Article

Prediction of Corrosion Loss on Weathering Steel Constructions by Direct Optimized Probabilistic Calculation Method

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Citation: Vacek, M.; Křivý, V.; Konečný, P.; Marťáková, M.; Kreislová, K.; Vlachová, M. Prediction of Corrosion Loss on Weathering Steel Constructions by Direct Optimized Probabilistic Calculation Method. *Coatings* **2023**, *1*, 0. https://doi.org/

Received:
Revised:
Accepted:
Published:

Abstract: The predicted corrosion losses is one of the most important factors in the proper design of a steel structure's service life. Corrosion coupon analysis will give a prediction of both short- and long-term corrosion loss. In the event of short-term exposure, the most useful data are often those that are available on an annual basis. Corrosion coupons must be exposed for an extended period (such as 10 years or more), which is not always practical prior to the construction of the building itself, particulary for long-term prediction of corrosion losses is needed. In steel buildings, designers frequently depend on corrosion maps and corrosion loss prediction models. While ISO 9223 and ISO 9224 serve as widely used analytical prediction models, alternative methods are also applicable. An additional option is to utilize an analytical model based on the UN/ECE ICP project or the Multi-Assess project. Temperature, average relative humidity, average annual deposition of chloride ions and sulfur dioxide, as well as the average annual concentration of dust particles, are just a few examples of the input parameters for these models. These equations only consider the annual average value; they do not consider inputs as random variables. The option of utilizing the input values as the probability distribution of a random variable is discussed in this article. The authors attempt to capture the variation of in-situ measurement values using the mentioned methods. These numbers may not always accurately represent the predictions made by the models. The thickness of the corrosion products after one year of exposure is then determined by processing the input parameters using stochastic methods. The comparison with in-situ measurement data at sites located near roadways is also included in the article.

Keywords: Corrosion loss; prediction; probability; DOProC; ISO 9223; UN ECE ICP; Multi-Asssess

1. Introduction

Civil engineering is specific due to the need for structures to be reliable and durable over an extended period. According to EN 1990 [1], there is a requirement for 50 years of service life for buildings and other common structures, and 100 years for monumental building structures or bridges. Consequently, it is necessary to take care of the building structure during its service life. A poor design can lead to significantly higher costs for maintenance and repairs. There are a lot of structures exposed to environmental influence, which include corrosion stimulants. However, corrosion stimulants are a dynamically changing variables. In the last century, the primary cause of atmospheric corrosion was sulfur dioxide in inland environment. Due to ecological pressure, sulfur dioxide now has a minor effect on corrosion rate [2]. In the context of increasing road traffic, there are local microclimates in the vicinity of roads. The main influence on corrosion rate occurs in the winter when deicing salt is used. Sodium chloride and brine are the main deicing agents used to maintain road passability. Passing vehicles splash deiced snow and emit aerosol and impurities. Chlorides have a significant influence on the service life of structures [3], [4], [5].

Corrosion processes on steel structures are accelerated by chlorides [6], [7], especially in the vicinity of roads. These actions can influence both the serviceability limit state and the ultimate limit state by reducing the cross-sectional area [8], [9]. Another significant factor is the potential development of fatigue damage [10]. It is necessary to consider all these phenomena in the design of steel structures, particularly in the case of weathering steel constructions [11], [12]. After considering these factors, it becomes possible to design the structure safely for its entire lifecycle.

Two main approaches are used for predicting corrosion loss and determining corrosion rates in the Czech Republic. The first approach is the corrosion map of the Czech Republic [13]. These maps allow for a simplistic determination of corrosion loss. However, it's essential to note that these corrosion maps are based on prediction models referenced in the following text. This approach is quite general and does not take into account local environmental influences, which are often crucial for accurately determining the corrosion aggressiveness of the local environment. Historically at the European region SO_2 has a significant influence to corrosion, but since 2000-2010 is minor influence due to ecological pressure, especially desulphurisation units in the industry [14] [3]. One of most significant influence is the deposition of chloride ions in the vicinity of roads, which depends on factors such as traffic density, the topography of the terrain near the road, and the structural and dispositional design of bridge structures. Corrosion maps are used when other data are absent to determine corrosion loss. In a local microclimate, such as the road surroundings, it is not advisable to use only corrosion maps. However, corrosion maps do not consider the influence of local microclimates.

Alternatively, there is another possibility for determining corrosion loss. If detailed information on environmental influences is available, an approach based on adjusting corrosion stimulants (e.g. chloride and sulphur dioxide), temperature, relative humidity and other input parameters can be used. Predicted corrosion loss (or corrosion class) can be used to determine corrosion allowances for weathering steel constructions. For structures designed from carbon steel, corrosion loss or corrosion class determines the suitable coating system. Therefore, it is crucial to study corrosivity in specific microclimates, like those near roads, and develop prediction models for accurate corrosion loss prediction.

Currently, numerous approaches exist for predicting corrosion loss and determining corrosion class. The aim of this article is to apply three prediction models:

- ISO 9223
- UN ECE ICP Effect on Materials
- Multi-Asses

The first approach considered is based on the ISO 9223 standard [15], which include the corrosion-damage equation. This equation predicts corrosion loss after one year of exposure, considering factors such as the annual deposition of chloride ions and sulfur dioxide, annual relative humidity, and temperature.

The second equation considered is from the UN ECE ICP Effect on Materials project [16], which takes into account the influence of sulfur dioxide, annual relative humidity, annual temperature, and time.

The third equation was developed within the Multi-Assess project [17], and consider account various environmental variables, including the influence of sulfur dioxide, pH of rain, and annual rainfall. A comprehensive list of variables is provided in Chapter 2.

It's important to note that the ISO 9223 approach [15] is the only one that directly considers the influence of chloride ions. The other two corrosion-damage equations do not account for this influence directly. However, a derived relationship exists between the amount of PM_{10} particles and the quantity of deposited chlorides, though it is not entirely accurate. It's worth mentioning that this does not involve the direct deposition of chloride ions, as might occur in cases of winter road maintenance.

The mentioned input parameters are not constant but rather random variables. Modern probabilistic methods exist, allowing engineers to work with input and output datasets as random variables [18], [19]. Input parameters can be analyzed through long-term measurements, allowing for the determination of their development in time and the expression of the distribution function. Simulation methods like DOProC, Monte-Carlo, or SBRA typically use histograms, instead of parametric distributions, for greater generality and robustness. This approach is also suitable for technical professionals who do not specialize in probabilistic assessments but use them as a tool for realized analyses. The quality of the relationship between raw data and the resulting histogram can be described, for example, by distribution fitness called closeness, which ranges from 0 to 1 [20]. In general, a higher closeness value indicates that the resulting histogram better represents the raw data.

There are various approaches for working with values in the form of random variables. Historically, methods like the Monte Carlo approach [21] or the follow-up approach in the SBRA probabilistic method have been utilized [22]. These approaches are still widely utilized. However, for large-scale tasks, they have the drawback of requiring a large number of simulations, resulting in extended computation times. This challenge can be addressed in a lot of cases with the Direct Optimized Probabilistic Calculation (DOProC) method [23]. Numerous optimization tools have been developed for the DOProC method, which can significantly accelerate computation speed without significantly compromising the quality of the outputs. Significantly, these tools open up the user environment to ordinary engineers who may not have deep expertise in probabilistic methods.

Well-described and processed input data are essential for accurate prediction. This article utilizes available environmental data pertinent to the Czech Republic, spanning the longest feasible observation period, to capture long-term trends.

Monika Marťáková - Kubzová et al. made original study for the locality Kopisty [24]. In the mentioned study, only normal and lognormal distributions are used without any distribution fitting analysis. In current research the improvement is in distribution fitting of applied parameters. Moreover , the comparation of predicted values with data from the vicinity of the road for horizontal and vertical surfaces for the year 2022 and statistical analysis of likelihood of prediction accuracy of studied models is conducted. Moreover, extrapolated prediction interval for each environmental input variables up to the year 2030 is provided in this article, in order to follow the predicted evolution of each input variable. The discussion focuses on this prediction.

2. Approaches to determine corrosion loss

The aim of this article is the utilization of three approaches for the determination of corrosion loss in steel constructions. In the following text, the consideration is given to one-year exposure of corrosion coupons or the application of equations designed for one-year exposure. Corrosion after one year is input for validating each of prediction approaches. At the same time, this is one of the basic findings that can be used to determine long-term corrosion rate (e.g. according to ISO 9224 [25]). Based on this knowledge it is possible to determine the corrosion allowance for new structures or to predict the corrosion damage of existing structures.

