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Risk Assessment and Route Optimization for Life and Health Self-Keeping During e-Cycling

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Abstract. The paper presents the creation of a general mathematical model of a two-step optimization problem which finds the most-safer route of an electric-bicycle cyclist. The first step is a multi-criteria problem which finds the average risk in the different segments which forms the complete route. To solve the problem, a scalarization method is used (also known as weighted sum method). In the second step, the safer route is found by applying a network optimization model. To find the solution a method for dynamic optimization is applied (Bellman's Principle). The generation of data is based on the a priori known information as well as on information which is periodic and stochastic in the time and space.

INTRODUCTION

In recent years, the increasing use of electric vehicles, and in particular those powered by renewable energy sources. This can play an important role in achieving the EU's goal of reducing greenhouse gas emissions and moving towards a low carbon future. These vehicles are becoming an interesting subject for scientific research in various fields of transportation, logistics and traffic safety.

One of the major factors influencing risk and its assessment when cycling is weather. A closed loop is obtained, in which the weather depends on the emissions released into the environment, which in turn affect the climate (global and local). The authors in [12] have made a study on the influence of exhaust gases such as CO, NOx and particulate matter (PM) of conventional vehicles (i.e. using internal combustion engines) resulting in serious health concerns for the general public. Another example is a research [4], showing that the mortality rate for people living in the most polluted cities can be 29% more than those living in the least polluted cities based on data in the past several decades. The authors in [7] have described the development of a useful tool for agencies and researchers for clustering of similar transportation patterns with respect to time-based events. The proposed supervision algorithm is conceived to take advantage of background knowledge of the dataset along with the similarity. Compared to analogous methods, this one stands out with scalarization and low computational complexity along with its other advantages. In [6] an analysis is made, after which the performance of linear models is compared against two types of adaptive NMs. The improved hybrid model of the NM using the look-up table does the best of all under specific conditions, such as average absolute voltage error and maximum peak power in test routes. An intelligent control of the traffic lights is studied in [13]. A feed-forward neural network is adopted to accomplish the traffic signal controller. The proposed solution has several advantages compared to traditional methods and in particular the self-learning ability. In [9] several types of stability are introduced and analysed (average, mean-squared, almost-sure stability etc.) with the aim of widening the optimization scope. After numerous iterations of the optimization, the stability conditions are expressed with several levels of conservatism and feasibility. The research in [11] is based on the Nash equilibrium for an infinite time horizon. Furthermore, various strategies are defined for the individual players in the competition. Their performance is then compared under equal conditions, with or without a feedback in the informational structure.

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This work presents the creation of a general mathematical model of a two-step optimization problem which finds the most-safer route of an electric-bicycle cyclist. The first step is a multi-criteria problem which finds the average risk in the different segments which forms the complete route. To solve the problem, a scalarization method is used (also known as weighted sum method). In the second step, the safer route is found by applying a network optimization model. To find the solution a method for dynamic optimization is applied (Bellman's Principle). The generation of data is based on the a priori known information as well as on information which is periodic and stochastic in the time and space. The similar problems are analysed and solved in [8] by using a multi-objective optimization approach. Various approaches to finding optimal routes by different criteria are described in [1], [2], [3], [5], [10], etc.

The research is specific because it is another point of view of the assigned problem. The problem arises from the increasing number of people in urban areas (urbanization) and the corresponding increase in human density. On the other hand, transport needs in the urban environment are specific (generally speaking). This means:

- A wide variety of vehicles (from e-bike to stand-alone trucks);
- Extensive amounts of data, such as vehicle technical information, travel profiles ("route + driving style + vehicle");
- Share Common Resource - Road infrastructure is used simultaneously by objects that are different in size, weight and speed. Accordingly, the interaction between road users is different from the point of view of the vehicle.

The significance of the research is that the benefit is maximum for cyclists who have to make a decision (related to the route) in an environment of uncertainty. Decision makers would like to assess the risks before they decide to understand the scope of the possible outcomes and the significance of the unwanted consequences.

The purpose of this article is to present a general methodology for finding the optimal route in the sense of the most risk-free for the life and health of a cyclist, depending on factors - obstacles on the road, quality of road surface, weather conditions.

