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Time-dependent reliability analysis of flood defences

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ABSTRACT

This paper describes the underlying theory and a practical process for establishing time-dependent reliability models for components in a realistic and complex flood defence system. Though time-dependent reliability models have been applied frequently in, for example, the offshore, structural safety and nuclear industry, application in the safety-critical field of flood defence has to date been limited. The modelling methodology involves identifying relevant variables and processes, characterisation of those processes in appropriate mathematical terms, numerical implementation, parameter estimation and prediction. A combination of stochastic, hierarchical and parametric processes is employed. The approach is demonstrated for selected deterioration mechanisms in the context of a flood defence system. The paper demonstrates that this structured methodology enables the definition of credible statistical models for time-dependence of flood defences in data scarce situations. In the application of those models one of the main findings is that the time variability in the deterioration process tends to be governed the time-dependence of one or a small number of critical attributes. It is demonstrated how the need for further data collection depends upon the relevance of the time-dependence in the performance of the flood defence system.

1. Introduction

Quantitative risk and reliability methods provide a rational basis for the design and operational management of flood defence systems [1–3]. Development of practical methods for reliability analysis of flood defence systems has tended to focus upon calculation of flood risk at present or at specific points in the future, see for example [4–10]. Other than in selected cases [11–14] less attention has been paid to the process of deterioration. However, a comprehensive understanding of deterioration forms an essential basis for any optimal maintenance strategy. Developed countries at risk from flooding now have extensive investments in flood defence infrastructure, so efficient maintenance of these systems is as much, if not more, of a priority as new capital works.

An example of a theoretical framework for optimal maintenance is discussed by Faber [15,16] and specifically for flood defence maintenance by Vrijling [17]. In the context of such a theoretical framework, the key objective of this paper is a practical approach to incorporating time-dependent processes in established reliability models of flood defence systems. Our focus is upon time-dependent processes associated with the flood defence assets themselves rather than processes that may influence multiple flood defence system components, such as geomorphologic change or sea level rise.

The main structure types in flood defence systems and their failure mechanism are reviewed by e.g. Floodsite [18], Environment Agency [19] and HR Wallingford [20]. The variables parameterising these failure mechanisms in the form of a process model constitute the basic variables in reliability analysis. There is a multitude of possible deterioration mechanisms that may modify the value of these variables through time. This paper offers a methodology that supports the construction of the most reasonable theoretical model in the absence of such understanding and testing opportunities. Knowledge becoming available at a later stage serves to test and improve that model [21]. Reliability analysis offers the ideal framework within which to incorporate available knowledge, even if that knowledge is only, on some occasions, derived from expert knowledge.

Therefore, in the following section of this paper, the theoretical structure for time-dependent reliability analysis as well as its numerical implementation is set out. In Section 3 the methodology is described for identifying relevant processes and relevant variables in those processes. The characterisation of those processes in the form of a statistical model is discussed. The

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approach is applied in Section 4 to a substantial example of an earth embankment subject to three deterioration mechanisms. Conclusions follow in Sections 5.

2. Theory and implementation of time-dependent flood defence reliability

2.1. Theoretical background information

This section covers three topics on the theoretical background of time-dependent reliability analysis of flood defences: (i) the definition of time-dependent reliability; (ii) introduction to stochastic processes for modelling time-dependence; and (iii) the incorporation of time-dependent processes in time-dependent reliability analysis. Section 2.2 subsequently describes generic aspects of the numerical implementation of these models.

Ad (i), in the definition of time-dependent reliability, and generally in flood defence management decision-making, a central concept is the distribution function of the lifetime L of the flood defence structure, $F_L(T)$. The lifetime distribution $F_L(T)$ corresponds with the probability of failure during a specified time period of interest $[0, T]$. Reliability-based planning of monitoring, repair or improvement activities is triggered by reaching a particular probability of failure threshold in such a period of interest. Another reliability-based concept that is of interest to flood defence management is the fragility curve as proposed by Dawson and Hall [22], which is the conditional probability of flood defence failure given load. Load refers to a variable such as the water level and wave conditions.

Let failure be defined by $Z(X(t),t)\leq 0$, where $X(t)$ is a vector of processes: $X_1(t),\ldots,X_n(t)$. The lifetime probability distribution $F_L(T)$ is then given by

$$F_L(T) = P(L\leq T) = 1 - P[Z(X(t),t)>0\,\forall t\in[0,T]] \quad (1)$$

Ad (ii), statistical representation of time-dependent processes is necessary to develop a model of time-dependent reliability. A variety of time-dependent processes, mainly directed at modelling loading conditions, have been discussed in the literature [23]. Here, following Vrouwenvelder [24], we consider three different types of statistical representation of time-dependent processes below. The first two types represent time-dependent processes with an increasing complexity. The third type is typical for a deterministic time-dependent engineering model where the variables are considered as random variables, rather than stochastic processes:

1. *Stochastic process*: the time-dependent variable of interest $X_i(t)$ is modelled by a stochastic process. This representation models a time-dependent process in aggregate by one stochastic process or models one time variant contributor.
2. *Hierarchical process*: consisting of random variables and has one or more stochastic processes embedded in it, so for example $X_i(t) = f(D_1,\ldots,D_i(t),\ldots,D_n)$, where $X_i(t)$ is a function of random variables D_1–D_n, among which $D_i(t)$ is a stochastic process. This model decomposes the time-dependent process more realistically into different relevant time variant or invariant contributors. A statistical model is applied individually to each contributor.
3. *Parametric process*: $X_i(t) = f(D_1,\ldots,D_n, t)$ so $X_i(t)$ is a function of random variables $D_1,\ldots, D_n$ and a deterministic time t. This approach models individual variables as time invariant contributors.

All three mentioned types, not just the first one, are stochastic processes according to the definition in Ross [25]. However, the distinction we adopt here between stochastic and parametric processes is relevant in the classification of different types of time series representations. The distinction in practice between the parametric and stochastic process (including the hierarchical process) is illustrated in Fig. 1, which shows realisations from a typical parametric process (centre panel) and a typical stochastic or hierarchical process (right-hand panel). The most realistic representation is a hierarchical process, which is based upon a decomposition of the process into contributing attributes.

Ad (iii), the individual time-dependent process is incorporated in the computation of an interval probability $P_f(\Delta t_i)$ and subsequently in the approximation of lifetime probability. Generic details about the numerical implementation of the methods are offered in Section 2.2. A method to approximate lifetime probability is necessary as Eq. (1) can generally not be solved analytically [26] and is described in the following. $F_L(T)$ in Eq. (1), or the probability of failure in specified time interval $[0,T]$ of interest, can be approximated with the outcrossing approach. The probability that the lifetime L is smaller than a duration T is

$$F_L(T) = P(L\leq T) \quad (2)$$

The outcrossing approach then approximates the lifetime probability $F_L(T)$ with a Poisson distribution based on the assumption of independent outcrossings [26]:

$$F_L(T) \approx 1 - \exp\{-E[N^+(T)]\} \quad (3)$$

where $E[N^+(T)]$ is the mean number of crossings of $X(t)$ into the failure domain during $[0,T]$. In the stationary case $E[N^+(T)] = \nu^+ T$, where ν^+ is the outcrossing intensity. In this paper the lifetime period of interest $[0,T]$ is subdivided into N time intervals Δt. The mean number of crossings in a time interval is approximated by $P_f(\Delta t_i)$, the time-dependent probability of failure during a period Δt_i. The numerical implementation to calculate $P_f(\Delta t_i)$ is described in the following section.

