A Risk-based UAS Traffic Network Model for Adaptive Urban Airspace Management

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This paper presents a risk-based model for UAV path planning in urban low altitude environments. Firstly, the risks in urban environments were identified and classified into four groups, and the corresponding risk costs were categorized into five different levels. A general risk cost model was then developed for qualifying all related risk costs. Secondly, a ConOps for urban air route network with plane and cubical diagonals was built and the obtained risk cost information were ingested into the network to assist path planning. Finally, an A*cost algorithm was developed to generate a safe and cost-effective path for UAVs in urban low altitude airspace. Simulation results show that the novel route network structure with diagonals has better performance, with an average reduction of 17.56% for path distance. While the proposed A*cost algorithm has good results in terms of total cost and computational time, outperforming traditional Dijkstra and Ant Colony algorithm.

I. Introduction

Unmanned Aircraft System (UAS) has been booming in recent years in many applications, especially in urban environments [1]. The contradiction between huge demand for low altitude operations and limited airspace resources becomes a big problem for UAS traffic management system. To deal with the UAS traffic management problem, Air Traffic Management Research Institute has proposed a scalable traffic management framework for urban airspace management (TM-UAS). Route/path planning plays an essential role in unmanned traffic management system [2-4]. Proper route network management and efficient path planning method can significantly reduce collision risk of UAS and improve the utilization efficiency in urban airspace [5-7].

Currently, investigations on UAV path planning in urban environment are fruitful [8-10]. In last decades, different models have been proposed to deal with UAV path planning problems, for instance, the Dijkstra algorithm [11], algorithm like A* [12-13], evolutional algorithm like genetic algorithm [14], as well as Particle Swarm Optimization (PSO) method also being used in cooperative path planning problems [15]. The objectives of these algorithms are from avoiding obstacles, minimizing path distance to cutting computational time [16]. Few of them take risk costs into account for UAV path planning in urban environments. Another branch of path planning algorithm employed sample-based techniques. Probabilistic Roadmaps (PRM) [17] and Rapidly-exploring Random Trees (RRT) methods are widely employed for UAV path planning in complex environments [18].

However, there are still weaknesses and drawbacks of current research. Most of the research assume that UAVs operate in areas where there have few physical obstacles (e.g. high buildings) and operational constrains (e.g. public safety and privacy), and consider distance is the only cost of route network link. Such assumption is not tangible

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because in urban environment there are many risks (physical obstacles, bad weather, etc.) can be the costs of route network that greatly affect UAV path planning. Such risk costs should be carefully considered when UAVs operate in urban low altitude airspace with uncertain hazards. Another popular family of research grid the search maps of path planning model for computation convenience, without adding diagonals in the meshed maps, ending the path planning results in zigzag trajectories, jeopardizing algorithms' performance in terms of travel distance and time.

In this paper, a risk-based UAV path planning model will be investigated. First, the risk costs for UAV path planning in urban low altitude environment will be identified and classified. After that, a general risk cost model will be developed, and the costs will be categorized into five different levels. Then, a three-dimensional route network with diagonals will be built and obtained risk cost information will be ingested into the network. Finally, an A*cost algorithm will be proposed to generate a safe and cost-effective path for UAVs in urban low altitude airspace.

The rest of the paper is organized as follows. The UAV path planning problems in urban low altitude environments are formulated in Section II and the methodology to deal with the problems are modelled in Section III. Section IV presents the case study with several groups of simulation and reports the results of, followed by conclusions presented in Section V.

II. Problem Statement

In this section, the risk-based path planning model is formulated as a route optimization problem. The goal is to produce a safe and cost-effective path for UAVs in urban low altitude environments.

A. Route Network in Urban Environment

This paper will base on AirMatrix traffic network (**Fig. 1**) [19] to form route network for UAV path planning. This traffic network has developed a standardized mechanism for the facilitation of UAS traffic, providing discrete and standardized units to manage urban airspace. Urban airspace is divided into uniform air blocks. This configuration allows quantitative analysis for a vast range of subjects. For example, the air blocks can encode information on risk costs of each links, Command and Control Signal Strength, Population Density underneath etc. Such information can be served as metrics for safe path planning.

However, this route network does not account for diagonals in its structure, which may cause zigzag path for UAV. That will increase the maneuvers of UAV, producing safety concerns and waste of travel distance. This work will consider diagonals to improve the current AirMatrix ConOps.

