Deducing design rules for junctions in urban areas based on multiple objectives

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Abstract

The performance of junctions is an important part of the performance of a traffic network. Therefore, the selection of junctions should be carried out with great care. Currently, most junction design rules used to determine the preferred main junction type and lane configuration require junction performances as input. Junction performances are obtained through modelling, which is too time-consuming to perform for many junction design alternatives. Therefore, a quick selection of feasible junction designs is made first, using only the expected traffic demand. This first selection is based on operational performance, neglecting other indicators, resulting in well performing junction designs being easily eliminated. Therefore, a new set of junction design rules is desired. These new rules should be based on a combination of multiple performance indicators, while requiring only the traffic demand and available space as input.

This paper proposes a methodology for the deduction of a new set of design rules. A combination of non-compensatory multi criteria analyses and decision tree training is used to derive junction design rules using operational, safety and emission performances of 24 different junction designs, for a large number of traffic demand patterns. Resulting design rules allow decision makers to make a quick first selection of feasible junction designs, showing the overall feasibility of the different designs, together with an insight in the performances of the junction types on the different indicators. The design rules show an accuracy of 89.9%.

Keywords: Junction design rules, design rule deduction, decision tree training, multi criteria analysis

Introduction

Road planners frequently need to determine the best junction design for a specific location. For the selection of the junction design, they have junction design rules at their disposal. Most junction design rules require junction performances, which need to be obtained through modelling. Modelling of junction design performances is time-consuming, with the computation time increasing with a larger number of junction designs. Therefore, in order to reduce the overall computation time, a first selection of junction designs is made, based on the expected traffic demand pattern and the available space. This first selection is based on operational performance only, neglecting other indicators such as safety, emissions and noise. As shown by Bezembinder et al. (2016), this results in well performing junctions being easily eliminated. A new set of junction design rules is therefore desired. The goal of this paper is to propose a methodology for systematically deducing junction design rules based on multiple performance indicators. Resulting design rules should allow junction designers to quickly select feasible junction types while requiring only the expected traffic demand and the available space.

For the systematic deduction of design rules, a large set of junction performance data is needed. Such data can be acquired either through field measurements or by using traffic models. Field measurements are expensive, and therefore undesirable if much data is required, and will result in a lack of comparison for different junction designs with similar traffic conditions. Therefore, data used in this paper is derived from traffic models, which also benefits from consistency in junction designs. Performances of 24 different junction designs on 100.000 different traffic demand patterns are used. Operational performances of the junctions are derived from the Highway Capacity Manual 2010 methodology (Transportation Research Board, 2010); safety performances are derived using the Highway Safety Manual 2009 methodology (Transportation Research Board, 2009); and emission performances are derived with a queue length based emission model using HCM output, as proposed by Gasthuis (2015).

Junction design rules have evolved over time into the rules now being used, instead of being derived systematically. Previously, studies have been conducted into systematically deducing junction design rules based on a single objective, for instance by Tarko et al. (2010), Vitins and Axhausen (2012) and Bezembinder et al. (2015). In all these cases, only the expected traffic demand and/or the available space is required as input. Both Tarko et al. (2010) and Bezembinder et al. (2015) have used decision tree training to categorise instances based on waiting time to deduce design rules, both with accurate results. In all three researches, however, only operational performances have been used as objectives for the design rules, neglecting other performance indicators such as safety and environmental indicators.

Deducing junction design rules based on multiple objectives is more complicated. In case of a single objective, the input of decision tree training consists of the junction designs with the best performances on the given objective. In case of more objectives, however, determining the best design is more difficult. Selecting the best designs for each objective would not necessarily result in the overall best design being selected. Weighing the objectives directly is also undesirable, due to the nature of the objectives, as it is ethically undesirable to compensate for a loss in traffic safety with an increased operational performance. Using Pareto optimality would by definition result in including the overall best design in the selection, but it would not necessarily return the full set of most feasible junction designs. This leaves multi-criteria decision making methods which do not require compensation among objectives. These so-called non-compensatory methods instead select feasible alternatives based on consecutive evaluations of the performances of the individual objectives; either through elimination of undesirable designs or through the selection of best performing designs on the given performance indicator. Criteria for the evaluations can be selected from existing junction design rules. In this paper, different combinations of non-compensatory methods, based on current junction design rules, are tested as pre-processing step before the decision tree training.

In this paper, the possibilities of deducing junction design rules for multiple objectives by combining a multi-criteria approach with decision tree training are presented. In the first section, current junction design rules, previous studies into junction design rule deduction and the concept of decision tree training are described in more detail. This is followed by a description of the models used to generate the dataset containing the junction design performances. The following section provides the framework used to derive junction design rules. Next, results are presented and discussed, followed by concluding remarks and recommendations for further research.

Current junction design rules

Current junction design rules are regarded both to illustrate the need for better design rules, and to find components for the selection of the best junction designs. The goal of this research is to find design rules suitable for the Dutch traffic situation; therefore existing Dutch design rules are evaluated. Junction design rules are found in a range of publication by CROW (2002, 2008, 2012, 2015). Although all publications provide designers a set of rules for the selection of the best junction design, the rules differ over the publications. In this section, the most important parts of the different publications are reviewed.

Generally, junction design rules can be divided into two categories, depending on the input required for the design rules. Most rules require junction performances, to be obtained through modelling; others only require the expected traffic demand. Both types of rules can either be used to eliminate insufficient junction designs or to select junction designs based on their performance.

A general rule is that the type of junction needs to be in concordance with the type of roads leading to the junction, meaning for instance that when there is a clear distinction in importance between the two roads, this must be visible in the design of the junction. (CROW, 2015)

Most of the rules base the choice of junction design on the operational performance of the junction, with constraints for the resulting performance on safety, noise and emissions, for the possibility of giving priority and for cost. In the ASVV (CROW, 2012), (static) capacities of different junction types are given, though for a limited number of general designs. In “Characteristics for Junctions and Roundabouts” (CROW, 2015), it is also expressed that for the choice of junction design, the expected traffic demand must be in accordance with the capacity of the junction, though without providing concrete capacities for all possible junction designs. A problem with junction capacity is that it depends on more than only the total traffic demand. For instance, fractions of left turning traffic and the distribution of major and minor traffic also influence the junction capacity. Besides capacity, the only specific requirement mentioned regarding operational performance is found in the publication “Turbo Roundabouts” (CROW, 2008): junctions are only feasible when the maximum delay on a major leg of the junction is below 35 seconds, and the maximum delay on a minor leg of the junction is below 50 seconds.

