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# RISK ANALYSIS AND ASSESSMENT METHODOLOGY OF UNDERGROUND CRITICAL INFRASTRUCTURES EXPOSED TO MUNITIONS HITS

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**Abstract**

Civil society is increasingly exposed to terror and war threats. The scenarios caused by these threats are highly relevant to the continuous performance and safety of Critical Infrastructures (CIs). Underground CIs might be exposed to guided munition hits with high penetration capabilities. Maintaining the continuous performance and physical state (structural and geotechnical) of underground CIs is crucial in ordinary times and even more so during emergency times. Underground facilities are used to protect sensitive installations such as military infrastructures and also Nuclear Power Plants (NPP's) from high explosive charges. The research objective was focused in the development of a risk informed optimal decision support methodology for advanced CIs resilience, exposed to Earth Penetrator Weapon (EPW) hits. The test cases were defined by threat scenarios of EPW penetration and detonation above an underground cavern that contains the NuScale Small Modular Reactor (SMR) reactor building (RXB). The research methodology was composed by the following phases: 1) Literature review; 2) Risk Analysis and Assessment: Underground critical energy infrastructures vulnerability assessment, focused on SMR; 3) Numerical simulations and Analytical-empirical formulation of the in-structure shock; 4) Damage assessment of the SMR critical components and its RXB structure exposed to munitions' hits; 5) Development of fragility curves due to blast waves based on NPP components' tolerance under airplane crash and seismic fragility curves. 6) Building deterioration Model of an NPP tunneled in rock: a) Reliability Analysis: Collection of large relevant data sets for the issue; Determine the parameters which affect the prediction; b) Apply the Random Forest (RF) algorithm for the service life prediction of the underground facility; c) Assess the results and specify data to be collected for future analysis. d) Define an equivalent physical state index (PSI) to assess the vulnerability of the tunneled NPP exposed to in-structure shock caused by blast.

**Keywords:** Cavern, Critical Infrastructures, Machine Learning, NuScale, Small Modular Reactor, Random Forest.



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## 1. Introduction

### 1.1 Background

CIs are exposed to gradually increasing scenarios of terror and war threats such as high explosive warheads and missile hits. Energy Infrastructures are of particular attention. Within its 2050 energy plan, Israel examines the

demographic consequences of a Nuclear Power Plant (NPP) in the Shivta Rogem site in the Negev. SMR is considered to be robust and resilient and safer than the current NPPs and has better resistance to external hazards due to its inherent passive safety features. The scenarios caused by high explosive warhead threats are highly relevant to the continuous performance, resilience, and safety of CIs. The engineering parameters of interest have several degrees of uncertainty and thus are defined as random variables that can be approached with probabilistic and computational methods [1]. Common basic engineering concept is that the capacity must be greater than or at least satisfy the demand. While capacity and demand are often conceived as time in-variant parameters, in modern design, which takes structural reliability into consideration, capacity (resistance) is no longer treated as time invariant [2] and thus should be modeled adequately relating to degradation processes e.g. wear and tear, deformations, creep, corrosion and erosion. Underground structures in particular are widely exposed to erosion and water damages [3] [4]. When looking at the demand (applied loads), the randomness and the uncertainty are intuitive, mostly handled by deterministic safety factors. The above leads to the research gap: CIs exposure to munition hit is not sufficiently researched and addressed. Appropriate protection must be designed, and capacity loss throughout time should be taken into consideration in order to keep the demand/capacity ratio at the desired range.

### 1.2 The Case study

A case study of a tunneled SMR NPP was tested showing the feasibility of the methodology. Existing seismic models were employed in order to focus on critical elements and their respective failure modes, and the theoretical background was put forward for the development of fragility curves. The basic scheme of the underground cavern of NuScale SMR (see figure 7) in Shivta Rogem rock was defined, based on [5], while adopting Adulam formation of the chalk according to [6]. The representative chalk characteristics are assumed as follows: Modulus of Elasticity of 9,500 MPa, Poisson ratio of 0.2, and yield strength of 32.9 MPa. PPV of 1 m/s was defined as spalling threshold value which must be avoided, in order to maintain the SMR cavern stability. The penetration capability in chalk of EPW-1 and EPW-2 with ~300 kg and ~2400 kg of TNT respectively were defined, and two cavern configurations were put forward, one for each munition scenario. Empirical data of the munitions hits ground shock were compared with simulation results [7] and were found to be in accordance with the literature [8].

