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A Systematic Review of β-factor Models in the Quantification of Common Cause Failures

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***Abstract*—Safety systems, i.e., systems whose malfunction can result in catastrophic consequences, are usually designed with redundancy in mind to reach high levels of reliability. However, Common Cause Failures (CCF), i.e., single failure events affecting multiple components or functions in a system, can threaten the desired reliability. To solve this problem, practitioners must use proven methods, such as those recommended by standards, to support CCF quantification. In particular, the β-factor model has become the de-facto model since the safety standard IEC 61508 considers it. As such standard applies to all industries, practitioners must figure out the industrial-specific implementation procedures. In this paper, we conducted a systematic literature review to understand how the β-factor model has been used in practice. As a result, we found 20 different models, which are industry/project-specific extensions of the first β-factor model proposed for the nuclear sector. We further classified those models by considering how the β-factor is estimated, and the level of redundancy support. Tool support for the models and their industrial use are also outlined. Finally, we present a discussion that covers the implication of our findings. Our study targets practitioners and researchers interested in using current β-factor models or evolving new ones for specific project needs.**

***Index Terms*—Common Cause Failure, β-factor model, Systematic Literature Review**

I. Introduction

Reliability is the probability that a system or component performs the intended function properly over a given period of time. In designing high-reliable systems it is common practice to include redundancy to critical elements to make the system work despite single failures. However, Common Cause Failures (CCFs) may lead to the failure of multiple units or components due to a single cause. The significance of CCFs has been demonstrated in almost all Probabilistic Safety Assessment (PSA) reports of nuclear power plants in the past [1]. The reports show that the CCFs are the main reason for the unavailability of redundant systems and their associated risks. A lot of research was carried out globally in many countries such as the US [1], UK [2], and Nordic countries [3] to address the common cause failures.

Safety standards, such as IEC 61508 [4], suggest the modeling of CCF by using the β-factor model, where $\beta\%$ of the failure rate is attributed to CCF and $(1 - \beta)\%$ to the random failure rate. In particular, to derive the β value, the standard proposes a methodology applicable to Electrical/Electronic/Programmable Electronic (E/E/PE)-based systems that reflects the effect of diagnostic tests in estimating the likely value of β. However, such methodology is too general leaving the implementation details up to the practitioners.

In the research area, there is an absence of research studies that explicitly focus on the β-factor model and its development toward the quantification of CCFs. Hence, to close this gap we conducted a systematic literature review (SLR) by following the guidelines provided by Kitchenham and Charters [5] which led to the identification of a set of β-factor models. We briefly described all the identified β-factor models and classified them based on their β-factor estimation methods. We further distinguished the models based on their redundancy support and required expert judgment. We also gave information on identified CCF modeling tools, models usage in industries, and implications for industry and research.

This paper is structured as follows. Section II presents the essential background. Section III discusses related work. Section IV gives an overview of the research methodology. Section V presents the research result. Section VI discusses the implications for industry and research. Section VII discusses the threats to the validity of our work. Section VIII explains the conclusion and future work.

II. Background

A. Redundancy

A modern industrial system typically is an interconnection of more than one sub-system or component. The systems can be electrical, mechanical, or digital. In addition, the systems are usually designed with redundancy and output voting techniques to achieve some desired reliability. The safety standard IEC 61508:2010 [6] defines redundancy as *"the existence of more than one means of performing a given function"*. Redundancy is used to improve reliability or availability. A safety instrumented system, for example with MooN voting redundancy in its architecture can be explained as a system with N units (i.e., components, channels, etc.,) where M is less than or equal to N, in which M out of N units are required to execute a safety function. That means M units must function for the system to be successful [7]. For instance, in configuration 1oo2 at least one of the two components must function to guarantee the safety function.

