Towards More Efficient and More Optimal Airport Ground Movement Using Artificial Intelligence

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Cumberland Lodge, The Greak Park, Windsor, Berkshire SL24 2HP

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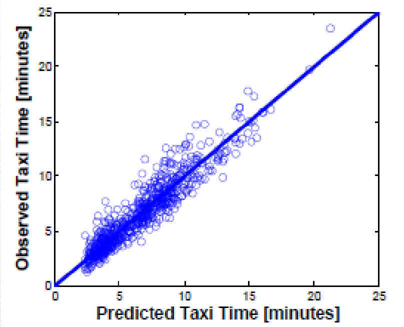
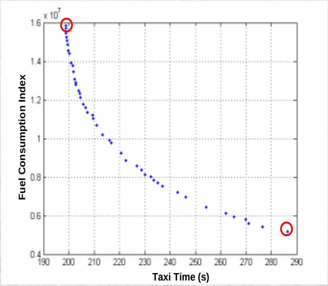
Outline

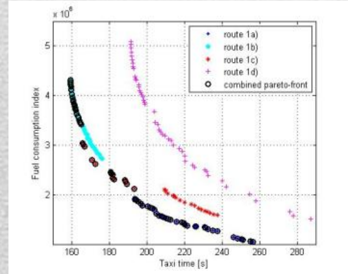
- Airside airport operations
- Taxi time estimation using Fuzzy Rule-based Systems



- Trade-off between time and fuel using multi-objective optimisation



- Combined Trade-off and Routing and scheduling algorithm

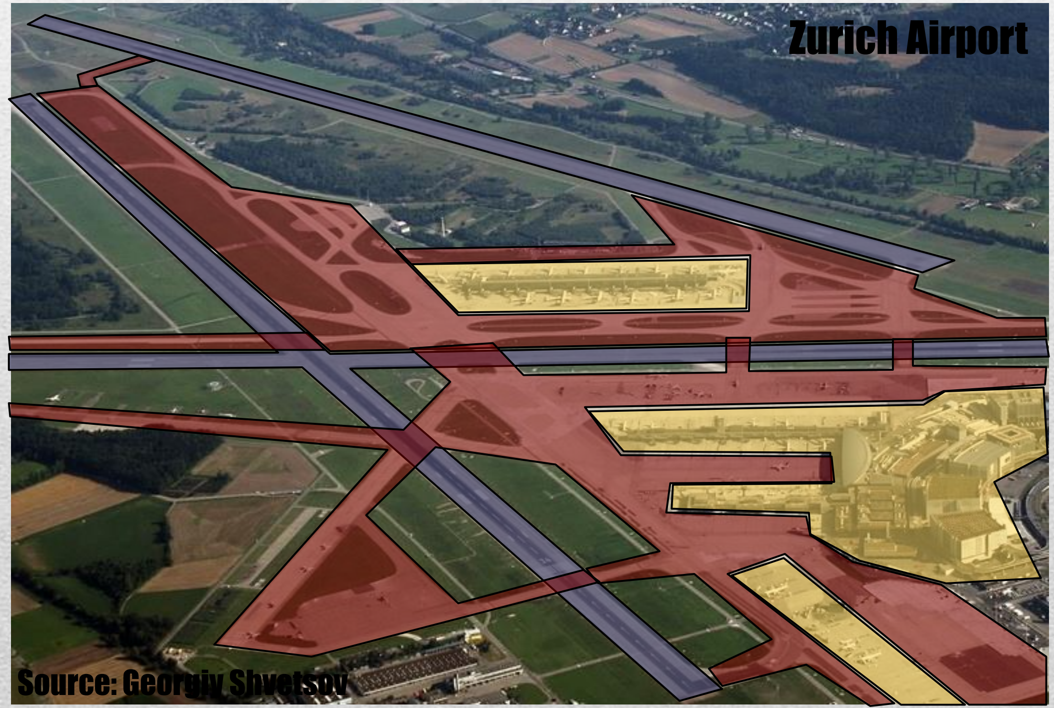


- Future Work

Airside Airport Operations

Linked Airport Operations

- With increasing complexity and load at airports, more **advanced decision support systems** are needed
- Airside airport operations are **highly connected**
  - Runway sequencing
    - Departures
    - Arrivals
  - Gate assignment
  - Ground movement



Taxiing Time Estimation using Fuzzy Rule-based Systems

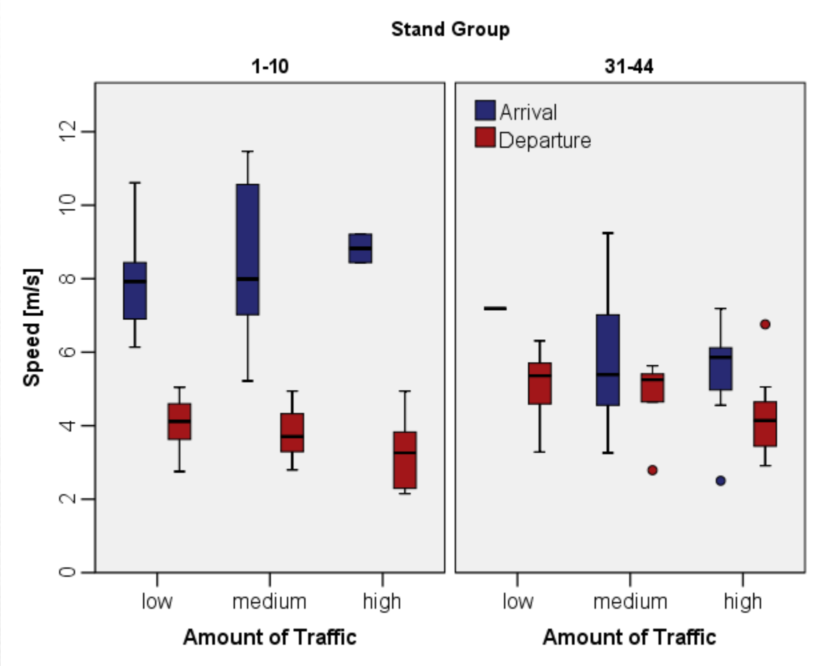
J. Chen, S. Ravizza, J. Atkin and **P. Stewart** (2011): On the Utilisation of Fuzzy Rule-Based Systems for Taxi Time Estimations at Airports. ATMOS’11, Germany, 09 September, 2011.

