Probabilistic time-specific risk load for PPP

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Abstract

Risk allocation is crucial for the success of a Public Private Partnership project. When looking for the optimal risk allocation, the risk-bearing capacity of the private party needs to be considered. The risk-bearing capacity is ensured if the risk coverage exceeds the risk load at all times during the contract phase. This paper presents a probabilistic approach that refines a simulation for the aggregation of a project's risk load using time-related information from subjective expert estimations. In the process, the concept of time-specific risk impact and risk periodicity is integrated in a Monte Carlo simulation model. In the simulation, the impact of single risk events is allocated to time units according to the underlying time-related random variables. The result is an "empirical" distribution function of the project's risk load resulting from the simulated artificial statistical data base for either just one specific point in time or the cumulative project's risk load until that specific point in time. The time-specific project risk load can be used to assess, if the private party is able to provide risk-bearing capacity and to determine the necessary financial risk coverage at this point in time.

Keywords: Monte Carlo simulation, Public Private Partnership, risk-bearing capacity, risk cost, risk load.

1. Introduction

Many national economies are confronted with infrastructure investment needs. To meet the needs, Public Private Partnership (PPP) has become an alternative to traditional public procurement. Finding the optimal risk allocation is of high importance for a PPP projects' success (Andersen and Enterprise LSE (2000)). Today's risk allocation (RA) takes place mainly in a qualitative way according to intuitive, habitual, opportunistic criteria or bargaining strength (Delmon (2009), Girmscheid and Pohle (2010)). A current research project at ETH Zurich aims for an implemented tool that determines the "optimal" RA quantitatively and consequently according to rational and traceable decision-making with clear criteria. Aside from being cost minimal, the RA is considered optimal in the present work, if the resulting private party's risk load does not exceed the according private party's risk coverage and thus risk-bearing capacity is ensured at all times. The presented work is based on the RA model developed by Girmscheid (2013) and related (see state of research).

The overall research project is presented in Fig. 1. The first part of the RA model covers rational information acquisition for a quantitative RA model (see Firmenich and Girmscheid

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(2013)). The modules of the RA model's first part follow the usual steps of the risk management process: risk identification, risk assessment and risk classification. The second part of the RA model contains the quantifiable and thus implementable decision-making: risk allocation / risk handling, risk load, risk coverage and risk-bearing capacity. The paper's subject and contribution to the overall research project is the quantitative time-specific calculation of the PPP project's risk load.

