Proceedings of the IISE Annual Conference & Expo 2023
K. Babski-Reeves, B. Eksioglu, D. Hampton, eds.

Logistics Planning for Disaster Housing Assistance under Demand Uncertainty

Abstract ID: 1734

Abstract

We propose and study a framework for disaster housing logistics planning under demand uncertainty. Specifically, we utilize the two-stage chance-constrained stochastic programming models here to achieve the balance between logistics operational cost and its resiliency towards extreme disastrous situations. This consideration is reflected in utilizing two operational modalities, one for the ordinary modality and the other for the emergency modality, and the emergency modality is only allowed to be activated for a limited number of scenarios among all that may arise, according to the underlying uncertainty associated with a linear regression model for characterizing the disaster housing demand based on a selected number of independent variables from historical data. Preliminary numerical results based on a case study on Hurricane Ian have shown the effectiveness of the proposed approach and provided managerial insights in disaster housing logistics planning.

Keywords
Disaster housing recovery, logistics planning, optimization under uncertainty, linear regression

1. Introduction

Direct housing is considered as the "last resort" in disaster housing assistance. It consists of preparing and mobilizing temporary housing units such as travel trailers and manufactured housing units (MHU) directly to the disaster victims to serve their housing needs after a major disaster. An effective direct housing plan is critical under extreme circumstances where the consequences of a disaster event are so severe that even exhausting all rental units will not be able to fully satisfy the housing demand from victims that are displaced by the disaster event. Prolonged displacement caused by a disaster event has been shown to result in significant social issues, such as unemployment and mental illness [1]. Direct housing plans must be constantly improved to address the logistics cost as well as the social cost.

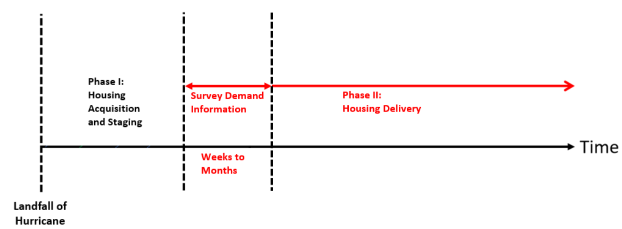

Figure 1: Timeline of operation: The housing preparation phase starts right after the hurricane makes landfall with some estimated demand information. The housing delivery/allocation phase starts after the housing demand information is collected.

To build such a logistics plan for direct housing assistance, it is essential to understand and incorporate the uncertainty in housing demand brought by the disaster event, with a focus on hurricane disasters in this paper. In order to ensure timely delivery, the logistics operation of direct housing assistance needs to commence shortly after the onset of the disaster event, such as a major hurricane's landfall, where only a rough estimation of the housing demand is available (See Figure 1). The actual demand information from victims, e.g., through FEMA's Individual Assistance (IA) program, can take weeks or even months to collect. The discrepancy between the estimated and the actual demand data, if left unaddressed, can lead to either over-preparation or under-preparation, both of which can incur significant economic and social costs. For instance, FEMA purchased more MHUs than needed in Texas after Hurricane Harvey in 2017, leading to unnecessary expenditure of up to $152 million [11]. Conversely, the under-utilization of disaster housing assistance led to 11,000 families in emergency shelters for nearly six weeks after the storm during Hurricane Sandy in 2012 [10]. Addressing the uncertain housing demand is critical to an effective disaster housing plan.

In this study, we apply a regression model based on historical data to predict housing demand given a set of selected explanatory predictors (variables). This regression model not only gives a point estimate for the housing demand given the values for the explanatory predictors, but also quantifies the prediction error/uncertainty, enabling us to generate a set of demand scenarios to incorporate into the disaster housing logistics planning. We propose and study a two-stage chance-constrained stochastic programming model for the logistics planning for disaster housing under demand uncertainty. In the first stage, planning decisions on housing acquisition and staging are made with predicted housing demand information to minimize the total expected logistics and social cost. In the second stage, operational decisions are made after the actual housing demand is realized. Furthermore, with the goal of creating a plan that is effective in most scenarios, while being capable of addressing the extreme scenario of having unexpectedly high demand, we introduce two contingency modalities for the second stage, the *ordinary modality* and the *emergency modality*. For the ordinary modality, all housing allocation decisions are made based on the housing acquisition decision in the first stage, and no emergency acquisition is allowed. For the emergency modality, we allow emergency acquisition decisions at the expense of a higher cost. Since the emergency modality should only be activated in the most extreme situations where an unexpectedly high demand is realized, we limit the chance that an emergency modality is activated among all scenarios to be under a given threshold, giving rise to a chance-constrained model. We evaluate this model in a case study and compare its performance with that of a *single-stage chance-constrained* model and a *wait-and-see* model. The single-stage chance-constrained model aims to satisfy the demand for most scenarios without considering the second-stage recourse decision, whereas the wait-and-see model only makes the housing logistics decisions after the actual demand is realized. We perform a variety of sensitivity analyses on key parameters, from which we gain some managerial insights to this problem.

