ANALYSIS OF FUTURE UAS-BASED DELIVERY

Mariusz A. Balaban Thomas W. Mastaglio Christopher J. Lynch

MYMIC LLC

1040 University Blvd. Suite 100 Portsmouth, VA 23703, USA Virginia Modeling, Analysis and Simulation Center 1030 University Boulevard Suffolk, VA 23435, USA

ABSTRACT

Commercial use of Unmanned Aerial System (UAS) has the potential to reshape the delivery market and to open new business opportunities to small businesses, e.g., local stores, pharmacies, restaurants, as well as to large international and national businesses and government entities, e.g., Amazon, Google, UPS, power companies, and USPS. Simulation models can examine the value added to current business operations, the effects of radical shifts in current operations, and the formation of new types of businesses. This paper presents an envisioned future UAS delivery business operation models and develops a theoretical constructive simulation model. The conducted simulation analysis based on full factorial design estimated causalities between multiple independent and dependent business and policy factors e.g. drone velocity, flying altitude, number of drones, delivery demand, route type, maximum drone fly-time, number of orders completed, time average drone density, order time, drone utilization, and reachability of customers.

1 INTRODUCTION

Although military is traditionally a major user of UASs (Blyenburgh 1999), commercial applications of UASs are clearly on the move. Small commercial drones are used to create marketing videos, capture news, develop movies, support agriculture, and in hobby activities e.g. racing. Teal Group calculated the 2015 UAS market at 72% military, 23% consumer, and 5% civil cumulative for the decade (Teal 2015). Of the three areas, civil UASs will grow most rapidly over the forecast period, but it grows from a very low base. Unmanned Aerial Vehicle (UAV) production will soar from current worldwide UAS production of \$4 billion annually to \$14 billion, totaling \$93 billion in the next ten years. Note that in this paper words "drone", "UAS", and "UAV" are used as synonyms. Finnegan said that "UAVs are no longer of interest only to aerospace companies, but increasingly technology companies like Google, Facebook and Amazon see a need to be in the market" (Teal 2015). The drone industry is expected to climb to a \$8.4 billion by 2019 (ABI 2015). "Application services, data services, licensing and legal services" are expected to fuel this climb, according to Dan Kara, an ABI Research Director, at the RoboUniverse Conference in New York (Kara 2015).

In the future, commercial UASs have the potential to open new opportunities to small businesses, e.g., local stores, pharmacies, restaurants, and international large businesses and government entities, e.g., Amazon, Google, UPS, power companies, and post offices. It is likely that UASs will enable both, the option for a direct delivery service offered by a business to their customers as well as the use of UASs in a business to business (B2B) model. In both cases services may be related to delivery of goods, inspections, and leisure activities.

The public can benefit from the use of drones as a service, such as on demand remote renting of a drone to take pictures or make videos. Similarly, government entities, including police and firefighters will find drones useful for information gathering. Business analysis to support decisions to invest in UASs including necessary infrastructure involves multiple considerations. For instance, the location of the hub(s) nodes that host UASs, size of the fleet, and business operations are important considerations to support efficient product delivery and other services. Beyond these concerns, technical and policy problems related to UAS reliability, safety, automatic route and schedule planning, among other issues require in depth analysis.

This paper presents an envisioned future UAS delivery business operation and a simulation-based study related to the most basic UAS delivery system scenario. The purpose of this research is to investigate requirements for the development of customizable business solutions related to a UAS delivery system.

2 ORIGINATION OF SIMULATION STUDY

A general concept of future low-altitude UAS delivery system is provided by (Amazon 2015a, b), but as of writing this paper the use of UAS for product delivery is not possible in the US due to lack of enabling regulations and the lack of standardization in the UAS market and supporting infrastructure. Amazon proposed four airspace classes below 500 feet. The best class of drones would not only use a collaborative vehicle to vehicle (V2V) communication, GPS, and other traditional way of controls, but also noncollaborative sense-and-avoid (SAA) technology and 4D trajectory planning to enable autonomous operations. NASA has initiated research that should led to development of a prototype of a UAS traffic management (UTM) (Kopardekar 2014). The direction of this market development will be driven by the FAA regulations which can lead to emerging options for product delivery systems. Kopardekar (2014) asked about possible business models to consider in developing and maintaining UTM infrastructures. Providing cheaper, faster, and more convenient delivery drones to customers could cause more people to choose drone enabled businesses and cause a decrease in customers for businesses that use traditional product delivery processes. The UAS delivery system could initially complement current supply chains, but in a long-term it could radically change the way supply chains work. Conducting analysis with various business models is a step to understanding risks associated with such a radical innovation, and can provide insights into businesses and the FAA. The following two subsections offer an overview of generic delivery business processes along with some of their tradeoffs, including traditional ground vehicle delivery and UAS delivery.