### 1.3 Research Framework and Objectives

The research objective is focused in the development of a risk informed optimal decision support methodology for advanced CIs resilience, in particular underground NPPs, exposed to ground penetrator weapon (EPW) hits. The test cases were defined by threat scenarios of EPW-1 and EPW-2 penetration and detonation above an underground cavern that contains the NuScale SMR RXB. The hypothesis is that placing CIs in an underground structure, which provides passive protection, will achieve its safety goals for a defined design period (decades) if established correctly according to the following: Protecting against the determined threat scenarios, considering the site geotechnical conditions, and design and building of blast resistant underground infrastructure to the in-structure motions resulted by the explosions. The critical components tolerance will be greater than the in-structure shock. Beyond the defined period two counter interconnected trends are expected to reflect the protective strategy. Primarily, weapons improvement: parameters of accuracy, precision, and blast energy (not a part of this research). Secondly, the assumption is that the mechanical and structural reliability of the underground cavern and the RXB structure will be deteriorated through time. The time dependent integrated model will assist in pointing out the time and framework of the strengthening and upgrading solutions along the infrastructure design life cycle.

## 2. Literature review

### 2.1 General

The external manmade events of explosions were compared to those of earthquakes (natural phenomena). Similarities and differences were found and presented. [9] [10] [11] [12]. PPV of 1 m/s was found as a common criterion for caverns exposed to adjacent explosions in order to avoid damages beyond cracking (spalling). Meaning a PPV of 1 m/s can be the threshold value which must be avoided in order to maintain the SMR cavern stability, and will directly affect the depth of burial resulting from the threat [13]. Tunneling is an important and developing branch of civil engineering which suffers from many forms of deterioration such as water leakage, cracks, deformations and more, see figure 1. Common rock classifications and tunneling practices were also reviewed [14] [15]. Structural reliability based on degradation mechanisms [16] can predict the physical state of infrastructures throughout its life cycle and is an important tool in asset management. The existing methods can contribute in assessing the resilience of a protective cavern\tunnel [17] and can be improved by new techniques of Machine Learning (ML), see figure 2.

Figure 1: Concrete deterioration progress (right to left) due to cracks, corrosion and rebar expansion.

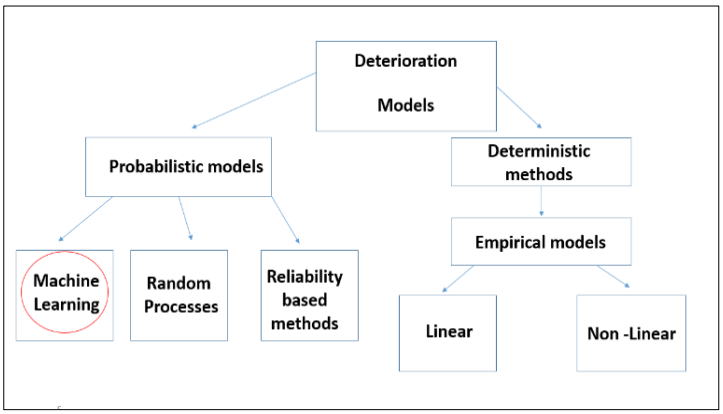


Figure 2: Deterioration modeling of infrastructures according to the state of the art review

### 2.2 Literature review of the case study

Although various papers were reviewed for the investigation of the core fragility parameters, suitable fragility parameters were found only for seismic loads. The published Seismic Margin Analysis (SMA) examined scenarios initiated by seismic events and led to damages of components or to structural events. In contrast to component failure which can be successfully mitigated and thus withstand the hit, the SMA determined that failure of major structural elements directly leads to Core Damage (CD) and to a Large Radioactive Release (LR). The summary of all the data regarding the significant structural failures is delineated in Table 1. The SMR analysis shows acceptable design in accordance with the NRC defined hazards. Beyond design events may endanger the SMR and must be examined carefully to ensure safety goals. [18] found that the underground rigid structure satisfactorily defends the modules, correlating with the acceleration levels found to be safe in this analysis. Though, [19] doubted the resilience, claiming that the underground positioning and small size are an advantage in the way that the structure is rigid and can be easily protected, however the disadvantage is that the vulnerability is higher and shock can easily be transferred due to the close positioning of the elements and the CNVs. Figures 3 and 4 reflect the data collected regarding the geometry of the SMR RXB (The blue fill represents water).

