Cost-Effectiveness of Vehicle Barriers and Setback Distance for Protecting Buildings from Vehicle Bomb Attack

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**Abstract:** Decision-making regarding implementing measures to protect buildings from vehicle bomb attack is often undertaken using highly judgment-based risk processes. This paper presents a quantitative risk-cost model for using vehicle barriers to create setback distance around a new office building. The model explicitly considers both the attack probability, and the damages in the event of an attack (both target building and collateral), as well as how both of these might change as mitigation measures are implemented. The attack damages are assessed using a new empirical blast model, which adapts the estimation methods used by the U.S. Geological Survey for earthquake damages, and is based on data from three well-studied vehicle bomb attacks. Monte Carlo simulation is used to carry the uncertainty in the inputs through to the final results. The model outputs are the mitigation costs, the attack damages, the “breakeven” attack probability (at which the benefits of the mitigation justify its costs), and the cost per statistical life saved (assuming an attack). The results suggest that this mitigation option is cost-effective only when the attack probability (for the case without the mitigation measures present) is rather high.

**Keywords:** terrorism risk, vehicle bombs, Monte Carlo simulation, value of a statistical life

1. **BACKGROUND**

Vehicle-borne improvised explosive devices (VBIEDs) are a favored terrorist weapon. Davis [1] calls them “stealth weapons of surprising power and destructive efficiency” – the “poor man’s air force” – and notes that over a person of 25 years, VBIED attacks have occurred in at least 58 countries. However, decision-making regarding blast protection for buildings is often undertaken using highly judgment-based risk processes. First, a design basis threat (that is, size of bomb) is specified, and a portfolio of mitigation measures is selected. The damages with the mitigation are then assessed and, if deemed to be reasonable, the cost is examined. If either the damages or the mitigation cost are deemed to be unreasonable, the portfolio of mitigation measures is reworked. As such, the attack probability tends to be treated as binary, with the benefits and costs of the mitigation examined somewhat separately of one another [2,3,4,5,6,7,8,9,10]. The need for more risk-informed methods for blast protection – including greater consideration of uncertainties – has been widely recognized [6,9,11,12,13,14,15,16,17,18].

2. **PREVIOUS WORK**

Various works (e.g., [11,13,15,16]) examine protective design using a quantitative risk framework, but rely on highly simplified assumptions regarding the avoided damages and costs (e.g., 90% reduction in risk for a 10% increase in building construction costs). Foo et al. [14] offer a blast risk assessment method for buildings; however, their model does not account for progressive structural collapse, and many aspects of it are not overly transparent.

3. **BLAST PRIMER**

When a high explosive detonates, a blast (or shock) wave is created that propagates through the air at multiple kilometers per second. Upon reaching a particular point, the pressure at that point rises abruptly.
to a peak overpressure, $P$ – perhaps many times atmospheric (ambient) pressure. The overpressure then falls back to atmospheric quasi-exponentially – ending the positive phase. The duration of the positive phase is measured in milliseconds, and the time integral of the overpressure during this period is the impulse, $I$. The overpressure then drops below zero for a time (the negative phase), before eventually returning to atmospheric. Soon after detonation, the blast wave engulfs the building – first loading the windows, façade, and exterior columns, and then entering the structure – pushing on the floor slabs and exposing the occupants directly to the airblast – and finally loading the structure globally, with inward pressure on all sides. Common causes of death and injury in VBIED attacks include flying debris (e.g., window glazing), being propelled against a rigid object (e.g., wall), and, in particular, structural collapse [6,8,19]. In analyses of blast phenomena, the cube root scaled distance is often used, defined as

$$Z \equiv \frac{R}{W^{\frac{1}{3}}}$$ (1)

where $R$ (m) and $W$ (kg) are the standoff distance from and TNT equivalent mass of the charge (or the mass of TNT needed to produce the same effects), respectively. Theoretical and empirical analyses over a wide range of charge weights show that the detonation of two explosives of identical shape – but unequal masses – yields the same peak overpressure at a given scaled distance [6,19].

