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Identifying the Input Uncertainties to Quantify When Prioritizing Railway Assets for Risk-Reducing Interventions

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Abstract: Railway managers identify and prioritize assets for risk-reducing interventions. This requires the estimation of risks due to failures, as well as the estimation of costs and effects due to interventions. This, in turn, requires the estimation of values of numerous input variables. As there is uncertainty related to the initial input estimates, there is uncertainty in the output, i.e., assets to be prioritized for risk-reducing interventions. Consequently, managers are confronted with two questions: Do the uncertainties in inputs cause significant uncertainty in the output? If so, where should efforts be concentrated to quantify them? This paper discusses the identification of input uncertainties that are likely to affect railway asset prioritization for risk-reducing interventions. Once the track sections, switches and bridges of a part of the Irish railway network were prioritized using best estimates of inputs, they were again prioritized using: (1) reasonably low and high estimates, and (2) Monte Carlo sampling from skewed normal distributions, where the low and high estimates encompass the 95% confidence interval. The results show that only uncertainty in a few inputs influences the prioritization of the assets for risk-reducing interventions. Reliable prioritization of assets can be achieved by quantifying the uncertainties in these particular inputs.

Keywords: railway management; risk management; uncertainty; maintenance

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1. Introduction

Railway managers are responsible for planning and executing risk-reducing interventions. To achieve this, they must estimate the risks due to failures as well as the costs and effects on service due to interventions for all the assets and then prioritize their interventions accordingly. There is a plethora of methods and models to estimate the risks due to railway asset failures, as well as the costs and effects on rail service due to failures and interventions. For example, [1–12] analyze the risk related to railways due to specific hazards. Many scholars have focused on the analysis of risk related to specific failure modes of the railway assets, e.g., [13–27]. Other scholars have investigated the occurrence of specific effects on the service, such as accidents (e.g., [28–36]), and delays (e.g., [37,38]).

The value of numerous variables must be determined to estimate the risks, costs, and effects on service due to failures and interventions to prioritize risk-reducing interventions. Railway managers often use a point value to represent the best estimate of an input variable. This best estimate of an input can be obtained using expert knowledge (e.g., [39–45]), historical data (e.g., [46–50]), or models (e.g., [51–54]). However, there is often uncertainty in the best estimates, as they are not precise estimations or distribution functions of the inputs. Consequently, once the assets to be prioritized for interventions have been identified using only best estimates of inputs, railway managers need to know if different assets would be prioritized, given the uncertainty in the inputs. To do this, they must examine how sensitive the prioritization of the assets for interventions is to input uncertainties.

In this paper, the term 'input uncertainties' refers only to the statistical uncertainties in the input values used to rank the assets for interventions. Although other uncertainties also exist, e.g., in the models used to estimate risks and costs, they are neglected. The input uncertainties, therefore, represent all the unknowns that can cause variations in the values of the input variables required to estimate the risks, costs, and effects due to interventions, which are subsequently used to rank the assets. Although often no distinction is made between the estimation of probabilistic risk and the quantification of uncertainties [55], e.g., in [56,57], in this analysis, such a distinction must be made because the uncertainty in the risk value is considered. To estimate the risk, the values of failure probability and the extent of consequences due to failure must be obtained. The uncertainties in values used to represent the probability and consequences of failure yield uncertainties in the risk value.

The necessity of a systematic consideration of input uncertainties has been widely acknowledged in railway management. Many scholars have investigated the effect of input uncertainties in the estimation of risks due to failures of railway assets (e.g., [32,58–65]), as well as of costs and effects on rail service due to interventions (e.g., [57,66–73]). As there are uncertainties in the estimations of risks, costs, and effects on service, the ranking of assets for interventions, which is based on these estimates, might not be reliable. The effect of the input uncertainties in the ranking of assets must be, therefore, quantified. For example, in [56], the effect of the input uncertainties on the prioritization of risk-reducing interventions for water supply infrastructure is quantified. Other examples of methods to quantify the uncertainty in prioritization problems are [74–76].

In practice, however, it is common to neglect the input uncertainties when prioritizing railway assets for interventions [77]. Railway managers know that there is a high cost in quantifying all these uncertainties and then in considering them when planning interventions. To quantify the input uncertainties, one must obtain the complete set of plausible values for each input, from which the probability distribution of each input is built. To consider the input uncertainties when prioritizing assets for interventions, one must first use these distributions to represent each input when modeling the risks, costs, and effects on service for each asset. Then, these results can be used to identify which assets should be prioritized for interventions. This process requires more data, more complex models, and higher computational effort, leading to higher costs than using the best estimates of the inputs.

However, quantifying and considering all the input uncertainties instead of using best estimates is beneficial for the railway managers only if the input uncertainties highly influence the ranking of the assets for interventions. It is reasonable to expect that the ranking of the assets will not be equally sensitive to all input uncertainties. If railway managers know how sensitive the ranking is to each input uncertainty, they can decide which inputs they must quantify and consider when prioritizing risk-reducing interventions. They can also, then, decide for which inputs the use of best estimates delivers reliable results. Railway managers can have a first impression of how likely it is that an input uncertainty affects the ranking of the assets by doing a simple analysis; evaluating how sensitive the ranking produced using only best estimates of inputs is to the use of extreme yet plausible input values as well as to the use of simple distribution functions of inputs.

This paper shows how reasonably extreme estimates of inputs were used, in addition to the best estimates, to identify the input uncertainties that highly influence which assets of a railway network should be prioritized for risk-reducing interventions. The network is located in Ireland and consists of 11 track sections, 23 switches, and 39 bridges. These assets were initially ranked for risk-reducing interventions using the best estimates of inputs. This initial ranking was compared to the rankings (1) when reasonably low and high estimates of the inputs were used, and (2) when 100 Monte Carlo samples from skewed normal distributions of the inputs were used, where the low and high estimates were assumed to encompass the 95% confidence interval. The results indicate where efforts should be concentrated to quantify the input uncertainties. They also provide clear guidance as to which input uncertainties should be considered when prioritizing risk-reducing interventions. It is shown that it is not necessarily the largest input uncertainties that cause the most changes in the ranking of the assets.

The remainder of the paper is divided as follows. Section 2 contains the methodology used to consider the input uncertainties in the ranking of risk-reducing interventions. Section 3 offers a description of the case study, the models, the input variables used to estimate risks, as well as costs and effects on rail service due to interventions and the results on the ranking of the assets and the identification of the influencing input uncertainties. Sections 4 and 5 provide the discussion and conclusion.

2. Methodology

The effect of the uncertainty in each input, x, was evaluated by comparing the ranking of possible risk-reducing interventions using:

1. the reasonable best estimate, x_{best}, and the reasonable high estimate, x_{high},
2. the reasonable best estimate, x_{best}, and the reasonable low estimate, x_{low}, and the reasonable best estimate, x_{best}, and the samples from skewed normal distributions, x, built assuming the high and low estimates, x_{high} and x_{low}, encompassed the 95% confidence interval and the best estimate, x_{best}, was the mean value ($\overline{x} = x_{best}$). Figure 1 shows the probability density function of a skewed normal distribution, $P(x)$, that was built using the best, x_{best}, low, x_{low}, and high, x_{high}, estimates of the input value x. This is a right-skewed distribution because it has a longer tail on the left.

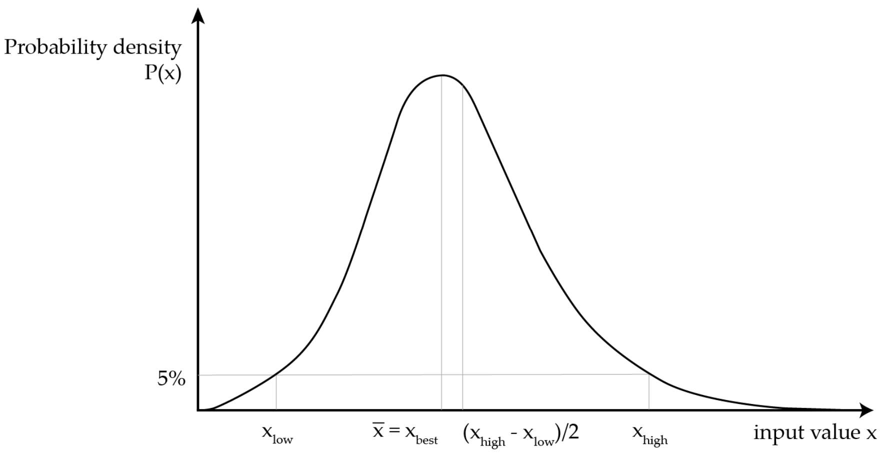

Figure 1. Illustration of the best, low and high estimates and a right-skewed normal distribution of input value X.

The reasonable low and high estimates were determined for each model input variable to investigate how sensitive the initial ranking, i.e., ranking using the best estimates for all inputs, was to the extreme yet plausible values. Monte Carlo sampling from skewed normal distributions developed by considering the best, low and high estimates for each input was used to investigate how sensitive the initial ranking was to if the inputs are aligned to normal distributions. The more sensitive the initial ranking was to the use of different input estimates, the more significant this input uncertainty is.