Concerning safety, the only specific rule is found in “Manual for Road Design” (CROW, 2002): For safety reasons, roundabout are strongly preferred over prioritised junctions, which are again preferred over signalised junctions. However, this preference only applies for junction designs which show a good enough performance on operational level and other levels. The exact requirements for junctions to comply with on other levels are not mentioned. No specific rules regarding emission performances are present in the existing manuals.

From the rules found in the manuals, the waiting time criterion and the preference for main junction type seem promising for the selection of the best junction design based on the performance of the designs. These criteria are therefore tested on their applicability.

Junction design rule deduction

Han et al. (2008), Tarko et al. (2010), Vitins and Axhausen (2012) and Bezembinder et al. (2015) all analysed possibilities of deducing junction design rules while only requiring data readily available in the junction design process, being traffic demands or related properties (i.e. left turn percentage) and available size. In all cases, the data used for the analyses were derived from traffic models. Han, Vitins and Axhausen, and Bezembinder all used volume average junction delay, determined using the Highway Capacity Manual (Transportation Research Board, 2010); while Tarko used the number of stops alongside the average junction delay, determined using VISSIM. The disadvantage of using a micro simulation model such as VISSIM is the long calculation times; such a model can therefore only be used for a relatively small number of runs. In two researches (Bezembinder et al., 2015; Tarko et al., 2010), decision tree training was used to deduce junction design rules, showing promising results. These researches show that for junction design rule deduction, the use of decision tree training in combination with traffic models such as the HCM are promising methods.

Research by Bezembinder et al. (2016) has shown the danger of basing the design of a junction on a single indicator, which was the case in all of the researches mentioned above. Hradil et al. (2012; 2014) have systematically executed junction design processes using different objectives (capacity and delay, safety, emissions, noise, costs and spatial restrictions) to determine the best junction design. They used a multi criteria analysis with two main steps to assess different junction designs on the different objectives: first, junction types were eliminated using threshold values, and secondly, the remaining junction designs were evaluated based on the performance on different objectives. Although they did not deduce junction design rules, they do provide a suitable method for the selection of the best junction design, of which the use in junction design rule deduction will be analysed in this paper.

No previous researches are performed in which junction design rules are deduced based on multiple objectives. However, from research into junction design rule deduction, promising features are obtained, such as decision tree training and the use of the HCM to obtain traffic data. Also, the use of elimination and evaluation in a multi criteria approach to obtain the best junction design seems promising.

Decision trees

Decision trees are rooted trees which can be used to classify instances based on their characteristics. A decision tree has exactly one incoming edge per node, except for the first node, which has no incoming edges. A node with outgoing edges has at least two outgoing edges (in case of exactly two outgoing edges at each node, the decision tree is called a binary tree), and is called an internal node. A node without outgoing edges is called a leaf. At each internal node, a split of the instance space is performed based on a certain criterion (splitting criterion) depending on the characteristics of the instances. Each leaf is assigned to the instances found in the instance space of the leaf. A leaf can either be assigned explicitly to one class, in which case the decision tree is a crisp classifier, or to a vector of probabilities for different classes, in which case the tree is a probabilistic classifier.

An example of a decision tree is given in Figure 1, in this case for the selection of a junction design based on waiting time. Here it is shown, for instance, that with a through volume of less than 1434.5, in 91.2% of the cases, a roundabout with design RA3 has the lowest waiting time. A signalised junction only performs best in most of the cases with a through volume higher than 2028.5 and a major through volume higher than 497.5; in which case the junction with design SIG8 has the lowest waiting time in 59.4% of the cases.

Decision trees can be created using decision tree inducers. A number of inducers are suggested in literature, differing in their use of split criteria (determining how to split the instance set), use of pruning (reducing the tree size after the tree growing process) and resulting tree type (binary, with only binary splits; or non-binary). The no free lunch theorem applies to decision tree inducers, meaning that no inducer is superior for all applications, but rather depends on the characteristics of the dataset used (Rokach and Maimon, 2008).

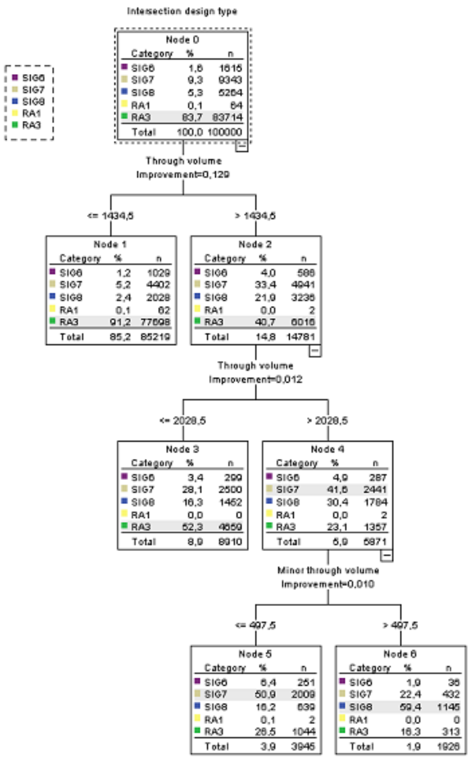

Figure 1. An example of a decision tree, from Bezembinder et al. (2015)

The five most used decision tree inducers, according to Rokach and Maimon (2008), are ID3, C4.5, CART, CHAID and QUEST. Both ID3 and C4.5 are designed by Quinlan (Quinlan, 1987, 1993), with C4.5 being an evolution of ID3. Both use information gain as splitting criteria. ID3 does not perform pruning, C4.5 performs error-based pruning. CART (Classification And Regression Trees) is developed by Breiman et al. (1984). CART constructs binary trees. Splits are selected either with the Twoing Criteria or the Gini impurity measure. CART performs pruning with Cost-Complexity Pruning. CHAID (Chi-squared Automatic Interaction Detection) was first proposed by Kass (1980). A Pearson chi-squared test or likelihood ratio test is used to determine splitting criteria. As opposed to CART, CHAID uses multi way node splitting instead of binary splitting. No pruning is performed by CHAID. Biggs et al. (1991) proposed Extensive CHAID, using a more thorough method for grouping predictor categories. QUEST (Quick, Unbiased, Efficient Statistical Tree) was proposed by Loh and Shih (1997).

