

Towards a Better Understanding of Agent-based Airport Terminal Operations Using Surrogate Modeling

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Modeling airport terminal operations is important

Bloomberg

Strikes and Labor Shortages Leave European Airports in Chaos

The Brussels Times

Brussels Airport expects long queues and braces for busy August weekend

NOS

Opnieuw grote drukte op Schiphol, mensen urenlang in de rij

AP AP NEWS

Airport chaos: European travel runs into pandemic cutbacks

 **REUTERS®**

Amsterdam airport asks airlines to cut flights to avoid chaos

B B C

NEWS

Heathrow flight cancellations cause queues and 'chaos'

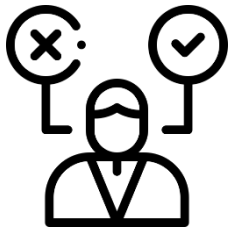
Effective decision support tools are needed



Tools should realistically represent the complexity of airport terminal operations



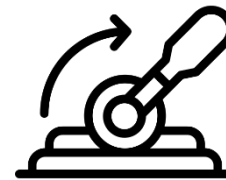
Tools are usually based on important KPIs



Tools should be able to generate accurate predictions for different circumstances

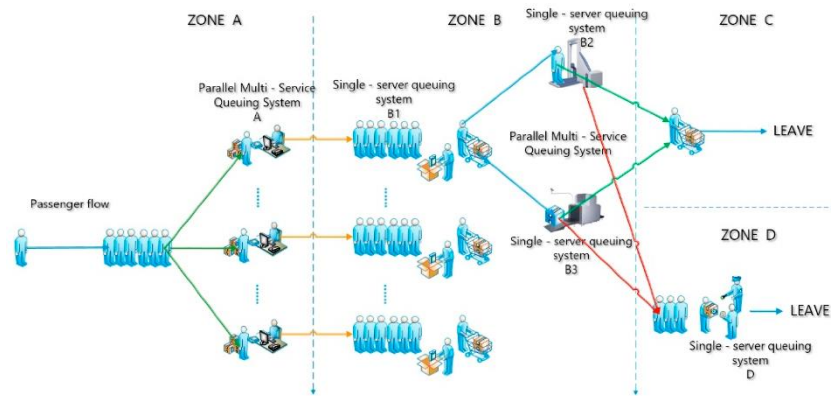


Tools should be possible to use in real time

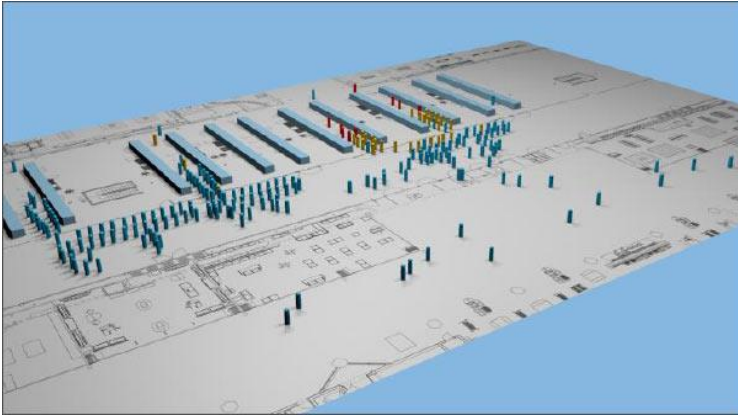


Tools should provide information about cause-effect relations to change a situation

Existing models have limitations



Simplified models (e.g., based on queuing theory) are fast, however, limited w.r.t. realism and scenarios that they can handle