The scaled distance (Equation 1) predicts that blast loads will decrease rapidly with distance, and so many authors contend (e.g., [5,6,8,16,20]) that setting a building back from all vehicle-accessible points is one of the most cost-effective blast mitigation options. This paper presents a quantitative risk-cost model for using vehicle barriers to create setback distance around a new office building. Many aspects of blast risk analysis are highly uncertain [6,11,12,13,15,17], so a stochastic approach is taken, with Monte Carlo simulation (100,000 trials) used to propagate the uncertainty in the inputs through to the predictions.

4. MITIGATION COSTS

The costs are assumed to be comprised of expenses for additional land (assuming no land around the building in the no mitigation case) and for the vehicle barriers themselves, and to be repaid over a 30 years, at 8% interest, with a 10% down payment, and to become sunk once incurred. The building footprint (and lot) is rectangular, with length (left to right) and depth (front to back) of $L$ and $D$ (m), respectively. The vehicle barriers span the entire lot perimeter, creating a setback distance of $R$ (m). The land cost is the product of the additional land area to be purchased and the unit land cost, $U_{\text{land}}$ ($/m^2$), or

$$C_{\text{land}} = (U_{\text{land}}) \cdot (2 \cdot R) \cdot [ (2 \cdot R) + L + D]$$ (2)

Land costs are highly variable. The Federal Bureau of Investigation (FBI) has field offices in 56 cities, each of which also has a federal courthouse. For as many of these as possible (or for a nearby lot, if data for the selected lot could not be located), the lot size and market (not tax assessed) value of the land (not the improvements) were obtained from the website of the local property tax assessor. According to Case [21], this represents the best source of data for local land values. For these properties, $U_{\text{land}}$ (or the ratio of the total land value to the area of the lot) is then well-modeled by a lognormal distribution with mean and standard deviation (non-logged) of $1,090/m^2$ and $4,100/m^2$, respectively ($n=91; \chi^2=11.6; p=0.31$). The mean error in the fitted cumulative distribution function (CDF) is $-1.5\%$ (90% c.i. $-20\%$ to $+17\%$).

For the vehicle barrier, we use anti-ram bollards, which are long, thick cylindrical posts, set in concrete foundations – one of the most common blast mitigation measures. The total bollard cost is

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1 Unless otherwise noted, all costs are in 2012 US$, with inflation adjustments made using the Producer Price Index, across all commodities (data from [http://www.bls.gov/ppi/data.htm](http://www.bls.gov/ppi/data.htm)). Note that a high p-value is sought, as this is the probability that the data are drawn from the distribution.
\[ C_{\text{bollards}} = \left( \frac{U_{\text{bollard}}}{\text{spacing}} \right) \left[ (8 \cdot R) + 2 \cdot (L + D) \right] \] 

where \( U_{\text{bollard}} \) is the unit bollard cost ($/bollard), \( \text{spacing} \) is the center-to-center gap (for which we use a uniform distribution over 1–2 m), and the bracketed term is the perimeter of the lot. For 8-inch diameter concrete-filled pipe bollards, the U.S. Veterans Administration [22] lists a unit cost of $1,100 (in 2012$), and to account for the variability in these costs, \( U_{\text{bollard}} \) is modeled as a lognormal distribution with a coefficient of variation (CoV; or the ratio of the standard deviation to the mean) of 10%.

For the building specifications, we use information from Persily & Gorfain [23], who for 100 randomly chosen U.S. office buildings present distributions for the: number of floors, \( F \); gross floor area, \( A_{\text{gross}} \); and occupant density, \( \rho \) (mean=0.027/m\(^2\), assuming gross floor area is 50% greater than occupied floor area). To solve for the distributions for \( L \) and for \( D \), the area of the building footprint \( (L \cdot D) \) is approximated as the ratio of \( A_{\text{gross}} \) to \( F \) (with the correlation between the two set equal to one), and the aspect ratio of the building’s footprint \( (L/D) \) is specified as a triangular distribution with mode of 2.6 (see Table 2, Oklahoma City) and range of 1–4. We use a floor height of 3.9 m (average of the values from Table 2).

5. NEW EMPIRICAL BLAST DAMAGE MODELS

This section presents a series of new empirical models for VBIED attack damage estimation, some of which were formulated by adopting the methods used to estimate damages from worldwide earthquakes.

