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Defining probability-based rail station catchments for demand modelling.

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Outline

- Research background
- Developing a station choice model
- Model results
- Generating probability-based catchments
- Conclusions and further work

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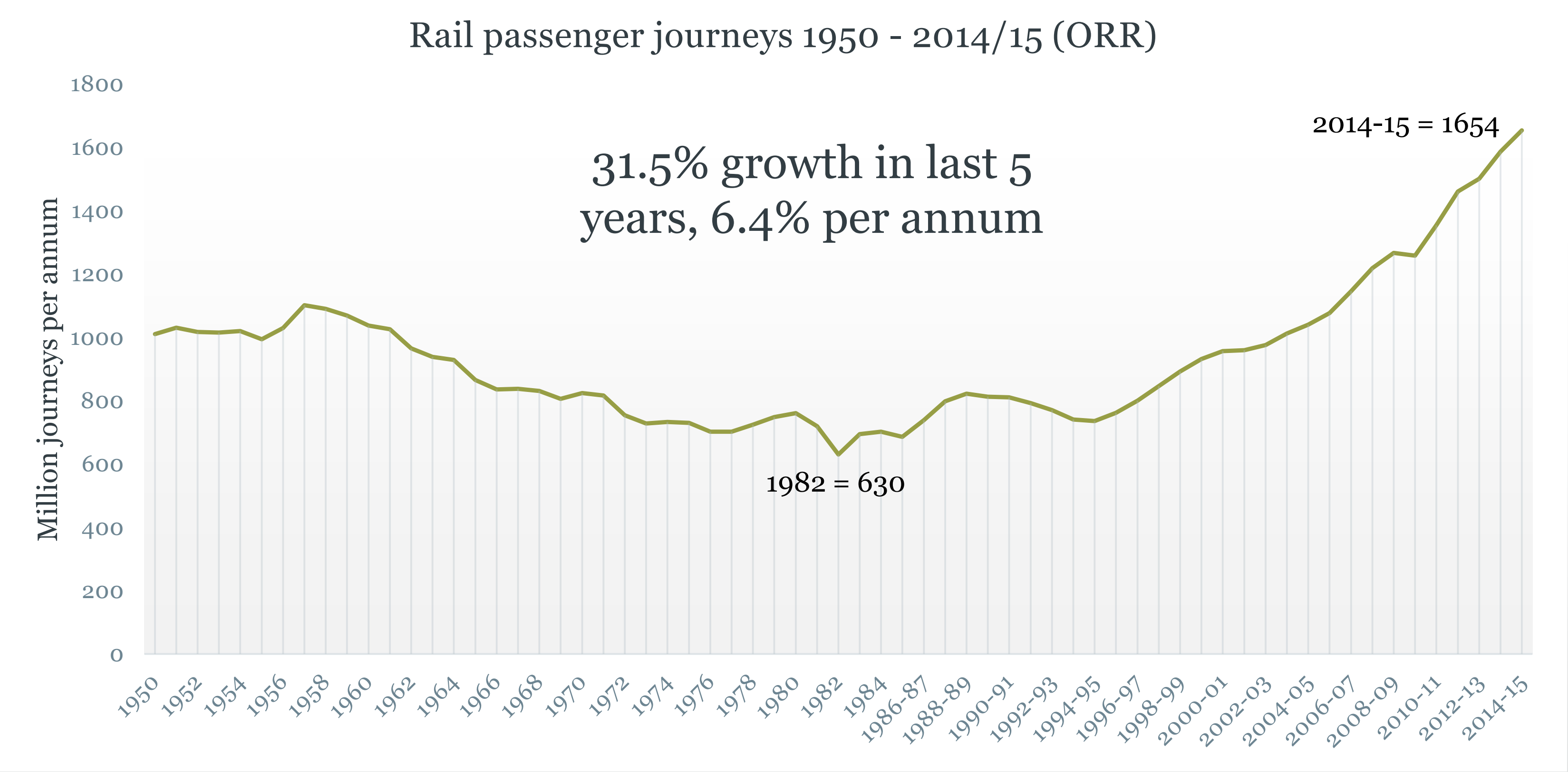
Research background

