Grouping detection of uncertain structural process by means of cluster analysis

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Summary:

Structural analysis under consideration of the uncertainty of input parameters, such as loads, material, and geometry leads to uncertain time-dependent results. Such uncertain structural process shows for the uncertain input parameters all possible behaviours of a structure. Modelling of uncertainty in input parameters when only incomplete or expert knowledge based information is available requires the introduction of the uncertainty model fuzziness. A fuzzy process is a fuzzy set of real valued processes, whereas each of them possesses an assigned membership value indicating the degree of possibility. In order to obtain an engineering interpretation of a fuzzy process some representative crisp processes have to be chosen from numerous realisations of this uncertain function. In this paper a cluster analysis based approach for grouping similar and detecting different time-dependent structure behaviours is introduced. The similarity of processes within one cluster is assessed with similarity metrics: neighbouring location, affinity, and correlation. The uncertain assignment of real valued realizations of fuzzy process to clusters is executed with the Fuzzy-c-Means cluster algorithm.

The capability of this approach is demonstrated within the controlled collapse simulation of a reinforced concrete framework structure carried out in LS-DYNA. In this example an analysis of a fuzzy process is performed by means of cluster methods and α-level discretization in order to select collapse sequences, significantly differing from each other and having other degrees of possibility.

Keywords:

structural processes, cluster analysis, uncertainty

1 Introduction

An appropriate structural analysis requires an adequate specification of input parameters, such as loads, material parameters and geometrical properties. These parameters are often affected by significant uncertainty. Data uncertainty is predominantly caused by the way the information in engineering practice is gained: from inexact observations, imprecise measurements or expert specifications. Thus, the consideration of input parameters with crisp values only can be misleading and may yield incorrect conclusions.

Generally, the uncertainty can be classified with respect to its source either as aleatory or as epistemic. Aleatory uncertainty is associated with objectivity and being principally described with the uncertainty model randomness. This model is investigated on the basis of the probability theory methods. In order to apply randomness some strict conditions have to be met – especially the i.i.d. (identically independently distributed) paradigm must be fulfilled. When describing an input parameter as a random variable a large sample size is expected and the available data has to be obtained in constant conditions.

In most engineering applications meeting those requirements is nearly impossible. The data reproduction conditions are unstable and the number of experiments is often insufficient for evaluating the distribution type and distribution function. This lack of information can be compensated by some expert knowledge based evaluations. The information gained in such a manner is often affected by subjective/epistemic uncertainty. In order to describe informal or lexical uncertainty the model fuzziness can be utilized. When the information content of uncertainty is mainly objective but some subjective influences are simultaneously taken into account the model fuzzy randomness is most suitable. In [4] the application of uncertainty models to the structural analysis is presented.

Considering data uncertainty within structural analysis leads to uncertain time-dependent results $\tilde{z}(\tau)$. Each trajectory $z(\tau)$ of such uncertain process represents an output of a single deterministic solution, for example a selected force, displacement or stress. Thereby, a fuzzy process $\tilde{z}(\tau)$ contains numerous real-valued processes $z(\tau)$. However, in the engineering practice often compact solutions, allowing a technical interpretation are valuable. To reconcile this need with complex, uncertain structural analysis results a grouping detection approach has been developed. This concept draws upon dividing all realisations of an uncertain process in groups with respect to the criterion of functions similarity. For each group a representative process, indicating some characteristic structural behaviour is identified.

The approach presented within this paper is based on algorithms of cluster analysis. These methods have found wide application in many fields, e.g. in data mining, pattern recognition, image analysis, bioinformatics and also in engineering sciences. In [2] the implementation of cluster algorithms for the evaluation of uncertain structural analysis results is shown. Explorative data analysis has been applied for solving the design problem with the aid of the inverse solution. In this paper a Fuzzy-c-Means cluster algorithm is adopted for the classification of fuzzy process trajectories.

The presented cluster algorithm based approach for structural analysis provides a realistic and applicable solution, because uncertainty of structural parameters is considered and merely several representative structural behaviours are chosen for the engineering interpretation. The above-mentioned method has been adapted to the controlled collapse simulation of a reinforced concrete structure. Reduction of the data base to a certain number of groups enables the detection of complicated interrelationships within a structure collapse.

