geq e^{b(D_m - \frac{\mu}{c_L})} - 1.$$

Part 1 of Proposition 2 implies that for a given average budget (μ), an increase in the average fleet size by one vehicle necessitates a reduction in the average operating level of $c_o/(c_f + \gamma(p - r))$ vehicles. As expected, because the average budget and the residual value of a used vehicle (r) have a positive impact on the total budget, they increase the bound μ/c_L on the fleet size and the operating level. However, it is easy to see that the bound μ/c_L decreases in fixed costs, c_f, operating costs, c_o, purchase price, p, and the probability of vehicle disposal, γ. This result implies that by decreasing the vehicle procurement costs (e.g., through a centralized procurement policy), fleet operating costs, vehicle depreciation costs and minimizing the chance of vehicle breakdown and accidents, management will save a larger portion of the budget that eventually enables it to fulfill additional critical transportation missions in the future. Therefore, a well-framed fleet management that maintains vehicles properly and trains drivers frequently seems to decrease not only the monetary costs of fleet management but also the expected deprivation costs.

4. Numerical Experiments

To avoid using synthetic data as inputs of our numerical experiments, we use field data to estimate the model parameters. Based on a dataset provided by the LIHO, we obtain point estimation for the variables of interest. Our dataset contains information on 1074 Toyota Land Cruisers that the LIHO owned from 2000 to 2015 in five countries; Iraq, Kenya, Liberia, Syria and Sudan (southern part—now South Sudan) that during the past few years have experienced different types of disasters, such as war and political conflicts, hunger and poverty. The LIHO has been among the leading organizations that supply a wide range of humanitarian services to these countries.[5]

Our dataset contains information on each vehicle's identification number, date of purchase, purchasing price, number and cost of accidents, maintenance history and operating costs, total mileage, mission type, and the location (office) in which the vehicle was used. We also know when and how a vehicle has been disposed of (i.e., sold, donated or scrapped) and its residual value. Furthermore, the dataset provides information on the monthly fleet size in each country over a period of 15 years. Through the data of maintenance history, we have information about the reason and cost of each repair, and how many days a vehicle was off the road. Data shows that only <5% of all repairs make a vehicle unavailable for 14 days or longer. Therefore, in our numerical experiments, we do not explicitly consider vehicle unavailability.

4.1. Parameter Estimation

Similar to Eftekhar et al. (2014), our model is based on vehicle monthly utilization, and we assume a generic average usage value for each variable. To calculate the average operating cost, we took into account each vehicle's total repair and preventive maintenance costs, accident cost, and fuel and driver cost based on the vehicle's cumulative odometer. Then, we divided this cost by vehicle age. The first two cost components were directly found from our dataset. However, to calculate the third component, we used the average fuel and driver cost per kilometer in each country of operations that was provided by a LIHO expert. Likewise, we calculated the average fixed cost of keeping an additional vehicle in the fleet, considering driver training and the refreshing cost, management and technical staffing cost, workshop and office cost, and monthly insurance cost. These data were also directly provided by an LIHO expert.

For the point estimations, we applied Bayesian analysis that relies on the assumption that the observed data is fixed while all parameters are random quantities and provides more robust estimations than frequentist methods (Kruschke et al. 2012). We estimated the posterior mean, standard deviation and minimum and maximum values of each variable. To estimate the posteriors, we assumed a non-informative uniform prior distribution, and estimated the posteriors via Markov chain Monte Carlo (MCMC) sampling. A non-informative prior assigns equal probabilities to all possible states of the parameter space to rectify the subjectivity problem. To increase the accuracy of our simulation results, we used 42,500 MCMC iterations with a warm-up period of 2500 iterations. The parameter for the seasonal demand variation was obtained from the fleet size information in the dataset. For the budget K_t, we used a truncated log-normal distribution (see also Okten and Weisbrod 2000). The mean of K_t was also obtained from the fleet size information, which gives a more accurate estimate, and σ was computed based on the variation in the budget data. We set $SB^{max} = 20\mu$ with a step size of c_o and $x^{max} = 1.8\max_t(D_t\mu/(c_L D_m))$. We set the maximum values sufficiently high such that it does not affect the results (it would be unlikely that these values are reached in practice). The cost and demand estimations, as well as all parameters used in the experiments are reported in Online Appendix OA-2.

We do not have information about the actual demand. Therefore, we consider different scenarios of the average demand, D_m, by keeping the average budget constant while changing the funding level (i.e. the ratio of the average budget to demand, $\mu/(c_L D_m)$), from 0.5 to 1. For example, we obtained $D_m = 24$ vehicles for Sudan under 0.5 funding level and $D_m = 12$ vehicles under a funding level of 1.

4.2. Performance Assessment of the SAO Heuristic

We used the Policy Iteration Method (Puterman 2005) to derive the optimal policy for the problem described by Equations (6)–(12). For each policy, we simulated the system with 50 replication runs to determine the average deprivation cost, J_0. Each replication run consisted of 82,000 iterations that included a warm-up period of 2000 iterations. Due to the size of the problem instances, it is impossible to obtain an optimal policy for fleet sizes larger than 30 vehicles in an acceptable runtime. Therefore, to assess the optimality gaps, we focused on the data for Sudan and Syria from 2000 to 2005, when both countries had comparably small fleets. We kept the average budget constant and systematically changed the average level of demand to obtain the ratio of the average budget to demand (i.e., funding level $\mu/(c_L D_m)$) of 0.5, 0.75 and 1. We also changed the factor of mission criticality (v) from 0.55 to 0.75. To make the scenarios comparable when varying v, we scaled the total potential deprivation costs to have the same total value under any v. In all our numerical experiments, we used a three-month interval as one period.

To analyze the performance of the heuristics, we use the *social service level* (*SSL*) corresponding to the ratio of the expected deprivation costs (obtained from our model) to the total deprivation costs without serving any missions, that is,

$$SSL = 1 - \frac{\mathbb{E}(R_t)}{e^{bD_m} - 1}, \tag{22}$$

where $e^{bD_m} - 1$ represents the highest possible deprivation costs, when no transportation mission is satisfied in any period. The social service level can attain values between 0% and 100%, with larger values indicating lower deprivation costs.

