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# A Parametric Model of Umbilical Cable with Siemens NX considering its Reliability

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**Abstract:** Umbilical cable is one of the key control equipment, for example, in the subsea oil and gas production system. That can be seen as a customized product related to specific parameters of use cases, e.g. installation site. In this paper, we first apply the calculation method for the reliability of the umbilical cable by advanced first-order second-moment method (AFOSM) and Monte Carlo method. Secondly, we demonstrate the use of Siemens NX and its framework for engineering knowledge representation called Knowledge Fusion (KF) to generate the parametric model of the umbilical cable design considering its reliability. Finally, we reveal the advantages of introducing a Knowledge-based Engineering (KBE) approach to integrate the CAD models extended with automated calculations for product reliability.



*Keywords:* Parametric Model, KBE, Knowledge Fusion, CAD, Product Design, Customized Product, Umbilical, Reliability, AFOSM, Monte Carlo Simulation

## 1. INTRODUCTION

One of the focuses on Industry 4.0 is to meet the growing demand for customized products. In the domain of subsea oil and gas production, the cross-section of the steel tube umbilical cable always varies depending on the specific project´s requirements, which is a typical customized product. A steel tube umbilical cable often consists of some structural and functional components, as shown in figure 1. The outside is the outer sheath, used to protect the tensile armors from seawater. Tensile armors, often appearing in double layers to balance the torque, are the main components to bear the tension load. The functional components are assembled into an inner core covered by an inner sheath, including central and external tubes, electrical cable, optical fiber, fillers (Lu et al. (2014)). Since the application water depth goes deeper, the traditional deterministic design method using the safety factor is difficult to satisfy the design requirements. Therefore the design method based on reliability is drawing more and more attention in the structural design of umbilical (Yan et al. (2017)).

The conventional CAD system focuses on geometrical aspects of a design, lacking the capability to consider non-geometrical aspects. Although CAD is adjusted toward interactive operations with limited ability to automate its operations via scripts, it is still difficult to generate robust parametric product models that permit topology changes and freedom to make adaptive modifications (Sobieszczanski-Sobieski et al. (2015)).

The KBE method, as the evolution of conventional CAD systems, can quickly generate different configurations and variants of a given product, and manage, learn and grow

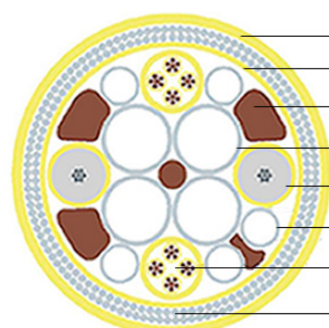


Fig. 1. Typical cross-section of steel tube umbilical cable (adapted from Yan et al. (2017))

on a large amount of multidisciplinary knowledge. This is a remarkable feature when developing a large number of almost identical parts, which is not practical to do “by hand” in a traditional way. The KBE method can also support the integration of heterogeneous sets of analysis tools in the Multidisciplinary Design Optimization (MDO) framework by automating the generation of the necessary disciplinary abstractions. This can relieve the optimizer from the burden of managing spatial integration constraints, which can be intrinsically guaranteed by properly defined generative models (Sobieszczanski-Sobieski et al. (2015)).

As mentioned above, steel tube umbilical cable is a customized product depending on the project’s requirement. However, only some minor modifications to the previous design solution is enough in most cases. After the initial design is provided by designing engineers, some routine analysis is necessary to conduct by analyzing engineers to guarantee the design to meet the requirement. Reliability


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performance is one of the routine analysis. The conventional design method with the traditional CAD model lacks flexibility in doing this kind of task. If the initial design needs to be modified, the designing engineers have to draw the model again, which can be time-consuming and tedious. And the same applies to the analyzing engineers as the data can not be transferred between different phrases. In such situations, the KBE method gives an advantage to complete the design loop in a time-saving way by providing a parametric model.

