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Prediction of time-dependent structural behaviour with recurrent neural networks for fuzzy data

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ABSTRACT

In the paper, an approach is described which permits the numerical, model-free prediction of uncertain time-dependent structural responses. Uncertain time-dependent structural actions and responses are modelled by means of fuzzy processes. The prediction approach is based on recurrent neural networks for fuzzy data trained by time-dependent results of measurements or numerical analyses. An efficient solution for network training and prediction is developed utilizing α-cuts and fuzzy arithmetic. The approach is verified using a fractional rheological model. The capability of the approach is demonstrated by predicting the long-term structural behaviour of reinforced concrete plates strengthened by textile reinforced concrete layers.

1. Introduction

The long-term behaviour of engineering structures depends on a multiplicity of environmental influences such as applied loadings, temperature and weathering. This results in uncertain time-dependent deformations and stress rearrangements inside the structure. This behaviour can be incorporated into a time-dependent structural analysis with rheological models [1], which are based mathematically on integer or fractional time derivatives of stresses and strains. Thereby, the model has to be selected a priori. The extension of conventional rheological models to fractional rheological models facilitates an improved fitting of material parameters to experimental data. However, the entire stress history has to be considered for the determination of the current stress and strain states, which leads to a high computational effort for fractional rheological models. As an alternative, a novel method for the numerical prediction of time-dependent structural responses under consideration of uncertain action processes is proposed here, which combines neural computing (artificial neural networks) and mapping of fuzzy data (fuzzy analysis, see e.g. [2]).

The artificial neural network concept is adapted from the structure and the functionality of the human brain. It is a powerful tool to capture and to learn functional dependencies in data. An overview of neural network applications in civil engineering is given e.g. in [3]. The widely-used type in engineering applications is the multilayer perceptron network with feed forward architecture [4]. Advanced network architectures have to be applied in order to consider time-dependent effects of the structural behaviour. In [5], the rate-dependency of materials is considered by means of additional input neurons in a feed forward network for the approximation of time-dependent constitutive material behaviour. Moreover, recurrent neural networks have been developed for temporal signal processing (see e.g. [6]). They are suitable for the mapping of structural processes, obtained by experiments or numerical monitoring (see Section 2), onto time-dependent structural responses.

If a structural process is observed experimentally with the help of measurement devices, it is not possible to assign precise values. Data uncertainty occurs which may result from scale-dependent effects, varying boundary conditions which are not considered, inaccuracies in the measurements, and incomplete sets of observations. Therefore, measured values are more or less characterized by data uncertainty which originates in imprecision (see e.g. [7]). In this contribution, the imprecision is modelled by means of fuzzy sets. However, intervals and deterministic data are also taken into account, as they represent special cases of fuzzy sets in view of the numerical treatment. Time-dependent structural parameters are quantified as fuzzy processes as described in Section 2.1.

The treatment of fuzzy data with artificial neural networks requires specific prediction and training algorithms. A survey of processing fuzzy data with feed forward networks is given in [8]. For the prediction of fuzzy processes, three types of mapping fuzzy input processes onto fuzzy output processes with recurrent neural

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networks are introduced in Section 3. A prediction and a training algorithm are presented. As an extension to [9], fuzzy network parameters are considered. Beside fuzzy data, also intervals and deterministic numbers may be processed.

The developed recurrent neural network approach for fuzzy data is verified using a fractional rheological material model in Section 4. Uncertain stress–strain–time dependencies obtained by numerical monitoring are trained. The resulting networks for fuzzy data are utilized for the prediction of further stress–strain–time dependencies.

The developed recurrent neural network approach is applied in Section 5 for the prediction of the long-term displacements of reinforced concrete plates which were strengthened with textile reinforced concrete (TRC) layers.

2. Monitoring of time-dependent structural behaviour

Time-dependent structural behaviour may be computed by means of structural monitoring. In the conventional meaning, parameters representing the structural behaviour are obtained with the aid of experimental investigations. However, mainly due to the increase in computational power, the numerical monitoring becomes important and provides insight into the behaviour of structures or structural members. Thereby, the time-dependent structural behaviour is numerically simulated utilizing nonlinear computational models (see e.g. [10]). Repeated numerical simulations with varying input parameters may be also interpreted as numerical experiments. The input parameters of the computational model may be determined by means of experiments with test specimens as well as parameter identification based on the results of in situ monitoring. In so far, numerical monitoring represents more an extension of the conventional monitoring then a substitute.

Results of experimental investigations are generally characterized by uncertainty because of physically originated variations and imprecision. The description of the observed phenomena close to reality requires the consideration of data uncertainty. The imprecision may be best modelled by means of the uncertainty model fuzziness. Imprecise measurements can be considered as fuzzy data. Time-dependent structural parameters are quantified by fuzzy processes (see e.g. [11]).