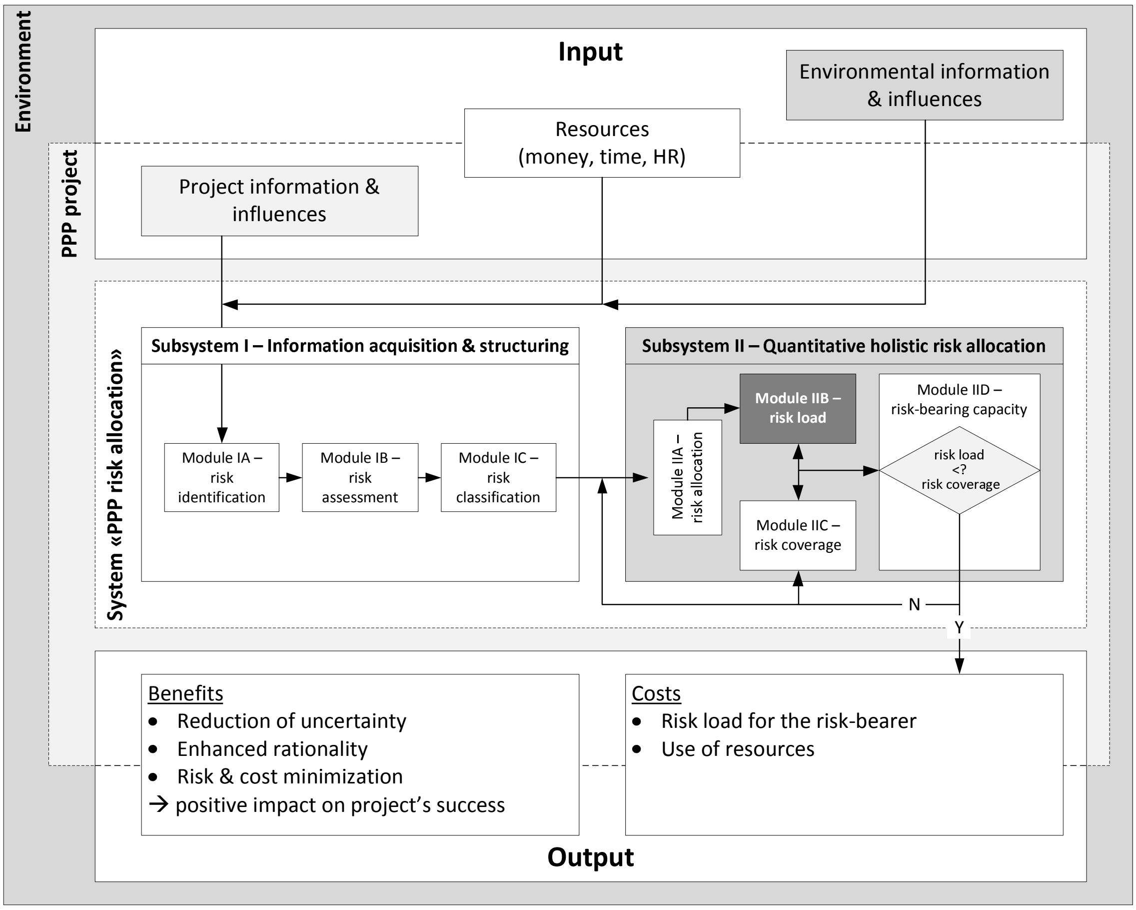

Figure 1: Concept of a quantitative holistic risk allocation model under consideration of the private party's risk-bearing capacity with focus on risk load calculation

The chosen approach is characterized by being probabilistic (i.e. input and output are random variables with an according distribution function), using a Monte Carlo simulation (MCS) for risk aggregation from single to project risk and including time-specific information into MCS. Because of the consistent quantitative modelling, this RA model part is readily implementable and complex causalities can be processed electronically. This is demonstrated with an example. Based on and in the frame of the relevant previous work (see state of research) this paper's objective is to integrate time-related risk modelling concepts like risk periodicity and time-specific single risk impact consistently into an established Monte Carlo simulation for risk aggregation (see Girmscheid (2013) and related). That's how a time-specific project risk load is derived for comparison with project risk coverage to ensure risk-bearing capacity.

2. State of research regarding risk assessment and risk load calculation in the context of risk allocation for PPP projects

The institutional PPP guidelines on the one hand often promote simple practice friendly deterministic approaches for risk management (e.g. European Commission (2003)). The research literature on the other hand often covers more sophisticated probabilistic methodologies using random variables, MCS and/or stochastic processes (e.g. Boussabaine and Kirkham (2004), Schöbener, et al. (2007), Alfen, et al. (2010)). The concept of analysing risk-bearing capacity with risk coverage exceeding the risk load was used in Girmscheid and Busch (2008) for risk aggregation on project and company level of the construction industry. Furthermore, the concept was integrated in a holistic probabilistc RA model for PPP developed by Girmscheid (2011) and Girmscheid (2013). In the following, Girmscheid (2013) is used as main reference, which implies the consideration of the other publications mentioned above. Firmenich (2011) as well as Firmenich and Girmscheid (2013) cover further hitherto results of the underlying research project. Girmscheid (2013) in particular, contains a probabilistic MCS approach for the aggregation of identified and assessed single risks to a cumulated probabilistic project's risk load over the contract phase. Furthermore, the concept of risk periodicity is introduced in that publication. This is taken as a basis to integrate time-specific information and MCS for risk aggregation in a probabilistic and implementable way to enhance the given state of research, as is presented in this paper. So far, time development of PPP project risks was either covered with stochastic processes (e.g. Irwin (2007), Schöbener, et al. (2007), Alfen, et al. (2010)) or two-dimensional random variables (Elbing (2006)).

3. General research methodology

The presented overall research is based on the research methodology according to Girmscheid (2007). Construction management science relates to the Third World of Popper's three worlds (Popper (1987)). The construction management's processes and models design the socio-technical environment of Popper's Third World according to the hermeneutic research paradigm. The presented research follows the radical constructivism science paradigm according to Von Glasersfeld (1997). In that context, the objectives to the corresponding problem and the target-means-relationship to solve the problem and achieve the objectives are developed. The actional decision model's structure is developed according to cybernetic systems theory and the methodological focus lies on the application of quantitative methods. Research quality will be ensured by viability, validity and reliability based on triangulation according to Yin (2009).

4. Concept of an enhanced Monte Carlo simulation for a time-specific probabilistic project's risk load determination

4.1 Preliminary work for the simulation

In the context of this research, risk load means the cost resulting from risk events, called risk cost. Single risk cost result from a single risk event whereas the project risk cost are the result from all risk events of the project. The determination of the project's risk load requires, firstly, the cause oriented identification of single risks. These single risks need to be assessed for risk load determination in a second step. As no statistical historical data is available, this is done by subjective expert estimation. It is suggested to use a combination of established methods like brainstorming and the Delphi method to conduct the required subjective expert estimations (see Firmenich and Girmscheid (2013)).

For risk load aggregation and thus determination under absence of statistical historical data the Monte Carlo simulation (MCS), as probabilistic approach, is common. It requires wider expert estimations than a deterministic approach that lead to distribution functions for all simulated random variables of every single risk entering the MCS. The simulation determines scenario values out of the inverse distribution functions by means of random numbers and then aggregates these values according to the underlying simulation model. The result of one iteration or scenario is stored and the process is repeated as often as specified. This leads to the generation of an artificial statistical data base from which an "empirical" distribution function of project risk can be derived and further processed. For further reading in that matter see Girmscheid (2013) and related. However, special care needs to be taken that the MCS result contains time-specific information.