In this paper, we choose the cross-section design of steel tube umbilical cable considering its reliability as the example to demonstrate the benefits to implement the KBE method instead of the conventional CAD approach in a customized product design. Firstly, the calculation method for the reliability of the umbilical cable by advanced first-order second-moment method(AFOSM) and Monte Carlo method is introduced. Secondly, the workflow to generate a parametric model of umbilical cable is demonstrated with Siemens NX and its engineering knowledge representation module called Knowledge Fusion (KF). Finally, the benefit and current limitation of introducing KBE approach to integrate the CAD models extended with automated calculation function is discussed and the advice on future research about KBE method in product design is given.

## 2. STATE OF THE ART

### *2.1 KBE*

KBE is the engineering using product and process knowledge that has been captured and stored in dedicated software applications, to enable its direct exploitation and reuse in the design of new products and variants (Sobieszczanski-Sobieski et al. (2015)). KBE systems are the software tools to reuse engineering knowledge combining the rule-based reasoning capabilities of knowledge-based systems (KBS) with the CAD-like geometry manipulation and data processing capabilities. A typical KBE system provides the user with a programming language, typically object-oriented and one integrated or tightly connected CAD engine. The programming language allows the user to capture and reuse engineering rules and processes, while the object-oriented modelling approach serves to abstract the system as collections of objects, defined by parameters and behaviour, connected by relations (Sobieszczanski-Sobieski et al. (2015)). Many CAD software introduced KBE features to support the rapid development of products. The KBE is supported in Siemens NX by Knowledge Fusion (KF), which is an interpreted, object-oriented language (Siemens website (2016)).

Some KBE CAD models have been established by researchers. Wang et al. (2012) used Knowledge Fusion (KF) to read the airfoil data files and generate the impeller model automatically, then used Fluent to analyse the auto-generated model to get proper aerodynamic parameters, which greatly improved the efficiency of modelling and flexibility of the CAD system. Gujarathi and Ma (2010) proposed a "common data model" (CDM) containing all the required parametric information for both CAD and CAE analysis, which is expected to integrate CAD and CAE processes. Soulat (2012) employed open-source KBE tools to develop an application to generate, visualize, and export aircraft configuration geometries, which improved the automation and optimization of the aircraft design process. Zhang et al. (2008) integrated KBE and modular design method to realize parametric drive and detailed design of the main frame of a tunnel boring machine, which effectively shortens the developing cycle. Lobov et al. (2020) proposed the use of Knowledge Fusion for generation of robot trajectories to support faster transition from a product information in CAD and KF till the robot code that should weld the product. Some KBE models considered the analysis and optimization function, however, the amount of this kind of cases is not large.

### *2.2 Reliability Estimation of Steel Tube Umbilical*

Structural reliability is to apply reliability engineering theories to structural analysis, which might replace traditional deterministic ways of design and maintenance(Choi et al. (2006)). This design method has been introduced in many structural analysis fields, e.g. architectural design (Dey et al. (2018)), mechanical engineering, and marine engineering(Yong Bai (2016)). Khan and Ahmad (2007) studied the riser fatigue reliability with response surface method (RSM) in conjunction with the First Order Reliability Method (FORM) and compared the result with the Monte Carlo simulation method. Li and Low (2012) investigated the influence of soil uncertainties on the SCR fatigue reliability, and concluded that the efficient first-order reliability method (FORM) and inverse-FORM (IFORM) analysis are fairly accurate compared with Monte Carlo simulation. Yan et al. (2017) investigated the reliability of the steel tube umbilical cable undertaking the most dangerous load cases with AFOSM and Monte Carlo simulation considering the uncertainty of components in the cross-section, and applied particle swarm optimization algorithm to find an optimized design with a higher reliability index.

It can be seen that the advanced first-order second-moment (AFOSM) method is widely used to estimate the failure probability and reliability index during the reliability analysis process. Meanwhile, the Monte Carlo Simulation (MCS) is commonly considered as the benchmark to verify the result obtained from AFOSM. Therefore, in this paper, AFOSM and MCS are applied as the calculator estimating the reliability of the product, to demonstrate the potential of KBE to integrate different knowledge used in design process.