In Table 1, we compare the optimal, heuristic and benchmark policies, as well as the lower bound (see Proposition 2), and report the expected deprivation costs, the social service level and the optimality gap. The values are determined with a simulation. The number of replication runs of the simulation should be chosen to allow for sufficient precision of the results. Therefore, we have chosen the number of replication runs to ensure that the half-width of the 95% confidence intervals are less than 1% of the average performance, that is, $t_{0.025,N-1}\frac{s}{\sqrt{N}} < 0.01\mathbb{E}(R_t)$, with s referring to the standard deviation of the average deprivation costs across the different replication runs, $t_{0.025,N-1}$ being the value of the student's t-distribution, and N denoting the number of replication runs. As shown in this table, the optimal policy achieves a performance fairly close to the lower bound. Furthermore, the SAO heuristic demonstrates a performance close to the optimal policy, with an average optimality gap of 0.33%, and it also outperforms the benchmark policy (an average optimality gap of 6.6%) by a wide margin.

4.3. Sensitivity Analyses and Discussion

Next, assuming that our proposed model captures the actual setting, we report the following insights based on the dataset that the LIHO made available to us. Unless otherwise noted, we used a funding level of 75% and a factor for differences in mission criticality of $v = 0.75$. Furthermore, for the analyses in which we varied the parameters c_L, p or γ, we also increased the average budget (μ) to keep the level of funding constant. In this subsection, we report results of the optimal policy for the two countries for which we could obtain optimal results, that is, Sudan and Syria. We also performed sensitivity analyses for all five countries, with the SAO heuristic and the benchmark policy. Due to space constraints, we summarize these additional results in a separate report, which can be obtained from the authors upon request.

Impact of Uncertainty and Variability—Our results indicate that budget uncertainty and variability in demand have negative consequences on the expected deprivation costs and on fleet utilization (i.e., the number of vehicles operated compared to the size of the total fleet). These results, graphically shown in Figure 4, are in line with conventional wisdom that uncertainty renders the operations problem more complex to manage. Moreover, an increase in the probability of vehicle disposal, which corresponds to a decrease in the average vehicle lifetime, increases the expected deprivation costs (Figure 5a) and increases the fleet utilization (Figure 5b and c). In fact, a greater vehicle disposal probability pushes the office to more quickly adjust the fleet size to demand seasonality. However, all other things being equal, the impact of the vehicle dismissal probability on the expected deprivation costs seems to be less severe than the impact of budget uncertainty (cf. Figure 4d).

Impact of Cost Parameters—With an increase in the operating unit cost (c_o), the decision-maker is more conservative and keeps resources for the more critical

Table 1 Expected Deprivation Costs and Social Service Levels of the Optimal Policy, the SAO Heuristic, and the Benchmark Policy (data of 2000–2005)

			v = 0.55				v = 0.65				v = 0.75			
Country	FL	Policy	Dep.	SSL	Gap	T	Dep.	SSL	Gap	T	Dep.	SSL	Gap	T
Sudan	0.5	LB	97.19	60.0%	—	—	51.06	79.0%	—	—	14.61	94.0%	—	—
		Opt.	98.26	59.5%	—	26,467	53.20	78.1%	—	20,145	16.60	93.2%	—	19,974
		SAO	99.17	59.1%	0.6%	876	53.95	77.8%	0.4%	1,023	17.25	92.9%	0.3%	723
		Benc.	119.37	50.8%	14.6%	49	83.41	65.6%	15.9%	49	50.10	79.4%	14.8%	49
	0.75	LB	43.70	82.0%	—		17.38	92.8%	—	—	2.95	98.8%	—	—
		Opt.	45.41	81.3%	—	21,113	19.79	91.8%	—	18,782	4.05	98.3%	—	18,546
		SAO	47.17	80.6%	0.9%	1,062	20.55	91.5%	0.3%	1,027	4.57	98.1%	0.2%	811
		Benc.	62.82	74.1%	8.8%	50	41.45	82.9%	9.7%	50	22.99	90.5%	7.9%	50
	1	LB	0.00	100.0%	—	—	0.00	100.0%	—	—	0.00	100.0%	—	—
		Opt.	7.97	96.7%	—	17,649	3.21	98.7%	—	16,493	0.55	99.8%	—	16,285
		SAO	10.26	95.8%	1.0%	1,196	3.84	98.4%	0.3%	1,028	0.70	99.7%	0.1%	638
		Benc.	10.49	95.7%	1.1%	49	4.00	98.4%	0.3%	49	1.76	99.3%	0.5%	49
Syria	0.5	LB	97.19	60.0%	—	—	51.06	79.0%	—	—	14.61	94.0%	—	—
		Opt.	97.96	59.7%	—	5,194	52.33	78.4%	—	4,583	15.77	93.5%	—	4,636
		SAO	98.02	59.6%	0.0%	1,110	52.67	78.3%	0.2%	1,046	16.21	93.3%	0.2%	645
		Benc.	109.32	55.0%	7.8%	48	68.65	71.7%	8.6%	49	32.26	86.7%	7.3%	48
	0.75	LB	43.70	82.0%	—	—	17.38	92.8%	—	—	2.95	98.8%	—	—
		Opt.	44.58	81.6%	—	4,509	18.71	92.3%	—	3,716	3.58	98.5%	—	4,231
		SAO	45.32	81.3%	0.4%	468	19.16	92.1%	0.2%	645	3.88	98.4%	0.1%	470
		Benc.	58.39	75.9%	7.0%	48	33.71	86.1%	6.7%	49	14.17	94.2%	4.4%	49
	1	LB	0.00	100.0%	—	—	0.00	100.0%	—	—	0.00	100.0%	—	—
		Opt.	5.68	97.7%	—	3,235	2.10	99.1%	—	2,851	0.33	99.9%	—	3,636
		SAO	6.88	97.2%	0.5%	936	2.41	99.0%	0.1%	787	0.43	99.8%	0.0%	543
		Benc.	8.65	96.4%	1.3%	49	4.58	98.1%	1.0%	49	1.60	99.3%	0.5%	49

Notes. In this table, Dep. refers to the expected deprivation costs; Gap shows the optimality gap; FL indicates the funding level; T shows the computational time, in seconds; LB is lower bound; Opt. refers to optimal policy; and Benc. refers to the benchmark policy.