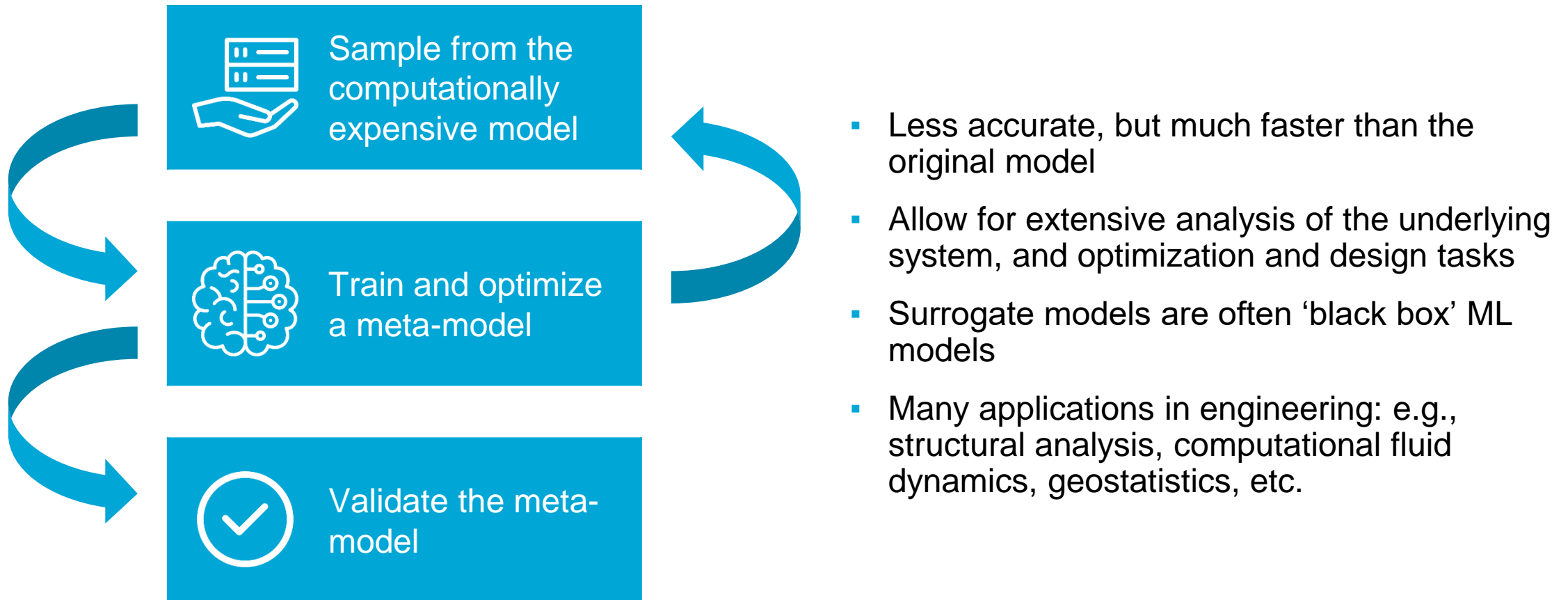
ABM can be detailed and realistic, however, could be computationally heavy

Agent-based model of interest



- **Agent-based Airport Terminal Operations Model**
- Modular; contains prebuilt components
- Rotterdam The Hague Airport
- Computationally intensive