B. Common Cause Failures

The definition and use of the term Common Cause Failure (CCS) were initially made by Fleming & Hannaman [8], as follows: *"A CCF is an occurrence of multiple equipment failures caused by a single (common) event"*. Standards and industries also developed similar definitions. For example,

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in IEC 61508, CCF is *"the result of one or more events, causing concurrent failures of two or more separate channels in a multiple channel system leading to system failure"*. The author in [9] separates CCF definitions for component-level and system-level functions. At the component level, a CCF is *"an event where a component is failed due to a certain cause, and the same cause has the potential to fail other redundant components"* while at the system level is, *"an event where multiple redundant component failures are due to a shared cause, and multiple component failures lead to system failure."*

C. IEC 61508 Standard based CCF Quantification

The standard IEC 61508 [6] suggest a methodology for defining the β-factor model required for quantifying the hardware-related CCF in E/E/PE systems. The methodology permits the calculation of overall CCF dangerous rates by considering both dangerous detected (DD) and dangerous undetected (DU) failure rates. β is the CCF factor for DU, while β_D is the CCF factor for DD. The equation to calculate CCF rate as per the standard is:

$$\lambda_{CC} = \lambda_{DU}\beta + \lambda_{DD}\beta_D \tag{1}$$

III. Related Work

Most available research studies discuss individual β-factor models or compare two or more models by considering case studies. Few identified secondary studies present reviews of different models, which capture some of the aspects we present. For example, in [10], the authors present a comprehensive list of models that practitioners can use as a reference for searching models. However, [10] does not contain such a detailed analysis as we do in this paper. In [11], the authors show the development of CCF models, including some of the β-factor models that we also list in our review. However, this work was done in the '90s, which means that many of the later developed β-factor models are not included. More reviews are presented in [12], [13] and [14], where the authors characterize the CCF modeling status, including the β-factor models. In [14], the authors also evaluate some of the β-factor models, providing the readers with a more rich view of such models and their adopted defense measures. Previous reviews present the role of the β-factor models as a part of other CCF models. In contrast, our study focuses only on the β-factor models existing in the state of the art. We also compare them by considering parameters such as the redundancy support of the models and the needed expert judgment. We also present their tool support and applicability in industrial settings.

IV. Research Method

For performing the SLR, we follow the research process proposed by Kitchenham and Charters [5]. We present the review protocol in Section IV-A and the data collection procedure in Section IV-B.

A. Review Protocol

The purpose of this SLR is to identify and characterize all the available models that have similarities or are derived from the β-factor model. We first got to know about the β-factor model from the standard IEC 61508 [6] (recalled in Section II-C). Accordingly, we define the research questions that should be addressed in this study (see Table I).

TABLE I: Research Questions

Id	Question
RQ1	How did the β-factor models evolve over time, and how could we classify them?
RQ2	How do the identified models provide support in the quantification of CCFs with respect to redundancy and expert judgment?
RQ3	What are the identified tools to model the β-factor models and the list of industries that are using different β-factor models?

For reaching the maximum amount of primary studies, we tried and compared different search strings and hits between them. The final search string is the following:

("Beta factor model" OR "β-factor model" OR "common cause failure model" OR "CCF model")

Primary studies are searched on five popular scientific online digital libraries: 1) Google Scholar, 2) ScienceDirect, 3) Springer Link, 4) Web of Science, and 5) IEEE Explore. Google Scholar permits the identification of papers in databases beyond the ones previously mentioned. All the databases except Google Scholar accepted all the words defined in the search string. For Google Scholar, we divided the search string into four strings and did four different searches. We did not make any restrictions related to the year of publication. The search was performed between December 2022 and January 2023. Papers published after this date are outside of the scope of our review. We made a checklist questionnaire to identify the primary studies (see [15]). The primary studies included in the selection are peer-reviewed articles and technical reports written in English that discuss β-factor models. In contrast, primary studies that do not provide appropriate answers to the checklist questionnaire, studies that are not peer-reviewed, and secondary/tertiary studies are excluded from the selection. Such criteria were adopted during the different filters of the SLR process (see Fig. 1).

