

Balancing a bike-sharing system in Real Time

Daniel Chemla, Frédéric Meunier, Roberto Wolfler-Calvo,
Houssame Yahiaoui, Thomas Pradeau

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Talk plan

- ▶ Introduction and motivation
- ▶ Modelization
- ▶ Exploitation methods
 - ▶ Using a truck
 - ▶ Online Tarification
- ▶ Evaluation
 - ▶ Simulator presentation
 - ▶ Results

Motivation: improving regulation issue

- ▶ *It is statistically impossible to be sure to find a bike or a park place in 100% of the cases*

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Le Figaro, 26 mars 2010

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System modelization

- ▶ Clients arrival rate at a station: Poisson process
- ▶ Destination choice: O-D matrix generated with gravity model
- ▶ Goal : improving client satisfaction
 - ▶ No bike: the client leaves the system unsatisfied
 - ▶ No parking: the client leaves the system unsatisfied and with the bike
- ▶ **S** the set of stations, $|\mathbf{S}| = \mathbf{n}$ and \mathbf{m}_n the total number of bikes

The Queue Modelization

- ▶ A station is modelled as a M/M/1 queue where servers are the users and bikes are in the queues (infinite capacity)
- ▶ The time spent in trajectory is modelled as a M/M/ ∞ queue
- ▶

$$\mathbf{N}_n(\mathbf{t}) = \{ \mathbf{N}_{ij}(\mathbf{t}), (\mathbf{i}, \mathbf{j}) \in \mathbf{S}^2, \mathbf{t} \geq \mathbf{0} \}$$

such that:

- ▶ $\mathbf{N}_{ij}(\mathbf{t})$ number of bikes going from station \mathbf{i} to \mathbf{j} at time \mathbf{t}
- ▶ $\mathbf{N}_{ii}(\mathbf{t})$ the number of bikes parked are station \mathbf{i}

The former process $\mathbf{N}_n(\mathbf{t}), \mathbf{t} \geq \mathbf{0}$ is an irreducible Markov Chain and has an invariant probability that is not easy to compute

The Queue Modelization

Asymptotic approximation to have exploitable results:

- ▶ Open network of independent network of N^2 queues
- ▶ The probability of the open network has a product form
- ▶ Asymptotically the original network in its stationary state is behaving as the open network

Exploitation system

- ▶ Improving efficiency: avoid stations to be empty or full
- ▶ First way: ordering trucks to balance the system, moving bikes from attractive stations to repulsive ones
- ▶ Second way: without trucks, incitating people to regulate the system by encouraging them to park bikes in empty stations

Exploitation system

Heuristic using trucks need a target state defined for each station.
Heuristic here are made for one truck

First heuristic: objective driven

- ▶ The truck is sent to the two most unbalanced stations
- ▶ Arriving at the station it tries to balance it for the best
- ▶ A new call to the operating system every two moves
- ▶ The evolution of the system not taken into account

Exploitation system

Heuristic using trucks need a target state defined for each station.

Heuristic here are made for one truck

First heuristic (bis): objective driven

- ▶ The truck is sent to the two most unbalanced stations - with a correction using the incoming flows of bikes
- ▶ Arriving at the station it tries to balance it for the best
- ▶ A new call to the operating system every two moves
- ▶ The evolution of the system not taken into account

Exploitation system

Second heuristic: DP

The truck is defined by its **state**. At timestep \mathbf{k}

$$\mathbf{E}_k = (\mathbf{V}_k, \mathbf{p}_k, \mathbf{l}_k, \mathbf{t}_k) \in \mathbf{S}_n^k \times \mathbf{V}_k \times [|\mathbf{0}, \mathbf{K}_c|] \times [|\mathbf{0}, \mathbf{T}_{\max}|]$$

where

- ▶ \mathbf{V}_k : list of the already visited stations since the start of the mission $|\mathbf{V}_k| = \mathbf{k}$,
- ▶ \mathbf{p}_k : truck position
- ▶ \mathbf{l}_k : truck load. ($\mathbf{K}_c =$ truck capacity)
- ▶ \mathbf{t}_k : time slop elapsed since the start of the mission