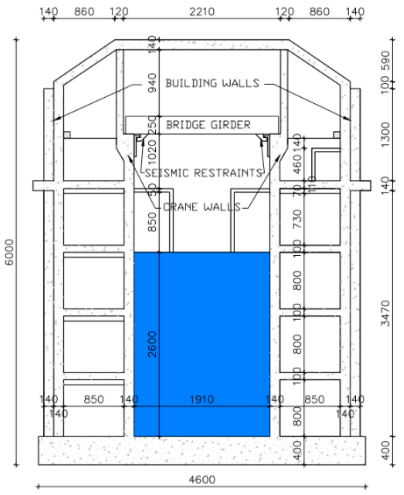


Figure 3: Reconstructed RXB vertical cross section, not to scale (cm)

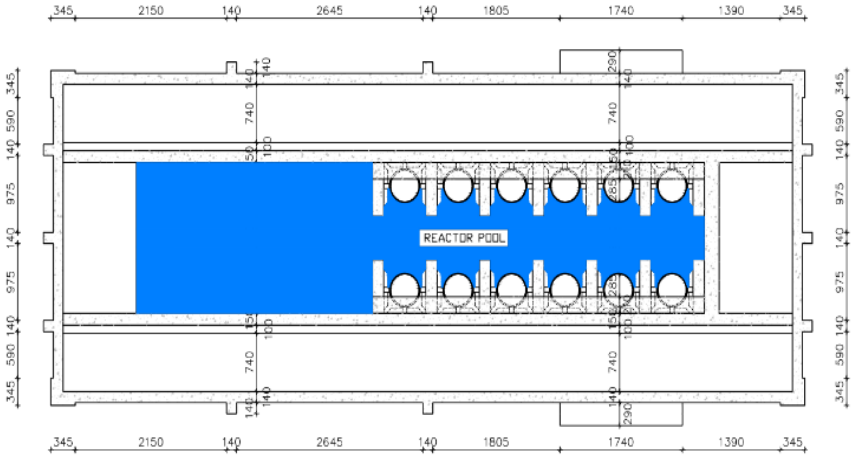


Figure 4: Reconstructed RXB Horizontal cross-section, not to scale (cm)

Table 1: Significant structural failures [20]

| Event | Element | Median (g) | $\beta_r$ | $\beta_\mu$ | HCLPF(g) |
|---|---|---|---|---|---|
| 1 | RBC | 2.64 | 0.28 | 0.39 | 0.88 |
| 2 | RXB Ext Wall | 1.92 | 0.12 | 0.33 | 0.92 |
| 3 | NPM supports | 1.98 | 0.12 | 0.35 | 0.92 |
| 4 | Bioshield | 11.62 | 0.28 | 0.37 | 3.99 |
| 5 | Bioshield (double stacked) | 4.05 | 0.28 | 0.41 | 1.30 |
| 6 | Pool walls | 2.31 | 0.21 | 0.33 | 0.95 |
| 7 | Crane support walls | 2.61 | 0.12 | 0.34 | 1.23 |
| 8 | Bay Wall | 2.65 | 0.12 | 0.31 | 1.31 |
| 9 | Roof | 2.22 | 0.12 | 0.26 | 1.2 |
| 10 | Basemat | 3.57 | 0.27 | 0.31 | 1.38 |

## 3. Methodology and results

This paper will focus on the final part of the methodology. The methodology is composed by the following phases:

- Literature review;
- Underground critical energy infrastructures vulnerability assessment, focused on SMR;
- Tracing on the SMR geometry and properties;
- Analytical-Empirical formulation of the in-structure shock;
- Damage assessment of the SMR critical components and its RXB structure exposed to munition hits;
- Development of fragility curves due to blast waves based on NPP components' tolerance under airplane crash, seismic fragility curves and analytical-empirical formulas;
- Building Deterioration Model of an NPP tunneled in rock: **Structural reliability analysis related to capacity deterioration trend through development of ML model to assess the future structural condition: Collecting data, determine parameters, applying the Random Forest (RF) Algorithm, assess the results and specify future data collection;**

- defining an equivalent physical state index (PSI) to assess the vulnerability of the tunneled NPP exposed to in-structure shock caused by blast.
- Specifications of data to be collected for future analysis.