B. Data Collection

The selection of primary studies was performed through multiple rounds as presented in Fig. 1. At first, we conducted title screening of the identified 2541 studies, in which we select the papers that match any one of the inclusion criteria. From the title screening, we got a total of 394 papers. In the second round, we removed duplicates from the papers, and we got 281 papers. Then in the third round, we did the abstract screening, from which we got 75 studies. The most common reasons for discarding many studies are their use of models for quantifying CCFs different from the β-factor model. In the fourth round, we found 41 studies relevant among 75 studies, through careful reading of full papers. Then

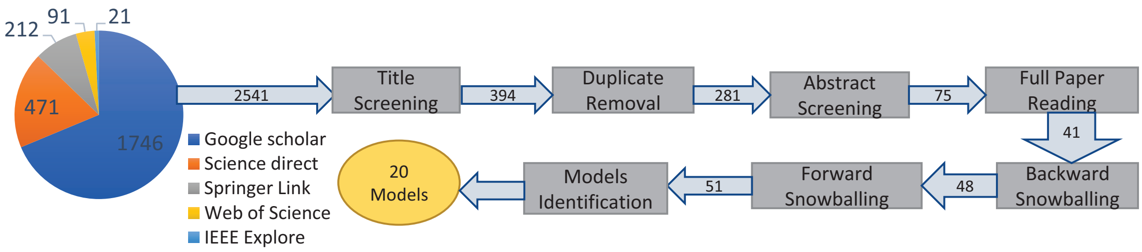

Fig. 1: SLR process steps and models selection

we applied the snowballing process [16] to the 41 articles to find more papers through reference checking, from which we got 7 more studies from backward snowballing and 3 more studies from forward snowballing. Thus, we collected a total of 51 primary studies based on our SLR via database search and snowballing process. Subsequently, we further analyzed the 51 primary studies and identified 20 distinct models based on pre-defined model identification criteria. In our data extraction process, we maintained our selected paper details in Excel sheets (see [17]), where we provided information about the paper title, author details, year, venue details, and collected data.

V. Research Results

A. Evolution and classification of β-factor models (RQ1)

In our SLR, we identified 20 models (see Table II). Based on the estimation of the β-values, they can be quantitative, qualitative, and hybrid approaches. Three types of models of recent times (21st century) are identified in the journal reliability engineering & system safety [18]. Five types of models of old times ('80s) are found in the reliability engineering journal [19]. Two models are identified in probabilistic safety assessment and management conference proceedings. The remaining ten models are identified in different types of venues. The first model evolution happened in the '70s. Consequently, six types of quantitative approaches and three types of qualitative approaches evolved in the '80s. In the '90s, only two types of qualitative approaches evolved. Whereas in the 21st century, two types of quantitative approaches, four types of qualitative approaches, and two types of hybrid approaches evolved. The historical evolution of the models is shown in Figure 2.

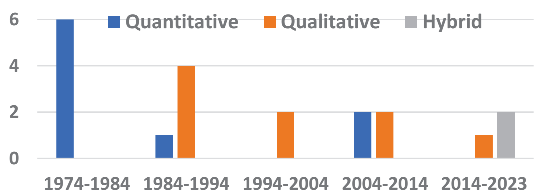

Fig. 2: Models Evolution Timeline

Quantitative Models: This classification estimates the β value from the existing historical CCF data sources. The first model is the *β-factor model* [M1] or BMF. This model, which

TABLE II: Historical Evolution of Beta Factor Models

Model Name	Year	Ref.
Quantitative approaches		
BFM model	1974	[M1]
MDFF method	1982	[M2]
Specialized BFM approach	1983	[M3]
MGL method	1983	[M4]
C-factor model	1984	[M5]
Extended MDFF method	1984	[M6]
Event-based method	1987	[M7]
Modified BFM approach	2012	[M8]
Advanced MGL method	2014	[M9]
Qualitative approaches		
BFM with limiting values	1987	[M10]
PBF method	1987	[M11]
Humphreys method	1987	[M12]
Enhanced PBF method	1990	[M13]
UPM approach	1996	[M14]
Multiple BFM approach	2004	[M15]
PDS method	2006	[M16]
IEC 61508 based framework	2013	[M17]
SLV approach	2015	[M18]
Hybrid approaches		
Alpha factor and BFM	2020	[M19]
Modified BFM and Humphreys method	2022	[M20]