## 3. METHODOLOGY OF RELIABILITY ESTIMATION

### *3.1 Structural Reliability of the Umbilical Cable*

Reliability is commonly defined as the ability of an item to perform its function in a certain period under a certain condition. Due to manufacturing errors, the geometric parameters of the umbilical cable will have errors from the design value (table 1, from Yan et al. (2017)), which brings the structural failure probability under the design load during its life span. And the central tubes are considered as the most dangerous part. The reliability of the umbilical cable in its design life span can be defined as $R = 1 - P_f$, where $P_f$ is the failure probability, determined by the

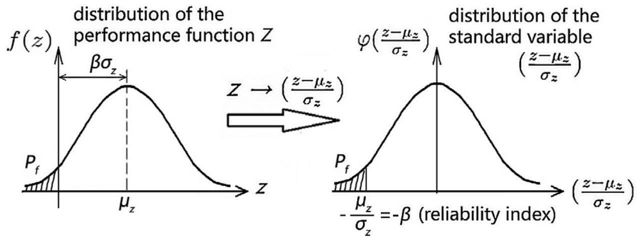


Fig. 2. Illustration of the reliability index $\beta$

distribution of the performance function $z$. When $z \leq 0$, the structure will fail, i.e. $P_f = P(z \leq 0)$.

Table 1. The statistics of 5 variables

| Items | $\mu$ | $\sigma$ |
|---|---|---|
| Out diameter of central tubes | 29.14 mm | 0.043 |
| Thickness of central tubes | 1.87 mm | 0.062 |
| Out diameter of external tubes | 15.52 mm | 0.043 |
| Thickness of external tubes | 1.41 mm | 0.047 |
| Yields stress of the material | 550 MPa | 22.6 |

Assuming the performance function $z$ conforms to the normal distribution $N(\mu_z, \sigma_z^2)$ with the probability density function of $f(z)$, the failure probability is equivalent to the area in shade in Figure 2. Obviously, the transformation $\frac{z-\mu_z}{\sigma_z}$ conforms to the standard normal distribution $N(0,1)$ with the probability density function of $\varphi(\frac{z-\mu_z}{\sigma_z})$. Thus, the relation between the failure probability and distribution of performance function can be represented by (1).

$$P_f = P(z \leq 0) = P(\frac{z-\mu_z}{\sigma_z} \leq \frac{-\mu_z}{\sigma_z}) = \Phi(\frac{-\mu_z}{\sigma_z}) \qquad (1)$$

Define reliability index $\beta = \frac{\mu_z}{\sigma_z}$, then $P_f = \Phi(-\beta)$ (Hasofer and Lind (1974)). Here, the reliability index $\beta$ represents the distance between the critical value and the mean value. The larger the reliability index $\beta$ is, the safer the structure is.

### *3.2 The Performance Function of the Umbilical Cable*

In this specified case, only steel components (central and external tubes, tensile armors) are considered to affect the reliability estimation. The central tubes are considered as the most dangerous components based on the engineering experience and mechanics analysis. Without consideration of plastic deformation, if Von Mises stress of the central tubes exceeds the yield stress of the steel, the central tubes are highly likely to break and the pressured liquid inside will leak to outside. Based on the assumption, considering the uncertainty of the 5 variables (table 1), the performance function is defined as

$$z = \gamma\sigma_y - \sigma_{equal} = g(x_1, x_2, ..., x_5) \qquad (2)$$

, where $\gamma$ is the utilization ratio of the material of central tube, $\sigma_y$ is the yield stress, and Von Mises stress is

$$\sigma_{equal} = \sqrt{\frac{1}{2}((\sigma_a - \sigma_r)^2 + (\sigma_a - \sigma_h)^2 + (\sigma_h - \sigma_r)^2)}. \quad (3)$$

Since the wall thickness of the central tube is much less than its radius, the central tube can be seen as a thin-wall cylinder model (see Figure 3). Considering a thin-wall

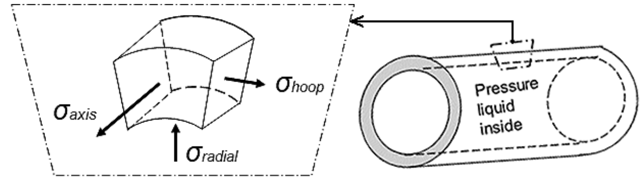


Fig. 3. Force analysis of the central tube as thin-wall cylinder

cylinder model subjected to internal pressure, the hoop, radial and longitudinal(axial) stress($\sigma_{hoop}, \sigma_{radial}, \sigma_{axial}$ respectively) produced in the wall can be calculated by (4), where $p$ is the pressure of the inside liquid, $D, d$ are outside and inside diameter of central tube.