QUEST also constructs binary trees, using Pearson chi-squared test to determine splitting criteria. Pruning is done using ten-fold cross-validation.

A review by Lim et al. (2000) of a number of decision tree inducers for thirty-two datasets has shown that from a large number of decision tree algorithms, C4.5, CART and QUEST provide the best results, with the remark that C4.5 tends to produce much larger trees than CART and QUEST. In a research by Oña et al. (2013) into decision rules for accident prevention, CART, ID3 and C4.5 are used, concluding that the applicability of CART is limited due to its binary nature, and that C4.5 tends to generate extensive trees, resulting in a large number of rules. An analysis of the applicability of decision trees in junction design rule deduction, performed by Bezembinder et al. (2015), has shown that of CART, CHAID and QUEST, CART gives the highest accuracy, which is defined as the percentage of cases for which the decision tree selects the correct instance.

For the choice of decision tree inducer, a subsequent analysis is performed, comparing CART, CHAID and QUEST with the data used in this paper. The different decision trees resulting from the different inducers were assessed on the types of classifications: correct classification, infeasible junction type selected (due to an average waiting time above the threshold value of 35 seconds), different main junction type selected or different junction design selected. Penalties were assigned to the different incorrect classification types: the highest for infeasible junction type, followed by different main junction type and the lowest for different junction design. 100.000 random cases were used to calculate the sums of the penalties for the different inducers, with the lower the penalty, the better the inducer. Of the different inducers, CHAID performed best; therefore, CHAID is used as decision tree inducer in this paper.

Dataset

The dataset consists of operational performance (average waiting time, maximum waiting time for turn flow on major/minor leg), safety performance (expected number of incidents) and emission performance (average exhaust of NO_x and PM_{10}) for 24 different junction designs (shown in Table 1) and 200.000 randomly generated traffic demand patterns (consisting of 12 flows, one for each turn direction), with a total flow between 500 and 8000 pcu/h. Each junction design is assigned to a size category, depending on the total area occupied by the junction design. The dataset is split randomly in a training set, used for decision tree training, and a test set, used to perform the cost-benefit analysis, both with 100,000 traffic demand patterns.

Table 1. Different junction design types

Main type	Junction type	Major road approaches				Minor road approaches				Size Cat.
		Entry lanes	Exit lanes	Circ.	CR	Entry lanes	Exit lanes	Circ.	CR	
AWSC	AW1	1: ↰↑↱	1	-	0.0	1: ↰↑↱	1	-	0.0	1
TWSC	TW1	1: ↰↑↱	1	-	0.0	1: ↰↑↱	1	-	0.0	1
	TW2	1: ↰↑↱	1	-	5.0	1: ↰↑↱	1	-	0.0	2
	TW3	2: ↰ ↑↱	1	-	0.0	1: ↰↑↱	1	-	0.0	2
	TW4	2: ↰ ↑↱	1	-	5.0	1: ↰↑↱	1	-	0.0	2
	TW5	2: ↰ ↑↱	1	-	5.0	2: ↰ ↑↱	1	-	0.0	2
Signalised	SIG1	1: ↰↑↱	1	-	0.0	1: ↰↑↱	1	-	0.0	1
	SIG2	2: ↰ ↑↱	1	-	0.0	1: ↰↑↱	1	-	0.0	2
	SIG3	2: ↰ ↑↱	1	-	0.0	2: ↰ ↑↱	1	-	0.0	2
	SIG4	3: ↰ ↑ ↱	1	-	0.0	2: ↰ ↑↱	1	-	0.0	2
	SIG5	3: ↰ ↑ ↱	1	-	0.0	3: ↰ ↑ ↱	1	-	0.0	3
	SIG6	4: ↰ ↑ ↑ ↱	2	-	0.0	2: ↰ ↑↱	1	-	0.0	3
	SIG7	4: ↰ ↑ ↑ ↱	2	-	0.0	3: ↰ ↑ ↱	1	-	0.0	3
	SIG8	4: ↰ ↑ ↑ ↱	2	-	0.0	4: ↰ ↑ ↑ ↱	2	-	0.0	3
	SIG9	6: ↰ ↰ ↑ ↑ ↱ ↱	2	-	0.0	4: ↰ ↑ ↑ ↱	2	-	0.0	4
	SIG10	6: ↰ ↰ ↑ ↑ ↱ ↱	2	-	0.0	6: ↰ ↰ ↑ ↑ ↱ ↱	2	-	0.0	4
Roundabout	RA1	1: ↰↑↱	1	1	0.0	1: ↰↑↱	1	1	0.0	3
	RA2	1: ↰↑↱	1	2	0.0	1: ↰↑↱	1	2	0.0	4
	RA3	2: ↰↑ ↱	1	1	0.0	1: ↰↑↱	1	1	0.0	4
	RA4	2: ↰↑ ↱	2	1	0.0	1: ↰↑↱	1	2	0.0	3
	RA5	1: ↰↑ ↱ *	1	1	0.0	1: ↰↑ ↱ *	1	1	0.0	3
	RA6	1: ↰↑ ↱ *	1	1	0.0	2: ↰ ↑↱*	1	1	0.0	4
	RA7	2: ↰↑ ↑↱	2	1	0.0	2: ↰↑ ↑↱	1	2	0.0	4
	RA8	2: ↰ ↑ ↱ *	2	2	0.0	3: ↰↑ ↱*	2	2	0.0	4

Junction types

In Table 1, the 24 different junction types are shown. Four different man junction types are used: all-way stop controlled junctions (AWSC), two-way stop controlled junctions (TWSC), signalised junctions and roundabouts. Further differentiation is made through the number of entry and exit lanes on major and minor approaches, the number of circulating lanes (circ.; in case of roundabouts) and the central reservation space (CR). Each junction type is characterised with a size category, depending on the total area of the junction: category 1 contains junctions with area up to 400 m2, category 2 up to 800 m2, category 3 up to 1600 m2 and category 4 contains all junctions with an area greater than 1600 m2.