appeared in 1974, was created to facilitate the calculation of CCFs in the nuclear industry. The BMF model considers common and independent failures simultaneously. For this purpose, the model introduced a new parameter called β, where the β value is taken from operational experience data. This model assumes λ as the failure rate, where independent and common mode failures are regarded as to be λ_1 and λ_2, respectively. The failure might be λ_1 or λ_2 but cannot be both. The equations defined in paper [M1] are:

$$\lambda = \frac{\text{number of failures}}{\text{part-hours of operation}} \tag{2}$$

$$\beta = \text{fraction of unit failures which are common mode} \tag{3}$$

$$\lambda_1 = (1-\beta)\lambda \tag{4}$$

$$\lambda_2 = \beta\lambda \tag{5}$$

The BFM model predicts appropriate system reliability for low levels of redundancy, e.g., 1oo2. However, it indicates lower reliability than observed for systems with higher redundancy. For accurate quantitative predictions, all the remaining quantitative approaches were proposed.

Models that evolved directly for the BFM (see the left side of Fig. 3) are the *Specialized BFM approach [M3]*, the *C-factor model [M5]*, the *Multiple Dependent Failure Fraction or MDFF model [M2]*, the *Multiple Greek Letter method (MGL) [M4]* and the *Modified BFM [M8]*.

In addition, improvements are applied to the previous models, giving birth to new ones. For example, the *Multiple Dependent Failure Fraction or MDFF model [M2]* predicts values much closer to the experienced ones, especially for a 1oo3 configuration. This work was later extended into the *Extended MDFF method [M6]* to derive reliability expressions for multiple redundant systems.

Another example is the MGL method, which evolved to consider explicitly higher-order redundancies by introducing a different set of parameters in addition to β factor. This model was used as a base to create the *Advanced MGL method [M9]* and the *Event-based Method [M7]*. The former allows components that share multiple common characteristics with more than one group of similar components. The latter uses parameters that are based on event statistics.

Qualitative Models*:* In this classification, the β value is calculated by considering the assessment of different defense factors against CCFs. The assessment is done by experts and historical data is not required. As presented in Table III, there are six types of factors, which in total contain 39 estimation factors, most of them related to the system design.

In particular, the *BFM with limiting values [M10]*, which was the first model considering qualitative measures, tackles design factors, such as the degree of components diversity, type of system, defense against CCF, and degree of redundancy. The β value, which is determined entirely by an expert, is inversely proportional to the CCF defenses.

The remaining models of this category base their estimation of the β factor on checklists. In particular, we see the first checklist in the *Partial Beta Factor method (PBF) [M11]*, where 19 defense factors are assessed. This model evolved into the *Enhanced PBF method [M13]* and the *Unified Partial Method (UPM) [M14]*. The former also considers the same 19 factors but includes more detailed information for audit purposes. The latter focuses on fewer factors (eight in total) that describe the impact of the system's design, as well as operational and environmental characteristics.

The *Humphreys'method [M12]* considers eight factors that are commonly related to electrical/electronic systems. For example, in the design, there are four factors, i.e., separation of components, similarities in the components, the complexity of the system, and analysis of the components. It also considers operation factors, like procedures and training. A context-specific model is the one created for the *Space Launch Vehicles (SLV) approach [M18]*, which is a model resulting from tailoring a pre-existing methodology for space launch vehicles, considering eight factors that contribute to CCFs. Scoring such factors requires expert judgment.

Finally, we have methods that are based on the standard IEC 61508. Those methods are the *PDS method (pålitelighet for datamaskinbaserte sikkerhetssystemer-Norwegian acronym) [M16]*, the *Multiple β Factor Method (MBF) [M15]* and the *IEC 61508 based Framework [M17]*; all of them estimate the β value based on 13 factors.