For each station $\mathbf{i} \in \mathbf{S}$ a target state \mathbf{T}_i is defined

Exploitation system

Cost of going from state \mathbf{E}_k to station \mathbf{E}_{k+1} :

$$J(\mathbf{E}_k, \mathbf{E}_{k+1}) = |\mathbf{T}_i - (\mathbf{N}_{ii}(\bar{\mathbf{t}}_i) + \mathbf{L}(\mathbf{l}_k, \mathbf{N}_{ii}(\bar{\mathbf{t}}_i)))| + \sum_{j \notin \{\mathbf{V}_k \cup \{i\}\}} |\mathbf{T}_j - \mathbf{N}_{jj}(\bar{\mathbf{t}}_i)|$$

where $\mathbf{p}_{k+1} = i \notin \mathbf{V}_k$

$$\bar{\mathbf{t}}_i = \mathbf{t}_k + \mathbf{T}_{\mathbf{V}_k, i}$$

Exploitation system

Cost of going from state \mathbf{E}_k to station \mathbf{E}_{k+1} :

$$J(\mathbf{E}_k, \mathbf{E}_{k+1}) = |\mathbf{T}_i - (\mathbf{N}_{ii}(\bar{\mathbf{t}}_i) + \mathbf{L}(\mathbf{l}_k, \mathbf{N}_{ii}(\bar{\mathbf{t}}_i)))| + \sum_{j \notin \{\mathbf{V}_k \cup \{i\}\}} |\mathbf{T}_j - \mathbf{N}_{jj}(\bar{\mathbf{t}}_i)|$$

where $\mathbf{p}_{k+1} = i \notin \mathbf{V}_k$

$$\bar{\mathbf{t}}_i = \mathbf{t}_k + \mathbf{T}_{\mathbf{V}_k, i}$$

▷ Backward DP thanks to Bellman equation to obtain the best command for the truck

$$J^*(\mathbf{E}_k) = \min_{s \notin \mathbf{V}_k} \mathbb{E} [J(\mathbf{E}_k, s) + J^*(\mathbf{E}_{k+1}(s)) | \mathbf{N}_s(\mathbf{t}_k)]$$

In practice, experiments done for small cities (up to **20** stations) and **2** to **3** timesteps

Third heuristic: The Colored Cluster balancing approach

- ▶ The truck's optimal decision is done taken into account the number of bikes at each stations and on the trucks
- ▶ a huge number of states if taken all these informations into account
- ▶ Clustering stations: a client does not mind changing stations if they are a few tens of meters away
- ▶ Coloring Cluster: the optimal decision should not be very depending of the exact number of bikes in a cluster but on the average level of filling; 3 levels are defined: deficit of bikes, average filling, excess of bikes
- ▶ → The number of states is then
NbStates = $3^{\text{NbCluster}} * 3 * \text{NbCluster} = 13122$ for **6** clusters.

Exploitation system

- ▶ With the probability matrix to go from a state to another and defining a target state in which all stations are balanced we can find the optimal policy to get to the target state for the least mean cost
- ▶ The optimal policy is obtained thanks to a classical policy iteration algorithm
- ▶ Problem : obtain the probability matrix
 - ▶ With the Queue modelization
 - ▶ With a nanosimulator

Fourth heuristic: The Online Tarification Approach

- ▶ Objective: Regulate **without any truck**
- ▶ Control: Prices on arrival stations
- ▶ → Defining a targeted level of filling for all stations

TargetFilling

- ▶ $x_{(i,j)}^k \geq 0$: People that wanted to go from station i to j but park at station k instead
- ▶ $c_{(i,j)}^k = C_{(i,k)}^B + C_{(k,j)}^F - C_{(i,j)}^V$: Cost to stop at station k instead of j and walk to station j