2. Literature Review

In this section, two relevant topics are reviewed. First, we review the disaster relief problems solved by stochastic programming most relevant to our research. Then, we review the papers on disaster housing assistance planning.

Even though the literature on disaster relief covers an extensive range, studies of emergency supply planning are the most relevant to this study. Emergency supply planning aims to preposition emergency supplies by integrating pre-disaster and post-disaster operations. Stochastic programming is often used in the planning to deal with various sources of uncertainty created by the disaster. Paul and Zhang [2] developed a two-stage stochastic programming model for hurricane preparedness. The goal of the model is to determine the location of distribution points, medical supply levels, and transportation capacity before the hurricane, and make transportation decisions after the hurricane. Similar hurricane preparedness studies can be found, for example, in [3, 4].

Compared with the general topic of disaster relief, the literature on disaster housing assistance planning is limit. Most of the relevant literature focuses on developing and testing housing design strategies [5], and applying optimization models [6] and simulation approaches [7] to tackle key decision-making trade-offs associated with disaster housing's key attributes such as locations, structures, and costs.

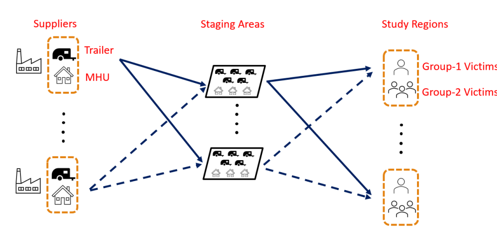

Figure 2: Illustration of the disaster housing logistic network considered in our problem.

3. Problem Description

We consider a logistics planning problem for direct disaster housing, which mainly concerns the planning decisions on disaster housing acquisition and staging shortly after a major hurricane makes landfall, and operational decisions on housing allocation after the disaster housing demand is realized. We model the logistics system as a network (see Figure 2 for an illustration) with three types of nodes: the disaster housing suppliers I, the staging areas W, and the study regions J. We consider a set P of different types of houses and a set G of different types of victim groups. Each group $g \in G$ has its preference for different types of houses. For example, a household with more than four members prefers MHUs over trailers due to the larger size of the MHUs. Allocating a housing type that is less desirable to a victim group will incur a mismatch penalty cost. To incorporate the uncertainty in the disaster housing demand into our model, we consider a set of K scenarios, each of which gives a set of housing demand realizations at the study regions. Below we provide a list of input parameters to our model:

$C_{s,w,p}$: unit transportation cost from supplier $i \in I$ to staging area $w \in W$ for type $p \in P$ houses.

$C_{w,j,p}$: unit transportation cost from staging area $w \in W$ to victims in region $j \in J$ for type $p \in P$ houses.

$O^F_{i,p}$: unit first-stage acquisition cost of type $p \in P$ houses from supplier $i \in I$.

$O_{i,p}^{S}$: unit second-stage acquisition cost of type $p \in P$ houses from supplier $i \in I$ (under the emergency modality).

U_w: inventory capacity of staging area $w \in W$.

u_p: amount of inventory capacity occupied by each type $p \in P$ house.

E_i: total production resources available at supplier $i \in I$.

$e_{i,p}$: production resources consumed by producing each type $p \in P$ house for supplier $i \in I$.

$D_{j,g}^{k}$: amount of demand for group $g \in G$ victims in region $j \in J$ in scenario $k \in K$.

$R_p^g \in \{0,1\}$ whether or not if group $g \in G$ victims can accept type $p \in P$ houses.

$C_{j,p,g}^{M}$: unit penalty cost incurred by fulfilling demand from group $g \in G$ victims using types $p \in P$ houses in region $j \in J$.