Hybrid Approaches*:* We found two models in this classification (see the bottom side of Fig. 3). In particular, the *Modified BFM and Humphreys method [M20]*, in which the β value is determined by the Humphreys method. The second model combines the *Alpha factor and BFM [M19]*. This model is suitable for multi-unit probabilistic safety assessment (PSA), which involves a large number of nuclear power plant units. It uses the Alpha factor for each modeled unit and combines them as in the BFM model.

B. Analysis of the Models support (RQ2)

The β-factor models are developed to identify and quantify CCFs for the reliability assessment of the systems. However, the CCF results produced by different β-factor models, which depend on different aspects within the system under study, produce conservative results (careful estimation) or less conservative ones (closest to reality). In general, the main factors of the models that are influencing the CCF results are their level of redundancy support and level of expert judgment.

Redundancy*:* In general, all the β-factor models found in this study claim to support all types of redundancy. However, better results (or less conservative) are found to be different for different models. In Table IV, we classify the models, according to the redundancy support (see Section II-A) that provides better results from the models. Three different redundancy types are used, such as low redundancy (e.g., 1oo2), low to medium redundancy (e.g., 1oo2, 1oo3), and low to high (e.g., 1oo2, 1oo3, 1oo4).

TABLE IV: Redundancy support of the models

Redundancy	Model type	Models
Low	Quantitative	[M1], [M2], [M5]
	Qualitative	[M11], [M12], [M13], [M14], [M18]
	Hybrid	[M19]
Low to medium	Quantitative	[M3], [M6], [M7], [M8], [M9]
	Qualitative	[M10]
	Hybrid	[M20]
Low to high	Quantitative	[M4]
	Qualitative	[M15], [M16], [M17]

Experts Judgement*:* All the models require expert judgment in their implementation. However, qualitative models require a high level of involvement of experts in the quantification of the factors (presented in Table III). In the quantitative models, the expert is required to estimate the β value giving her expertise from similar projects by checking the historical CCF data (e.g., event reports) to estimate the value.

C. Identified Industries and Tools (RQ3)

In our review, we found different industries that were the pioneers of the models. We also found the available tools supporting some of the models.

Industries*:* From our analysis, we identified that a large number of quantitative approaches have been used in the past probabilistic risk assessment of the nuclear industry. The models BFM model, Specialized BFM approach, Extended