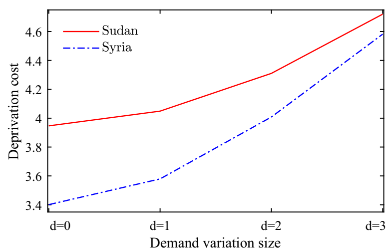
transportation missions (Figure 6a and b). Therefore, as shown in Figure 6a, an increase in operating cost causes a decrease in fleet utilization. In contrast, when the vehicle purchase price increases, the decision-maker will maintain a smaller fleet but will use the available vehicles as often as possible, thus resulting in higher fleet utilization (Figure 6c and d).

Impact of the Differences in Mission Criticality—Figure 7a indicates that the expected deprivation costs decrease with the differences in the criticality of the transportation missions (v). This means that in situations where the most critical transportation missions are considerably more important than the least critical transportation missions, the average expected deprivation costs are lower than in situations where the difference between the most and least critical transportation missions is small. The reason is that in the case of a large v, with a small budget, the HO can address the transportation missions that are the main concerns of the beneficiaries. Furthermore, when the variations in mission criticality increase, the number of operating vehicles (i.e., the number of transportation missions fulfilled) and the utilization of the fleet decrease. This happens because the cost of missing an important transportation mission in the future is high, such that a forward-looking manager avoids covering the less important transportation missions in the current period and saves some of the budget for the future; the management needs to protect the budget for future *more critical* transportation missions. This observation is confirmed by Figure 8, which indicates that the level of budget savings between periods increases with v.

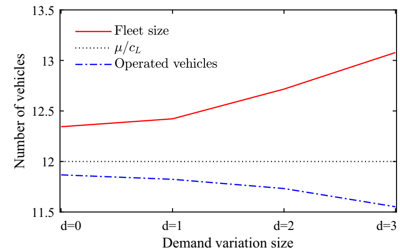
4.4. Comparison between Benchmark Policy and SAO Heuristic

Figure 9 is an illustrative example that shows the trends that we consistently saw throughout our numerical experiments. It compares fleet sizing and operating capacity of the heuristic and benchmark policies, assuming a v = 0.75 and a funding level of 0.75. Compared to the heuristic (and also to the optimal policy), the benchmark results in a larger average fleet size but lower operating level, and thereby much lower fleet utilization. The larger fleet size is due to the fact that the benchmark policy chases the demand, which also leads to a larger variation in the fleet size. The lower operating capacity is due to the fact that the benchmark policy does not perform efficiently when budget uncertainty exists, while one of the goals of the heuristic is to cope with budget uncertainty. However, Table 1 shows that the benchmark policy performs similar to the heuristic when the funding level is sufficiently large (i.e., both models

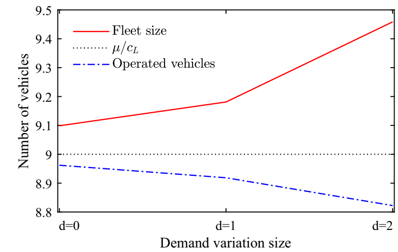
Figure 4 Impact of Demand and Budget Variation on Expected Deprivation Costs and Fleet Utilization [Color figure can be viewed at wileyonlinelibrary.com]



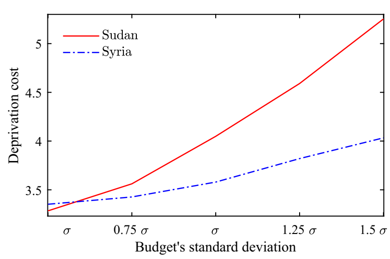
(a) Impact of demand variation on expected deprivation costs (d refers to the demand magnitude)



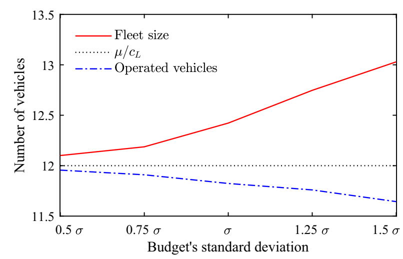
(b) Impact of demand variation on fleet utilization (data of Sudan)



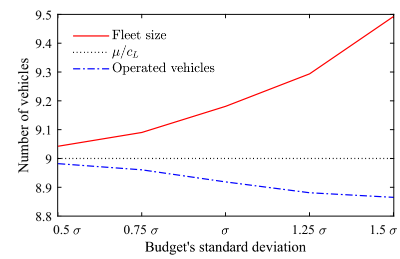
(c) Impact of demand variation on fleet utilization (data of Syria)



(d) Impact of budget variation on expected deprivation costs

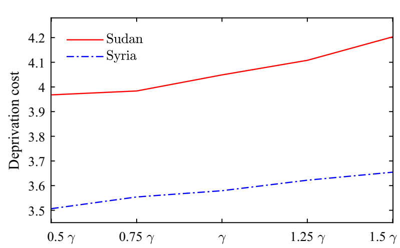


(e) Impact of budget variation on fleet utilization (data of Sudan)

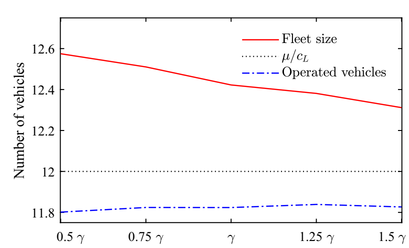


(f) Impact of budget variation on fleet utilization (data of Syria)

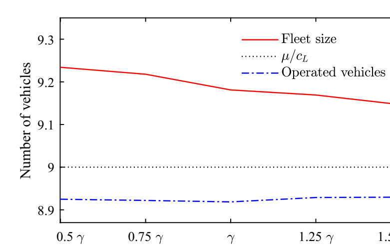
Figure 5 Impact of the Rate of Vehicle Dismissal on Expected Deprivation Cost and Fleet Utilization [Color figure can be viewed at wileyonlinelibrary.com]



(a) On expected deprivation costs



(b) On fleet utilization (data of Sudan)



(c) On fleet utilization (data of Syria)

fulfill nearly all the transportation missions). Furthermore, we observed that when v increases fewer vehicles are required to minimize the total deprivation cost, in all policies.