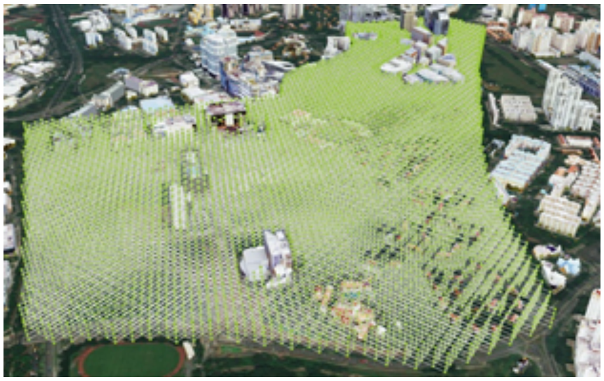


Fig. 1 ConOps of AirMatrix traffic network [18]

B. Risk Costs in Urban Environment

This section provides a concept of risk cost in urban environments. The risks can be generally classified into four categories:

1) Physical obstacles, which are more static objects like buildings, power grid, trees, etc. Path planning should strictly avoid these obstacles to prevent drone from collisions;

2) Weather; in low altitude, weather conditions like rain, fog, thunderstorm, etc. will affect UAV path greatly, and weather conditions are always the dynamic risks need to be considered;

3) Operational constrains; operational constrains represent Communication, Navigation and Surveillance (CNS) capabilities of route network. For example, GPS signal lost can be risk for UAV operation in urban environment;

4) Regulation and policy limitations, societal issues. This kind of risks comprise noise and privacy sensitive areas, critical infrastructure areas, etc. UAV may not be able to allow to fly above these areas in certain condition. Such areas can be the risks for path planning of UAV.

Risks in urban environment are generally identified and classified above. Assuming risk cost is equivalent to risk level. The higher risk level, the bigger risk cost will be. Risk level can be presented as the relationship (see **Fig. 2**) between probability and severity of the risk. Here, probability is the likelihood that a risk happens. Severity is the damage/cost caused when a risk happens. Initially, the risk level and related costs are categorized as five groups.

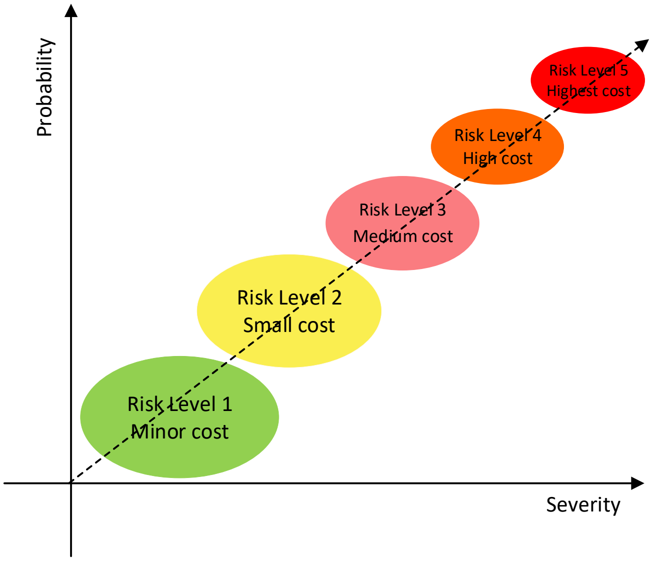


Fig. 2 Illustration of risk levels

Based on the analysis about risk cost above, a matrix of risk cost can be obtained, denoted as (x, y, z, c). (x, y, z) is the position of the risk; c presents the risk cost value. In low altitude airspace, any position will have a risk cost. The risk cost will be integrated into links of route network supporting path planning. For risks within the safety protection zone of the link, their costs will be counted on to this link. The total risk cost of the link is the sum of all risk costs within its protection zone.

C. Method of Path Planning

Based on the route network and risk cost matrix, the UAV path planning for producing a safe and cost-effective route will be conducted. A* is the classic algorithm for path planning with the objective of shortest distance. This paper will account for risk cost of network link, so a A*cost algorithm will be used to search for a cost-effective path for UAV. Other path planning algorithms will also be compared with A*cost in terms of performance of reducing cost and computational time.

III. Methodology

As the foundation of path planning, route network with diagonals will be modelled, and risk cost model and cost matrix will be developed. A*cost algorithm will be explained and presented in this section.