5.1. PAGER Earthquake Damage Model

The U.S. Geologic Survey’s (USGS) Prompt Analysis of Global Earthquakes for Response (PAGER) model estimates fatalities [24] and property damage [25] from earthquakes. PAGER models the loss ratio \( (LR) \) – or the expected damage divided by the maximum potential damage – using the CDF of the lognormal distribution (which is bounded between zero and one), as a function of the level of ground shaking (assessed using the Modified Mercalli Index, MMI), with parameters fitted to empirical data.

5.2. Blast Flux

For earthquake hazards (previous), an intensity metric is already available in the form of the MMI. For the case of VBIED attacks, we formulate an analogous intensity metric using the concept of flux, which relates to the flow of a quantity through a surface. The blast flux through a building is defined as

\[ \beta \equiv \left[ \frac{1}{Z} \cdot \frac{1}{\sqrt{L^2 + D^2 + H^2}} \right] = \frac{W^{1/3}}{R \cdot \sqrt{L^2 + D^2 + H^2}} \] 

where \( L, D, \) and \( H \) are the building’s length, depth, and height, respectively. In Equation 4, the first term in the parenthesis assesses the blast intensity, using the (inverse) scaled distance (Section 3), and the square root term gives the distance from one (extreme) building corner to another, thereby accounting for the distribution of the occupants in all three dimensions. The occupant vulnerability is then specified as

\[ V_{\text{blast}} = 10^3 \cdot \beta \cdot \sqrt{V_n \cdot V_s} \] 

where \( V_c \) and \( V_n \) (0<\( V \leq 1 \)) are vulnerability coefficients associated with different building structural and wall types, respectively, which are specified using information from FEMA [7] (Table 1). In Equation 5, the factor of \( 10^3 \) is used so as to yield \( V_{\text{blast}} \) values on the order of 1–100 (see Table 2), and the square root is used on the basis that \( V_n \) and \( V_s \) each imply some unit of vulnerability per unit of \( \beta \). In the calculations, a uniform distribution is used over all wall and all structural system coefficients in Table 1.
The errors are: –40% for Khobar Towers (K-predicted=11; K-actual=18); +3% for Oklahoma City (K-predicted=167; K-actual=163); and –13% for the AMIA building (K-predicted=71; K-actual=82).

2. The blueprint for the AMIA building (obtained from D. Ambrosini – see Table 2) was also examined. In two cases (Khobar, AMIA), those victims whose locations (target building vs. other) were unknown were allocated in proportion to the number of victims known to be in each location. When a source notes only the total number of victims, their locations are assessed using the portions from either the “prime” source for the attack (Khobar), or the average of the portions from the “prime” sources for the other two bombings (AMIA). Finally, the dimensions of the Khobar Towers building were estimated based on drawings in the sources (presented to scale).

3. The errors are: –40% for Khobar Towers (K-predicted=11; K-actual=18); +3% for Oklahoma City (K-predicted=167; K-actual=163); and –13% for the AMIA building (K-predicted=71; K-actual=82).

Table 1: Blast Vulnerability Coefficients for Different Building Wall and Structural Systems [7]

<table>
<thead>
<tr>
<th>Wall Type</th>
<th>Structural System Type</th>
<th>$V_v$ or $V_f$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cast-in-place reinforced concrete</td>
<td>Reinforced concrete shear walls, or bundled tubes</td>
<td>0.10</td>
</tr>
<tr>
<td>Curtain wall</td>
<td>Braced exterior frame</td>
<td>0.74</td>
</tr>
<tr>
<td>Precast panels, or reinforced masonry</td>
<td>Frame with core, or precast</td>
<td>0.84</td>
</tr>
<tr>
<td>Massive unreinforced masonry</td>
<td>Precast tilt-up, or frame with (concrete or masonry) infill, or reinforced masonry, or belt truss</td>
<td>0.93</td>
</tr>
<tr>
<td>Light frame or slender unreinforced masonry</td>
<td>Light metal frame, or brick, or timber</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Note: the source provides two sets of $V$-values, depending on whether the bomb is more or less than 100 ft away from the building. However, when converted into relative terms (as shown above), these discrepancies disappear.