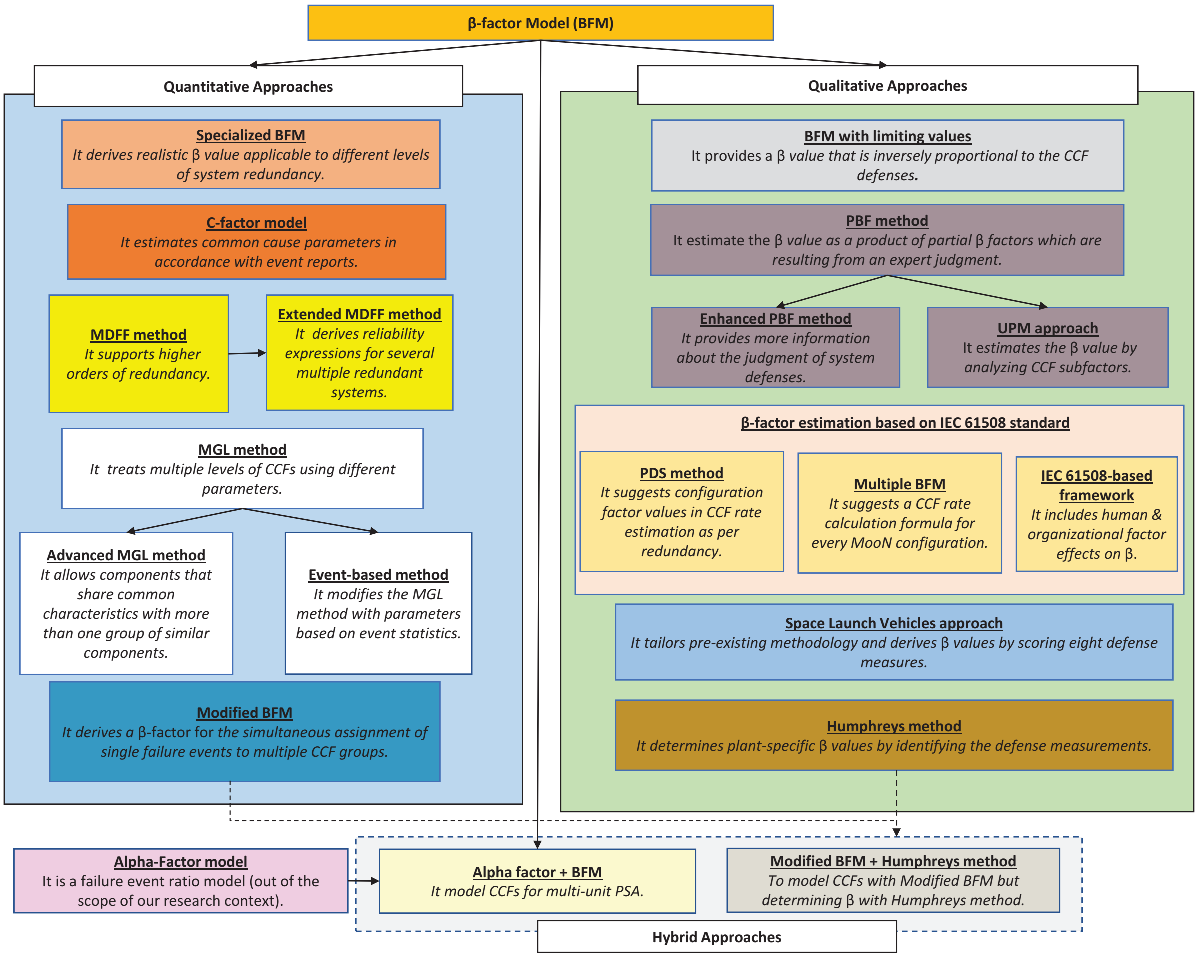

Fig. 3: Models evolution with distinguishing features and relationships

MDFF method, C-factor model, and Extended MDFF method are among those quantitative approaches which have been widely used during the period between 1975-1985 in the nuclear industry across various countries. The studies that present these models also show their usability and the availability of past experience CCF data for the utilization of these quantitative approaches.

From our analysis, we identified that one of the qualitative approaches (BFM with limiting value) is also used in the nuclear industry. As the qualitative models do not depend on past experience CCF data, it has been used widely in distinct industries during the period 1987-2015. The UPM approach is used in the aviation industry, and the PDS method is used in the offshore and railway industry. Other models, such as the SLV approach was developed especially to use in the space industry. The Humphreys method was developed for industries that are using electrical/electronic systems.

The two types of hybrid approaches are mainly developed for the nuclear industry in the recent period 2020-2022. The first hybrid approach (Alpha factor and BFM) was developed to model CCFs for multi-unit probabilistic safety assessment of nuclear chemical plants. The second hybrid approach (Modified BFM and Humpheys method) was developed to model software CCFs within digital instrumentation and control systems of the nuclear industry. The evolution and development of the β-factor model begin initially with a focus on the nuclear industry and its systems that rely on their past CCF data. In later years, the industries that are using electrical/electronic systems developed other methodologies that do not rely on past CCF data. However, industry-specific β-factor models are not yet developed/identified.

Identified Tools: : In our SLR process from primary studies, we identified four commercial tools that support two of the identified β-factor models (i.e., [M1] and [M4]). In particular, the *SAPHIRE software*, which stands from Systems Analysis Programs for Hands-on Integrated Reliability Evaluations [20], is a tool that supports defining a CCF object with a piece of minimal information like the number of redundant components, failure criteria, choosing a CCF model type among the available models, associated model parameters and other details. It supports the models M1 and M4. Another tool is called *CAFTA software*, which stands for Computer Aided