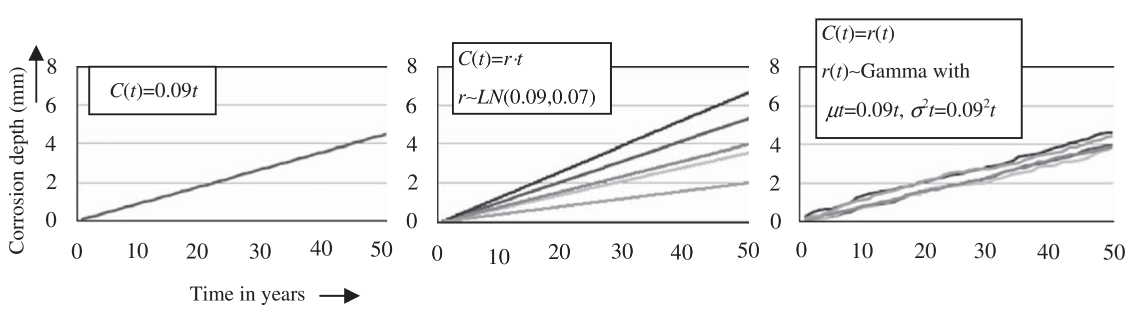

Fig. 1. Examples of corrosion depth time series samples for a deterministic model (left), a parametric process (middle) and a stochastic process (right).

2.2. Numerical implementation

Generic aspects of the numerical implementation of time-dependent processes in a flood defence reliability model are discussed in Section 2.2.1 for stochastic processes, and Section 2.2.2 on the incorporation of these processes in a reliability-based approach. Section 4 illustrates the site specific implications for the numerical implementation of time-dependent processes. The approach is based upon Monte Carlo simulation methods because many of the time-dependent processes are rather complex and do not succumb to algebraic solutions.

2.2.1. Stochastic processes

Generic aspects about the numerical implementation of parametric, stochastic and hierarchical processes according to the definition in Section 2.1 are discussed below.

2.2.1.1. Parametric processes. As defined in Section 2.1, a parametric processes is a function $X_i(t) = f(D_1, \ldots, D_n, t)$ of random variables $D_1, \ldots, D_n$ that are constant in time and a deterministic time t. Therefore, in Monte Carlo simulation of these processes only the first simulation in the time series, for example for time $t = 1$, requires sampling of $D_1, \ldots, D_n$. This sampled set of $D_1, \ldots, D_n$ remains equal throughout the rest of the time series, since they are constant in time, also illustrated in the middle panel in Fig. 1. The variables $D_1, \ldots, D_n$ can be any type of flood defence property such as soil properties, revetment weight or geometry.

2.2.1.2. Stochastic processes. Monte Carlo simulation of a stochastic process requires repeated samples of increments in the time series. If a stochastic process represents one variable $X_i(t)$ as defined in Section 2.1, the first simulation in the time series, for example for time $t = 1$, requires sampling of the increment of $X_i(t)$ between $t = 0$ and $t = 1$. For each subsequent time step the increment of $X_i(t)$ is sampled and accumulated. The result of such type of time series samples is illustrated in the right panel in Fig. 1.

2.2.1.3. Hierarchical processes. A hierarchical process is defined in Section 2.1 as a function $X_i(t) = f(D_1, \ldots, D_i(t), \ldots, D_n)$ where $D_1, \ldots, D_{i-1}, D_{i+1}, \ldots, D_n$ are constant variables in time and $D_i(t)$ is a stochastic process. In Monte Carlo simulation, the first step in the time series sample requires sampling of $D_1, \ldots, D_{i-1}, D_{i+1}, \ldots, D_n$ and a sample of the increment of $D_i(t)$ in the interval $t = 0$ and $t = 1$. In subsequent time steps the sample of $D_1, \ldots, D_{i-1}, D_{i+1}, \ldots, D_n$ remains equal to the first and constant throughout the time series. The increment of $D_i(t)$ is sampled and accumulated for each subsequent time interval. Based on $D_1, \ldots, D_{i-1}, D_{i+1}, \ldots, D_n$ and the accumulated $D_i(t)$ the overall quantity $X_i(t)$ is calculated for each time step. The appearance of time series samples is similar to those illustrated for the stochastic process in Fig. 1 (right panel).

2.2.2. Incorporation of stochastic processes in time-dependent reliability analysis of flood defences

In reliability analysis of flood defences, the flood defence system is typically subdivided into a number of flood defence sections (see for example [8]). Each of these sections is characterised by one cross section, with details of geometry, revetment, soil properties etc.. Each cross section can fail in multiple ways, the failure mechanisms. A limit state equation is used to define each failure mechanism. The logical relations between the failure mechanisms are organised according to a fault tree. The flood defence properties (e.g. geometry, soil parameters, etc.) in the limit state equations form a vector of random variables $X_1, \ldots, X_{i-1}, X_i(t), X_{i+1}, \ldots, X_n$. One or more of these variables is a time-dependent process, $X_i(t)$, according to the definitions in Section 2.1. Therefore, in Monte Carlo simulation, the first realisation in the time series, for example for time $t = 1$, requires sampling of all random variables $X_1, \ldots, X_{i-1}, X_i(t), X_{i+1}, \ldots, X_n$. If $X_i(t)$ is a time-dependent function $X_i(t) = f(D_1, \ldots, D_i(t), \ldots, D_n)$, the vector $D_1, \ldots, D_i(t), \ldots, D_n$ is also sampled. Based on the sample of the random variables the limit state equations corresponding with the different failure mechanisms are computed and evaluated whether $Z(X(t) \leq 0)$. According to the logical relations in the fault tree between the failure mechanisms an evaluation is made of whether the cross section fails or not. For the subsequent time steps only the time-dependent quantities $X_i(t)$ are sampled and accumulated as explained in Section 2.2.1, the time-independent flood defence properties remain equal to the first sample. For the subsequent time steps and the newly sampled values of $X_i(t)$ the limit state equations are evaluated. After completing the evaluation of the limit state equations for one time series all the time-dependent and time-independent variables are sampled in a second time series simulation. The sample of the time-independent variables remains equal throughout the time series, while the time-dependent quantities $X_i(t)$ are sampled and accumulated as explained in Section 2.2.1. This simulation procedure is repeated a large number of times to calculate the overall probability of failure of the cross section as a function of time, $P_f(t)$:

$$P_f(t) = \frac{N_{top \leq 0}}{N_{tot}} \tag{4}$$

where $N_{top \leq 0}$ is the number of simulations for which the evaluation of the limit state equations entails failure of the cross section and N_{tot} is the total number of simulations. During the simulations the time period $[0,T]$ is discretised into a number of time intervals Δt_i for which the time-dependent processes are sampled and the probability of failure is calculated. The probability of failure $P_f(\Delta t_i)$ is representative for the time interval Δt_i and is implemented in Eqs. (4) and (3).

As mentioned before, a further result of interest is time-dependent fragility, or the probability of failure conditional upon different loading variables. The procedure is similar to that described above except that the loading variables are not considered as random variables. The loading variables are instead subdivided into a number of intervals. The time interval $[0,T]$ is discretised into time intervals Δt_i and for each moment in time the probability of failure given a loading variable h is calculated as $P_f(t|h)$

$$P_f(t) = \frac{N_{tot \leq 0||h}}{N_{tot|h}} \tag{5}$$

where $N_{top \leq 0|h}$ is the number of simulations for which the evaluation of the limit state equations entails failure of the cross section given a water level h and $N_{tot|h}$ is the total number of simulations given a loading variable h.

3. Modelling methodology for long-term behaviour of flood defence assets

3.1. General outline of the modelling methodology

3.1.1. Introduction and definitions

The data availability on time series of time-dependent processes of flood defence assets is usually severely limited. Sample of flood defence properties is expensive. Monitoring of flood defence condition is typically done by visual inspection which does not yield measurements of the relevant flood defence properties. Particular measurement campaigns may be implemented occasionally, but these do not yield the time series of observations that would ideally required to parameterise deterioration models. This section describes a methodology that supports the construction of the most reasonable theoretical model in the absence of such understanding and testing opportunities. Knowledge becoming available at a later stage serves to test and improve that model [21]. The methodology intends to offer a transparent and evidence-based process, consisting of a series of careful theoretical decisions and practical judgements.

In this paper our focus is upon time-dependent processes associated with the flood defence assets rather than processes that may influence multiple flood defence system components, such as sea level rise. These 'asset time-dependent processes' are mostly, but not exclusively deterioration processes. An example of a time-dependent process that does not lead to deterioration is beach accretion which may lead to reduction in the probability of failure through time.