The net benefit of executing a risk-reducing intervention on each asset was estimated. The risk-reducing intervention considered for all the asset is the renewal, which results in the greatest possible elimination of risk. The assets were prioritized for risk-reducing interventions in the upcoming intervention-planning period based on the net benefit of renewing them. Net benefit, nb, was defined as the difference between the reduction in risk achieved within the planning period by, and the costs and effects on rail service of executing the risk-reducing intervention. This method was used in [78] to compare intervention strategies for different railway assets, and it is based on balancing the costs and benefits of interventions [79–81]. The net benefit was calculated using Equation (1)

$$nb_{k,a} = \left(r_{a\backslash k} - r_{a|k}\right) - c_{k,a} \tag{1}$$

where $nb_{k,a}$ is the net-benefit of executing the risk-reducing intervention k on asset a; $r_{a\backslash k}$ is the risk related to asset a without the execution of the intervention k; $r_{a|k}$ is the risk related to asset a after the execution of the intervention k; and $c_{k,a}$ is the costs and effects on service resulting from the execution of the intervention k. The net benefit of an asset was the difference between the reduction in risk achieved by, and the costs of, renewing the asset to a like-new state.

As one risk-reducing intervention was examined for each asset, the higher the net benefit of this intervention, the higher the asset was ranked. The set of assets $a = \{a_1, \ldots, a_A\}$ was converted to ranks $W = \{1, \ldots, A\}$ in descending order of the net-benefit, NB_a, of restoring them where $W(i_a)$ denotes that asset a takes the position i in the W rank.

The use of each of the different input estimates—i.e., best, low, high or a value from the skewed normal distribution—resulted in a different ranking. The sensitivity of the initial ranking, i.e., ranking using the best estimates for all inputs, was evaluated by comparing it to the rankings using the low estimate, high estimate, and an estimate from the distribution. To compare the rankings, two metrics were used: (i) the cumulative number of position changes, i.e., Spearman's rank coefficient, and (ii) weighted cumulative number of position changes, i.e., Spearman's rank coefficient with position weights.

The cumulative number of position changes was calculated using Equation (2)

$$SF_X = \sum_{i=1}^{A} \left| W_{i_a|best} - W_{i_a|X} \right| \tag{2}$$

where SF_X is the sum of position changes for all the assets between the ranking from the estimation of the net benefit for each asset using the best estimates for all the inputs, W_{best}, and the ranking from the estimation of the net benefit for each asset using either the low or high estimate or the distribution of the estimates of the model input X and the best estimates for the rest of the inputs, W_X.

As this metric does not account for the location of the changes in the list, the Spearman's rank coefficient [82] with position weights was also used to differentiate from changes occurring in the higher positions of the rank from changes occurring in the lower positions. This method is described in [83], and the Spearman's rank coefficient is calculated by Equation (3)

$$SF_{X|\theta} = \sum_{i=1}^{A} \overline{\theta_{i_a}}(W_{i_a|X}) \cdot \left| \sum_{j:j\le i_a} \overline{\theta_j}(W_{i_a|X}) - \sum_{j:W_{j|X} \le W_{i_a|X}} \overline{\theta_j}(W_{i_a|X}) \right| \tag{3}$$

where $SF_{X|\theta}$ is the weighted difference between the ranking W_{best}, and the ranking W_X, and $\overline{\theta_{i_a}}$ is the average position weight of changing the position of the asset a. It was calculated using Equation (4)

$$\overline{\theta_{i_a}}(W_{i_a|X}) = \frac{\theta_{W_{i_a|best}} - \theta_{W_{i_a|X}}}{W_{i_a|best} - W_{i_a|X}} \tag{4}$$

where $W_{i_a|best}$ and $\theta_{W_{i_a|best}}$ is the position and the position weight θ of asset a, according to the ranking W_{best} and $W_{i_a|X}$ and $\theta_{W_{i_a|X}}$ is the position and the position weight θ of asset a, according to the ranking W_X. The position weights were calculated by Equation (5)

$$\theta_{W_{i_a}} = \sum_{j=1}^{W_{i_a}-1} \delta_j = \sum_{j=1}^{W_{i_a}-1} \frac{nb_{a|best} + \left|\min(NB_{best})\right|}{\left|\max(NB_{best})\right| + \left|\min(NB_{best})\right|} \tag{5}$$

where δ is the weight of changing asset a in position W_{i-1} with an asset in position W_i, $nb_{a|best}$ is the net benefit of executing the on asset a and $max(NB_{best})$ and $min(NB_{best})$ are the highest and lowest net benefit among all the assets, calculated using the best estimates for all the inputs. Note that by using this position weight, the position changes are weighted according to the net benefit estimated using the best estimates of all input values.

Tables 1–3 presents an example comparison of only the high estimates of two model inputs for four assets, a_1–a_4, using the two metrics, i.e., the cumulative number of position changes, SF_X, and the weighted cumulative number of position changes, $SF_{X|\theta}$. The use of the high estimate, instead of the best estimate, for each value results in the inversion of two assets in the ranking W. The two inputs are associated with equal SF_X. This metric indicates that the uncertainty in the upwards direction for both inputs is equally important in the identification of the assets for which it is beneficial to plan a risk-reducing intervention. The high estimate of $X1$, however, results in an inversion on the two first positions of the ranking (Tables 1 and 2), while the high estimate of $X2$ results in an inversion on the two last positions of the ranking (Tables 1 and 3), resulting in $SF_{x1.high|\theta}$ being higher (2) than $SF_{x2.high|\theta}$ (1.11). This second metric indicates that the uncertainty in the upwards direction for *X1* results in more significant changes in the ranking of the assets compared to the $X2$.

Table 1. Example of ranking using the best estimates of two model inputs, $X1$ and $X2$.

Assets	Net Benefit	Rank	Weight of Position Change	Position Weight
	$NB_{a\|best}$ Equation (1)	$W_{i_a\|best}$	δ_{j_a} Equation (5)	$\theta_{i_a\|best}$ Equation (5)
a_1	100	1	1.00	0.0
a_2	20	2	0.47	1.0
a_3	0	3	0.33	1.5
a_4	−50	4	0.00	1.8

Table 2. Example of ranking using the high estimate of one model input, $X1._{high}$, and the best estimate of one model input, $X2._{best.}$

Assets	Net Benefit	Rank	No. of Position Changes	Position Weight	No. of Weighted Position Changes
	$NB_{a\|X1.high}$ Equation (1)	$W_{i_a\|X1.high}$	$SF_{X1.high}$ Equation (2)	$\theta_{i_a\|X1.high}$ Equation (5)	$SF_{X1.high\|\theta}$ Equation (3)
a_1	120	2	1	1.0	1.00
a_2	150	1	1	0.0	1.00
a_3	50	3	0	1.5	0.00
a_4	0	4	0	1.8	0.00
Sum			2		2.00

Table 3. Example of ranking using the best estimate of one model input, $X1._{best}$, and the high estimate of one model input, $X2._{high.}$

Assets	Net Benefit	Rank	No. of Position Changes	Position Weight	No. of Weighted Position Changes
	$NB_{a\|X2.high}$ Equation (1)	$W_{i_a\|X2.high}$	$SF_{X2.high}$ Equation (2)	$\theta_{i_a\|X2.high}$ Equation (5)	$SF_{X2.high\|\theta}$ Equation (3)
a_1	150	1	0	0.0	0.0
a_2	120	2	0	1.0	0.0
a_3	50	4	1	1.8	0.6
a_4	100	3	1	1.5	0.6
Sum			2		1.11

3. Case Study

3.1. Assets and Hazards

The track sections, switches, and bridges used in this case study belong to the part of the Irish railway network (Figure 2), which connects four stations, and serves both intercity and urban commuter passenger trains [84]. It consists of 11 track sections of 5 km total length and 23 switches. As the rail line crosses the city of Dublin at this part of the network, the railway is elevated above the ground level and is built on 39 bridges, which have 17,000 m^2 of combined deck surface area.

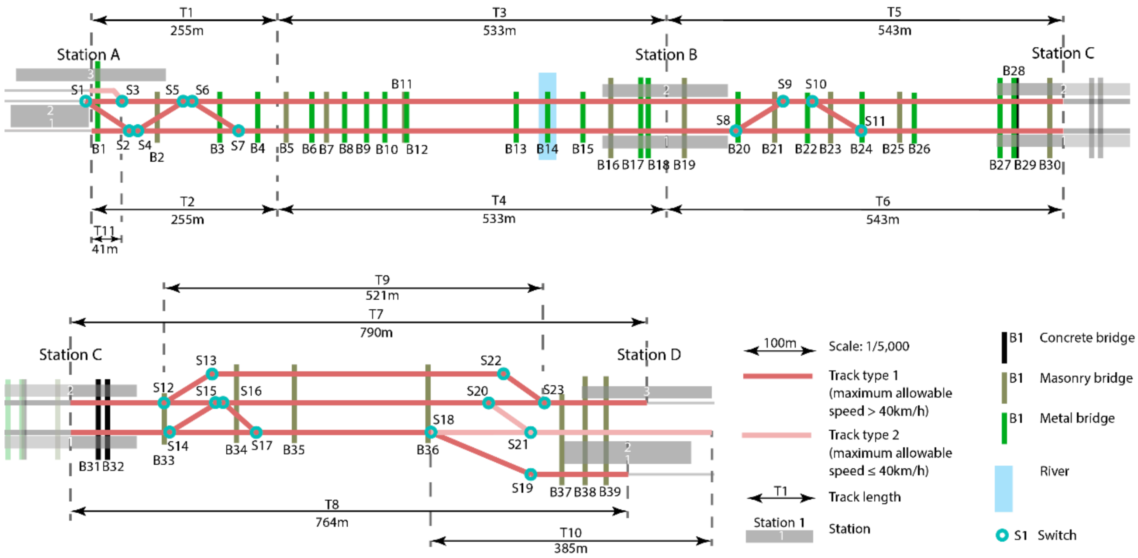

Figure 2. Infrastructure assets: track sections, switches and bridges.