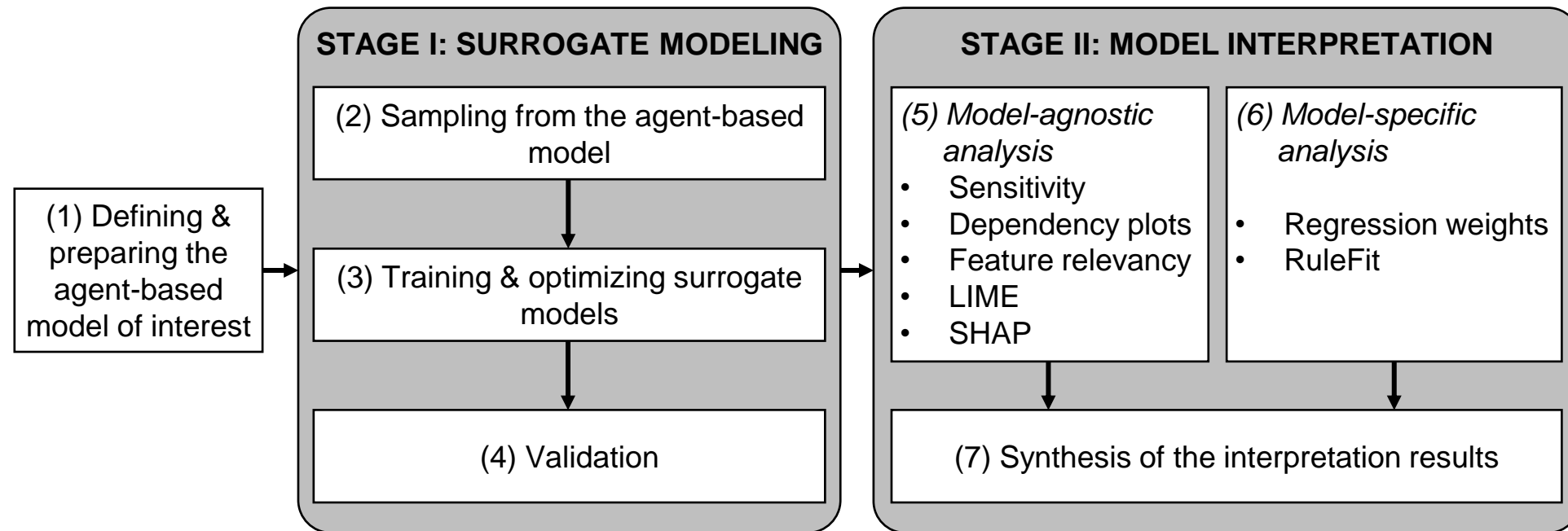
Possible solution: Surrogate modeling



Proposed approach

Objective

To accurately abstract and explain the dynamics of airport terminal operations by means of computationally efficient and interpretable surrogate models, based on an existing agent-based simulation model



STAGE I – Sampling from the agent-based model

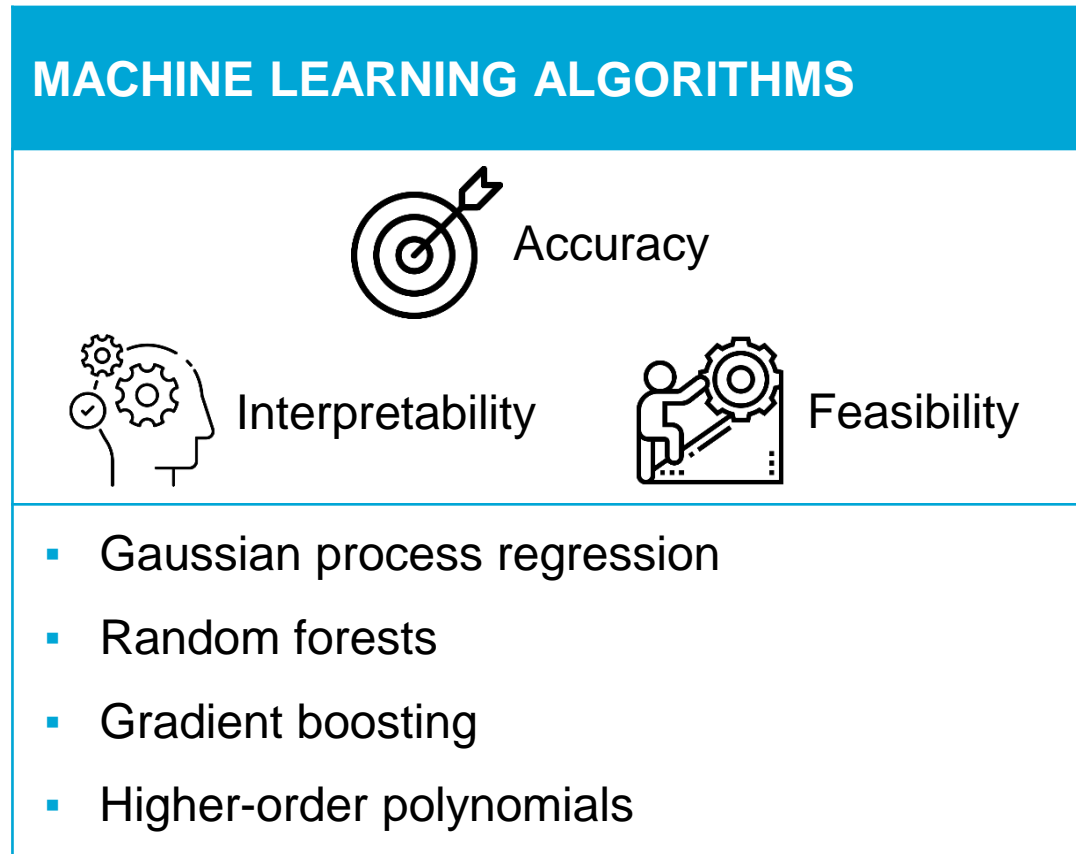


ACTIVE LEARNING STRATEGY

- Hammersley sequence
- Gaussian process regression

▪ Expected improvement for global fit: for f in $D \in \mathbb{R}^n$, $\mathbf{x}_{\text{next}} = \arg \max_{\mathbf{x} \in D} \left[\alpha \left(\hat{\sigma}^2(\mathbf{x}) \right) + (1 - \alpha) \left(\hat{f}(\mathbf{x}) - f(\mathbf{x}^*) \right)^2 \right]$