2.1. ISO 9223

First prediction model is from ISO 9223 standard [15]. The outcome of the prediction equation represents the corrosion loss for carbon steel after one year of exposure. The ISO 9223 model can be applied to weathering steel, as the impact of a protective layer is not substantial during the first year of exposure [26]. The ISO 9224 standard also mentions an equation for long-term corrosion loss [25]. However, this concept of long-term corrosion loss is not suitable for this article. Article only includes data from a one-year exposure of corrosion coupons. The protective effect of the patina only becomes apparent with prolonged exposure of the surface to a corrosive environment [27].

$$r_{corr} = 1,77 \times P_d^{0,52} \times e^{0,02 \times RH + f_{st}} + 0,102 \times S_d^{0,62} \times e^{0,033 \times RH + 0,04 \times T} \tag{1}$$

where if T≤ 10°C:

$$f_{st} = 0,150 \times (T - 10), \tag{2}$$

else:

$$f_{st} = -0,054 \times (T - 10), \tag{3}$$

r_{corr} - average annual corrosion loss (μm/year)
P_d - average annual deposition rate of sulfur dioxide (mg/(m^2×day))
S_d - average annual deposition rate of chlorides (mg/(m^2×day))
RH - average annual relative humidity (%)
T - average annual temperature (°C)
e - Euler's number.

CHMI reports, except other environmental values, only the concentration of sulfur dioxide (SO_2), not the deposition rate. It is necessary to incorporate the deposition rate of sulfur dioxide into the equation. In this case, it is possible to use the equation from ISO 9223 standard [15] for converting between the concentration and deposition rate of sulfur dioxide.

$$P_d = 0,8 \times P_c \tag{4}$$

where
P_d - average annual deposition rate of sulfur dioxide (mg/(m^2×day))
P_c - average annual concentration of sulfur dioxide (mg/m^3).

2.2. UN ECE ICP Effect on Materials

From the project called UN ECE ICP Effect on Materials [16], [28] was derived equation for dataset from 1987 and 1995. This project continue to these days. This study of corrosion attack includes an equation for determining corrosion loss on weathering steels:

$$ln(r_{corr}) = 3,54 + 0,33 \times ln(t) + 0,13 \times ln(P_c) + 0,02 \times RH \times f_{st} \tag{5}$$

from which it can be expressed:

$$r_{corr} = P_c^{0,13} \times t^{0,33} \times e^{0,02 \times RH \times f_{st} + 3,54} \tag{6}$$

where if T≤ 10°C:

$$f_{st} = 0,059 \times (T - 10), \tag{7}$$

else:

$$f_{st} = -0,036 \times (T - 10), \tag{8}$$

r_{corr} - average annual corrosion loss (μm/year)
P_c - average annual concentration of sulfur dioxide (mg/m^3)
RH - average annual relative humidity (%)
T - average annual temperature (°C)
t - exposition time (years)
e - Euler's number.

2.3. Multi-Assess

The Multi-Assess project investigated corrosion damage to materials at 50 sites across Europe between 1970 and 2005 [17]. This research project spanned the years when the concentration of SO_2 was gradually decreasing due to environmental pressures, primarily on industrial production. It's worth noting that the reduction in sulfur dioxide (SO_2) concentration also affects the magnitude of corrosion loss on exposed surfaces [3].

The equation (9) contains more environmental variables than the previous two mentioned, but does not directly include the effect of chloride ion deposition. The influence is included in the average annual concentration of PM_{1_0}, which contain approximately 7 % of chlorides for Czech republic [29]. The final equation is:

$$r_{corr} = 29,1 + (21,7 + 1,39 \times P_c^{0,6} \times RH_{60} \times e^{f_{st}} + 1,29 \times RAIN \times [H^+] + 0.593 \times PM_{10}) \times t^{0,6}, \tag{9}$$

where

$$[H^+] = \frac{10^{-pH}}{V} \times M \times 1000 \tag{10}$$

and where if T$\leq$ 10°C:

$$f_{st} = 0,150 \times (T - 10), \tag{11}$$

else:

$$f_{st} = -0,054 \times (T - 10), \tag{12}$$

r_{corr} - average annual corrosion loss (μm/year)
P_c - average annual concentration of sulfur dioxide (mg/m^3)
RH_{60} - average annual relative humidity (%)
if RH < 60 %, then RH_{60}=0, else RH_{60} = RH
RH - average annual relative humidity (%)
T - average annual temperature (°C)
RAIN - annual rainfall (mm)
$[H^+]$ - molar concentration of hydrogen in rainfall (mg/l)
pH - potential of hydrogen (-)
V - volume of rainfall (l)
M - water molar mass (g/mol)
PM_{10} - average annual concentration of particles smaller than 10 μm (**mg**/m^3)
t - exposition time (years)
e - Euler's number.

3. Inputs

Due to the challenge of directly measuring all input variables at all of the exposure site, the nearest relevant CHMI station, which measure investigated environment variable, is selected. The data from the CHMI databases [30], [31] originate from the listed stations, the distance and position are depicted in the Figure 1:

- Opava, Kateřinky
- Opava, Otice
- Ostrava-Poruba/CHMI

The predicted data is extrapolated to the year 2030 for climate data. The resulting distributions are determined using the HistAn software [32]. Prediction is made for the year 2022 and comparsion with in-situ measured data is mentioned in Chapter 5.

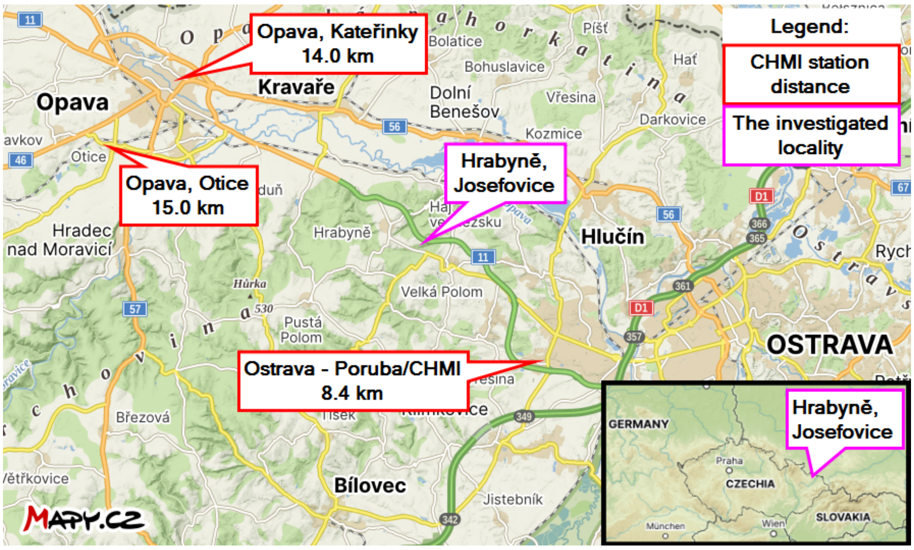

Figure 1. Overview map of the test site and distance to the CHMI stations (source: mapy.cz)

3.1. *Average annual temperature*

The average annual temperature data for the Opava, Otice site from 1961 to 2022 was investigated [30], [31]. The Laplace distribution of average annual temperature is selected. 64 intervals of Laplace distribution is used. Closeness of the selected Laplace distribution is 0.43, Normal distribution has closeness 0.20. Therefore, Laplace distribution was selected.

Temperature has a significant influence on the corrosion rate. When the temperature is above 0°C [33], the atmospheric corrosion started. However, when the temperature drops below 0°C, the influence on the corrosion rate decreases because water can change its state from liquid to solid - freezing. This temperature can be changed by using chlorides (NaCl or brine) as a deicing salt to maintain roads. On the other hand, at high temperatures and when the relative humidity is not close to 100 %, evaporation occurs, and water loses its influence on the corrosion rate because surfaces dry out [34]. These factors are pertinent for atmospheric corrosion.

The Czech republic is in the mild climate zone and average annual temperature is between 6°C to 11°C. Average number of freezing days is historicaly about 40 days [35], [36].

The linear regresion analysis with prediction and confidence interval is in the Figure 2. Prediction for the year 2022 is marked by the dotted line and the distribution is in the Figure 3. Input parameters of the distribution are in the Table 1.