The track sections are classified into two subcategories, i.e., those with a maximum allowable speed greater than 40 km/h, and those with a maximum allowable speed lower than or equal to 40 km/h. The bridges are classified into three subcategories, i.e., concrete, masonry, and metal bridges. Each asset is considered to be in one of four possible states:

1. like-new,
2. slightly deteriorated,
3. significantly deteriorated, and
4. severely deteriorated

The states of the assets are shown in Figure 3. It is assumed that trains can operate according to the timetable in all four of these states, but that there is a probability of failure associated with each of these states. The hazards that can affect the assets were excessive traffic tonnage and two natural hazards:

1. extreme heat affecting the track sections and switches, and
2. river flooding affecting the bridge B14 (see Figure 2)

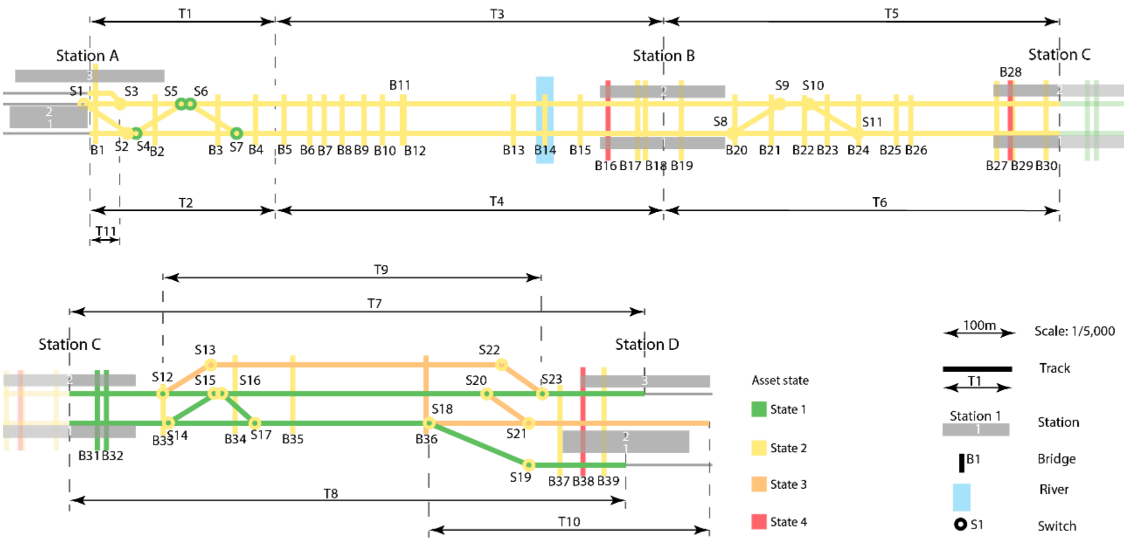

Figure 3. State of assets without the execution of risk-reducing interventions, $O_{a\setminus k}$.

3.2. Risks

The risks, R, in the upcoming intervention-planning period were calculated as the probability of failure, P, multiplied with the consequences of failure, C_F (Equation (6)), according to [85]. They were estimated using event trees [86] comprised of load, infrastructure, network use and societal events (Table 4). Different event trees were used for the estimation of risks related to each hazard type, i.e., traffic tonnage, extreme heat, and river flooding. As an example, the event tree used to estimate the risks related to track section T1 due to traffic tonnage is shown in Figure 4. The methodology used to develop the event trees can be found in [87]. Each branch of the event tree models a failure scenario, SC. The probability of occurrence of one branch of the event tree was calculated as a result of societal events F_{se}, network use events F_{ne}, infrastructure events F_{ie}, and load events F_{le}, using Equation (7) (Figure 4). The probability of cascading or multiple simultaneous failures were not considered. This simplification might yield either an underestimation or an overestimation of the risks [88]; however, as a railway manager in this situation dealing with such approximations, it is warranted. The risk, r, is calculated, as shown in Equation (8)

$$R = P[F] \cdot C_F \tag{6}$$

$$P[F_{SC}] = P[F_{ie}] \cdot P[F_{ie}] \cdot P[F_{ne}] \cdot P[F_{se}] \tag{7}$$

$$r_a = \sum_{w=1}^{W} (P[F_{SC}^{TR}] \cdot C_{SC}) + \sum_{w=1}^{W} (P[F_{SC}^{NH}] \cdot C_{SC}) \tag{8}$$

where $P[F_{SC}]$ is the probability of a failure scenario SC, due to traffic, TR, or due to the natural hazard, NH, i.e., extreme heat for track sections and switches or river flooding for bridge B14, and $C_{F|SC}$, is the consequences, i.e., costs and effects on service, due to the failure scenario, SC.

Table 4. Event types.

Type	Notation	Description	Example of Event Used in the Case Study for the Track Section T1 [1]
Hazard	h	An event that may lead to a change in the load and stress level applied on a railway asset	Traffic
Load	le	An event that may change the load and stress levels applied on a railway asset	Annual tonnage on the track section T1 based on the timetable (1043 trains during a weekday and 318 trains during the weekend)
Infrastructure	ie	An event that may change the structural or functional properties of a railway asset	Damages that partially affect the geometry or the rail condition of the track section T1
Network use	ne	An event that may change the level at which the railway network is used	The operation of the track section T1 is possible only when the speed is less than 40 km/h
Societal	se	An event that may change the level of the railway service provided to the stakeholders	Track section T1 is renewed, and its operation is possible only when the speed is less than 40 km/h until the renewal is complete

[1] All the events are provided in the Appendix A.

The consequences, i.e., costs and effects on service, of a failure scenario c_{sc} were calculated for each failure scenario using Equation (9).

$$c_{sc} = c_{Q|sc} + c_{D|sc} + c_{Z|sc} + c_{E|sc} \tag{9}$$

where c_Q is the cost of restoration (Equation (10)), c_D is the additional travel time cost for the passengers (Equation (11)), c_Z is the cost for fatalities and injuries due to accidents (Equation (12)), and c_E is the cost of environmental impacts (Equation (13)).

$$C_{Q,a} = l_a \cdot C_{QI,a}(g_a, QI) + C_{QS,a}(g_a, QS) \tag{10}$$

where $C_{Q,a}$ is the cost of restorations due to failure of asset a of type g. It depends on the extent of the asset l; the unit costs c_{QI} of executing restoration interventions of type QI on asset a; and the costs C_{QS} of site restoration works QS after the failure of the asset.

$$C_{D,a} = \left[l_a \cdot DD_{D|QI,a}(g_a, QI) + DD_{D|QS,a}(g_a, QS)\right] \cdot DT_a(a, D) \cdot u_t \tag{11}$$

where $C_{D,a}$ is the cost due to additional travel time D caused by the unavailability of asset a. An asset can be unavailable due to one of two types of traffic restrictions, (1) limiting the maximum speed at 40 km/h and (2) closing the section to traffic entirely. When a traffic restriction must be applied due to the asset's failure, it affects the entire block section where the asset is located. The effects on passengers due to the additional travel time depend on the type and duration of traffic restrictions and the total additional travel time caused when the traffic is disrupted on the block section where the asset is located. These depend on the extent of the asset l; a vector of durations of each traffic restriction type DD_{QI} due to the execution of restoration intervention QI; a vector of durations of each traffic restriction type DD_{QS} due to the site restoration QS; a vector of the additional travel time in minutes per traffic restriction type DT; and the unit cost of time u_t.

$$C_{Z,a} = Z_a(g_a, QS) \cdot U_z \tag{12}$$

where $C_{Z,a}$ is the effects due to fatalities and injuries Z incurring after accidents caused by the failure of asset a. It depends on a vector of the expected number of fatalities and injuries occurring due to accidents on the site QS caused by the failure of the asset a; and a vector of the socioeconomic costs per injury and fatality U_z.

$$C_{E,a} = l_{E|a} \cdot [c_{E|QI,a}(g_a, QI) + c_{E|QS,a}(g_a, QS)] \tag{13}$$

where $C_{E,a}$ is the effects due to environmental impacts E caused by the execution of interventions and restorations on the site. It depends on the length of the asset used for the estimation of the environmental impacts l_E; the unit cost $c_{E|QI}$ of the environmental impact of executing restoration intervention QI; and the cost $c_{E|r}$ of the environmental impact of site restoration QS after the failure of the asset. The same environmental impacts were assumed for all the interventions and restorations of the same type and all assets of the same type g.

