Optimal Truck Dispatch Scheduling of Ready Mixed Concrete: A Case Study from Bolivia

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Abstract

The use of scheduling techniques in ready mixed concrete (RMC) firms in Bolivia is a complex problem. The authors developed a linear model for a Bolivian RMC firm taking into account the research context. This model integrated RMC truck dispatch data to decide the optimal RMC supply schedule. The authors used historical dispatching data, interviews, and field measurements to build a database and characterize the firm's demand to build an optimized model. A solution algorithm using Solver from Excel was developed to efficiently solve the optimal RMC supply scheduling problem. Afterward, the solution was compared using actual operational data. The results show that the solution algorithm increases RMC supply efficiency and saves costs.

Keywords
Efficiency, Scheduling, Optimization, RMC Supply Schedule, Linear Programming.

1. Introduction

RMC is a material composed of cement, water, sand, and gravel and is mostly used in the construction industry (Afzal & Khan 2018). This material has some physical and chemical characteristics that generate certain limitations in its production and distribution. Specifically, different to other industries, in the RMC industry, due to the fast-solidifying nature of concrete, it cannot be produced in advance and subsequently stored in a finished product warehouse (Feng et al. 2004). On the other hand, it follows specific formulations depending on the requirements of each customer (Afzal & Khan 2018). Moreover, time is a significant factor in this type of industry. According to (Biruk 2015), the time elapsed between mixing and placement of RMC on-site should not exceed its solidification time. Thus, according to Afzal & Khan (2018), RMC is only productive if distributed promptly to customers. Moreover, Biruk (2015) states that time is the crucial factor because delays can lead to wastage of the whole batch, making it mathematically complex to model and optimize. Therefore, due to material characteristics and time constraints, RMC supply scheduling is critical for construction firms.

Bolivia is experiencing rapid infrastructure growth and, thus, RMC demand (INE 2021). Inside RMC Bolivian firms' day-to-day operations, the dispatch process is not based on technical knowledge but instead on the experience of its personnel. Moreover, to the best of our knowledge, there is no study of supply cycle times in Bolivia to determine the process times and the factors that affect them. Also, a firm's data are not adequately processed, which generates a large amount of wasted information. Hence, Bolivian RMC firms do not efficiently process and distribute their products. We studied an RMC firm in Cochabamba-Bolivia to analyze and optimize their supply cycle time. In particular, we performed interviews with the firm's personnel and collected raw data from the supply process. Next, through linear programming, we developed a solution using Excel to help the firm schedule the RMC delivery in Cochabamba-Bolivia. The following section will present relevant literature to our study, followed by the methodology, data collection, and analyses. Finally, we will present the results, discussion, and conclusion.

2. Literature Review

In recent decades, there has been an increase in studies related to RMC supply scheduling. For example, Afzal & Khan (2018) recognized the importance of correct scheduling because delays cause the loss of the RMC batches. Moreover, Lin et al. (2010) indicate that optimal programming is related to just-in-time (i.e., products must be produced only upon request). Similarly, Hao (2012) suggests that optimization is a traditional line of research to efficiently RMC delivery scheduling problems. Hence, as Albayrak & Albayrak (2016) found, optimization solves RMC supply problems.

In this regard, Matsatsinis (2004) indicates the existence of hundreds of optimization solutions. Ramos (2000) classifies these optimization solutions into two large groups: traditional and metaheuristic methods. In the first case, the advantages of traditional methods are the assurance of having a significant number of restrictions and finding optimal solutions. On the negative side, these methods take more significant times to compute. For example, Yan et al. (2008) developed an integrated model combining RMC production scheduling and RMC truck supply schedules.
In the other case, compared to traditional methods, metaheuristic methods are faster in reaching satisfactory (not optimal) solutions but with fewer restrictions. Literature suggests that metaheuristic methods are used when supply functions are too complex. In particular, Taha (2012) indicates that an optimization solution is satisfactory if it considers all constraints. For example, due to model complexity, Asbach et al. (2009) used metaheuristic solutions to minimize RCM transportation costs when there are penalties for not fulfilling orders.

Regarding metaheuristic solutions and RMC delivery scheduling, Feng et al. (2004) found that delivery times, RMC unloading time, and the number of RMC trucks influence the RMC delivery process. Next, using this information, these authors used genetic algorithms and simulation techniques to find optimal dispatching schedules that minimize RMC trucks waiting time. Similarly, Naso et al. (2007) studied RMC time restrictions, such as RMC anticipated and late deliveries. Specifically, these authors developed a metaheuristic approach to scheduling supply.