3.1.2. Outline modelling methodology

The methodology begins with a problem formulation. This phase entails an analysis of (i) the failure mechanisms in the flood defence system and (ii) the processes that may lead to time-dependent behaviour in those failure mechanisms. As Eq. (1) implies, time-dependent behaviour may act through change in the distribution of basic variables, or through change in the limit state function, though in practice the latter of these is parameterised by introducing new basic variables.

The overall process of setting up a conceptual statistical model for the time-dependent behaviour is summarised in Fig. 2. The process consists of five steps which are discussed in more detail with more general modelling aspects in Section 3.2. The relevant flood defence contributors referred to in Fig. 2 are subdivided into (i) excitation features which are flood defence properties that actively initiate or drive the time-dependent process (wave climate, rainfall, third party interference); (ii) ancillary features which are flood defence properties that transform the process; and (iii) affected features which are the time-dependent flood defence properties in the performance model.

3.2. The steps in the modelling methodology in detail

Fig. 2 presents the main steps in the modelling methodology of time-dependent processes. These steps are explained in more detail in the following.

3.2.1. Identify existing knowledge

The starting point is the identification of existing scientific understanding about the time-dependent process of the flood defence asset. This analysis can make use of site specific information as well as more generic reviews of flood defence processes, see for example [27,18].

3.2.2. Identify relevant flood defence properties

The second step in the modelling methodology identifies the flood defence properties that are relevant to the time-dependent process of interest. The uncertainties associated with the flood defence properties provide insight in how time variability is introduced in the time-dependent process.

Excitation features are the flood defence properties that initiate and drive the time-dependent process of interest. Without those features no asset time-dependence takes place. The wave climate is an example of an excitation feature. Environmental influences that are not part of the basic variables in the original reliability model can also form excitation, e.g. the presence of oxygen and moisture to corrosion. Table 1 tabulates a number of excitation features and their time-dependent behaviour.

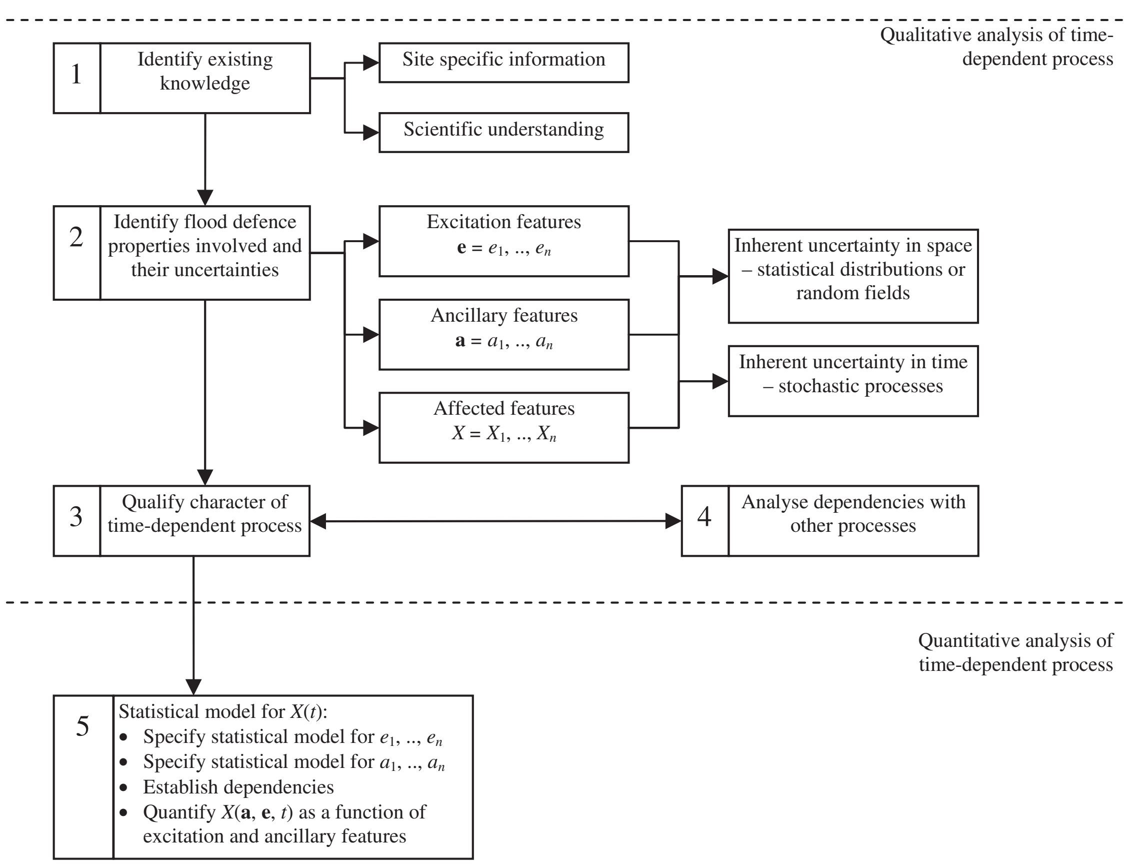

Fig. 2. Proposed steps in the modelling process of asset time-dependent processes.

Table 1
Some examples of excitation features.

Excitation feature	Characteristic time-dependent behaviour
Wave climate: significant wave height, wave period and wave direction	Recurrent/storm sequence
River current velocity	Reversing tides (estuary)/recurrent high water events
Pore pressure distribution in flood defence structure or foundation	Rainfall and drought cycles/seasons/ event sequence/accumulation
Water head difference over flood defence	Tides/recurrent/storm sequence/ rainfall events/rainfall sequence
Third party loading, e.g. traffic (vehicle weight, tyre acceleration, profile)	Recurrent/event sequence
Third party loading, e.g. animal burrowing	Three-dimensional random walk/ entrance shifting with river water levels
Superimposed loading, e.g. raising a crest level of a dike	Constant in time
The presence of oxygen and moisture in or around the steel flood defence structure components, in relation to corrosion	Seasonal/climate

Each of these features are inherently uncertain in both space and time, with the exception of the superimposed self-load of the structure which tends to stay constant in time and only varies in space.

The ancillary features are the flood defence properties that additionally influence the time-dependent process by transforming the excitation features into the time-dependent process. For example, the damage of the revetment caused by wave impact is dependent on the structure slope, shape and weight of the revetment, as well as the excitation features of wave height and period.

3.2.3. Qualify the character of the time-dependent process

The character of the time-dependent process depends on how the variability in time is introduced and transformed. Table 2 shows examples of suitable stochastic processes for different types of time-dependent behaviour. These stochastic process models are suitable for both excitation and ancillary features introducing time variability. The character of the overall process is then quantified as a function of ancillary features conditional on the excitation of the asset time-dependent process. Subsequently, the statistical models for the ancillary features are incorporated in the reliability model.

3.2.4. Represent the dependencies between time-dependent processes

The fourth step in the modelling methodology in Fig. 2 is to represent the dependencies among asset time-dependent processes. Examples of such dependencies are: processes sharing the same excitation, one process forming (partly) the excitation of the other process, and processes sharing similar ancillary features. Modelling such dependencies is fairly straightforward if process-based models are available for both time-dependent processes. The common excitation and/or ancillary features then appear in both process models. Dependence models in the form of threshold values and fault tree analysis provide a structured approach to representing dependence.

Alternatively dependencies may be expressed in terms of multivariate distributions. The multivariate distribution may be represented directly. For example in case of gamma process marginal distributions an example of an appropriate bivariate distribution function is the double-gamma distribution [28]. It is a suitable bivariate structure to represent the correlation between two linearly correlated singular gamma processes. Alternatively, for continuous distributions the marginal variables may be transformed to standard normals and the dependence represented in multivariate normal space. More generally, copulas functions [29,30] may be used to represent the dependence structure.

Table 2
Stochastic processes and the type of time variability that they represent.