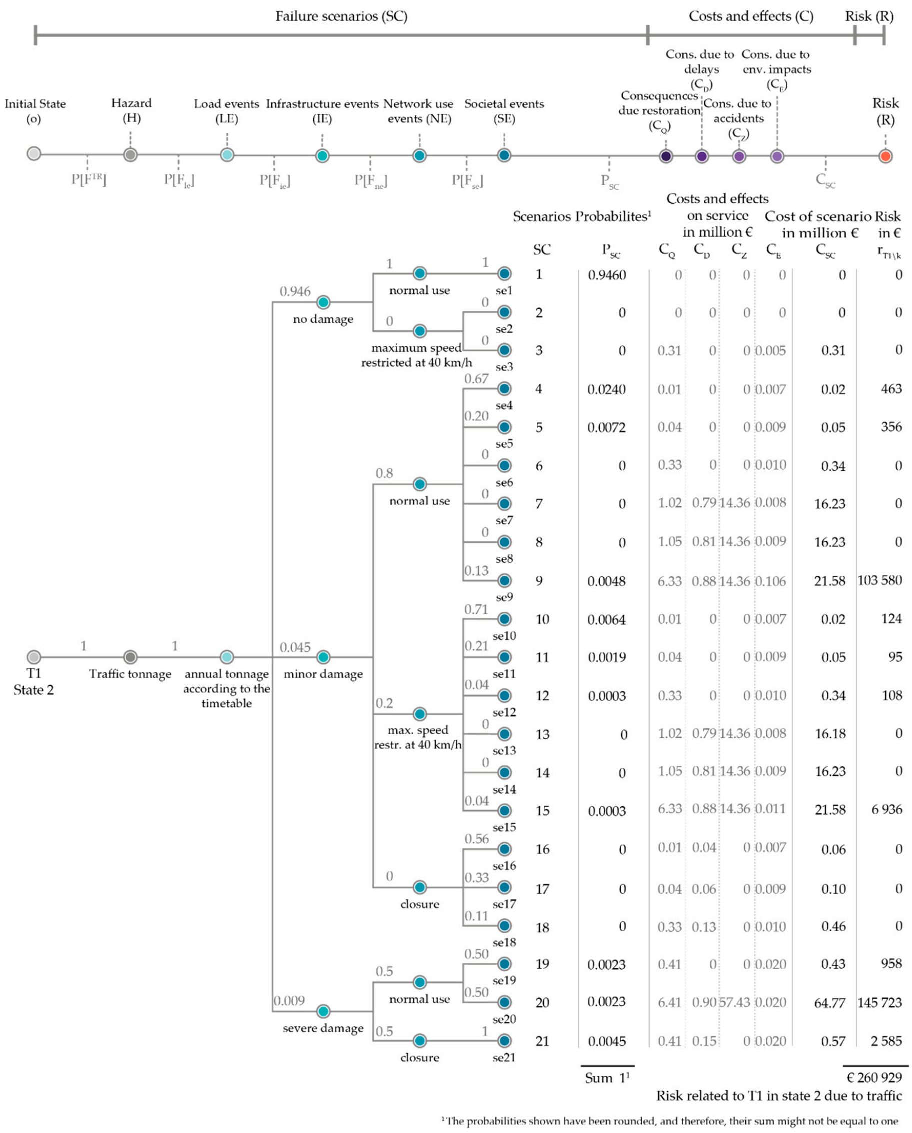

Figure 4. The event tree used to estimate the risk related to T1 due to traffic tonnage without the execution of the risk-reducing intervention (adopted from [87]). The societal events are described in Tables A4 and A5 in the Appendix A.

3.3. Costs and Effects on Service of Risk-Reducing Interventions

The costs and effects on service of executing risk-reducing interventions considered were intervention costs, and the effects due to additional travel time, accidents, and environmental impacts. These are the same costs and effects on service considered for risks. They were calculated using Equations (14)–(18). In their estimation, it was assumed that:

- no damages occur on the site due to the execution of the risk-reducing interventions,
- no accidents occur due to the execution of the risk-reducing interventions, and
- the risk-reducing interventions are executed with the least possible traffic restrictions.

$$c_k = c_{i|k} + C_{D|k} + C_{Z|k} + C_{E|k} \tag{14}$$

$$C_{I,a} = l_a \cdot c_{k,a}(g_a, k) \tag{15}$$

$$C_{D,a} = l_a \cdot DT_{h|k,a}(g_a, k) \cdot D_{h,a}(a) \cdot u_t \tag{16}$$

$$C_{Z,a} = 0 \tag{17}$$

$$C_{E,a} = l_{E|a} \cdot c_{E|k,a}(g_a, k) \tag{18}$$

3.4. Variables

An overview of the variables required to estimate the net-benefit used to rank the assets for risk-reducing interventions and how they are related is given in Figure 5. An example of how Figure 5 can be read is as follows: the probability of load events is estimated as a function of the state of the asset before and after a risk-reducing intervention is executed, $o\backslash k$ and $o|k$ respectively, a given amount of traffic TR or a natural hazard NH, and the type of asset g. It affects the estimation of the probability of a failure scenario $P[F_{SC}]$, which in turn affects the estimation of risks with $r_{o\backslash k}$ and without a risk-reducing intervention $r_{o|k}$, and consequently the net benefit nb_k. This set-up allows updating the input values used to represent the uncertain variables when new data is collected, and, therefore also updating the net benefit related to the renewal of each asset and the ranking of the assets. This is essential, as the purpose of this analysis is to identify the input variables for which more accurate estimates must be collected to reduce the uncertainty in the ranking of the assets.

For each input uncertainty, three types of estimates were determined:

1. the best estimate
2. the reasonable low estimate, and
3. the reasonable high estimate.

These estimates were derived from the input of experts from Irish Rail and the partners in the EU Horizon 2020 founded project DESTination RAIL, which developed a decision support tool to facilitate railway managers in intervention planning. The experts based their estimates for the assets in the case study on existing models and historical data. The analyses of the experts are described in [89–93]. A sample of these estimates is given in Tables 5 and 6. The complete dataset can be found in the Supplementary File. These input values are meant to illustrate the estimation of the net benefit only for the assets of this case study and purposes of this work. The input values used in this case study might be different in other parts of the railway network in the Republic of Ireland. Further explanations on the estimation of risks related to the assets of this network can be found in [87] and [92], and on the estimation of costs and effects on service due interventions on these assets can be found in [78]. It was considered that the methods and models used to estimate the input values, as well as the risks, costs and effects on service are validated for prioritizing these assets for renewal because the scope of this analysis is to examine the effect of the input uncertainties. Hence, the effect of other uncertainties, e.g., in the models used to estimate the input values or risks, was not considered. Information on existing models and data to estimate such values can be found in the scientific literature, e.g., [1,94–97].

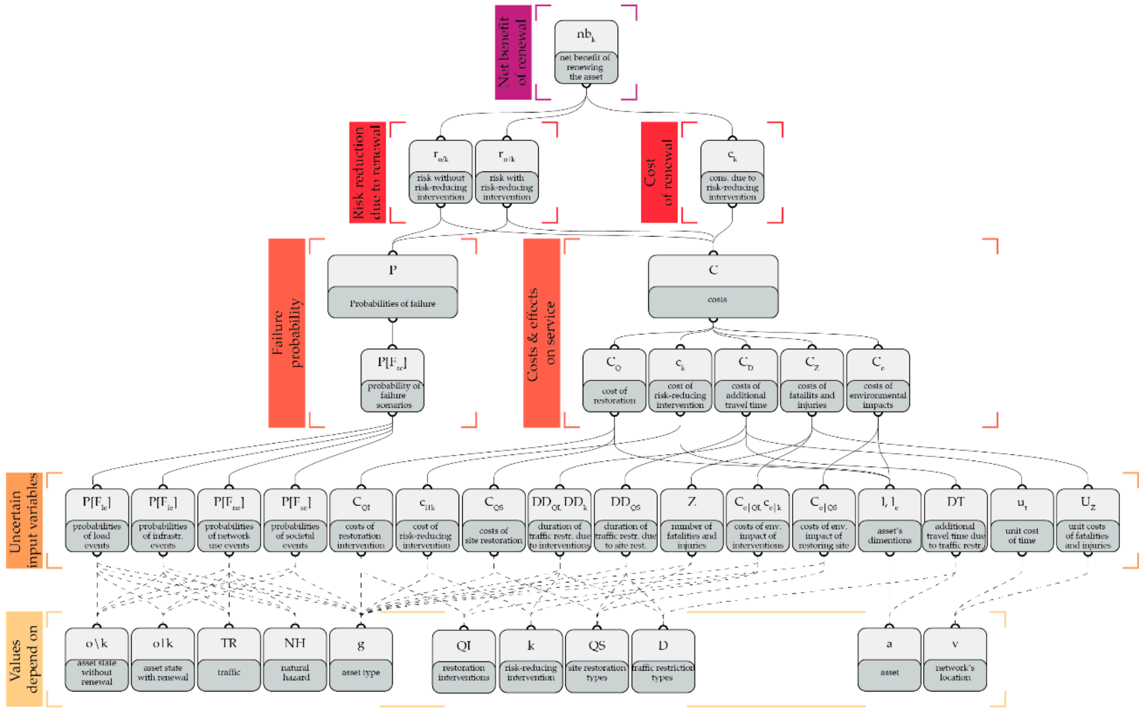

Figure 5. Overview of the variables required to estimate the net benefit.