Some researchers have combined traditional and metaheuristic methods to find optimal supply scheduling solutions. For example, Albayrak & Albayrak (2016) aimed to solve a transport problem where all supply data must satisfy all the demand while minimizing costs. They used linear programming (traditional method) and genetic algorithms (metaheuristic method) and compared both methods. Moreover, some researchers improve their results using simulations to evaluate different solutions (under different contexts). For example, Biruk (2015) used RMC delivery times to simulate and evaluate different delivery scenarios. Similarly, Panas & Pantouvakis (2013) used simulation to determine RMC truck size.

We found some research on optimization solutions for supply problems in Latin American literature. For example, Ayllon et al. (2017) use a transportation model to minimize fruit supply costs. However, we did not find published studies related to RMC supply scheduling problems to the best of our knowledge. Furthermore, in the particular case of Bolivia, we did not find any research related to RMC supply scheduling problems.

3. Methodology

To optimize the cycle delivery times of a Bolivian RMC firm, we used a methodology based on the stages proposed by Belda (1986) and Panas & Pantouvakis (2013) (see Fig. 1). All the stages are sequential, and each one covers different sub-objectives in optimizing the cycle delivery times scheduling of mixer truck dispatches in an RMC firm. Figure 1 shows the proposed phases.

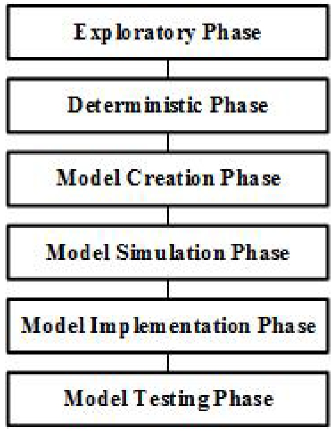

Figure 1. Methodological phases

Exploratory Phase: The main objective of this phase was to know the process in detail through a flow chart and semi-structured interviews with the firm's mixer truck operators. In addition, we collected historical information on truck travel times.

Deterministic Phase: We determined the average supply cycle times by decomposing the entire cycle into sub-processes.

Model Creation Phase: First, we created a linear transportation model based on the variables in the previous phases. Next, we used Solver from Microsoft Excel to solve the model. We decided to use this software due to Albayrak & Albayrak (2016) suggestions and the firm's internal policies. Based on Ayllon et al. (2017), we present the steps followed to develop the transportation model:

1) *Determination of RMC production capabilities*. The firm shared with us data about its production capabilities for every month.
2) *Determination of the demand for each district and each type of job.* Based on the demand data received, we calculated the actual demand using the following equation:

$$District\ demand = \frac{Number\ of\ orders\ per\ district}{Total\ number\ of\ orders}$$

Next, we calculated the job demand regarding each type of job, following the next equation:

$$Job\ type\ demand = \frac{Number\ of\ orders\ by\ type\ of\ job}{Total\ number\ of\ orders}$$

3) *Production time calculation.* We calculated the time (in minutes) for each production plant to place the orders, type of job, and supply cycle time to each district.
4) *Decision variables definition.* We identified 30 decision variables. The identification used the combinations between truck destination districts, construction type, and RMC production plant.
5) *Objective function definition.* For this step, we used the principles of the transportation model developed by Hitchcock (1941). Moreover, we defined the cost objective function in terms of time as follows:

$$\boldsymbol{Min} \sum_{i=1}^{i=m} \sum_{j=1}^{j=m} \boldsymbol{Cij} * \boldsymbol{Xij} \text{ (Objective Function)}$$

6) *Define the restrictions.* Next, we defined the supply and demand restrictions that the problem should have. We established these restrictions following the physical limitations of the model. In other words, no more

RMC can be distributed to each district than the current production capacity and at least the customer's demanded quantity. Next, we present the restriction equations:

- **Restrictions**

$$\sum_{j=1}^{j=n} Xij \leq Si \; (i = 1,2, \dots n) \; (Supply\ Restriction)$$

$$\sum_{j=1}^{j=m} Xij \geq dj \; (j = 1,2, \dots n) \; (Demand\ Restriction)$$

$$Xij \geq 0 \; (i = 1,2 \dots . m; j = 1,2 \dots n)$$

Model Simulation Phase: In this phase, we performed simulations of both models, current and optimal, using different demand values, districts, and jobs.