Stochastic process	Type of time-dependent behaviour
Rectangular wave process (e.g. Borges Castanheta)	Seasonality in hydraulic loading variables such as: high river discharges/floodplain water levels/pore pressures
Pulse/Poisson process	Arrival of storm events/arrival of trafficking events/arrival of pit corrosion
Gamma process	Strictly increasing excitation features, ancillary features or overall quantity $X_i(t)$
Compound renewal process (e.g. superposed, alternating, cumulative)	Arrival of trafficking events causing cumulative damages
Gaussian/Brownian	Continuous process

3.2.5. Definition of the statistical model

This paper demonstrates three main types of stochastic process models (as defined in Section 2.1) on the case study site: a hierarchical process, a parametric process and a gamma process model.

The first type of statistical model is a hierarchical process developed according to the modelling methodology described in Sections 3.1.2 and 3.2. The hierarchical process model allows the decomposition of the time-dependent process into contributions by different flood defence properties (see type 2 in Section 2.1).

The second type of statistical model that is demonstrated in Section 4 is a conventional engineering approach based on a parametric process, consisting of time invariant random variables and deterministic time (see type 3 in Section 2.1). An existing engineering process-based model or, in the absence of such a model, a random deterioration rate as a function of deterministic time serves this purpose. The model is included in the analysis as a basis for comparison with the hierarchical process model.

In Section 4 the gamma process model is demonstrated in the form of an aggregate model as the second type of statistical model (see type 1 in Section 2.1). A gamma process model is a stochastic process approach allowing expert elicitation on the average rate of the time-dependent process [13]. This model provides a strictly increasing time-dependent stochastic process and therefore represents deterioration. The gamma process either takes the behaviour according to an existing process model into account or allows expert elicitation on the average deterioration rate.

Under some circumstances it may be preferable to choose for an aggregate representation of the time-dependent process instead of a hierarchical process model. One reason might be for example that lack of scientific understanding does not allow for the formulation of a more detailed statistical model. A stochastic process model allows in that case a rough estimate of the time-dependent process. Another reason might be the presence of field data on the deteriorating quantity but limited data availability on the flood defence properties to populate a process-based model. Broad risk assessments are a third example of a suitable application of aggregate time-dependent processes. Broad risk assessments require a computationally feasible stochastic process representation given the financial, time and information constraints of such an assessment. An aggregate approach offers an approximation of the time-dependent behaviour and is computationally feasible.

For the reasons outlined above, historical time series samples of the time-dependent quantity $X_i(t)$ are usually scarcely populated. Calibration is then supported by checking whether the time series samples of the asset time-dependent quantity $X_i(t)$ are in a sensible order of magnitude and display a sensible variation. Corroboration of the model is supported by comparing the qualitative behaviour of the process following from the modelling methodology with the behaviour of the time series samples. The increasing availability of future observations can be used for further calibration and corroboration or for Bayesian updating of the prior distributions.

4. Application to earth flood defence embankments

The time-dependent reliability methods are demonstrated on the Dartford Creek to Swanscombe Marshes flood defence system along the Thames Estuary in the UK (Fig. 3). Flooding in 1953 was the motivation for a major flood defence improvement scheme which was carried out in the 1970s and 1980s. As part of this improvement scheme new earth embankments were designed, reinforced concrete walls added to raise existing embankments, private frontages raised and existing sheet pile walls refurbished. The design standard was for a 1:1000 year return period water level, with additional freeboard allowances for wave overtopping. This system of defences continues to provide a high standard of protection to the urbanised floodplain. Considerable sums are invested annually in inspection and maintenance, and the strategy for maintaining and/or upgrading the defences during the coming decades is now being reviewed.

The main structure types, failure mechanisms and time-dependent processes are listed in Table 3. Here, by way of illustration, we address the deterioration of the earth embankments, focussing upon three dominant deterioration mechanisms: (i) long-term crest level settlements due to compaction, (ii) trafficking damage to crest and vegetation and (iii) internal erosion of water conductive layer leading to seepage length reduction.

Analysis of the anchored sheet pile walls and reinforced concrete walls is reported in Buijs [31]. The earth embankments at the site were improved during the 1970s by the construction of a higher embankment landward of the original structure, see Fig. 4. The embankments are founded on the alluvium layer with a thickness of 10–20 m under which a water conductive mixed sand gravel layer is present [32]. Behind the embankments drainage pipes have been installed relieving overpressures in the water conductive layer in case of high tides.

4.1. Compaction

This section applies the modelling methodology presented in Section 3 to the time-dependent process that entails compaction of the foundation of the embankment.

Compaction of embankments reduces the crest height and thus increases the probability of the overtopping failure mechanism. Changes to the overall geometry of the structure may influence other failure mechanisms. The hierarchical process, parametric process and gamma process model simulations are compared below.

Scientific understanding of the compaction behaviour of the embankments is provided by numerical soil models or analytical solutions such as the Anglo-Saxon or Koppejan method [33]. Compaction is driven by the excess in pore pressures created by the constant superimposed loading, i.e. the excitation. The development in time of the pore pressures is a function of this difference in water pressures. Ancillary features are the soil stratification and the soil compression characteristics. The pore pressures are subject to seasonal and environmental fluctuations. The character of compaction conditional on the constant excitation in time is logarithmic. Here hierarchic, parametric and stochastic process models are compared.

A hierarchical process model of compaction has been formulated as follows, based on CUR 162 [33]:

$$\frac{\Delta h_p}{h}+\frac{\Delta h_s}{h}=s_1\left(\frac{C_c}{1+e_0}\log\left(\frac{(\sigma_i-\gamma_w(s_2h_g-l_i))+\Delta\sigma'}{(\sigma_i-\gamma_w(s_2h_g-l_i))}\right)\right.$$
$$\left.\times[U(t_{i+1})-U(t_i)]+C_\alpha[\log(t_{i+1})-\log(t_i)]\right) \quad (6)$$

where Δh_p is the primary compression increment (m), Δh_s is the secondary compression increment (m), h is the thickness of the loaded soil strata (m), whereby it is possible to take multiple soil strata into account, C_c is the compression index (-), e_0 is the ratio between the volume of pores and of the total soil volume at the start of the compression process (-), σ_i is the grain stress in soil strata i (kN/m^2), γ_w is the volumetric weight of water (kN/m^3), h_g is the freatic surface level (mOD), l_i is the layer level (mOD), $\Delta\sigma'$ is the change in grain stress caused by superimposed loading on the

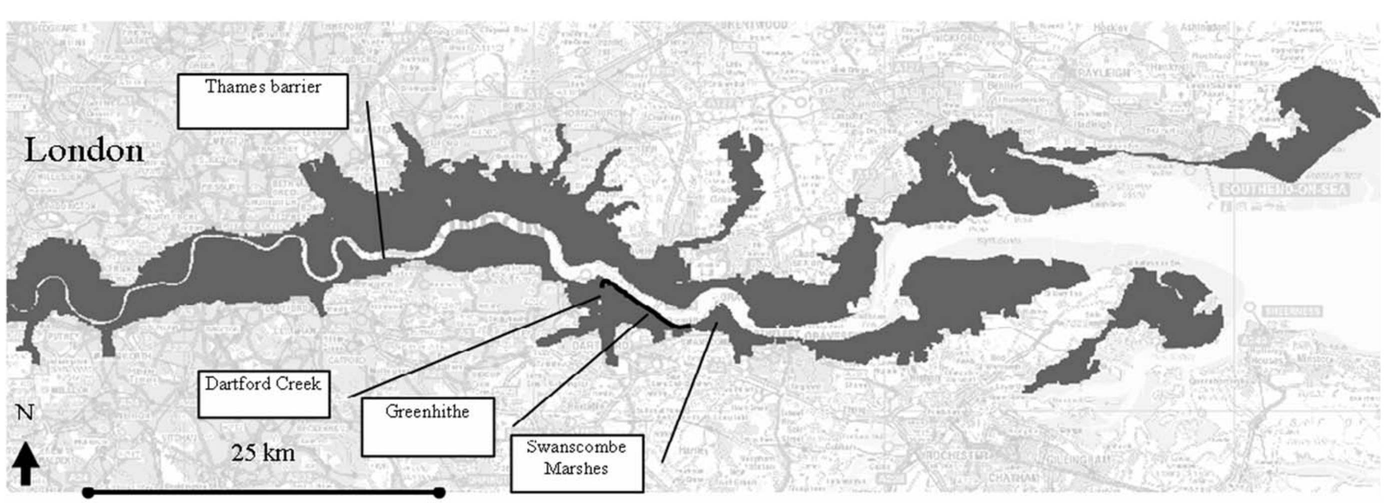

Fig. 3. An indication of 1000 year return period flood contours along the Thames Estuary.