Performance indicators

The operational performances are modelled using the HCM 2010 methodology (Transportation Research Board, 2010). For required parameters other than junction design attributes and flow rates, the values suggested in the HCM 2010 are used. Signal control settings were determined using the "Quick Estimation Method" from the HCM 2010 (Chapter 31).The model returns the flow average delay for each turn, from which the maximum delay for a major direction, the maximum delay for a minor direction and the overall average delay are determined.

Safety performances were modelled using the HSM 2009 methodology (Transportation Research Board, 2009). This methodology determines both the number of fatal-and-injury incidents and the property-damage-only incidents, requiring only junction characteristics, signal properties and major and minor AADT (annual average daily traffic) flows. The AADT flows are derived from the hourly flows (in pcu/h) by multiplying the hourly flow by ten, as derived from CROW (2008). The HSM methodology can be used to determine the number of incidents for prioritised junctions and signalised junctions. For roundabout junctions, the number of incidents can be calculated from the number of incidents on a corresponding prioritised junction (equal number of entry and exit lanes) using a conversion factor. For all-way stop controlled junctions, no parameters are given; therefore, parameters for prioritised junctions are used to calculate the number of incidents at all-way stop controlled junctions. According to the "Sustainable Safe" program in the Netherlands (CROW, 2013), the focus in increasing traffic safety lies on decreasing the number of casualties and injuries due to traffic incidents. Therefore, the number of fatal-and-injury incidents is used in the multi criteria approach.

The emissions of NO_x and PM_{10} were calculated using the queue length based emission model proposed by Gasthuis (2015), using the HCM methodology and Little's Law to calculate queue lengths. For this model, only traffic flows and junction design attributes are required. Not all emission substances are modelled; therefore, these emission levels can only be used to compare different alternatives. The emission performance used in the multi criteria approach is a weighted combination of the emissions of NO_x and PM_{10}, using the external costs of the substances as found in (CE Delft, 2008) as weight factors.

Research framework

The research framework, as shown in Figure 2, consists of three steps. In the first step, a multi criteria assessment is performed to select the set of best junction designs for 400.000 different combinations of traffic demand pattern and size category. If no feasible design is returned in the multi criteria approach, the label 'no feasible design' is assigned. All cases are then used as input for decision tree training. This is done for eight different multi criteria assessments, resulting in eight different decision trees. In the third step, the different approaches are analysed using a cost benefit analysis and by determining the accuracy of the resulting design rules. Of the two datasets available, both containing 100.000 traffic demand patterns, as previously described in the section 'Dataset', the training set will be used for step 1 and 2. The test set will be used for step 3.

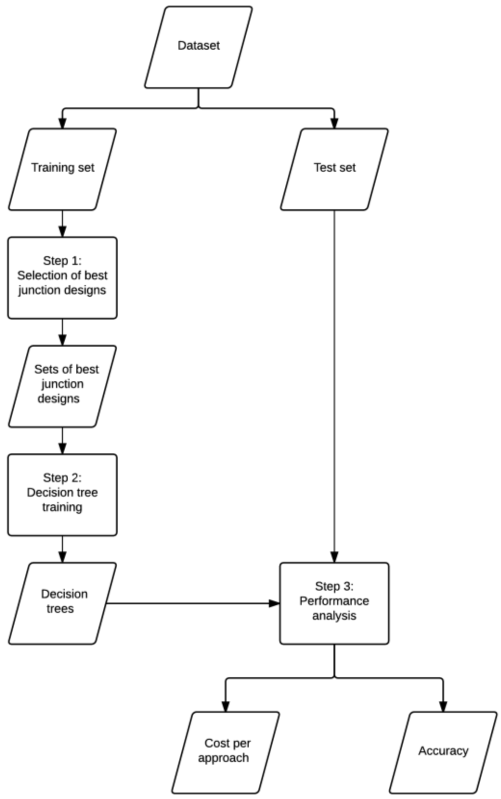

Figure 2. Research framework

Step 1. Selection of best junction designs

For each combination of demand pattern and size category, one or more best junction designs are determined using a multi criteria assessment. Three components were used in the different approaches, of which two were derived from current junction design rules (in the section "Current junction design rules"): a maximum delay criterion and a selection based on main junction type. These first two components are used to eliminate undesirable junction types, but they do not compare the performances of the junction types. Therefore, a sequential elimination method is used to compare the designs on the three objectives consecutively, resulting in a small set of preferred junction designs. Approaches were tested either with or without the delay criterion and main type selection, and with either of two sequential elimination methods: Lexicographic Elimination (LE), selecting the absolute best junction designs; or Lexicographic Semi-order (LS), selecting all designs within a significance level.

The maximum delay criterion eliminates all alternatives with an average delay on a major approach higher than 35 seconds and/or with an average delay on a minor approach higher than 50 seconds. In some cases, this results in all possible designs being eliminated, in which case, "no design" is used as input for the decision tree training.

The main junction type selection eliminates designs based on a preference for certain main junction types: roundabouts are preferred over other non-signalised junctions, which are again preferred over signalised junctions. Therefore, if any roundabout design is still present in the set of feasible junction designs, all non-roundabout designs are eliminated. Else, if non-signalised designs (AWSC, TWSC) are present in the set of feasible junction designs, then all signalised junction designs are eliminated.

The sequential elimination methods, LE and LS, both regard the three performance indicators one by one. The sequence in which the performance indicators are regarded is: first safety, then operational performance and lastly emissions performance; except when a selection based on main junction type has been performed (which is based on safety performance of main junction types), in which case safety is regarded last.

In case of LE, the junction designs are sorted based on the performance of the indicator in question, and the top *n* designs are selected (where *n* is 3 for the first indicator, 2 for the second and 1 for the third). When an eliminated design has the exact same performance as a selected design, it is nonetheless selected. In case of LS, all junction designs with a performance on the indicator in question of more than 10% worse than the best design are eliminated in each step. In some cases, more than one best junction design is found, because of small differences between the performances of the designs. In that case, all feasible junction designs are used as input for the decision tree.

With the three components, eight different approaches are formulated, as shown in Table 2. For instance, approach 1 first uses the maximum delay criterion, then main junction type selection and finally LS; while approach 8 only uses LE.