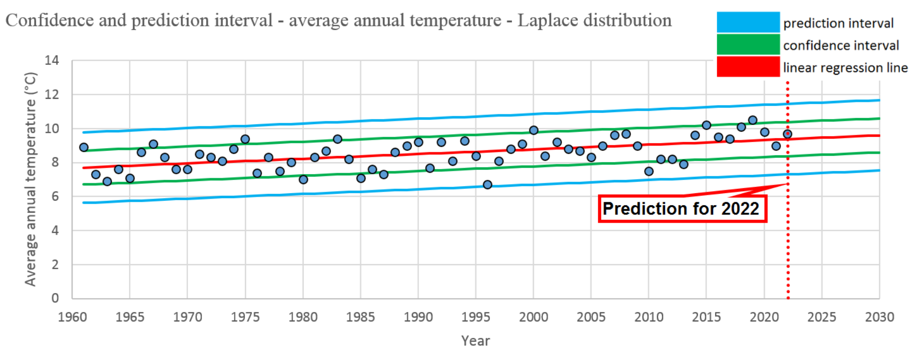

Figure 2. Confidence and prediction interval - average annual temperature - Laplace distribution

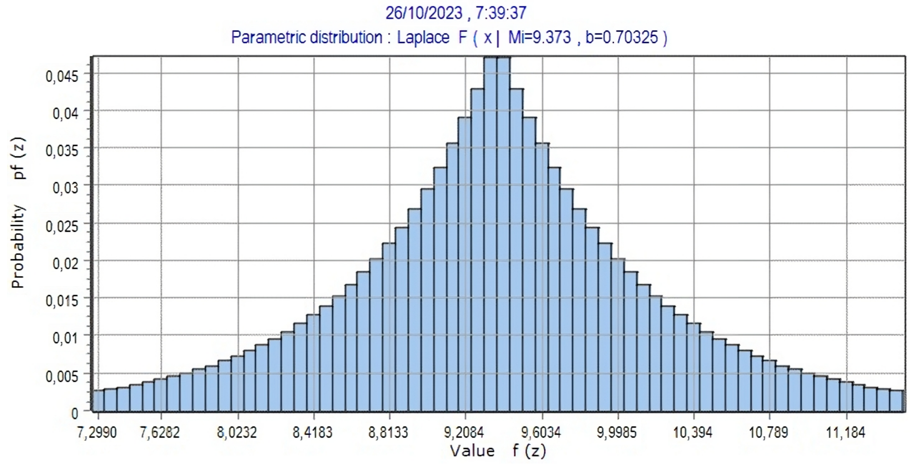

Figure 3. Prediction of average annual temperature for the year 2022 - Laplace distribution

Table 1. Laplace distribution - average annual temperature (°C)

	Intervals (-)	μ(°C)	β(°C)
Temperature	64	9,373	0,70325

3.2. *Average annual relative humidity*

The average annual relative humidity data for the Opava, Otice site from 1961 to 2022 was investigated [30], [31]. The Laplace distribution of average annual relative humidity is selected. 64 intervals of Laplace distribution is used. Closeness of the selected Laplace distribution is 0.44, Normal distribution has closeness 0.37. Therefore, Laplace distribution was selected.

The average annual relative humidity is associated with the time of wetness on the surface. If there is higher value of relative humidity, it is more likely that precipitation happen. Water is one of important factors for progress of corrosion reaction [37]. For example, in Multi-Assess approach if the average annual relative humidity is smaller than 60 % then influence of relative humidity is neglected [17].

The linear regresion analysis with prediction and confidence interval for RH is in the Figure 4. Prediction for the year 2022 is marked by the dotted line and the distribution is in the Figure 5. Input parameters of the distribution are in the Table 2.

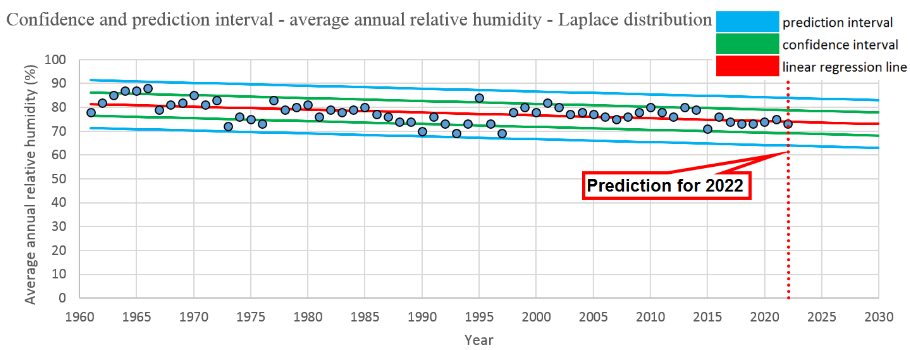

Figure 4. Confidence and prediction interval - average annual relative humidity - Laplace distribution

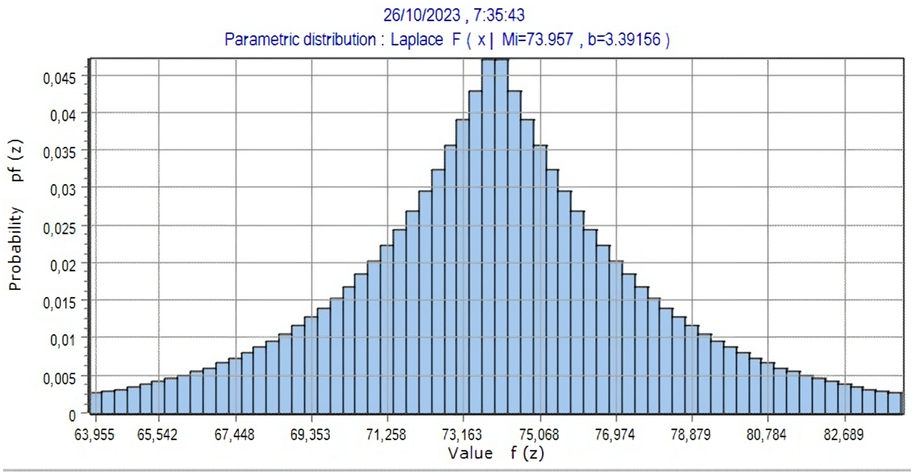

Figure 5. Prediction of average annual relative humidity for the year 2022 - Laplace distribution

Table 2. Laplace distribution - average annual relative humidity (%)

	Intervals (-)	μ(%)	β(%)
RH	64	73,957	3,39156

3.3. *Annual rainfall*

The annual rainfall data for the Opava, Otice site from 1961 to 2022 was investigated [30], [31]. The Laplace distribution of annual rainfall is selected. 64 intervals of Laplace distribution is used. Closeness of the selected Laplace distribution is 0.79, Normal distribution has closeness 0.60. Therefore, Laplace distribution was selected.

Annual rainfall is very important for non-covered structures, as for example railway truss bridges. For other covered construction parts, as steel-concrete coupled road bridges, it is not so important as direct influence. If there is covered steel, without direct exposure, there is still some influence by evaporation from the ground and this can localy increase relative humidity and possibility to water precipitating on the surface [38]. Another next important factor of annual rainfall is the frequency and intensity of rainfall [39].

The linear regresion analysis with prediction and confidence interval is in the Figure 6. Prediction for the year 2022 is marked by the dotted line and the distribution is in the Figure 7. Input parameters of the distribution are in the Table 3.

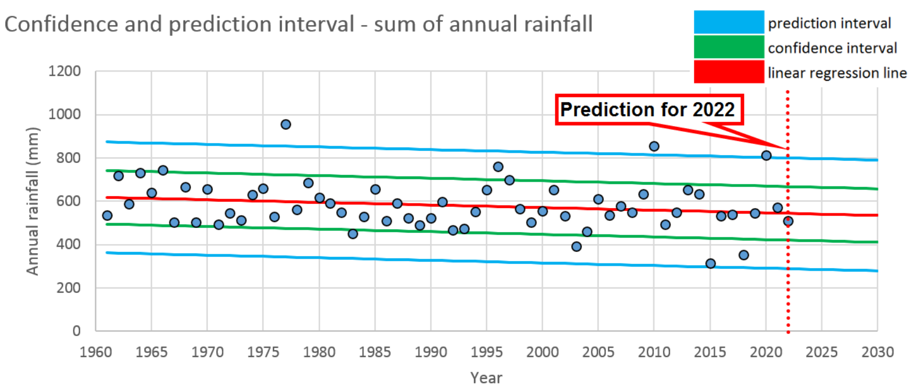

Figure 6. Confidence and prediction interval - annual rainfall - Laplace distribution

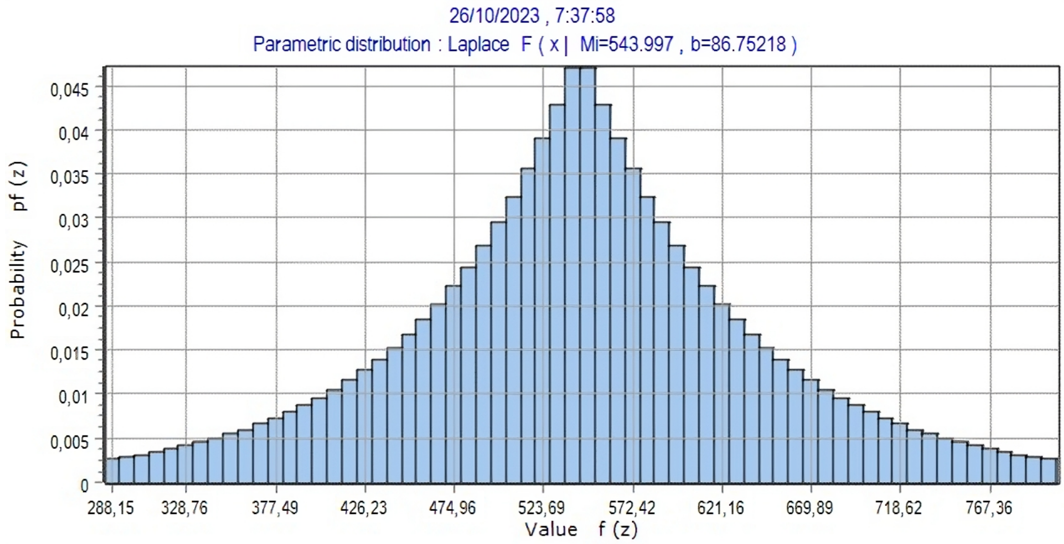

Figure 7. Prediction of annual rainfall for the year 2022 - Laplace distribution

Table 3. Laplace distribution - annual rainfall (mm)

	Intervals (-)	$\mu(mm)$	$\beta(mm)$
Rainfall	64	543,997	86,75218

3.4. Average annual concentration of SO_2

The average annual concetration of SO_2 data for the Ostrava-Poruba/CHMI site from 1961 to 2022 was investigated [30], [31]. The Rayleigh distribution of average annual concentration of SO_2 is selected. 64 intervals of Rayleigh distribution is used. Closeness of selected Rayleigh distribution is 0.80, Normal distribution is not mentioned in results from HistAn software. Therefore, Rayleigh distribution was selected.