### 3.1 The model's database

Due to lack of raw data regarding typical deterioration patterns and aging of caverns and in order to complete and demonstrate the novel methodology, roadway tunnel data collected by the Federal Highway Administration (FHWA) was chosen due its similar characteristics. I chose to follow [21] and to create an element-based condition state prediction model based on [22] database using RF algorithm in MATLAB. Table 2 stresses differences and similarities between the two types of underground structures, which should be noticed while analyzing the model's result.

Table 2: Preliminary comparison between caverns to road tunnels

| Topic | Underground Structure | |
|---|---|---|
| | Caverns | Roadway Tunnels |
| Definition | *"Natural cave or chamber or man-made large underground opening".*[23] | *"An enclosed roadway for motor vehicle traffic with vehicle access limited to portals, regardless of type of structure or method of construction".*[15] |
| Similarities | Complexity, Underground location, building methods and stabilizing methods, similar deterioration processes and required maintenance. | |
| Differences | Length and width of a cavern are of similar size while in a tunnel the length is significantly greater than the width. Caverns can reach significantly large spans (up to 100 m width) and large free height. | |

An inherent weakness of this existing database is in a simplistic soil/rock description of only three types without specific geological data.

### 3.2 Preliminary results – statistical data analysis

The data consists 7107 elements of 553 tunnels. Average age: 61.9 years while 25.7% were rehabilitated. Figure 5 shows the condition state distribution over time.

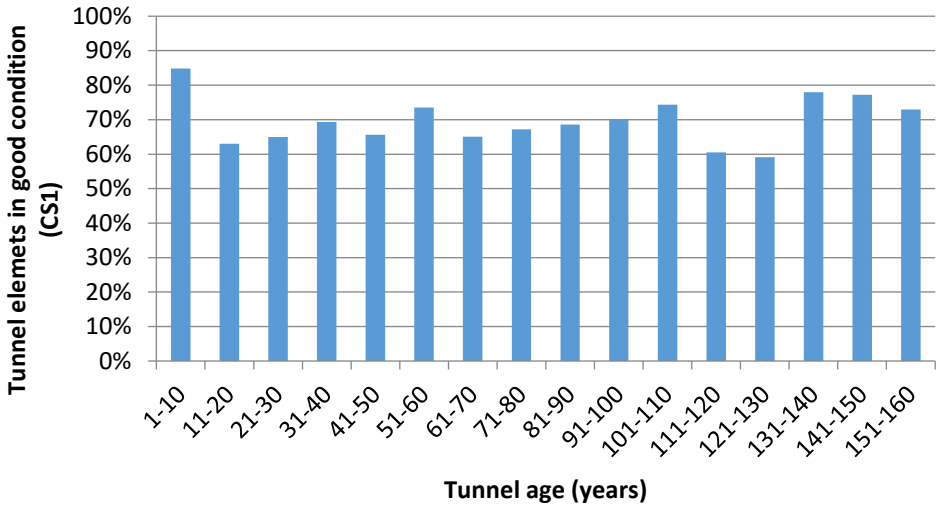


Figure 5: Tunnel Condition State (CS1 – good only) vs. Time

Possible explanations for the tunnel condition to be similar through the years are:

1. The FHWA keeps a high quality level of design, construction and maintenance.
2. Tunnels that severely deteriorate are out of service and thus are not part of the statistics.
3. The data contains both tunnels that were retrofitted which obviously improves the condition of older tunnel elements.

Table 3 presents the distribution of different condition states.