A simulation purely aiming for aggregation, as described above, results in project risk cost that reflect the cumulative value at the end of the simulated period. Consequently, such MCS results would not show the risk load at a certain point in time during the simulation period. This, however, is relevant to ensure risk coverage and risk-bearing capacity at every point in time during the contract phase. The following sections present a MCS approach that is based upon a probabilistic simulation of risk impact (using "probability of occurrence" $P(O_i = 1)$ and "impact of occurrence" I_i) as shown in Girmscheid (2013). The integration of several combined random variables into MCS allows modelling of more complex and realistic causalities. This enhancement integrates, therefore, not only the idea of risk periodicity into MCS, but also the idea of single risks occurring probabilistically over time as random variables (new random variable "frequency of occurrence" F_i and "time of occurrence" T_i). The concept of risk periodicity is described by Girmscheid (2013), meaning single risks that represent potential multiple risks. The risk periodicity implemented as F_i characterizes a single risk i as one-time or multiple risk and allows the derivation of how often one risk will occur in the simulation. The risk periodicity has a strong influence on the project's risk cost because of a potential multiplier effect.

Depending on the cause, a single risk's impact usually cannot occur during all the PPP's contract phase. It is relatively easy to let the experts specify in what project phases single risks actually could occur (single risk impact phases). For example, construction risks usually cannot occur in the operation phase anymore. After comparing several PPP project phase classifications of relevant literature in a thorough review, the main phases after contract signing (altogether "contract phase") are outlined as follows: "construction phase", "operation phase" and "termination phase". The construction phase is divided into "excavation phase", "structure phase" and "finishing phase".

4.2 MCS model for time-specific project risk load aggregation

Any modelling of the input parameters should aim for a realistic possible solution space of the project. The simulation model includes expert estimations, derived density or distribution functions of the simulation model's random variables ($P(O_i = 1)$, I_i, F_i, T_i) and single risk impact phases. The MCS produces a certain number of iterations. The higher the total number of iterations, the more reliable the probabilistic result is. Each iteration leads to a scenario of how the modelled risk situation could have taken place according to the underlying governing simulation model. Random numbers $Z \in [0,1]$ are used as input for the single risk's random variables' inverse distribution function G to generate a scenario value. For each random variable of each single risk, a random number is needed that will be generated newly for each iteration.

The following section describes the risk scenario derivation for every simulation's iteration. The risk assessment provides a probability of occurrence $P(O_i = 1)$ for every single risk i, which can be translated into a Binomial distribution for the risk occurrence O_i (1)(2). With the according random number of the random variable O_i of the single risk i for the iteration k ($Z_{O,i,k}$) as input for the inverse distribution function $G(F(O_i))$, the single risk occurrence is determined (3). $O^*_{i,k} = 1$ means that the single risk i occurs in scenario k and $O^*_{i,k} = 0$ means that the single risk i does not occur in scenario k. The process mentioned before is described in Girmscheid (2013) and related. In a next step, this result is used to determine the frequency of occurrence in case the single risk is assessed as multiple single risk ($F_i^{max} > 1$). The according subjective three-point-estimation (min a, mode b, max c) of the experts for every single risk is used to derive a fitting distribution function (4). Again a random number $Z_{F,i,k}$ is generated for every single risk i for every iteration k as input for the inverse distribution function $G(F(F_i))$ of random variable F_i (5). The result depends on $O^*_{i,k}$ and on whether the single risk i is a one-time or multiple risk. The same procedure applies for the random variable I_i (6)(7). Neglecting a specific time of occurrence and that multiple occurrences $F^*_{i,k} > 1$ could have a different $I_{i,k}$ every time, the single risk's impact of occurrence for the whole simulation period calculates according to (8) $I^{**}_{i,k} = I^*_{i,k} \cdot F^*_{i,k} \cdot O^*_{i,k}$ for $\forall t \in [t_0, t_{end}]$ as a simple alternative.

As described before, the single risk's specific risk impact phases are estimated subjectively by experts. Assuming these phases are always sequential, the result is a single risk impact period with a beginning $\hat{a}$ and end $\hat{c}$ of possible impact within the simulation period. Depending on whether a single risk i could have a constant, a decreasing or an increasing probability of occurrence over time in that single risk impact period between $\hat{a}$ and $\hat{c}$, the random variable T_i is modelled as a continuous uniform distribution or BetaPERT distribution (9). In both cases the density and distribution function are scaled to fit the specific single risk impact period within $\hat{a}$ and $\hat{c}$ (10). The actual time of occurrence $T^*_{i,k}$ for the impact $I^*_{i,k}$ of the single risk i in scenario k is determined as before with a random number and the inverse distribution function $G(F(T_i))$ (11)(12). The interim result (see Fig. 3) after one iteration is a scenario k that probabilistically determines for all project's single risks i, whether the risk occurred or not ($P(O_i = 1) \rightarrow O^*_{i,k} = 0$ or $O^*_{i,k} = 1$), how often the risk occurred, if it occurred at all ($O^*_{i,k} \rightarrow F^*_{i,k}$), with what impact the risk occurred ($I^*_{i,k}$), and when the risk occurred ($T^*_{i,k} \rightarrow I^*_{i,k,t}$).