2 Uncertain process within a structural analysis

2.1 Structural analysis with respect to uncertainty

In deterministic structural analysis crisp vectors of simulation input parameters $\underline{x}$ including loads, material and geometry parameters are mapped with the aid of a computational model M onto vectors of simulation result parameters $\underline{z}$, containing e.g. internal forces, stresses and displacements. The problem may be formulated as follows:

$$M : \underline{x} \rightarrow \underline{z} . \quad (1)$$

Therefore, the mapping model M, also denoted as fundamental solution, represents a crisp dependency between structural parameters and structural responses. In the herein presented approach the uncertain simulation input parameters are modelled with the characteristic fuzziness. In consequence, the simulation result parameters $\underline{\tilde{z}}$ are obtained as fuzzy quantities.

$$F_{FA} : \underline{\tilde{x}} \rightarrow \underline{\tilde{z}} . \quad (2)$$

In Eq. (2) fuzzy input vectors $\underline{\tilde{x}}$ are mapped onto fuzzy result vectors $\underline{\tilde{z}}$ with the aid of the deterministic fundamental solution, represented in this particular case by the finite element method. The numerical realization of a fuzzy structural analysis is shown in Fig. 1.

The application of α-discretization to fuzzy-variables $\tilde{x}_1,...,\tilde{x}_n$ enables the specification of α-level sets $X_{1,\alpha_k},...,X_{n,\alpha_k}$ at the level α_k, where $k \in [0,\ 1]$. The α-sets from several input parameters form the n-dimensional crisp subspace $\underline{X}_{\alpha_k}$. Each point from the subspace $\underline{X}_{\alpha_k}$ represents a combination of simulation input parameters and defines a crisp vector $\underline{x}$.

For a chosen input vector $\underline{x}$ the deterministic fundamental solution is executed and a crisp result vector $\underline{z}$ is obtained. The aim of the fuzzy structural analysis is to determine a membership function $\mu(z)$ for a particular response $\tilde{z}$. Therefore, on each α-level α_k all possible result values have to be identified. This may be realized by determining the minimal and the maximal result values $z_{\min}$, $z_{\max}$ with the aid of α-level-optimization [1]. Repeating the α-level-optimization on each α_k leads to the specification of the membership function $\mu(z)$.

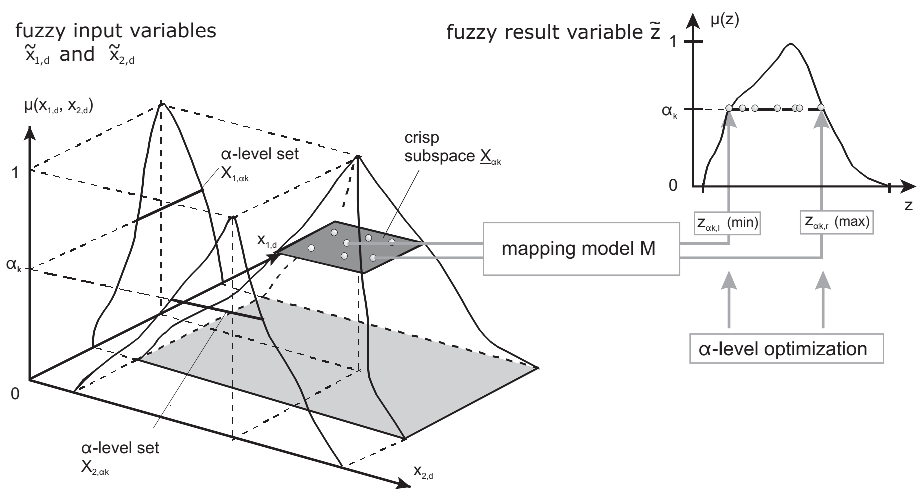

Figure 1: Fuzzy structural analysis

The presented approach may be extended by introducing simulation input parameters $\underline{\tilde{x}}$ as fuzzy functions $\underline{\tilde{x}}(\underline{t})$. In result, the output parameters $\underline{\tilde{z}}$ are obtained as fuzzy functions $\underline{\tilde{z}}(\underline{t})$, as well. If the argument $\underline{t}$ represents the time coordinate a fuzzy function is defined as a fuzzy process and denoted by $\underline{\tilde{z}}(\tau)$.

2.2 Numerical treatment of uncertain processes

When introducing fuzzy processes as input and output parameters Eq. (2) turns to:

$$\mathrm{F}_{\mathrm{FA}} : \underline{\tilde{x}}(\tau) \rightarrow \underline{\tilde{z}}(\tau) . \tag{3}$$

A fuzzy process $\tilde{z}(\tau)$ can be interpreted as a sequence of fuzzy variables evaluated for certain points in time, see Fig. 2.

$$\tilde{z}(\tau) = \left\{ \tilde{z}_t = \tilde{z}(\tau) \quad \forall\, \tau \;\middle|\; \tilde{z}_t \in \mathrm{F}(Z) \right\} \tag{4}$$