Table 5. Sample of reasonable best, lowest and highest estimates of uncertain input variables (part 1 of 2).

Variable	Value Depends on	Description	Estimates		
			Best	Low	High
Probability of load event ($P[F_{le}]$)	Asset type (g) and the hazards (TR or NH) considered	Probability of annual traffic tonnage based on the timetable to be applied on a track section of type 1	1	0.8	1
Probability of infrastructure event ($P[F_{ie}]$)	Asset type (g), the state of the asset (o) and the hazards (TR or NH) considered	Probability of minor damage to occur on a metal bridge in state 4 due to traffic loads	0.00005	0.00004	0.00006
Probability of network use event ($P[F_{ne}]$)		Probability of closure of a block section due to a switch being severed damaged from extreme heat	0.8	0.64	1
Probability of societal event ($P[F_{se}]$)	Asset type (g) and the state of the asset (o)	Probability of accident to occur due to severe damage of a track section of type 1 in state 3 due to traffic	0.8	0.76	0.84
Cost of restoration intervention (C_{QI})	Asset type (g) and the type of restoration intervention (QI)	Renewal of 1 m track section of type 1 to restore it after damage	€1200	€1080	€1320
Cost of risk-reducing intervention ($C_{i\|k}$)	Asset type (g) and the risk-reducing intervention (k)	Renewal of 1 m track section of type 1 to reduce the risk	€1200	€1080	€1320
Cost of site restoration (C_{QS})	Asset type (g) and the restoration work due to damages or accidents at the site (QS)	Cost of site restoration after severe damage of a switch	€4000	€2000	€12,000
Duration of traffic restriction due to intervention (DD_I)	Asset type (g), the type of restoration (QI) or risk-reducing (k) intervention and the traffic restrictions (D) considered	Duration in hours of speed restriction due to the renewal of 1 m of a type 1 track section	168	168	168

Table 6. Sample of reasonable best, lowest, and highest estimates of uncertain input variables (part 2 of 2).

Variable	Value Depends on	Description	Estimates		
			Best	Low	High
Duration of traffic restriction due to site restoration (DD_{QS})	Asset type (g), the restoration work due to damages or accidents at the site (QS) and the traffic restrictions (D) considered due to the intervention the asset type (g), damages or accidents at the site (QS)	Duration in hours of closure due to site restoration after the failure of a concrete bridge	120	30	360
Number of fatalities and injuries (Z)	Asset type (g), the type of restoration (QI) or risk-reducing (k) intervention	Number of fatalities due to an accident occurring by minor damage of a switch	0.027	0.023	0.034
Cost of the environmental impact of interventions ($C_{e\|I}$)		Cost of the environmental impact of executing a minor restoration on 1m of type 1 track section	€10	€5	€20
Cost of the environmental impact of site restoration ($C_{E\|QS}$)	Asset type (g), the restoration work due to damages or accidents at the site (QS)	Cost of the environmental impact of site restoration due to failure of 1m of type 1 track section	€29	€24	39
Asset dimensions (l)	Asset ID (a)	Deck surface area in m^2 of bridge B1	720	718	722
Additional travel time (DT)	Asset ID (a), and the traffic restrictions (D) considered	Cumulative additional travel time in minutes due to one-hour closure of the block sections where switch S1 is located during a day in the weekday	4735	3788	9470
The unit cost of time (u_t)	Location of the network (v)	Cost of one minute of delay in Dublin	€0.515	€0.34	€1.03
The unit cost of fatalities and injuries (U_Z)	Location of the network (v)	Cost of one fatality in Dublin	€1.5 million	€1 million	€3 million

3.5. Results

3.5.1. Initial Ranking Using Best Estimates

The net benefit and rank of the assets for possible risk-reducing interventions using the best estimates of the uncertain variables are shown in Figure 6. The assets were ranked from 1 to 73, and assets with the same net benefit were given the same position. The three assets with the highest net benefit were B16, B38, and T9. The net benefit of executing a risk-reduction intervention on each of these assets in the upcoming intervention-planning period was above €100,000, compared to postponing them until the next planning period. The next four assets with positive net benefit were S13, S22, T11, and B28. A risk-reducing intervention on these seven assets in the next intervention-planning period using the best estimates was beneficial because the costs and effects on service due to their renewal were less than the reduction in risk achieved by renewing them.

The remainder of the assets are switches, track sections, and bridges with a negative net benefit. If these assets were to be renewed in the upcoming intervention-planning period, the achieved reduction in risk in that period would be less than the costs and effects on service occurring due to their renewal. This certainly does not mean that it is not worthwhile to execute the risk-reducing intervention, which can only be said when the asset life-cycle costs are also evaluated. This analysis simply indicates that as regards the consequences of their renewal, there would not be a significant reduction in the risk related to these assets if they were to be renewed during the upcoming intervention-planning period.

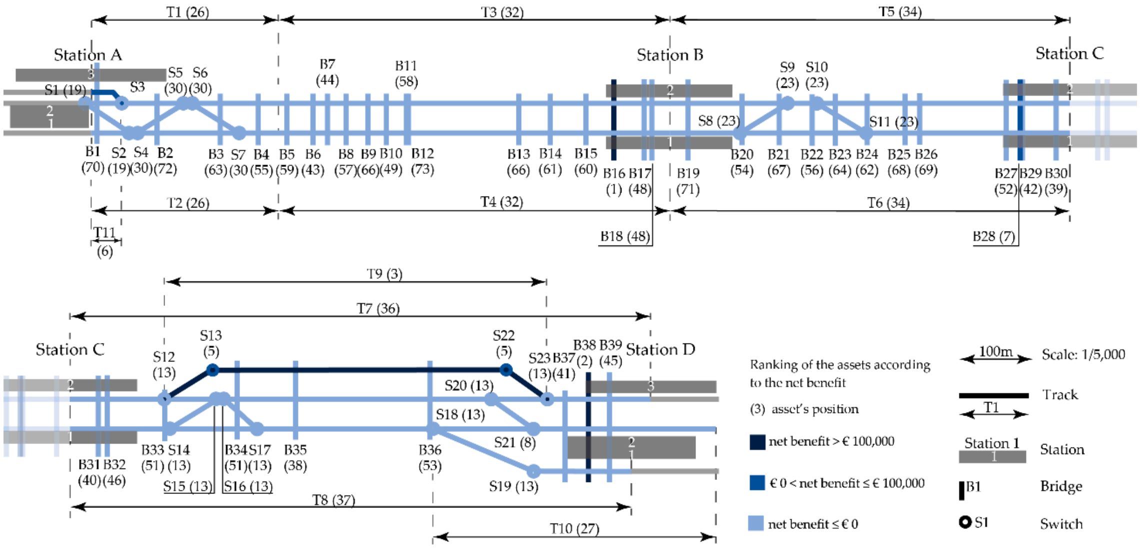

Figure 6. Assets ranked according to net benefit, using the best estimates for all the uncertain input variables.

3.5.2. Effect of Input Variable Uncertainties on Asset Rank

The effect of the input uncertainties on asset rank is presented in Tables 7 and 8 for each uncertain variable. It can be read as follows: the low estimates of the probabilities of occurrence of load events resulted in eight position changes when no position weights were considered. They resulted in 12 position changes when position weights were considered. Contrarily, the high estimates resulted in no position changes. The use of Monte Carlo sampling from skewed normal distributions resulted in a mean of two-position changes when no position weights were considered. However, when position weights were considered, it resulted not only in a mean of five-position changes.

Table 7. Effect of uncertain input variables on asset rank (part 1 of 2).

Variable	No. of Position Changes in the Ranking due to the Use of					
	Low Estimates		**High Estimates**		**Skewed Normal Distributions of Estimates**	
	Without (w/o) Weights	**Weighted**	**W/o Weights**	**Weighted**	**W/o Weights**	**Weighted**
	$SF_{X.low}$	$SF_{X.low\vert\theta}$	$SF_{X.high}$	$SF_{X.high\vert\theta}$	$\overline{SF_{X.distr}}$	$\overline{SF_{X.distr\vert\theta}}$
Probability of load event ($P[F_{le}]$)	8	18	0	0	3	5
Probability of infr. event ($P[F_{ie}]$)	118	19	64	4	41	10
Probability of network use event ($P[F_{ne}]$)	202	84	68	59	71	27
Probability of societal event ($P[F_{se}]$)	228	106	108	43	110	53
Cost of restoration int. (C_{QI})	32	52	8	18	12	20
Cost of risk-reducing int. ($C_{i\vert k}$)	32	52	8	18	12	20
Cost of site restoration (C_{QS})	8	15	116	257	22	48
Duration of traffic restriction due to int. (DD_I)	0	0	28	49	10	17

Table 8. Effect of uncertain input variables on asset rank (part 2 of 2).