A. Route Network Structure

Assuming cubical configuration (**Fig. 3**) with unit length, the theoretical maximum distance reductions for adding planar diagonal and cubical diagonal are 29.3% and 42.3%, respectively. For real-life UAV operations, adding diagonals will increase the flexibility of UAV flight, but increase airspace complexity as well. **Fig. 4** shows the route network with both planar and cubical diagonals. To validate the performance of adding diagonals in the network in real life scenarios, a simulation in Singapore town area will be conducted in case study section.

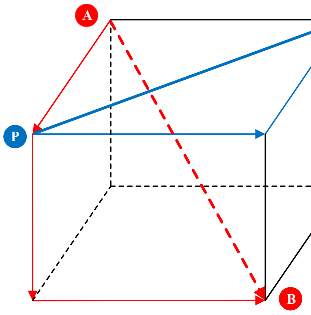


Fig. 3 Schematics of diagonal connection

Fig. 4 AirMatrix with diagonal connections

B. Risk Cost Model

Risk cost model consists two parts. First is an array to store risk cost value of all link in route network. Second is the model to calculate specific cost value in different environments. The risk cost value matrix can be denoted as (x, y, z, c), where (x, y, z) is the location of Point O (see **Fig. 5**). c is the total risk cost in the link (dashed line in red), consisting of all risk costs within its safety boundary (shaded area in red), as well as the risks underneath. All the risk cost of the links in the route network will be store in an array for consumption of path planning algorithm.

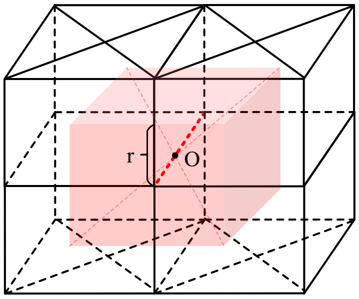


Fig. 5 Illustration for potential high-risk airspace

Array M is to store risk cost matrix in different links, denoted as:

$$M = \begin{bmatrix} (x_1, y_1, z_{1,} C_{t(1)})_1 \\ (x_2, y_2, z_{2,} C_{t(2)})_2 \\ \vdots \\ (x_i, y_i, z_{i,} C_{t(i)})_i \end{bmatrix} \tag{1}$$

where $C_{t(i)}$ is the total risk cost value at the position of (x_i, y_i, z_i) where there is the location of middle point at the links in the route network.

According to previous research, the risk cost value is defined as follows. Particularly, the risk cost is proportional to the probability of incident of the risk [20]. The total risk cost of the link is the sum of all risk costs, denoted as follows:

$$c = wP_{risk} \tag{2}$$

$$C_{t(i)} = \sum_i^n a_i c_i = \sum_i^n a_i w_i P_{risk(i)} \tag{3}$$

c_i is the particular risk cost (e.g. cost of drone hitting people). a_i is the variable and $a_i = \{0,1\}$, if a particular risk is not in the safety boundary of the link, then its cost will not be accounted for in total cost $C_{t(i)}$. In that situation $a_i = 0$. $P_{risk(i)}$ is the probability of the incident; w_i is the weight coefficient to normalize risk cost values in the same scale.

As mentioned above, the risk level and risk cost will be categorized. Assuming the range of total cost $C_t = [C_{t(0)}, C_{t(range)}]$, the different categories of risk cost range can be described as $[C_{t(0)}, C_{t(range)}]$. Here $C_{t(0)} = 0$, meaning that no risks in the safety boundary of the link. $C_{t(range)}$ is maximum of total risk cost. Detailed categorization is presented in Table 1.

Table 1. Categorization of risk costs

Category	Risk level	Risk cost category	Cost range: $C_{t(range)}$
C1	L1	Minor	$[C_{t(0)}, C_{t(1)})$
C2	L2	Small	$[C_{t(1)}, C_{t(2)})$
C3	L3	Medium	$[C_{t(2)}, C_{t(3)})$
C4	L4	High	$[C_{t(3)}, C_{t(4)})$
C5	L5	Highest	$[C_{t(4)}, C_{t(5)}]$

This categorization is used show the risk cost categories and capacities of the links. The path planning algorithm, however, will base on specific risk cost values to produce a safe and cost-effective path for UAVs in urban low altitude environments.

C. Path Planning Method

In this work, UAV path planning problem will be formulated. The problem is to pre-plan a flight path for UAVs before its mission started. A route network with diagonals considering link costs will be input, and A*cost, an A*-based [21] graph search algorithm, will be employed to conduct the cost-effective path planning. The output is a backed pointed path containing a sequence of nodes, originating from the destination tracing back to the origination.