Table 2. Multi criteria approaches

Approach	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Maximum delay	Y	Y	Y	Y	N	N	N	N
Main junction type selection	Y	Y	N	N	Y	Y	N	N
LS/LE	LS	LE	LS	LE	LS	LE	LS	LE
Sequence of indicators in LS/LE	1. O 2. E 3. S	1. O 2. E 3. S	1. S 2. O 3. E	1. S 2. O 3. E	1. O 2. E 3. S	1. O 2. E 3. S	1. S 2. O 3. E	1. S 2. O 3. E

O=Operational performance, E=Emissions performance, S=Safety performance

In the first four approaches, for size categories 1 and 2, no feasible junction designs were found for total traffic demands of over respectively 2500 pcu/h and 3500 pcu/h. Therefore, the ranges of total traffic demands over 2500 pcu/h for size category 1 and over 3500 pcu/h for size category 2 were no longer analysed in the remainder of the research.

Resulting from this step is, per approach and combination of size category and traffic demand pattern, a set of one or more best junction designs or ‘no design’. These results are used as input for the next step, the decision tree training.

Step 2. Decision tree training
In the decision tree building process, several parameters must be chosen, which influence the size of the tree. In order to keep the tree size within limits, the maximum number of levels is set at three, the minimum number of parent and child nodes are set at, respectively, 10.000 and 5000. These parameters are determined heuristically.

In the decision tree training, the explanatory variables used to split the instance spaces are based on the demand flows of the junction, i.e. total volume, total major volume and through volume, and on the fractions of the different flows, i.e. percentage of major volume or percentage of left volume, together with size category. The explanatory variables used in the decision tree training are displayed in Table 3. All explanatory variables, with exception of size category, are determined using the original twelve turn flows.

Table 3. Demand variables

Total volume	Northbound volume
Major volume	Eastbound volume
Minor volume	Southbound volume
Major through volume	Major percentage
Major left volume	Minor percentage
Minor through volume	Major through percentage
Minor left volume	Major left percentage
Major through & left volume	Minor through percentage
Minor through & left volume	Minor left percentage
Left volume	Major through & left percentage
Through volume	Minor through & left percentage
Major through & minor left volume	Left percentage
Westbound volume	Through percentage
Size category	

Step 3. Performance analysis
Analysis of the design rules resulting from the decision tree training is difficult. With one objective, the performance of the rules can be tested using the performances of the designs chosen in the design rules. With more objectives however, the performances on the different objectives cannot be compared directly. A possibility is to compare the sets of design rules on the different objectives separately, but this does not enable an overall comparison. Weighing the different objectives is therefore inevitable. This is done using a cost-benefit analysis, using the external traffic costs of the different objectives. The performance of the best performing decision tree is then analysed through

its accuracy, defined as the correct classification rate; and the differences in performance in case of incorrect classification are mapped.

Cost benefit analysis
The decision trees consist of leafs. Each leaf returns for each design the probability of the given design being the best design. For this analysis, only designs with a probability higher than 20% are regarded for a given leaf. For all combinations of traffic demand patterns and size categories, the junction designs resulting from the decision tree are determined. The yearly costs of the resulting designs are calculated using the operational, safety and emissions costs, using the external traffic costs shown in Table 4.

The number of fatal-and-injury incidents are converted into fatal, severe and slight injuries using proportions of these incidents found in Dutch incident data from 1993-2009 (CROW), distinguishing different main junction types (roundabout, signalised and other).

Table 4. External traffic costs (CE Delft, 2008)

Objective	*Indicator*	*Cost*	*Unit*
Operational	Waiting time	8.48	€/hour
Safety	Fatal injury	1,782,000	€/injury
	Severe injury	236,600	€/injury
	Slight injury	19,000	€/injury
Emission	NO_x	6,600	€/kg
	PM_{10}	54,500	€/kg

For instance, if the average waiting time for a junction is 10 seconds, with a total hourly flow of 2000 vehicles, the yearly costs are calculated as 10*2000*8.48*24*365=€1.49*10^10 (14.9 billion euro).

In case of more than one feasible design per combination of traffic demand and size category, the design with the lowest cost is selected. If the decision tree returns no feasible design, then the instance is not used in the evaluation. This way, for each of the 400.000 combinations of demand pattern and size category, either a cost is returned, or the instance is dismissed, for each of the eight approaches. The overall cost of an approach is calculated as the sum of the costs of all instances. The number of instances for which a cost is found differs between the approaches; therefore, the average costs per instance for the different approaches are compared. The best approach is the approach with the lowest average costs.

Accuracy
The accuracy of the design rules resulting from the best approach, as determined in the cost benefit analysis, is calculated as follows. For each instance (combination of size category and traffic demand pattern) in the test set, the set of feasible junction designs is determined using the decision tree. Again, only the designs with a probability higher than 20% are taken into account. Also, for each instance, the best junction design is determined using the multi criteria approach as described in step 2. If the best junction design matches one of the feasible junction designs from the decision tree, then the instance is accurate; else, the instance is inaccurate. The accuracy of the tree is then determined as the percentage of the instances regarded as inaccurate.

For each of the inaccurate results, the additional costs are determined, in terms of additional waiting time and additional expected number of incidents. For this, the waiting time and expected number of incidents of the best junction design are compared with the lowest waiting time and expected number of incidents of the designs in the set of feasible junction designs.

Results

For 100.000 traffic demand patterns in four size categories, the best junction types were selected using eight different multi criteria analyses. This resulted in eight sets of 400.000 best junction designs. The sets of best junction designs were used as input for decision tree training, resulting in eight different decision trees, one for each multi criteria approach. The resulting decision trees are analysed using a cost-benefit analysis. The performance of the best decision tree is studied in more detail; its accuracy (correct classification rate) and additional costs for inaccurate instances are determined.

Cost-benefit analysis

The different decision trees were evaluated with a cost-benefit analysis using the test set (as opposed to the training set used in the decision tree training). For each combination of traffic demand pattern and size category, the corresponding feasible junction designs were determined using the decision trees. With the operational, safety and emission performances of the feasible junction designs, the costs of the junctions were calculated. For cases with more than one feasible junction design, the junction design with the lowest overall costs was selected (resulting in the minimal costs for the given case). In approaches one up to four, the combinations of traffic demand and size category for which no junction design passes the maximum waiting time criterion have no result. These cases are therefore not used in this analysis. Due to the decision tree training, the number of cases with a result differs between the approaches.