Variable	No. of Position Changes in the Ranking due to the Use of					
	Low Estimates		High Estimates		Skewed Normal Distributions of Estimates	
	W/o Weights	Weighted	W/o Weights	Weighted	W/o Weights	Weighted
	$SF_{X.low}$	$SF_{X.low\|\theta}$	$SF_{X.high}$	$SF_{X.high\|\theta}$	$\overline{SF_{X.distr}}$	$\overline{SF_{X.distr\|\theta}}$
Duration of traffic restriction due to site restoration (DD_{QS})	0	0	16	31	2	8
Number of fatalities and injuries (Z)	84	218	72	4	30	41
Cost of the environmental impact of int. ($C_{e\|I}$)	16	31	0	0	6	11
Cost of the environmental impact of site restoration ($C_{E\|QS}$)	0	0	0	0	0	0
Asset dimensions (l)	16	31	0	0	6	11
Additional travel time (DT)	310	161	107	232	41	73
Unit cost of time (u_t)	18	11	84	237	19	43
Unit cost of fatalities and injuries (U_Z)	36	68	108	38	54	36

These results can be used to identify the influencing input variables whose uncertainty affects the ranking of the assets significantly. The results presented in Table 7 can be interpreted more easily by focusing on the maximum number of position changes only when the extreme estimates were used, and on the average number of position changes only when estimates from the distributions were used. This relationship is illustrated in Figure 7 with two circles for each variable: an empty circle when the position weights were not considered, SF_X, and a filled circle when the position weights were considered, $SF_{X|\theta}$. The input variables in Figure 7 are grouped as a function of the influence of their uncertainty in the ranking of the assets:

- Group A consists of input variables where the use of extreme values and value distributions resulted in a high number of weighted position changes, i.e., the highest-ranked assets are likely to change if the input uncertainties associated with these variables are considered.
- Group B consists of input variables where the use of extreme values and distributions of values resulted in a high number of position changes but with a low number of weight position changes, i.e., the rank of the lowest-ranked assets is likely to change if the input uncertainties associated with these variables are reduced. However, this does not occur in the rank of the highest-ranked assets. The effect of these input uncertainties is more prominent when low or high values are considered than when distributions of values are considered.
- Group C consists of input variables where the use of extreme values and distributions of values resulted in very few changes to the ranking. Considering the input uncertainties associated with these variables is unlikely to change the ranking of assets; therefore, the use of best estimates is sufficient in order to prioritize the assets for risk-reducing interventions accurately.

The most influencing input variables belong to Group A. The uncertainties in the values of these inputs were found to have the greatest effect on the highest-ranked assets. These input variables are the 'additional travel time' DT, the 'cost of site restoration' C_{QS}, the 'unit cost of time' u_t, and the 'number of fatalities and injuries' Z. They are all indicated in Figure 7 with red circles.

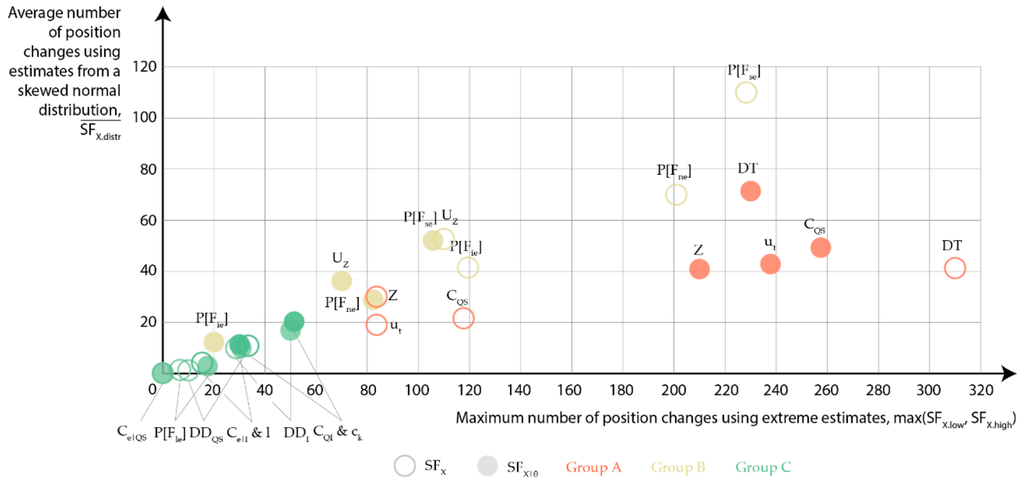

Figure 7. Effect of input variable uncertainties on asset rank.

These results prompt the following question: does the sensitivity of the ranking depend on the range of plausible values considered for each input variable? To answer this question, we examined if all the variables with the highest variance were also the most influencing ones. The variance of each input variable was considered equal to the average variance of all the skewed normal distributions used for this variable in the Monte Carlo sampling. The five input variables with the greatest variance were the 'duration of traffic restriction due to site restoration' DT_{QS}, the 'number of fatalities and injuries' Z, the 'probabilities of load events' $P[F_{le}]$, the 'extent of the assets' l and the 'duration of traffic restriction due to interventions' DD_I. Out of these five variables, only one is in Group A: the 'number of fatalities and injuries' Z. The remaining four variables are in Group C. These results indicate that it is not necessarily the greatest input uncertainties that yield the greatest changes in the ranking of the assets.

Identifying the most influencing variables is often not enough to limit the input uncertainties that must be quantified to a manageable amount. This is because an input variable might take different values depending on different parameters. For example, in the case study, the input variable 'additional travel time' takes different values for each asset and traffic restriction type, as shown in Figure 5. Hence, to quantify the uncertainties associated with this input variable, the uncertainties in the value 'additional travel time' for each asset and traffic restriction type must be quantified. In this case, it is useful to identify the assets, whose rank is affected significantly when there is uncertainty in the values used to represent the 'additional travel time'. This helps the railway manager focus on quantifying the input uncertainties of a variable only when they affect the ranking significantly. In situations when the input uncertainties of a variable do not affect the ranking of the assets, the railway manager can save resources by using the best estimates.

To identify the assets, whose rank is sensitive to the uncertainties in the variable 'additional travel time', we examined first how the use of samples from skewed normal distributions for this variable affects the rank of each asset. Then, we examined how many positions each asset changes in the ranking when skewed normal distributions for this variable are considered.

Figure 8 shows the average rank of each asset when samples of the skewed normal distributions for the variable 'additional travel time' and the best estimates of the rest of the variables were used. When this ranking is compared to the initial ranking (Figure 6), it can be seen that:

- 24 assets change their rank
- the first three assets with net benefit above €100,000, namely the bridges B16 and B38 and the track section T9, maintain their rank
- there are no changes in the rank of the assets with a positive net benefit
- track sections T1 and T2 have, on average, the most significant change in the ranking (6 positions).

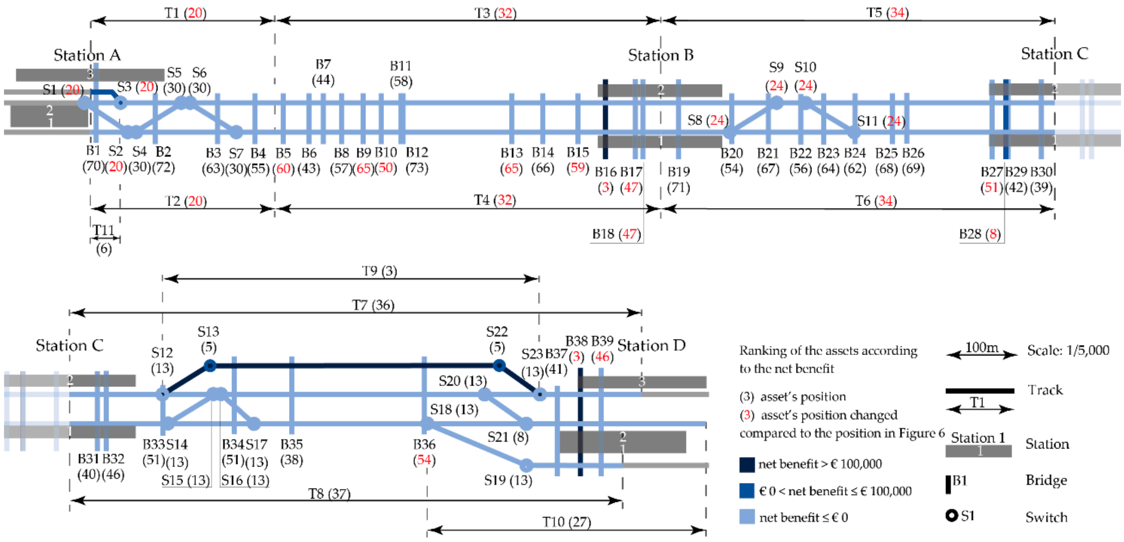

Figure 8. Assets ranked using Monte Carlo sampling from skewed normal distributions for the variable 'additional travel time' (*DT*) and the best estimates for the rest of the uncertain variables.

The results shown in Figure 8 indicate that the additional travel time uncertainties affect the rank of certain assets more than others. To identify the assets whose rank is affected by the additional travel time uncertainties, we examined how many positions each asset changed in the rank when samples of skewed normal distributions were used instead of best estimates for this input variable. Figure 9 shows these results. It can be seen that:

- assets T1 and T2 have the largest number of changes in rank (more than 10 positions)
- 15 switches change between one and five positions
- 56 assets change one position or less in the rank.