Table 3
Some of the most relevant failure mechanisms and time-dependent processes for three flood defence structure types.

Structure type	Failure mechanisms	Time-dependent processes influencing asset performance, except offshore water level and wave conditions
Earth embankments	• (Wave) overtopping and erosion • Combination of uplifting and piping	• Long term crest level settlements: compressible layers • Trafficking damage to crest and vegetation • Internal erosion of water conductive layer • Fissuring/cracking • Bathymetrical changes of Thames • Third party activities loading embankment slopes • Vermin infestation, e.g. damage to the revetment, animal burrows • Seepage • Third party damage, e.g. vandalism or cattle trampling • Shallow slips
Revetted embankments with concrete return walls	• Uplifting and piping underneath overall earth embankment • Sliding of the concrete wall • Overturning of the concrete wall • Reinforcement failure in the vertical concrete slab • Shear failure in the vertical concrete slab	• Carbonation and reinforcement corrosion • Damage by residential developments: concrete cracking; joint failure; settlements • Abrasion • Loss of beach in front of structure/toe erosion • Foreshore erosion • Leakage through wall
Anchored sheet pile walls	• Breaking of the ground anchor • Sliding of the ground anchor due to insufficient shear strength of the soil • Breaking of the sheet pile cross section • Rotational failure of the sheet pile after failure of the ground anchor	• Corrosion of the sheet pile surface in the splash zone • Corrosion of the ground anchors • Toe accretion/erosion • Abrasion • Loss of beach in front of structure/toe erosion • Foreshore erosion • Leakage through wall (probably after abrasion or corrosion)

earth embankment (kN/m^2), C_α is the secondary compression index representing creep in the grain structure after the primary compression has taken place (-), t_{i+1} is the time in days of the increment with number i+1, t_i is the time in days of the increment with number i and $U(t)$ is the degree of consolidation in the form of the ratio between the excess in water pressure and the actual water pressure, which is given by

$$U(t) = 6\sqrt{\frac{T^3}{T^3+0.5}} \tag{7}$$

and

$$T = \frac{c_v t}{(ah)^2} \tag{8}$$

where c_v is the vertical consolidation coefficient (m^2/s), a is the coefficient for the type of outflow, whereby 1.0 is single-sided outflow and 0.5 is two-sided outflow (-).

The following expressions capture the seasonality in the settlements by a constant model uncertainty and a component modelled with a wave renewal model:

$$s_1 = s_{11} - s_{12} \tag{9}$$

$$s_2 = s_{21} + s_{12} \tag{10}$$

where s_{11} is the time-independent model uncertainty due to e.g. discontinuities in the granular structure (-), s_{12} is the seasonal effects in the model uncertainty related to the outflow process in the consolidation process or the limitations to fully model this process (-), s_{21} is the time-independent uncertainty in the freatic surface (-). The influence of s_{12} relates to the pore pressures, if these are higher there are less settlements, the influence on the primary compression and consolidation components is different. The parametric process model is expressed by (6)–(8) without the seasonality s_{11}, s_{12} and s_{21}.

A gamma process model given by an average settlement rate μ with a standard deviation σ was employed as a stochastic process model of the consolidation process:

$$P(\Delta h) \sim Ga(\Delta h|a,b) = [b^a/\Gamma(a)]\Delta h^{a-1}\exp\{-b\Delta h\}I_{(0,\Delta h)}(\Delta h) \tag{11}$$

where $\Gamma(\ )$ is the gamma function and $I_{(\ )}(\ )$ is an indicator function,

$$a = \frac{\mu^2 t}{\sigma^2} \text{and} b = \frac{\mu}{\sigma^2}. \tag{12}$$

The use of gamma processes for modelling deterioration of coastal structures is discussed by Van Noortwijk and Van Gelder [34].

In establishing these alternative models of the consolidation process, the distribution functions of the variables of the compaction model are estimated based on geotechnical field measurements [35], and adjusted with indicative values from CUR 162 [33]. Crest level surveys were conducted about 30 years after construction in the early 2000s. Fig. 5 shows the time series samples for the hierarchical model, the parametric model and the gamma process model. The moment of $t = 25$ years corresponds with present, $t = 0$ is the moment of construction.

The expected value of the hierarchical model at $t = 25$ years is 0.67 m, the observation in this case falls within the significance level of 0.05. The information availability is unfortunately insufficient to carry out significance tests or to establish the type II error [36], i.e. accepting a parameter set which is in fact false. The parametric process model samples (time series in black in Fig. 5) display a slightly larger variance than the hierarchical process model (time series in grey in Fig. 5), suggesting that including seasonality in the pore pressures does not alter the predictions a great deal. The time variability is therefore mainly driven by the superimposed load of the soil that raises the crest level, which is a time-independent excitation. After the steep initial development of the settlement model two crest level observations allow an estimate of the settlement rate of the gamma process model, Fig. 6, for example at $t = 20$ and 25 years. The gamma process model predictions are not comparable to those of the hierarchical and parametric process model as they are based on different assumptions. The gamma process model predictions are based on an average settlement rate rather than the behaviour of the soil directly and the estimates start 20–25 years later.

4.2. Trafficking

This section applies the modelling methodology presented in Section 3 to the time-dependent process damage to the crest and

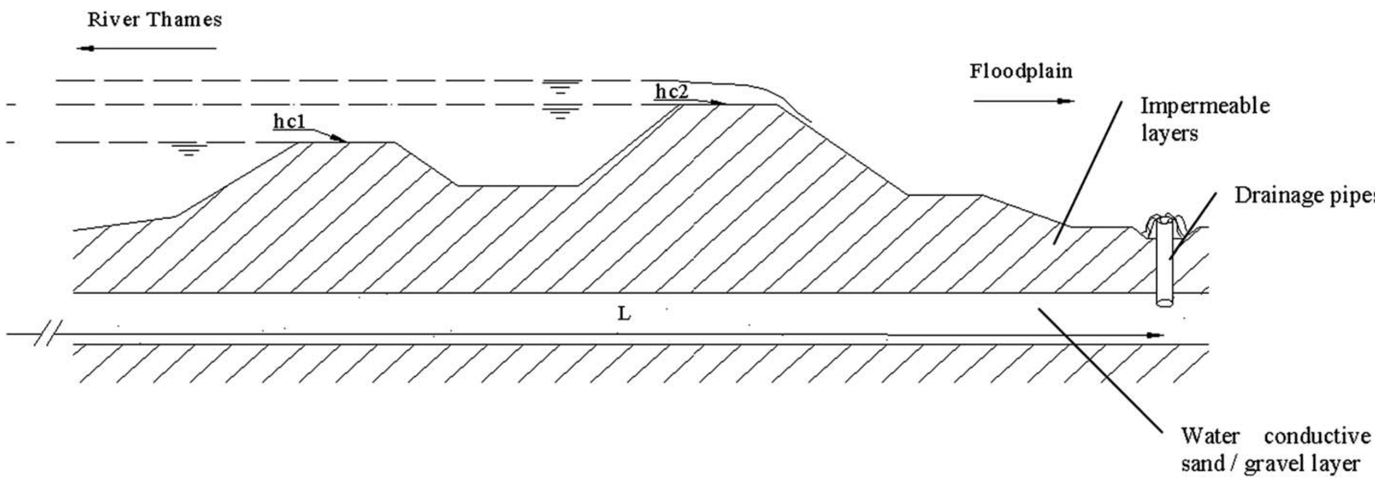

Fig. 4. Earth embankments along the Dartford Creek to Swanscombe Marshes flood defence system, hc1 is the riverward crest level, hc2 is the landward crest level and L is the seepage length.

