A Simulation Approach to Optimize Concrete Delivery using UAV Photogrammetry and Traffic Data

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Abstract –

Unmanned Aerial Vehicles (UAVs) are an emerging technology that serve a range of applications for construction purposes including the creation of site survey maps, jobsite monitoring for routine progress reports, and structural inspections. Though while promising, drones have not yet been widely utilized by the construction industry to their fullest potential and there are still many areas to explore. One such activity is utilizing drones to optimize concrete delivery to a jobsite. Ready-mix concrete is an essential part of many projects, but its quick setting time makes proper delivery planning essential. The purpose of this paper is to investigate the application of UAVs and traffic data in scheduling a concrete delivery and develop an overall framework to optimize this activity. The proposed Automated Construction Data Acquisition and Simulation (ACDAS) framework is comprised of three main steps: collection, simulation, and reporting. To implement the concept, traffic data of a construction site in San Luis Obispo, California was collected and EZStrobe discrete event simulation modelling was used to model three potential routes from a local concrete batch plant to the specified job site. The model was able to predict the most efficient route for concrete delivery in a congested traffic area.

Keywords – Unmanned Aerial Vehicles; UAVs; optimization; ready mix concrete; construction planning, delivery

1 Introduction

A large amount of information is involved in the planning of construction projects and the interdependency among information imposes a heavy burden on planners [1]. Construction projects often involve huge operations, with activities taking place over large areas so one of the major issues that construction practitioners struggle with is having real-time control of the project. This is simply because real-time control requires a high volume of real-time data. Without a comprehensive set of real-time data about all parameters that impact the project, it will be difficult to reach the optimum productivity of construction activities. The most common tools used for recording visual data on construction sites include digital cameras, smart phones, tablets, laser scanning devices, and terrestrial and aerial unmanned vehicles [2,3]. Information that is collected manually generally is not comprehensive and does not relate the data to other parameters that impact the project. In recent years, Unmanned Aerial Vehicles (UAVs) have gained popularity thanks to their demonstrated superiority over traditional methods in various construction tasks by offering an opportunity to capture information for visualizing site layout, planning, and organization in real-time [4]. Drones are currently used in construction to examine terrain at future construction sites, track progress at existing construction sites, inventory the assets, and provide routine facility maintenance [5]. They achieve this by using LiDAR (a detection method utilizing lasers) or a technique called Photogrammetry which uses photography to extract measurements of the environment. Overlapping imagery provides multiple perspectives of the same feature and allows for distance and volume measurements to be taken and provides outputs in the form of “point clouds”, 3D images used to render the observed environment in a virtual setting [6]. While drones are a proven powerful tool, they have not yet been widely utilized by the construction industry. This has been partly due to low familiarity and autonomy of project teams with the use of the visual data technologies [7]. Because of this, many aspects of the construction process could still incorporate drones to improve efficiency.

One integral activity that could benefit from UAV incorporation is scheduling concrete deliveries to a construction site. Delivering concrete to a jobsite is an essential step in many construction projects and must be completed with precision. Procuring, delivering, and pouring concrete is a major milestone in many projects as concrete is often the foundation. Propper planning is essential as conflicts between delivery and production will arise during the execution of plans which can cause chaos in operations management [8]. Planning is especially important for the ready-mix concrete (RMC) industry as it has more potential transport barriers than any other manufacturing industry since RMC has a low value-to-weight ratio and is highly perishable as it must be laid on site before it solidifies [9]. Per ASTM C94, concrete discharge should occur within 90 minutes after the introduction of the mixing water to the cement and aggregates [10]. Going over this threshold can result in the batch being sent back to the plant and essentially wasted. Therefore, optimizing the travel time and distance the concrete travels in the truck is extremely important to ensure the concrete is poured within the 90-minute window.

Unfortunately, this time constraint can pose a problem since transportation of RMC is heavily influenced by current traffic conditions such as traffic congestions [11]. Understanding the access routes available for travel to the construction site and their potentials for congestion. While the traffic impact caused by isolated incidents such as car accidents cannot be predicted, understanding overall traffic patterns can be an important tool in concrete delivery planning. The time chosen for a concrete delivery can have a significant impact on the success of the delivery as the travel time between concrete batching plants and construction sites can significantly fluctuate at different hours of the day and on different days of the week [12]. Therefore, barring the unexpected, historical traffic data is a useful resource in selecting the optimal time to leave. In addition to traffic delays, pedestrian and bicycle traffic can also impact concrete dispatch by increasing the amount of time the concrete is in transport. This issue can be assumed to be especially pertinent to college campuses and city centres, locations often undergoing construction activities. All these hurdles pose the question: how can concrete be delivered efficiently?