5.3. Empirical Blast Data

The mortality and morbidity models are based on data from the three well-studied VBIED attacks, or:

1. AMIA building (Jewish community center, Buenos Aires, Argentina, 1994);
2. Oklahoma City (Murrah federal building, U.S., 1995); and

All sources were peer-reviewed journal articles, books, government reports, and some media accounts in major newspapers available through LexisNexis [26]. The prime references were: Oklahoma City–[27]; AMIA–[28]; and Khobar Towers–[29]. In cases where multiple estimates of a quantity were available, the average was taken (with identical values considered as one). Three degrees of injury are examined: killed ($K$), hospitalized injuries ($HI$), and non-hospitalized injuries ($NHI$; in general, emergency room treated and released). The building occupancies were estimated on the basis of a density of $0.027/m^2$ (Section 4). For Oklahoma City (where the number of building occupants is known reasonably well), the estimated occupancy is 369, which compares well with the actual occupancy of 361 [27]. Various data related to these bomb attacks is summarized in Table 2. The calculated blast vulnerabilities ($V_{blast} = Equation 5$) are 8.8 for Khobar Towers, 30.5 for Oklahoma City, and 43.9 for AMIA (all $kg^{1/3}/m^2$).

5.4. Mortality and Morbidity in Target Building

Table 2 indicates that $LR(K)$ is increasing in $V_{blast}$. This is cogent: as $\beta$ increases (Equation 4), so should the number of persons in the target building who are killed. So $LR(K)$ is modeled using the CDF of the lognormal distribution (Section 5.1), with mean and standard deviation of $\mu=3.53$ and $\sigma=0.96$ (both logarithmic), respectively (selected by minimizing the sum of squares error). The mean error in the predicted number of deaths is –17%. Both $LR(HI)$ and $LR(NHI)$ are U-shaped in $V_{blast}$ – presumable because as $V_{blast}$ increases, persons who would have only been injured at lower $V_{blast}$ values are instead killed. So we model these loss ratios as piecewise exponential functions that asymptotically approach zero as $V_{blast}$ increases without bound, as indicated in Table 3. The number of victims in each injury group $(x)$ is then equal to $N \cdot LR(x)$, where $N$ is the total number of building occupants.
The loss ratios for the target building as a function of $V_{\text{blast}}$ are plotted in Figure 1a, along with the empirical data on which the models are based (data points aligned vertically by bombing event). The total number of persons in the target building who are affected (injured or killed) reaches a local maximum at $V_{\text{blast}}=30.5 \text{ kg}^{1/3}/\text{m}^2$ (corresponding to Oklahoma City), then decreases somewhat, before asymptotically approaching one. The number of injuries (both hospitalized and non-hospitalized) also peaks at $V_{\text{blast}}=30.5 \text{ kg}^{1/3}/\text{m}^2$, and then asymptotically approaches zero as $V_{\text{blast}}$ increases without bound.

### 5.5. Blast Flux Limitations

The blast flux (Section 5.2) has various limitations. For example, some building areas may present greater risk because of the particular things (e.g., window glass) nearby. The damage in one area might also not be independent of the damages elsewhere (for instance, as the blast interacts with and imparts energy to the building, less residual energy is available to damage the remainder of the building). The blast flux is also based on only three attacks, collectively covering a somewhat narrow range of $Z$-values (0.34–1.30 m/kg$^{1/3}$). Some of these issues are partially addressed through the use of empirical data to fit the model parameters, although it remains unknown how truly applicable the model might be to the “next” VBIED attack. The primary value of the blast flux model is that it:

1) is a simple metric to assess the (aggregate) vulnerability of a building’s occupants to blast;