Taxiing Time Estimation using Fuzzy Rule-based Systems-Why Important?

- Major differences in taxi times and speeds

- Required for taxi planning:
  - Taxi times when no other surface traffic is considered
  - fuzzy rule-based systems

    (Chen *et al*. 2011)



Source: Atkin *et al*.

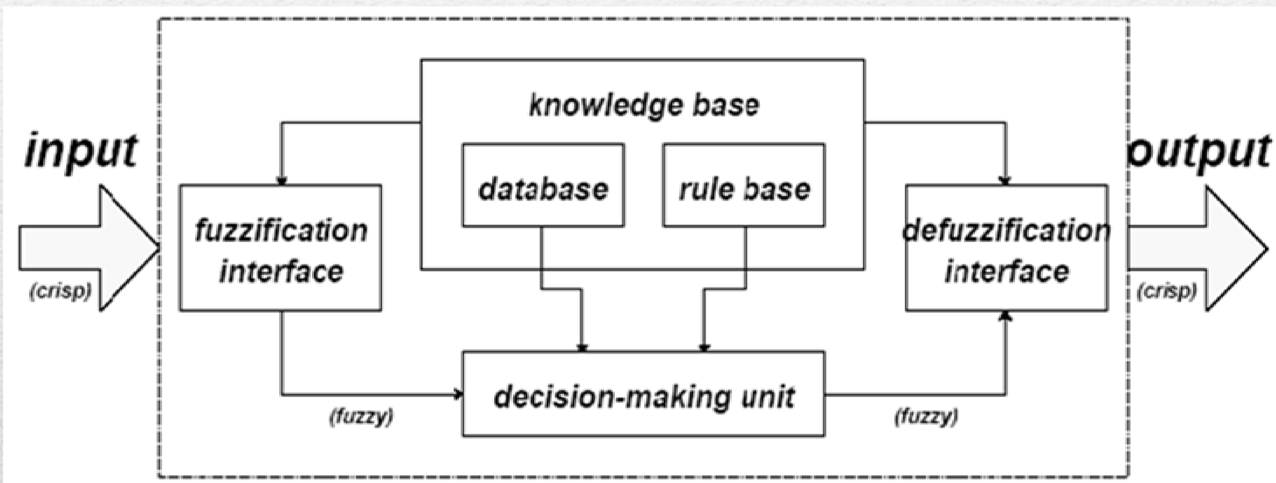
J. Chen, S. Ravizza, J. Atkin and P. Stewart (2011): On the Utilisation of Fuzzy Rule-Based Systems for Taxi Time Estimations at Airports. ATMOS'11, Germany, 09 September, 2011.

- Only accurate taxi time predictions allow realistic **comparison with real-world data**

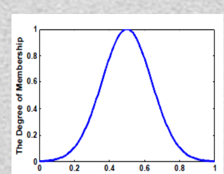
S. **Ravizz**., J. **Atkin**, E. **Burke and** M. **Maathuis**,, "A combined statistical approach and ground movement model for improving taxi time estimations at airports", *JORS*, 2012

Taxiing Time Estimation using Fuzzy Rule-based Systems-Why Fuzzy?

- Ability to approximate complex nonlinear systems:
  - **FRBS decomposes the system into several sub regions**
  - **modelling these via different combinations of rules in the rule base**
  - **the nonlinearity embedded in each membership function**



$$R_i : \text{If } x_1 \text{ is } A_i^1 \text{ and } x_2 \text{ is } A_i^2, \ldots, \text{and } x_j \text{ is } A_i^j, \ldots, \text{and } x_n \text{ is } A_i^n \text{ Then } y_i = Z_i,$$



$$\mu_{A_i^j}(x_j) = \exp\left[-\frac{1}{2} \cdot \frac{(x_j - c_i^j)^2}{(\sigma_i^j)^2}\right]$$

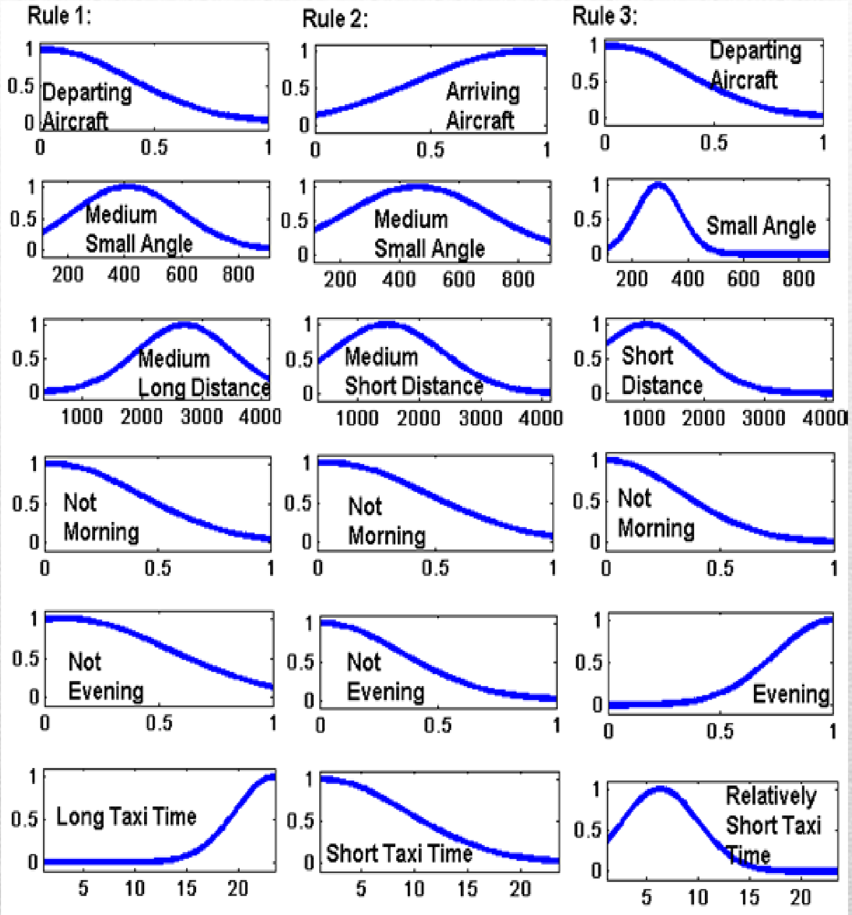
$$\mu_{B_i}(y) = \frac{1}{1 + \left(\frac{y - c_i^y}{\sigma_i^y}\right)^2}$$