DESCRIPTION AND AIM OF THE TWO-STAGE PROBLEM

1st stage: Description of problem 1

A cyclist is riding a pedal-assisted electric bicycle and is travelling from a certain point of departure to his destination. This can be performed via a number of routes including combination of their sections The routes can be represented by a network model of an oriented graph $V(G, D)$, where $G = \{G_i\}_{i=1}^{k}$ are the nodes and $D = d_{ij}, i = 1, \dots, k-1; j = 2, \dots, k; i < j$, are the graph arcs (figure 1).

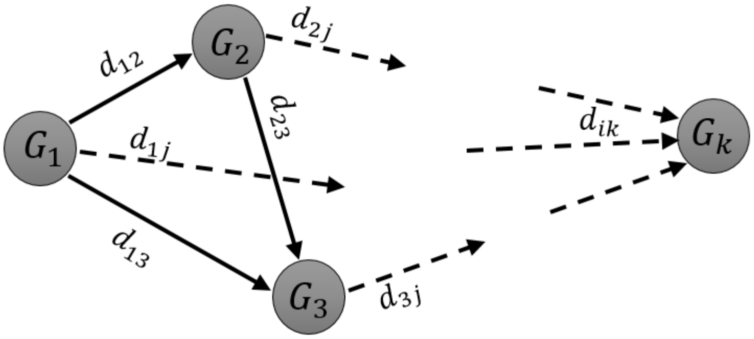

FIGURE 1. Network model of the oriented graph $V(G, D)$

The risk to the life and health of a cyclist during an electric bicycle management is directly related to the number of obstacles, the quality of the road surface and the weather conditions on the e-bike routes.

Aim of problem 1

To determine the probability of occurrence of risk $Q_{ij} \in [0; 1], i = 1, \dots, k-1; j = 2, \dots, k; i < j$, for each arc $d_{ij}, i = 1, \dots, k-1; j = 2, \dots, k; i < j$, from the possible routes of the cyclist in this case.

2nd stage: Description of problem 2

Let the arcs of the graph $d_{ij}, i = 1, \dots, k-1; j = 2, \dots, k; i < j$, are associated with probability $p_{ij} = 1 - Q_{ij}$, $p_{ij} \in [0; 1], i = 1, \dots, k-1; j = 2, \dots, k; i < j$, for the absence of risk to the life and health of the cyclist when he managing the e-bike for each arc $d_{ij}, i = 1, \dots, k-1; j = 2, \dots, k; i < j$, of the possible routes.

Aim of problem 2

Find the route of the cyclist from the starting point to the end point where the risk to his life and health is minimal in this case.

SOLUTION OF THE TWO-STAGE PROBLEM

Solution of problem 1

Input data for each arc $d_{ij}, i = 1, \dots, k-1; j = 2, \dots, k; i < j$, from the cyclist's route:

- number of obstacles;
- quality of the road surface;
- possible weather condition.

Input data and processing:

Number of obstacles:
Let *X* be a discrete random quantity, characterizing the number of obstacles made by observations for each arc of the path $d_{ij}, i = 1, \dots, k-1; j = 2, \dots, k; i < j$, every hour of day for *S* number of days - table 1:

TABLE 1. Data obtained by observation

Day	**Hour**			
	00:00	**01:00**	**…**	**23:00**
	Number of obstacles			
1	$x_{1,1}$	$x_{1,2}$	…	$x_{1,24}$
2	$x_{2,1}$	$x_{2,2}$	…	$x_{2,24}$
…	…	…	…	…
S	$x_{S,1}$	$x_{S,2}$	…	$x_{S,24}$
$EX_t \to$ $t = 1, \dots, 24$	$EX_1 = \frac{1}{S}\sum_{s=1}^{S} x_{s,1}$	$EX_2 = \frac{1}{S}\sum_{s=1}^{S} x_{s,2}$	…	$EX_{24} = \frac{1}{S}\sum_{s=1}^{S} x_{s,24}$