In Table 5, the average cost per junction is shown for the different approaches, along with the number of cases for which a feasible junction type was found. For all three indicators applies that a lower cost corresponds to a higher performance.

Table 5. Average junction cost per approach

	Approach							
	1	2	3	4	5	6	7	8
total cost (m€)	4,6	4,4	2,7	5,8	17,5	17,1	17,6	16,1
operational cost (m€)	4,4	4,3	2,5	5,6	17,2	16,8	17,3	15,9
safety cost (m€)	0,12	0,12	0,11	0,12	0,15	0,15	0,13	0,13
emission cost (m€)	0,030	0,029	0,018	0,039	0,123	0,122	0,127	0,109
number of cases with result	216705	203298	198028	212299	273731	273731	273731	273731

The results for approaches 5 up to 8 are significantly worse than for approaches 1 up to 4. This can be explained by the fact that no upper limit for waiting time was used in approaches 5-8, resulting in very high operational costs. In practice, this would render the decision makers a set of junction designs, all unfit for the given design problem. This makes approaches 5-8 undesirable.

The operational costs of all approaches are significantly higher than the costs for the other objectives. The added value of a comparison between the approaches based on the total costs is therefore small. However, approach 3 performs best on all three indicators.

The number of cases showing a result differs for approaches 1-4. The cases for which no feasible design is found (due to excessive waiting times) are mostly the cases with the highest total traffic demand, and therefore usually with the highest cost, as all three indicators are positively correlated to the total traffic demand. The fact that approach 3 shows the lowest average cost could therefore be due to the fact that approach 3 has the lowest number of cases rendering a result. Therefore, an analysis is performed using only the cases which provide a solution for all four approaches. The results of this analysis, seen in Table 6, show again that approach 3 performs best on all performance indicators.

Table 6. Average junction cost per approach, for cases with a solution for all approaches, with 178708 cases

	Approach			
	1	2	3	4
total cost (m€)	1,46	1,48	1,36	1,55
operational cost (m€)	1,35	1,38	1,26	1,45
safety cost (m€)	0,102	0,101	0,094	0,095
emission cost (m€)	0,0081	0,0077	0,0075	0,0085

There is a big difference in the total costs between Table 5 and Table 6. This difference can be explained by the fact that the cases with no solution in one or more approaches all have high traffic demands; and therefore high operational costs.

For the different approaches, the cases with no solution are not the same. Comparing the result from the decision tree (feasible or not feasible) with the original best junction design (feasible or not) gives one of four results: A feasible design is returned in the decision tree for a case whose original costs show a feasible design ('true true'), the decision tree returns a feasible design, but the original costs do not ('false true'), a decision tree does not return a feasible design, but the original costs do ('wrong false') or neither the decision tree nor the original costs return a feasible design ('true false'). The results of this analysis are shown in Table 7.

Table 7. Classification of feasibility according to decision tree and original dataset

	Approach			
	1	2	3	4
True true	60%	62%	62%	59%
Wrong false	8,6%	6,4%	6,1%	9,7%
Wrong true	3,6%	5,2%	4,7%	4,4%
True false	28%	26%	27%	27%

Approach 3 has the highest rate of correct classifications ('true true' and 'true false'), closely followed by approaches 1 and 2. It has the lowest number of 'wrong falses', but has a significantly larger portion of 'wrong trues'. It is debatable which of the two categories is the least preferable: a wrong false would mean that a design is sought for in a higher size category, resulting in higher construction costs; a wrong true could result in the construction of an insufficiently performing junction, but only if not properly checked.

The previous analyses have shown that overall, approach 3 scores best. However, it could be that in certain areas regarding the total traffic demand and/or for different objectives, other approaches score better than approach 3. Therefore, the performances of the different approaches against the total traffic demand are compared. The patterns found in operational performance and emissions performance were very similar; therefore only the operational and safety performance are regarded. All statements regarding operational performance also apply to emission performance.

In Figure 3 and Figure 4, the average operational (note: logarithmic scale) and safety performances (linear scale) for all cases within steps of 100 vehicles per hour are shown. It is shown that for size category 3 and 4, approach 3 performs best on operational level, and as well as the other approaches on safety level. In size category 1 and 2 however, approach 3 performs worse on operational performance with low total traffic demand. The safety performance of approach 3 in those regions, however, is significantly better than the performance of the other approaches. Therefore, approach 3 is deemed the overall best approach.

When regarding the different components of the approaches, there is no clear preference visible. It would be logical that either LS (used in approaches 1 and 3) or LE (approaches 2 and 4) would perform better *and* including (approaches 1 and 2) or excluding (approaches 3 and 4) main junction type preference would result in better results. It would therefore be logical, with approach 3 performing best, that the opposite of approach 3, being approach 2, would perform worst. However, this is not the case; it seems that the performances of the different components of the approaches influence each other. Therefore, no conclusions can be drawn concerning the performances of the isolated components.