$$\begin{aligned} \sigma_{hoop} &= p\frac{D^2 + d^2}{D^2 - d^2} \\ \sigma_{radial} &= -p \\ \sigma_{axial} &= \sigma_t + \sigma_M + \sigma_e. \end{aligned} \qquad (4)$$

The stress in axial direction ($\sigma_{axial}$) is a sum of three components: the stress caused by internal pressure($\sigma_e$), the stress caused by bending moment($\sigma_M$), and the stress caused by tensile load($\sigma_t$), which can be calculated by (5), where $T, \frac{1}{\rho}$ are the tension load and the curvature of the umbilical at the end, calculated by a professional simulation software(OrcaFlex)(Yan et al., 2017).

$$\begin{aligned} \sigma_e &= p\frac{\pi d^2}{4}\frac{1}{A_t} \\ \sigma_M &= E_t\frac{D}{2}\frac{1}{\rho} \\ \sigma_t &= \frac{T}{K}\frac{K_t}{A_t}. \end{aligned} \qquad (5)$$

The tension stiffness of the umbilical cable and its components can be calculated by (6), where $K$ is the overall tension stiffness of the umbilical cable, $A_t, A_o$ are the cross-section area of a central tube and an external tube, $K_t, K_o$ are the tension stiffness of a central tube and an external tube, $E_t$ is Young's modulus of steel, $\alpha_o, \alpha_i$ are outside and inside helix angle between tensile armor and the axis, $n_o, n_i$ are the number of outside and inside tensile armors.

$$\begin{aligned} K &= 4K_t + 5K_o + n_iE_tA\cos^3\alpha_i + n_oE_tA\cos^3\alpha_o \\ A_t &= \pi\frac{D^2 - d^2}{4} \\ K_t &= E_tA_t \\ K_o &= E_tA_o \end{aligned} \qquad (6)$$

### *3.3 Advanced First Order Second Moment method*

The Advanced First Order Second Moment (AFOSM) method is a widely used method to estimate the reliability of structure with a performance function of insignificant non-linearity. AFOSM has high efficiency and acceptable accuracy in most cases. It is adapted from the Mean value First Order Second Moment (MFOSM) method, which is easy to apply but has shown to be inferior to AFOSM (Madsen et al., 2006).

It is beneficial to introduce the MFOSM method firstly. Starting from a simple case, consider a structure with a linear performance function $z = f(x_1, x_2, ..., x_n) = \sum_{i=1}^{n} c_ix_i$, where $f$ is a linear function, $c_i$ are constant,

$x_i$ are independent random variables conforming to normal distribution $N(\mu_i, \sigma_i^2)$. According to the property of normal distribution, $z \sim N(\sum_{i=1}^n c_i\mu_i, \sum_{i=1}^n c_i^2\sigma_i^2)$. Then the reliability index of this system can be calculated by

$$\beta = \frac{\mu_z}{\sigma_z} = \frac{\sum_{i=1}^n c_i\mu_i}{\sqrt{\sum_{i=1}^n c_i^2\sigma_i^2}}.$$

The reliability index of a system with a linear performance function is easy to calculate. However, the performance function in many cases are nonlinear, thus the distribution of performance function is not easy to calculate directly. Consider a general case: a structure with a general performance function $z = g(x_1, x_2, ..., x_n)$, where $x_i$ are independent random variables conforming to normal distribution $N(\mu_i, \sigma_i^2)$. The performance function can be expanded by a Taylor series at the mean value point $\boldsymbol{\mu}$ and linearized by taking the two first-order items:

$$z \approx z^* = g(\mu_1, \mu_2, ..., \mu_n) + \sum_{i=1}^{n} \frac{\partial g(\mu_1, \mu_2, ..., \mu_n)}{\partial x_i}(x_i - \mu_i). \quad (7)$$