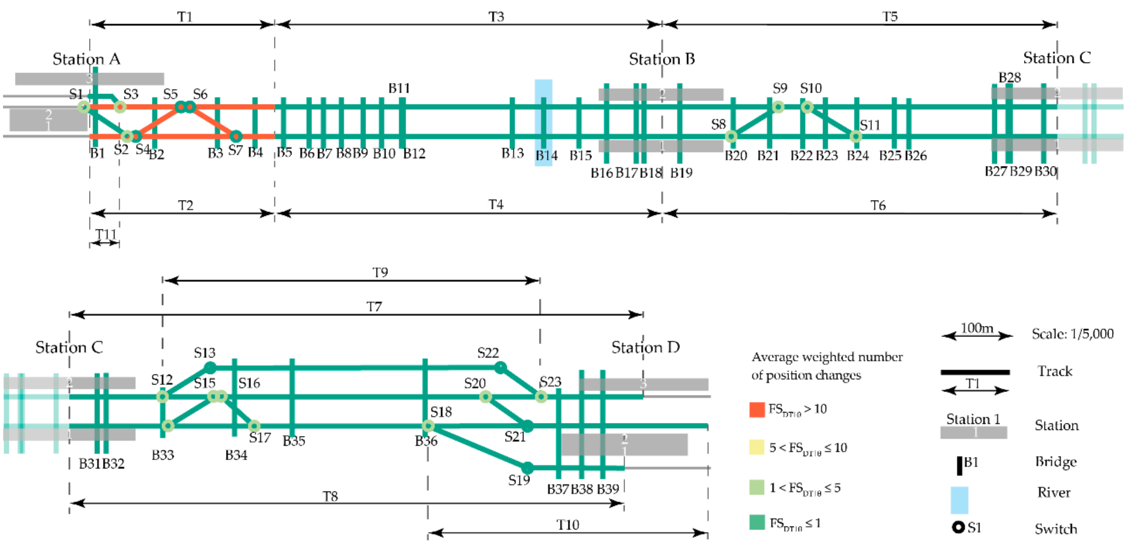

Figure 9. Expected number of weighted position changes using Monte Carlo sampling from skewed normal distributions for the variable 'additional travel time' (*DT*) and the best estimates for the rest of the uncertain variables.

The results shown in Figure 9 indicate that the additional travel time uncertainties affect the rank of track sections T1 and T2 significantly. However, this uncertainty is not expected to be important in order to obtain the rank of the rest of the assets accurately. This means that quantifying the uncertainties in the values used to represent the additional travel time only for two assets might be enough to accurately identify which assets should be prioritized in this case study for risk-reducing interventions.

One possible way to quantify these input uncertainties is to use sophisticated calibrated models to determine the distribution of this value, e.g., a microscopic traffic model, like the one presented in [93]. This model uses Kronecker Algebra to estimate with high accuracy the train runs and the additional travel time caused by closures or speed restrictions due to asset unavailability. For the rest of the assets, the use of the best estimates to model the additional travel time, when they are unavailable, should be sufficient to decide whether or not they should be prioritized for interventions.

4. Discussion

This section presents how the results can be interpreted to evaluate the effect of input uncertainties and how the methodology used in this paper compares to previous studies. The implications and limitations of the presented work are also discussed, while future research directions are mentioned at the end of the section.

The results show that railway managers can identify which input uncertainties are worth quantifying by examining if the assets are prioritized differently for risk-reducing interventions when, in addition to best estimates, extreme input values and skewed normal distributions of inputs are used. This analysis offers essential information to the railway manager who wants to quantify the uncertainty when prioritizing risk-reducing interventions using best estimates of inputs. The implications of the analysis presented in this work are discussed in this section.

In this analysis, the best, low, and high estimates were determined by experts using existing models and historical data. Although data-based methods should be preferred over experts' estimates when determining the inputs, in reality, it is often necessary to incorporate expert knowledge and experience to obtain initial results, due to data and budget constraints. This is related to a significant drawback. The input estimates might vary depending on the expert's experience, resources, and other factors [98], which cause uncertainty in the inputs. This paper does not address the challenges obtaining input estimates from experts. Examples of such methods to are described in [39,58,99]. This paper focuses on identifying the input uncertainties that significantly affect intervention planning, regardless of the cause of uncertainty in the input estimates. The results, therefore, can only be used to identify the influencing inputs, for which the uncertainties and their sources must be identified and assessed.

Monte Carlo sampling from skewed normal distributions was used as part of the methodology to identify the input uncertainties that affect which assets are prioritized for risk-reducing interventions. Although other distributions could be used for the input variables, the use of skewed normal distributions as shown in [57,61–66], is a reasonable simplification in this analysis. This is because its scope was not to quantify the uncertainty in the ranking but to obtain an initial impression of the effect on the ranking when distribution functions of the inputs are used instead of best estimates.

There are several implications and limitations related to the methodology and results presented in this paper to discuss. By evaluating the effect of varying one input at the time, while for the rest the best estimates were used, the uncertainties in the input variables were considered to be independent. Although investigating the correlation between inputs (for example, as done in [57]) would yield a more accurate evaluation of the input uncertainties, it would also require more data and more sophisticated modeling. This would require a more resource-demanding analysis. Once initial impressions of the sensitivity of the ranking to the different input uncertainties are obtained with the analysis presented here, the railway manager knows if certain input uncertainties are likely to affect the ranking significantly. If these highly influencing input uncertainties are also likely to be correlated, the railway manager can decide to invest in determining their correlation using precise modeling.

The results provide a clear indication of which input uncertainties are likely to affect the prioritization of assets for risk-reducing interventions. These results, however, do not provide any indication of the resources required to quantify these input uncertainties and to consider them in the estimation of risks, costs and effects on service. Assessing these resources should be the next step, in order to decide which input uncertainties are worth quantifying.

The assets in the case study were prioritized based on the reduction in risk achieved after being renewed, given the costs and effects on the service of this intervention. In this case, the renewal of the assets was used as an indication of how beneficial it is to execute a risk-reducing intervention on each asset. This is a simplification, as in reality, renewing an asset is not the only way to reduce its risk. However, this simplification is justified by the scope of this analysis, which is to identify the most influencing input uncertainties when prioritizing assets for risk-reducing interventions at a high level.

The methodology presented in this paper allows railway managers to consider the input uncertainties that affect which assets are prioritized for risk-reducing interventions. To this end, risks due to asset failures—as well as the costs and effects on service due to interventions—were estimated for different railway assets at a high level. Other researchers have focused on improving the understanding and modeling of one of those factors—i.e., risks, costs and effects on service—and for specific asset types. For example, [3] presents a detailed model that simulates the causal chain from climate change to scour risk related to the bridges of Network Rail. A detailed model to estimate risks related to railway accidents, when considering different environmental conditions is presented in [100]. A detailed model to estimate and minimize passenger delays due to train delays is presented in [38]. If desired, such detailed models could be used to improve the estimates of risks, costs, and effects on service. However, often the computational effort and cost are prohibitive for large asset portfolios. Thus, this approach is taken to enable railway managers to identify the influencing uncertainties at a high level first. Then they can decide where to invest resources to improve the estimates of risks, costs, and effects on service using more detailed approaches.

Future work in this area should investigate how reliable estimates of the input variables can be obtained from experts when resource limitations do not allow to use data-based methods and how the correlation of uncertainties of these estimates can be considered. The effect of using different distribution types to model the input uncertainties should also be examined. Additionally, future work should also address the ease of reducing the input uncertainties for each variable. Finally, the complexity of planning risk-reducing interventions should be integrated by considering, for example, different intervention types for each asset and the effects on service when interventions are executed simultaneously, which is now becoming possible to analyze using the model presented by [41] or others.

5. Conclusions

This paper shows how the input uncertainties that significantly affect the assets prioritized for risk-reducing interventions were identified. It was achieved by using reasonable low and high input estimates, as well as samples from skewed normal distributions in addition to the best estimates. This approach is suitable for railway managers who have already obtained initial impressions of which assets should be prioritized for risk-reducing interventions using best estimates of the input values and who would then like to know which input uncertainties are likely to influence these results, and therefore must be quantified.

This approach was implemented on a case study to prioritize track sections, switches, and bridges for renewal. The results indicate the input variables that are related to highly influencing uncertainties. Efforts should be focused to quantify these uncertainties and efficiently improve the planning of risk-reducing interventions.

Supplementary Materials: The following are available online at http://www.mdpi.com/2673-4109/1/2/0008/s1, A supplementary file with the input values is submitted with the paper.

Author Contributions: Conceptualization, N.P. and B.T.A.; Methodology, N.P.; Software, N.P.; Formal analysis, N.P.; Resources, N.P.; Data curation, N.P.; Writing—Original draft preparation, N.P.; Writing—Review and editing, N.P. and B.T.A.; Visualization, N.P.; Supervision, B.T.A. All authors have read and agreed to the published version of the manuscript.

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Appendix A

Tables A1–A3 present the load, infrastructure, and network use events, respectively, per asset type. The societal events for track sections are given in Tables A4 and A5, while Tables A6 and A7 present the societal events for switches and bridges, respectively.

Table A1. Load events, *LE*, per asset type.