2.1 Traditional Delivery Business Process

Figure 1 displays a basic traditional delivery business process that presumably involves a ground vehicle operated by a delivery person. This delivery business process involves a human in the loop so it is quite easy to enable various options related to paying at the time of delivery and conducting deliveries at multiple locations in sequence. The delivery person can take a significant amount of cargo, which makes delivery more economic by saving time and fuel. Except for accessing highly remote locations such as islands, ground based vehicles running on gas have few limitations due to their long range. Ground delivery vehicles contribute to increased traffic volume and produce negative environmental effects due to carbon emission. Moreover, delivery drivers can experience car accidents, robberies, and other problems during the delivery because of sanitary, safety, and trust issues. Depending on the type of delivery customers may be encouraged to give a tip to a delivery person. While most people are accustomed to this, the increased cost of the product can be sometimes detrimental.



Figure 1: Traditional product delivery business process.

2.2 UAS Delivery Business Process

Figure 2 shows a basic UAS direct delivery business process where a product is loaded onto a drone after a customer places an order and a business prepares the order. This can take different amounts of time depending on the availability of business resources and the availability of drones. A loaded drone ascends to a prescribed altitude and flies to the customer along a route. Upon arrival at a customer's location, the drone descends and sends a notification to the customer. When the customer is ready to receive the product at the landing location, the drone lands and releases the product. Next, the drone ascends to the designated altitude and flies back to its business's location where it descends again. Then, depending on the type of drone, the drone is recharged or its batteries are swapped. It soon may be possible to assume that drones operate as fully autonomous vehicles as in the airspace class defined as "best" access proposed by Amazon (2015a).



Figure 2: Direct delivery business process using drones owned by a business.

Major differences exist when comparing traditional delivery processes with UAS direct delivery. In traditional human delivery customers can pay by cash or by a credit card at the time of delivery, these options may be restricted to card or online based payments for drone delivery. The transaction phase when a drone arrives at the customer's location will likely need advanced technology to confirm ready status before the customer receives the cargo/product e.g. shake-hand and authentication. Considering current drone fly-time, max cargo weight capacity, and additional technical requirements during the transaction step, deliveries to multiple locations during one trip may be very challenging at this time. Figure 3 provides extensions to the process presented in Figure 2 where a customer owns a standardized drone and can send it to drone enabled businesses or organizations to pick up orders. In this manner, the costs of initial hardware investment and maintenance transfer to the customer; thereby, reducing the startup burden placed on businesses. Additionally, this option allows customers to choose adequate hardware to meet their specific needs based on their geographical locations and other purposes.



Figure 3: Direct delivery business process using drones owned by a customer.

2.3 Drone Hub as a Service Process

Figure 4 introduces a business process for drone hub as a service. It consists of a hub that hosts drones used by other businesses who sell products to a shared customer base. This process requires interoperability between businesses selling products, a drone hub business, and the customers. A designation of UASs to operate within a certain geographical area to support multiple types of operations could boost local economies by increasing drone utilization and making a drone hub-based business more profitable. For instance, a small local food store would not need to buy a fleet of drones but instead use the services provided by a "hub" company for on demand delivery of products offered by the store to its customers. However, it may be more profitable for some companies to invest in UASs, but this is difficult to determine without knowing future FAA rules. Figure 5 shows a drone hub extended to a network of interoperable hubs. It consists of a network of hubs, where each hub node hosts and services drones used by other businesses that sell physical products. This option could extend the geographical reach of the business if sufficient infrastructure was put in place and UASs were redesigned to enable automatic or manual swapping of cargos, batteries, and/or charging at nodes. The use of drones can facilitate new B2B opportunities. Moreover, the characteristics of this new market requires close collaboration between businesses and public entities to ensure safety policies and well-thought-out business rules. Finally, a combination approach is possible, such as using drones owned by a business or by a customer as the end connectors to a hub network.







Figure 5: Network of hubs.