TABLE III: β Estimation Factors for Qualitative Models

No.	Type of factor	Estimation Factor	Models
1	Design factors	Degree of component diversity	[M10], [M15], [M16], [M17]
2		Type of system	[M10]
3		Defense against CCF	[M10]
4		Degree of redundancy	[M10], [M11], [M13], [M14], [M15], [M16], [M17], [M18]
5		Design control	[M11], [M13]
6		Design review	[M11], [M13]
7		Functional diversity	[M11], [M13]
8		Equipment diversity	[M11], [M13]
9		Fail-safe design	[M11], [M13]
10		Operational interfaces	[M11], [M13]
11		Protection and segregation	[M11], [M13], [M15], [M16], [M17], [M18]
12		Derating and simplicity	[M11], [M13]
13		Separation of components	[M12], [M15], [M16], [M17], [M18]
14		Similarity in the components	[M12]
15		Complexity of the system	[M12], [M15], [M16], [M17], [M18]
16		Analysis of the components	[M12], [M15], [M16], [M17], [M18]
17		Isolation	[M14]
18		Understanding	[M14]
19		Evaluation	[M14]
20	Construction factors	Construction and control	[M11], [M13]
21		Testing and commissioning	[M11], [M13]
22		Inspection	[M11], [M13]
23		Construction standards	[M11], [M13]
24	Operation factors	Operational control	[M11], [M13]
25		Reliability monitoring	[M11], [M13]
26		Maintenance	[M11], [M13]
27		Proof test	[M11], [M13]
28		Operations	[M11], [M13]
29		Procedures	[M12], [M15], [M16], [M17], [M18]
30		Training	[M12], [M14]
31		Interface	[M14]
32	Environment factors	Environmental control	[M12], [M15], [M16], [M17], [M18]
33		Environmental test	[M12], [M15], [M16], [M17], [M18]
34	Condition factors	Control	[M14]
35		Experiment	[M14]
36	Other factors	Design/application/maturity/experience	[M15], [M16], [M17], [M18]
37		Assessment and feedback of data	[M15], [M16], [M17], [M18]
38		Human interface	[M15], [M16], [M17], [M18]
39		Competence/training/safety culture	[M15], [M16], [M17], [M18]

Fault Tree Analysis system [21]. It is used by both single analysts and project teams. It supports the modeling of CCF events with model M4. The *Risk Spectrum* [22] is a Probabilistic Safety Assessment software, which provides choices for selecting different hazard analysis techniques such as event tree, fault tree, and to model CCFs. It supports the models M1 and M4. Finally, we found *Isograph* [23] tool, which provides efficient support in safety analysis through its product Fault Tree+. It supports the models M1 and M4. However, in most of the studies models are used manually, without tool support.

VI. Discussion

A. Implications for the Industry

There are some aspects related to the review presented in this paper that we consider worth highlighting and discussing. The first aspect is related to the selection of models for industrial applications. In particular, there are various β-factor models to be chosen. However, not all of them are appropriate for all systems. Therefore, we need to do an analysis of the system under study and reflect on the type of results we are willing to accept (conservative or less conservative) as well as the implications of those results.

For example, it is important for the practitioners to understand if past information regarding CCFs (for similar models) exists. In that case, practitioners can select quantitative models (see the left side of Fig. 3). In the absence of past data, the most appropriate models are those classified as qualitative (see the right side of Fig. 3). However qualitative models also varied according to the type of estimation factor that they support (see Table III).

In addition, safety systems are configured with different redundancy levels. To get more appropriate results (or, in other words, less conservative results), it is better to select a model that copes with the type of redundancy that is being considered for the system (see Table IV). Practitioners can also consider the existing tools (presented in Section V-C) and the models they support to facilitate their application.

In most cases, industries start their CCFs analysis from the model provided by the standard IEC 61508 (which is qualitative) to be able to comply with the standard. However, they move to more appropriate models as soon as data is available. The reason for this change is that industries are in search of better CCF quantification that reduces the number of safety requirements needed to be considered. Reduction of safety requirements means a reduction of cost, which is one of the goals that drive industries.