J. Chen, S. Ravizza, J. Atkin and **P. Stewart** (2011): On the Utilisation of Fuzzy Rule-Based Systems for Taxi Time Estimations at Airports. ATMOS'11, Germany, 09 September, 2011.

Taxiing Time Estimation using Fuzzy Rule-based Systems-Why Fuzzy?

- Ability to interpret the underlying systems via linguistic terms :

Rule 1: If the aircraft is taxiing during the 'day period' **and** the total turning angle is 'medium small', **and** the distance is 'medium long', **then** taxi time is going to take 'long'.



- ➢**LAN** is an important correlation factor with the taxi time;
- ➢Generally **arrivals** tend to taxi quicker than **departing** aircraft, due to the departure queue time.
- ➢**Distance** and **Angle** are also two important correlation factors, with a positive impact on the taxi time.
- ➢**Evening** Mode tends to be more efficient in terms of taxing.

J. Chen, S. Ravizza, J. Atkin and **P. Stewart** (2011): On the Utilisation of Fuzzy Rule-Based Systems for Taxi Time Estimations at Airports. ATMOS'11, Germany, 09 September, 2011.

Taxiing Time Estimation using Fuzzy Rule-based Systems-Why Fuzzy?

- Ability to integrate human expertise due to the rule-base structure and linguistic expression of each rule
- Ability for rules to differ in different regions which makes it easier to understand how the effects of different explanatory variables change according to the values of other explanatory variables

$$y^{crisp} = \frac{\sum_{i=1}^{r} c_i^y \cdot \mu_i(X) \cdot \int_y \mu_{B_i}(y)dy}{\sum_{i=1}^{r} \mu_i(X) \cdot \int_y \mu_{B_i}(y)dy}$$

$$\mu_{A_i^j}(x_j) = \exp\left[-\frac{1}{2} \cdot \frac{(x_j - c_i^j)^2}{(\sigma_i^j)^2}\right]$$

$$\mu_{B_i}(y) = \frac{1}{1 + \left(\frac{y - c_i^y}{\sigma_i^y}\right)^2}$$

Constrained back-error propagation learning algorithm

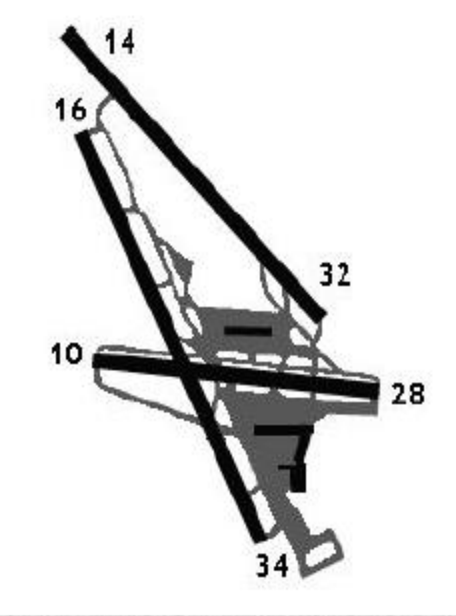
J. Chen and M. Mahfouf (2012): Improving Transparency in Approximate Fuzzy Modeling using Multi-Objective Immune-Inspired Optimisation. Special Issue on Evolutionary Fuzzy Systems in the International Journal of Computational Intelligence Systems. 2012 5 (2), pp. 322-342.

Taxiing Time Estimation using Fuzzy Rule-based Systems-Problem Description

An entire day's operation for the 19th of October 2007 consisting of 679 movements.

A rigorous statistical analysis (Stefan *et al*. in press) **suggests:**

- **Distance**
- **Log(Distance)**
- **Log(Angle)**
- **LAN: 0 for the departing and 1 for the arrival**
- **Q and N values: indicate the amount of other traffic on the airport surface while the aircraft under consideration is taxiing**
- **Operational Modes: before 7am, during the day and after 9pm**



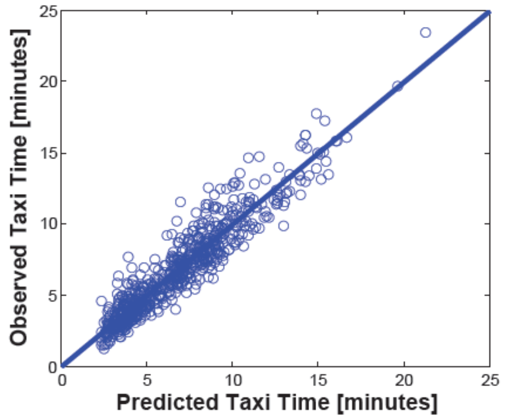
Sketch of airport layout for ZRH

S. **Ravizz**., J. **Atkin**, E. **Burke and** M. **Maathuis**,, "A combined statistical approach and ground movement model for improving taxi time estimations at airports", *JORS*, 2012

Taxiing Time Estimation using Fuzzy Rule-based Systems-Results

Results (1) – Comparison to Linear Regression:

	± 3 minutes	± 5 minutes
Linear regression	95.6%	99.4%
Mamdani FRBS	98.8%	100%



Results (2) – Validiity of Approach without Explicit Transformations:

	± 2 minutes	± 3 minutes	± 5 minutes	R^2
With log transformations	93.4%	98.8%	100%	0.894
Without log transformations	92.9%	98.7%	100%	0.890

(1) Decomposing of the system into sub regions using a set of cooperative rules

(2) An extra degree of freedom to fine-tune a fuzzy model

(3) The hidden transformation functions is learnt, which may not be included within an a priori transformation

J. Chen, S. Ravizza, J. Atkin and **P. Stewart** (2011): On the Utilisation of Fuzzy Rule-Based Systems for Taxi Time Estimations at Airports. ATMOS’11, Germany, 09 September, 2011.