Rail renaissance



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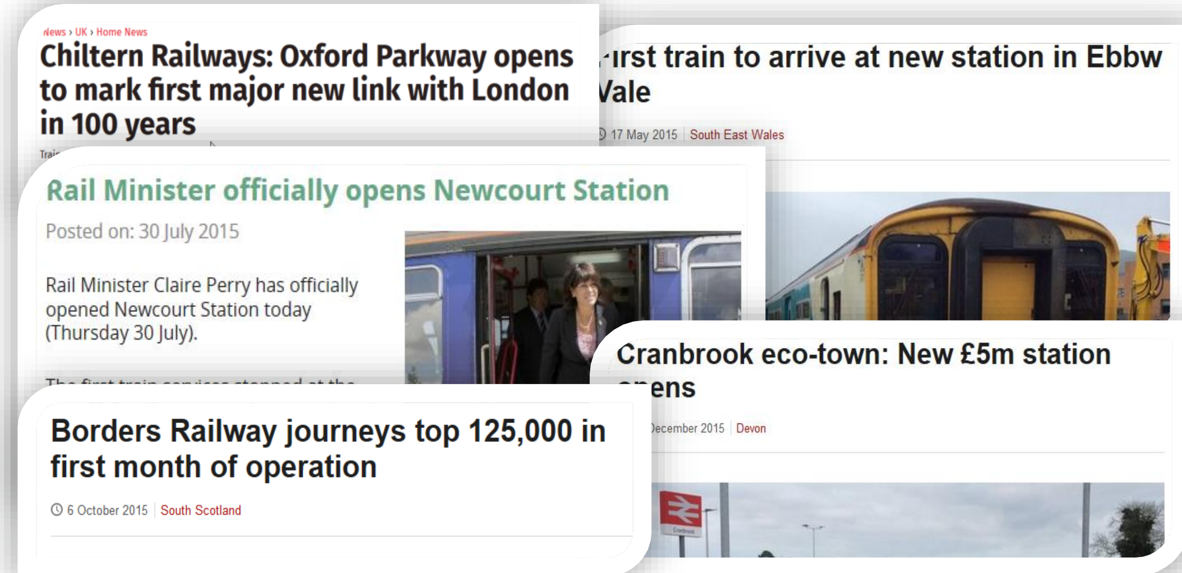
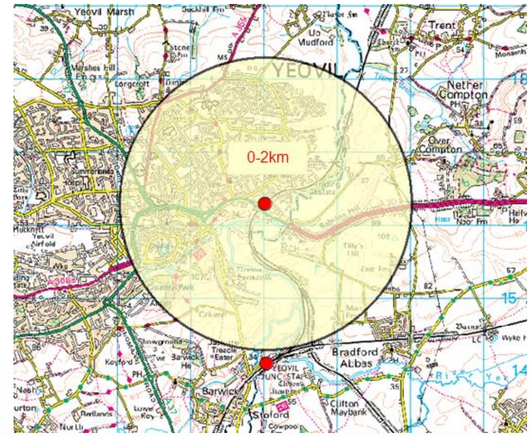
New stations

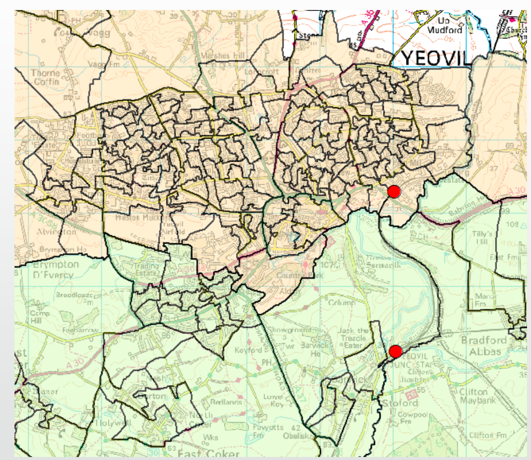


- Increasing interest in using rail to meet transport needs or drive economic growth
- Need accurate demand forecasts