This constraint can be referred to as the Concrete Delivery Problem (CDP). The CDP aims to find efficient routes for a fleet of (heterogeneous) vehicles, alternating between concrete production centres and construction sites, adhering to strict scheduling and routing constraints. Procuring and coordinating a fleet is especially important since the amount of concrete requested by a single customer typically exceeds the capacity of a single truck [13]. When multiple deliveries are needed, the temporal spacings between the consecutive deliveries may not exceed certain limits (time lags) to prevent the concrete already poured from partially hardening before the rest of the supply arrives at the site [14]. Therefore, with multiple deliveries (variables) required, optimizing the concrete delivery path is essential to avoid time-induced failure.

2 Background

With such a high level of uncertainty in concrete operations travel times, traditional practices for scheduling concrete production and delivery are largely based on trial and error and depend on the dispatcher's experience [15]. Transitioning from this reliance on human intuition to sophisticated data collection and modelling techniques can help to optimize concrete delivery time. This paper seeks to utilize data collected by UAV, Google Maps, and local transportation departments to model and simulate concrete delivery to a construction site. The model output is expected to impact the construction schedule and provide more reliable dates and times to pour the concrete.

2.1 Traffic Impacts on RMC Delivery

Concrete delivery is an integral part of the construction process. RMC delivery planning is mainly determined by skilled batch plant managers that schedule truck assignments to single deliveries and estimate the vehicles needed such that the total demand can be satisfied. The goal is to plan the whole process optimally to ensure utilization of machinery and workers of the batch plant and construction site [11,16]. A major variable in concrete delivery is traffic. Because of this, traffic patterns and their effects on construction activities have been investigated. Carr 2000 created a Construction Congestion Cost system for the Michigan Department of Transportation to balance construction productivity and traffic delay using 5 excel sheets to produce an output of daily user cost, total user cost, and project cost [17]. Naso et al. 2007 determined that on-time delivery of RMC can be significantly affected by peak-hour and non-peak-hour traffic [18]. Hadiuzzaman et al. 2014 directly utilized traffic information by creating a construction-traffic interdisciplinary simulation (CTISIM) framework based on high level architecture [19]. After determining the optimal arrangement of truck-mixers, their deviation between simulated and requested arrival of truck mixers was reduced by 68.7%, compared to the deviation for the arrangement as in the off-peak hour. In addition, their requested and optimized arrival intervals were all below 5.0 min, showing the feasibility of their integrated simulation model. These studies highlight that any useful simulation model for concrete delivery must consider traffic factors and conditions.

2.2 Simulation Modeling

The construction industry has embraced the power of simulation in recent years. Construction Simulation can be defined as the science of developing and experimenting with computer-based representations of construction systems to understand their underlying behaviour [20]. Various researchers have utilized this to solve problems related to construction planning and activities.

Simulation modelling has been investigated as a means for optimizing scheduling of various construction-related activities. Maghrebi et al. 2015 investigated six machine learning algorithms tailored to RMC dispatching and compared them to observed human decision data that was employed for a specific case study [21]. While some models worked faster than others, they all were more successful than the human-decision control. Torjai and Kruzslicz 2016 sought to optimize the delivery of biomass from satellite storage locations to a central biorefinery and found that the mean trip duration is a good estimation of the minimal number of required trucks and a schedule without truck idle time was always found even when the number of trucks had been locked at its minimum [22]. Razavialavi and AbouRizk 2017 outline a framework to enable planners to anticipate site layout variables (temporary facilities size, location, orientation) and construction plan variables (resources and delivery plans) to simultaneously optimize them in an integrated model [23]. Khan et al. 2017 describes the implementation of a failure mode, effects, and criticality analysis (FMECA) tool and discrete event simulation to assess supply chain risks, identify vulnerabilities, and measure the impact of disruptions of a ready-mix concrete supply chain [24]. Kim et al. 2020 proposes a dynamic model for precast concrete production scheduling by using discrete-time simulation method to respond to due date changes in real time and by using a new dispatching rule that considers the uncertainty of the due dates to minimize tardiness [25]. The results of these studies indicate that simulation modelling is a viable method for planning and optimizing activities and should be investigated for applying to ready mix concrete delivery.