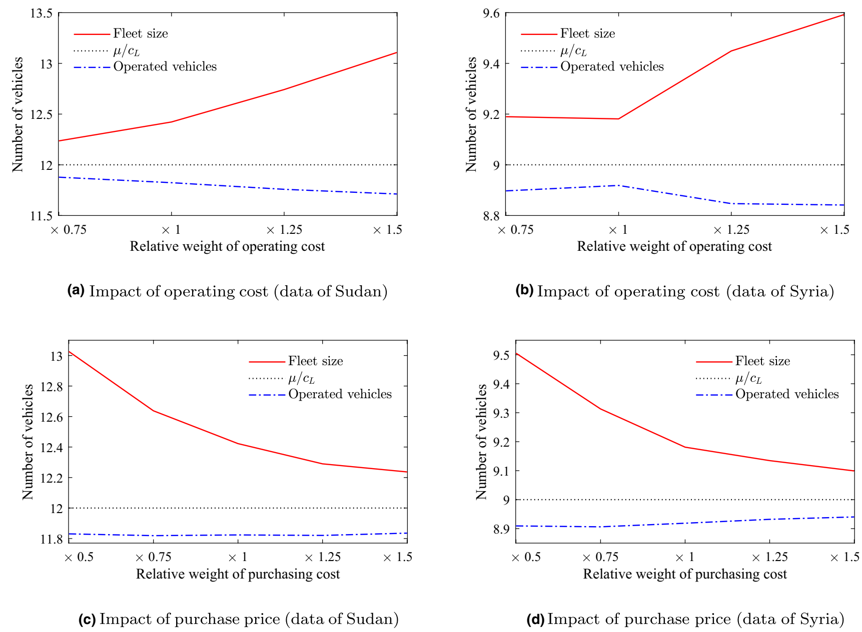
5. Model Extensions

We extend our model in four directions; We analyze the impact of the flexibility on budget savings, as well as the impact of procurement lead time on the expected deprivation costs and fleet utilization. Then, in Appendices D and E, we demonstrate how to extend the model to a low- and high-cost status vehicle, and to the case of stochastic demand.

5.1. Impact of Flexibility on Budget Savings

In previous sections, we assume that budget can be fully saved for future periods. This may not be always possible (e.g., for earmarked budgets that have to be used within a given period). We extend our model to allow for partial savings by introducing a new parameter $0 \le \rho \le 1$ that indicates the flexibility of savings; a value of $\rho = 1$ corresponds to the model that we have studied thus far in which saving is fully possible, while a value of $\rho = 0$ refers to a situation in which the budget has to be spent entirely in the same period in which the funding is received. We can incorporate this new parameter by updating the state Equation (9) to

Figure 6 Impact of the Operating Cost and Purchasing Price on Fleet Utilization [Color figure can be viewed at wileyonlinelibrary.com]



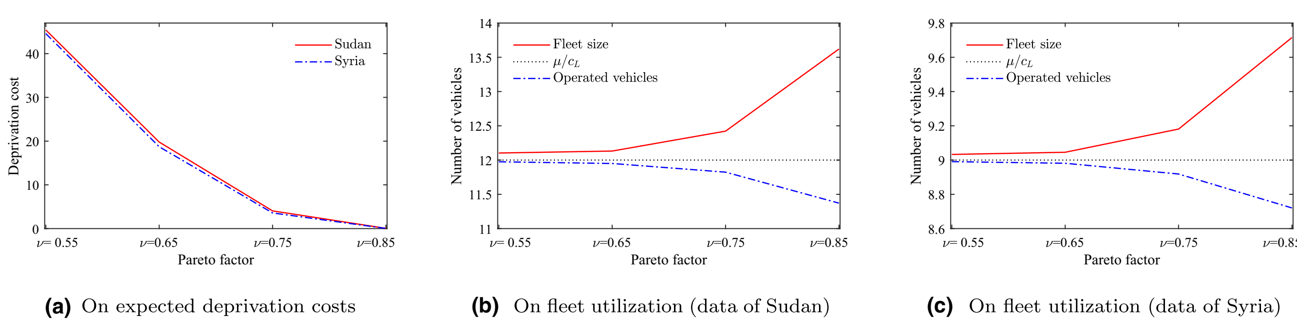
(a) Impact of operating cost (data of Sudan)

(b) Impact of operating cost (data of Syria)

(c) Impact of purchase price (data of Sudan)

(d) Impact of purchase price (data of Syria)

Figure 7 Impact of the Differences in Mission Criticality on Expected Deprivation Costs and Fleet Utilization [Color figure can be viewed at wileyonlinelibrary.com]



(a) On expected deprivation costs

(b) On fleet utilization (data of Sudan)

(c) On fleet utilization (data of Syria)

$$SB_{t+1} = \min\{\rho S_t + r(x_t - L(x_t)) + K_{t+1}, SB^{max}\}. \quad (23)$$

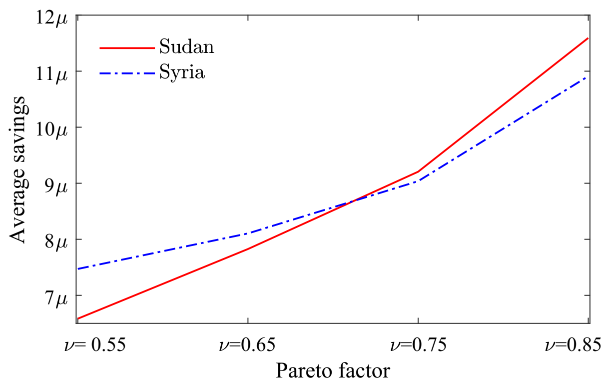
Because the SAO heuristic has been designed for full savings flexibility, we numerically determined the optimal policy for analyzing the impact of parameter ρ on the results and show the results for the data of Sudan in Figure 10. We obtain similar results for the data of Syria. Figure 10a and b indicate that the possibility of budget savings can significantly reduce the expected deprivation costs, regardless of the budget variation and differences in mission criticality. The importance of saving seems to be particularly critical when the budget variation is high.

The opportunity for budget savings between periods seems to neutralize the negative effect of budget uncertainty to some degree. This result confirms that a non-earmarked budget, which can also be used for later periods, has more value than earmarked budgets. Interestingly, we also observe that the saving option has a positive impact on fleet utilization (Figure 10c and d). This result is similar to that of Besiou et al. (2014) that shows a negative impact of an earmarked budget on the performance of humanitarian operations.