Then for each arc $d_{ij}, i = 1, \dots, k-1; j = 2, \dots, k; i < j$, the average number of obstacles is:

$$EX_{ij} = \frac{1}{24}\sum_{t=1}^{24} EX_t = \frac{1}{24.S}\sum_{t=1}^{24}\sum_{s=1}^{S} x_{s,t}. \tag{1}$$

And for each arc of the route the average number of obstacles $Ex_{ij}, i = 1, \dots, k-1; j = 2, \dots, k; i < j$, is associated to the probability (relative frequency) is of being risky due to the number of obstacles that can appear by cycling through it. Therefore, the probability is expressed by $q_{ij} \in [0; 1], i = 1, \dots, k-1; j = 2, \dots, k; i < j$, where

$$q_{ij} = \frac{Ex_{ij}}{\sum_{i=1}^{k-1}\sum_{j=2}^{k} Ex_{ij}}, i = 1, \dots, k-1; j = 2, \dots, k; i < j. \tag{2}$$

Quality of road surface:

For each arc d_{ij} of the route the road quality (for cycling) $b_{ij}, i = 1, \dots, k-1; j = 2, \dots, k; i < j$, is rated by $b_{ij} = 1, \dots, U$. A higher value of b_{ij} means a worse quality of the pavement. This value for d_{ij}, is associated with a corresponding weight $w_{ij}, i = 1, \dots, k-1; j = 2, \dots, k; i < j$, characterizing the road pavement:

$$w_{ij} = \frac{b_{ij}}{U}, i = 1, \dots, k-1; j = 2, \dots, k; i < j. \tag{3}$$

Weather conditions:

For each arc d_{ij} of the route the environment conditions (weather conditions) a_{ijr} are defined (scaled) so $a_{ijr} = 1, \dots, E$ and as the value of a_{ijr} is greater, so the environment conditions are worse for the bicyclist. For each arc of the route d_{ij} for every state of the environment a weight is defined $\omega_{ijr}, r = 1, \dots, R, i = 1, \dots, k-1; j = 2, \dots, k; i < j$:

$$\omega_{ijr} = \frac{a_{ijr}}{E}, r = 1, \dots, R,\ i = 1, \dots, k-1; j = 2, \dots, k; i < j. \tag{4}$$

For a particular state of nature $r,\ r = 1, \dots, R$:

$$Q_{ij} = q_{ij}.w_{ij}.\omega_{ijr}, i = 1, \dots, k-1; j = 2, \dots, k; i < j. \tag{5}$$

In the first stage, there is solved problem for finding the probability of the occurrence of risk, at risk being the gradual addition of the factors: obstacles - mobile and stationary; quality of road surface; weather conditions in the different arcs that form the complete route. The input parameters are stochastic and discretized, pre-processed by statistic methodology. To solve the problems, a scalarization method is used (also known as weighted sum method).

Solution of problem 2

The probability of a risk-free ride (the lack of risk) for each arc $d_{ij}, i = 1, \dots, k-1; j = 2, \dots, k; i < j$, is:

$$p_{ij} = 1 - Q_{ij}, i = 1, \dots, k-1; j = 2, \dots, k; i < j. \tag{6}$$

A network model of the route is developed (figure 2) where each arc $d_{ij}, i = 1, \dots, k-1; j = 2, \dots, k; i < j$, is characterized by the probability $p_{ij}, i = 1, \dots, k-1; j = 2, \dots, k; i < j$.