Demand models – defining catchments

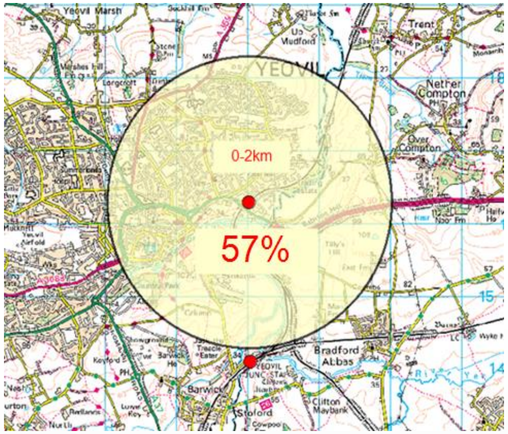
- Trip rate, trip end and flow models
- Must define a catchment first:
  - circular (buffer) around station
  - nearest station – zone based
- Choice of station is deterministic
- Catchments are discrete, none overlapping

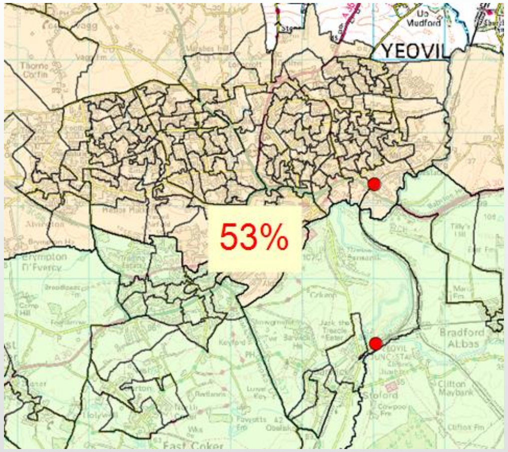




Catchments in reality

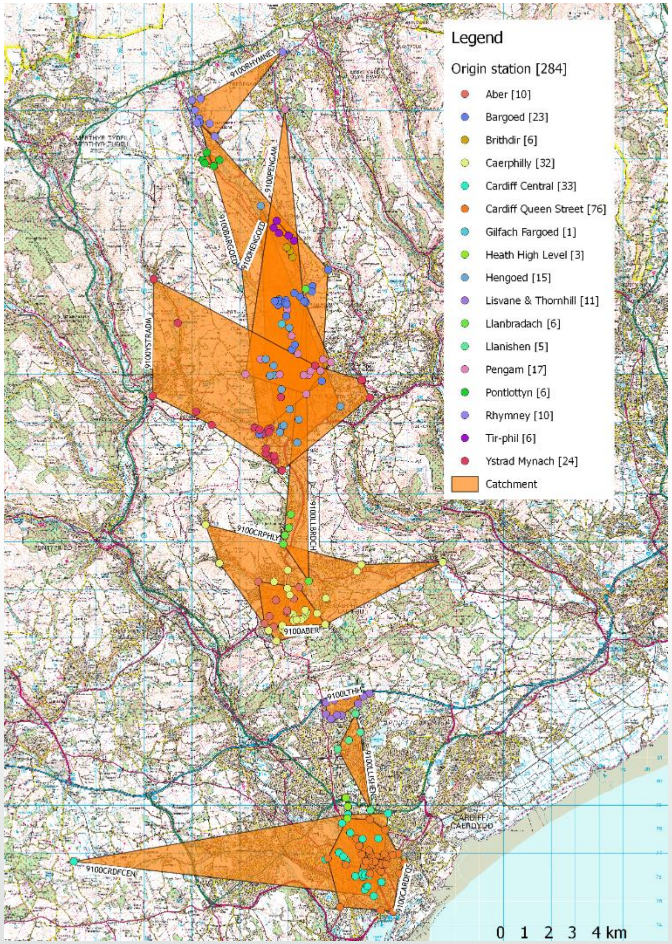
- 2km circular catchments account for 57% of observed trips, 0-20% for some stations (Blainey and Evens, 2011)
- 53% of trip ends located within nearest station zone-based catchments (Blainey and Preston, 2010)
- 47% of passengers in the Netherlands do not use their nearest station (Debrezion et al., 2007)