for all single risks $i \in I \in \square$ and every iteration $k \in \square$

using values from subjective expert estimations: $p_i = P(O_i = 1) \in [0,1]$,

$\overline{a}_i = F_i^{min}, \overline{b}_i = F_i^{mode}, \overline{c}_i = F_i^{max}, \overset{\square}{a}_i = I_i^{min}, \overset{\square}{b}_i = I_i^{mode}, \overset{\square}{c}_i = \max I_i^{max}$

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Probabilistic Single Risk Impact of Occurence Determination

$$(1)\ f_{O_i}(x) = \begin{cases} 1 - p_i & x = 0 \\ p_i & x = 1 \end{cases} \quad F_{O_i}(x) = \begin{cases} 1 - p_i & x = 0 \\ 1 & x = 1 \end{cases}$$

$$(2)\ O_i \sim \text{Binomial}(1, p_i)$$

$$\mathbf{(3)\ O^*_{i,k} = G(F_{O_i}(x)) = F^{-1}_{O_i}(Z_{O_{i,k}})} = O_{i,k}(Z_{O_{i,k}}) \in \{0;1\}$$

$$(4)\ F_i \sim \text{DUniform}(\overline{a}_i, \overline{c}_i) \text{ or } F_i \sim \text{BetaPERT}(\overline{a}_i, \overline{b}_i, \overline{c}_i)$$

$$\mathbf{(5)\ F^*_{i,k} = G(F_{F_i}(x)) = F^{-1}_{F_i}(Z_{F_{i,k}})} = \begin{cases} 0 & O^*_{i,k} = 0 \\ 1 & O^*_{i,k} = 1 \wedge F_i^{max} = 1 \\ F^{-1}_{F_i}(Z_{F_{i,k}}) & O^*_{i,k} = 1 \wedge F_i^{max} > 1 \end{cases}$$

$$(6)\ I_i \sim \text{PERT}(\overset{\square}{a}_i, \overset{\square}{b}_i, \overset{\square}{c}_i) \text{ or } I_i \sim \text{Triangle}(\overset{\square}{a}_i, \overset{\square}{b}_i, \overset{\square}{c}_i) \text{ or } I_i \sim \text{CUniform}(\overset{\square}{a}_i, \overset{\square}{c}_i)$$

$$\mathbf{(7)\ I^*_{i,k} = G(F_{I_i}(x)) = F^{-1}_{I_i}(Z_{I_{i,k}})}$$

Probabilistic Single Risk Time of Occurence

$$(9)\ T_i \sim \text{BetaPERT}(\hat{a}, \hat{b}, \hat{c}) \text{ or } T_i \sim \text{CUniform}(\hat{a}, \hat{c}) \text{ with}$$

$$(10a)\ F_{T_i}(t = \hat{a}) = 0;\ \hat{a} = T_i^{min} \in (t_0; t_{end}) \in \square \text{ beginning of single risk impact period}$$

$$(10b)\ F_{T_i}(t = \hat{c}) = 1;\ \hat{c} = T_i^{max} \in (t_0; t_{end}] \in \square \text{ end of single risk impact period}$$

$$(10c)\ \hat{b} = T_i^{mode} = \begin{cases} \hat{a} & T_i \text{ decreasing over time} \\ \hat{c} & T_i \text{ increasing over time} \end{cases}$$

$$\mathbf{(11)\ T^*_{i,k} = t^{I*}_{i,k} = G(F_{T_i}(t)) = F^{-1}_{T_i}(Z_{T_{i,k}})}$$

$$\mathbf{(12)\ I^*_{i,k,t} = I^*_{i,k}(t = t^{I*}_{i,k})}$$

After k iterations the result is k simulated scenarios as described above representing artificial statistical data that can be aggregated probabilistically. The three aggregation dimensions are the single risks i, the time t and the iterations k. The aggregation over i and t is a simple summation within the data set of a scenario k. The aggregation over all scenarios k is the building of an "empirical" distribution function. If only the single risks' impact is summed up at a certain point in time t, the aggregation over all scenarios k leads to an "empirical" distribution function of the project's risk load for the simulated year t of the project (13). This result is exemplified in Fig. 4. If the single risks' impact is summed up itself and over certain time units of the simulation period as well (14a), the result after aggregation of this value over all scenarios k is an "empirical" **cumulative** distribution function (14b). For $t = t_{end}$ this equals the original MCS result of a probabilistic project's risk load at the end of the simulated period as described in section 4.1. This result is exemplified in Fig. 5. Because of applying a more time-specific MCS approach, the project's risk load accumulation can be derived in form of an "empirical" cumulative distribution function now for every point in time t between t_0

and t_{end} of the simulation period (see Fig. 6 and 7). This result can be used to check the risk coverage and risk-bearing capacity at every point in time t.