Load Event Type	Notation	Description		
		Track	**Switches**	**Bridges**
Traffic load	le|TR	Annual tonnage on the track section based on the timetable	Annual wheel load on the switches due to train movements based on the timetable	Normalized annual traffic loads due to the daily traffic based on the timetable
Level 1 load due to natural hazard	le1|NH	Thermal stresses on the track section caused by 17 °C ambient temperature	Neglectable thermal stresses on the switch elements	Neglectable increase in river flow speed
Level 2 load due to natural hazard	le2|NH	Thermal stresses on the track section caused by 25 °C ambient temperature	Moderate thermal stresses on the switch elements	River flow speed that corresponds to a 25-year flood event
Level 3 load due to natural hazard	le3|NH	Thermal stresses on the track section caused by 40 °C ambient temperature	High thermal stresses on the switch elements	River flow speed that corresponds to a 50-year flood event
Level 4 load due to natural hazard	le4|NH	Thermal stresses on the track section caused by 43 °C ambient temperature	Thermal stresses beyond the designed level on switch elements	River flow speed that corresponds to a 100-year flood event
Level 4 load due to natural hazard	le5|NH	Thermal stresses on the track section caused by 60 °C ambient temperature	-	-

Table A2. Infrastructure events, *IE* per asset type.

Infrastructure Event Type	Notation	Description		
		Track	**Switches**	**Bridges**
No damage	ie1	No noticeable damages on the track section due to the load event	No noticeable damages on the switch due to the load event	No noticeable damages on the bridge due to the load event
Minor damage	ie2	Damages that partially affect the track geometry or the rail condition	Damages that partially affect either the condition of the elements or the operation of the switch	Damages that partially affect the structural stability
Severe damage	ie3	Potential lack of stability of the track section to support the dynamic wheel load according to the required speed	Damages that significantly affect either the condition of the elements or the operation of the switch	Potential lack of structural stability

Table A3. Network use events, *NE*, per asset type.

Network Use Event Type	Notation	Description		
		Track	Switches	Bridges
Normal use	ne1	Fully operational track section	Fully operational block	Fully operational block
Maximum speed restriction	ne2	The operation of the track section is possible only when the speed is less than 40 km/h	The operation of all affected blocks is possible only with speed below 40 km/h	The operation of the block where the bridge is located is possible only with speed below 40 km/h
Closure	ne3	Closure of track section and all the blocks located in this track section	Closure of switch and all the affected blocks	Closure of the bridge and all the affected blocks

Table A4. Societal events, *SE*, used for the estimation of risk related to track sections (first part se1–se14).

Notation	Description	Notation	Description
se1	No accident; no restoration at the site and no intervention; no traffic restriction	se8	Accident; minor restoration at the site, rail replacement and tamping of the track section; traffic restrictions due to restoration, rail replacement, and tamping
se2	No accident; no restoration at the site and no intervention; maximum speed restriction for 24 hours	se9	Accident; minor restoration at the site and renewal of the track section; traffic restrictions due to restoration and track section replacement, and maximum speed restriction for a week after renewal
se3	No accident; no restoration at the site and track section renewal after a month; maximum speed for a month until track section replacement and for a week after the renewal	se10	No accident; minor restoration at the site and tamping of the track section; maximum speed restriction until the restoration of the site is complete, and the track section is tamped
se4	No accident; minor restoration at the site and tamping of the track section; traffic restrictions due to restoration and tamping	se11	No accident; minor restoration at the site, and rail replacement and tamping of the track section; maximum speed restriction until the restoration of the site is complete, and the rail is replaced, and the track section is tamped
se5	No accident; minor restoration at the site and rail replacement and tamping of the track section; traffic restrictions due to restoration and rail replacement	se12	No accident; minor restoration at the site and track section renewal; maximum speed restriction until the restoration of the site is complete, the track is renewed and for a week after renewal
se6	No accident; minor restoration at the site and renewal of the track section; traffic restrictions due to restoration and track section replacement and maximum speed restriction for a week after renewal	se13	Accident; minor restoration at the site and tamping of the track section; maximum speed restriction until the restoration of the site is complete, and the track section is tamped
se7	Accident; minor restoration at the site and tamping of the track section; traffic restrictions due to restoration and tamping	se14	Accident; minor restoration at the site and rail replacement and tamping of the track section; maximum speed restriction until the restoration of the site is complete, the rail is replaced, and the track section is tamped

Table A5. Societal events, *SE*, used for the estimation of risk related to track sections (second part se15–se21).

Notation	Description	Notation	Description
se15	Accident; minor restoration at the site and track section renewal; maximum speed restriction until the restoration of the site is complete, the track section is renewed, and for a week after renewal	se19	No accident; major restoration at the site and track section renewal; traffic restrictions until the restoration of the site is complete, and the track section is renewed; maximum speed restriction for a week after renewal
se16	No accident; minor restoration at the site and tamping of the track section; closure of the section until the restoration of the site is complete, and the track section is tamped	se20	Accident; major restoration at the site and track section renewal; traffic restrictions until the restoration of the site is complete, and the track section is renewed; maximum speed restriction for a week after renewal
se17	No accident; minor restoration at the site, and rail replacement and tamping of the track section; closure of the section until the restoration of the site is complete, the rail is replaced and the track is tamped	se21	No accident; major restoration at the site and track section renewal; closure of the section until the restoration of the site is complete, and the track section is renewed; maximum speed restriction for a week after renewal
se18	No accident; minor restoration at the site and track section renewal; closure of the section until the restoration of the site is complete, and the track section is renewed; maximum speed restriction for a week after renewal		

Table A6. Societal events, *SE*, used for the estimation of risk related to switches.

Notation	Description	Notation	Description
se1	No accident; no restoration at the site and no intervention; no traffic restriction	se9	No accident; minor restoration at the site and switch renewal; maximum speed restriction until the restoration of the site is complete, and the switch is renewed
se2	No accident; no restoration at the site and no intervention; maximum speed restriction for 24 hours	se10	Accident; minor restoration at the site and welding or grinding of the switch; maximum speed restriction until the restoration of the site is complete, and welding or grinding is performed on the switch
se3	No accident; no restoration at the site and switch renewal after a month; maximum speed for a month until switch renewal	se11	Accident; minor restoration at the site and switch renewal; maximum speed restriction until the restoration of the site is complete, and the switch is renewed
se4	No accident; minor restoration at the site and welding or grinding of the switch; traffic restrictions due to restoration and interventions	se12	No accident; minor restoration at the site and welding or grinding of the switch; closure of the section until the restoration of the site is complete, and the switch is welded or ground
se5	No accident; minor restoration at the site and switch renewal; traffic restrictions due to restoration and switch renewal	se13	No accident; minor restoration at the site and switch renewal; closure of the section until the restoration of the site is complete, and the switch is renewed
se6	Accident; minor restoration at the site and welding or grinding of the switch; traffic restrictions due to restoration and welding or grinding	se14	No accident; major restoration at the site and switch renewal; traffic restrictions until the restoration of the site is complete, and the switch is renewed
se7	Accident; minor restoration at the site and switch renewal; traffic restrictions due to restoration and switch renewal	se15	Accident; major restoration at the site and switch renewal; traffic restrictions until the restoration of the site is complete, and the switch is renewed
se8	No accident; minor restoration at the site and welding or grinding of the switch; maximum speed restriction until the restoration of the site is complete, and the switch is welded or ground	se16	No accident; major restoration at the site and switch renewal; closure of the section until the restoration of the site is complete, and the switch is renewed

Table A7. Societal events, *SE*, used for the estimation of risk related to bridges.

Notation	Description	Notation	Description
se1	No accident; no restoration at the site and no intervention; no traffic restriction	se9	No accident; minor restoration at the site and bridge renewal; maximum speed restriction until the restoration of the site is complete, and the bridge is renewed
se2	No accident; no restoration at the site and no intervention; maximum speed restriction for 24 hours	se10	Accident; minor restoration at the site and strengthening of the bridge; maximum speed restriction until the restoration of the site is complete, and the bridge is strengthened
se3	No accident; no restoration at the site and bridge renewal after a month; maximum speed for a month until bridge renewal	se11	Accident; minor restoration at the site and bridge renewal; maximum speed restriction until the restoration of the site is complete, and the bridge is renewed
se4	No accident; minor restoration at the site and strengthening of the bridge; traffic restrictions due to restoration and interventions	se12	No accident; minor restoration at the site and strengthening of the bridge; closure of the section until the restoration of the site is complete, and the bridge is strengthened
se5	No accident; minor restoration at the site and renewal of the bridge; traffic restrictions due to restoration and bridge renewal	se13	No accident; minor restoration at the site and bridge renewal; closure of the section until the restoration of the site is complete, and the bridge is renewed
se6	Accident; minor restoration at the site and strengthening of the bridge; traffic restrictions due to restoration and intervention on the bridge	se14	No accident; major restoration at the site and bridge renewal; traffic restrictions until the restoration of the site is complete, and the bridge is renewed
se7	Accident; minor restoration at the site and renewal of the bridge; traffic restrictions due to restoration and bridge renewal	se15	Accident; major restoration at the site and bridge renewal; traffic restrictions until the restoration of the site is complete, and the bridge is renewed
se8	No accident; minor restoration at the site and strengthening of the bridge; maximum speed restriction until the restoration of the site is complete, and the bridge is strengthened	se16	No accident; major restoration at the site and bridge renewal; closure of the section until the restoration of the site is complete, and the bridge is renewed

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