$C_{j,g}^{U}$: unit penalty cost incurred by unmet demand for $g \in G$ victims in region $j \in J$.

$C_{w,p}^{V}$: unit penalty cost incurred by unused inventory for type $p \in P$ houses in staging area $w \in W$.

In our decision making framework, the first-stage problem determines the acquisition and staging decisions on disaster houses, while the second-stage problem focuses on the delivery decisions to the demand study regions under each scenario. We use the notation below for the decisions of interest:

- First-stage decision variables: $x_{i,w,p}$ denotes the number of type $p \in P$ houses delivered from supplier $i \in I$ to staging area $w \in W$.
- Second-stage decision variables: $y_{w,j,t,g}^{k}$ denotes the number of type $t \in T$ houses delivered from staging area $w \in W$ to region $j \in J$ to satisfy group $g \in G$ housing demand in scenario $k \in K$. $r_{j,g}^{k}$ denotes the unmet demand for group $g \in G$ victims in region $j \in J$ in scenario $k \in K$. $v_{i,j,g}^{k}$ denotes the emergency order and delivery for group $g \in G$ victims from supplier $i \in I$ to region $j \in J$ in scenario $k \in K$. $\ell_{w,t}^{k}$ denotes the unused inventory of type $t \in T$ houses in staging area $w \in W$ in scenario $k \in K$.

As mentioned earlier, we provide two contingency modalities for the second-stage problem, the ordinary modality and the emergency modality. Under the ordinary modality, the housing allocation decisions are made based on the first-stage acquisition and staging decisions, without the opportunity to obtain additional housing units. Under the emergency modality, emergency acquisition and delivery decisions are permitted. Next, we present the formulations of the second-stage problem under the ordinary modality and the emergency modality.

$$\textbf{(Ordinary)}\ f(x,k) = \min_{y} \sum_{w\in W}\sum_{j\in J}\sum_{p\in P}\sum_{g\in G} C_{w,j,p} y_{w,j,p,g}^{k} + \sum_{j\in J}\sum_{g\in G} C_{j,g}^{U} r_{j,g}^{k}$$
$$+ \sum_{j\in J}\sum_{w\in W}\sum_{p\in P}\sum_{g\in G} C_{j,p,g}^{M} y_{w,j,p,g}^{k} + \sum_{w\in W}\sum_{p\in P} C_{w,t}^{V} \ell_{w,p}^{k} \tag{1a}$$
$$\text{s.t.} \sum_{j\in J}\sum_{g\in G} y_{w,j,p,g}^{k} + \ell_{w,p}^{k} = \sum_{i\in I} x_{i,w,p},\ \forall w \in W, p \in P \tag{1b}$$
$$r_{j,g}^{k} + \sum_{w\in W}\sum_{p\in P} y_{w,j,p,g}^{k} = D_{j,g}^{k},\ \forall j \in J, g \in G \tag{1c}$$

All variables are nonnegative

$$\textbf{(Emergency)}\ \bar{f}(x,k) = \min_{y} \sum_{w\in W}\sum_{j\in J}\sum_{p\in P}\sum_{g\in G} C_{w,j,p} y_{w,j,p,g}^{k} + \sum_{j\in J}\sum_{g\in G} C_{j,g}^{U} r_{j,g}^{k}$$
$$+ \sum_{j\in J}\sum_{w\in W}\sum_{p\in P}\sum_{g\in G} C_{j,p,g}^{M} y_{w,j,p,g}^{k} + \sum_{j\in J}\sum_{i\in I}\sum_{p\in P}\sum_{g\in G} C_{j,p,g}^{M} v_{i,j,p,g}^{k}$$
$$+ \sum_{w\in W}\sum_{p\in T} C_{w,p}^{V} \ell_{w,p}^{k} + \sum_{i\in I}\sum_{j\in J}\sum_{p\in P}\sum_{g\in G} O_{i,p}^{s} v_{i,P,j,g}^{k} \tag{2a}$$
$$\text{s.t. (1b)}$$
$$r_{j,g}^{k} + \sum_{i\in I}\sum_{p\in P} v_{i,j,p,g}^{k} + \sum_{w\in W}\sum_{p\in P} R_t^g y_{w,j,p,g}^{k} = D_{j,1}^{k},\ \forall j \in J, g \in G \tag{2b}$$