The general idea of A*cost algorithm, similarly to the traditional A*, is to look through the graph to minimize the total cost. The cost function is denoted as [10]:

$$f_{(x)} = g_{(x)} + \delta h_{(x)} \tag{4}$$

where $f_{(x)}$ is the estimated cost corresponding to the cost-effective path from x_O to x_D passing node x; $g_{(x)}$ is the accumulated motion cost of the path from node x to the origination node x_O, constant δ is weighted variable, $h_{(x)}$ is the heuristic cost.

A*cost algorithm ingests risk cost information in the cost function $C_{t(x)}$. For a generic node x_n, the motion cost $g_{(x_n)}$ is denoted as:

$$g_{(x_n)} = \int_{x_O}^{x_n} C_{t(x)} dx \tag{5}$$

where $g_{(x_n)}$ is the integral of the risk cost between original state x_O and state x_n. $C_{t(x)}$ is the function of risk cost of the link.

The heuristic function cost can be therefore denoted as:

$$h_{(x_n)} = \int_{x_n}^{x_D} C_{t(x)} dx \tag{6}$$

where $h_{(x_n)}$ is the integral of the risk cost between state x_n and the destination state x_D.

IV. Simulation Results and Discussions

A. Simulation Results of Different Network Structures

To verify the performance of adding diagonals to the route network, simulations were carried out in the section. The AirMatrix network allows diagonal connections between centroids of airblocks in both planes (AirMatrix2.0) and cubical (AirMatrix2.1) neighbors [22], i.e. in all directions (see **Fig. 2**). Such route structure has increased the connections of the traffic network, thus can be able to reduce the distances of planned routes in the same airspace compared to the first version (AirMatrix1.0) [2] of the traffic network.

Simulations were independently performed three times with structure of no diagonal (AirMatrix1.0), only having plane diagonal (AirMatrix2.0), with plane and cubical diagonal (AirMatrix2.1). Twenty UAV Origination to Destination (OD) pairs were planned to run the simulations. Output is the distances of 20 flights traveled in each simulation. Obtained results are shown in **Fig. 6**., and detailed information is presented in Appendix (**Table A1**.)

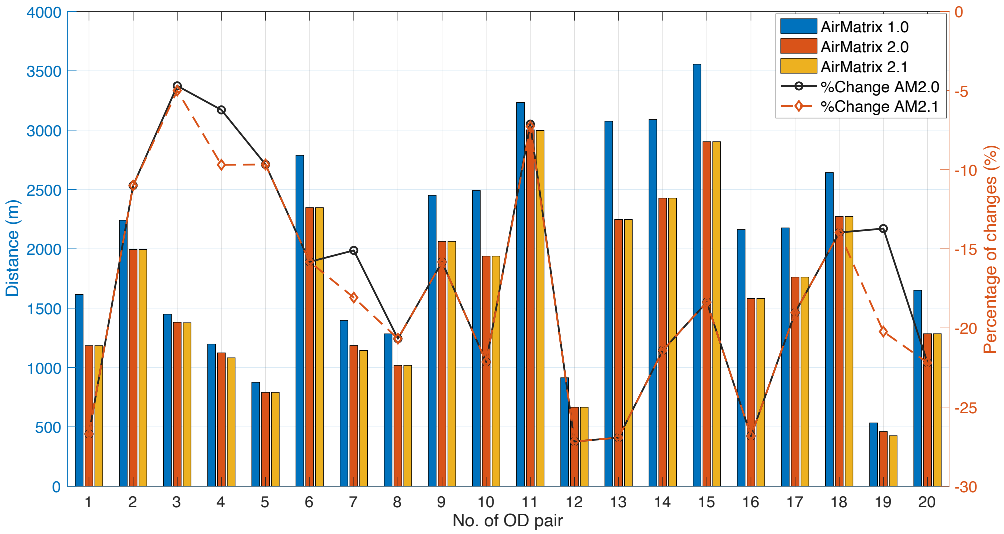


Fig. 6 Simulation results among different version of AirMatrix

The average flight distance in AirMatrix2.0 and AirMatrix2.1 cases both significantly decreases by 17.23% and 17.90%, compared with AirMatrix1.0. AirMatrix2.1 has the best performance in reducing flight distance, but not exceeds much compared with that of AirMatrix2.0. The adding of cubical diagonal contributes only 0.67% in the reduction of the distance in our simulation case. The reason is that each OD mission, UAV will take most of the time in cruise stage in the same flight level (same plane), while few vertical movements.