STAGE I – Training & optimizing surrogate models



STAGE I – Validation

COMMONLY USED VALIDATION METRICS

- Coefficient of determination (R^2): gives the proportion of explained variation in the response
 - Root-mean-square error (RMSE): indicates the expected prediction error
 - Mean absolute error (MAE): similar to the RMSE, but less sensitive to outliers
 - Mean absolute percentage error (MAPE): similar to the MAE, but expresses the error relatively
-
- An additional test set is created by randomly sampling from the parameter combinations that have not yet been selected for the training set

Agent-based model of interest

RELEVANT INPUT PARAMETERS

- The number of passengers on the flights:
 - Time slot 1
 - ...
 - Time slot 7
- Call-to-gate strategy
- Check-in staffing strategy
- Security checkpoint staffing strategy

RELEVANT OUTPUT PARAMETERS

- Average waiting time:
 - Check-in
 - Security
- Throughput:
 - Check-in
 - Security
- Number of missed flights
- Total expenditure to discretionary activities

Evaluating meta-model performance

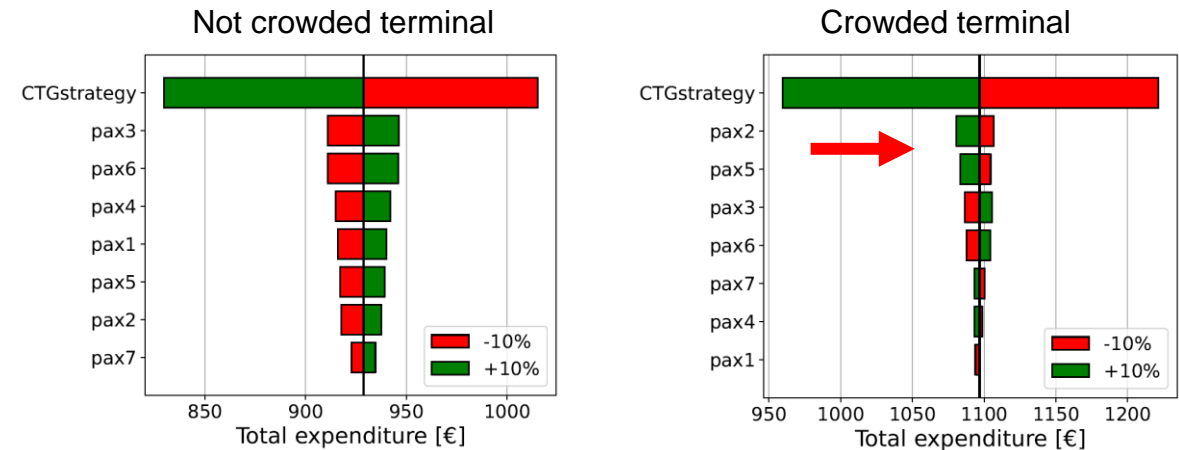
PaxCompleted_SC	GP	PR	RF	GB	NumMissedFlights	GP	PR	RF	GB	PaxCompleted_CI	GP	PR	RF	GB
R ²	0.90	0.90	0.79	0.93	R ²	0.70	0.80	0.53	0.43	R ²	0.93	0.94	0.86	0.98
RMSE	17.52	17.62	25.75	14.94	RMSE	9.28	7.51	11.58	12.85	RMSE	7.55	7.40	11.17	4.14
MAE	12.59	12.86	20.29	11.51	MAE	7.09	4.42	6.94	6.60	MAE	5.02	5.66	8.11	3.30
MAPE	0.02	0.02	0.03	0.02	MAPE	nan	nan	nan	nan	MAPE	0.01	0.02	0.02	0.01