There was a significant influence of SO_2 on corrosion rate in the 20th century in the Czech republic, especially in 1970s and 1980s [40], [41]. Because of the poor air quality, there was pressure to improve the air quality and the main air polluters (coal power stations, heavy industry etc.) were forced to implement desulphurisation units. The concentration of sulphur dioxide was decreased and approximately from year 2000 is slightly decreasing [3], [24], [42]. For this article was used data from 2011, because in this year was started measuring concentration of sulphur dioxide by station Ostrava-Poruba/CHMI [30].

In the case of SO_2 only values after a significant decrease due to the installation of desulphurisation units in heavy industry since 2000 are considered. This information is only valid for newly constructed structures. However, in the case of older structures, it is very important to take into account the entire time history of the SO_2 concentration and to consider the effect of the increased sulphur dioxide concentration on the structure.

The linear regresion analysis with prediction and confidence interval is in the Figure 8. Prediction for the year 2022 is marked by the dotted line and the distribution is in the Figure 9. Input parameter of the distribution is in the Table 4.

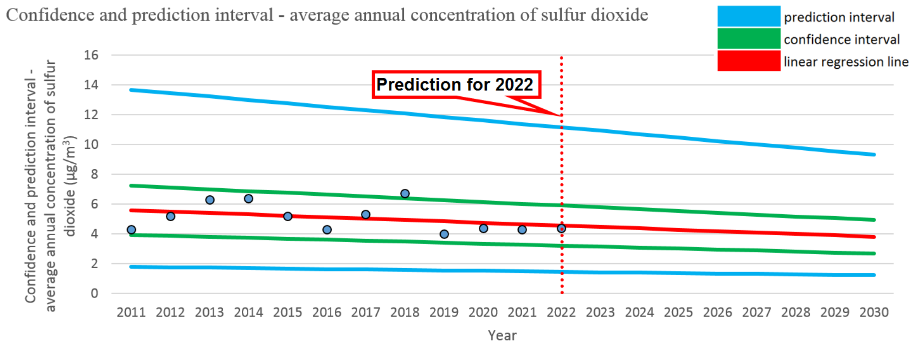

Figure 8. Confidence and prediction interval - average annual concentration of SO_2 - Rayleigh distribution

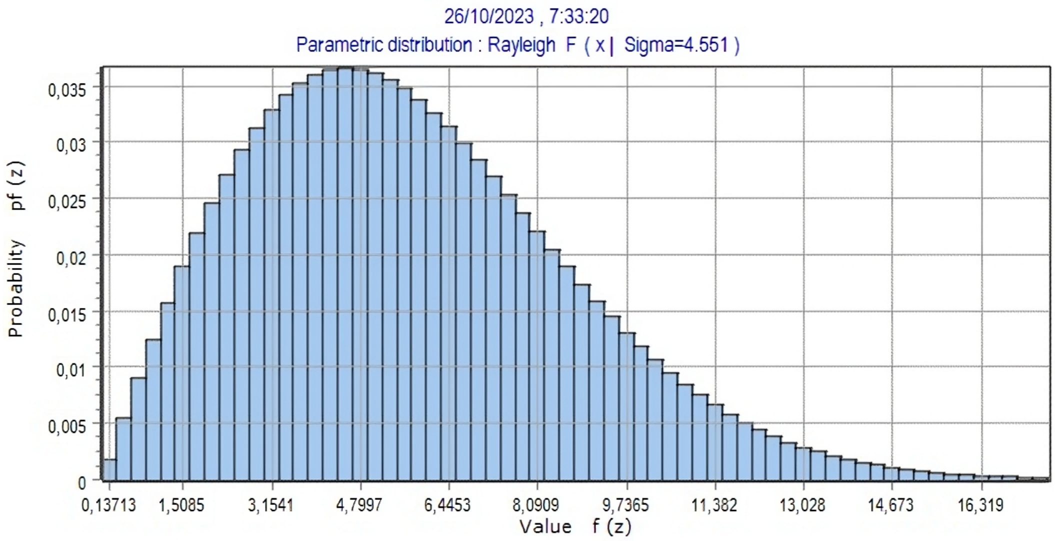

Figure 9. Prediction of average annual concentration of SO_2 for the year 2022 - Rayleigh distribution

Table 4. Rayleigh distribution - average annual concentration of SO_2 (mg/m^3)

	Intervals (-)	σ(mg/m^3)
SO_2	64	4,551

3.5. *Average annual concentration of PM_{10}*

The average annual concetration of PM_{10} data for the Opava, Kateřinky site from 1961 to 2022 was investigated [30], [31]. The Rayleigh distribution of average annual concentration of PM_{10} is selected. 64 intervals of Rayleigh distribution is used. Closeness of selected Rayleigh distribution is 0.89, Normal distribution is not mentioned in results from HistAn software. Therefore, Rayleigh distribution was selected.

There is a relationship between PM_{10} and chloride ions [43] [44]. This relationship varies across different environmental situations. In the Czech Republic, studies conducted to create corrosion maps have found that PM_{1_0} particles contain approximately 7 % chloride ions [29]. This information is crucial because in the Multi-Assess [17] approach, the direct influence of chloride ions is not considered as part of the prediction model. Instead, it indirectly affects the equation through the presence of PM_{10} particles.

The linear regresion analysis with prediction and confidence interval is in the Figure 10. Prediction for the year 2022 is marked by the dotted line and the distribution is in the Figure 11. Input parameter of the distribution is in the Table 5.

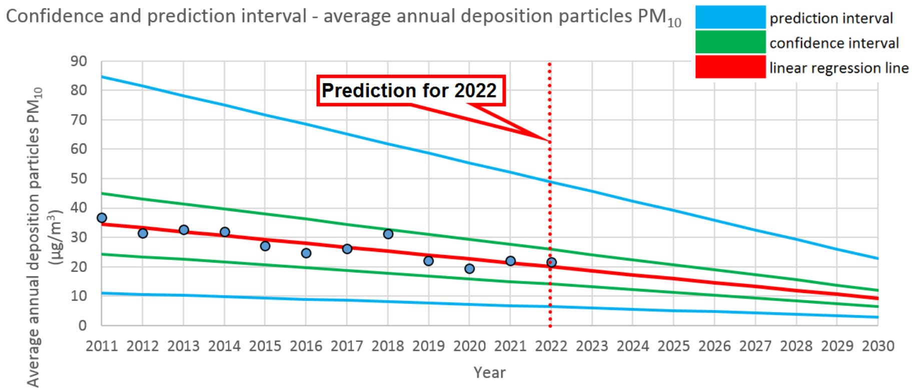

Figure 10. Confidence and prediction interval - average annual concentration of PM_{10} - Rayleigh distribution

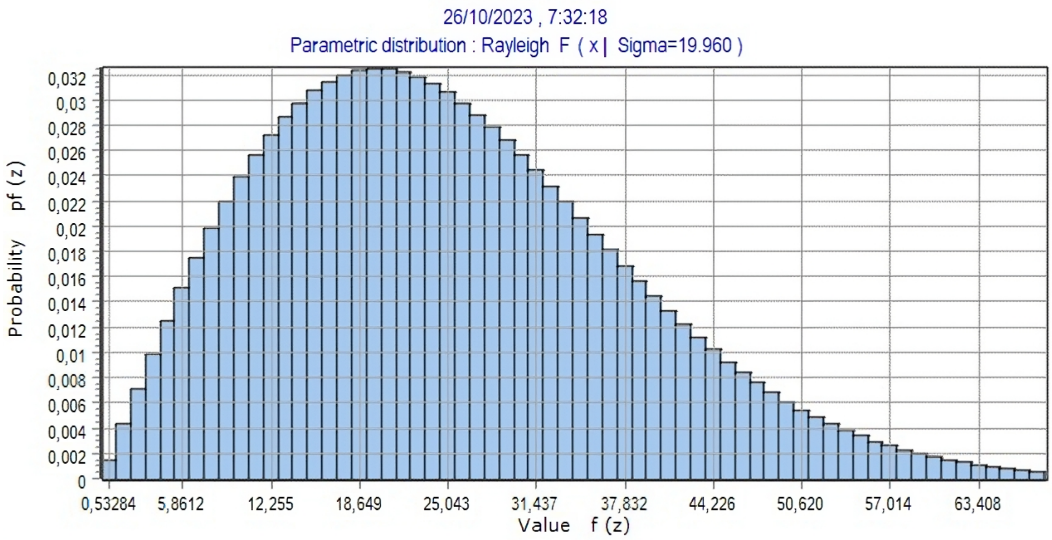

Figure 11. Prediction of average annual concentration of PM_{10} for the year 2022 - Rayleigh distribution