2.1. Fuzzy processes

A fuzzy process is defined according to

$$\tilde{x}(\tau) = \{\tilde{x}_\tau = \tilde{x}(\tau) \forall \tau | \tilde{x}_\tau \in \mathbf{F}(\mathbf{X})\} \quad (1)$$

as a set of fuzzy values belonging to the set $\mathbf{F}(\mathbf{X})$ of all fuzzy values defined on a fundamental set $\mathbf{X}$. The uncertain functional values $\tilde{x}_\tau$ are gradually assessed by membership functions $\mu(x)$.

In this paper, convex fuzzy values subdivided into fuzzy numbers and fuzzy intervals (see [11]) are applied. For fuzzy numbers, one deterministic argument (kernel value) x exists with $\mu(x) = 1.0$. The membership function of a fuzzy interval consists of a kernel interval $[{}_{1.0l}x, {}_{1.0r}x]$ with $\mu(x) = 1.0$ for all $x \in [{}_{1.0l}x, {}_{1.0r}x]$.

A fuzzy triangular number $\tilde{x} = \langle x_1, x_2, x_3 \rangle$ is a special fuzzy number whose membership function $\mu(x)$ is characterized by linear functions between $\mu(x) \to 0+$ and $\mu(x) = 1.0$. It is completely identified by the values x_1, x_2, and x_3 for which hold $\mu(x_1) \to 0+$, $\mu(x_2) = 1.0$, and $\mu(x_3) \to 0+$, respectively.

2.2. Discretization of fuzzy processes

For the numerical prediction of the long-term structural behaviour under consideration of fuzzy processes, two modes of discretization are required. At first, all fuzzy processes have to be discretized in time resulting in sets of fuzzy values. Then the membership functions of the obtained fuzzy values are subdivided in sets of α-cuts.

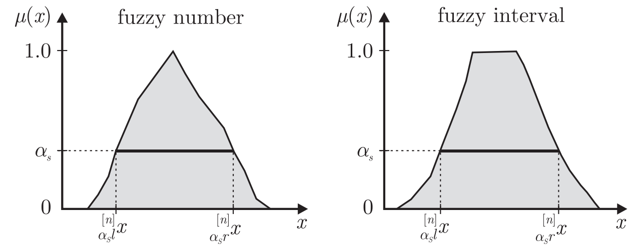

Fig. 1. α-Cuts of a fuzzy number and a fuzzy interval.

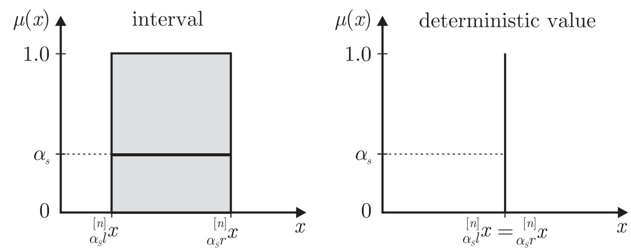

Fig. 2. α-Cuts of an interval and a deterministic value.

The fuzzy process $\tilde{x}(\tau)$ is discretized in time by N equidistant time steps $[n = 1, \ldots, N]$ obtaining the fuzzy values ${}^{[n]}\tilde{x}$ for every time point ${}^{[n]}\tau$. As the fuzzy processes represent structural parameters, the applied discretization algorithm depends on the experimentally or numerically available data base resulting from structural monitoring.

- If the time step length in monitoring is identical to the time step length of discretization, the results obtained by structural monitoring may be applied directly within the numerical prediction approach.
- Otherwise, the fuzzy values ${}^{[n]}\tilde{x}$ may be determined by interpolation using the values before and after ${}^{[n]}\tau$ or by combination of multiple values within the time period ${}^{[n-1]}\tau < \tau < {}^{[n+1]}\tau$.

In the second step, the membership functions $\mu({}^{[n]}\tilde{x})$ of the fuzzy values ${}^{[n]}\tilde{x}$ are subdivided into $s = 1, \ldots, S$ α-cuts (see [2]). Regarding convex fuzzy values, a connected interval $\left[{}^{[n]}_{\alpha_s l}x, {}^{[n]}_{\alpha_s r}x\right]$ with the left bound

$${}^{[n]}_{\alpha_s l}x = \min\left[{}^{[n]}x \in \mathbf{X} | \mu({}^{[n]}x) \geqslant \alpha_s\right] \quad (2)$$

and the right bound

$${}^{[n]}_{\alpha_s r}x = \max\left[{}^{[n]}x \in \mathbf{X} | \mu({}^{[n]}x) \geqslant \alpha_s\right] \quad (3)$$

is obtained for each α-cut (see Fig. 1).

The interval $\left[{}^{[n]}_{\alpha_1 l}x, {}^{[n]}_{\alpha_1 r}x\right]$ of α-cut $\alpha_1 = 0$ is defined by $\mu(x) \to 0+$. For fuzzy numbers holds ${}^{[n]}_{\alpha_s l}x = {}^{[n]}_{\alpha_s r}x$.

In Fig. 2, α-cuts for the special cases interval and deterministic value are presented.

3. Recurrent neural networks for fuzzy data

The long-term behaviour of engineering structures is influenced by time-dependent uncertain alterations which can be modelled by means of fuzzy structural processes. These fuzzy structural