5.2. Impact of Procurement Lead Time

Besiou et al. (2014) compare vehicle procurement models (i.e., centralized, hybrid and decentralized) by analyzing the procurement costs (e.g., vehicle purchase prices from global versus local markets, lead time costs). They highlight that vehicle procurement costs in a decentralized model (where each office purchases vehicles from the domestic market) are higher than in a centralized model (in which the headquarters purchases vehicles directly from the manufacturer). Their results indicate that for development programs a decentralized model provides a higher

Figure 8 Impact of Differences in Mission Criticality on the Savings Pattern [Color figure can be viewed at wileyonlinelibrary.com]



service level—even in the presence of constraints imposed by earmarking of the budget—driven by the shorter procurement lead time. In their study, service level is defined as the ratio of available vehicles to the total number of required vehicles. We looked at the same question with a different objective function, where service level is based on the expected deprivation costs.

To analyze the impact of procurement lead time on the expected deprivation costs, we define two new models, one with a zero procurement lead time and one with two periods of procurement lead time. The case of one period of lead time corresponds to the standard case described in section 2.

In the scenario with zero lead time, the purchased vehicles in period t are readily available to use in the same period. Thus, to allow for the immediate availability of u_t vehicles, we replace the term x_t with $x_t + u_t$. Likewise, due to unpredictable events (e.g., an accident in the field), all vehicles are equally subject to sudden disposal. Therefore, we have to adapt Equations (7), (9) and (10) with

$$a_t \leq x_t + u_t, \tag{24}$$

$$SB_{t+1} = \min\{S_t + r(x_t + u_t - L(x_t + u_t)) + K_{t+1}, SB^{max}\}, \tag{25}$$

$$x_{t+1} = \min\{L(x_t + u_t), x^{max}\}. \tag{26}$$

In the case of two periods of procurement lead time, the vehicles purchased in period $t-1$ arrive in period $t+1$. Therefore, we have to add a new state variable w_t to address the state of these vehicles in period t. In other words, w_t represents the number of brand-new vehicles that are purchased in period $t-1$ but are added to the fleet in period $t+1$. Thus, we should replace u_t with w_t and replace Equation (10) with

$$x_{t+1} = \min\{L(x_t) + w_t, x^{max}\}, \tag{27}$$

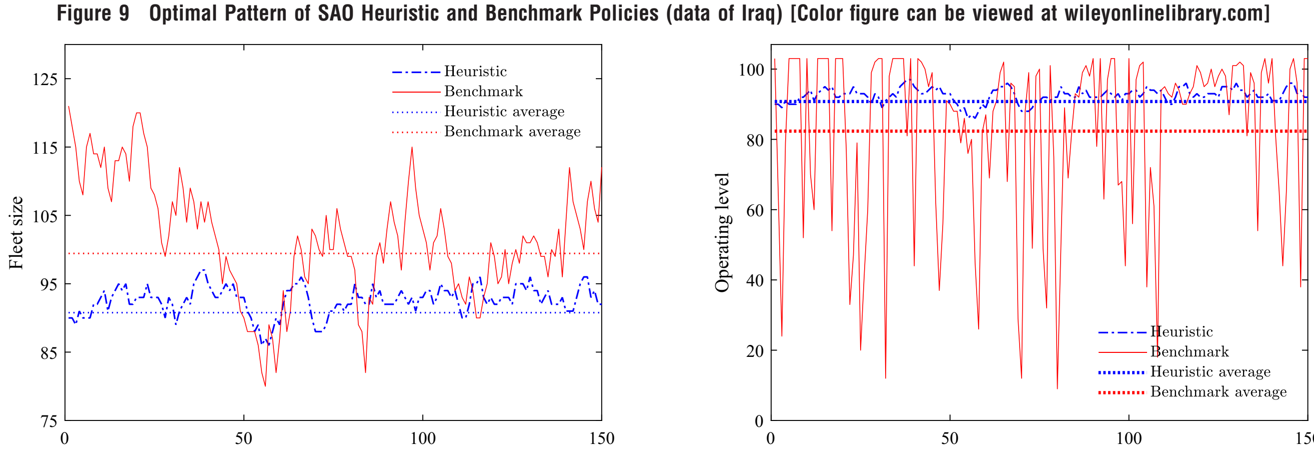
and add the additional constraint

$$w_{t+1} = u_t. \tag{28}$$

Models with lead times longer than two periods can be defined equivalently through the introduction of additional state variables but lead to significantly higher computational complexity.

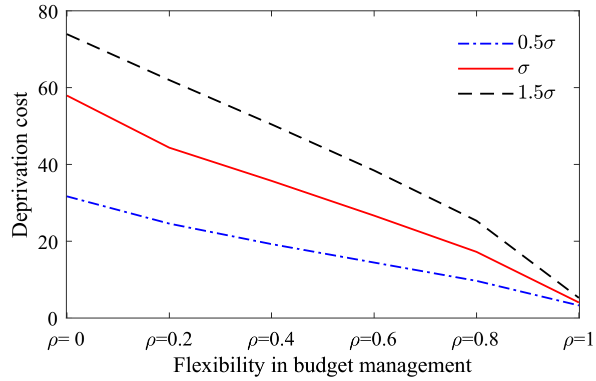
Similar to the trade-off of Besiou et al. (2014), our trade-off is based on the assumption that shorter lead times often come at additional procurement costs. Thus, we compare the impact of higher vehicle procurement costs in the case of zero lead time by considering price mark-ups of 0%, 50% and 100% on the

Figure 9 Optimal Pattern of SAO Heuristic and Benchmark Policies (data of Iraq) [Color figure can be viewed at wileyonlinelibrary.com]