Model Implementation Phase: We based our implementation on Feng et al. (2004). Specifically, we programmed a customized Microsoft Excel Worksheet to calculate the optimal supply scheduling of RMC. The data to be entered into the worksheet are order scheduled time (time a truck must be at the construction site), RMC volume demand (in cubic meters), the district where the construction site is, and the type of construction site. Based on this information, the worksheet automatically calculates: (a) the number of trucks needed to fulfill the order; (b) the time the batching must start at the plant; (c) the time the truck must leave the plant; (d) the time the truck must arrive at the site to start pouring RMC; (e) the time it should finish pouring to return to the plant; and (f) the time it should arrive at the production plant to wait to be batched again (for the same or another order). Also, the worksheet indicates which of the two production plants the truck should go to be batched again with RMC.

Model Testing Phase: Next, we performed simulations and comparisons between the optimal model and the current model to determine the existence of statistically significant differences using one-factor ANOVA. Additionally, we developed KPIs to quantify the improvements objectively.

4. Data Collection

The following sections describe the dispatching process and the different information we collected in the firm.

Mixer truck dispatching process:

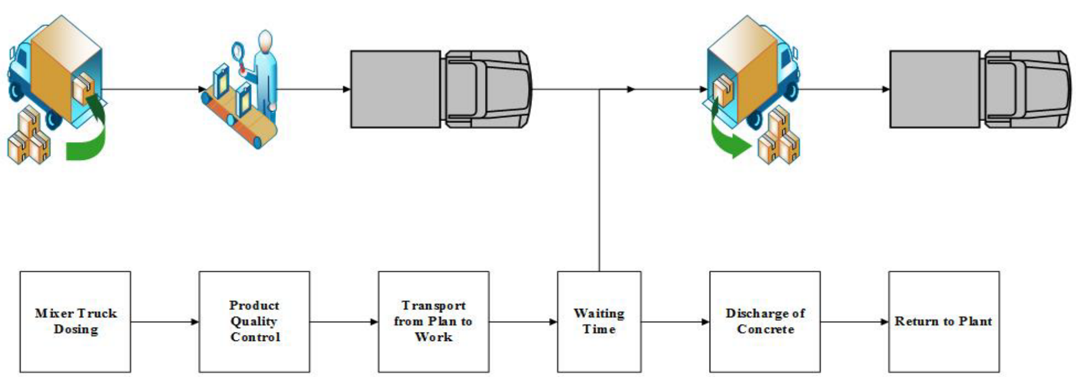

Figure 2. Mixer truck supply process

First, we analyzed the dispatching process through visits to the production plant. As shown in Fig. 2, we found that the first step in the supply process is related to the dosing of the truck. Subsequently, quality control activities are performed on the RMC to verify that it meets consumer requirements. Once the product fulfills customer requirements, the truck is authorized to leave the production plant for the construction site. When the truck arrives at the construction site, the allotted possible waiting time is given to unload the product. Finally, the mixer truck returns to the plant once the unloading is finished and new dosing starts again.

Supply cycle time influencing factors

Next, we performed semi-structured interviews with mixer truck operators to determine the supply cycle time influencing factors. As shown in Table 1, the mixer truck operators indicate the existence of controllable and uncontrollable factors. Controllable factors are job type, district and distance, traffic, and team lack of communication. On the other hand, they indicate that uncontrollable factors are related to climate, construction delays, and other unpredictable factors, such as power outages.

Table 1. Factors that influence supply cycle time

Controllable Factors	Uncontrollable Factors
Job type	Climate
District and distance	Construction delays
Traffic	Unpredictable factors in construction
Team lack of communication	

Job types

Next, using the data provided by the firm, we found that three types of jobs are the most demanded by consumers. In particular, we found that, on average, 83% of jobs were related to slabs, slab floors, and columns. We also found that these job types are significantly different in their supply cycle times ($F = 69.69$; $p < 0.01$).

Percentage of waiting time on site

Next, we analyzed the percentage of time trucks spend waiting on the construction sites before unloading their loaded RMC. As shown in Table 2, 78% of the RMC trucks waited 5 min, 56% waited more than 15 minutes, and 37% waited more than 30 minutes. These results suggest the existence of idle times that consume person-hours waiting and influence the quality of RMC, leading to solidification and unusability.

Table 2. Percentage of waiting times on site

More than 5 min	More than 15 min	More than 30 min
6.292	4.493	2.942
78%	56%	37%

Average supply cycle time

Next, we calculated the average supply cycle times using the firm's database of 8036 points collected from January 2019 to February 2020. Table 3 shows the current average supply cycle times. Based on our analyses and type of jobs, the optimal supply cycle times should be characterized by no waiting times on-site.