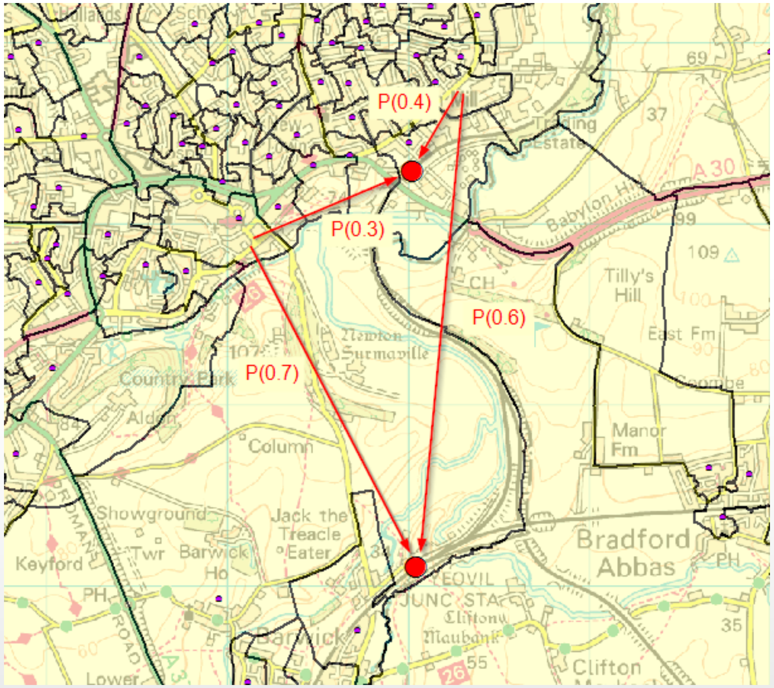
Catchments in reality

- Catchments are not discrete. They overlap and stations compete
- Catchments vary by access mode, station type and destination
- Station choice is not homogenous within zones
- Station choice more complex than definitions allow



Alternative – probability-based catchment

- For each zone calculate the probability of each competing station being chosen
- Allocate zonal population to each station based on the probabilities
- Need a station choice model



Developing a station choice model

Discrete choice models

- Individual chooses the alternative that maximises their utility

Utility (U) = measured utility (V) + unobserved utility (ε)

- Measure utility: attributes and estimated parameters, e.g.

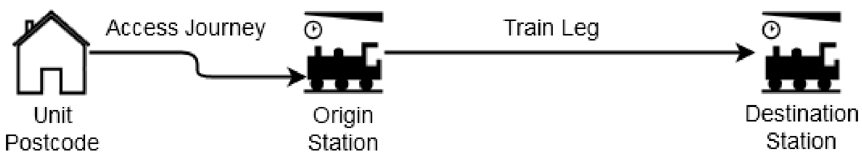
$$V = \alpha Freq + \beta Dist + \gamma Time$$

- Calculate the probability of each alternative being chosen

Factor	Change	Expected affect on utility
Frequency of service	↑	↑
Car parking spaces	↑	↑
Fare	↑	↓
Access distance	↑	↓
Interchanges	↑	↓
Journey time	↑	↓

Data requirements

- Observed choice data - on-train survey Cardiff Central to Rhymney line, 284 usable observations
- Attribute data