UAS-based product delivery, as presented in this section, does not yet exist; therefore, simulationbased research is used to provide initial insights into important factors that business stakeholders should consider. Better understanding of system behavior can help avoid design problems, and identify business requirements. When analyzing a drone delivery process one could ask multiple business questions: is this delivery model a viable option using current technology; can it be competitive in some areas, e.g., cheaper or faster as compared to ground-based vehicle delivery; what are the potential problems during delivery; how delivery transaction should be designed; and what are the main constraints one should consider. This analysis tackles policy, as well as technical considerations for businesses and UASs. The main objective is to investigate the causalities between independent and dependent variables, as introduced in the next section. The simulation model is based on a direct delivery business process using drones owned by a business as shown in Figure 2. The study has theoretical, generic characteristics that are not related to any particular real business operation.

3 SIMULATION MODEL

The expansion toward using UAS systems in supply chains could open the doors for creating new business opportunities. The main application areas where Modeling and Simulation (M&S) can support this nascent industry are simulation analysis of new business models, UAS test and evaluation (T&E), and UAS simulation-based training. Currently, simulation research focuses primarily on capabilities related to T&E and training activities. No previous simulation studies which focus on analyzing UAS delivery services were found in the literature. During initial exploration of future UAS delivery system three M&S methods were considered: Discrete Event Simulation (DES); Agent Based Modeling (ABM); and State charts (SC). AnyLogic® simulation software was used to implement a simulation model. The first of the two following subsections introduces several important variables, while the second one briefly describes key features of a developed simulation model.

3.1 Independent and Dependent Variables

The business related independent variables consist of a number of available drones (ND), product demand (D), drone maximum fly-time (MFT), and an option to swap batteries (BS). The policy related independent variables include route type (RT), drone velocity (DV), and flying altitude (FA).

The policy for a low altitude UAS-based delivery system will likely specify permitted FA, DV, and RT. Similarly, when businesses design their operations they will have to consider drone MFT. It is important to consider how different values of DV, likely set by FAA policy, change business output measures. These factors affect the distance that drones can travel to reach potential customers. The maximum flying time from a business location to a customer location can be expressed in a simplified equation: $F_{max} = 4 * vertical time + 2 * horizontal time + transaction time$. The vertical time depends on vertical velocities of drones and prescribed FA, while horizontal time depends on the distance between business and customer and the horizontal DV. Assuming a constant DV standard, this equation can be used to estimate whether orders can be realized for given business and customer locations and drone MFT. The routing can affect performance of the whole system because it changes the distance between customers and businesses. Only two routing approaches are considered in this paper as follows. First RT mimics car-based traffic system where drones fly above the streets. In the other approach drones fly via straight paths toward customers.

The business related dependent variables will include average waiting time in the queue for a drone (AWTQD), number of orders completed per day (OC), order time (OT), drone utilization (DU), and percent of reached customers (RC). The policy related dependent variable will include time average drone density in the airspace (TADD). AWTQD is expressed as $\sum_{i=1}^{n} \frac{WQ_i}{n}$ where WQ_i is order's waiting time for a drone in a queue and n is number of processed orders. OC is simply a number of all orders completed by a business in a day. This measure could be used by businesses in cost-volume-profit (CVP) analysis. OT

is a time interval from the time the order is placed until the drone returns from the delivery. This time includes preparation of delivery (both product and a drone), transit times, and transaction time. DU is expressed as $\int_0^{T(n)} \frac{B(t)dt}{T(n)}$ where $B(t) = \begin{cases} 1 & if \ drone \ is \ busy \ at \ time \ t \\ 0 & if \ drone \ is \ idle \ at \ time \ t \end{cases}$. RC is based on a logical check that uses F_{max} to determine if a customer order is within business's reach. It is expressed in percent as $\frac{customers \ reached}{potential \ customers} * 100$. Finally, TADD is expressed as $(\int_0^{T(n)} \frac{AD(t)dt}{T(n)})/area$ where AD is a number of drones in the airspace at time t, and T(n) is the time to observe the airspace during n intervals at given AD levels.