Probabilistic Aggregation

(13a) $I^{tot}_{k,t} = \sum_{\forall i} I_{i,k,t} \quad \forall t \in [t_0, t_{end}]$ and (13b) $F_{I^{tot}_t}(x) \ \forall k \ \forall t \in [t_0, t_{end}]$

(14a) $I^{tot,cum}_{k,t} = \sum_{t=t_0=0}^{t} I^{tot}_{k,t} = \sum_{t=t_0=0}^{t} \sum_{\forall i} I_{i,k,t} \quad \forall t \in [t_0, t_{end}]$ and

(14b) $F_{I^{tot,cum}_t}(x) \ \forall k \ \forall t \in [t_0, t_{end}]$

4.3 Implemented example

As demonstration, a generic example of the MCS model presented above was implemented with 9 exemplary single risks i over a 10 year contract phase in MS-Excel using VBA and “ModelRisk” from “Vose Software”. The results after 1’000 simulation runs are shown in the following Figures. The demonstration considers specific I^*_i and T^*_i for $F^*_{i,k} > 1$. Reference for the input estimations of the single risks’ impact is a project volume of 100m$. The simulation period covers t_0 to t_{end} and corresponds to the contract phase.

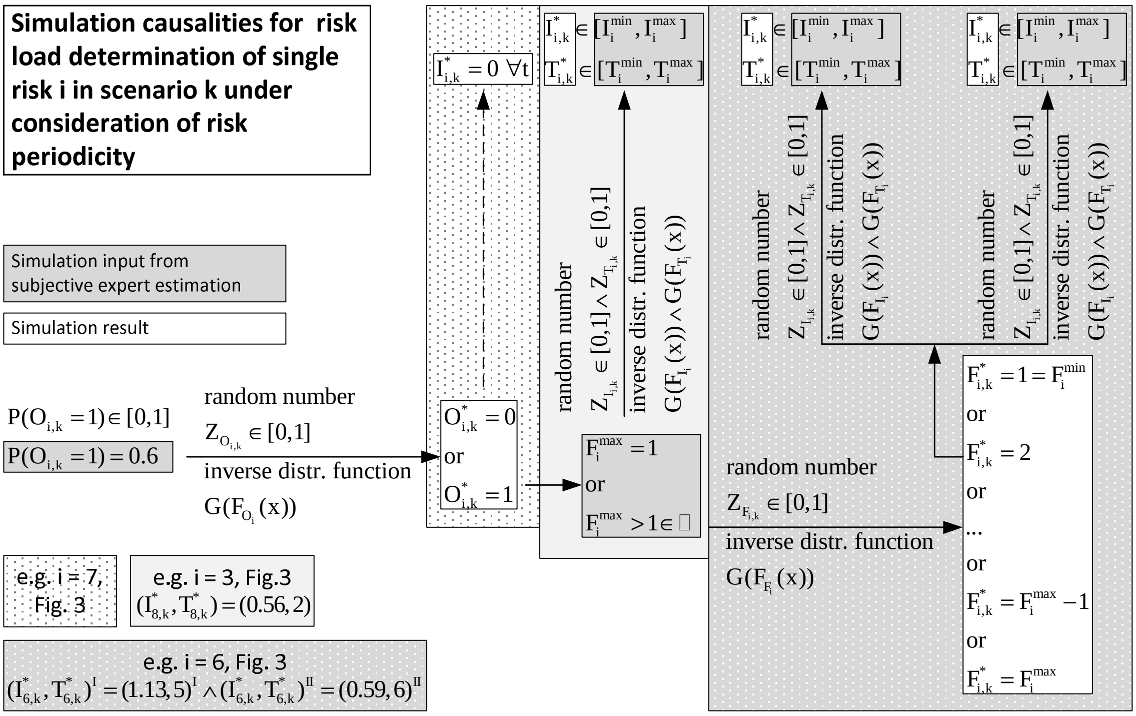

Figure 2: Simulation causalities for risk load determination

Fig. 3 presents the scenario after one MCS iteration k as interim result of the simulation causalities shown in Fig. 2. The single risks did not occur (e.g. i = 7), occurred once (e.g. i = 3) or occurred multiple times (e.g. i = 6) in the simulation. The event occurrences have a specific impact and are assigned to different points of time t. After the probabilistic allocation of all risk events to points of time in the simulation period, all single risk occurrences can be summed up for one point in time t, resulting in a time-specific risk scenario of one iteration k.

For example, in the first year (t = 1) of the scenario displayed in Fig. 3, the ground risk (i = 1) occurred with I_1 = 0.25m$ and the technical risk of construction (i = 2) occurred with I_2 = 0.40m$. Consequently, the project's risk load of this scenario in year one sums up to 0.64m$ (rounding error). The single risks occur only in possible single risk impact phases considered. For example, the technical risk of operation (i = 4) occurred only in the operation phase between t = 4 and t = 9. The row sum of this paper's Fig. 3 at the bottom was simulated already in Girmscheid (2013) and related. The column sum in Fig. 3 at the right represents the contribution of this paper in the form of additional time-specific information of a project's risk load. The risk costs in t_end sum up to 0.28m$, while the **cumulated** risk cost of all periods ($t \in [1,10]$) is 5.78m$ for the scenario shown in Fig. 3.