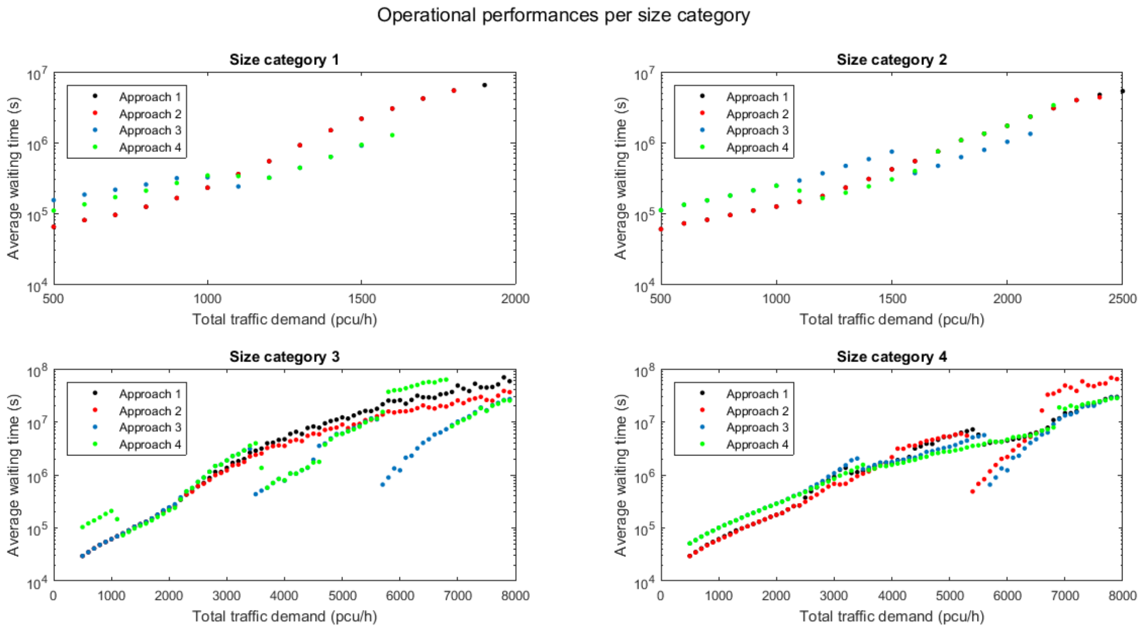

Figure 3. Average operational performance per junction per total traffic demand

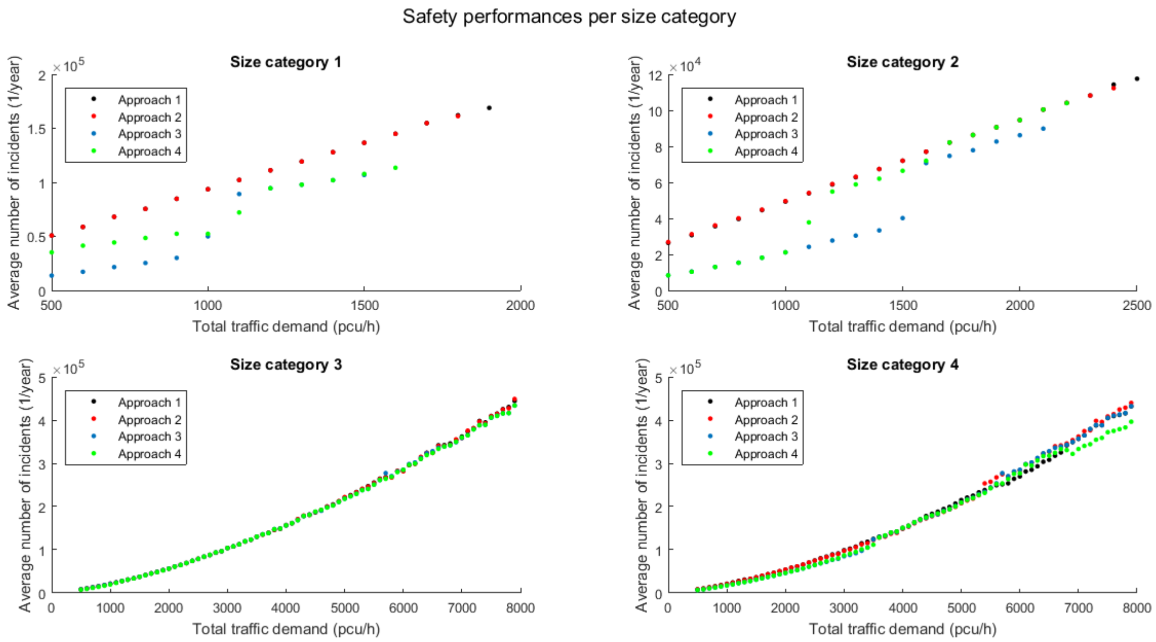

Figure 4. Average safety performance per junction per total traffic demand

Accuracy

The accuracy of the decision tree resulting from approach 3 is determined by comparing the results from the decision tree for approach 3 with the original best junction designs. For each leaf in the decision tree, all junction designs with a share higher than 20% are used in this evaluation. For each case, the corresponding leaf is determined: if the best design from the original dataset is found in the leaf, then the case is accurate; otherwise, the case is not accurate. The accuracy of the tree is then the percentage of cases which were found to be accurate. The accuracy of the tree is 89.9%.

For the non-accurate cases, the average extra waiting time per case is 17.8 seconds, which is a substantial increase. However, the average extra waiting time is as high as it is because of a small number of cases with extreme waiting times, all with a high total traffic demand. In 60% of the cases, the extra average waiting time is lower than 2 seconds. The highest increases in waiting time are found in cases with high traffic demand, where differences in waiting time between junction designs are substantial. On the other hand, safety mostly increases in case of non-accurate cases: on average the best performing junction design from the decision tree has 0.44 incidents per year less than the original best junction design. This shows that in cases with high traffic demand, the decision tree is less reliable than in cases with less traffic demand.

In Figure 5 and Figure 6, the performances (delay and safety) of the junction designs resulting from the decision tree in approach 3 are shown against the performances of all junction designs in size category 4. The results show that with total traffic demand below 4500 pcu/h, the junction designs performs well on safety and also relatively well on delay. Above 4500 pcu/h, the junction designs which perform well on safety are eliminated based on average waiting times exceeding the limits posed. Therefore, junction designs with better operational performance are chosen, resulting in an increase in operational performance and decrease in safety. Similar patterns are found in other size categories.

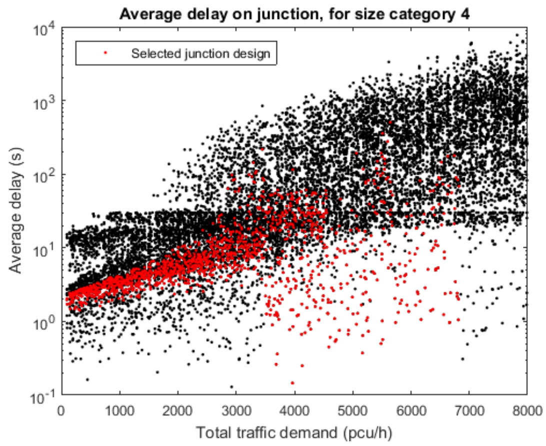

Figure 5. Junction average delay, for cases in size category 4

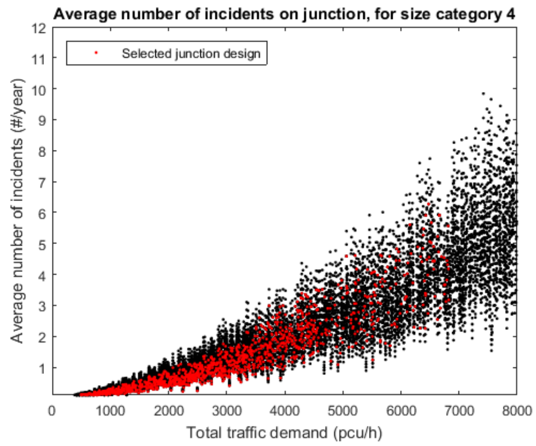

Figure 6. Average number of incidents on junction, for cases in size category 4

In Figure 7, the part of the decision tree for size category 3, for approach 3 is shown. Each leaf contains, for each junction design, the share of best junction designs and the normalised performances on the three indicators. A value of 0 indicates that the junction design consistently shows the worst performance, a value of 100 indicates a consistent best performance. This addition enables decision makers to incorporate their preferences regarding the different indicators in their choice of potential junction designs.