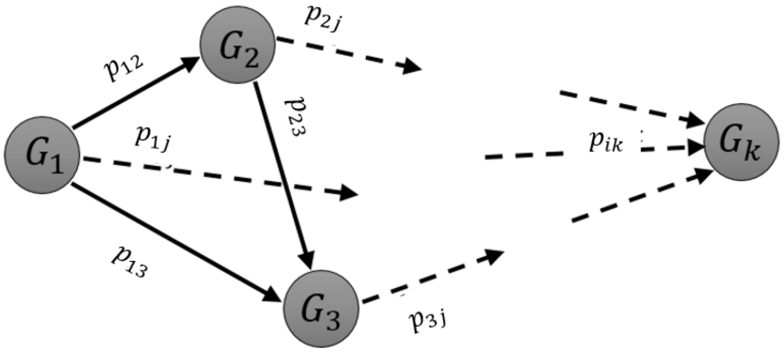

FIGURE 2. Network model of the oriented graph $V(G, P)$

The problem of finding the less risky route from the starting point to the final destination is modelled as a network problem, but in fact it is also a reliability problem. This complex problem can be solved by a dynamic programming method by decomposing it into sub-problems which are easier to solve. The decomposition consists in dividing the solution into stages and formulation of optimization problems for each stage that are less complex than the global problem. For each stage there is a scalar (control) variable whose value can be optimized and then the results are linked by a recursive algorithm. Therefore, the solution of the global problem is obtained finally after consecutive solution of a number of sub-problems. This method, based on recursive iterations relies on the Bellman optimality principle that states: "The optimal strategy is composed of optimal sub-strategies".

The objective function if a generalized characteristic of the decisions taken and the results obtained by solving the problem. It reflects the way in which the global problem is decomposed in less complex sub-problems. In the problem of optimal path, the objective function is multiplicative and the global result is a product of the results obtained each stage. It is similar to the reliability of a system built by consecutive addition of a number of elements (building blocks).

The number of stages after decomposition of the main problem is k. At each stage $E_n, n = 1, \dots, k$, the problem of finding the less risky path between nodes G_1 and $G_n, n = 1, \dots, k$. A Bellman's function $f_N, N = 0,1, \dots, k$, is introduced. It gives a quantitative measure of the less risky way from the initial point to the n^{th} $(n = 1, \dots, k)$ and is defined by a recursive dependence:

$$f_j = \max_{i<j} \{p_{ij}.f_i\}, i = 1, \dots, k-1; j = 2, \dots, k; \tag{7}$$

$$f_0 \equiv 1, f_1 = 1. \tag{8}$$

The optimal value is then obtained at the final stage E_k and it is:

$$f_k = f_{max}. \tag{9}$$

By inversion of this principle, the less risky for the cyclist path from his initial point of departure to his destination is obtained (figure 3).

FIGURE 3. Optimal cycling path

Then:

$$f_{max} = \prod_{V=1}^{v} p_{mV}. \tag{10}$$

NUMERICAL EXAMPLE

The proposed methodology is applied to a specific numerical problem. In reality the e-bike cyclist is choosing his route just before or during the cycling, but when he arrives he can recapitulate his path and analyse if it has been the less risky from all possible routes. The presented methodology is made to help the cyclist to make a decision when choosing a route. Figure 4 gives an example of the possible routes that he can choose. The number of routes is finite and includes combinations of their sections.