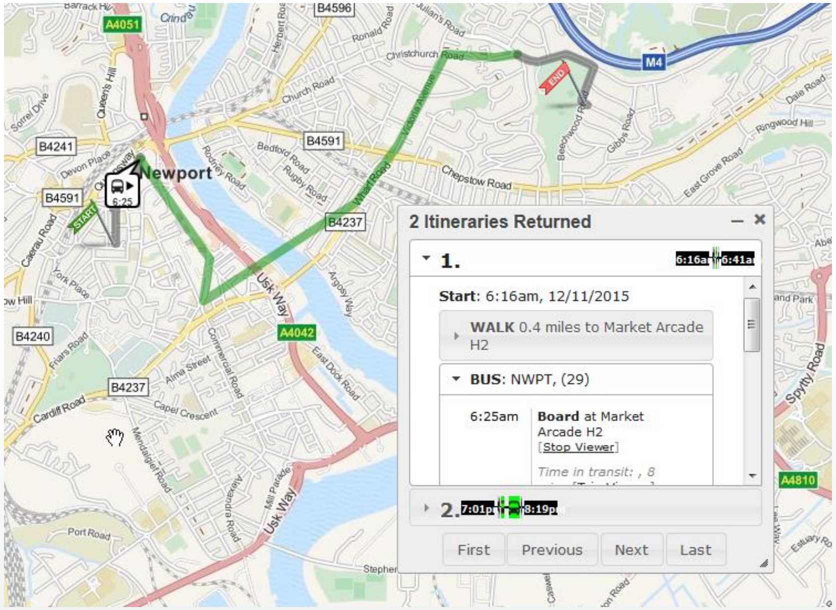


individual	chosen	alternative	cardist	rank	cartime	cctv	choice	nearest	unstaffed	partTime
1	9100CRPHLY	9100TYGLAS	7.65	10	16.3	1	0	0	1	0
1	9100CRPHLY	9100RHIWBNA	7.36	9	15.05	1	0	0	1	0
1	9100CRPHLY	9100LLISHEN	7.08	8	16.93	1	0	0	1	0
1	9100CRPHLY	9100BCHGRV	6.83	7	13.97	0	0	0	1	0
1	9100CRPHLY	9100TAFFSWL	6.46	6	13.95	1	0	0	0	1
1	9100CRPHLY	9100LTHH	5.73	5	11.77	1	0	0	1	0
1	9100CRPHLY	9100LLBRDCH	4.83	4	9.38	0	0	0	1	0
1	9100CRPHLY	9100ERGNCHP	2.81	3	7.93	0	0	0	1	0
1	9100CRPHLY	9100ABER	2.06	2	5.87	1	0	0	0	1
1	9100CRPHLY	9100CRPHLY	1.06	1	3.02	1	1	1	0	1

Choice Set

Data – OpenTripPlanner

- Open source multi-modal route planner with API
- OpenStreetMap – for street and path routing
- GTFS feeds – for train and bus routing
- API wrapper written in R



Data – explanatory variables

Access journey	Origin station facilities	Train leg
• Drive distance[1] • Drive time[1] • Walk time[1] • Bus time[1] • Nearest station (y/n)[4]	• CCTV (y/n)[2] • Car parking spaces[2] • Staffing level[2] – Unstaffed – Part-time – Full-time	• Journey duration[1] • No. of transfers[1] • Fare[3] • Difference between actual and desired departure time[1]

Data sources:

1. OpenTripPlanner
2. NRE Knowledgebase XML Feed
3. BR Fares
4. Derived from data

Model details

- Choice set varies by individual, defined for each origin unit postcode
  - 10 nearest stations by drive distance (99% of observed choice)
  - threshold based – bus route available; maximum walk time (45 minutes)
- Multinomial logit
- Calibrated using R package, mclogit

Model results

Results – basic choice sets

	1	2	3	5	10
Drive distance	-1.03***	-0.93***	-1.10***	-0.82***	-0.81***
Staffing (PT)		-3.42***	-2.16***	-2.22***	-2.59***
Staffing (None)		-4.48***	-2.72***	-2.77***	-2.71***
Train time			-0.21***	-0.21***	-0.20***
Nearest station				0.98***	0.99***
CCTV					1.43***
logLik	-348.81	-248.57	-212.34	-203.25	-196.38
Adj R^2	0.46	0.62	0.67	0.69	0.70