AvgQueueTime_SC	GP	PR	RF	GB	AvgQueueTime_CI	GP	PR	RF	GB	TotalExpenditure	GP	PR	RF	GB
R ²	0.90	0.92	0.57	0.86	R ²	0.91	0.95	0.87	0.95	R ²	0.97	0.98	0.94	0.97
RMSE	68.63	63.46	142.90	80.69	RMSE	19.46	14.13	23.73	15.13	RMSE	52.05	42.44	69.23	52.25
MAE	52.50	49.54	118.74	64.33	MAE	13.79	9.78	16.16	10.25	MAE	40.34	33.76	55.61	42.00
MAPE	0.08	0.08	0.18	0.10	MAPE	0.05	0.04	0.06	0.04	MAPE	0.03	0.03	0.04	0.03

Computational time: 0.3 sec per run (original model 5 min per run)

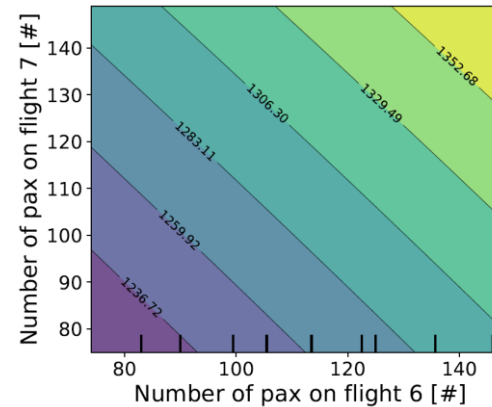
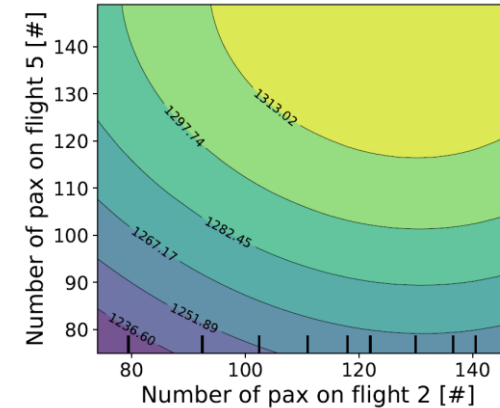
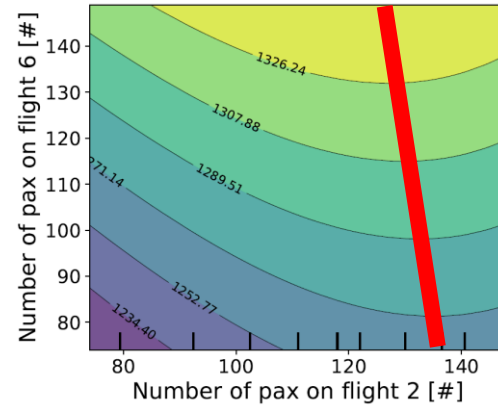
Model interpretation (1): Total expenditure on discretionary activities

- Examine the spending behavior of passengers on non-aeronautical activities, such as shopping and dining
- Not mandatory and hence not a priority, so passengers will only consider them if they have enough time in the airport terminal