Taxiing Time Estimation using Fuzzy Rule-based Systems-Comparison

Comparisons among different regression approaches:

- Historic data from two major European airports
- 15 repetitions and 10-fold cross-validation

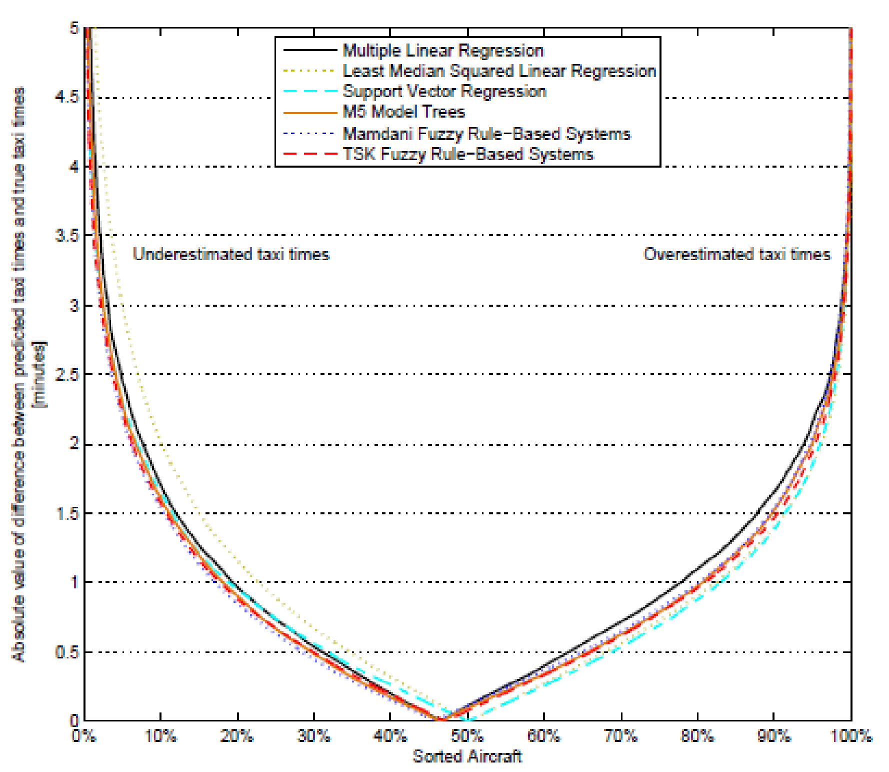


Figure 2: Taxi time prediction accuracy at Zurich Airport

S. Ravizza, **J. Chen**, J. A. D. Atkin, **P. Stewart** and E. K. Burke (2013): Aircraft Taxi Time Prediction: Comparisons and Insights. Journal of Applied Soft Computing. (Submitted)

Taxiing Time Estimation using Fuzzy Rule-based Systems-Comparison

R_1 : If x_1 is A_1^1 and x_2 is A_1^2, ..., and x_j is A_1^j Then $y_1 = b_1^0 + b_1^1 \cdot x_1 + \ldots + b_1^j \cdot x_j$

...

R_k : If x_1 is A_k^1 and x_2 is A_k^2, ..., and x_j is A_k^j Then $y_k = b_k^0 + b_k^1 \cdot x_1 + \ldots + b_k^j \cdot x_j$.

Table 2: Comparisons of performance measures for Stockholm-Arlanda Airport and Zurich Airport

Performance Measure	Airport	LinReg	LMS	SMOreg	M5P	Mamdani	TSK
Root mean-squared error	ARN	1.52	1.57	1.50	1.51	1.46	**1.44**
	ZRH	1.47	1.60	1.32	1.36	1.33	**1.30**
Mean-absolute error	ARN	1.14	1.14	1.09	1.13	1.07	**1.06**
	ZRH	1.08	1.10	**0.96**	0.99	0.97	**0.96**
Root relative-squared error	ARN	45.70%	47.47%	45.27%	45.54%	44.19%	**43.53%**
	ZRH	29.29%	31.76%	26.28%	27.00%	26.41%	**25.89%**
Relative-absolute error	ARN	45.80%	45.92%	43.98%	45.61%	43.28%	**42.83%**
	ZRH	26.85%	27.52%	**23.87%**	24.55%	24.30%	23.93%

Table 3: Comparisons of accuracies for Stockholm-Arlanda Airport and Zurich Airport

Accuracy	Airport	LinReg	LMS	SMOreg	M5P	Mamdani	TSK
Accuracy within ± 1 min	ARN	54.28%	56.02%	57.86%	54.61%	58.21%	**58.80%**
	ZRH	58.38%	59.66%	**64.05%**	62.49%	62.97%	63.33%
Accuracy within ± 2 min	ARN	85.30%	85.18%	84.91%	85.19%	86.73%	**86.81%**
	ZRH	86.12%	85.99%	88.98%	88.15%	88.55%	**89.07%**
Accuracy within ± 3 min	ARN	95.40%	94.80%	94.32%	95.43%	95.72%	**96.16%**
	ZRH	95.55%	94.26%	96.60%	96.46%	96.54%	**96.89%**
Accuracy within ± 5 min	ARN	99.16%	98.81%	99.16%	**99.18%**	98.97%	99.08%
	ZRH	99.21%	98.56%	99.45%	99.46%	99.53%	**99.62%**
Accuracy within ± 10 min	ARN	**99.92%**	**99.92%**	**99.92%**	**99.92%**	**99.92%**	**99.92%**
	ZRH	99.92%	99.87%	99.97%	99.97%	**99.98%**	99.97%