3.2 Simulation Model Structure and Assumptions

A simulation model realizes a business scenario involving a single business receiving orders placed by a population of customers, which are then fulfilled using delivery drones in order to investigate causalities between the independent and dependent variables. Figure 6 presents the main components of a simulation model and the M&S methods used. ABM is used to represent overall multi-level model structure allowing for embedding processes, behaviors, and interactions of actors (i.e. delivery businesses, customers, orders, and drones. DES represents product deliveries that involve processing orders with UASs representing resources required to process orders. Orders and UASs combine properties of both agents and entities because they are (1) part of DES processes and (2) include internal behaviors that trigger other agents or monitor conditions that are triggered by other agents. SC represent drones' states during operations and their transactions with customers. An alternative view presenting a structure of multi-method simulation model using method formats (MF) based on Balaban (2015) is presented in the Appendix (Figure 8).



Figure 6: Structure of the simulation model.

Figure 7 presents a graphical overview and a simulation screen capture. While the experimental design discusses the use of independent and dependent variables, several assumptions were made in the theoretical scenario, including variable values. The business is centered at 36.77016 latitude and negative 76.20129 longitude of a rectangular GIS area with a 15.89 mile long longitude direction and a 15.25 mile long latitude direction that covers a total of 242 square miles.



Figure 7: Single business UAS delivery.

The area covers a portion of Hampton Roads including the intersection of Norfolk, Chesapeake, and Virginia Beach, Virginia, USA. The locations of customers are randomly generated at latitudes and longitudes using a uniform distribution within boundaries of the area of operation. It is assumed that drone moves on perfect vertical and horizontal trajectories maintaining constant velocities. UAS ascending velocity is 10 mph. Time to load a drone is represented using a triangular distribution with minimum, maximum, and most likely values at 1, 3, and 2 minutes, respectively. A business takes orders for 10 hours daily and finishes transporting all of the placed orders before closing for a day resulting in a terminating simulation. A customer balking due to excessive delivery wait time is not represented.

4 SIMULATION ANALYSIS

This section discusses the design of experiment (DOE) and the results of the simulation analysis.

4.1 **Design of Experiment**

High and low values for 5 input factors were chosen based on a 2^k factorial design, while battery swap and routing type factors were given two options each. The values of input factors are usually estimated by subject matter experts or study sponsors (Law 2007), but since this is a theoretical, non-existent system and the study is not sponsored by any external entity, values for independent variables were chosen based on results from initial runs. Values were spread sufficiently far apart in an attempt to observe a difference in the dependent variable and to avoid nonsensical configurations. Battery swap after product delivery may be permitted or not depending on technical features of the hardware used. A battery swap factor consists of two time options to prepare the drone for the next flight after completing an order, one requiring charging a battery and the other requiring a battery swap. A triangular distribution represents the time to charge a drone with minimum, maximum, and most likely values at 0.5, 1.5, and 1 hours, respectively. The battery swap is represented as 3 minute constant-time task. Two route options between customers and businesses are examined: (1) a straight line route; and (2) a street-based route.

Table 1 summarizes DOE factors and levels. A full factorial design of 7 factors at two levels each with 30 iterations per each level translated into a total of $(2^7 \times 30)$ or 3,840 simulation runs.

Independent variable	Input values	Metric	Dependent variables	Metric		
Drone velocity (DV)	25, 55	Miles per hour	Number of orders completed	Orders per workday		
Flying altitude (FA)	100, 200	Feet	Time average drones density	Average number of drones per area unit		
Number of available of drones (ND)	6, 10	Quantity	Average wait time in queue for drone	Minutes		
Delivery demand (D)	4,6	Orders per hour	Order time	Hours		
Maximum drone fly-time (MFT)	0.5, 1	Hours	Drone utilization	Percent of time drone was used per 100		
Batteries swap (BS)	Yes, no	N/A	Reached customers	Percent		
Route type (RT)	Street, straight	N/A				

Table 1: Input values of the independent variables, and metrics for both independent and dependent variables.

4.2 Results of Simulation

The aggregated difference between high and low levels using upper and lower boundaries of expected effects for each independent factor based on a 0.05 confidence level were calculated to identify causalities between independent and dependent variables. First two columns of Table 2 show low level confidence boundaries of expected effects, while columns 3 and 4 show high level boundaries of expected effects. The 'zero' column displays 1 if the difference between the two level boundaries does not contain zero, and 0 otherwise. Red color indicates significant negative relations and green color significant positive relations. This aggregate analysis discovered 12 relations.