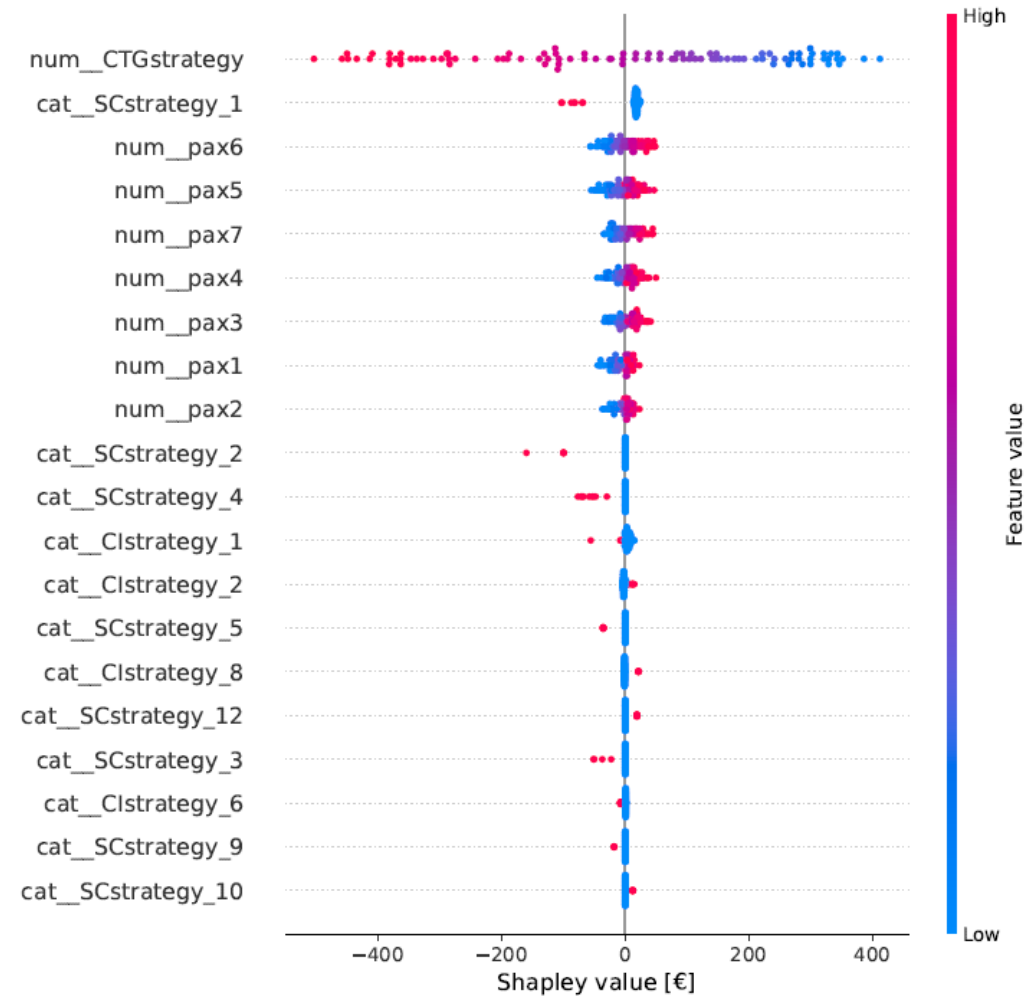


	FLIGHT	TIMESLOT	CHECK-IN	
	1	04:55	9 – 12	
→	2	04:55	1 – 4	
→	3	05:00	13 – 16	
	4	05:05	13 – 16	←
→	5	05:10	5 – 8	
	6	05:30	1 – 4	←
	7	05:45	5 – 8	←

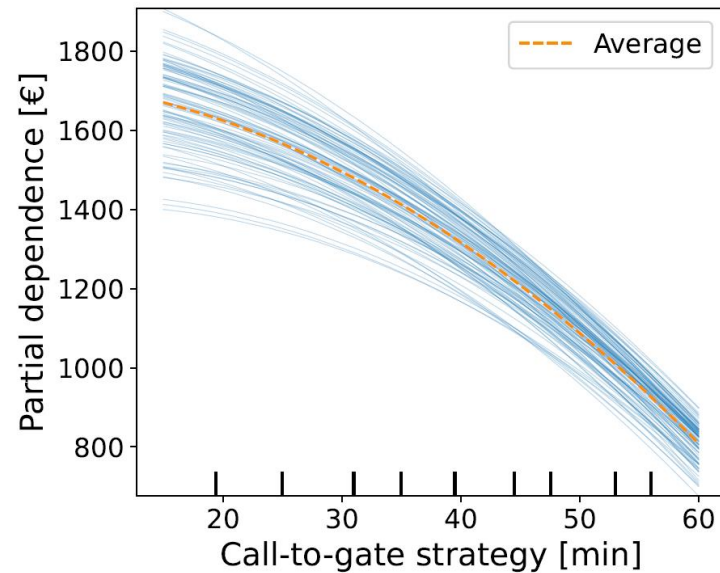
Model interpretation (2): Total expenditure on discretionary activities



Model interpretation (3): Bee swarm plot of the total expenditure



Model interpretation (4): Regression weights of the total expenditure



$$\text{Expenditure} = 1162.4 - 506.6 \text{ CTG}^2 + \dots$$

Lessons learned and conclusions

- An approach for development of efficient and accurate surrogate models for airport terminals was developed
- The proposed approach allows for more detailed analysis, better understanding and interpretation of airport processes
- Model outputs (KPIs) were averaged over periods of time; in the future the temporal dimension will be explored more
- Synthesis of different analysis results requires a systematic approach
- RuleFit produces unstable results; requires further analysis
- The approach has been used for evaluating new airport designs and operations