S. Ravizza, **J. Chen**, J. A. D. Atkin, **P. Stewart** and E. K. Burke (2013): Aircraft Taxi Time Prediction: Comparisons and Insights. Journal of Applied Soft Computing. (Submitted)

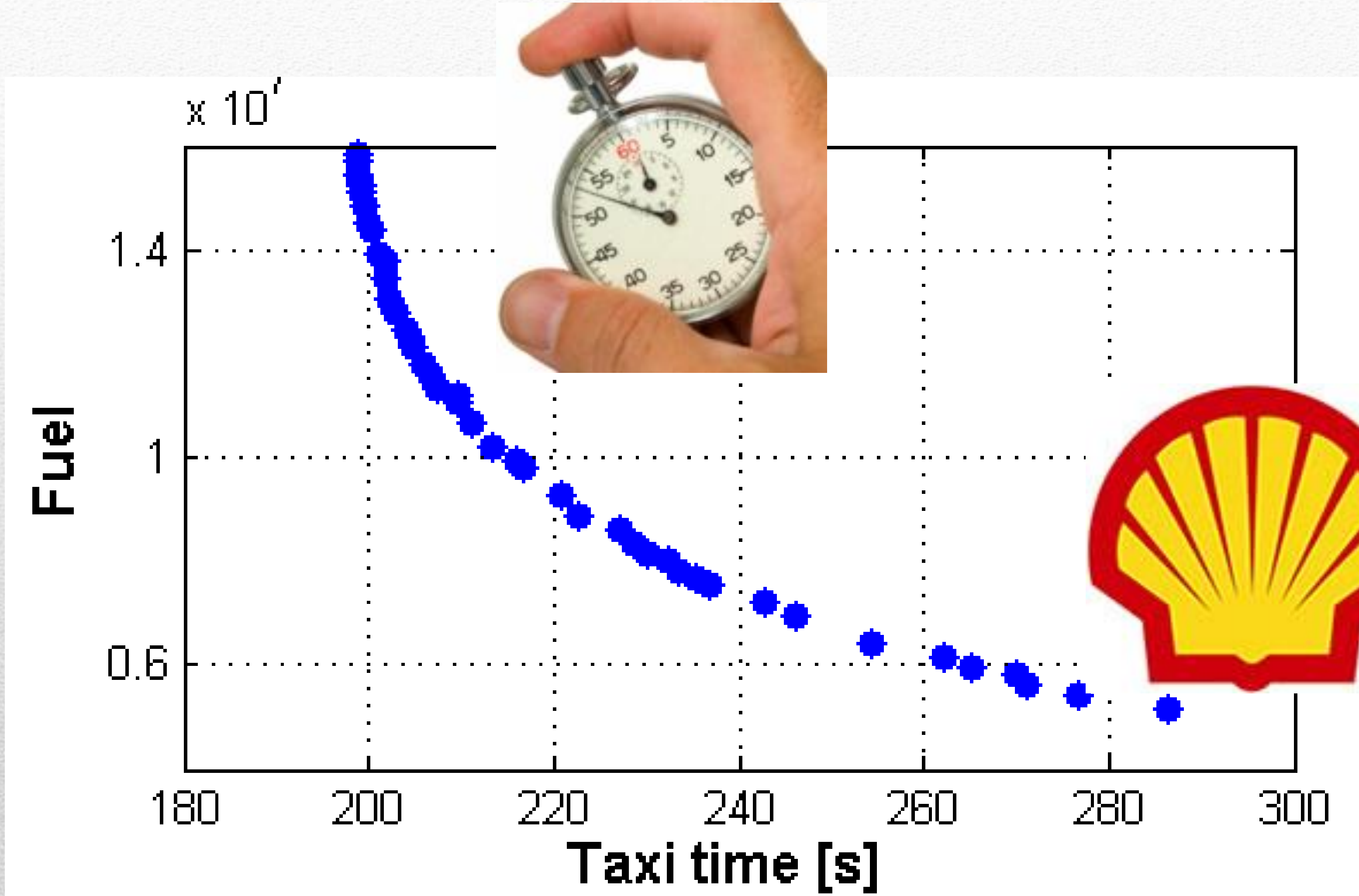
Taxiing Time Estimation using Fuzzy Rule-based Systems-Conclusions

Taxiing time estimation can be used for **ground movement optimiser**

- Algorithms need taxi time predictions for isolated aircraft.
- The effects of the amount of traffic can be eliminated by setting all the corresponding variables to 0.
- Unlike multiple linear regression, Mamdani and Sugeno FRBS presents certain corporation among different rules which is believed to be able to deal with the transition behaviour between different sub regions.
- Fuzzy rule-based systems are not used quite often and deserve more exploration in this field for other airport, such as **Manchester International Airport**.

S. Ravizza, **J. Chen**, J. A. D. Atkin, **P. Stewart** and E. K. Burke (2013): Aircraft Taxi Time Prediction: Comparisons and Insights. Journal of Applied Soft Computing. (Submitted)

Trade-off between Time and Fuel using Multi-Objective Optimisation



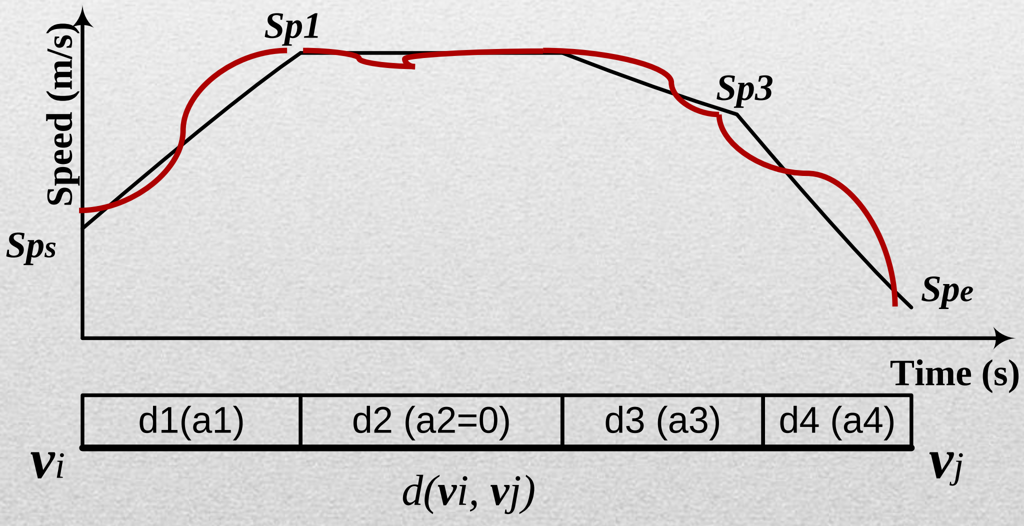
J. Chen and **P. Stewart** (2011): Planning Aircraft Taxiing Trajectories via a Multi-Objective Immune Optimisation ICNC'11-FSKD'11, Shanghai, China, 26-28 July, 2011.