All variables are nonnegative

The objective function (1a) minimizes the total cost of shipping, unmet demand penalty, mismatch penalty, and unused inventory penalty. Constraints (1b) represents the inventory balance between the first-stage and second-stage decisions. Constraints (1c) ensure the flow balance in each study region between housing supply and demand. The emergency modality model is similar to the ordinary modality model, except that we have an extra set of decision variables to represent the emergency acquisition decisions. Based on the two modalities, the proposed two-stage chance-constrained stochastic programming model is given by:

$$\min \sum_{i\in I}\sum_{w\in W}\sum_{p\in P}(C_{i,w,p}+O^F_{i,p})x_{i,w,p}+\frac{1}{|K|}\sum_{k\in K}((1-z_k)f(x,k))+z_k\bar{f}(x,k)) \tag{3a}$$

$$\text{s.t. } z_k=0 \Rightarrow x\in P_k, k\in K \tag{3b}$$

$$\sum_{k=1}^{|K|} z_k \leq \varepsilon\cdot K \tag{3c}$$

$$\sum_{i\in I}\sum_{p\in P} u_1 x_{i,w,p} \leq U_w,\ \forall w\in W \tag{3d}$$

$$\sum_{w\in W}\sum_{p\in P} e_{i,p}x_{i,w,p} \leq E_i,\ \forall i\in I \tag{3e}$$

$$z_k\in\{0,1\}, k\in K, x \text{ is nonnegative}$$

The objective function (3a) minimizes the total expected cost of purchase, shipping and second-stage expected cost under the limitation of staging area capacity (3d) and supplier productivity (3e). (3b) and (3c) limit the number of scenarios that the emergency modality can be activated, where ε is the user-specified risk tolerance parameter, and P_k represents the feasible region of the decisions in scenario k under the normal modality, which is defined as:

$$P_k=\left\{x \mid \exists y^k, r^k, \ell^k \text{ such that (1b),(1c) hold}\right\}.$$

4. Case Study: Disaster Housing Logistics Planning for Hurricane Ian

In this section, we present the experiment results of the proposed approaches via a case study based on Hurricane Ian 2022, with Florida (FL) as the study region. Hurricane Ian caused extensive damage, estimated to be between $50 billion and $65 billion damages, after its landfall in western Florida with extreme winds and torrential rain. Mandatory evacuation orders were issued for parts of multiple counties. However, post-disaster disaster housing assistance was inefficient and delayed [8]. In Section 4.1, we start with how we apply the linear regression model to predict the disaster housing demand based on a selected set of explanatory predictors, including the hurricane attributes and, geographical features, as well as socioeconomic information of the study regions. In Section 4.2, we show how to apply our framework to the case and present some preliminary computational results. In Section 4.3, we present our sensitivity analysis results on key parameters.

4.1 Linear Regression

To apply linear regression, we collected the disaster direct housing demand data, the hurricane severity level data, and socioeconomic indicators data. The demand data is inferred from the OpenFEMA Dataset on major hurricanes by converting the amount of financial assistance allocated via the Individual Assistance (IA) program into the number of trailers and MHUs, FEMA's customary housing unit types, based on their market prices. Collected hurricane severity level data include: (i) the number of days that a county experienced a certain sustained wind speed from NOAA's (National Oceanic and Atmospheric Administration) HURDAT2 database; (ii) the high water marks from USGS's (U.S. Geological Survey) database, and (iii) the distance between the study region and the hurricane's landing location. The collected socioeconomic indicators data includes the social vulnerability index (SVI) from ATSDR (Agency for Toxic Substances and Disease Registry), population, homeownership numbers and the number of housing units from U.S. Census Bureau. After all the datasets are collected, we perform data aggregation into the county level, ending up with 156 data points in total. We perform two separate linear regressions, one for the trailer demand and the other for the MHU demand. These two regression models are used to generate demand scenarios for the two types of houses. We input the hurricane severity level data and the socioeconomic data to the model and generate different scenario demands by sampling the error distribution from the linear regression model.