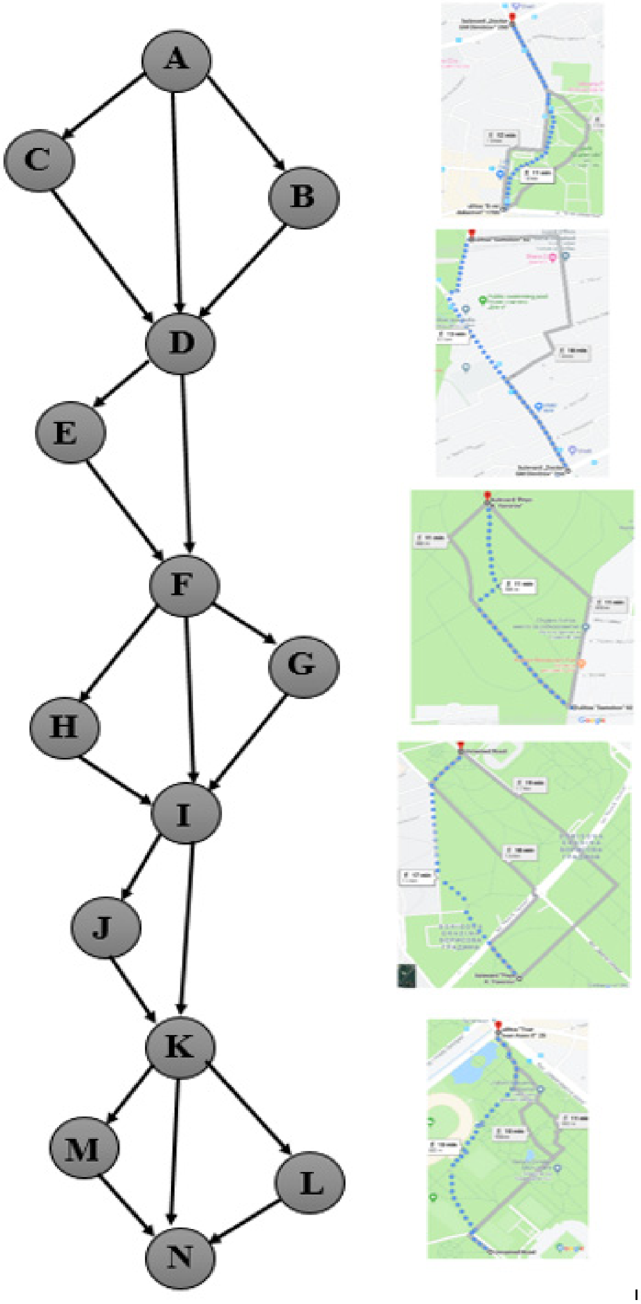

FIGURE 4. Routes considered for the numerical example

Input data and processing:

Number of obstacles:

After determination of the possible routes, input data of the hourly number of obstacles is collected for each arc of the routes for ten days. In this numerical example random data is generated and each arc of the routes includes an hourly number of obstacles in the range from 0 to 120 (table 2).

TABLE 2. Randomly generated distribution of the number of obstacles in randomly taken arcs of the route

ABD	_00:00	_01:00	_02:00	_03:00	_04:00	_05:00	_06:00	_07:00
1	12	85	109	64	99	15	1	113
2	72	83	6	6	112	31	35	92
3	120	27	1	89	52	23	66	70
4	82	114	35	54	51	15	38	9
5	12	98	76	84	44	56	46	40
6	59	72	115	74	34	67	115	119
7	35	119	53	100	50	39	80	64
8	98	75	69	3	108	111	116	23
9	9	6	112	22	33	49	48	58
10	97	36	4	5	106	58	54	36
ABD	_08:00	_09:00	_10:00	_11:00	_12:00	_13:00	_14:00	_15:00
	…	…	…	…	…	…	…	…
ABD	_16:00	_17:00	_18:00	_19:00	_20:00	_21:00	_22:00	_23:00
1	3	89	97	62	4	39	80	87
2	26	52	86	29	17	21	8	116
3	36	29	101	6	49	45	61	105
4	8	92	13	18	86	30	55	54
5	12	103	37	53	62	27	74	24
6	3	67	5	62	64	77	58	116
7	119	52	113	90	57	14	6	93
8	98	74	47	48	99	75	45	117
9	34	54	91	56	10	57	25	74
10	92	80	92	73	44	59	82	79
FI	_00:00	_01:00	_02:00	_03:00	_04:00	_05:00	_06:00	_07:00
	...	...	...	...	...	...	...	
FI	_16:00	_17:00	_18:00	_19:00	_20:00	_21:00	_22:00	_23:00
1	57	96	61	104	11	89	48	10
2	76	87	109	26	15	58	95	24
3	100	109	61	45	101	110	68	56
4	116	70	35	1	90	49	111	99
5	76	110	95	86	95	14	102	67
6	21	73	112	107	62	39	81	112
7	44	65	93	77	23	24	39	61
8	45	52	52	38	92	63	65	60
9	98	26	62	83	118	20	51	21
10	101	110	7	36	36	3	91	5
...	...	...	...	...	...	...	...	...

The input data from table 2 are processed and presented in table 3.