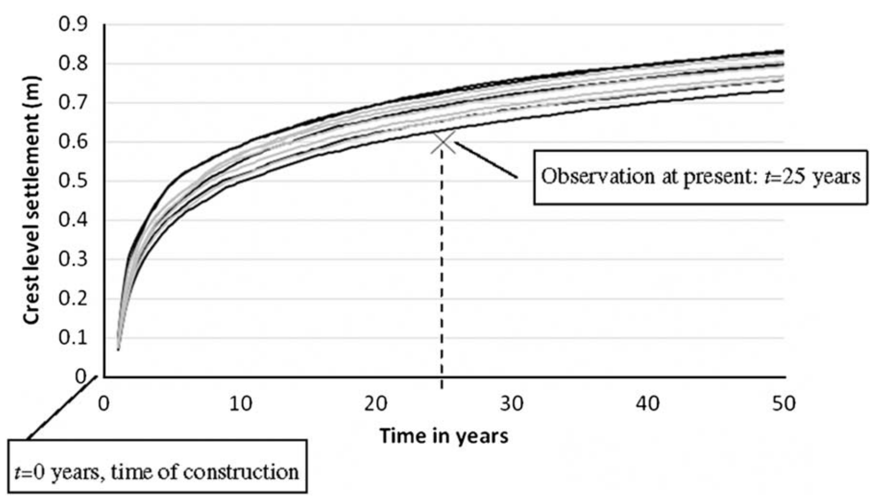

Fig. 5. Crest level settlement simulations due to compaction with the hierarchical process model (grey simulations) and the parametric process model (black simulations), compared with the observation.

vegetation due to trafficking. The hierarchical process and gamma process model simulations are compared.

The earth embankments at the site in question are subject to occasional damage due to the passage of vehicles, which can damage the vegetation and reduce the crest level. The crest level and vegetation damage affect the overtopping failure mechanism. The excitation features are the recurrent vehicles causing damage to the crest level and vegetation according to the vehicle characteristics (e.g. weight, tyres, amount of vehicles). Ancillary features are for example the soil type, the soil properties, compressibility, pore pressures and the vegetation strength. The character of the time-dependence due to trafficking events should reflect the development in the form of shock damages. Here hierarchical and gamma process models of trafficking damage are developed.

The hierarchical process models the arrival of trafficking events with a Poisson distribution, whereby the number of trafficking events is N_t. The cumulative damage Δh to the crest level at a moment in time is then modelled as follows:

$$\Delta h(t) = \begin{cases} \sum_{i=1}^{N_t} W_i : & N_t > 0, \\ 0 : & N_t = 0. \end{cases} \tag{13}$$

where W_i is the increment caused by trafficking event i, and is broken down into a spray component $\Delta h_{s,i}$ and a compaction component $\Delta h_{c;i}$:

$$W_i = \Delta h_{s;i} + \Delta h_{c;i} \tag{14}$$

The spray component is linear incremental. The compaction component is a function of the previous compaction increments:

$$\Delta h_{c,i} = m_c c_1 \log(1 + \sum_{j=1}^{i-1} \Delta h_{c,j}) \tag{15}$$

where m_c is the modelling uncertainty associated with compaction due to trafficking and c_1 is a coefficient involved with the compaction of the top layer of the embankment. m_c takes seasonality in the moisture in the top layer of the embankment into account.

The damage to the vegetation is caused by the same Poisson distributed trafficking events. The total damage to the vegetation at a moment in time $Z_{cg}(t)$ is given by

$$Z_{cg}(t) = \begin{cases} \sum_{i=1}^{N_t} \Delta c_{g,i} : & N_t > 0, \\ 0 : & N_t = 0, \end{cases} \tag{16}$$

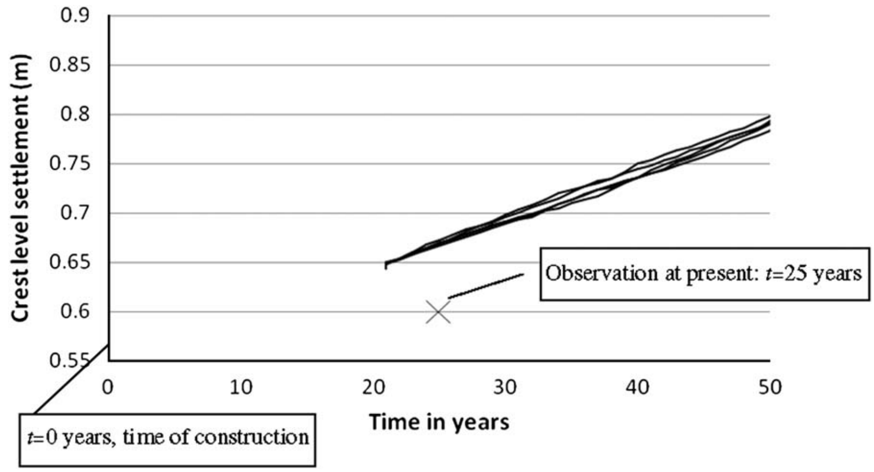

Fig. 6. Estimation of crest level settlement over a period of 30 years with the gamma process model 20 years after raising the embankment.

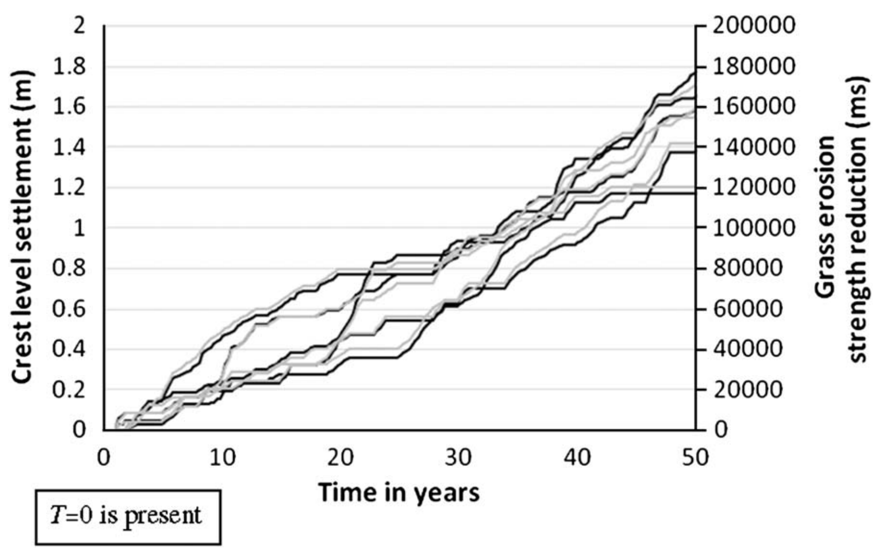

Fig. 7. Some time series samples of the hierarchical process model for crest level settlements (black simulations on the primary axis) and vegetation damage (grey simulations on the secondary axis) due to trafficking.

where $\Delta c_{g;i}$ is the damage to the vegetation resulting from one trafficking event, referred to in Figs. 7 and 8 with 'grass erosion strength reduction'. Eq. (16) is an indicative model to represent damage to the grass strength. c_g occurs in a grass turf failure model [37] which requires further research and the credibility of a linear incremental model for the erosion strength in this context is disputable. However, there are no other models and the influence of vegetation damage is not yet fully researched.

The gamma process model for the correlated asset time-dependent processes crest level settlements, Δh_{gamma}, and damage to the vegetation, $\Delta c_{g;gamma}$, is developed according to Buijs et al. [38]. Each singular asset time-dependent process is modelled with the gamma process model according to Eqs. (11) and (12) allowing estimates for the mean rates of deterioration and standard deviations. The correlations between the processes are represented by a double-gamma distribution [29], and simulated with trivariate reduction methods according to Devroye [39].