Table 5. Rayleigh distribution - average annual concentration of PM_{10} (mg/m^3)

	Intervals (-)	σ (mg/m^3)
PM_{10}	64	19,960

3.6. Average annual deposition of Cl^-

A constant deposition rate of chloride ions for 2022 was determined through linear regression analysis based on the authors' in-situ measurements from 2019 to 2022 [2], [40], [45], [46] in the Hrabyně, Josefovice locality. It is a long term measurement of deposition of chloride ions. Chloride deposition analysis is carried out for each month of the year. The values given are a weighted average for each year. There are five measurement sites, but corrosion coupons are placed only on three of them (B1, B3 and B5). For this reason only data from wet candle measurement for mentioned sites are used. Test sites are depicted in the Figure 12.

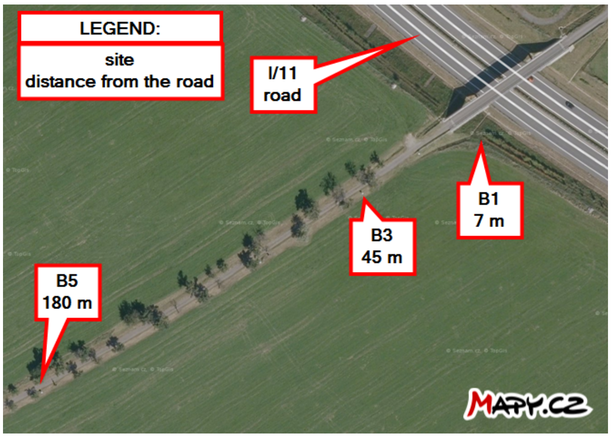

Figure 12. Overview map of the test sites in the Hrabyně, Josefovice locality (source: mapy.cz)

The linear regresion analysis with prediction and confidence interval is in the Figures 13, 14 and 15. Prediction for the year 2022 is marked in each Figure. There is still a lack of long-term measurements to define the input of chloride ion deposition rates as a specific type of distribution. For the prediction of corrosion losses are used predicted values of deposition of chloride ions, due to consideration of the chloride ion deposition trend. The prediction and confidence interval is determined assuming a normal distribution.

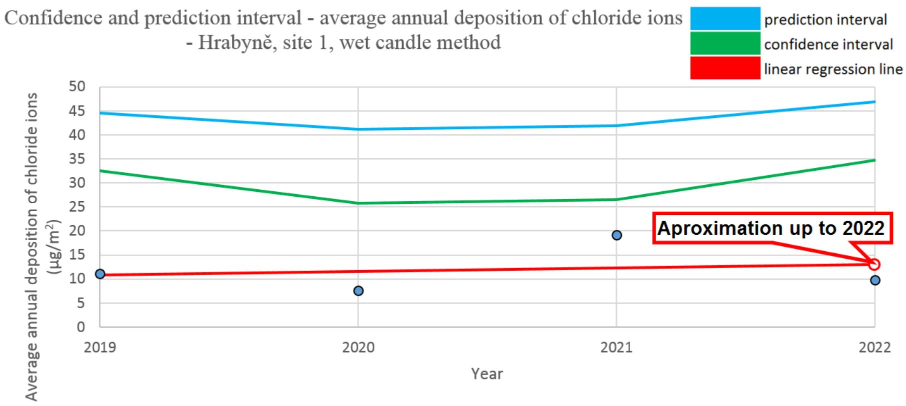

Figure 13. Confidence and prediction interval - B1 site

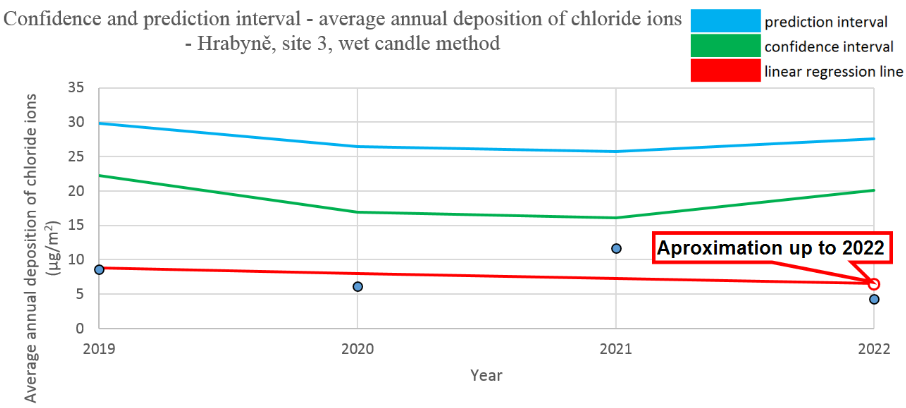

Figure 14. Confidence and prediction interval - B3 site

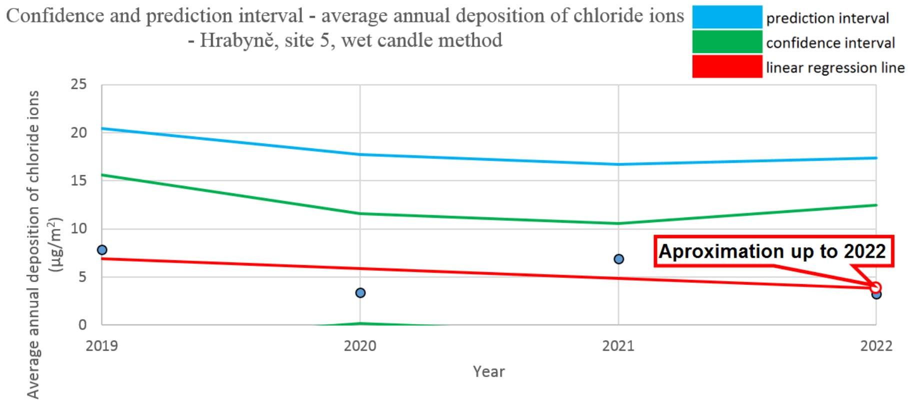

Figure 15. Confidence and prediction interval - B5 site

Table 6. Predicted deposition rate of chloride ions (mg/(m^2$*day$))

Test site	Value (mg/(m^2$*day$))
B1	13.05
B3	6.55
B5	3.80

3.7. Rainfall *pH* 296

The rainfall pH distribution is in the Figure 16 and its parameters in the Table 7. 297
Parameters are used from available literature [47], [48], [45]. 298

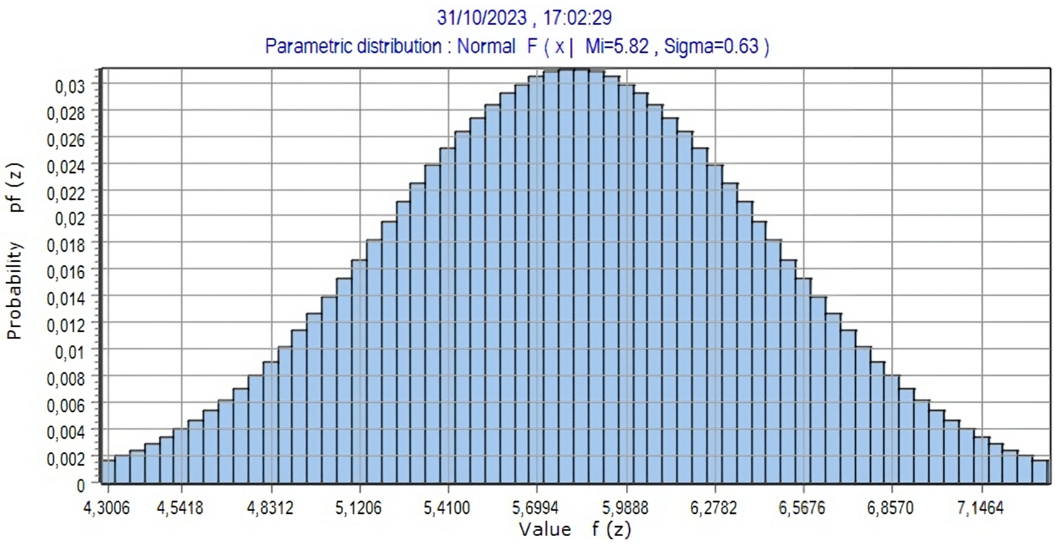

Figure 16. Confidence and prediction interval - Rainfall pH - Normal distribution