Table 3. Average supply cycle times

District	Type of work	Load (min)	Arrive to district (min)	Waiting time (min)	RMC pouring (min)	Return (min)	Supply cycle time(min)
Center and east	Slab	15	23	38	22	26	124
Center and east	Floor slab	15	23	35	15	26	114
Center and east	Column	15	23	25	54	26	143
North	Slab	15	27	30	22	32	126
North	Floor slab	15	27	46	15	32	135
North	Column	15	27	16	54	32	144
West	Slab	15	20	33	22	25	115
West	Floor slab	15	20	34	15	25	109
West	Column	15	20	23	54	25	137

South	Slab	15	19	13	22	25	94
South	Floor slab	15	19	15	15	25	89
South	Column	15	19	20	54	25	133
Southeast	Slab	15	34	23	22	45	139
Southeast	Floor slab	15	34	13	15	45	122
Southeast	Column	15	34	62	54	45	210

Supply capacity
Next, we collected information related to the firm's RMC production capacity. As Table 4 shows, the production capacity of Plant 1 (64%) almost doubles Plant 2 (36%). On the other hand, Table 4 also shows that the firm's mixer truck fleet working times per month (3.840 hours)

Table 4. Supply Capacity

	Capacity	Unit
Plant 1	10.752	m3/month
Plant 2	6.144	m3/month
Mixer truck	192	hours/month
Mixer truck fleet	3.840	hours/month

Average demand by district
Using historical data given by the firm, we calculated the average RMC demand for each district. The results in Table 5 indicate that the highest demand is in the center and east districts of Cochabamba, followed by the west district. These results are not surprising because, in recent years, these districts have shown the higher economic growth in Cochabamba (Cadecocruz, 2018).

Table 5. Average demand by district

District	% Average
Center & east	70,1
North	6,7
West	20,5
South	0,2
Southeast	2,5

Average demand by job type
Based on the data given by the firm, we found that slabs are the most demanded product (66.7%), followed by floor slabs (22,6%) and columns (10,7%) (see Table 6).

Table 6. Average demand by job type

Job type	% Average
Slab	66,7
Floor slab	22,6
Column	10,7

Average supply cycle times for each RMC production plant and district
As shown in Table 7, we found the average supply cycle times from each RMC production plant to all districts.

Table 7. Average supply cycle times for each district

District	Type of work	Plant 1 (min)	Plant 2 (min)
Center & east	Slab	124	130
Center & east	Floor slab	114	120
Center & east	Column	143	149
North	Slab	126	132
North	Floor slab	135	141
North	Column	144	150
West	Slab	115	121
West	Floor slab	109	115
West	Column	137	143
South	Slab	94	100
South	Floor slab	89	95
South	Column	133	139
Southeast	Slab	139	145
Southeast	Floor slab	122	128
Southeast	Column	210	216

5. Results and Discussion

5.1 Numerical Results

Current supply model
Using historical data, we found that the maximum historical RMC demand was 14,785 m3. Hence, this is the maximum volume the firm can distribute under the current conditions. Based on this information, we inferred that both plants still have enough production capacity. However, the collected data also suggest that its transportation capacity has already reached its maximum transportation volume.

Optimized supply model
Using our optimized model, we found that the maximum demand value to be met is 16,896 m3/month. This result suggests the existence of available transportation capacity but with the highest production capacity. Moreover, as Table 8 suggests, Plant 1 should be prioritized higher. In particular, Table 8 indicates that the demand is 14,785 m3/month at current conditions (91.74% production capacity), and thus the current transportation capacity has reached its maximum. On the other hand, based on the optimized model, at maximum demand (16,896 m3/month), the transportation capacity reaches 83% utilization and total production capacity (100%). Therefore, compared to the current conditions, these results indicate that the optimized model improves production use and transportation capacity.

Table 8. Comparison of production and transport capacity of both models

Demand	Objective function (current)	Objective function (optimal)	Production capacity	Transport capacity (current)	Transport capacity (optimal)
8.952	2.294	1.649	52,98%	59,74%	42,94%
9.843	2.523	1.813	58,26%	65,70%	47,21%
7.929	2.032	1.461	46,93%	52,92%	38,05%

10.000	2.563	1.842	59,19%	66,74%	47,97%
14.500	3.763	2.718	88,78%	97,99%	70,78%
14.785	3.840	2.774	91,74%	100,00%	72,24%
16.896	---	3.190	100,00%	---	83,07%

Based on Table 8 results, we calculated the cost reduction per m3. As shown in Table 9, implementing the optimized model will reduce the cost from 10 USD to 7 USD per m3. Moreover, we also found a reduction in total variable costs per m3 from 65 USD to 62 USD.