4.2 Preliminary Experiments and Numerical Results

In this section, we present preliminary results for the proposed two-stage chance-constrained model (denoted “TS") compared to the static (single-stage) chance-constrained model (denoted “SS") and the wait-and-see model (denoted “WS"). The SS model gives preparation decisions only without considering the post-hurricane logistics costs and unused penalty costs. On the other hand, the WS model makes no planning decisions and only makes acquisition and delivery decisions after collecting the actual housing demand. We test the performance of each model with the same set of scenarios sampled from the regression model explained above. We implemented all the models via Gurobi Python API, solved by Gurobi 10.0 (Gurobi Optimization, Inc., 2023) with default parameters. All the experimental results were conducted on a single-thread 3.00GHz CPU with 8GB RAM.

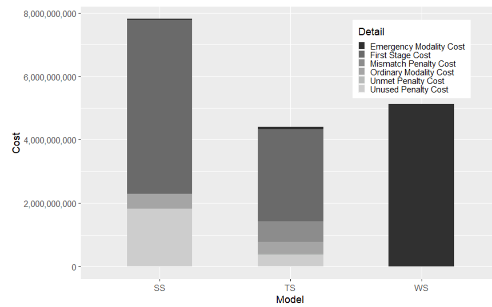

Figure 3: Comparison between models.

We consider the following setting for the logistics network in this case study. For the supplier locations, we chose Selma, AL (center of Dallas County), Beeville, TX (center of Bee County), and Cumberland, MD (center of Allegany County). Note that these counties are the actually home to FEMA’s permanent disaster housing storage sites. For the staging areas, four locations were randomly picked from Florida’s boundary inland. For the study regions, all counties in FL were selected. The distance between each location were calculated by Google map, and the unit transportation cost (per mile) was set to be \$10. The first-stage acquisition cost of a trailer and an MHU were \$33,364 and \$73,735 [9], respectively, and the emergency acquisition cost is set to 1.5 times higher as a default. For each staging area, the unit penalty cost incurred by unused inventory were set to be $0.1\times$\$33,364 and $0.1\times$\$73,735 for trailers and MHUs, respectively. For each county, we set the unit penalty costs incurred by unmet demand for each type of house as c times its acquisition cost, where c was randomly sampled from a uniform distribution $U(2,6)$. Similarly, the unit mismatch cost is randomly sampled from a a uniform distribution $U(0,1.5)$. The risk tolerance parameter for the two chance-constrained models, SS and TS, is set to be 5%.

Figure 3 shows the total expected cost, as well as the breakdowns of the first-stage cost, planning costs, and penalty costs under at most 5% of all scenarios activating the emergency modality with $|K| = 100$. Their cost structure is distinct. It is clear that all the costs of WS come from emergency modality costs since all its decisions are made after the actual demand data is realized. Also, no penalty cost is incurred for WS due to such perfect demand information. The two most considerable portions of the total cost of SS are the first-stage acquisition and staging cost, and the unused inventory penalty cost, respectively. In our setting, SS makes acquisition and logistic decisions to satisfy housing demands in all but the worst 5% of the scenarios (in terms of the demand levels). As long as the worst scenario of the remaining scenarios remains large enough, the cost of acquisition and logistic decisions remain large. Also, making such decisions by neglecting the impact of the unused penalty in the objective function, SS results in a high unused penalty cost and almost zero shortage cost. Unlike SS, TS makes acquisition and logistics decisions by considering the second-stage recourse decisions with two possible modalities, and incorporating mismatch penalty, unmet penalty, and unused penalty costs. Another difference is that TS addresses the worst 5% of the scenarios with emergency modality. Overall, we observe that TS can make more effective logistics decisions that balance operational decisions in the second stage, unused penalty, mismatch penalty, and unmet penalty.

4.3 Sensitivity Analyses

Depending on regional differences, people have varying tolerances for the housing demand shortage, and TS can give corresponding acquisition and logistics decisions on adjustment of the unmet penalty parameter. When the expected housing shortage in a region is not acceptable, we can raise the value of the unmet penalty parameter until the housing shortage is at an acceptable threshold. Indeed, increasing the value of the unmet penalty parameter leads to an increase in total cost. Figure 4 shows the trade-off on the MHU between shortages and total cost. On the other hand, SS does not consider any penalty, so the SS solution stays the same. The same process can be used to address the nonacceptance of expected housing mismatch costs and the nonacceptance of expected unused housing costs.