Trade-off between Time and Fuel using Multi-Objective Optimisation

Assumptions:

Less taxi time → **Less fuel consumption and pollutant**

Trajectories Planning for a single unimpeded aircraft

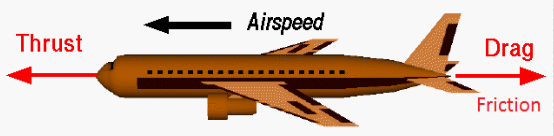


NB: a2=0; a3=f(d3,d4,a4,*Sp1*); a4=0.1*g*; d3=*d(vi, vj)-d1-d2-d4*

Aircraft Model:

Mass point model: mass, friction, thrust

Newton's basic mechanics



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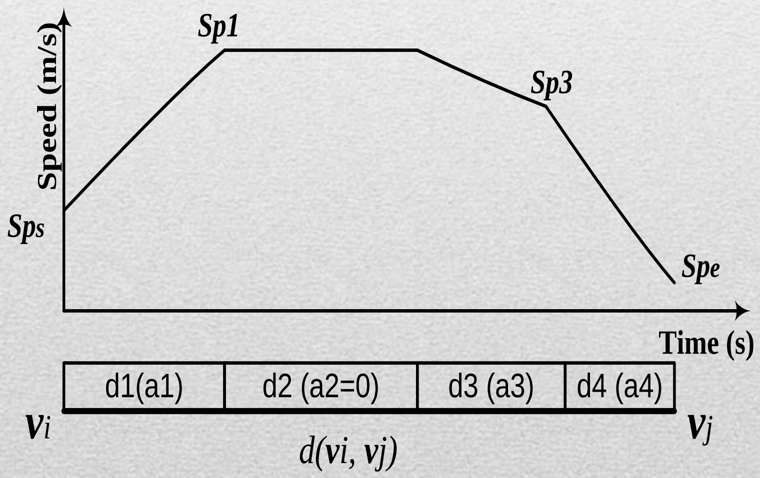
Trade-off between Time and Fuel using Multi-Objective Optimisation: PAIA

- **Objectives:**
  - 1st Objective: Total Taxiing Time T
  - 2nd Objective: Fuel Consumption Index

$$\int_0^T \left[TR(t) \cdot \left(1 + a(t)\right)\right] \cdot dt$$

- **Decision Variables and Constraints:**



NB: a2=0; a3=f(d3,d4,a4,*Sp1*); a4=0.1*g*; d3=*d(vi, vj)-d1-d2-d4*

{a1, d1, d2, d4}

(1) a: $a(t) \leq a_{max}$.

(2) a1: $a_{1}\_l = \dfrac{Sp_e^{\,2} - Sp_s^{\,2}}{2 \cdot d(v_i, v_j)}$.

(3) d1: $d_{1}\_l = \dfrac{Sp_e^{\,2} - Sp_s^{\,2}}{2 \cdot a_1}$.

(4) d2:

$$d_{2}\_u = d(v_i, v_j) - d_1 - \frac{Sp_1^{\,2} - Sp_e^{\,2}}{2 \cdot a_{max}}.$$

$$d_{2}\_l = d(v_i, v_j) - d_1 - \frac{Sp_1^{\,2} - Sp_e^{\,2}}{2 \cdot a_{min\_d}}.$$

(5) d4:

$$d_{4}\_u = \frac{Sp_1^{\,2} - Sp_e^{\,2}}{2 \cdot a_{max}}.$$

$$d_{4}\_l = 0$$

J. Chen and **P. Stewart** (2011): Planning Aircraft Taxiing Trajectories via a Multi-Objective Immune Optimisation ICNC'11-FSKD'11, Shanghai, China, 26-28 July, 2011.

Trade-off between Time and Fuel using Multi-Objective Optimisation: Data Sets

Needed Information about Aircraft Taxiing:

(i) The length of each Arc;

(ii) The taxi speed at the start of each Arc;

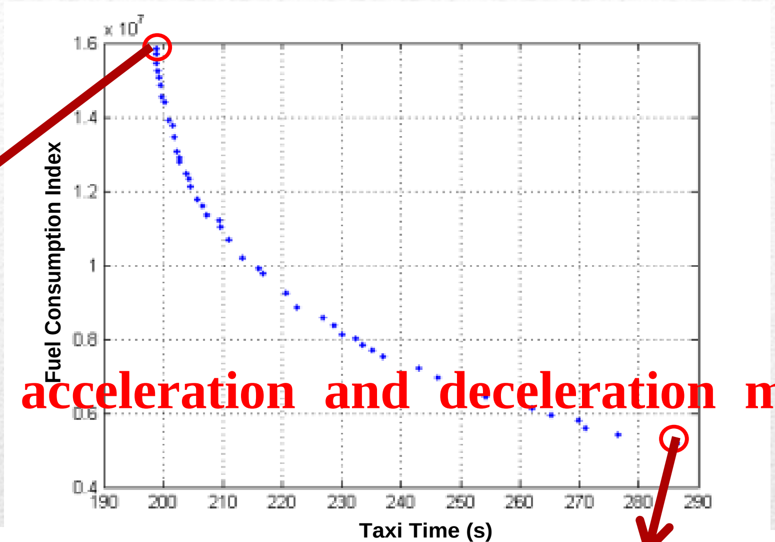
(iii) The taxi speed at the end of each Arc;