Results – threshold-based choice sets

	11	12
Drive distance	-0.60***	
Access time (car driver)		-0.29***
Access time (car passenger)		-0.32***
Access time (bus)		-0.18***
Access time (walk)		-0.13***
Staffing (PT)	-2.71***	-3.00***
Staffing (None)	2.62***	-3.00***
Train time	-0.21***	-0.20***
Nearest station	1.09***	0.78***
CCTV	1.68***	1.8***
logLik	-177.59	-158.89
Adj R^2	0.61	0.65

Access mode specific parameters

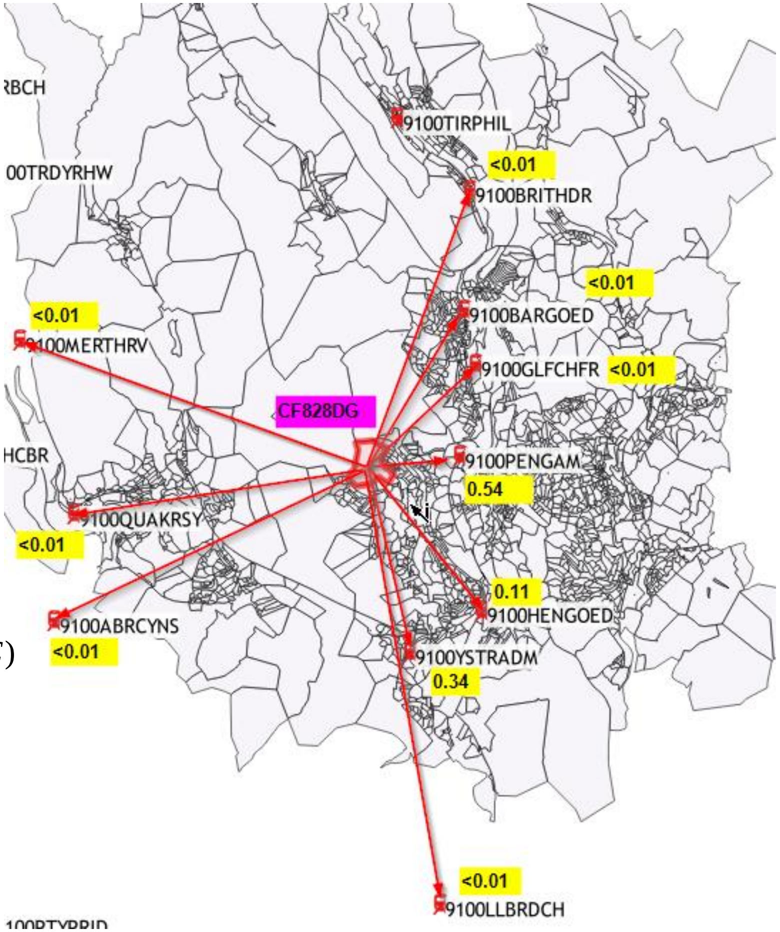
Generating probability-based catchments

Generate a probability-based catchment

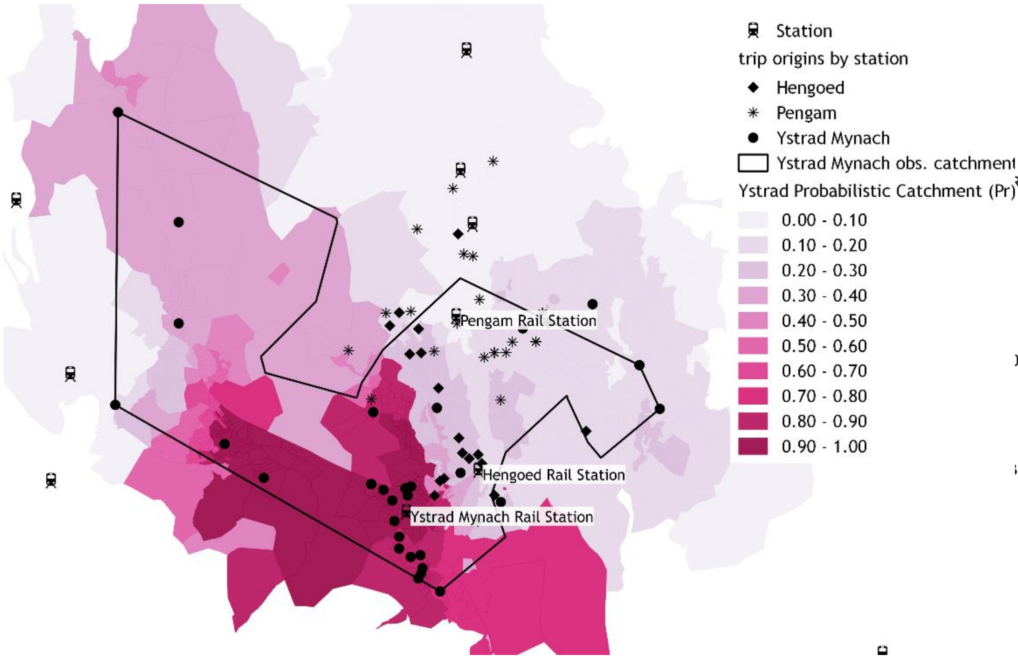
- Find 10 nearest stations by drive distance for each postcode
- Generate attribute values (for specific destination)
- Calculate utility of each station using model 10.

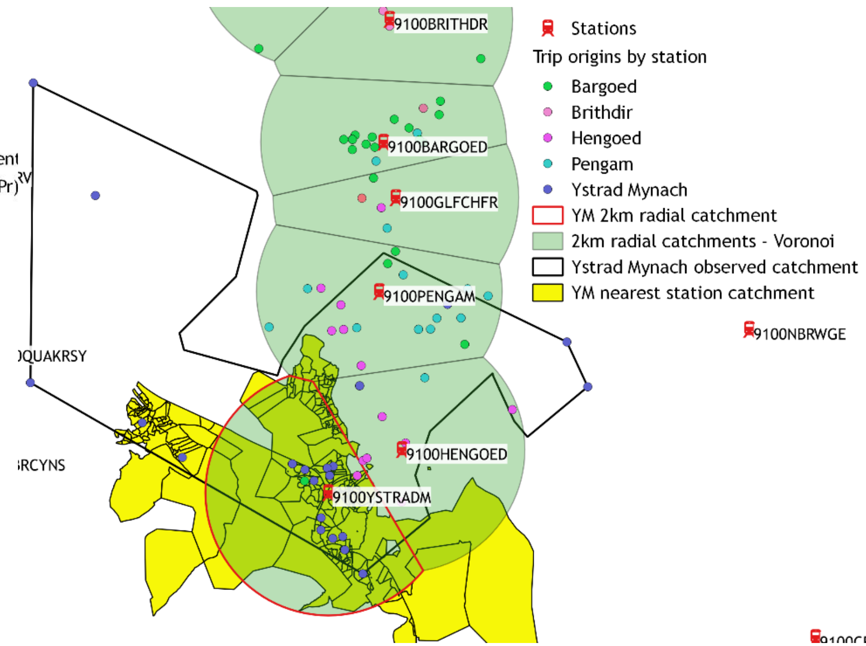
$$V = (-0.81 \times D) + (-2.6 \times Spt) + (-2.7 \times Sno) + (-0.2 \times T) + (0.99 \times Ns) + (1.4 \times C)$$

- Calculate probability of each station being chosen



Example – Ystrad Mynach





Probability-based catchment – to Cardiff Central

2km radial and nearest station catchments

Conclusions and further work

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Conclusions

- It is possible to calibrate a relatively simple station choice model that fits the observed data well
- The model can be used to generate probability-based station catchments that are a realistic representation of observed catchments
- The probability-based catchments perform better than deterministic station catchments

Future work

- Apply methods to larger surveys
- Develop more sophisticated models - multinomial logit models suffer from proportional substitution behaviour
- Need to ensure a realistic representation of abstraction from existing stations – this effect could undermine the business case for a new station
- Incorporate probability-based catchments into the rail demand models