Table 9. Cost reduction per m3

Component	Current (USD/m^3)	Optimal (USD/m^3)
Raw material	55	55
Distribution	10	7
Total variable cost	65	62

5.3 Suggested improvements

As previously indicated, we developed a Microsoft Excel Worksheet based on the optimized model. This worksheet allowed the firm's supply personnel to program daily RMC deliveries optimally. Table 10 shows the results from the worksheet that automatically and optimally assigned clients to trucks, RMC plants, truck departure and arrival times to construction districts, RMC loading and unloading times, and truck departure and arrival times to RMC plants. In particular, first, the user introduces the client code and is assigned to one or more free RMC trucks (Truck code). Next, depending on the demand, the worksheet schedules each loading truck with their plant departure time, district arrival time, RMC unloading starting and finish times, district departure time, and plant arrival time.

Moreover, when scheduling, the worksheet compares loading times and plant departure times to determine which RMC plant will be used for loading. For example, Table 10 shows how Truck 1 is assigned to Client 1 and should return at 6:48. Next, the worksheet compares the hour at which available trucks should be loaded and adjust the schedule accordingly. Furthermore, the worksheet will reassign Truck 1 (6:50) when all the other available trucks are assigned, and Truck 1 has already arrived at the plant (6:48).

Table 10. Worksheet scheduling

Client code	Truck code	Plant	Loadin g time	Plant departur e time	District arrival time	RMC unloading starting time	RMC unloading finish time	District departure time	Plant arrival time
1	1	1	05:22	05:37	06:00	06:00	06:22	06:22	06:48
1	2	1	05:44	05:59	06:22	06:22	06:44	06:44	07:10
1	3	1	06:06	06:21	06:44	06:44	07:06	07:06	07:32
2	4	2	06:18	06:33	07:00	07:00	07:22	07:22	07:54
1	5	1	06:28	06:43	07:06	07:06	07:28	07:28	07:54
2	6	2	06:40	06:55	07:22	07:22	07:44	07:44	08:16
1	1	1	06:50	07:05	07:28	07:28	07:50	07:50	08:16
2	7	2	07:02	07:17	07:44	07:44	08:06	08:06	08:38

5.4 Model validation

Next, we used random demand values to compare the historical and optimized supply cycle times from the model included in the Excel worksheet. Compared to historical data, we found that the optimized model reduces the supply cycle times by 28% (see Table 11). Moreover, using ANOVA, we found that the reduction in supply cycle times was statistically significant ($F = 15.48$; $p < 0.05$). Hence, the optimized supply model significantly increases RMC supply efficiency.

Table 11. Historical supply times vs. optimized supply times

Demand (m^3)	Historical supply cycle times (Hours)	Optimized supply cycle times (Hours)	Difference (Hours)	Improvement %
8.952	2.294	1.649	645	28
9.791	2.509	1.804	705	28
7.929	2.032	1.461	571	28
10.000	2.563	1.842	721	28
14.500	3.763	2.718	1.045	28
14.785	3.840	2.774	1.066	28

6. Conclusion

Our study makes two contributions to Latin American and Bolivian literature. First, to the best of our knowledge, this is the first study to develop an optimized RMC supply model. Second, based on Feng et al. (2004) and Albayrak and Albayrak (2016), we propose an optimized supply model for RMC firms. Hence, our findings suggest the usability of optimized models in developing countries, such as Bolivia. Specifically, we developed a flow chart to develop the optimized supply model, performed semi-structured interviews with the firm's mixer truck operators, and collected historical information on truck supply cycle times. Next, using the collected information, we determined the average supply cycle times, and thus we created an optimized linear transportation model based on Feng et al. (2004) and Albayrak and Albayrak. Afterward, we used Solver from Microsoft Excel to solve the model. Then, we performed simulations of both current and optimized supply models using different demand values, districts, and jobs. Later, we implemented the solution in a Microsoft Excel Worksheet to automatically and optimally assign clients to trucks, RMC plants, truck departure and arrival times to construction districts, RMC loading and unloading times, and truck departure and arrival times to RMC plants. Next, we validated the model using random demand values to compare the historical and optimized supply cycle times. The optimized supply model decreases average supply cycle times by 28%. Moreover, our optimized model reduces the RMC supply costs from 10 to 7 USD/m^3.

All studies have limitations, and ours is no exception. First, future studies can increase the accuracy of our results using RMC geospatial data to develop better scheduling models. Second, our study context was in Cochabamba, a small city with a concentration of construction sites in specific districts. Future studies can determine if our model shows similar performance in bigger cities where construction sites are evenly distributed. We expect that our model will inspire future researchers in Bolivia and Latin America to develop optimized RMC supply models according to the context where they live.

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