Table 3: Basic statistics of the data:

| Condition State (CS) | Mean | S.D. |
|---|---|---|
| CS1 good | 0.68 | 0.42 |
| CS2 fair | 0.20 | 0.35 |
| CS3 poor | 0.07 | 0.22 |
| CS4 severe | 0.05 | 0.2 |

3.3 Random Forest algorithm

*"Random forest is a commonly-used machine learning algorithm trademarked by Leo Breiman and Adele Cutler, which combines the output of multiple decision trees to reach a single result... it utilizes both bagging and feature randomness to create an uncorrelated forest of decision trees… generates a random subset of features, which ensures low correlation among decision trees.… reduce the risk of overfitting, bias, and overall variance, resulting in more precise predictions."* [25]

3.4 Tunnel Condition state

*"Element-level inspection techniques are used to rate each tunnel element....The four condition states, CS1, CS2, CS3, and CS4, represent good, fair, poor, and severe, respectively."* [15]

3.5 Data preparation for the model

The following modifications and adaptations were made in cleansing the road tunnels database:

- Variables which were unrelated to the condition of tunnels were removed from the original data set. Only the parameters or independent variables that were relevant to the condition of the tunnel were selected to be the initial input data in the development of the model. Table 4 gathers the altered data.
- Rehabilitation was changed manually from year of rehabilitation to Y/N (binary).
- Tunnel age was calculated (2023 - year built).

Table 4: Data preparation for the model

| Index | Variable name | Description |
|---|---|---|
| X1 | Tunnel age | Refers to the service life duration of the tunnel |
| X2 | Rehabilitation | Renovated or not (Y/N) |
| X3 | Tunnel length | Refers to the length of the tunnel |
| X4 | Tunnel width | Refers to the width of the tunnel |
| X5 | Tunnel height | Refers to the height of the tunnel |
| X6 | Tunnel geometry | 1 = oval, 2 = horseshoe, 3 = rectangular, 4 = circular |
| X7 | Ground Conditions | 1 = soil, 2 = rock, 3 = mixed |
| X8 | Complex | Contains special structural elements or not (Y/N) |
| Y | Tunnel Condition | Refers to the Condition State (CS1,CS2,CS3,CS4) |

### 3.5 The code

The code is written in MATLAB software, while the objective is predicting tunnel condition according to the existing observations and information regarding its geometry, ground conditions and upgrading (rehabilitation) status, age and more. The RF creates random decision trees based on all the variables listed above and replies its prediction as a yes/no classifier that represents a chance to be in different combinations of good/fair condition state at a level that is predefined by a vector of  results.

- The *Training_Data* file which contains the parameters of the tunnel was imported into the *raw data* variable.
- Variable *g* with normalized CS1 and variable *h* with normalized CS2 were defined.
- Vector *newVal* which converts (*g*+*h*) into a vector according to a predetermined threshold was defined.
- New table *data* with the parameters relevant to the model and with the normalized variable was created.
- *Predictors* matrix that contains all of the variables in the table except *newVal* and the response vector that contains *newVal* was created.
- Random partition on data according to a division of training and test was created.
- Four additional variables were obtained (according to random distribution): *dataTrain* matrix containing the predictors, *responseTrain* vector containing the response matrix *dataTest* containing the predictors of the test, *responseTest* containing the response of the test.
- The data was divided to training and test via *cvpartition* from the Statistics and Machine Learning ToolBox.
- The preliminary number of trees chosen for the initial code is 300 (according to common guidelines).
- The variable *model* received the result of the *TreeBagger* function (Statistics and Machine Learning ToolBox of Matlab) according to the parameters defined beforehand.
- In order to check the accuracy of the model, *predict* function from the Deep Learning ToolBox was in use.
- In order to improve the code (the initial development was carried out iteratively), the optimal number of trees was found using a "for" loop that runs over the algorithm on a range from 1 to 300 trees, for each run the out-of-bag error  (oob Error) was calculated. The result is an optimal number of trees, see figure 6.

### 3.6  Results

For CS1+ CS2>0.8 and a training/test ratio of 80/20 The algorithm achieved prediction accuracy of up to 85.43%. The optimal number of trees was 163 at minimum cross-validation error of 0.176 as shown in figure 6.