(iv) The maximum taxi speed for each Arc;

Edge No.	Information			
	Edge Description	***(knot)***	***(knot)***	***(m)***
1	**Straight T.W.[a]**	**0**	**10**	**153.8**
2	**Turning T.W.**	**10**	**10**	**61.5**
3	**Straight T.W.**	**10**	**10**	**92.3**
4	**Turning T.W.**	**10**	**10**	**61.5**
5	**Straight T.W.**	**10**	**10**	**246.2**
6	**Turning T.W.**	**10**	**10**	**153.8**
7	**Straight T.W.W.[b]**	**10**	**0**	**215.4**
8	**Straight T.W.**	**0**	**10**	**138.5**
9	**Turning T.W.**	**10**	**10**	**92.3**
10	**Runway Acc. H.[c]**	**10**	**0**	**230.8**

J. Chen and **P. Stewart** (2011): Planning Aircraft Taxiing Trajectories via a Multi-Objective Immune Optimisation ICNC'11-FSKD'11, Shanghai, China, 26-28 July, 2011.

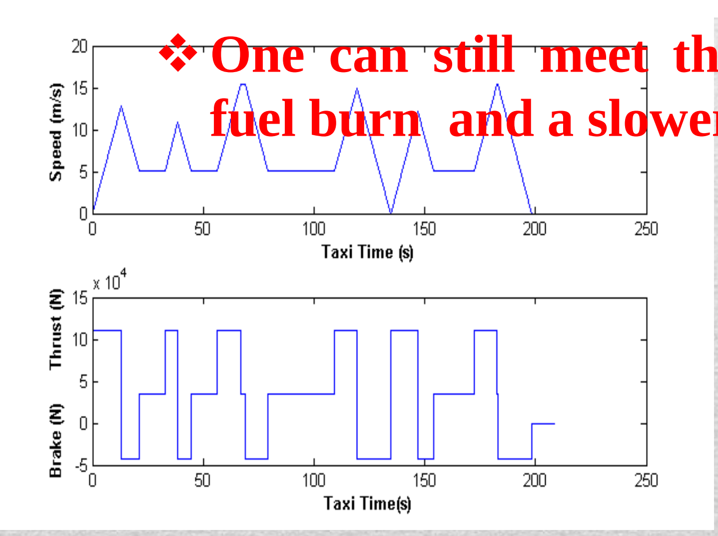
Trade-off between Time and Fuel using Multi-Objective Optimisation: Results

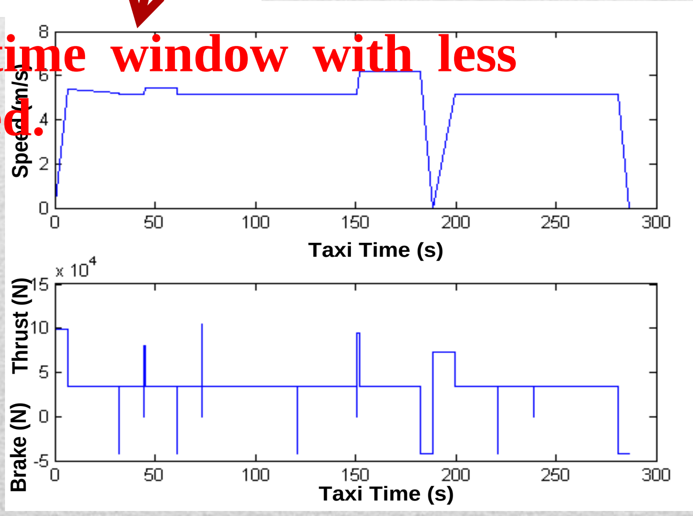


Fast taxi speed
Higher fuel consumption

Slow taxi speed
Lower fuel consumption

- ❖ **Excessive acceleration and deceleration may not be favoured**
- ❖ **One can still meet the target time window with less fuel burn and a slower taxi speed.**





J. Chen and **P. Stewart** (2011): Planning Aircraft Taxiing Trajectories via a Multi-Objective Immune Optimisation ICNC'11-FSKD'11, Shanghai, China, 26-28 July, 2011.

Trade-off between Time and Fuel using Multi-Objective Optimisation: Insights

- **The actual modelling of fuel burn objective function plays an important role:**

$$\int_0^T [TR(t) \cdot (1 + a(t))] \cdot dt$$

- **Using Base of Aircraft Data (BADA)**
- **A More Realistic Aircraft Model: Physical models, throttle to thrust to fuel burn data, brake to thrust data, etc.**

- **The information of the following is really important :**

(i) The taxi speed at the start of each Arc;

(ii) The taxi speed at the end of each Arc;

(iii) The maximum taxi speed for each Arc;

Combined Trade-off and Routing and Scheduling Algorithm

Interactions between multiple aircraft

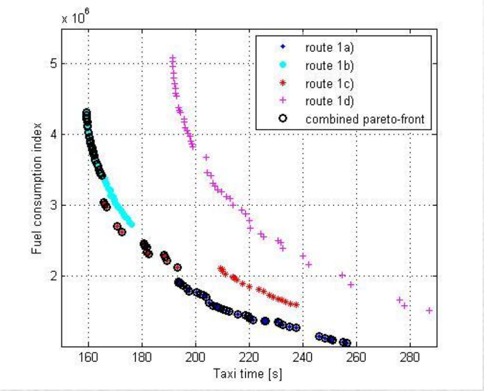
S. Ravizza, **J. Chen**, J. A. D. Atkin, E. K. Burke and **P. Stewart** (2013): The Trade-off Between Taxi Time and Fuel consumption in Airport Ground Movement. Journal of Public Transportation.DOI 10.1007/s12469-013-0060-1.