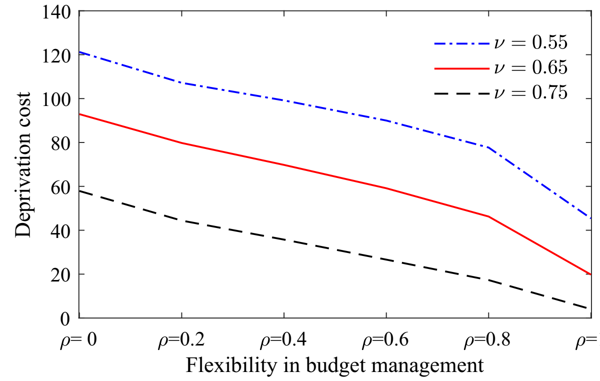


(a) Fleet size over time **(b)** Operating level over time

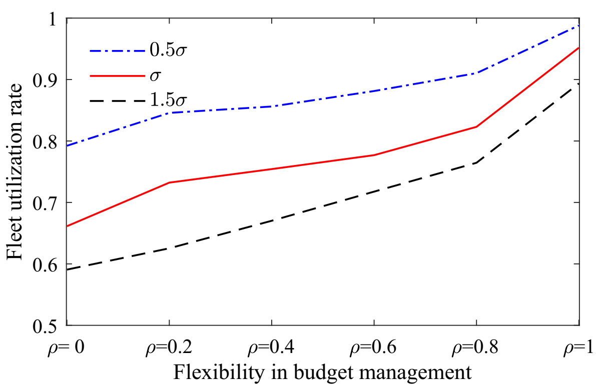
Figure 10 Impact of the Possibility for Budget Saving (optimal policy, data of Sudan) [Color figure can be viewed at wileyonlinelibrary.com]



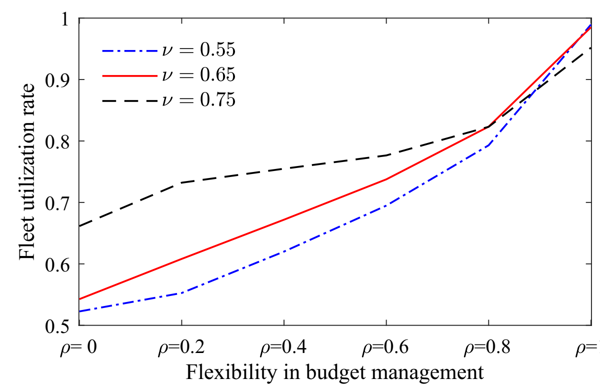
(a) On expected deprivation costs for different budget uncertainties



(b) On expected deprivation costs for different mission criticality values



(c) On fleet utilization for different budget uncertainties



(d) On fleet utilization for different mission criticality values

base vehicle price. Furthermore, we vary the standard deviation of the budget and the rate of vehicle disposal. Table 2 reports the expected deprivation costs for each scenario for Syria, based on the optimal policies. When we introduce a 2-period lead time, the computation times increase significantly. Therefore, we choose Syria that had the smallest fleet size.

The results indicate that a procurement lead time of one period (which corresponds, in our setting, to three months) has a negative impact on the expected deprivation costs only if the manager is able to procure the same vehicle at the same price and with no lead time, which is nearly impossible in the real world. Although decreasing the procurement lead time reduces per se the expected deprivation costs, this effect is mitigated by the vehicle price markups, which limit the financial resources for current and future operations.

In addition, results indicate that the advantages of a centralized fleet policy are particularly strong when the degree of uncertainty is high. Finally, we find that the centralized model is more affected by budget variation; that is, the sensitivity with respect to the budget variation is higher than the sensitivity with respect to the vehicle disposal rate, whereas the decentralized model seems to be more affected by the vehicle disposal rate.

6. Conclusion

In this article, we develop a model for purchasing and operating asset capacity in the setting of humanitarian development programs. The objective of our model is to minimize the expected human suffering due to insufficient capacity of operating assets to deliver humanitarian aid. We extend existing research by considering mission criticality, budget uncertainty and time-restricted budgets, and uncertainty in asset replacement. We develop a heuristic based on a portfolio approach, which achieves close-to-optimal results, with an average optimality gap in our numerical experiments of 0.33%, outperforming existing policies by a wide margin. To develop our model and run numerical experiments, we focus on vehicles

Table 2 Expected Deprivation Costs for Scenarios with Different Lead Time, Total Purchasing Price, Budget Variation, and Dismissal Rate

		σ			γ		
Lead time	Price markup	× 0.5	× 1	× 1.5	× 0.5	× 1	× 1.5
2	—	3.433	3.746	4.160	3.579	3.746	3.800
1	—	3.352	3.579	4.033	3.507	3.579	3.654
0	0%	3.213	3.487	3.884	3.445	3.487	3.491
0	50%	6.540	6.914	7.351	5.102	6.914	8.675
0	100%	10.779	11.296	11.625	7.045	11.296	15.152

representing long-life operating assets that are one of the most critical assets to fulfill humanitarian transportation missions. Based on a real dataset of vehicle fleets in five countries from 2000 to 2015, we perform numerical experiments and derive managerial insights. We also show how to adapt our solution to settings in which some of the model assumptions are violated.

We find that budget variability increases the expected deprivation costs and decreases fleet utilization. Our results indicate that a way to mitigate the negative effects of system uncertainty (such as budget uncertainty) is to allow the offices to save a portion of the budget between periods for future operations. Our results also demonstrate that it is not always preferable to operate all vehicles at full capacity in all periods, which renders fleet management for humanitarian development programs different from fleet management in the commercial sector. Finally, we find that differences in mission criticality, even though they decrease the expected deprivation costs, lead to fewer transportation missions served.

This study also has some limitations. First, we do not explicitly model the repair process of vehicles. It is possible that the repair process of some vehicles takes a considerable amount time and temporarily affects the availability of those vehicles. Second, planning horizon might significantly impact the optimal procurement policies. While this study develops a policy for an infinite time horizon, it is interesting (and valuable for certain HOs) to develop policies when the planning horizon is finite. We believe that this avenue of research could be further developed in other directions as well. It can be developed by empirical analysis and/or analytical work to better understand deprivation costs in humanitarian development settings. Furthermore, while we studied a single-type asset procurement policy, further research could explore multi-type asset settings. Finally, analyzing settings in which an HO should trade-off between operating assets and consumable relief items seems worthwhile.

Acknowledgments

We gratefully thank Luk Van Wassenhove (who facilitated our access to the data), Jason Acimovic, Maria Besiou, and John Fowler (for their comments on earlier versions of this study). We also appreciate the comments shared by the review team that helped us improve the study. Any remaining errors are the responsibility of the authors.