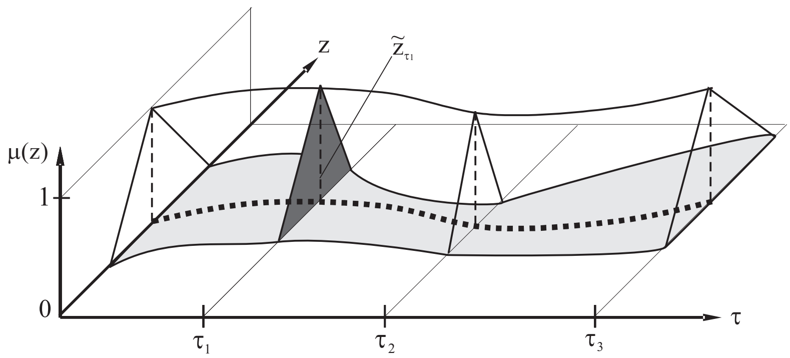

Figure 2: Fuzzy process

In order to allow a numerical treatment of $\tilde{z}(\tau)$ the fuzzy-bunch parameter representation is applied. A fuzzy process can be described with the aid of fuzzy bunch parameters $\underline{\tilde{s}}$ and crisp argument τ

$$\tilde{z}(\tau) = z(\underline{\tilde{s}}, \tau) = \left\{ \tilde{z}_\tau = z(\underline{\tilde{s}}, \tau) \quad \forall\, \tau \;\middle|\; \tilde{z}_\tau \in \mathrm{F(Z)} \right\}. \tag{5}$$

Each crisp bunch parameter vector $\underline{s} \in \underline{\tilde{s}}$ with an assigned membership value $\mu(\underline{s})$ describes exactly one crisp process $z(\tau) = z(\underline{s}, \tau) \in \tilde{z}(\tau)$ with $\mu(z(\tau)) = \mu(\underline{s})$. Therefore, a fuzzy process can be considered as a fuzzy set of real-valued processes $z(\tau) \in \tilde{z}(\tau)$. A gradual membership of a fuzzy process trajectory to a fuzzy set is expressed with $\mu(\underline{s})$.

In consequence, a fuzzy bunch parameter can be interpreted as a representation of $\tilde{z}(\tau)$ within the fuzzy analysis. If a fuzzy process with a fuzzy-bunch parameter $\underline{\tilde{s}}$ is considered as input parameter, then the application of α-level-discretization to $\underline{\tilde{s}}$ yields α-sets S_α. They form – together with α-sets from other input variables – the n-dimensional crisp subspaces $\underline{S}_\alpha$. Further steps of fuzzy analysis are then executed as described in section 2.1.

Assuming that one bunch parameter vector $\underline{s}$ from the subspace $\underline{S}_{\alpha_k}$ determines one real valued process on the level α_k, then evaluating many vectors $\underline{s} \in \underline{S}_{\alpha_k}$ results in a bunch of processes forming a set on α_k. Such α-function set $Z_\alpha(\tau)$ is formulated as follows:

$$Z_\alpha(\tau) = \left\{ z(\underline{s}, \tau) \quad \forall \underline{s} \;\middle|\; \underline{s} \in \underline{S}_\alpha;\; \alpha \in (0,\ 1] \right\}. \tag{6}$$

If the number of α-levels is sufficiently high, then $\tilde{z}(\tau)$ can be represented by the assigned α-function sets.

$$\tilde{z}(\tau) = z(\underline{\tilde{s}}, \tau) = \left\{ \left(Z_\alpha(\tau), \mu(Z_\alpha(\tau))\right) \;\middle|\; \mu(Z_\alpha(\tau)) = \alpha \quad \forall\, \alpha \in (0,1] \right\} \tag{7}$$

In each α-function set real valued processes are contained, that posses at least the assigned membership α. In addition, on every α-level bounding functions are specified with respect to α–function sets. They indicate the interval boundaries at function discretization points.

3 Cluster analysis approach

The principal idea of cluster analysis approach is to detect some data structures within the analysed sample in order to obtain an appropriate data classification. The cluster analysis is carried out under the assumption that some similarities exist between the elements of the available data set. Elements are available in various forms: as points of the data set or as functions/processes. The classification of points succeeds within the division of the whole data set into smaller groups – so called clusters. As a classification criterion the similarity of set elements is introduced. An appropriate classification is obtained when the requirements of homogeneity and heterogeneity are met. On the one hand, homogeneity of a cluster can be assumed when the elements of a cluster indicate high similarity. On the other hand, heterogeneity of cluster classification is meant when elements of different clusters show distinct dissimilarity.