### Table 2: Empirical Mortality and Morbidity Data for Vehicle Bomb Attacks ($n=3$)

<table>
<thead>
<tr>
<th>Building and Bomb Information</th>
<th>Description, Notation (Units, if applicable)</th>
<th>Khobar Towers$^a$</th>
<th>Oklahoma City</th>
<th>AMIA Building</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bomb size, $W$ (kg TNT)</td>
<td>10,270 (6)</td>
<td>1,810 (4)</td>
<td>270 (5)</td>
<td></td>
</tr>
<tr>
<td>Standoff distance to building, $R$ (m)</td>
<td>28 (8)</td>
<td>4.1 (8)</td>
<td>2.7 (3)</td>
<td></td>
</tr>
<tr>
<td>Scaled distance, $Z$ (m/kg$^{1/3}$)</td>
<td>1.3</td>
<td>0.34</td>
<td>0.42</td>
<td></td>
</tr>
<tr>
<td>No. of occupants (estimated), $N$</td>
<td>138</td>
<td>369</td>
<td>118</td>
<td></td>
</tr>
<tr>
<td>No. of floors (above ground), $F$</td>
<td>8 (4)</td>
<td>9 (10)</td>
<td>6 (5)</td>
<td></td>
</tr>
<tr>
<td>Floor-to-floor height (average), $H_f$ (m)</td>
<td>3.4 (1)</td>
<td>4.0 (3)</td>
<td>4.2 (1)</td>
<td></td>
</tr>
<tr>
<td>Building length, $L$ (m)</td>
<td>40-near, 10-far$^c$ (1)</td>
<td>63 (6)</td>
<td>17 (1)</td>
<td></td>
</tr>
<tr>
<td>Building depth, $D$ (m)</td>
<td>9-near, 28-far$^a$ (1)</td>
<td>24 (6)</td>
<td>43 (1)</td>
<td></td>
</tr>
<tr>
<td>Blast flux, $\beta$ (kg$^{1/3}$/m$^2$)</td>
<td>0.030</td>
<td>0.039</td>
<td>0.046</td>
<td></td>
</tr>
<tr>
<td>Wall vulnerability coefficient, $V_w$</td>
<td>0.85$^b$</td>
<td>0.74$^b$</td>
<td>1.00$^b$</td>
<td></td>
</tr>
<tr>
<td>Structural vulnerability coefficient, $V_s$</td>
<td>0.10$^b$</td>
<td>0.85$^b$</td>
<td>0.93$^c$</td>
<td></td>
</tr>
<tr>
<td>Blast vulnerability, $V_{\text{blast}}$ (kg$^{1/3}$/m$^2$) (Equation 5)</td>
<td>$(4.6 + 4.2) = 8.8^b$</td>
<td>30.5</td>
<td>43.9</td>
<td></td>
</tr>
</tbody>
</table>

Note: values in parenthesis indicate the number of sources/estimates underlying the (average) value presented.

$^a$ Building was T-shaped, so $V_{\text{blast}}$ was calculated separately for each segment, and the results were then summed.

$^b$ Personal communication, E. Hinman, President, Hinman Consulting Engineers, San Francisco, CA, 2014.

$^c$ Personal communication, D. Ambrosini, Professor of Structural Engineering, National University of Cuyo, Argentina, 2013.
2) can be applied to any building and any size of bomb; and
3) is consistent with the damage estimation methods used for earthquakes (a hazard area in which empirical data are far more abundant than for VBIED attacks).

5.6. Property Damage to Target Building

The damage to the target building itself is modeled using Wilton and Gabrielsen [30], who review a variety of U.S. government tests wherein dwellings (one and two story brick, wood, and concrete block construction) were exposed to high explosive and nuclear detonations. Although based on data for residential dwellings, and not commercial office buildings, their model considers both the damage to individual building components, and the replacement cost of each component, and expressed damage in dollar terms. Their data are well-modeled (adjusted R²=0.91; n=19) by a log-linear function of the form

$$\ln(DC) = -3.0 + (3.6 \times 10^{-5}) \cdot (P) + (1.1 \times 10^{-4}) \cdot (I)$$

(6)

where the damage cost, DC, is specified as the portion of the building replacement cost (0<DC≤1), P and I are in metric units (see below), and all of the coefficients are highly significant (p<0.001). R.S. Means [31] lists average construction costs for U.S. office buildings (1–20 floors) of $1,600–$2,000/m², so we model the unit replacement cost (U_RC) as a lognormal distribution with non-logged mean of $1,800/m² and CoV of 20%. Finally, according to Willis & LaTourette [32], from an analysis of the RMS terrorism risk model, the value of the damage to a building’s contents is around 60% of the value of the damage to the building itself, and the business interruption losses associated with the event are about 170% of the value of the damage to the builidng itself, so we inflate U_RC accordingly to account for these losses.