Although these studies indicate that simulation modelling is a proven tool that can be used to charter the optimal path from a concrete batch plant to a job site, they all share a limitation in that they do not account for the impacts smaller scale factors, mainly pedestrians and bicyclists, can have on deliveries to populated areas and many do not explicitly use data collected by drones, which could prove a beneficial addition.

While there are many studies on the impact construction activities have on pedestrians, no previous studies have been found that investigate how pedestrians and bicyclists impact the construction schedule. While this may not seem like an issue at first glance, underestimating the impacts of non-vehicles on construction can have just as much impact when trying to prevent delays. Take, for example, a model that perfectly simulates the local traffic data in San Luis Obispo, California and schedules the optimal concrete delivery to Cal Poly to arrive at 8:05 AM on a Tuesday. This falls during a passing period where thousands of students will be entering and leaving campus on foot and on bike. This severely compromises the simulation model and what was originally thought to be the best choice based solely on vehicular traffic can end up being the worst when pedestrian and bicycle data is included. Therefore, data should be collected on pedestrian and bicycle patterns around populated job sites; this can be accomplished with unmanned aerial vehicles (UAVs).

3 Methodology

The literature review conducted by the authors revealed both drones and simulation modeling are effective tools for construction practitioners, but they have not been combined for concrete delivery applications. The following is a contribution to bridge this gap. Traffic data and drones can be used to provide data to model the optimal delivery scenarios. The proposed framework is named Automated Construction Data Acquisition and Simulation (ACDAS) and consists of three modules.

3.1 Simulation Model

The following sections detail the framework modules created. The steps in sequence are Collect, Simulate, and Report. Fig. 1 summarizes the steps of this framework.

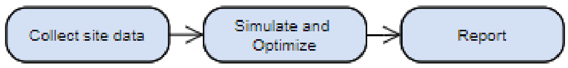

Figure 1. Main Steps of ACDAS Framework

3.1.1 Data Collection

The first step of this framework is to capture relevant traffic data for the potential concrete delivery routes. For this proposal, the data collected is two-fold: traffic data for the roads leading to the site and traffic data immediately on and around the site. Historical traffic data for the roads leading from the concrete batch plant to the job site will be collected from Google Maps, a common GPS system used by drivers (Fig. 2). Google Maps not only provides data for how long a trip will take at the given time; it can also predict the duration of a trip planned in the future based on historical precedents. This allows the eventual model to compare the durations of different paths and different departure times. In addition to Google Maps data, local databases can be utilized to determine information about the roads relevant to the planned delivery. For our experimental study in San Luis Obispo, the County of San Luis Obispo provides Traffic

Counts can provide valuable information to our model [26]. This site lists the peak hour (the time and traffic volume for the highest AM and PM peak hour for the duration of the count) and peak day volume (the day of the week and the traffic volume on the highest day for the duration of the count) for all county maintained roads. This information is compiled for every day of the year from 2015 to present and thus can provide good estimations of historical precedents.

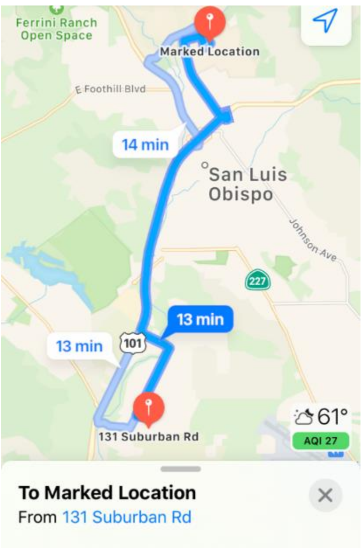

Figure 2. Sample Google Maps routes between a concrete batch plant and construction site.

While traffic data can predict the impact vehicles will have on deliveries, other site-specific factors such as pedestrian traffic and bicycles should be incorporated into the analysis. Drones can be utilized on construction sites to survey conditions around the site to determine when any pedestrian- or bicycle-induced traffic could occur. Drone data collected daily can be fed into the model to determine if there are any patterns in small-scale traffic at specific times in the day to allow the model to account for and avoid these bottlenecks. The following case study is the first iteration of this framework so data from drones was not included but will be the focus of future expansions.

If the collected data is not sufficient, the collection process can be expanded to fill in any gaps. Once all required data is captured and complied, the next step is to input that data into a simulation model.