Exploitation system

$$\begin{aligned} \text{Min} \quad & \sum_{(i,j,k) \in S^3} x_{(i,j)}^k c_{(i,j)}^k \\ \text{s.t.} \quad & \sum_{(i,j) \in S^2} x_{(i,j)}^k = T_k \quad \text{for all } k \in S \quad \text{(i)} \\ & \sum_{k \in S} x_{(i,j)}^k = \gamma \lambda_i P_{ij} \quad \text{for all } (i,j) \in S^2 \quad \text{(ii)} \\ & x_{(i,j)}^k \geq 0 \quad \text{for all } (i,j,k) \in S^3 \quad \text{(iii)} \end{aligned} \quad (1)$$

Where

- ▶ $T_k = \max\{0, \text{TargetFilling} - \text{Load}_k\}$: current default in bikes
- ▶ λ_i : Mean arrival rate per station
- ▶ $\gamma = \frac{\sum_{k \in S} T_k}{\sum_{k \in S} \lambda_k}$: normalization constant

Exploitation system

$$\begin{aligned} \text{Max} \quad & \sum_{(i,j) \in S^2} \gamma \lambda_i P_{ij} \beta_{(i,j)} + \sum_{k \in S} T_k \mu_k \\ \text{s.t.} \quad & c_{(i,j)}^k - \mu_k - \beta_{(i,j)} \geq 0 \quad \text{for all } (i,j,k) \in S^3 \quad \text{(i)} \\ & \beta_{(i,j)}, \mu_k \in \mathbb{R} \quad \text{for all } (i,j,k) \in S^3 \quad \text{(ii)} \end{aligned} \quad (2)$$

Exploitation system

$$\text{Max} \quad \sum_{(i,j) \in \mathbf{S}^2} \gamma \lambda_i \mathbf{P}_{ij} \beta_{(i,j)} + \sum_{k \in \mathbf{S}} \mathbf{T}_k \mu_k$$

$$\text{s.t.} \quad \begin{array}{l} \mathbf{c}_{(i,j)}^k - \mu_k - \beta_{(i,j)} \geq 0 \quad \text{for all } (\mathbf{i}, \mathbf{j}, \mathbf{k}) \in \mathbf{S}^3 \quad \text{(i)} \\ \beta_{(i,j)}, \mu_k \in \mathbb{R} \quad \text{for all } (\mathbf{i}, \mathbf{j}, \mathbf{k}) \in \mathbf{S}^3 \quad \text{(ii)} \end{array} \quad (2)$$

▷ a set of dual prices $\{\mu_k, \mathbf{k} \in \mathbf{S}\}$

Exploitation system

$$\begin{aligned} \text{Max} \quad & \sum_{(i,j) \in \mathbf{S}^2} \gamma \lambda_i \mathbf{P}_{ij} \beta_{(i,j)} + \sum_{\mathbf{k} \in \mathbf{S}} \mathbf{T}_{\mathbf{k}} \mu_{\mathbf{k}} \\ \text{s.t.} \quad & \mathbf{c}_{(i,j)}^{\mathbf{k}} - \mu_{\mathbf{k}} - \beta_{(i,j)} \geq 0 \quad \text{for all } (i, j, \mathbf{k}) \in \mathbf{S}^3 \quad (\text{i}) \\ & \beta_{(i,j)}, \mu_{\mathbf{k}} \in \mathbb{R} \quad \text{for all } (i, j, \mathbf{k}) \in \mathbf{S}^3 \quad (\text{ii}) \end{aligned} \quad (2)$$

▷ a set of dual prices $\{\mu_{\mathbf{k}}, \mathbf{k} \in \mathbf{S}\}$

▷ when a client appears at station \mathbf{i} and want to go to \mathbf{j} he can go to \mathbf{k} instead for the following cost:

$$\mathbf{u}(\mathbf{k}) = \mathbf{c}_{(i,j)}^{\mathbf{k}} - \mu_{\mathbf{k}}$$

Each client chooses the solution that has the least cost for him.