The peak overpressure and impulse are evaluated using DoD [33]. For the detonation of hemispherical TNT charges at ground level, the peak overpressure (P; Pascals) is well-modeled (adjusted R²>0.99) by

$$\ln(P) = 14 + 0.28 \cdot (Z) - (3.3 \times 10^{-3}) \cdot (Z^2) - 2.3 \cdot \ln(Z) - 0.29 \cdot [\ln(Z)]^2$$

(7)

and the impulse (I; Pascal-sec) is well-modeled (adjusted R²=0.97) by

$$\ln\left(\frac{I}{W^{1/3}}\right) = 5.3 - 0.33 \cdot (Z) + (4.4 \times 10^{-3}) \cdot (Z^2) - 0.14 \cdot \ln(Z) + 0.29 \cdot [\ln(Z)]^2$$

(8)

In each case, n=200 points were selected from each curve. Equations 7 and 8 may appear ad hoc, but all coefficients are highly significant (p<0.01; p<0.001 for all but one). From a review of peak overpressure curves from several sources, Baker et al. [19] assess the variation across them as a factor of ±/–2, so we multiply P and I each by a lognormal distribution with (non-logged) mean of 1 and CoV of 50%.

5.7. Collateral Damages

The numbers of collateral deaths and injuries (that is, outside the target) are non-monotonic in W (Table 2) – perhaps in part because of the low sample size (Section 5.5). So the numbers of collateral deaths and injuries are modeled as lognormal distributions, using the (non-logged) means and standard deviations of the values in Table 2. The collateral property damage (PDc; $) is estimated using data from Oklahoma City (Table 2). For that attack (W=1810 kg), which damaged a total of 348 buildings, the estimated cost to the state of Oklahoma was about $1.06 B in 2012$ [34] – including rebuilding costs, police officer overtime, and lost tax revenue. For lack of other data, PDc is assumed to be linear in W, with a slope therefore equal to (5.9x10⁵).

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4 Note that the source expresses damage costs in percent rather than fractional terms, and also use non-metric units.
Table 3: Empirical Blast Mortality and Morbidity Models for the Target Building (n=3)

<table>
<thead>
<tr>
<th>Damage Quantity</th>
<th>Model Parameter</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loss ratio–killed, LR(K)</td>
<td>$\mu$</td>
<td>3.5</td>
</tr>
<tr>
<td></td>
<td>$\sigma$</td>
<td>0.96</td>
</tr>
<tr>
<td>Loss ratio–hospitalized injury, LR(HI)</td>
<td>$V_{\text{blast}} \leq 30.5$</td>
<td>$a$ 0.10</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$b$ (8.7x10^{-3})</td>
</tr>
<tr>
<td></td>
<td>$V_{\text{blast}} \geq 30.5$</td>
<td>$a$ 0.52</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$b$ -0.044</td>
</tr>
<tr>
<td>Loss Ratio–non-hospitalized injury, LR(NHI)</td>
<td>$V_{\text{blast}} \leq 30.5$</td>
<td>$a$ 0.10</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$b$ 0.035</td>
</tr>
<tr>
<td></td>
<td>$V_{\text{blast}} \geq 30.5$</td>
<td>$a$ 0.98</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$b$ -0.039</td>
</tr>
</tbody>
</table>

Note: in all cases, the independent variable, $V_{\text{blast}}$, is specified using Equation 5.

5.8. Threat Scenario and Attack Probability Specifications

The minimum setback distance that a decision-making might consider is assumed to be 5 m, and the standoff distance in the no mitigation case, $R_0$ (m), is modeled as a uniform distribution from 1–5 m. With the bollards, the bomb is assumed to be detonated right at the line of barriers. The bomb size is specified using data from $n=103$ actual VBIED attacks (see Section 5.3 for search procedure description). With the Khobar Towers bomb removed (which was nearly five times the size of the second largest bomb size), $W$ (kg) is modeled as an exponential distribution with mean (and standard deviation) of 340 kg ($\chi^2=14.8; p=0.14$). The mean error in the fitted CDF is –6.1% (99% c.i. –26% to 8%). So as to account for the fact that some of these estimates are not in terms of TNT equivalent mass (Section 3), we multiply $W$ by a triangular distribution with mode of 1 and range of 0.5–1.8, based on the table of TNT equivalents in ASCE [20]. Furthermore, the bomb size is often estimated from the size of the bomb crater, and based on a study of craters from two hundred accidental explosions, Kinney & Graham [35] report a CoV of about one third for $W^{1/3}$ when estimated in this way, so we also multiply $W^{1/3}$ by a lognormal distribution with mean of 1 and standard deviation of 0.33 (both non-logged).