Table 7. Normal distribution - rainfall pH (-)

	Intervals (-)	μ (-)	σ (-)
pH	64	5,82	0,63

4. Application of Direct Optimized Probabilistic Calculation (DOProC) 299

Since input data is represented as functions of random variables, probabilistic methods 300
are necessary to express the results. In this case, the Monte Carlo method or its application 301
in the SBRA method [22] can be used. However, due to the complexity of the problems 302
to be solved, especially in the Multi-Assess method, this approach can be computation- 303
ally demanding, particularly for very low probability events. To address this, the Direct 304
Optimized Probabilistic Calculation (DOProC) [49] and ProbCalc software [50] are used. 305

Due to the presence of conditional functions in all the approaches mentioned in this paper, stochastic analysis requires the use of Delphi 7 scripts [51]. Scripts are compiled into .dll libraries and utilized within the Probcalc software [50]. An additional benefit of using .dll libraries is the acceleration of the calculations. The full text of the scripts is in Appendix A.

In the case of the ISO 9223 and UN ECE ICP Effect on Materials approaches, optimization is not necessary because the computing time takes only a few seconds. However, the situation is different for the Multi-Assess approach, where the computing time is significant due to a large number of combinations. The number of combinations is much larger than in the ISO 9223 or UN ECE ICP Effect on Materials approaches. In this case, it is advisable to utilize zonal and interval optimization of input parameters [20], [49].

The result of these optimizations is a reduction in the intervals of individual histograms, thereby reducing the number of combinations and the complexity of the task. However, these optimizations did not have a significant impact given the number of variables used. The estimated computation time before and after optimization was on the order of days.

A substantial reduction in computation time was achieved through a technique called grouping [20], where a portion of the original combinations is isolated and computed separately. The results from these groups are then used for the subsequent calculations while maintaining sufficient accuracy. In the case of the Multi-Assess-based approach, two groups were used, represented by equations 13 and 14. Subsequently, the entire problem was computed using the results from these groups by solving equation 15. This reduced the computation time to mere seconds.

$$group1 = 1,39 * P_c^{0,6} * RH_{60} * e^{f_{st}} \tag{13}$$

$$group2 = 1,29 * RAIN * [H^+] + 0.593 * PM_{10}, \tag{14}$$

$$r_{corr} = 29,1 + (21,7 + group1 + group2) * t^{0,6}, \tag{15}$$

The resulting values of all three analysed models are shown in the Table 8 and distribution of the predicted values for each approach from the Figure 17 to the Figure 21. There are mentioned 5% quantile, 95% quantile, mode and median for the relevant approach in each picture. There is predicted values with 64 intervals for each approach. For the subsequent analysis, the value of the 95% quantile is important because this value expresses the 95% probability that the predicted value is smaller than the magnitude of the value and only 5 % of the values will be teoretically greater.

Table 8. Predicted corrosion loss value for 2022 by DOProC method and by mean value (μm/year)

	ISO 9223 (μm/year)			UN ECE ICP (μm/year)	Multi Assess (μm/year)
	B1	**B3**	**B5**		
min	7.39	5.37	4.30	8.50	8.40
max	53.87	49.37	47.15	26.37	94.14
median	25.68	22.68	21.16	18.48	42.43
mode	24,91	22.68	21.16	18.89	41.07
5% quantile	16.69	13.93	12.48	15.06	23.81
95% quantile	36.22	32.93	31.30	22.03	63.86
prediction by mean value	22.22	19.31	17.74	17.51	37.57

From the Figure 17 to the Figure 21 are also marked in-situ measurement values. See Chapter 5 for a more detailed description of the markings.

$$r_{corr,B1} = 1,77 \times P_d^{0,52} \times e^{0,02 \times RH + f_{st}} + 0,102 \times S_{d,C1}^{0,62} \times e^{0,033 \times RH + 0,04 \times T}$$

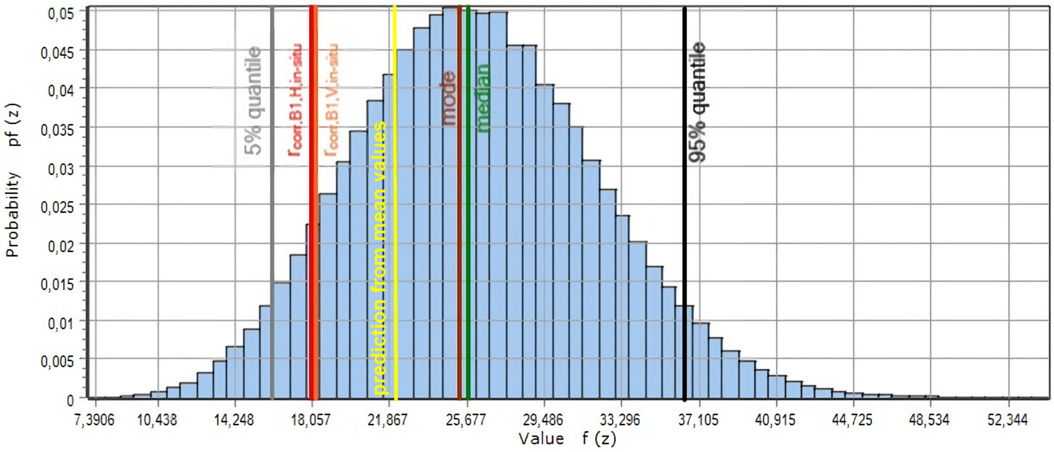

Figure 17. Distribution of the predicted corrosion loss values for the ISO 9223 approach and the B1 site for the year 2022 (μm/year)

$$r_{corr,B3} = 1,77 \times P_d^{0,52} \times e^{0,02 \times RH + f_{st}} + 0,102 \times S_{d,C3}^{0,62} \times e^{0,033 \times RH + 0,04 \times T}$$

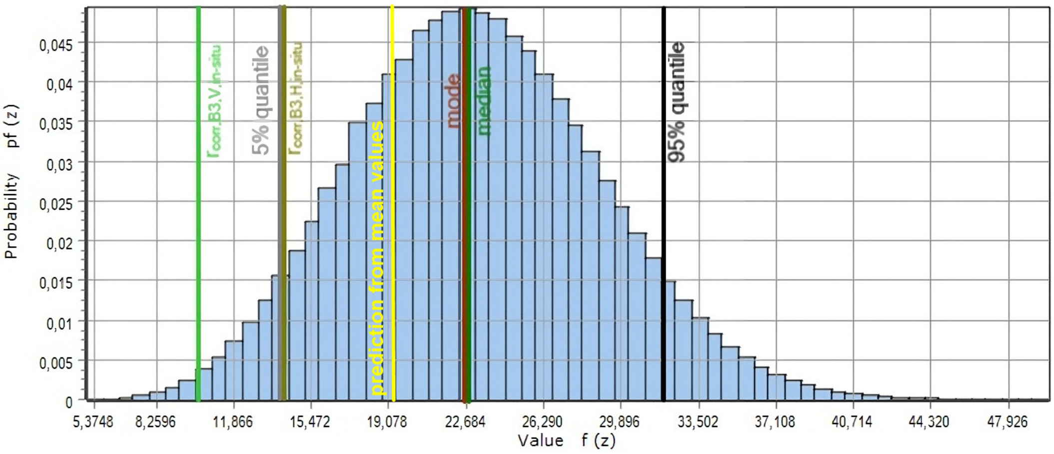

Figure 18. Distribution of the predicted corrosion loss values for the ISO 9223 approach and the B3 site for the year 2022 (μm/year)

$$r_{corr,B5} = 1,77 \times P_d^{0,52} \times e^{0,02 \times RH + f_{st}} + 0,102 \times S_{d,C5}^{0,62} \times e^{0,033 \times RH + 0,04 \times T}$$