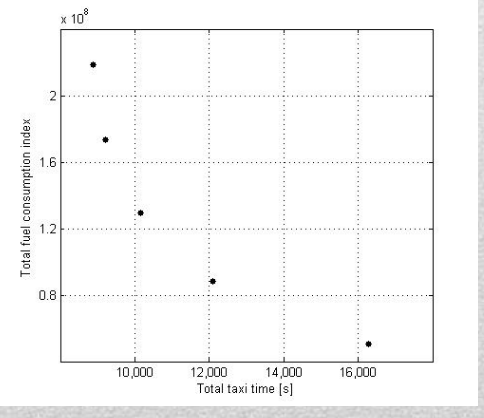
Combined Trade-off and Routing and Scheduling Algorithm: Integration

Novel concept using combined:

- **k-QPPTW**: Finds best possible routes for an aircraft
- **PAIA**: Finds Pareto-front for different speed profiles for each of these routes

```
Sort all flights by pushback/landing time
foreach objective function discretisation i ← 1 to l do
    foreach aircraft a do
        Find best k routes w.r.t. minimal taxi times using k-QPPTW algorithm
        foreach route k of aircraft a do
            Approximate pareto-front of both objectives, using population adaptive
            immune algorithm (PATT-PAIA)
        Generate combined pareto-front for source-destination pair of aircraft a
        Discretise this pareto-front into l roughly equally spaced points
        Select the ith point and reserve the relevant route for aircraft a
    Save the accumulated values for all aircraft for both objective functions for the
    global pareto-front
Output: Global discretised pareto-front
```





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Combined Trade-off and Routing and Scheduling Algorithm: Results

- One week's operation at Zurich Airport
- 2nd objective function: $F_{Total} = F_{Resistance} + F_{Acceleration}$

	Mon	Tue	Wed	Thu	Fri	Sat	Sun
∅ Taxi time							
Time-efficient [s]	156	157	128	174	152	165	154
Fuel-efficient [s]	285	293	214	320	292	316	295
Growth	83%	87%	67%	84%	92%	91%	91%
∅ Fuel cons. index							
Time-efficient [$\times 10^3$]	3832	3291	3492	4002	3173	3754	3718
Fuel-efficient [$\times 10^3$]	884	762	742	922	700	849	823
Growth	334%	332%	371%	334%	353%	342%	352%
Number of aircraft	57	58	46	58	56	63	52

S. Ravizza, **J. Chen**, J. A. D. Atkin, E. K. Burke and **P. Stewart** (2013): The Trade-off Between Taxi Time and Fuel consumption in Airport Ground Movement. Journal of Public Transportation.DOI 10.1007/s12469-013-0060-1.

Combined Trade-off and Routing and Scheduling Algorithm: Results

- 2 different fuel burn types:
  - Acceleration (10% of maximal fuel flow)
  - Taxiing with constant speed, deceleration, holding (5.5%)

	Different objective function
∅ Taxi time	
Time-efficient [s]	155.5
Fuel-efficient [s]	156.7
Growth	0.8%
∅ Fuel flow	
Time-efficient [kg]	23.8
Fuel-efficient [kg]	23.5
Growth	1.2%

M.E.J. **Stettler**, S. **Eastham**, S.R.H. **Barrett**, "Air quality and public health impacts of UK airports. Part I: Emissions", *Atmospheric Environment* ,45(31), 2011.

Combined Trade-off and Routing and Scheduling Algorithm: Conclusions

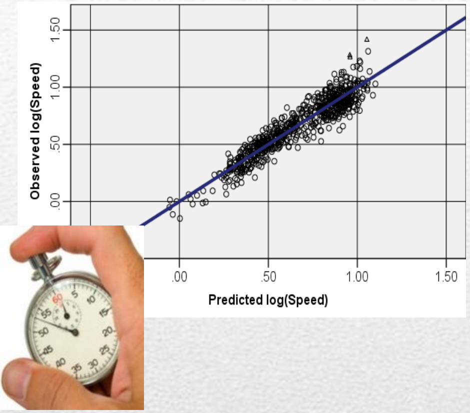
- Depends very much upon the actual modelling of the fuel-based objective function (physics-based vs. fuel flow).

- If the more realistic modelling of the fuel-based objective function suggests that we can gain significant improvement in terms of fuel consumption using the optimised speed profiles, this information should also feedback to pilots so that they will follow such speed profiles.

- These appear not to be well understood and deserve more investigation on different airport.

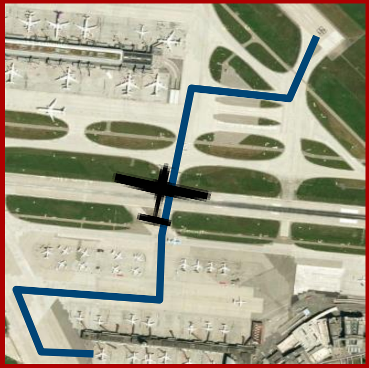
Future Work

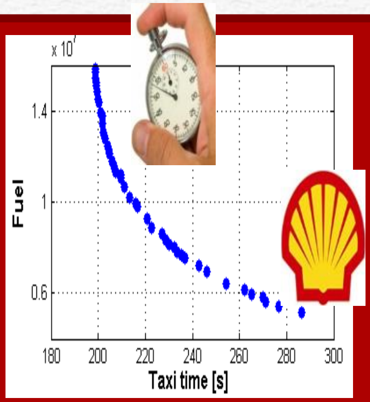
Taxiway Arc No.	Start Speed	End Speed	Maximum Speed	Taxi Time	Fuel consumption
No. 1					
No. 2					
No. n					

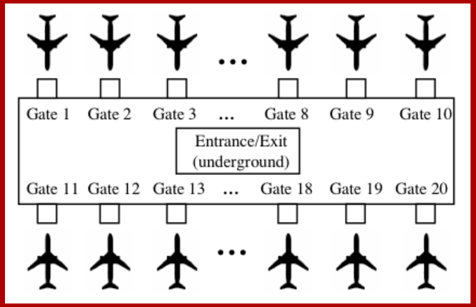


More accurate prediction

Multi-domain
Modelling
System identification







Integration

- Semi atuomated taxiing
- Fully automated taxiing

Novel concepts

Thanks!!