The implementation of the mitigation measures will presumably cause the attack probability to decrease. We account for this using a simple – but physically meaningful – approach. If $\theta$ (radians) is the angle between the line connecting the bomb and a point at some arbitrary height on the building’s face ($H_o$) – an angle which necessarily decreases as $R$ increases – the annual attack probability is specified as

$$p = (p_0 \cdot \theta) = p_0 \cdot \arctan \left( \frac{H_o}{R} \right)$$

(9)

where $p_0$ is what the annual attack probability would be in the case without the mitigation. From the boundary condition $p(R=R_o=3 m)=p_0$, it follows that $H_o=4.672$ (note that 3 m is the mean of $R_o$ – Section 5.8). However, the nature of the attack probably is highly uncertain, so we model it as a triangular distribution with mode from Equation 9 and range of zero (complete decay) to $p_0$ (no decay).

6. RISK AND COST-EFFECTIVENESS CALCULATIONS

The benefit of the mitigation measures is the net present value of the risk reduction, or

$$B_{npy} = \sum_{n=1}^{\infty} \left[ \frac{\text{risk}_{n0} - \text{risk}}{(1 + dr)^n} \right] = \sum_{n=1}^{\infty} \left[ \frac{(p_0 \cdot d_0) - (p \cdot d)}{(1 + dr)^n} \right]$$

(10)
where \( \text{risk} \) is the product of the annual attack probability, \( p \), and the (monetized) damages in the event of an attack, \( d \) (\$; see below), \( dr \) is the annual discount rate, \( \text{life} \) is the building service life (we use 50 years), and a zero subscript denotes the base (no mitigation) case. As such, the model considers both the attack probability, and the damages in the event of an attack, and how both of these might change as mitigation is implemented. We use a 5\% annual discount rate, but do not discount future deaths and injuries.

Injury severity is assessed using the Abbreviated Injury Scale (AIS) [36] (Table 4). For each AIS level, DOT [37] gives the quality-adjusted portion of remaining life lost, which is then multiplying by the value of a statistical life (VSL) (middle=$9.1$ M; range=$5.4$–$12.9$ M) to obtain the monetary value of injury at each AIS level. These do not represent the value of any particular person’s life or injury, but rather the willingness to pay to prevent one statistical death or injury of some level of severity. At each AIS level, we use a triangular distribution over the range of injury values in Table 4. We apply the geometric mean of AIS 1–2 to non-hospitalized injuries (on the basis that lower rather than higher AIS values are more likely to occur), the geometric mean of AIS 3–5 to hospitalized injuries, and AIS 6 to fatalities.

We evaluate the mitigation measures using various metrics: the breakeven attack probability, or the value of \( p_0 \) (the attack probability in the no mitigation case) at which \( B_{\text{NPV}}=C_{\text{NPV}} \); the cost per statistical life saved, assuming an attack occurs at some point during the building’s service lifetime; and the deterrance value and mitigation measure effectiveness, or the (absolute value of the) percentage change (decrease) in the attack probability \( (p – \text{using Equation 9}) \) and the (monetized) attack damages \( (d) \), respectively.

7. RESULTS

The cost of the mitigation is considerable. Even with only 5 m of setback distance, the average cost is $1.5 M (90\% c.i. $0.3$ M–$5.8$ M); at \( R=25 \) m, the average cost is $8.9 M (90\% c.i. $0.6$ M–$38$ M); and for \( R=50 \) m, the average cost is $23 M (90\% c.i. $1.2$ M–$100$ M). At all setback distances, the majority of the total cost is land, and not the bollards themselves (59\% of the total at \( R=5 \) m, steadily rising to 86\% of total costs at \( R=50 \) m). The attack damages are summarized in Table 5. For the target, while all of the damages generally decrease as \( R \) increases, the drop in the number of deaths is the most marked. Table 5 also indicates that most of the damage reduction occurs within the first 25 m of setback distance.