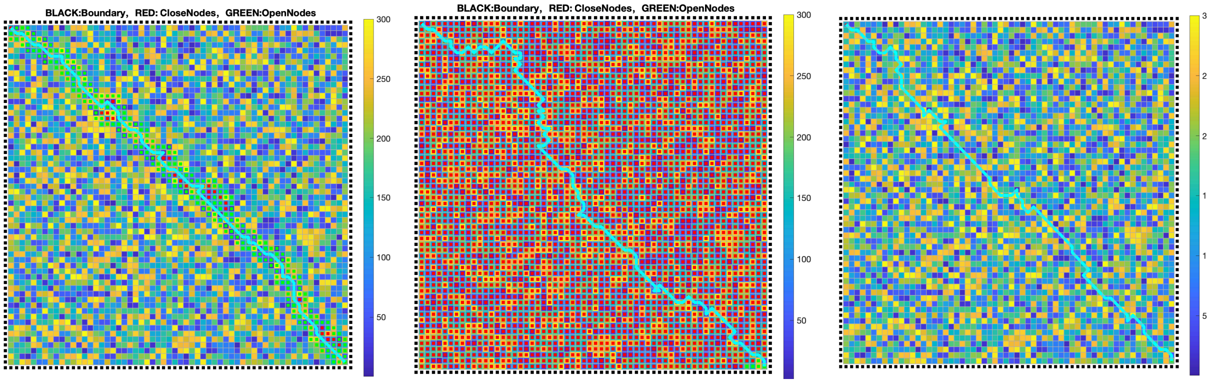
Apparently, adding diagonals is able to increase the flexibility and reduce the flight distance, however, as mentioned before, which will also increase the airspace complexity, especially the cubical diagonal. While adding cubical diagonal may not has a significant improvement for the efficiency by reducing flight distance. Hence, this study may help for further explore of the relationship between flexibility and complexity by adding diagonals.

B. Risk-cost-based Path Planning Simulations

Simulation studies were performed in two scenarios: 1) 2D simulated environment where the cost map was generated by randomly producing the risk cost value in each cell of the map; 2) 3D real-life environment in which a local town of Singapore was selected and AirMatrix platform was employed to conduct the simulation.

In simulated environment, a test field with 60x60 cells was generated and risk costs in each cell is randomly produced from 10 to 300. The proposed A*cost algorithm was then used to produce path for UAV operation. In this work, the A*cost algorithm is neither using Manhattan Distance nor Euclidean Distance as its heuristic distance but introducing cost-equivalent distance (taking the minimum and maximum of the costs in 3,600 cells) as the heuristic information for the searching algorithm. The path planning results are shown in **Fig. 7**.

As we can see in **Fig. 7**. The risk cost map was gridded with 60x60 cells. The cost value of each cell was randomly generating from 10 to 300, which are presented by the color of the cell. The black points are the boundaries of the map, while red and green points represent CloseNodes (the nodes have been searched) and OpenNodes (the nodes are open to be searched). **Fig. 7(a)** presents the A*cost searched path. To verify the performance of A*cost, comparison studies were conducted by Dijkstra and Ant Colony algorithm. The results obtained are demonstrated in **Fig. 7(b)** and **Fig. 7(c)**, respectively. Detailed results in terms of total path cost and computational time are listed in **Table 2**.



(**a**). A*cost (**b**). Dijkstra (**c**). Ant Colony Algorithm

Fig. 7 Risk-based path planning algorithm comparison results

We can see from **Fig. 7** and **Table 2** that A*cost performed the best in terms of computational time with 1.559 seconds, while the Dijkstra is the best in reducing the total risk cost, with the minimal cost of 9824. The Ant Colony algorithm, in this case, is inferior in both computational speed and risk cost, compared with A*cost. While the total cost of A*cost is slightly higher than that of the Dijkstra, the computation efficiency of A*cost greatly outperforms the Dijkstra, making it more suitable for fast computation of risk-based path planning.

Table 2. Comparison results of three path planning algorithms

Algorithms	A*Cost	Dijkstra	ACO
Total risk cost	10373	9824	11293
Computational time (s)	1.559	18.044	4.820

To validate the proposed methodology in urban airspace with real-life environment for UAS operations. A local town in Singapore was selected for UAS traffic management simulation. The selected area consists of residential, industrial and commercial segments. The severity of incidents would differ according to the area, thus different segments represent different risk levels. In addition, other risk factors such as weather and communication signal strength can be integrated into the AirMatrix with the same update function demonstrated in this work.