	Average wait time in queue for drone (AWTQD)						Time average drones density (TADD)					Orders completed (OC)				
	upper 1	lower 1	upper 2	lower 2	zero	upper 1	lower 1	upper 2	lower 2	zero	upper 1	lower 1	upper 2	lower 2	zero	
DV	10.24	2.34	9.87	2.47	0	2.12	1.68	1.89	1.61	0	29.66	19.16	38.26	29.06	0	
FA	10.06	2.41	10.05	2.40	0	2.01	1.64	2.02	1.64	0	34.35	24.22	33.87	23.71	0	
ND	15.97	5.86	2.51	0.58	1	1.96	1.61	2.06	1.67	0	34.07	23.93	34.15	24.00	0	
D	5.90	1.32	13.66	4.04	0	1.83	1.53	2.18	1.76	0	27.06	19.42	40.54	29.12	1	
MFT	0.39	0.01	17.22	7.30	1	1.19	1.12	2.60	2.39	1	13.36	9.27	49.49	44.02	1	
BS	17.26	7.35	0.20	0.10	1	1.94	1.60	2.08	1.68	0	33.99	23.95	34.23	23.98	0	
RT	10.56	2.70	9.54	2.12	0	2.01	1.65	2.02	1.63	0	37.55	27.55	30.51	20.53	0	
	Order time (OT)					Drone utilization (DU)					Reached customers (RC)					
DV	0.69	0.37	0.59	0.30	0	0.16	0.10	0.13	0.09	0	58.87	38.85	75.97	59.06	1	
FA	0.64	0.33	0.64	0.34	0	0.14	0.09	0.15	0.09	0	68.10	49.09	67.39	48.17	0	
ND	0.85	0.44	0.37	0.28	1	0.17	0.11	0.11	0.07	0	67.73	48.58	67.77	48.67	0	
D	0.43	0.30	0.81	0.41	0	0.12	0.08	0.17	0.11	0	67.74	48.56	67.75	48.69	0	
MFT	0.20	0.19	0.97	0.59	1	0.03	0.02	0.23	0.19	1	26.49	18.73	96.46	91.07	1	
BS	0.88	0.47	0.33	0.27	1	0.13	0.09	0.16	0.10	0	67.77	48.68	67.72	48.58	0	
RT	0.65	0.32	0.63	0.35	0	0.14	0.09	0.15	0.09	0	74.46	55.96	60.70	41.63	0	

Table 2: Upper and lower confidence boundaries of aggregated expected effects.

A paired two sample t-test for means and Analysis of Variance (ANOVA) tests were conducted to determine if the simulation is sensitive to the values of these variables. Values of the t statistic are shown in Table 3 in the first column of each dependent variable. Critical one-tail t value for df = 63 is 1.669, while two-tail is 1.998. The ANOVA p-values display if there exists a systematic difference between group means or if differences are due to chance (Iversen and Norpoth 1987). The p values are presented

in Table 3 in the second column of each dependent variable. Only p vales above or equal 0.05 are listed as numerical values, whereas p values indicating higher orders of significance are listed using significance codes, which are explained at the bottom of Table 3. A comparison of outcomes between t-test and ANOVA for the relation between FA and RC indicates inconsistency. The ANOVA's p-values indicate a significant difference while the t-test values do not. The interactions between factors were observed for multiple configurations, hence the significance of t-test and p values should be considered with caution especially when near critical values.

	Average wait time in queue for drone (AWTQD)					Time average drones density (TADD)					Orders completed (OC)				
	t stat	ANOVA p value	low	high	total	t stat	ANOVA p value	low	high	total	t stat	ANOVA p value	low	high	total
DV	0.23	0.77	10.9	32.8	43.8	2.70	***	35.9	39.1	75.0	5.25	***	0.0	25.0	25.0
FA	0.04	0.99	3.1	0.0	3.1	1.08	0.4	0.0	1.6	1.6	2.66	*	1.6	0.0	1.6
ND	4.41	***	40.6	1.6	42.2	3.86	***	0.0	15.6	15.6	0.45	0.75	0.0	0.0	0.0
D	3.97	***	1.6	56.3	57.8	9.04	***	0.0	62.5	62.5	12.06	***	0.0	92.2	92.2
MF T	4.93	***	0.0	85.9	85.9	21.05	***	0.0	100	100	29.83	***	0.0	100	100
BS	4.94	***	59.4	0.0	59.4	4.33	***	0.0	18.8	18.8	0.71	0.56	0.0	0.0	0.0
RT	1.46	0.05	1.6	32.8	34.4	0.10	0.78	26.6	37.5	64.1	9.37	***	0.0	75.0	75.0
	Order time (OT)					Drone utilization (DU)					Reached customers (RC)				
DV	2.88	***	40.6	4.7	45.3	2.14	***	34.4	50.0	84.4	11.93	***	0.0	76.6	76.6
FA	0.97	0.81	0.0	6.3	6.3	0.33	0.86	0.0	0.0	0.0	1.00	**	1.6	0.0	1.6
ND	3.76	***	28.1	0.0	28.1	8.63	***	98.4	0.0	98.4	0.53	0.79	0.0	0.0	0.0
D	3.36	***	0.0	26.6	26.6	8.47	***	0.0	90.6	90.6	0.45	0.77	0.0	0.0	0.0
MF T	6.18	***	0.0	100. 0	100. 0	18.76	***	0.0	100	100	45.53	***	0.0	100	100
BS	4.04	***	42.2	0.0	42.2	3.64	***	0.0	21.9	21.9	0.51	0.76	0.0	0.0	0.0
RT	0.12	0.84	34.4	9.4	43.8	0.32	0.34	28.1	57.8	85.9	10.27	***	0.0	70.3	70.3