B. Implications for Research

The research and development towards the quantification of CCFs using β-factor models began in the 1970s. Several models have been created after this time, for coping with the different needs of different industries (but especially for the nuclear industry). However, it is still difficult to find a more general model that is able to cope with different needs at the same time. Therefore, the visualization of models and their support may be a good starting point for practitioners aiming at using them, but also for researchers wanting to evolve models into new (and more appropriate) ones without repeating past efforts. There is also a strong need for research towards tool support for β-factor models because from our analysis we found only four tools (see subsection V-C), which are supporting two β-factor models (among the 20 models found in our study - see Table II). The high prominence of models, M1 and M4 in industries has led to the development of tools only for these models. However, tools like Isograph [23] supports the standard IEC 61508, and the models which estimate the β-factor values following this standard could utilize this Isograph tool support.

VII. Threats to Validity

Potential threats that could undermine the validity of an SLR are publication bias, missing primary studies, and data extraction inconsistencies. This section presents the strategies adopted during our review to address these threats. However, we made an efficient review protocol, following the guidelines [5] and a thorough review of two research experts. We provided access to our detailed strategy used in the identification of primary studies and the data collection (see Section IV).

A. Publication Bias

This threat refers to the problem that positive results are more likely to be published than negative results. To mitigate this threat, we designed a review protocol according to best practices. Such a protocol was done by the first author and reviewed by the second and third authors who had experience of performing systematic reviews, e.g., [24], and [25] respectively. Hence, the first author is a data extractor and the other two authors are data checkers. The data checkers reviewed and analyzed the results by conducting meetings and discussions.

B. Missing Primary Studies

This threat refers to the inability to collect all possible primary studies and can be addressed by an appropriate search strategy. To mitigate this threat, we aimed to ensure the search addresses our review intentions. We carefully characterized the topic to discover all possible concepts, synonyms, and acronyms. Then, we tested it in known digital libraries. However, the search string may not be sufficient for all possible studies. To mitigate this threat we perform a snowballing process. In particular, we manually scanned and analyzed the references of primary studies obtained from the automated search (backward snowballing) and citations of those studies found in Google Scholar (forward snowballing). The first author performed the process, while the second and third authors evaluated the work. The inclusion of Google Scholar amplified the considered sources. However, we found several old dated studies with difficult accessibility. Some of them were provided in printed form by the university library. However, some other identified studies, i.e., original reference articles of models M4, M14, and M16 were not found. We based their analysis on newer obtained references.

C. Data Collection Inconsistencies

This threat can be tackled by an appropriate strategy to extract all data required to address the review questions in a consistent manner. In particular, the data available contains the information of primary studies citation and the answers related to the three research questions. The data extraction process and the identified studies from the beginning of the database search till the identification of models are maintained in different sheets of an Excel file, which is made available online. We followed the practice of highlighting the important text in the identified studies. The extracted data is cross-checked by the senior researchers. Thus, we make sure of collecting data in a consistent manner.

VIII. Conclusion and Future Work

In this paper, we conducted a systematic literature review to understand how the β-factor model has been used in practice. Our review found 20 different models (listed in Table II). Such models have a common origin, namely, they are based on the model [M1], which was proposed for the nuclear industry. However, different contexts bring different details that make the first model not suitable for all projects. Therefore, new models emerged to tackle different projects and industrial needs (see Fig. 3). In particular, some models require data from previous project experiences - quantitative approaches, whereas other models rely on questionnaire results or expert judgment - qualitative approaches, and there are models that use a combination of both - hybrid approaches. The results provided by those models also vary in accordance with the level of redundancy and the required expert judgment (see Section V-B). Finally, there are tools available for supporting some models, but the majority of them lack tool support (see Section V-C). This information can be useful for practitioners and researchers that are interested in using a method that better matches their project-specific needs.

In the future, we plan to perform case studies with selected β-factor models to contrast their results in practice. We also plan to create guidelines that can facilitate the selection and use of different models. In addition, surveys with practitioners will be conducted, to understand their specific needs regarding CCFs identification and evaluation. Finally, we plan to test the accuracy and usability of the available tools to see if they meet industrial needs or if more appropriate tools are required.

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