An accepted classification of cluster methods distinguishes between deterministic and uncertain cluster approaches. The essential difference between those two proceedings lies in the type of the assignment of elements to clusters – it can be either deterministic or uncertain. With deterministic cluster approach one element is assigned to exactly one group. Several types of such methods have been developed, including especially the hierarchic and partitionate cluster algorithms. A deterministic algorithm that found wide application, inter alia, in engineering sciences is the k-Medoid-Cluster approach.

The uncertain cluster approaches are considered within the concepts of probabilistics and fuzziness. Fuzzy cluster methods base on gradual assignment of elements to a cluster. This gradual assignment is determined within the membership function μ_k , taking values in [0,1]. If a membership of an element to a cluster is defined with the value 1, then the element certainly belongs to the mentioned cluster. Otherwise, the membership value 0 indicates that no affiliation of the element to a cluster can be stated. The gradual assignment is restricted by a rule, assuming that for a single element of the set the sum of membership values to all obtained clusters is equal to 1. In this paper the uncertain cluster approach: Fuzzy-c-Means is introduced.

In order to obtain essential results of cluster analysis it is indispensable to find a number of clusters, which optimally describes the available data set. Commonly, cluster analysis for different number of clusters is performed and afterwards the obtained data classification is assessed with respect to several quality criterions. These are, inter alia, a partition coefficient, partition entropy and silhouette coefficient.

Partition coefficient is used as a measure for assessing the unambiguousness of the classification.

$$PC(\underline{U}) = \frac{1}{m}\sum_{k=1}^{n_C}\sum_{i=1}^{m}\mu_{k,i}^2 \quad (8)$$

High values of the partition coefficient indicate that a clear division of m elements into n_C clusters was obtained.

The partition entropy bases upon the SHANNON entropy. It refers to the information content of the investigated data.

$$PE(\underline{U}) = -\frac{1}{m}\sum_{k=1}^{n_C}\sum_{i=1}^{m}\mu_{k,i} \bullet \ln(\mu_{k,i}) + (1 - \mu_{k,i}) \bullet \ln(1 - \mu_{k,i}) \quad (9)$$

Low entropy signifies an unambiguous classification.

Silhouette coefficient, see Eq. (10), is a measure for assessing the homogeneity and heterogeneity of cluster configuration.

$$SC = \frac{1}{m}\sum_{k=1}^{n_C}\sum_{i=1}^{m}\left(\frac{b_i - a_i}{\max[a_i, b_i]} \cdot \mu_{k,i}\right) \text{, where} \quad (10)$$

$$a_i = \frac{\sum_{h=1}^{m} (d(x_i, x_h)\mu_{k,h} \forall\, i \neq h)}{\sum_{h=1}^{m} (\mu_{k,h} \forall\, i \neq h)} \tag{11}$$

$$b_i = \min_{h=1,\ldots,n_C, h\neq k} \left[\frac{\sum_{j=1}^{m} (d(\underline{x}_i, \underline{x}_h)\mu_{h,j} \forall\, i \neq j)}{\sum_{j=1}^{m} (\mu_{h,j} \forall\, i \neq j)} \right]. \tag{12}$$

The cluster classification quality can be assessed on the basis of silhouette coefficient, as shown in Table 1.

Table 1: Quality of cluster classification on basis of silhouette coefficient

SC	Cluster classification quality
0,71 – 1,00	very good
0,51 – 0,70	good
0,26 – 0,50	bad - an artificial classification is obtained
$\leqslant$ 0,25	no appropriate classification

Presented methods can be successfully adapted to grouping of functions, in this case to grouping of fuzzy process realizations $z(\tau) \in \tilde{z}(\tau)$. It is assumed that fuzzy processes are discretized in the time domain. The application of Fuzzy-c-Means cluster approach should yield a cluster classification, characterized by homogeneity and heterogeneity. The execution of Fuzzy-c-Means algorithm requires the specification of similarity measures for processes. Several aspects, like neighbouring location, affinity, and correlation are taken into account by the similarity assessment. All these measures are combined under consideration of user-specified weights. Thereby, the neighbouring location has a high priority in the presented approach. It is defined as a difference between functional values of two processes $z_1(\tau)$ and $z_2(\tau)$, where $z_1(\tau), z_2(\tau) \in \tilde{z}(\tau)$.

$$d(z_1(\tau), z_2(\tau)) = \frac{1}{n_t} \sqrt{\sum_{i=1}^{n_t} (z_1(\tau_i) - z_2(\tau_i))^T (z_1(\tau_i) - z_2(\tau_i))} \tag{13}$$

4 Grouping detection of structural processes

In the approach presented within this paper a special case of Eq. (3) is introduced. Uncertain time independent input parameters are mapped with the aid of a deterministic fundamental solution onto time dependent structural responses $\underline{\tilde{z}}(\tau)$.