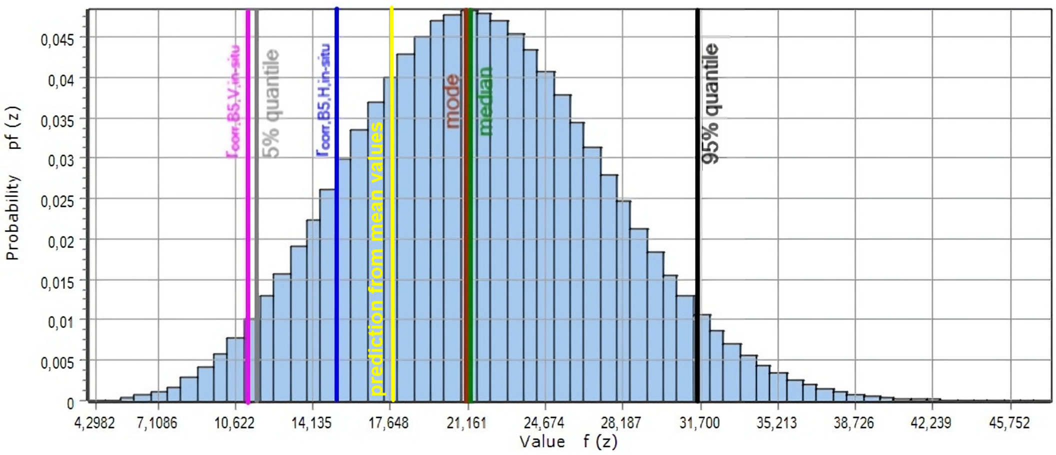

Figure 19. Distribution of the predicted corrosion loss values for the ISO 9223 approach and the B5 site for the year 2022 (μm/year)

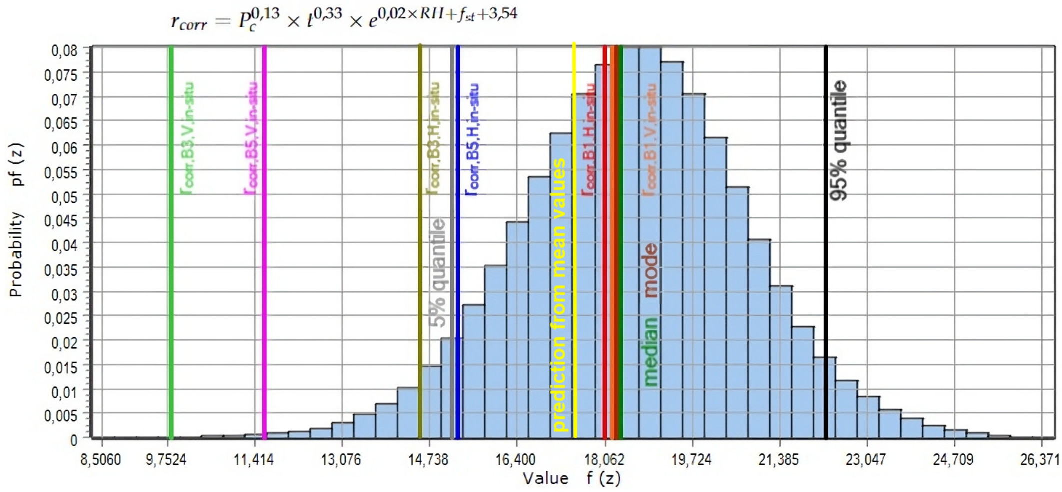

Figure 20. Distribution of the predicted corrosion loss values for the UN ECE ICP Effect on Materials approach for the year 2022 (μm/year)

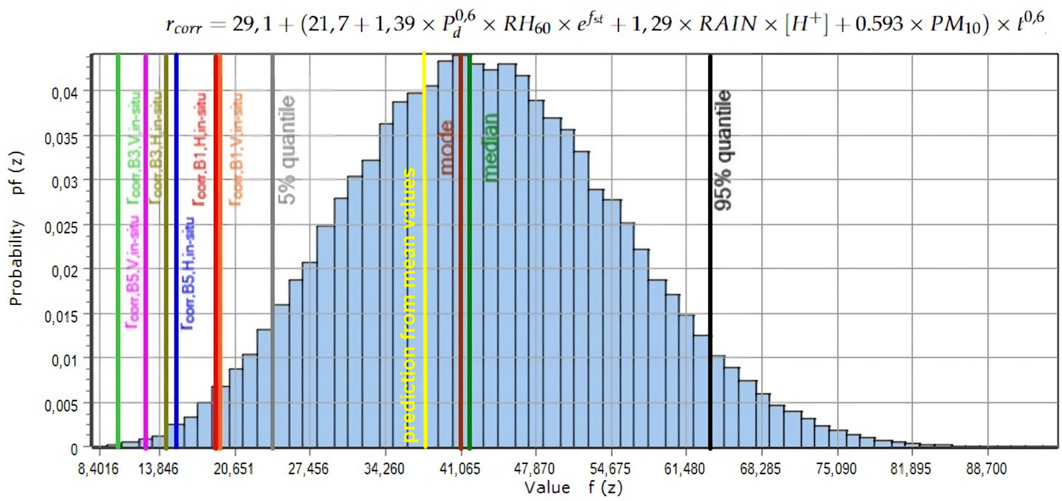

Figure 21. Distribution of the predicted corrosion loss values for the Multi-Assess approach for the year 2022 (μm/year)

5. Results of in-situ corrosion loss - site Hrabyně, Josefovice

The site Hrabyně, Josefovice and year 2022 were selected for the analysis of the suitability of the chosen approaches for corrosion loss prediction. The positions of each test sites are depicted in Figure 12. Values of chloride ion deposition and corrosion loss on both horizontal and vertical corrosion coupons have been monitored over an extended period near the I/11 road in the vicinity of Hrabyně, Josefovice. The orientation of the corrosion coupons (H - horizontal, V - vertical) corresponds to the orientation of the major groups of exposed real steel construction parts of bridges. The results of in-situ measurements and statistical comparisons with output data from DOProC are presented in Table 9. Values in the column ISO 9223, UN ECE ICP and Multi-Assess are fractiles from each approach. There are also shown each in-situ measurement in relevant Figures from 17 to 21.

Table 9. Measured corrosion loss values after one year exposure on exposed corrosion coupons - site Hrabyně, Josefovice - year 2022

Loc./ Or.		r_{corr}		ISO 9223	UN ECE ICP	Multi Assess
		$(g/(m^2 * year))$	(µm/year)	(fractile)	(fractile)	(fractile)
B1	H	141,47	18.0	0.0823	0,385	0.0113
	V	144,33	18.4	0.0941	0.460	0.0127
B3	H	112,45	14.3	0.0579	0.0242	0.00255
	V	77,65	9.9	0.00516	0.0000584	0.0000728
B5	H	121,15	15.4	0.140	0.0672	0.00435
	V	91,32	11.6	0.0336	0.00119	0.000602

Note: Values in the columns ISO 9223, UN ECE ICP and Multi-Assess are fractiles related to measured corrosion loss from respective predicted statistical distribution.

6. Discussion

6.1. Probabilistic calculation

For predictive models with only a few input variables and distribution featuring a limited number of intervals, the advantages of the DOProC method are not significantly apparent. Models like the one from the ISO 9223 standard [15] and the approach from the UN ECE ICP Effect on Materials [16], which fall into this category, can be solved in a matter of seconds using today's mainstream computing power. Further optimization steps are unnecessary for computational efficiency.

However, a different situation arises in predictive models with numerous variables or distribution featuring many intervals. In this article, it is examine the Multi-Assess approach [17], which involves seven variables. One of these variables is time, which remains constant at one year. The remaining six variables have 64 intervals each, resulting in significantly longer computational times, estimated to be on the order of days. Zone and interval optimization can certainly reduce the computational complexity of the problem, bringing the estimated computation time down to aproximately one day. To achieve a substantial acceleration in the calculation, the use of grouping is advisable, as it can significantly reduce computational complexity. After employing both grouping and optimization, the computation time for the Multi-Assess approach [17] becomes comparable to that of the ISO 9223 [15] or UN ECE ICP Effect on Materials [16] approaches.

Additionally, to reduce computational time, the usage of a .dll script is implemented, which is more efficient for the processor compared to running ProbCalc without the .dll script.

6.2. Comparison of prediction models with in-situ measurements

From the Table 8 and equation (5), (6) and (9), it is evident that only the equation from the ISO 9223 standard [15] takes directly into account the influence of annual deposition of chloride ions. The other two equations do not consider this influence, preventing the consideration of the trend of decreasing chloride ion deposition with increasing distance from the road [40]. Additionally, the Multi-Assess approach incorporates the influence of PM_{1_0} particles, which contain about 7 % chloride ions in the Czech Republic area [29].

Notably, the ISO 9223 approach [15] shows the smallest minimum values, while the equation from UN ECE ICP Effect on Materials [16] exhibits the highest values across all basic characteristic limits. The variance of the maximum and minimum values in the UN ECE ICP Effect on Materials [16] is smaller than for the other two approaches. This means that the UN ECE ICP Effect on Materials [16], if used as a probabilistic prediction approach, can quickly become non-safe for the prediction of corrosion loss after one year exposure and is directly related to the corrosion class. If the predicted value of the 95% quantile is smaller than real corrosion loss value, it is dangerous situation. It is necessary to say, it is not in this case, but the authors feel it is important to point this out.