TABLE 3. Probability of occurrence of obstacles in each arc of the road

d_{ij}	q_{ij}	d_{ij}	q_{ij}
ABD	0.08096	FHI	0.08523
AD	0.08173	IK	0.08190
ACD	0.08170	IJK	0.08550
DF	0.08187	KLN	0.08286
DEF	0.08255	KN	0.08235
FGI	0.08453	KMN	0.08453
FI	0.08680		

Quality of road surface:

TABLE 4. Quality of the road surface for each arc of the road on a scale of 1 to 10 and weights quantifying the road surface

d_{ij}	ABD	AD	ACD	DF	DEF	FGI	FI	FHI	IK	IJK	KLN	KN	KMN
b_{ij}	1	8	5	4	2	9	4	2	6	7	7	6	3
w_{ij}	0.1	0.8	0.5	0.4	0.2	0.9	0.4	0.2	0.6	0.7	0.7	0.6	0.3

Weather conditions:

TABLE 5. Influence of the weather conditions on each arc of the road on a scale of 1 to 10

d_{ij}	ABD	AD	ACD	DF	DEF	FGI	FI	FHI	IK	IJK	KLN	KN	KMN
a_1	8	5	10	5	2	1	5	9	6	2	9	8	3
a_2	8	4	2	1	5	2	1	1	9	10	1	4	7
a_3	10	7	9	3	4	4	8	10	1	2	2	2	8
a_4	4	8	2	7	10	10	3	6	10	9	5	7	6
a_5	5	1	5	2	5	5	3	6	1	6	4	4	8
a_6	10	6	5	4	9	1	4	10	2	9	7	4	5
a_7	2	3	5	4	8	7	10	3	8	9	6	5	8
a_8	5	9	10	9	2	4	4	9	6	8	3	10	2
a_9	2	9	2	3	5	2	10	2	1	9	4	7	6
a_{10}	7	9	9	1	10	1	5	7	5	9	7	1	5

TABLE 6. Weights of influence of the weather conditions for each arc of the road

d_{ij}	ABD	AD	ACD	DF	DEF	FGI	FI	FHI	IK	IJK	KLN	KN	KMN
a_1	0.8	0.5	1	0.5	0.2	0.1	0.5	0.9	0.6	0.2	0.9	0.8	0.3
a_2	0.8	0.4	0.2	0.1	0.5	0.2	0.1	0.1	0.9	1	0.1	0.4	0.7
a_3	1	0.7	0.9	0.3	0.4	0.4	0.8	1	0.1	0.2	0.2	0.2	0.8
a_4	0.4	0.8	0.2	0.7	1	1	0.3	0.6	1	0.9	0.5	0.7	0.6
a_5	0.5	0.1	0.5	0.2	0.5	0.5	0.3	0.6	0.1	0.6	0.4	0.4	0.8
a_6	1	0.6	0.5	0.4	0.9	0.1	0.4	1	0.2	0.9	0.7	0.4	0.5
a_7	0.2	0.3	0.5	0.4	0.8	0.7	1	0.3	0.8	0.9	0.6	0.5	0.8
a_8	0.5	0.9	1	0.9	0.2	0.4	0.4	0.9	0.6	0.8	0.3	1	0.2
a_9	0.2	0.9	0.2	0.3	0.5	0.2	1	0.2	0.1	0.9	0.4	0.7	0.6
a_{10}	0.7	0.9	0.9	0.1	1	0.1	0.5	0.7	0.5	0.9	0.7	0.1	0.5

TABLE 7. Probability of absence risk of number of obstacles and quality of road surface in each arc of the road under specified weather conditions

p_{ij}	ABD	AD	ACD	DF	DEF	FGI	FI
S_1	0.99352	0.96731	0.95915	0.98363	0.99670	0.99239	0.98264
S_2	0.99352	0.97385	0.99183	0.99673	0.99175	0.98478	0.99653
S_3	0.99190	0.95423	0.96324	0.99018	0.99340	0.96957	0.97222
S_4	0.99676	0.94769	0.99183	0.97708	0.98349	0.92392	0.98958
S_5	0.99595	0.99346	0.97958	0.99345	0.99175	0.96196	0.98958
S_6	0.99190	0.96077	0.97958	0.98690	0.98514	0.99239	0.98611
S_7	0.99838	0.98038	0.97958	0.98690	0.98679	0.94675	0.96528
S_8	0.99595	0.94115	0.95915	0.97053	0.99670	0.96957	0.98611
S_9	0.99838	0.94115	0.99183	0.99018	0.99175	0.98478	0.96528
S_{10}	0.99433	0.94115	0.96324	0.99673	0.98349	0.99239	0.98264