The comparison of the hierarchical process model and the double-gamma model for settlements and vegetation damage due to trafficking is only qualitative as there are no field measurements. Fig. 7 contains some time series samples of the hierarchical process model, where settlements in the crest level Δh (in m) are the black simulations on the primary axis and grass erosion strength reduction are the grey simulations $Z_{cg}(t)$ (in m s) on the secondary axis.

Fig. 8 contains simulations for the double-gamma model. The hierarchical process model samples clearly reflect the shock damages introduced by the trafficking events. The gamma process model aims to make an approximation of the amount of crest level and vegetation damage based on average deterioration rates.

At first glance, the overall settlement in both hierarchical and gamma process models of around 1.5 m after 50 years may seem fairly high. However, the settlement after 10 years according to the samples is in the more reasonable order of magnitude of 0.3 m. Three comments are made here. Firstly, the damage due to trafficking can be very localised to where for example the embankment is poorly compacted. Secondly, it is unlikely that such trafficking damage is allowed to develop over the course of 50 years without any maintenance or intervention in the form of recreational prohibition. Thirdly, the linear contributions in the hierarchical model dominate the development. It is difficult to say without further research which function the increments should really follow. It would for example be possible that a logarithmic function introducing diminishing increments on a longer term is applicable.

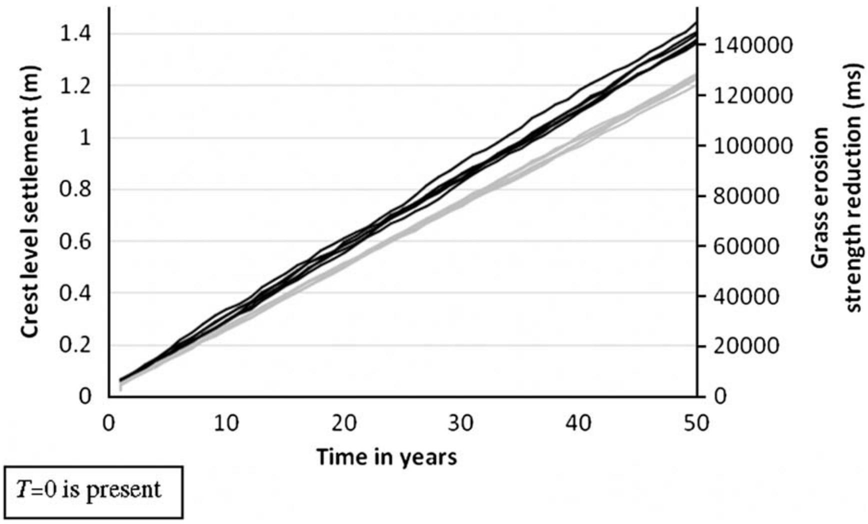

Fig. 8. Some time series samples with a double-gamma process model for crest level settlements (black simulations on the primary axis) and vegetation damage (grey simulations on the secondary axis) due to trafficking.

4.3. Seepage length reduction

This section applies the modelling methodology presented in Section 3 to the time-dependent process internal erosion in the water conductive layer underneath the embankment, see Fig. 4. The hierarchical process, parametric and gamma process model simulations are compared.

Internal erosion of the water conductive layer underneath the embankment can lead to a reduction in the seepage length and hence increasing likelihood of piping failure. The water head difference between the river level and the upper end of the drainage pipe is the excitation of the time-dependence as it initiates flow through the water conductive layer underneath the embankment. There is no filter applied in the drainage pipe, hence the assumption that fine sand particles can be conducted in the drainage flow, leading to seepage length reduction. Ancillary features for this deterioration mechanism are the density, size and grading of the soil (sand/gravel) particles and the diameter and height of the drainage pipes, which all display inherent uncertainty in space. An empirical process model for the threshold of piping failure under impervious structures is described in Sellmeijer [40].

The hierarchical process is formulated as follows:

$$L_{i+1} = L_i - \Delta L_i, \tag{17}$$

where L_{i+1} is the seepage length at $t = i+1$ and L_i is the seepage length at $t = i$. ΔL_i is the deterioration of the seepage length between $t = i$ and $t = i+1$. This quantity is roughly estimated by:

$$\Delta L_i = ck\frac{\Delta h}{L_i}t_s, \tag{18}$$

where c is a dimensionless coefficient, k is the permeability of the water conductive layer, t_s is the storm duration, $\Delta h = h–h_p$ where h is the water level and h_p is the level of the water in the floodplain. Only storms with a water level in excess of the top of the drainage pipe level lead to erosion. Subsequently, the seepage length reduction depends on the magnitude of the water head difference and the state of the progression of the internal erosion process. L_i is the seepage length at $t = i$.

This expression is a function of the water level, the storm duration and the time-dependent seepage length. The number of storms N_{st} in an interval dt is modelled with a Poisson distribution. Each storm is represented by a pair of a water level, h, and a storm duration, t_s (Fig. 9).

$$\overbrace{h_1\ t_{s1}}^{1},\ \overbrace{h_2\ t_{s2}}^{2},\ \ldots,\ \overbrace{h_{N_{st}}\ t_{s;N_{st}}}^{N_{st}}$$

Fig. 9. A sequence of the pairs of water level and storm duration that represent each storm.

N_{st} storms give $N_{st}!$ sequences which is computationally impossible to simulate for high numbers of N_{st}. There is a probability of $1/N_{st}$ that each of the pairs occurs first, a probability of $1/(N_{st}-1)$ that one of the remaining events occurs second, $1/(N_{st}-2)$, etc. The procedure is then as follows:

1. Establish a number of storms N_{st} that is Poisson distributed.
2. For $1, \ldots, N_{st}$ randomly draw a pair of h_i and $t_{s;i}$ providing:

$$\begin{bmatrix} h_1 & t_{s1} \\ \vdots & \vdots \\ h_{N_{st}} & t_{sN_{st}} \end{bmatrix} \tag{19}$$

3. Select the first pair with probability $1/N_{st}$ and eliminate it from the matrix, calculate the corresponding ΔL, determine $L_2 = L_1 – \Delta L$ (at the start $L = L_1$)
4. Select the second pair from the remaining matrix with probability $1/(N_{st}–1)$
5. Etc. until N_{st}, L_i is carried on to the next time interval dt.
6. Select a new N_{st} for dt and carry out the same procedure with the resulting L_{Nst} from the previous round.

The gamma process model is applied according to Eq. (11) and (12). Fig. 10 displays the time series samples of the hierarchical process model and Fig. 11 those of the gamma process model for seepage length reduction. The seepage length L is considered as a deterministic variable (black simulations) as well as a random variable (grey simulations). In the latter model the initial variance in the seepage length overshadows the variance introduced by the erosion process. The gamma process model provides a good approximation of the hierarchical process model.

Observations of the seepage length in time are not available, the time series predictions presented in Figs. 10 and 11 are

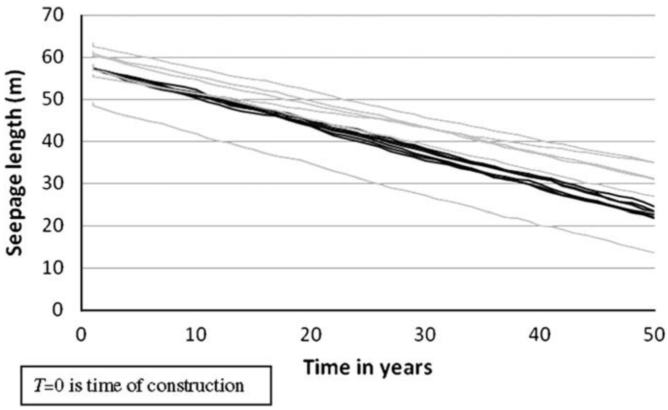

Fig. 10. Hierarchical process model for seepage length whereby L is deterministic (black simulations), and L is a random variable (grey simulations).