$$F_{FA} : \underline{\tilde{x}} \rightarrow \underline{\tilde{z}}(\tau) \tag{14}$$

The application of α-level-discretization to N simulation input parameters $\tilde{x}_1,\ldots,\tilde{x}_N$ yields α-level sets $X_{1,\alpha},\ldots,X_{N,\alpha}$, defined as intervals $< x_{1,\alpha l}, x_{1,\alpha r} >,\ldots,< x_{N,\alpha l}, x_{N,\alpha r} >$. The assignment of a trajectory $z(\tau) \in \tilde{z}(\tau)$ to a certain α-level is defined within the membership of $z(\tau)$ to an appropriate α-function set $Z_\alpha(\tau)$. Forming α-function sets $Z_\alpha(\tau)$ is essential for the presented approach. According to Eq. (14) an α-function set $Z_{\alpha k}(\tau)$ on the α-level α_k consists of all functions $z(\tau)$ obtained for the simulation input parameter values within the intervals $< x_{1,\alpha_k l}, x_{1,\alpha_k r} >,\ldots,< x_{N,\alpha_k l}, x_{N,\alpha_k r} >$.

As mentioned in the section 2.2 each α-function set comprises all real valued functions, that posses at least the assigned membership α. Each realization of the k-th α-function set $z(\tau) \in Z_{\alpha k}(\tau)$ is contained in the l-th α-function set $Z_{\alpha l}(\tau), l < k$, while not all $z(\tau) \in Z_{\alpha l}(\tau)$ are contained in $Z_{\alpha k}(\tau)$. The application of cluster analysis requires the identification of highest possible α-level for each realization $z(\tau) \in \tilde{z}(\tau)$.

If the trajectory $z(\tau)$ is obtained through the evaluation of the m-dimensional input vector $\underline{x}$, containing variables $x_i,\ i \in [1,\ m]$,then:

$$\mu(z(\tau)) = \min(\mu(x_i)) \,. \tag{15}$$

The assignment of $z(\tau)$ to the highest α-level (α-function set) is determined by the minimal membership value of an input variable x_i .

In the proposed approach the cluster analysis, based on the Fuzzy-c-Means algorithm is applied to the fuzzy process $\tilde{z}(\tau)$. Grouping of trajectories is conducted on the α-function set $Z_{\alpha=0}(\tau)$. Thereby, N cluster centres are obtained, whereas each of them identifies one deterministic, discrete function $p_{0,i}(\tau)$, $i \in [1,\ N]$. Since the function values at certain points in time were obtained with the Fuzzy-c-Means cluster approach, the function $p_{0,i}(\tau)$ doesn't represent a trajectory of a fuzzy process $\tilde{z}(\tau)$. However, the Fuzzy-c-Means algorithm proposes a gradual assignment of fuzzy process realizations to clusters. Therefore, a real valued process $p_{k,i}(\tau)$ with the highest membership to a cluster μ_k can be identified and regarded as a representative process for this particular cluster.

In general, the grouping detection algorithm yields representative processes exemplifying a particular structural behaviour. Since, those processes $p_{k,i}(\tau)$ are trajectories of a fuzzy process $z(\tau) \in \tilde{z}(\tau)$, they are characterized by a membership value $\mu(z(\tau)) = \alpha$, indicating the degree of possibility.

5 Application of grouping detection approach to controlled collapse simulation

The approach presented in section 4 is applied to the controlled collapse simulation of a three-storied framework structure of reinforced concrete. The blasting strategy presumed a tilt collapse of the structure, obtained by blasting two front columns on the first floor. Removing those supports causes failure zones in the upper part of remaining first floor columns and leads to a desired kinematic chain.

A numerical model of the above mentioned framework structure consists of 2330 eight-node hexahedral finite elements. Within the proposed finite element discretization some structural parts of the building – e.g. columns and ceilings are considered as rigid. After removing of two front columns a collapse kinematics is initialized and areas of intensified local damage arise. In order to detect those failure zones an erosion model was applied. The identified local damage zones act like hinges. Within the erosion model plastic strain is verified in every time step and elements, that satisfy the condition from Eq. (16), are removed from the simulation.

$$\varepsilon_{pl} \geqslant \varepsilon_{pl,crit} \tag{16}$$

Reinforced concrete was described with the aid of a piecewise linear plasticy model. Parameters of this material model were obtained for insufficient data and are thus affected by uncertainty. Due to the predominantly epistemic character of the uncertainty, quantities describing erosion and plastic effects were modelled as fuzzy-variables. Uncertain parameters of the material model with the uncertain stress-strain curve are shown in Fig. 3.