3.1.2 Discrete Event Simulation Model

The modelling steps of the concrete delivery process are shown in Fig. 3. The first step involved is developing a discrete simulation that depicts the real-world scenario of the concrete delivery process. The model for this study was built using EZStrobe simulation software [27]. EZStrobe is used in the construction industry as a general-purpose simulation system designed for modelling construction processes. However, it is also utilized to model other types of systems because it is domain independent. EZStrobe takes multi-step activities, such as concrete delivery, and models them as just one activity and provides a duration that represents the time it takes to perform all n steps. After the simulation model is generated, it can be run for each of the route alternatives. The model results for each scenario are then analysed and summarized to highlight the most efficient route.

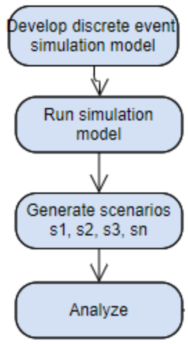

Figure 3. Development of the discrete event simulation model.

3.1.3 Reports

The purpose of this framework is to generate a report that accurately outlines the most efficient delivery path for a truck to take from a concrete batch plant to a job site. The report outputs include: the optimal route to take to the job site, the total delivery duration, the optimal time to start the delivery, the forecasted arrival time, and the number of trucks required. This report will aid Project Managers in planning the concrete pour activities months in advance and will allow the activity to proceed as efficiently as possible when the time comes.

3.2 Experimental Study

The proposed framework was implemented to verify its applicability. The implementation was specifically tried to verify how collected traffic data can help in developing an optimum schedule for the concrete delivery to the construction site. The site investigated in this study is a four-level 102,000 square foot construction project at the California Polytechnic State University campus in San Luis Obispo, California (Fig. 4). This site was selected because it can only be accessed by a limited

Figure 4. An image of the construction site investigated for this study.

number of heavy traffic routes. The goal is to utilize simulation modeling to determine the best route to deliver the concrete to the site to assist the project team in planning this activity efficiently. The preliminary implementation collected traffic data on three routes that started at a local batch plant and ended at the job site; these routes are denoted as R1, R2, and R3 (Fig. 5).

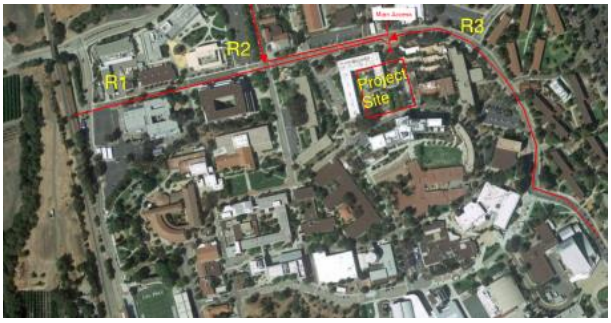

Figure 5. Project site layout before construction with potential delivery routes (Google Maps).

The traffic data collected was sourced using a combination of Google Maps data and local data. This data was fed into a developed simulation model that held the number of trucks available, number of mixing stations, and total amount of concrete required constant for each route (Table 1).

Table 1. Constants used in the simulation model.

nTrucks	Number of Mixer trucks	6
nStations	Number of loading Stati	1
AmtOfConc	Amount of Concrete in CY	720

Three simulations were run to account for each of the three routes. Each analysis follows the life cycle of a single truck and uses statistical modelling to determine the total durations of each step in the concrete pour activity and the total duration of the concrete pour event. The flowchart in Fig 6. summarizes the simulation model created in EZStrobe for Route 1. The circles represent the

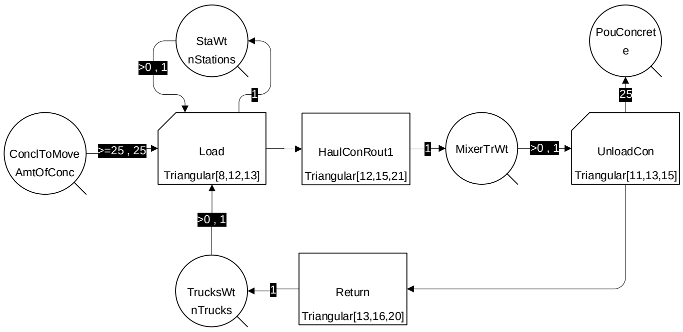

Figure 6. EZStrobe simulation model flow for Route 1.

queuing systems the trucks encounter such as loading and pouring while the rectangles represent the truck entity. When the entity (truck) and its resource (concrete) are two units (i.e. the truck cannot leave until all concrete is loaded or poured) the rectangle has a corner missing and when the entity and resource are one unit (i.e. the truck and concrete traveling together to the job site) the rectangle is intact. The model assumes each truck has a capacity of 25 CY and estimates of the minimum, mean, and maximum durations for each segment in the event (values denoted in brackets in each rectangle). A triangular distribution is used based on these values to determine the overall duration of each 25 CY delivered to the site; this process is repeated until all 720 CY of concrete have been delivered. At the end of the simulation a total activity duration is outputted. The process is repeated for Routes 2 and 3. A summary of the preliminary results for each of the three routes is highlighted in Table 2.