It may appear that the performances of TS and WS are similar with our baseline setting according to Figure 3. However, the gap between TS and WS becomes unlikely to ignore when we incorporate the *deprivation cost*, which is defined as the economic value of the human suffering caused by the lack of a good or service. Since WS only starts housing acquisition after observing the actual demand, it takes much longer for victims to receive the houses under WS, leading

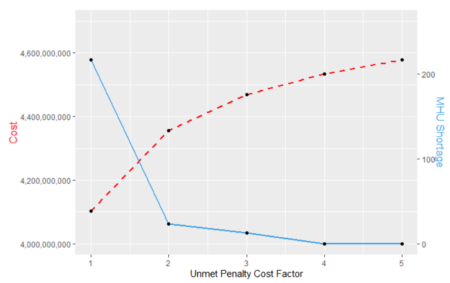

Figure 4: Sensitivity analysis: the impact of the unmet penalty cost factor.

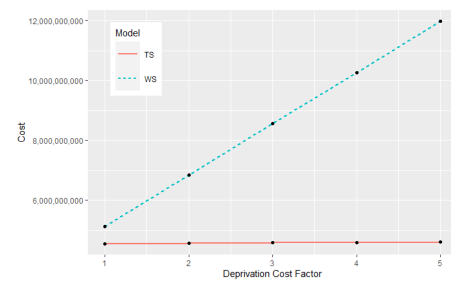

Figure 5: Sensitivity Analysis: the impact of the deprivation cost factor.

to a much higher deprivation cost than TS. In Figure 5, we show that the performance gap between TS and WS becomes significantly large as we increase the deprivation cost factor in the objective function.

5. Conclusion

In this work, we have proposed a modeling and solution framework for the direct disaster housing planning problem under demand uncertainty. We have formulated the problem as a two-stage chance-constrained stochastic program with disaster housing scenarios generated in a data-driven fashion based on a linear regression model that characterizes the housing demand based on a selected set of explanatory predictors. We have conducted a preliminary experiment with a case study for Hurricane Ian, based on which we have shown the advantage of the proposed model compared to some alternative approaches. For future research directions, we will investigate other factors affecting the distribution of housing demand and gain a deeper understanding of each potential factor. In addition, the model can be more granular by including more logistics details, possibly with the help of a time-indexed formulation, to better quantify the deprivation time for housing delivery.

References

[1] Hori, M., & Schafer, M. J. (2010). Social costs of displacement in Louisiana after Hurricanes Katrina and Rita. Population and environment, 31(1), 64-86.

[2] Paul, J. A., & Zhang, M. (2019). Supply location and transportation planning for hurricanes: A two-stage stochastic programming framework. European Journal of Operational Research, 274(1), 108-125.

[3] Sütiçen, T. C., Batun, S., & Çelik, M. (2022). Integrated reinforcement and repair of interdependent infrastructure networks under disaster-related uncertainties. European Journal of Operational Research.

[4] Sanci, E., & Daskin, M. S. (2021). An integer L-shaped algorithm for the integrated location and network restoration problem in disaster relief. Transportation Research Part B: Methodological, 145, 152-184.

[5] Wagemann, E. (2017). Need for adaptation: transformation of temporary houses. Disasters, 41(4), 828-851.

[6] El-Anwar, O., & Chen, L. (2016). Automated community-based housing response: offering temporary housing solutions tailored to displaced populations needs. Journal of Computing in Civil Engineering, 30(6), 04016019.

[7] Perrucci, D. V., & Baroud, H. (2021). Temporary housing operations: A simulation-based inventory management approach using the newsvendor model. International Journal of Disaster Risk Reduction, 65, 102512.

[8] Knapp, K. FEMA: Out of 3,200 Requests for a Trailer, Only 13 Southwest Florida Families Are in One. FOX4. https://www.fox4now.com/news/local-news/lee-county/fema-out-of-3-200-requests-for-a-trailer-only-13-southwest-florida-families-are-in-one?_amp=true. Last access: December 3, 2022.

[9] Squerciati, J. (2020). Disaster Recovery Alternative Housing Study Findings Report.

[10] Sewell, A. (2012). FEMA has up to 1000 trailers — why not give to Sandy victims? Digit J.

[11] McCauley, S. (2020). FEMA Purchased More Manufactured Housing Units Than It Needed in Texas After Hurricane Harvey, OIG Report OIG-20-15.