According to the property of normal distribution, plus the independence of variables $x_i$, the relations (8) can be get based on the linearized performance function (7):

$$\begin{aligned} \mu_z &= g(\boldsymbol{\mu}) \\ \sigma_z^2 &= \sum_{i=1}^{n}\sum_{j=1}^{n} \frac{\partial g(\boldsymbol{\mu})}{\partial x_i}\frac{\partial g(\boldsymbol{\mu})}{\partial x_j} cov(\boldsymbol{X_i}, \boldsymbol{X_j}) \\ &= \sum_{i=1}^{n}(\frac{\partial g(\boldsymbol{\mu})}{\partial x_i}\sigma_i)^2 \end{aligned} \quad (8)$$

, thus $\beta = \frac{\mu_z}{\sigma_z} = \frac{g(\boldsymbol{\mu})}{\sqrt{\sum_{i=1}^n (\frac{\partial g(\boldsymbol{\mu})}{\partial x_i}\sigma_i)^2}}$.

As the performance function is extended at the mean value point and uses a first-order Taylor series and the first and second moments of the input variables, this method is called Mean value First Order Second Moment (MFOSM) methods.

The essential of MFOSM method is to find the limit state surface in variable space by the approximated Taylor expansion at the mean value point. However, since the mean value is not on the limit state surface, a more accurate result can be gained by a Taylor expansion at a point which is on the limit state surface. The Advanced First Order Second Moment method (AFOSM) is developed based on this logic. AFOSM is to find a point which is on the limit state surface and meanwhile has the shortest distance to the mean value point. The point of meeting the criteria is called the design point and is usually solved by an iteration method. The steps are as follows.

1. Choose the initial value of the design point($\boldsymbol{x^*}$) by $x_i^* = \mu_i (i = 1, 2, ..., n)$.
2. Calculate sensitive coefficient($\alpha_i$) by (9).

$$\alpha_i = \frac{\sigma_i \frac{\partial g(x_1^*, ..., x_n^*)}{\partial x_i}}{\sqrt{\sum_{i=1}^n (\sigma_i \frac{\partial g(x_1^*, ..., x_n^*)}{\partial x_i})^2}} (i = 1, 2, ..., n) \quad (9)$$

3. Get the equation group about $\beta$ and the current design point ($\boldsymbol{x^*}$) by (10).

$$x_i^* = \mu_i - \beta\alpha_i\sigma_i (i = 1, 2, ..., n) \quad (10)$$

4. Put the current design point (10) into the limit state surface equation (11) to get an equation containing only $\beta$, then solve it to get $\beta$.

$$z = \gamma\sigma_y - \sigma_{equal} = g(\boldsymbol{x}) = g(x_i, x_2, ..., x_n) = 0 \quad (11)$$

5. Update the value of the design point ($\boldsymbol{x^*}$) by (10).
6. Iterate step 2-5 until $|\Delta\beta| \leq threshold$ (e.g. 1e-5).
7. Calculate the failure probability by $P_f = \Phi(-\beta)$.

### 3.4 Monte Carlo Simulation

Since the AFOSM method is an estimation method, Monte Carlo simulation is commonly applied to verify the accuracy of the result gained by AFOSM method if possible. It is a broad class of computational algorithms that rely on repeated random sampling to obtain numerical results. The underlying concept is to use randomness to solve problems that might be deterministic in principle(Kroese et al., 2014). In this paper, the Monte Carlo simulation is applied in the following steps.

1. Generate random variables($x_i$) conforming to normal distribution $N(\mu_i, \sigma_i^2)$, based on the statistics in table 1.
2. Call the performance function (2) $N_{total}$ (e.g. 100000) times to get the distribution of $z$.
3. Calculate the failure probability by $P_f = \frac{N_{fail}}{N_{total}}$, where $N_{total}$ is the total times of the Monte Carlo tests, and $N_{fail}$ is the times when $z \leq 0$.
4. Fit the distribution of $z$ to get reliability index ($\beta = \frac{\mu_z}{\sigma_z}$).

### 3.5 Comparison of Reliability Results from Two Methods

By realizing the two methods in Python, two reliability results are gained. From table 2, it can be seen that the two results are close to each other, which can be seen as proof of the feasibility of the two methods. It can also be observed that the reliability and the index will meet the requirement or not when a different requirement is set.