p_{ij}	FHI	IK	IJK	KLN	KN	KMN
S_1	0.98466	0.97052	0.98803	0.94780	0.96047	0.99239
S_2	0.99830	0.95577	0.94015	0.99420	0.98024	0.98225
S_3	0.98295	0.99509	0.98803	0.98840	0.99012	0.97971
S_4	0.98977	0.95086	0.94614	0.97100	0.96541	0.98478
S_5	0.98977	0.99509	0.96409	0.97680	0.98024	0.97971
S_6	0.98295	0.99017	0.94614	0.95940	0.98024	0.98732
S_7	0.99489	0.96069	0.94614	0.96520	0.97530	0.97971
S_8	0.98466	0.97052	0.95212	0.98260	0.95059	0.99493
S_9	0.99659	0.99509	0.94614	0.97680	0.96541	0.98478
S_{10}	0.98807	0.97543	0.94614	0.95940	0.99506	0.98732

The numerical example is implemented and solved by using the software environments MatLab and Maple.

RESULTS

The solution of the risk optimization problem is obtained according to a multiplicative objective function and the result is a product of the sub-problem solutions. It reflects the reliability of a system constructed by a number of separate elements. The numerical solution of the problem is depicted in figure 5 by using this method.

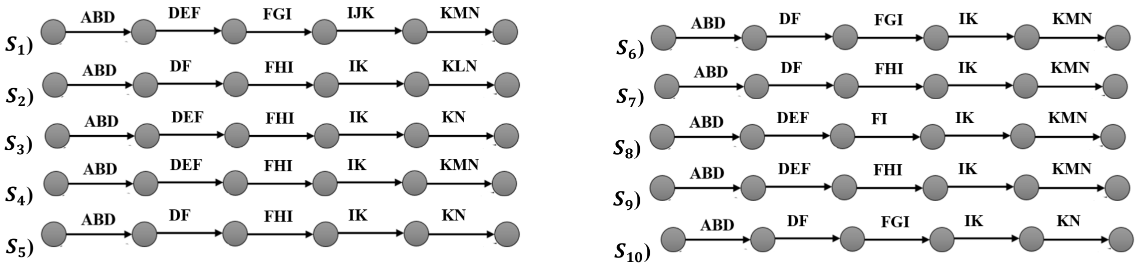

FIGURE 5. Optimal cycling route

Depending on the weather conditions is given in table 8.

TABLE 8. The best probability of absence of risk (in % is the most risk-free route) under given weather conditions

	f_{max}
S_1	**96%**
S_2	**94%**
S_3	**95%**
S_4	**91%**
S_5	**96%**
S_6	**95%**
S_7	**92%**
S_8	**95%**
S_9	**97%**
S_{10}	**95%**

Discussion of the results

Problem 2 is solved using an iterative method. Through the appropriate elements of the model, the complex problem is decomposed into simpler ones, which are solved almost independently. The solutions found at each stage are optimal and acceptable. This is due to the fact that the problem of the size of the problem is solved by being reduced in stages through the recurrent dependence. And this increases the capabilities of using this method to solve complex problems.

Regarding the results obtained by application of the Bellman's optimization principle, the following observations can be made:

- The shortest path from the numerical example has a length of 5.15 km. For example, the length of the least risky path for bad environment conditions (S_4) is 5.75 km; for a better environment conditions (S_9) the length is 5.45 km which is an increase with 10% for (S_4) and 6% for (S_9**)**. Anyway, the risk in the first case is reduced by 11% and in the second one is 13% - figure 6.