Table 2. Preliminary Results of the Simulation Model

Model Parameters	**S01**	**S02**	**S03**
Number of Mixer trucks	6	6	6
Number of loading Stations	1	1	1
Amount of Concrete in CY	720	720	720
Factory Loading Station Utilization	0.87	0.87	0.85
Mixer Truck utilization	1	1	1
Time of operation in hours	5.9	3.1	5.95
Production rate in CY/hr	133	131	135

The results of this experiment highlight the complex relationship between route selection and delivery time.

Immediately, it is noted from Table 2 that S01 and S03 (R1 and R3) are very similar with total operation times of 5.9 and 5.95 hours, respectively. Conversely, the results for S02 (R2) yield a duration of 3.1 hours, almost three hours faster than the previous two options. Looking at the results for all three routes shows the impact route selection has on the overall duration of a large concrete pour activity. The conclusion that can be drawn from this is R2 should be chosen over R1 or R3 for the concrete delivery in this specific task.

It is important to note that this analysis held the number of trucks present at the jobsite constant at 6 and only compared the different routes. If the number of trucks available were to change this model can quickly show how, if at all, that would impact the optimal route selection. Determining the number of trucks present is another key part of project optimization and is a function of the cycle time of each truck. Because the cycle time is in part determined by how long the trucks are driving from location to location, changing the selected route may (in some cases) allow for additional trucks to be added in the system if their cycle times are reduced substantially. This may be beneficial for projects prioritizing saving time over the incurred costs of expanding the truck fleet. If the number of available trucks is not subject to change under any circumstances this model will still optimize the trucks in their present condition.

Currently, we are working on including UAV data into the simulation model to account for small-scale factors such as bicycle and pedestrian traffic around the job site. Once the university population is back to normal, UAVs will collect data around the job site to determine time frames of peak-traffic. These times are hypothesised to occur in the morning and at passing periods throughout the day when students and faculty are going to and from classes. Our future analysis will reveal the magnitude of influence of these small-scale factors and if they should be considered in future simulation models. Through data collection, simulation, and analysis of multiple scenarios, better construction productivity can be achieved.

3.3 Conclusion

This paper proposes a framework for simulation modeling and drone integration in planning the delivery of a concrete pour activity. This framework is known as Automated Construction Data Acquisition and Simulation (ACDAS) and is achieved through a three-step process. First, the site conditions are quantified using vehicular traffic data and pedestrian and bicycle traffic data, with vehicular data sourced from Google Maps and local databases and pedestrian and bicycle data sourced from on-site UAVs. Second, a simulation model is developed using the collected information to investigate the many possible scenarios the delivery could take. Third, the model determines the most efficient option and outputs the optimal delivery path and delivery time the trucks will take from the batch plant to the construction site. This study will contribute to the construction industry in two major ways. Firstly, utilization of the ACDAS framework in concrete delivery will improve project performance by increasing the efficiency of concrete deliveries to a job site. This will minimize waste and maximize productivity which will lead to lower costs, fewer delays, and less wasted concrete in concrete activities. Secondly, the easy-to-follow nature of the ACDAS steps busts one of the major myths involving using drones (and other advanced technologies) in the construction industry, implementation is too difficult. With this ACDAS path laid out, it will be much easier for interested parties to invest in the new technologies described and utilize their benefits to improve concrete pour deliveries in their projects. Gaining experience in these technologies could also lead to improvements in other aspects of their projects as simulation modeling and drones have proven to be useful for other construction applications.

Our preliminary experiment proved the efficacy of using vehicular traffic data in a simulation model to determine the optimal route for trucks to take while delivering concrete to the jobsite. These findings are not exclusive to just concrete delivery. The constants in our model (Number of trucks, distance of R1, distance of R2, etc.) can be adjusted to fit other activities and routes relevant to the construction process and a similar analysis can be performed to find the optimal course of action.

A limitation of this framework is the lack of a major case study utilizing the ACDAS process in a large-scale construction project. Because of this, while optimization of individual activities has been tested and proven to work, the theorized effects of this framework have yet to be confirmed. Further research is already under way on expanding this topic to include UAV data and future publications will seek to qualitatively measure the efficacy and results of the ACDAS framework.

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