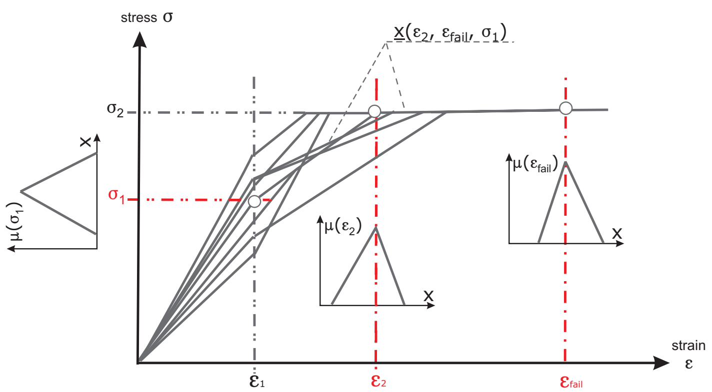

Figure 3: Fuzzy material model; piecewise linear plastic material behaviour

The application of those uncertain quantities to the controlled collapse simulation yields multiple collapse scenarios. For each of them several time-dependent structural responses are obtained. Within the presented example a displacement of a node, located in the failure zone 1 is chosen for further investigation, see Fig. 4.

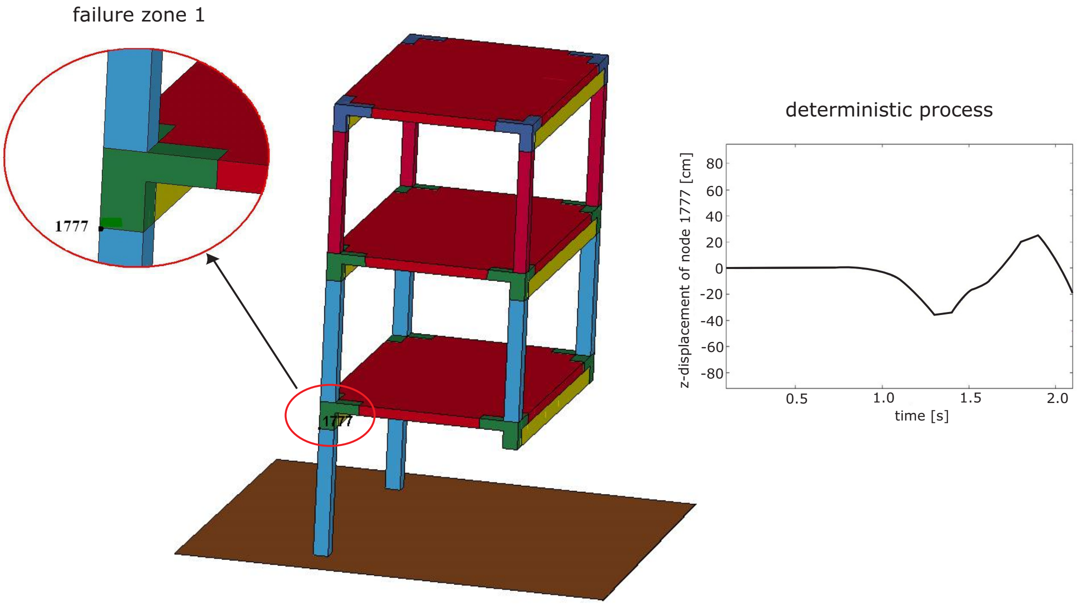

Figure 4: Finite element model of the framework structure

The analysed time-dependent displacement is a fuzzy process $\tilde{z}(\tau)$. The application of Fuzzy-c-Means cluster approach to $\tilde{z}(\tau)$ leads to the classification of all computed trajectories $z(\tau) \in \tilde{z}(\tau)$ into five clusters, see Fig 5. The Fuzzy-c-Means algorithm yields an gradual assignment of each trajectory to every cluster, described with a membership value μ_k. In Fig. 5 for a particular $z(\tau)$ a crisp assignment to a cluster is obtained taking into account the highest value of μ_k.