$$\beta_{(i,j)}^* = \min_{\mathbf{k} \in \mathbf{S}} \mathbf{c}_{(i,j)}^{\mathbf{k}} - \mu_{\mathbf{k}}$$

is the price that will finally pay a client who wants to go from \mathbf{i} to \mathbf{j} .
He will go to station $\mathbf{k}^* \in \mathbf{S}$ such that $\mathbf{c}_{(i,j)}^{\mathbf{k}^*} - \mu_{\mathbf{k}^*} = \beta_{(i,j)}^*$

Evaluation of the system

Simulator

- ▶ Clients are generated with respect to a Poisson process
- ▶ Their targeted destination is taken with respect to a O-D matrix that has been generated with a gravity model
- ▶ The time elapsed while driving from a station to another is computed with respect to the distance and altitude between two stations
- ▶ Clients who do not find bikes or parking spots can visit several stations before leaving the system with respect to a bound in time and stations given by their profil type

Indicator

- ▶ Number of satisfied clients
- ▶ Number of clients who did not find a bike
- ▶ Number of clients who did not find a parking
- ▶ Number of clients who change their targeted station for another one (tarification approach)

Evaluation of the system

Result: Low case demand - edoras

Size	Indicator	Empty	OB	OB-corr	DP	CC	OT
20	Satisfied	677	962	963	738	714	829 + 156
	No bikes	199	1	1	154	171	
	No parking	124	29	28	104	124	
50	Satisfied	2027	2265	2281			2279 + 166
	No bikes	323	144	133			67
	No parking	174	106	97			6
100	Satisfied	3213	3401	3437			4165 + 424
	No bikes	1385	1230	1210			554
	No parking	618	570	556			32
250	Satisfied	8720	8870	8880			—
	No bikes	3615	3495	3481			—
	No parking	1464	1423	1426			—

Evaluation of the system

Result: Medium case demand - edoras

Size	Indicator	Empty	OB	OB-corr	DP	CC	OT
20	Satisfied	1130	1649	1666			1556 + 288
	No bikes	660	210	191			97
	No parking	188	104	104			23
50	Satisfied	3849	4173	4234			4330 + 311
	No bikes	973	714	661			397
	No parking	269	198	185			44
100	Satisfied	5290	5589	5641			7096 + 790
	No bikes	4283	4021	3970			2385
	No parking	918	863	862			128
250	Satisfied	12817	13024	13051			—
	No bikes	13058	12863	12830			—
	No parking	2161	2132	2137			—

Evaluation of the system

Result: High case demand - edoras

Size	Indicator	Empty	OB	OB-corr	DP	CC	OT
20	Satisfied	1535	2333	2393			2364 + 457
	No bikes	1579	825	762			430
	No parking	219	144	145			45
50	Satisfied	5845	6364	6436			6533 + 468
	No bikes	2309	1850	1782			1391
	No parking	353	260	250			74
100	Satisfied	6977	7392	7482			9858 + 1193
	No bikes	9588	9188	9096			6176
	No parking	1113	1073	1072			242
250	Satisfied	15285	15560	15537			—
	No bikes	29447	29173	29193			—
	No parking	2364	2343	2348			—

Some remarks for the pricing experiments

Update of the prices: all **15** minutes

Walk/Bike: a travel of x seconds by bike 'costs' $5x$ seconds when done on foot

The prices in simulator: in seconds. For instances with size

- ▶ **20**: maximal price: **3000**
- ▶ **50**: maximal price: **4200**
- ▶ **100**: maximal price: **6000**

To make the conversion, take (value of travel time in a Western city)

$$8 \text{ euros} = 1 \text{ hours}$$

A web-site where the simulator can be downloaded:

<http://cermics.enpc.fr/~meunief/OADLIBSim.Site/index.html>