Table 2. Comparison of 2 methods

| | MC simulation | AFOSM | REQMT 1 | REQMT 2 |
|---|---|---|---|---|
| $R$ | 0.99455 | 0.99498 | 0.99 | 0.999987 |
| $\beta$ | 2.5459 | 2.5746 | 2.33 | 4.2 |

## 4. APPLICATION: MODELING OF THE UMBILICAL CABLE IN SIEMENS NX WITH KF

### 4.1 Parametric Model

The steel tube umbilical cable is parameterized considering the geometric and non-geometric aspects. A list containing all the parameters can be seen in table 3. The parameters also appearing in table 1 are for reliability calculation. Regarding the definition of the geometric parameters, the umbilical is firstly decomposed into some basic shapes which can be represented with different ready classes of Siemens NX Knowledge Fusion, and then the basic features of these shapes are extracted. When it comes to the non-geometric aspect, all the variables relating to the reliability estimation are defined as input parameters.

With the help of some ready basic shape classes and some features in Siemens NX Knowledge Fusion, the geometric

```
#central_tubes color depending on reliability
(Child list) body_colored_central_tubes:{
   Class, ug_body;
   Feature, {nth(child:index:, central_tubes:)};
   quantity, num_cen_tube:;
   color,  if (relibility_cts_real: < relibility_cts_required:)
              then ug_askClosestColor(RED)
           else if(relibility_cts_real: > relibility_cts_required:)
              then ug_askClosestColor(GREEN)
           else ug_askClosestColor(YELLOW); };
```

Fig. 4. Excerpt from Knowledge Fusion code (DFA file)

model of steel tube umbilical cable becomes possible to establish. The most frequently used shape class is the cylinder class. Plus the operation of subtraction, a tube can be easily modelled. A helix tensile armor wire can be modelled with sample line class and sweep feature. After establishing every elementary part, the array of these parts can be achieved using a child list feature. When the geometric parts are finished, the process will handle some of the non-geometric parameters according to the user's need. In this paper, the central tubes will be displayed in different colours depending on whether their reliability meets the requirement. If they meet the requirement, they will be in green, otherwise in red. (see figure 4)

Table 3. Parameters list

| Type | Part | Parameter |
|---|---|---|
| geometric | whole model | length |
| geometric | central tube | diameter(mean value) |
| geometric | central tube | diameter(std. deviation) |
| geometric | central tube | thickness(mean value) |
| geometric | central tube | thickness(std. deviation) |
| geometric | central tube | number |
| geometric | external tube | diameter(mean value) |
| geometric | external tube | diameter(std. deviation) |
| geometric | external tube | thickness(mean value) |
| geometric | external tube | thickness(std. deviation) |
| geometric | external tube | number |
| geometric | inner sheath | diameter |
| geometric | inner sheath | thickness |
| geometric | inner tensile armor | diameter |
| geometric | inner tensile armor | number |
| geometric | inner tensile armor | helix angle |
| geometric | other unit | diameter |
| geometric | other unit | number |
| geometric | outer sheath | diameter |
| geometric | outer sheath | thickness |
| geometric | outer tensile armor | diameter |
| geometric | outer tensile armor | number |
| geometric | outer tensile armor | helix angle |
| non-geometric | central tube | pressure |
| non-geometric | whole model | tension load |
| non-geometric | whole model | curvature |
| non-geometric | all steel parts | Young's Modulus |
| non-geometric | central tube | material utilization |
| non-geometric | central tube | calculated reliability |
| non-geometric | central tube | required reliability |

### *4.2 Workflow*

The workflow to generate the parametric model considering reliability (stored in a file with DFA extension that contains Knowledge Fusion code) can be seen in figure 5. The whole process can be divided into 4 steps: parameters input, performance calculation (reliability in this case), the DFA file generation, model visualization. In the first step, the user is guided to input parameters including geometric and non-geometric ones into a Python script. This end-user interface could be replaced by a graphical user interface (GUI) to improve the user-friendliness if needed. After the program receives the user input parameters, the user-cared calculation will be conducted and the result will be transferred to the next step. In this paper, we only consider reliability as an example. However, some other calculation can be added in this step according to the user concerns. With all the needed parameters prepared, the program will output the parametric model into the DFA file, which contains the geometric and non-geometric parameters. Eventually, the user can visualize the model with Siemens NX and see whether the reliability of this design meets the requirement intuitively.