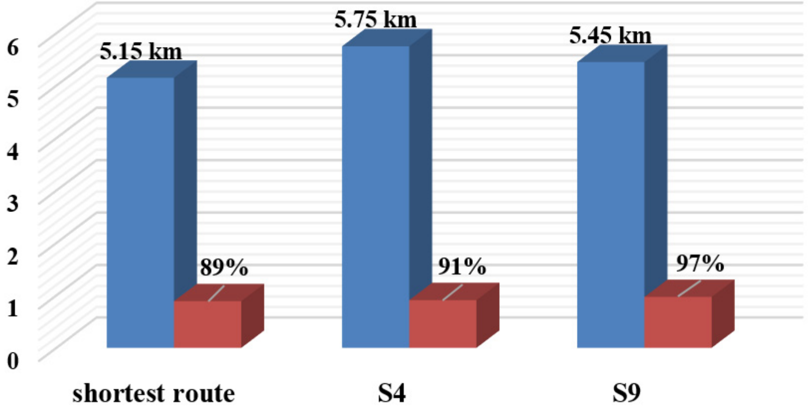

FIGURE 6. Comparative chart between the shortest and the most risk-free route for the conditions S_4 and S_9

- The duration of the fastest route is 39 min and the time needed for travelling along the least risky route for bad environment conditions (S_4) is e 49 min, which points out that an increase by 10 min would reduce the risk by 18%; for a better environment conditions (S_9) the time is 44 min which means an increase with 5 min and reduced risk with 23% (figure 7).

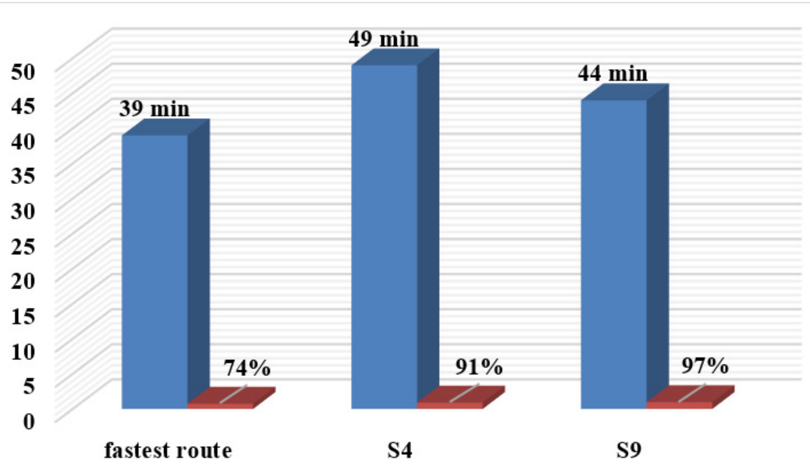

FIGURE 7. Comparative chart between the fastest and the most risk-free route for the conditions S_4 and S_9

In conclusion, the bad weather has a significant influence on the route selection and the risk associated with it.

This research is a continuation of studies associating the risk to the life and health of a bicycle driver when driving an electric wheel. It also includes the meteorological time factor to maximize the theoretical model to reality.

The purpose of examining the impact of time on the overall risk and the individual sections of the route is achieved by combining exploration of all individual loops in the route.

CONCLUSION AND FUTURE WORKS

The cyclist would like to make a decision and assess the risks of possible routes before making a decision to understand the ranges of possible outcomes and the importance of unwanted consequences. Decision making is a study to identify and select alternatives, which choice is based on the preference of the decision maker. Also, decision making is a process of sufficiently reducing uncertainty and suspicion of alternatives in order to make it possible to make a reasonable choice from among them. The information gathering function is important when making a decision.

It should be noted that the uncertainty is reduced and not eliminated. Thus, any solution is associated with a certain risk. If there is no uncertainty, no decision is needed, and an algorithm already exists - a set of steps or a recipe that is followed in order to achieve a certain result. The work proposes a methodology that specifies the parameters of the specific studies proposed, their boundaries, what is the necessary information to be collected and processed so that it is in favor of the cyclist to decide on which route to pass before he left.

Route optimization in this research is based on a dynamic programming approach, adding the factors that characterize the cycling of electric bikes and pedal bicycles in urban environments. Due to the significant urban traffic dynamics, the input data of the optimization problem are highly variable in the daily and hourly scales and are also influenced by weather conditions and other factors or events.

The next stages of the research will be focused at optimizing the energy needs of the bicycle and other vehicles.

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