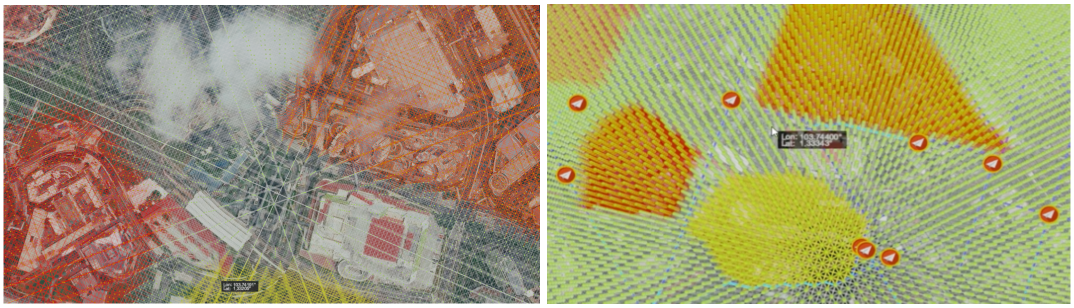


Fig. 8 Simulated AirMatrix Platform

We can see from the simulated platform in **Fig. 8** that the urban airspace is categorized with different risk levels, and the affected links will be updated with risk weighted cost coefficient and change the link attribute for search-based algorithm. In summary, this work has provided a concept of risk-based air traffic management network, AirMatrix, for UAS operations in compact urban environments. Compared to the state-of-the art, the risk-based AirMatrix is able to cover and integrate external information.

V. Conclusion

This work proposed a ConOps for risk-based adaptive airspace management. Common risks in urban environments were identified and classified into four categories. While the A*cost risk-based path planning method was presented by introducing novel heuristic function. Simulations were conducted in both simulated and real-life environments to validate the proposed ConOps and method. Results show that improved A*cost algorithm is able to achieve a good trade-off between computational time and total cost. It performs better in computational time compared with Dijkstra and Ant Colony algorithm, while the total cost is only slightly higher than the minimal one obtained by Dijkstra. The ConOps of AirMtraix with different connectivity were also illustrated and demonstrated by simulations.

This work proposed the ConOps for the risk-based adaptive airspace management, while did not carefully investigate the risk itself. The scope of improved path planning algorithm is about offline stage and cannot deal with online issues considering dynamic risk cost map. These unsolved problems need more efforts to investigate in future works.

Appendix

Table A1. Simulation results of different network structures

No. of OD pair	AirMatrix 1.0 (m)	AirMatrix 2.0 (m)	AirMatrix 2.1 (m)	%Change AM2.0	%Change AM2.1
1	1615.17	1183.9	1183.9	-26.70%	-26.70%
2	2241.03	1994.61	1994.61	-11.00%	-11.00%
3	1449.43	1381.25	1377	-4.70%	-5.00%
4	1197.62	1123.12	1081.62	-6.22%	-9.69%
5	875.39	790.75	790.75	-9.67%	-9.67%
6	2787.98	2346.98	2346.98	-15.82%	-15.82%
7	1395.19	1184.48	1142.93	-15.10%	-18.08%
8	1283.64	1018.22	1018.22	-20.68%	-20.68%
9	2450.82	2062.87	2062.87	-15.83%	-15.83%
10	2490.56	1938.86	1938.86	-22.15%	-22.15%
11	3232.47	3002.47	2997.49	-7.12%	-7.27%
12	913.76	665.37	665.37	-27.18%	-27.18%
13	3075.55	2247.27	2247.27	-26.93%	-26.93%
14	3088.99	2427.47	2427.47	-21.42%	-21.42%
15	3555.92	2902.66	2902.66	-18.37%	-18.37%
16	2162.01	1581.9	1581.9	-26.83%	-26.83%
17	2176.22	1762.1	1762.1	-19.03%	-19.03%
18	2642.23	2273.08	2273.08	-13.97%	-13.97%
19	532.91	459.79	425.09	-13.72%	-20.23%
20	1650.93	1284.44	1284.44	-22.20%	-22.20%
Average	2040.891	1681.5795	1675.2305	-17.23%	-17.90%
Standard deviation	852.4863796	708.675647	714.4985266	6.95%	6.61%

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