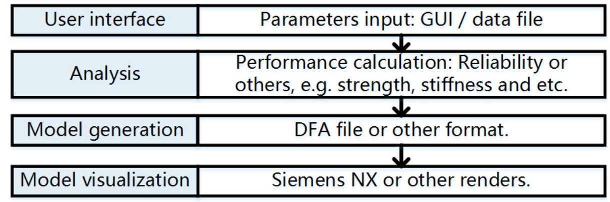


Fig. 5. Workflow to generate the parametric model

If the design fails to meet the criteria, the user can input a new set of parameters and immediately get an updated DFA file. When the result is satisfying, both the 3D model and calculation have been available. Compared with the conventional design process, the data in this method can be transferred between the different phrases automatically. Consequently, the design loop can be conducted in a time-saving and intuitive way, which is a significant benefit in the customized product design.

### *4.3 Result Demonstration*

As mentioned above, the central tubes will be in green or red depending on if the reliability meets the requirement. In this paper, different requirements are set to demonstrate this function as an example. From table 2, it can be seen that if a relatively low standard ($\beta = 2.33, R = 0.99$) is set, the central tubes can pass the criteria and will be in green (see in figure 6 (a)). Oppositely, if a relatively high standard ($\beta = 4.2, R = 0.999987$) is used, the central tubes will be displayed in red (see in figure 6 (b)). The colors are being set following the rules of the 'body colored central tube' object defined in the DFA file (see figure 4).

## 5. DISCUSSION

Umbilical cable is a typical customised product as its cross-section always varies depending on the specific project´s requirements. By applying the KBE method to establish the parametric model instead of the conventional design method, together with the proper calculation tool, the design loop can be done in a time-saving way. Additionally, the parametric model has the potential to combine with design generation and optimization algorithm, which may lead to automatic design and optimization.

Currently, there are still some design processes difficult to parameterize and represent, e.g. the layout design of the umbilical cable. This kind of processes is usually easy to

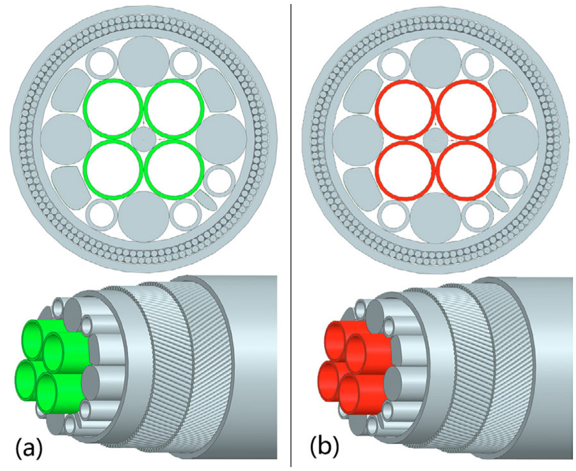


Fig. 6. Result demonstration

handle by human but difficult to be coded into a program. Since the difficulty of the program is in some cases more significant than to manipulate by hand, the KBE method is seen as a bad investment sometimes. If the product is not a customized one which needs to change the design frequently, the disadvantages are more significant.

## 6. CONCLUSION

A parametric model of steel tube umbilical cable considering its reliability has been established aiming at boosting the design loop of the cross-section. This work shows the potential of KBE method to consider not only the geometric parameters but also the non-geometric aspect. Compared with the conventional way, the benefits of KBE method are significantly demonstrated. Data can be transferred between upstream and downstream processes automatically, which saves significant time to get through the design loop. Additionally, this kind of parametric models lay the foundation for future automation of design and optimization.

Future investment is advised to focus on how to make KBE method easier to implement by design engineer without high requirement on programming skills, e.g. some basic and commonly used analysis code and programs which are easy to use and embed into KBE framework, especially some mathematics functions.

The current work can be extend to consider some more complex engineering process to find more obstacles to apply the KBE method in real engineering application and show the potential of KBE method to design automation, such as the above-mentioned layout automatic design and optimization.

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