The established quantiles demonstrate that the in-situ measurements from 2022 fall safely below the 95% quantile values established by all considered approaches. On site B1, the measured value is closest to the predicted 95% quantile value from the UN ECE ICP Effect on Materials [16]. However, a different situation arises at sites B3 and B5, where the fractile values are relatively low. It is because this approach does not consider the effect of chlorides directly or indirectly. Predicted values are constant for all mentioned sites without difference of distance from the road, as same as in the Multi-Assess approach. In the case of predictions from Multi-Assess [17], all quantile values are notably small, with none exceeding 5%. This mean that approach is very conservative. Comparatively, the corrosion loss values determined by the ISO 9223 standard [15] closely align with the measured values, falling between the 5% and 95% quantiles in four out of six instances. This shows that this approach is not overly conservative and, on the other hand, not dangerously close to the 95% quantile limit. Greatest value of quantile is 0.140, which mean, that 14.0 % of the predicted values are smaller than in-situ measurement. On the other hand the smallest quantile is 0.00516 (0.516 %), so it is little bit conservative, but still on acceptable level.

When comparing the in-situ measured values from site B1 with vertically oriented corrosion coupons to the predicted values from the UN ECE ICP Effect on Materials equation [16], a good agreement is observed at the 46.0% quantile. However, for sites B3 and B5, the in-situ measured values are situated near the 5% quantile. This shows that while the distance to the emitter is relatively small, this strategy produces more accurate forecasts; but, as the distance increases, the approach becomes more conservative. This points out the influence of chloride, which is not directly or indirectly included in this method. The authors do not consider this method unsafe for use even in close proximity to a chloride emitter, in this case 7 m from the guide strip of the road. The predicted values are still at an acceptable level of confidence. However, as the distance increases and therefore the effect of chloride ions on corrosion loss decreases, this approach becomes more conservative.

On comparing the measured values from the Hrabyně, Josefovice locality with the predicted values from the Multi-Assess project [17], it becomes evident that this method is overly conservative for this particular locality. Even at site B1, which is closest to the road, the quantile value remains below 5%. For sites B3 and B5, the quantile values are nearly negligible. In all cases, the predicted corrosion loss values are higher than the measured values, indicating that the Multi-Assess approach [17] tends to predict on the safe side. If this approach is utilized, the predicted values may be excessively conservative. In all mentioned cases of in-situ measurement, this approach is most conservative in comparation with another two ones.

In contrast, using the equation from the ISO 9223 standard [15] allows for reliable prediction of corrosion loss values without excessive conservatism. This demonstrates the critical importance that taking into account the impact of chloride ion deposition (and its prediction) plays in precisely estimating corrosion loss. The authors conclude that the equation from the ISO 9223 standard [15] is well-suited for predicting corrosion loss in the vicinity of roads. This is mainly because the ISO 9223 [15] approach includes the effect of chloride ions, which is a major corrosive agent in the vicinity of roads. The effect of chloride is mainly in the winter season, but neverthless its effect on steel structures in the vicinity of roads is major.

The evaluation of these approaches consisted a comparison with experimental data obtained from corrosion coupons at the Hrabyně, Josefovice locality in the year 2022. The authors conducted long-term measurements at the locality and these measurements are ongoing.

Additionally, linear regression predictions, along with each distribution prediction and confidence interval, are extrapolated to the year 2030. With the increase in temperature, the need for de-icing salt is reduced, as it can be predicted that there might be fewer freezing days. This assumption cannot be confirmed yet due to the lack of long-term data on measured chloride ion deposition rates. However, it can be indirectly supported by the linear regression analysis of PM_{1_0} particles, which are also decreasing. Additionally, the decrease in relative humidity can reduce the duration of surface wetness, thereby reducing the occurrence of corrosion reactions. Lastly, there is a decreasing concentration of SO_2, which is also a corrosion stimulant. Overall, the prediction of all environmental data indicates a potential decreasing trend in corrosion rates in the future.

7. Conclusion

The study focuses on the crucial task of predicting corrosivity for designing steel structures in corrosive environments. Utilizing probabilistic approaches enhances the accuracy of annual corrosion loss predictions compared to traditional deterministic methods. Three applied prediction models demonstrate satisfactory results in locations less affected by chloride ion deposition. However, in proximity to chloride ion emitters, the ISO 9223 standard is recommended for determining local corrosion aggressiveness, while caution is advised against using the UN ECE ICP Effect on Materials equation for surfaces in very close proximity to emitters due to long-term safety concerns. The Multi-Assess project equation is considered conservative for the site under consideration.

The research introduces the concept of stochastic calculation and computational complexity using the ProbCalc software. Techniques such as zone and interval optimization, along with the use of groups for numerical optimization, are discussed to reduce computational time. The study involves comparing prediction models with experimental data from installed corrosion coupons at a single site, with ongoing measurements at additional sites to establish more general validity. The article also includes predictions extending to 2030, indicating a potential decline in corrosion rates and a trend towards reduced corrosion in the studied areas. The authors plan to continue monitoring various localities to validate predictions and record corrosion loss and environmental aggressiveness.

Author Contributions: Conceptualization, M.Vac., V.K. and P.K.; methodology, M.Vac., V.K., M.M., K.K. and M.Vla; software, M.Vac. and P.K.; validation, M.Vac., V.K. and P.K.; formal analysis, M.Vac.; investigation, M.Vac.; resources, M.Vac.; data curation, M.Vac.; writing—original draft preparation, M.Vac.; writing—review and editing, M.Vac., V.K., P.K., M.M. and K.K.; visualization, M.Vac.; supervision, V.K. and P.K.; project administration, M.Vac., V.K. and P.K.; funding acquisition, M.V. and P.K. All authors have read and agreed to the published version of the manuscript.

Funding: The work was supported by the Student Grant Competition of VŠB-TUO. The project registration number is SP2023/070. This contribution has been developed as a part of the research project GACR 22-19812S "Effect of gaseous and traffic induced pollutants on the durability of selected construction materials" supported by the Czech Grant Agency.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

In the case of the ISO 9223 approach, this Delphi 7 script is used:

```
library ISO9223;
uses SysUtils,math,Classes;
function Fx ( NumModel :  integer; P: array of double) :  double;
- Logic function -
function poz (x:double):integer; begin if (x>0)
then poz := 1 else poz := 0 end;
function neg (x:double):integer; begin if (x<0)
then neg := 1 else neg := 0 end;
function nul (x:double):integer; begin if (x=0)
then nul := 1 else nul := 0 end;
var // Local variables
```

```
fstISO: double;
begin
//fst
if P[2]<=10 then
begin
fstISO := 0.15*(P[2]-10);
end
else
begin
fstISO := -0.054*(P[2]-10);
end;
case NumModel of
- Model -
1:  Fx := 1.77*power(P[0],0.52)*
exp(0.02*P[1]+fstISO)+0.102*
power(P[3],0.62)*exp(0.033*P[1]+
0.04*P[2]);
end
end;
exports Fx;
begin
end.
```

In the case of the UN ECE ICP Effect on Materials approach, this Delphi 7 script is used:

```
library UNECE;
uses SysUtils,math,Classes;
function Fx ( NumModel :  integer; P: array of double) :  double;
- Logic function -
function poz (x:double):integer; begin if (x>0)
then poz := 1 else poz := 0 end;
function neg (x:double):integer; begin if (x<0)
then neg := 1 else neg := 0 end;
function nul (x:double):integer; begin if (x=0)
then nul := 1 else nul := 0 end;
var // Local variables
fstUN: double;
begin
//fst
if P[2]<=10 then
begin
fstUN := 0.059*(P[2]-10);
end
else
begin
fstUN := -0.036*(P[2]-10);
end;
case NumModel of
- Model -
1:  Fx := 3.4*power(P[0],0.13)*
exp(0.02*P[1]+fstUN)*power(P[3],0.33);
end
end;
```

```
exports Fx;
begin
end.
```

In the case of the Multi-Assess approach, this Delphi 7 script is used:

```
library MultiAssessGrupa;
uses SysUtils,math,Classes;
function Fx ( NumModel :  integer; P: array of double) :  double;
- Logic function -
function poz (x:double):integer; begin if (x>0)
then poz := 1 else poz := 0 end;
function neg (x:double):integer; begin if (x<0)
then neg := 1 else neg := 0 end;
function nul (x:double):integer; begin if (x=0)
then nul := 1 else nul := 0 end;
var // Local variables
RH, fstMA: double;
begin
//fst
if P[2]<=10 then
begin
fstMA := 0.15*(P[2]-10);
end
else
begin
fstMA := -0.054*(P[2]-10);
end;
//Model Multi Assess - RH;
if P[1]<=60 then
begin
RH := 0;
end
else
begin
RH := P[1];
end;
case NumModel of
- Model -
1:  Fx := power(10,6)*(29.1+(21.7+P[0]+
P[1])*power(P[2],0.6))/(7850*1000);
- Grups -
2:  Fx := 1.39*power(P[0],0.6)*RH*
exp(fstMA);
3:  Fx := 1.29*P[0]*power(10,-P[1])+
0.593*P[2];
end
end;
exports Fx;
begin
end.
```

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