Appendix A. Table of Symbols

Model variables and parameters	
a_t	The operating decision in period t
b	Convexity factor of the deprivation cost function
c_f	Fixed cost of a vehicle per period
c_L	The average per period logistics cost of a vehicle in case of 100% utilization rate
c_o	Operating cost of a vehicle per period
D_m	Average demand
D_t	Demand in period t
γ	The probability of having to dismiss a vehicle in one period
$J_t(x_t, SB_t, \omega_t)$	The average deprivation cost under the optimal policy, with state variables x_t and SB_t, and demand phase ω_t
K_t	Financial donations received at the beginning of period t
$L()$	Part of the fleet size in period t that can be used in period t+1
μ	The average financial donations received per period
n	Number of periods in one cycle
v	Pareto parameter identifying the relative importance of the transportation missions
ω_t	Demand phase at period t
p	Purchasing cost of a vehicle
r	Residual value of a dismissed vehicle
R_t	The deprivation cost incurred in period t
S_t	Budget remaining as savings at the end of period t
SB^{max}	Maximum amount of budget
SB_t	Available budget at the beginning of period t
SSL	Social service level
σ	The standard deviation of financial budget
t	Indicator of a period
u_t	The purchasing decision in period t
x^{max}	Maximum number of vehicles
x_t	Available vehicles at the beginning of period t
Heuristic and benchmark variables and parameters	
a_t^b (u_t^b)	Benchmark operating (purchasing) policy in period t
a_t^h (u_t^h)	The heuristic policy for operating (purchasing) in period t under a given value of θ
$\bar{a}_t$	Optimal number of vehicles to operate in period t of the simplified problem
b'	Coefficient of the gain function V^s
D_t^k	k^{th} possible realization of demand in period t

(continued)

K	Number of demand realizations in the model with stochastic demand
ϵ_t (ϵ_t^k)	Error term of the demand distribution in period t (k^{th} realization)
$\hat{S}$	Upper threshold for savings
θ	Heuristic parameter
$\bar{u}_t$	Optimal purchasing decision in period t of the simplified problem
$V_t^a(i)$	Social gain from operating i vehicles in period t
$V^s(s\|\theta)$	Estimated social gain from a saving s under the heuristic parameter θ
$V_t^u(i, x_t)$	Estimated social gain from purchasing i vehicles in period t, when the fleet size is x_t

Appendix B. Optimization of the Deterministic Model

The deterministic problem of subsection 3.2 can be written as follows:

$$\min \quad \frac{1}{n}\sum_{t=1}^{n} R_t(\bar{a}_t), \tag{B1}$$

subject to

$$\bar{a}_t \leq x_t, \tag{B2}$$

$$S_t = SB_t - c_f x_t - c_o \bar{a}_t - p\bar{u}_t, \qquad 1 \leq t \leq n \tag{B3}$$

$$SB_{t+1} = \min\{S_t + r\gamma x_t + \mu, SB^{max}\}, \qquad 1 \leq t \leq n \tag{B4}$$

$$x_{t+1} = \min\{(1-\gamma)x_t + \bar{u}_t, x^{max}\}, \qquad 1 \leq t \leq n \tag{B5}$$

$$(x_1, SB_1) = (x_{n+1}, SB_{n+1}), \tag{B6}$$

$$\bar{a}_t, \bar{u}_t \geq 0, \qquad 1 \leq t \leq n \tag{B7}$$

where n was defined as the number of seasons and the minimization is taken over the controls $\bar{u}_t$ and $\bar{a}_t$.

For a simple case of constant demand, Proposition 3 expresses the optimal number of vehicles to operate, $\bar{a}_t$, and the optimal number of vehicles to purchase, $\bar{u}_t$, and describes the system in steady state.

PROPOSITION 3. *For a constant demand,*

- *the optimal number of operating vehicles is equal to the fleet size* $\bar{a}_t = x_t$.
- *the optimal purchasing decision is given by*

$$u_t = \frac{SB_t - c_f x_t - c_o a_t}{p}. \tag{B8}$$

- *the steady state fleet size,* $\bar{x}$, *is given by*

$$\bar{x} = \min\left\{D_m, \frac{\mu}{c_L}\right\}, \tag{B9}$$

where, in the steady state, the number of operating and purchasing vehicles are $\bar{a}_t = \bar{x}$ *and* $\bar{u}_t = \gamma\bar{x}$.

Appendix C. Deriving $V_t^s(s|\theta)$

To design a proper function that estimates the social gain from a certain amount of savings, we note that according to Equation (9), budgets larger than SB^{max} will be lost. Expression $r\gamma x_t + \mu = \mathbb{E}(r(x_t - L(x_t)) + K_{t+1})$ is the expected budget to be received at the end of period t. Therefore, we set the social gain of any value of savings greater than $SB^{max} - r\gamma x_t - \mu$ to zero in our estimation. To simplify, we define the following variable:

$$\hat{S} = SB^{max} - r\gamma\frac{\mu}{c_L} - \mu, \tag{C1}$$

where μ/c_L comes from Proposition 3 and estimates the average fleet size in each period. For any $s < \hat{S}$, the behavior of $V^s(s|\theta)$ should resemble the behavior of $J_t(x_t, SB_t)$ in SB_t, where J_t is the minimum deprivation cost from period t onward. The following lemma presents an important characteristic of J_t.

LEMMA 1. *The average deprivation cost is decreasing in the budget, that is,* $J_t(x_t, SB_t, \omega_t)$ *is (non-strictly) decreasing in* SB_t.

Since the objective in Equation (18) is to maximize the social gain, which is the inverse of the objective in the main model (minimization of the deprivation costs), we need to propose a function V^s that is increasing in s, so that it provides a similar behavior. Moreover, since our value function is the sum of exponential functions, we also use an exponential function for V^s. We assume $V^s(s|\theta) = -e^{b'(\theta\hat{S} - s)} + b''$, where θ is the heuristic parameter. b' and b'' are functions of θ, where we use the following equations to determine their values:

$$V^s(0|\theta) = 0, \tag{C2}$$

$$V^s(\hat{S}|\theta) = e^{bD_m}. \tag{C3}$$

Equation (C2) implies that the expected social gain from no saving is zero, while Equation (C3) expresses that for any $s \geq \hat{S}$, the expected social gain is equal to the social gain from satisfying all the demands in one period. Therefore, $V^s(s)$ can be written as in Equation (17), where b' and b'' are calculated by solving the following equations:

$$e^{b'\hat{S}\theta} - e^{b'\hat{S}(\theta-1)} = e^{bD_m}, \tag{C4}$$

$$b'' = e^{b'\theta\hat{S}}. \tag{C5}$$

Appendix D. Extension to a *Status-Based* Costing Model

Let us assume that each vehicle is labeled either as low-cost or high-cost; for example, one may separate between two types of vehicles, new and old, where old have higher cost of maintenance, lower salvage values, and higher probability of disposal. While this classification theoretically makes sense, in practice a new vehicle being used in a conflict zone or in poor geographical conditions might turn to a high-cost status, while a well-maintained old vehicle keeps a low-cost status. Accordingly, let x_t^l and x_t^h refer to the number of low-cost (i.e., fairly fresh) and high-cost (i.e., fairly depreciated) vehicles at period t, respectively. At the end of any period, a low-cost vehicle is disposed with probability γ^l, becomes high-cost with probability γ^{lh}, or maintains its status as new vehicle with probability $1 - \gamma^l - \gamma^{lh}$. A high-cost vehicle is disposed with probability $\gamma^h > \gamma^l$ at the end of a given period. Let c_o^l, c_f^l and r^l refer to the operating cost, fixed cost, and residual value of a low-cost vehicle, while c_o^h, c_f^h and r^h denote the same values for a high-cost vehicle. We assume that $c_o^h \geq c_o^l$, $c_f^h \geq c_f^l$ and $r^h \leq r^l$, which implies that a high-cost vehicles is costlier to operate and to maintain and has lower residual value than a low-cost vehicle.

With few modifications, the SAO heuristic can be adjusted to the extended model. Function $V_t^a(a_t)$ remains unchanged. Function $V_t^u(u_t, x_t^l, x_t^h)$ also remains largely unchanged, except for $L(x_t)$ which is replaced by the function $L(x_t^l, x_t^h)$, taking into account the dismissal probabilities of both vehicle types. The deterministic formulation of the model presented in Appendix B should be adjusted to the new model.

For function V^s, Equation (17) remains unchanged, except for $\hat{S}$, where the term referring to the expected revenue from selling dismissed vehicles has to be updated. Moreover, the value of the key parameter c_L in the new setting is given by

$$c_L = \frac{\gamma^h(c_f^l + c_o^l) + \gamma^{lh}(c_f^h + c_o^h) + \gamma^h(\gamma^l + \gamma^{lh})p - \gamma^h(\gamma^l r^l - \gamma^{lh} r^h)}{\gamma^h + \gamma^{lh}}. \tag{D1}$$

The derivation of c_L is available from the authors on request.

Table E1 Comparison of Expected Deprivation Costs of the SAO Policy under Stochastic Demand and Different Funding Levels (ν = 0.75)

Country	CV	Funding level = 0.50	Funding level = 0.75	Funding level = 1.00
Sudan	0.0	17.25	22.99	1.76
	0.1	18.62	24.34	2.11
	0.2	24.38	30.66	3.89
	0.3	36.51	44.27	10.36
Syria	0.0	16.21	14.17	1.60
	0.1	17.56	15.02	2.08
	0.2	22.94	18.88	3.79
	0.3	34.28	27.30	10.06

It is easy to show that the low-cost vehicles should be used with priority over high-cost vehicles.

Appendix E. Extension to Stochastic Demand

To demonstrate the flexibility of the SAO heuristic, we show how to extend it to situations in which demand is uncertain.

We assume that the demand in each period includes a stochastic term ϵ_t that is identically distributed in periods of the same demand phase and independent between periods, with the expected value of zero ($\mathbb{E}(\epsilon_t) = 0$). Assume that ϵ_t has $K > 0$ realizations, ϵ_t^k, each with known probability $P(\epsilon_t^k)$ and $\sum_{k=1}^K P(\epsilon_t^k) = 1$.

We write the demand in period t under demand scenario k as $D_t^k = \mathbb{E}(D_t) + \epsilon_t^k$. In each period, the decision-maker first observes D_t^k, and then decides upon the operating and purchasing level. Therefore, we need to change V_t^u of Equation (16).

The simplified model for calculating $\bar{a}_t$ in Appendix B needs to be modified to consider stochastic demand by changing the objective function to

$$\min \frac{1}{n} \sum_{t=1}^{n} \sum_{k=1}^{K} R_t(\bar{a}_t | D_t = D_t^k) P(D_t^k). \tag{E1}$$

Under stochastic demand it is not possible to compute the optimal solution and consequently, we cannot compare the results of the SAO heuristic with the optimal performance. Nevertheless, we analyze the performance of the adapted SAO heuristic for different levels of uncertainty.

We calculate the average deprivation costs for the heuristic policy. We modified the second argument of Equation (14) to adapt the benchmark policy to the assumption of stochastic demand. We chose Syria and Sudan between 2000 to 2005, so that we can compare the results with those of the default model presented in Table 1. We set ν = 0.75 and change the funding level from 50% to 100%. We assume that demand follows a Normal distribution in each period and change the coefficient of variation (CV) from 0 to 0.3, where a CV = 0 refers to the default model (Table 1). Table E1 reports the deprivation costs of the SAO heuristic and indicates that the deprivation costs are increasing in the demand variability.

Notes

[1]World Vision International. https://www.worldvision.org/wp-content/uploads/F_630269_16_WorldVision_FS.pdf (accessed date February 9, 2017).

[2]For instance, during 2002–2006, the United Nations High Commissioner for Refugees (UNHCR) spent an average of only USD 9.6 million a year on the purchase of new vehicles. In 2011, the UNHCR's annual operating cost (i.e., procurement, operations, and disposal) of its 6500 light vehicles was estimated to be USD 130 million (Arsenault et al. 2018).

[3]While we choose to consider the average costs as the objective (and show that the limit of Equation (6) exists), an alternative is to consider a discounted sum as the objective function. We refer an interested reader to Severens and Milne (2004).

[4]Throughout this project, we held discussions with executives of the International Committee of the Red Cross (ICRC), Mercy Corps, American Red Cross, Catholic Relief Services and several freelance consultants specializing in the humanitarian sector.

[5]The source organization of our data is the same as Eftekhar and Van Wassenhove (2016). However, the sample countries (or locations) are different.

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Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Appendix S1: Proofs and Other Supporting Material.