	ground risk	*techhnical risks construction*	*logistical risk cosntruction*	*technical risks operation*	*termination risk*	*refinancing risk*	*inflation risk*	*change of political conditions*	*insolvency risk*		
Single risks i →	1	2	3	4	5	6	7	8	9	∑	
Time t [year] ↓											
0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	t0
1	0.25	0.40	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.64	t_exc
2	0.00	1.26	0.56	0.00	0.00	0.00	0.00	0.00	0.00	1.82	t_str
3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	t_fin
4	0.00	0.64	0.00	0.31	0.00	0.00	0.00	0.00	0.00	0.95	-
5	0.00	0.00	0.00	0.00	0.00	1.13	0.00	0.00	0.00	1.13	-
6	0.00	0.00	0.00	0.22	0.00	0.59	0.00	0.00	0.00	0.82	-
7	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-
8	0.00	0.00	0.00	0.15	0.00	0.00	0.00	0.00	0.00	0.15	-
9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	t_ope
10	0.00	0.00	0.00	0.00	0.28	0.00	0.00	0.00	0.00	0.28	t_end
∑	0.25	2.30	0.56	0.68	0.28	1.72	0.00	0.00	0.00	OK	5.78
Project's cumulated risk load after t_end in run k [monetary units] →										5.78	

Figure 3: Interim result after one MCS iteration (time-specific risk scenario)

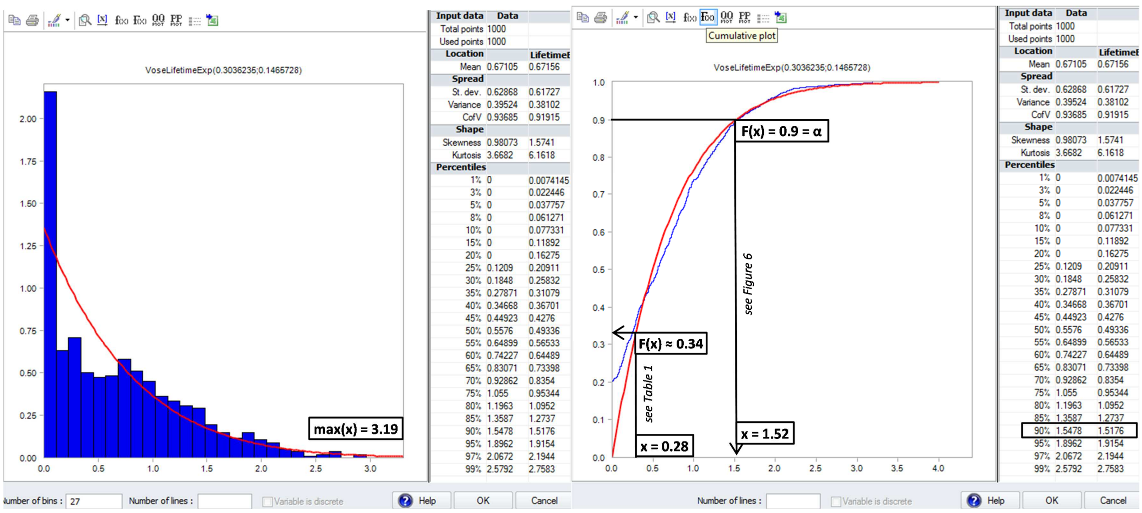

Figure 4: Density and distribution function of project risk load in period t_end only

After k iterations, the "empirical" distribution function can be derived for the project risk load that just has occurred at a point in time t (see Fig. 4) or for the **cumulated** risk load that has occurred until a point in time t (see Fig. 5). The difference of the risk load at one point in time and the accumulated risk load until this point in time becomes apparent, when comparing the maximum value of Fig. 4 being 3.19m$ to the maximum value of Fig. 5 being 39.28m$. This means that the maximum risk load of all simulation scenarios in the last time unit of the simulation was 3.19m$ and that the maximal simulated risk load cumulated over all time units was 39.28m$. If the 90%-quantile ($\alpha = 0.9$) of the according "empirical" distribution function is chosen, the project's cumulated risk load until t_{end} is 18.84m$ as shown in Fig. 5 and Fig. 7.