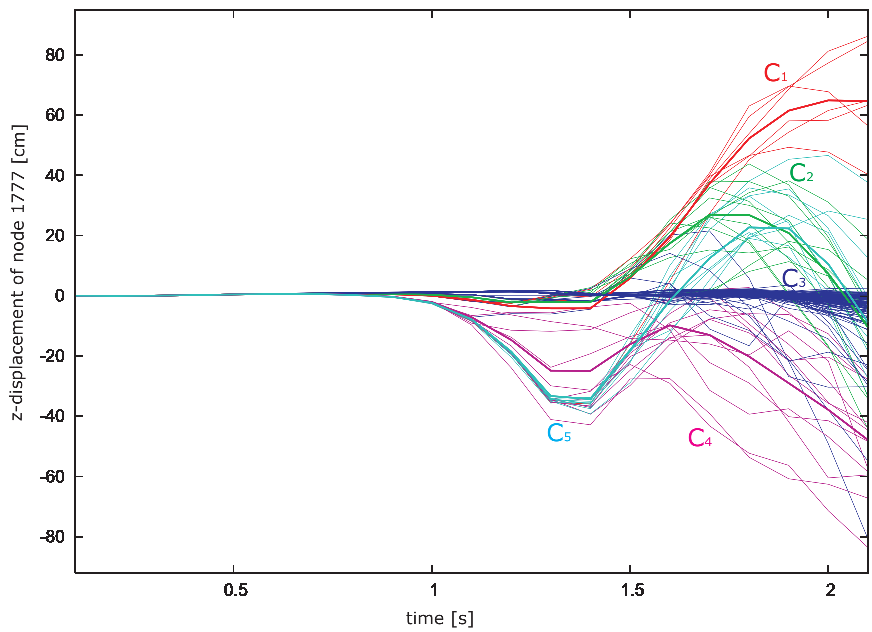

Figure 5: The assignment of fuzzy process realizations to clusters

The appropriateness of obtained classification is assessed with quality criterions as shown in Table 2. A relatively high value of the silhouette coefficient indicates that heterogeneity of cluster configuration and homogeneity within each cluster has been achieved. The comparison of obtained values with Table 1 suggests a good classification result. The partition coefficient as well indicates an unambigous assignment of fuzzy process realisations to clusters.

Table 2: Quality criterions values

Value	Quality criterion
0.402	Entropy
0.816	Partition coefficient
0.668	Silhouette coefficient

Within the fuzzy-cluster approach representative processes $p_{k,i}(\tau)$ have been identified, which exemplify five different collapse kinematics. The main differences between those structural behaviours appear in the failure zone 1 and influence the further kinematic chain. Within models 1 and 2, associated with $p_{k,1}(\tau)$ and $p_{k,2}(\tau)$ a tilt-vertical collapse can be observed, see Fig. 6. Due to the high plastic strain values a separation within the failure zone proceeds. The isolated upper part of the building falls at remaining two columns of the first floor. Such a tilt-vertical collapse significantly differs from the planned strategy and should be concerned as impermissible. The only distinction between those models can be made relative to the buckling behaviour of the first floor pillars. Diverse formulation of the material law implies different compliance of the remaining columns. Within models 3 and 4 ($p_{k,3}(\tau)$ and $p_{k,4}(\tau)$) the division of the failure zone occurs as well, but the separated upper part of the structure falls forward on the prepared fall zone, avoiding the collision with columns. Some differences between those two models appear in the later collapse stage, due to diverse kinetic energy of the falling part shortly after the separation. In effect, the successive formation of failure zones proceeds differently. Model 5 ($p_{k,5}(\tau)$) represents the desired tilt collapse. The separation within the connection of first floor columns and the ceiling does not occur, which implies the intended formation of further failure zones.