Table 3: Paired two sample t-tests for means, ANOVA p values and directions of causality.

Significance codes for p values follow R statistical toolkit nomenclature: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' 1

Next, the direction of causality for each pair of dependent and independent variables was analyzed. The chosen procedure avoids replicating the whole design in order to lessen the impact of interactions between factors. The difference between upper and lower boundaries of expected effects for two levels of each independent factor were calculated separately for each of 64 levels. A score of 1 was added to one of three counters if: (1) the difference did not contain zero and the effect was negative i.e. independent variable at low-level generated response greater than at high-level; (2) the difference did not contain zero and the effect was positive i.e. independent variable at high-level generated response greater than at low-level; or (3) the counters 1 or 2 were increased. All three counters were normalized and converted to percent values. The values of three counters are shown in Table 3 in the third, fourth, and fifth columns of each dependent variable as 'low', 'high', and 'total' respectively. The values in 'low' and 'high' columns indicate the causality in positive and negative directions. The third counter is the cumulative percent of 'low' and 'high' columns, meaning significant counts where the difference did not contain zero. Purple color indicates significant relation, but no prevailing direction of causality.

The increase of DV from 30 and 55 mph did not significantly affect AWTQD, which is likely attributed to the constraining effect of F_{max} . DV has positive significant relations with OC and RC, and a significant negative relation with OT. When looking at F_{max} with a higher DV the number of customers increases, which means DV affects the actual demand. As a result of more customers being served, more

time may be required to prepare the product which impacts OT. DV also has a significant impact on both TADD and DU, but direction of the influence changed with other factors due to their interaction. The time necessary for vertical movement is very low in comparison to a horizontal movement causing FA to have generally less effect on responses than DV. FA did not have a significant effect on AWTQD, TADD, OT, and DU, while it did have a significant negative effect on OC and RC. ND negatively affected AWTQ, ND, and DU, while positively affecting only TADD. We expected a positive relation between ND and OC, but that was not the case. This was caused by the terminating rule of the simulation and no representation of customers canceling orders or deciding not to order due to excessive delivery wait or estimated wait times before placing an order. As a result, a business completes work later but OC is the same with less ND. With D increased AWTOD, TADD, OC, OT, and DU also increased, while no difference was observed in RC. MFT had positive relations with all responses. This illustrates that MFT is likely one of the most important business factors when designing a future UAS delivery system because with higher MFT businesses could reach more customers. With battery swap, the time spent on charging is eliminated, hence BS has positive relations with TADD and DU, and negative relations with AWTQD and OT. As a side note, if batteries could have been swapped at the customer location the effective range of drones would have doubled. RT had positive relations with OC and RC. RT relation with AWTQD is at 0.05 for ANOVA p value and not too far from a significant positive for one-tail t stat value, i.e., 1.669 -1.46 = 0.209 below the critical one-tail t value. One should also take into account that 32.8 percent of AWTQD samples were significantly higher for straight routes than for street routes. Customers in the straight RT scenario resulted in a higher AWTQD, OC, and RC in comparison to street routes. Finally, because AWTQD is included within OT similarity in their results can be observed.