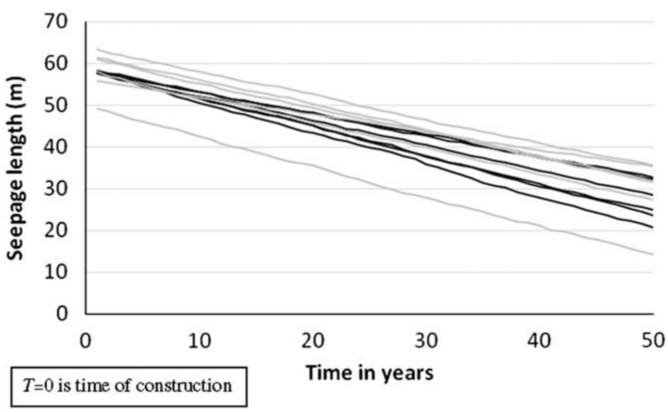

Fig. 11. Time series sample simulations with the gamma process model for the reduction in seepage length, whereby L is deterministic (black simulations) and L is a random variable (grey simulations).

therefore not quantitatively testable. Moreover, the chance of improving the opportunity for such a quantitative assessment is small, as the size of the seepage length as a function of time is hard to measure. The water conductive layer is over 10 m from the ground surface and the erosion process is three dimensional.

4.4. Time-dependent reliability analysis

The results are presented as time-dependent fragility curves, as these are the most convenient way of embedding the results in a systems reliability analysis. Section 2.2 describes the steps in the numerical implementation of the time-dependent processes and the incorporation in fragility. Fig. 12 shows the total fragility for the three failure mechanisms of an earth embankment for a number of different time steps.

The increase in probability of failure given different moments in time visible in the graph is the part of fragility dominated by overtopping and erosion. The time-dependent processes are represented with the hierarchical process models. Compaction and seepage length reduction are taken into account from time of construction ($t = -20$ years in these calculations), and trafficking damage from present ($t = 0$) onward. The time-dependence in the dominant failure mechanism is introduced by a combination of compaction and crest level damage due to trafficking. The compaction time-dependence is responsible for the difference in curves between $t = -20$ years and present, also clear from the logarithmic behaviour between the first three curves from the right. Trafficking damage is mainly responsible for the fairly large

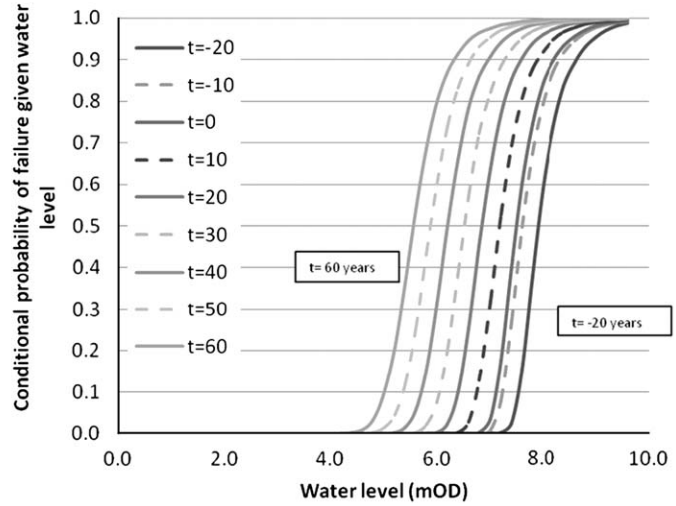

Fig. 12. Fragility of an earth embankment for a number of time steps, $t = 0$ is present.

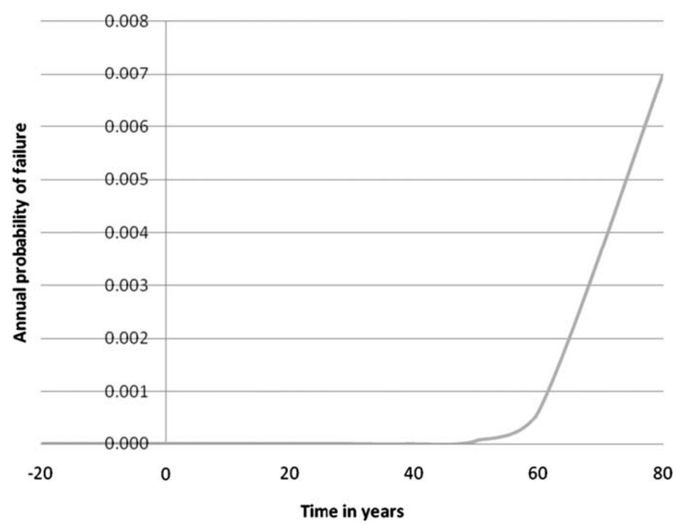

Fig. 13. The do-nothing probability of failure as a function of time for a typical earth embankment section.

increases in probability of failure from $t > 0$. The comments on this model are given at the end of Section 4.2. Seepage reduction influences the probability of piping, however, it is combined with the probability of uplifting which is low relative to overtopping. The increase due to seepage reduction is therefore not visible in Fig. 12.

The projected probability of failure in time, hence integrated over the probability density of the water level, for an earth embankment is displayed in Fig. 13. Wave overtopping and erosion dominates the probability of failure. The increase in probability of failure is mainly caused by damage due to trafficking, indicating the priority of this deterioration process as a target for preventative action. It is noted that this suggestion is subject to the quality of the results, i.e. the possibility to make an appropriate estimate of the trafficking damage as discussed at the end of Section 4.2.

5. Conclusions

Existing structural reliability methods are suitable for the analysis and incorporation of time-dependent processes in flood defence (system) reliability. The modelling methodology in this paper offers a structured practical approach to define statistical models for time-dependent processes of flood defences. The formulation of a hierarchical process model enables the decomposition into different excitation and ancillary contributors. This decomposition allows the attribution of the origin of the time variability in the deterioration process to the relevant contributor, which is often the excitation. Knowledge of the relevant contributor facilitates the selection of a realistic stochastic process model and enables focussing efforts to increase scientific understanding in the deterioration. In addition to hierarchical process models, this paper has explored the use of parametric, and random process models for representing flood defence deterioration.

Parametric processes are often applied as a statistical approach to a deterministic time-dependent engineering process model, employing time invariant random contributors and a deterministic time. The comparison of time series samples according to the hierarchical process and parametric process allows insight in the improvement achieved with a decomposed representation of the time variability. For example, compaction in time has a time-independent excitation. The difference between the parametric and hierarchical process models is small. Trafficking on the other hand is driven by occasional recurrent events. The hierarchical process model enables the representation of the shock damages, where the parametric process model does not offer a solution as time is a deterministic continuous variable. The deviation between a more realistic representation of time variability by a hierarchical process model and an approximation by a parametric process model depends on the nature of the time variability of the excitation.

Random process models represent the aggregate time-dependent quantity. Random process models parameterise the time-dependent process model without taking the contributions of different components to the time-dependence into account. These models can serve a suitable approximation as a replacement of a more detailed hierarchical process model under time or resource constraints.

Whilst the data with which to establish statistical models is inevitably scarce, some corroboration with field observations has been possible and additional insights are gained by inter-comparison of alternative models. Even in the absence of extensive data for parameter fitting and calibration, a time-dependent model of asset performance is an essential starting point for maintenance planning. To date these models, where they exist in practice, have been based upon simplified versions of parametric processes. Whilst an improvement upon a deterministic approach to deterioration, reliance upon parametric processes can imply unrealistic representation of deterioration behaviour. In this paper we have demonstrated that establishing credible hierarchical and stochastic process models is feasible and provides new insights into the time-dependent behaviour of flood defence structures.

The amount of effort invested in establishing a deterioration model of course needs to reflect the significance of the deterioration process, in terms of its influence on system reliability and its potential significance as a target for inspection and maintenance activity. The development of a deterioration model therefore needs to proceed via iterative refinement based upon insights into system sensitivity to relevant processes.

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