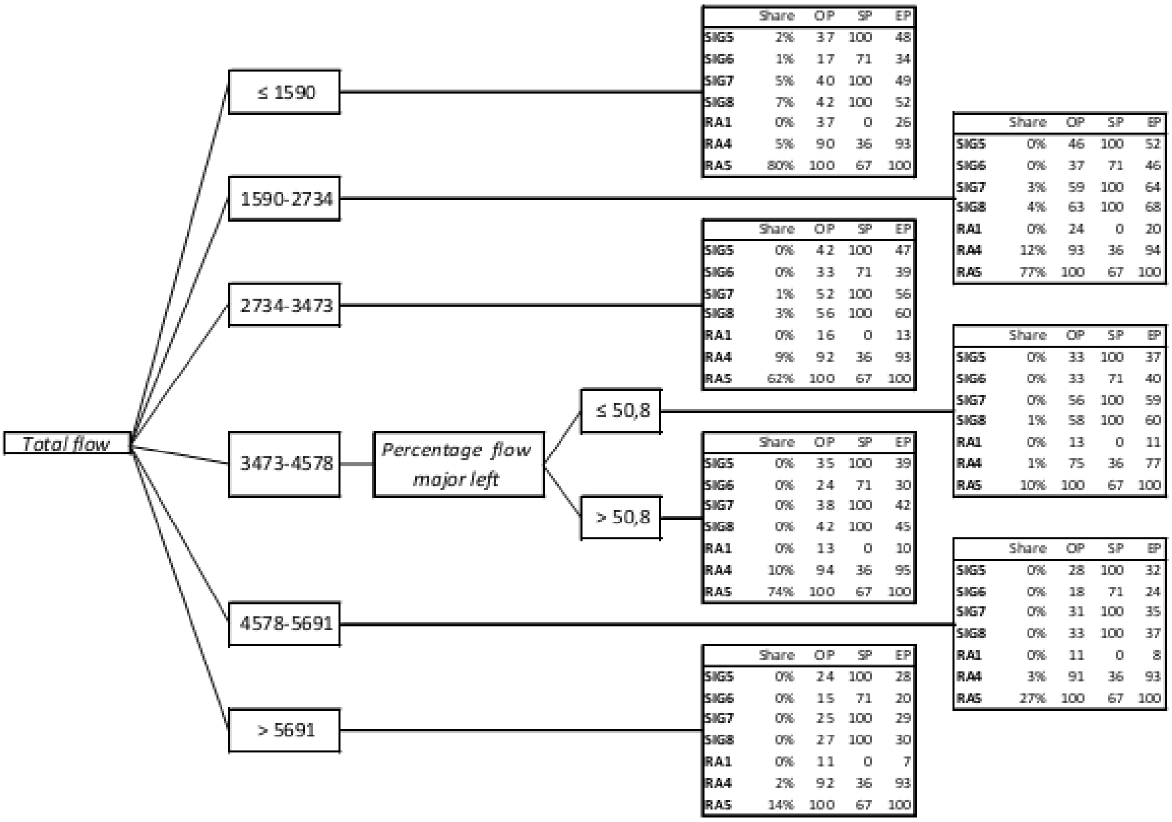

Figure 7. Decision tree for size category 3

The abbreviations used in the decision tree correspond to the names in Table 1. SIG corresponds to signalised junctions, RA corresponds to roundabouts.

With the resulting decision tree, a designer can select from the leaf corresponding to his case the feasible junction types based on the first column, containing the shares of best performing designs. The normalised performances show the designer an indication of the performances on the different objectives. These indications are also useful when the designer has a strong preference for one of the objectives. Ultimately, the decision tree renders the designer a set of most feasible junction types, from which he can make his final selection.

Conclusions and recommendations

The goal of this research was to propose a method for the systematic deduction of junction design rules, based on the junction performance regarding safety, throughput and emissions. The resulting design rules could only require the expected traffic demand and the space available for the junction, in order for the design rules to be usable without the need for additional modelling. Therefore, the possibilities of using different combinations of decision tree and non-comparative multi criteria analysis to create junction design rules were explored. The effects of the combination of different analyses on the performance of the resulting design rules were compared. It is found that the use of a threshold value for waiting time strongly increases the performance of the resulting design rules. The design rules resulting from the best approach showed an accuracy of 89.9%. Non-accurate results showed, as expected, a higher average waiting time, but also a decrease in the number of incidents.

The resulting design rules provide decision makers a quick method for the first selection of feasible junction types, requiring only available data. The design rules incorporate performances on multiple objectives, and also provide an insight in the relative performance of the different junction types on the different objectives. This renders the designers the option of selecting feasible junction types not only on the overall performance, but also on the performances of the individual objectives, which is useful if the designer has a strong preference for a certain performance indicator.

In this research, an existing decision tree inducer is used. However, all decision tree algorithms found in literature aim to isolate instances in the end nodes of trees. In the application of junction design rules however, further analyses will be performed with the results of the design rules. It is therefore less important that a single design results from the design rules; on the contrary, as a small set of feasible designs enables designers to adapt the junction to the preferences applying for the location in question. As no inducers are available which seek to group more than one design per end node, it may be worth to further investigate the possibilities for such an algorithm.

Furthermore, this research has made a start into investigating which components are needed to produce suitable junction design rules, but no exhaustive research has been performed into identifying all possible components. For instance, network characteristics are not taken into account; further research into suitable components of junction design rules is therefore recommended.

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