### Table 4: Monetary Values of Injury (2012\$) for the Abbreviated Injury Scale (AIS) [36]

<table>
<thead>
<tr>
<th>Severity Level</th>
<th>AIS 1</th>
<th>AIS 2</th>
<th>AIS 3</th>
<th>AIS 4</th>
<th>AIS 5</th>
<th>AIS 6 (fatal)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Example Injuries (^a)</td>
<td>Abrasion; laceration; contusion</td>
<td>Simple broken bone; serious strain/sprain</td>
<td>Complcated fracture; concussion</td>
<td>Heart laceration; loss of limb</td>
<td>Massive head injury</td>
<td>Usually (though not invariably) fatal</td>
</tr>
<tr>
<td>General Prognosis (^a)</td>
<td>Treated and released</td>
<td>Follow-up and weeks to months to heal</td>
<td>Substantial follow-up; some minor disability</td>
<td>Hospitalization; moderate long-term disability</td>
<td>Extended hospitalization; significant long-term disability</td>
<td></td>
</tr>
<tr>
<td>DOT[37] Injury Value</td>
<td>Low</td>
<td>$16,000</td>
<td>$240,000</td>
<td>$550,000</td>
<td>$1.4 M</td>
<td>$3.1 M</td>
</tr>
<tr>
<td></td>
<td>Middle</td>
<td>$27,000</td>
<td>$430,000</td>
<td>$960,000</td>
<td>$2.4 M</td>
<td>$5.4 M</td>
</tr>
<tr>
<td></td>
<td>High</td>
<td>$39,000</td>
<td>$610,000</td>
<td>$1.4 M</td>
<td>$3.4 M</td>
<td>$7.6 M</td>
</tr>
</tbody>
</table>

\(^a\) Source: Willis & LaTourrette [32].
A plot of the breakeven attack probability (that is, the minimum attack probability for the mitigation to be cost-justified) is given in Figure 1b. For all setback distances, the mean breakeven annual attack probability is on the order of $10^{-4}$, which corresponds to a return period of around once every 10,000 years. The 5th percentile of the breakeven annual attack probability is on the order of $10^{-6}$ for $R=5–35$ m, and $10^{-5}$ for $R=40–50$ m, while the 95th percentile swings as high as $10^{-3}$ for $R>20$ m.

Figure 1c plots the cost-effectiveness of the mitigation ($/life-saved), assuming that the building is attacked at some point during its service lifetime (that is, an annual attack probability of 0.02 or greater). Also plotted in Figure 1c are dashed lines corresponding to the minimum, average, and maximum VSLs (see Section 6). The curve for the mean value of cost-effectiveness is below the mean VSL ($9.1$ M) at all setback distances (it also decreases somewhat from $R=5$ m to $R=10$ m), and it only begins to exceed the minimum VSL ($5.2$ M) between $R=45$m and $R=50$m. The 95th percentile curve begins to exceed the minimum VSL ($5.2$ M) between $R=25$ and $R=30$, but does not exceed the mean VSL ($9.1$ M) until $R=40–45$ m, and it never reaches the maximum VSL (the 5th percentile curve is essentially flush with the $R$-axis). These results suggest that this mitigation option is cost-effective for buildings that will be attacked during their lifetime.

Figure 1d gives the deterrence-effectiveness ($D-E$) plot (average values). The red dot at the origin represents the risk in the base case (that is, without the mitigation); points on the curve closer to the origin correspond to less setback distance; and the dashed lines along the top and right represent a state of zero risk. The $D-E$ curve’s position above the dashed diagonal line (that is, the line where $D=E$) suggests that most of the risk reduction of the mitigation derives from its deterrence value (that is, the reduced attack probability), rather than its effectiveness (that is, the reduction in damages in the event of an attack).

8. CONCLUSION

This paper presents a quantitative risk-cost model for using vehicle barriers to create setback distance around a building for protection from vehicle bomb attack. While highly empirical, and based on a relatively small number of bombing events, the model considers both the attack probability and the damages in the event of an attack, and how both of these quantities might change as mitigation is implemented to a greater degree. Results suggest that this mitigation option is worthwhile, but only in the case of buildings that would be at especially high probability of attack without the mitigation.

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Figure 1: a) Estimated Loss Ratios for the Target Building Versus Blast Vulnerability ($V_{\text{blast}}$); b) Breakeven Attack Probability Versus Amount of Setback Distance; c) Cost Effectiveness Versus Amount of Setback Distance; d) Deterrence-Effectiveness Plot.
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