CONCLUSIONS

This paper analyzed a basic concept of the future use of UASs for delivery of products. There are countless possible applications of UASs for the delivery of goods, in emergency situations, and for other services. The new UAS-based delivery business has huge potential value, and this research is an initial step toward its evaluation. The paper has introduced a simple approach to analyze business considerations related to UAS delivery system, which when refined can be used by companies interested in UAS delivery to better understand, plan, and evaluate their potential UAS operations. This work can also provide some insights to the FAA. The experience gained during the analysis of UASs delivery system using the developed simulation model offered insights into selected factors for UAS business delivery. The gained expertise will inform further analysis related to design of low altitude UAS delivery traffic system. Various other UAS-based business models should be conceptualized and analyzed, including both delivery and services provided to B2B and to end users.

APPENDIX



Figure 8: A structure of model using MFs.

REFERENCES

- ABI. 2015. "Here's Where the Real Money Is in Drones." ABI Research. Accessed March 4, 2016. http://www.cnbc.com/2015/05/13/heres-where-the-real-money-is-in-drones.html.
- Amazon. 2015a. "Determining Safe Access with a Best-Equipped, Best-Served Model for Small Unmanned Aircraft Systems." Accessed March 4, 2016. https://images-na.ssl-imagesamazon.com/images/G/01/112715/download/Amazon_Determining_Safe_Access_with_a_Best-Equipped Best-Served Model for sUAS.pdf.
- Amazon. 2015b. "Revising the Airspace Model for the Safe Integration of Small Unmanned Aircraft Systems." Accessed March 4, 2016. https://images-na.ssl-imagesamazon.com/images/G/01/112715/download/Amazon_Revising_the_Airspace_Model_for_the_Safe_ Integration of sUAS.pdf.
- Balaban, M. A. 2015. "Toward a Theory of Multi-Method Modeling and Simulation Approach." Ph.D. thesis, MSVE, Old Dominion University, Ann Arbor.
- Blyenburgh, P. V. 1999. "Uavs: An Overview." Air & Space Europe 1 (5):43-47.
- Iversen, G. R., and H. Norpoth. 1987. Analysis of Variance, Sage University Papers Series on Quantitative Applications in the Social Sciences, 07-001. Thousand Oaks, CA: Sage
- Kara, D. 2015. "Opening Keynote: Robotics: Where Are We Now, and Where Are We Going?". Accessed March 4, 2016. http://www.robouniverse.com/new-york/2015/ and http://www.cnbc.com/2015/05/13/heres-where-the-real-money-is-in-drones.html.
- Kopardekar, P. 2014. Unmanned Aerial System (Uas) Traffic Management (Utm): Enabling Low-Altitude Airspace and Uas Operations. Moffett Field, California: Ames Research Center
- Law, A. M. 2007. Simulation Modeling and Analysis. 4th ed. New York: McGraw-Hill
- Teal. 2015. "Uav Production Will Total \$93 Billion." Accessed December 10, 2015. http://www.tealgroup.com/index.php/teal-group-news-media/item/press-release-uav-production-will-total-93-billion.

AUTHOR BIOGRAPHIES

MARIUSZ A. BALABAN, Ph.D. is an M&S Scientist/Engineer at MYMIC. He received a Ph.D. in Modelling and Simulation (M&S) from Old Dominion University. His research interests are R&D governance, innovation, test and evaluation methods, social systems, enterprise decision support systems, maritime systems, robotics, applied and methodological aspects related to M&S; especially, the multi-method (hybrid) M&S approach. He is a member of SCS, ACM SIG, ITEA and GK International. His email addresses are mariusz.balaban@mymic.net and marbalamarbala@gmail.com.

CHRISTOPHER J. LYNCH is a Senior Project Scientist at the Virginia Modeling, Analysis and Simulation Center. He received his M.S. in Modeling and Simulation from Old Dominion University in 2012 and a B.S. in Electrical Engineering from Old Dominion University in 2011. He is currently pursuing a Ph.D. in M&S from Old Dominion University. His research interests include multi-paradigm modeling, conceptual modeling, and verification of simulation models. His email address is cjlynch@odu.edu.

THOMAS W. MASTAGLIO, Ph.D. is the Chairman of the MYMIC family of companies. He has over 25 years of experience conducting research and developing modelling and simulation solutions in the academia and industry. His Ph.D. is in Computer Science from the University of Colorado. His research interests include: modelling and simulation, user interface design, big data applications, artificial intelligence, virtual reality and human-computer interaction. His email address is Tom.Mastaglio@mymic.net.