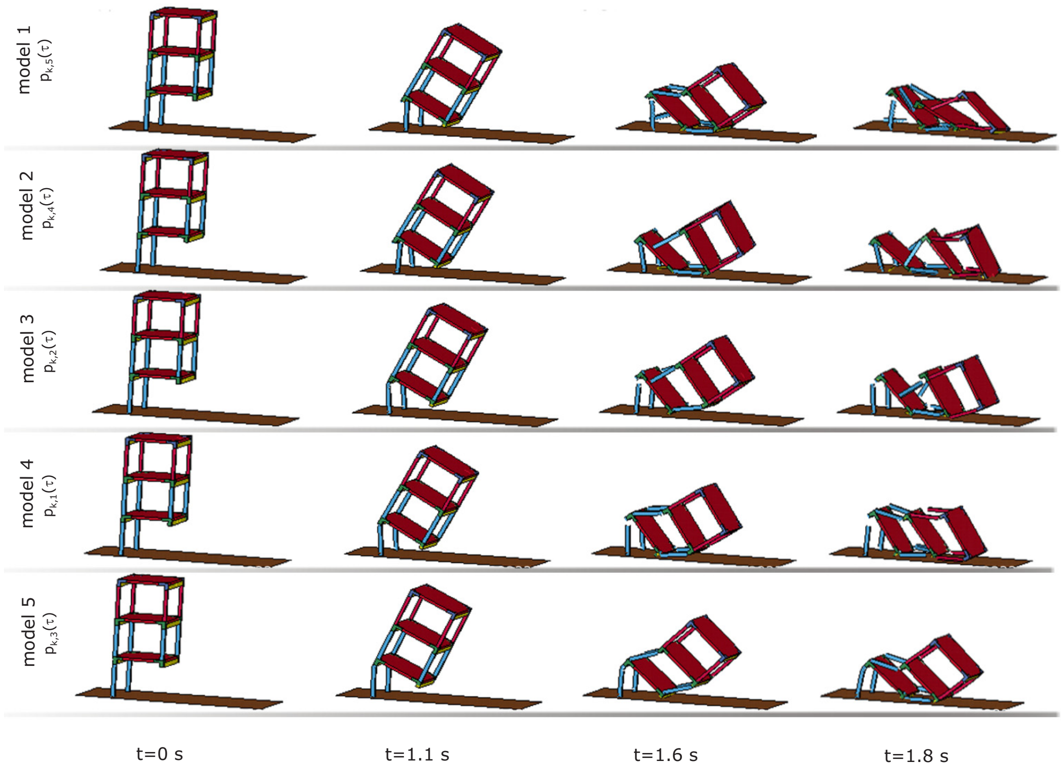

Figure 6: Different collapse kinematics, identified with the cluster approach

Since the identified displacement curves are realisations of a fuzzy-process, they are assessed by membership values, indicating the degree of possibility. In Fig. 7 representative processes are shown.

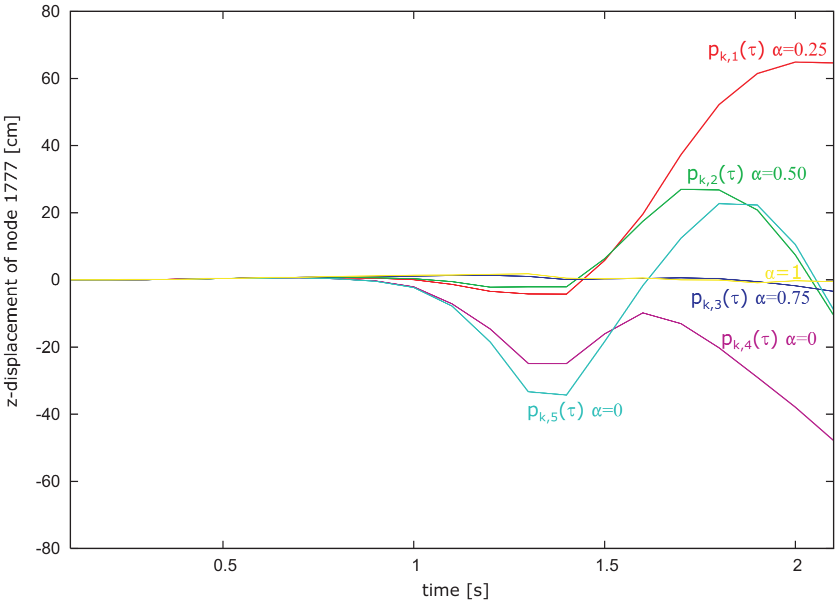

Figure 7: Representative processes $p_{k,i}(\tau)$

Hence, some conclusions can be drawn regarding the degree of possibility of the identified processes. The process $p_{k,5}(\tau)$, associated with the structural behaviour of model 5 belongs to the α-set $\underline{S}_{\alpha=0.75}$ and is therefore described with the degree of possibility 0.75. For the fuzzy input parameters, specified as mentioned above the occurrence of this structural behaviour seems to be quite possible. According to Fig.6 similarity between processes, characterised with bunch parameters 0.75 and 1 can be stated. Since both collapse kinematics correspond to the intended blasting strategy, such a result suggests a successful realization. The membership values of the remaining representative processes indicate lower degrees of possibility. Even though, they should be taken into consideration during planning of the blasting strategy in order to guarantee a safe realization of structure collapse.

6 Conclusions

In this paper a grouping detection approach, based on cluster algorithms has been presented. The application of this method to uncertain processes enables an engineering-oriented interpretation of uncertain structural analysis results. As input parameters are predominantly specified on the basis of incomplete, dubious or fluctuating information, the model fuzziness has been applied for the uncertainty quantification. Numerous realizations of fuzzy process have been classified into definite number of clusters with the Fuzzy-c-Means cluster approach. Thereby, each cluster has been characterized by a representative process, that exemplifies a particular structural behaviour. Representative processes obtained with presented grouping detection approach are assessed by a membership value indicating the degree of possibility. Thus, the proposed method yields realistic results, because uncertainty is considered and on the other hand provides an applicable solution, because merely several representative structural behaviours are chosen for the engineering interpretation. The capability of the approach was demonstrated by means of controlled collapse simulation.

7 Literature

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