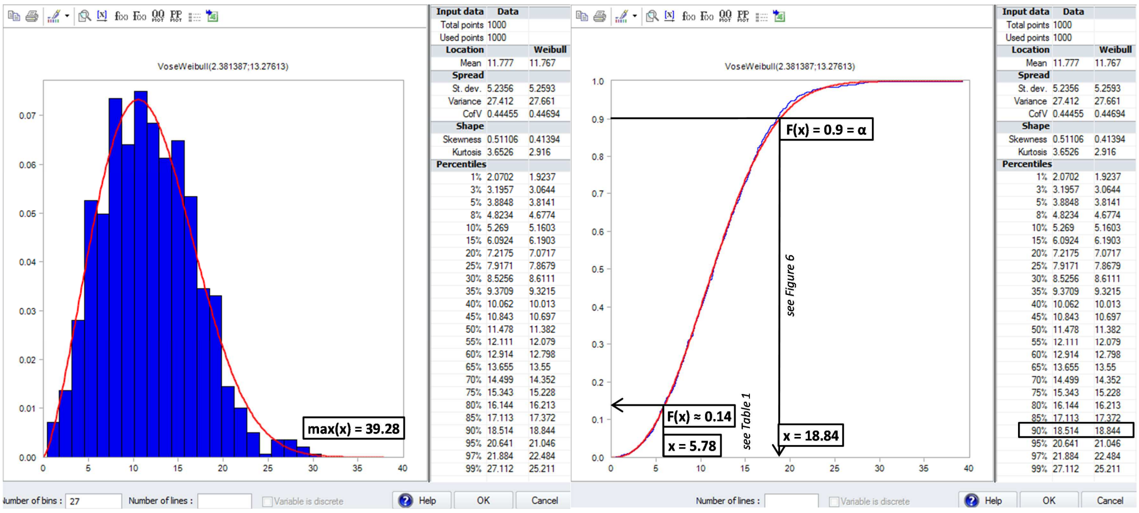

Figure 5: Density and distribution function of cumulated project risk load until t_end

Fig. 6 shows the expected MCS results in the three dimensions time t, impact of occurrence I and probability of impact P(I). The concept displayed on top of Fig. 6 is based on Girmscheid (2011), part 2, Fig. 2 and was now integrated in a MCS for the determination of the project specific risk load results, not only retrospectively a the end of the project, but also for the points in time inbetween. Over time, the maximum value of the according density function increases because the cumulated project load increases because the longer the project run's, the more risk could have occurred and caused an impact and thus cost. The bottom of Fig. 6 shows the accumulation of the project risk load after applying a confidence level α to the MCS results, which makes the results of different points in time comparable. Fig. 7 represents basically the same illustration as the bottom of Fig. 6 with the results of the implemented example for a confidence level $\alpha = 0.9$ applied to the project risk load distribution as MCS result. The **accumulating** project risk load is shown for every simulated time unit t (I_tot_cum_α) as well as the decreasing project risk load of each time unit t (I_tot_α).

5. Discussion and outlook

The MCS accumulation curve "I_tot_cum_α" is concave as shown in Fig. 7. This relates to "I_tot_α" decreasing over time. Thus, a modelling based on linear trends or convex functions (e.g. Brownian bridge) would tend to underestimate the risk load development. However, the simulation result depends strongly on the form of the distribution functions chosen for T_i.