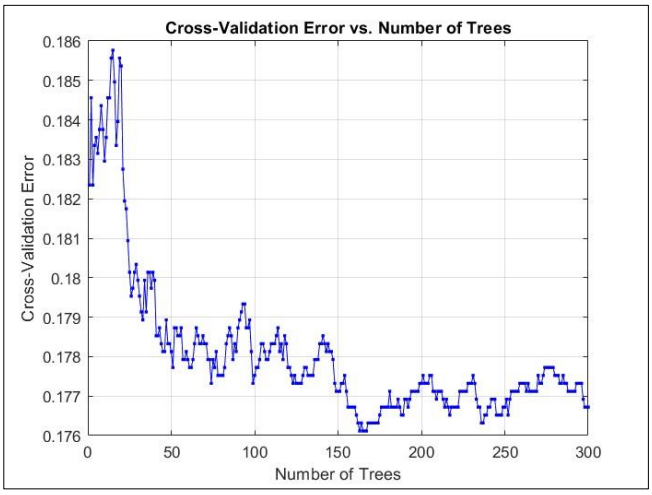


Figure 6: Cross validation errors Vs. number of trees

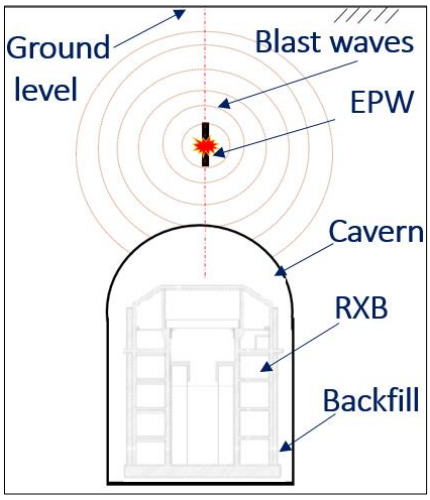


Figure 7: Vertical cross-section of the tunneled  NPP under the threat scenario [7]

3.7 Summary of the prediction process

Random Forest (RF) is a Machine Learning (ML) technique that was found to be adequate for development of service life prediction. Service life prediction of CIs Caverns is a multidisciplinary domain that will have a substantial impact on the future of critical infrastructures resilience and should be further developed. The machine learning model is a significant part of the methodology developed for the purpose of predicting the condition of underground protected critical infrastructures over time. The model presented here shows the programming methodology for approximately 7,100 data points. Obviously, the wider the database, the more accurate the model will be. While conducting the research, the use of machine learning is becoming more and more common, which strengthens the selection of this path and encourages to continue research and data gathering in order to reach accurate, applicable results that will have an impact on the life cycle of critical underground infrastructures.

## 4. Discussion and conclusions

This research offers a novel integrated model that delivers comprehensive risk analysis and assessment of underground CI's exposed to high explosive warheads hits. The innovation of the methodology is that it encompasses the whole cycle, from identifying the failure mechanisms, through the depth of burial, in structure shock effects and long term deterioration modeling. The use of existing information regarding seismic events is innovative and the combination between the deterministic approach (focusing the models for blast events on specific elements which are chosen due to their failure mode in seismic events) and the probabilistic approach (fragility curves) can significantly reduce computational efforts without compromising the quality of the results. The importance of this research is to emphasize that underground infrastructures should be analyzed according to the threat scenario of an external explosion, and if necessary, mitigation solutions should be implemented. The research treated a unique case study: a life cycle of an underground cavern protecting an SMR NPP exposed to munition hits. It should be noted that the advantage offered in the case study of an underground SMR is first of its kind (FOAK) and should be analyzed thoroughly. The case study also sets the demand of nuclear energy infrastructure resistance against blast induced ground shock, and not only aircraft impact or natural extreme events such as earthquakes. The research develops a comprehensive approach combining Integrated fragility model for explosive dynamic loads in underground facilities with RF ML model for assessment of the resilience of an underground cavern. The outcome of the research establishes a novel methodology for vulnerability and resilience analysis of underground critical facilities to warheads threats. Preventive maintenance based on prediction is more efficient and economical than breakdown maintenance. Thanks to ML it can be made more accurate, in the field of underground structures in particular and civil engineering in general. Given the continuous rising in war situations in the world, the use of passive shielding and underground caverns will increase. This fact, in combination with the reduction of the available areas for construction will point out the need for establishing underground caverns, especially for CI's. The maintenance of caverns and life cycle analysis is important and interesting. Hopefully, future studies will combine innovative AI methods along with physical developments such as sensors in order to learn and improve the whole process of design establishment and maintenance of protected underground infrastructures.

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