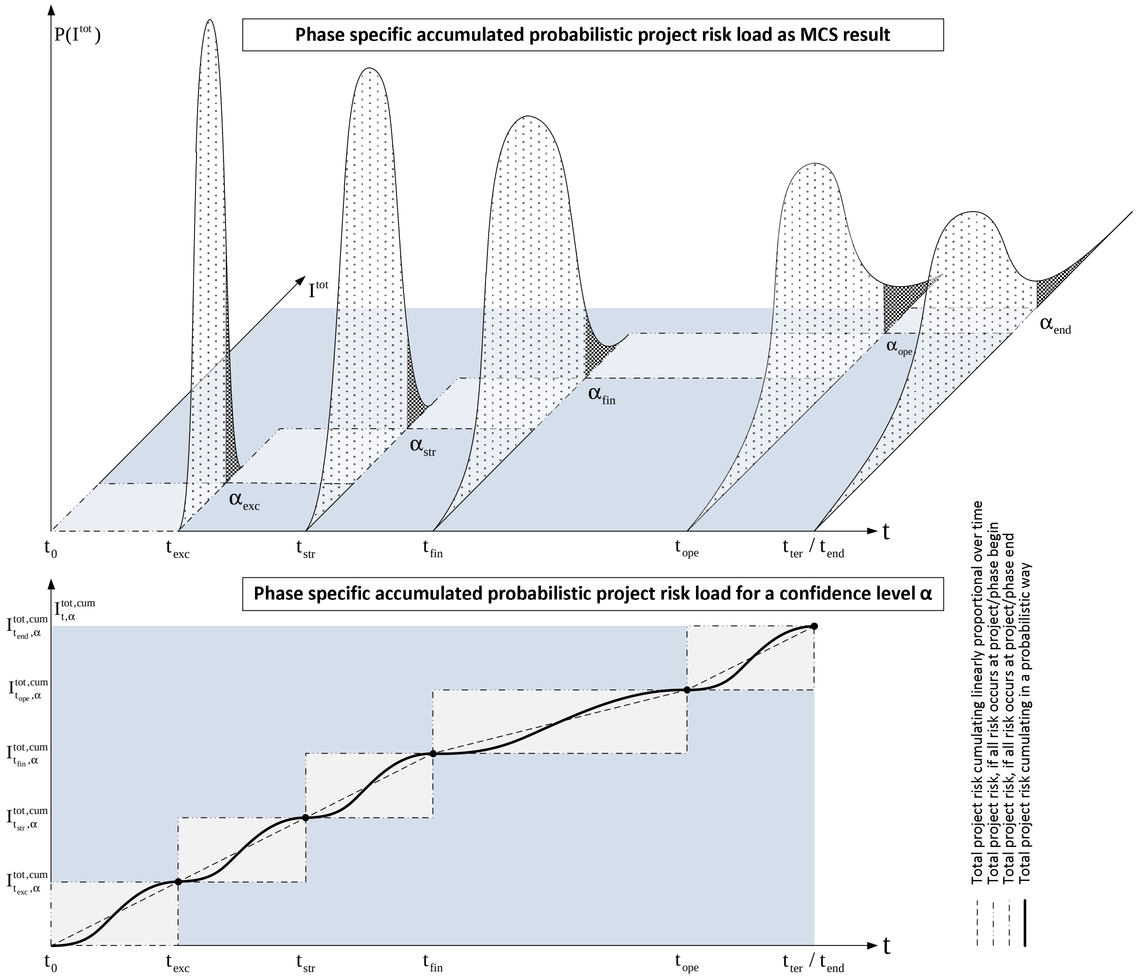

Figure 6: Concept of phase specific accumulated project risk after MCS

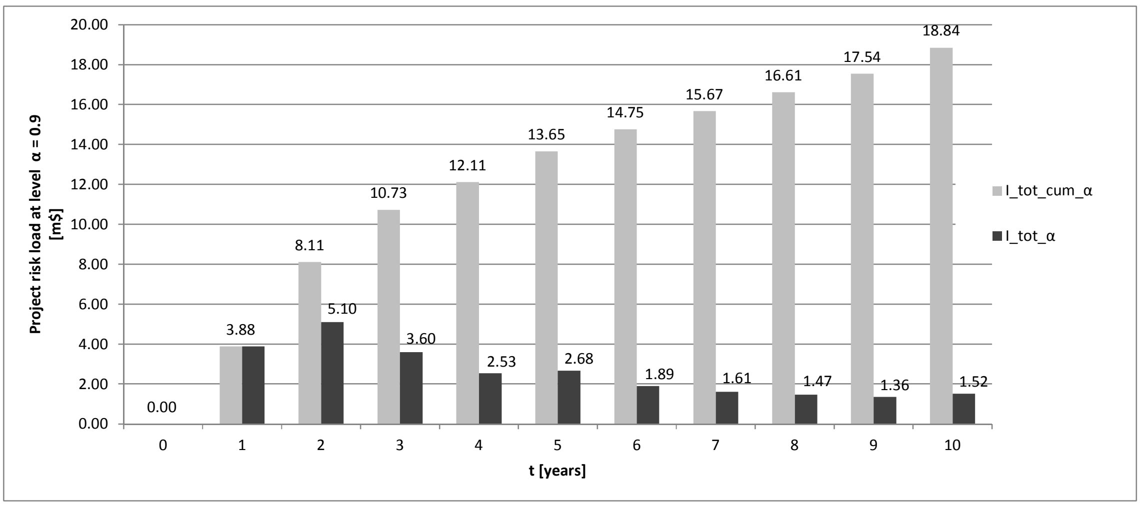

Figure 7: Accumulation development of project risk load for confidence level α = 0.9

Fig. 7 assumes the resulting cumulative distribution functions are normally distributed, according to the central limit theorem. However, the MCS results tend to be positively skewed distributions (see Fig. 4 and 5). Consequently, the general assumption of the normal distribution would lead to an approximation error in the tails, which can be important to the RA model user, depending on the interest in extreme events. This raises the question how the explicit interest in extreme events can be integrated in the present approach. Further development of the risk load calculation will include differentiation of single risks into periodic and non-periodic occurrence of these risks, e.g. to model risk like HVAC replacement in a better way (see Girmscheid (2013)), and consideration of correlations. The principle of prudence requires that the positive correlations must be considered at least in order to avoid underestimation of the project's risk load. Furthermore, the algorithm will be adapted to run a Latin Hypercube sampling. The implementation will be expanded to other modules as shown in Fig. 1, with the aim of an implemented prototype tool that calculates the quantitative RA automatically, under consideration of the private party's risk-bearing capacity. After completion of this task, the RA model will be tested with real project data. While the overall research project is tailored to PPP projects, the presented concept can be applied to any life-cycle oriented construction project for probabilistic quantitative determination of the risk load. Of course, the results will only be as good as the according input data from subjective expert estimations.

6. Conclusion

Within the limitations described above, the aim of probabilistically determining a time-specific project risk load for PPP building projects was achieved. Time-related random variables were integrated into a given MCS approach for project risk aggregation to enhance the methodology accordingly. Rational and traceable decision-making next to the use of clear and unambiguous criteria allows for the implementation of a generic example, which underpins the theoretical ideas. Because of the implementation, more complex and realistic causalities can be processed easily with reduced resource use, as long as sound input data is available. The main benefit is the availability of a PPP project risk load at every point in time over the contract phase. The project's risk load is determined to check the private party's risk-bearing capacity and the risk coverage for the PPP project. With the concept presented above, the project's risk load can be simulated not only for the end of the contract phase but for every point in time in between. As a consequence, the financial resources for risk coverage can be derived more time specifically, which might lead to reduced financing cost. Furthermore, the presented approach leads to more transparency in the calculation of risk costs and might help to avoid bounded rationality, opportunism and alike. The given time specificity of the project's risk load allows for the proper consideration of price increases, interest, etc. The presented research was co-financed by the Swiss Commission for Technology and Innovation (CTI).

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