Multi-state Models for Chronic Kidney Disease Prevalence Projections in Ontario

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Background

- Chronic kidney disease (CKD) typically involves various forms of treatment over a period of time.
- Each of these forms of treatment (bundles) have different funding requirements which depend on the demand and costs per patient year associated with each bundle.
- The Ontario Renal Network is responsible for providing funding for these treatment bundles.

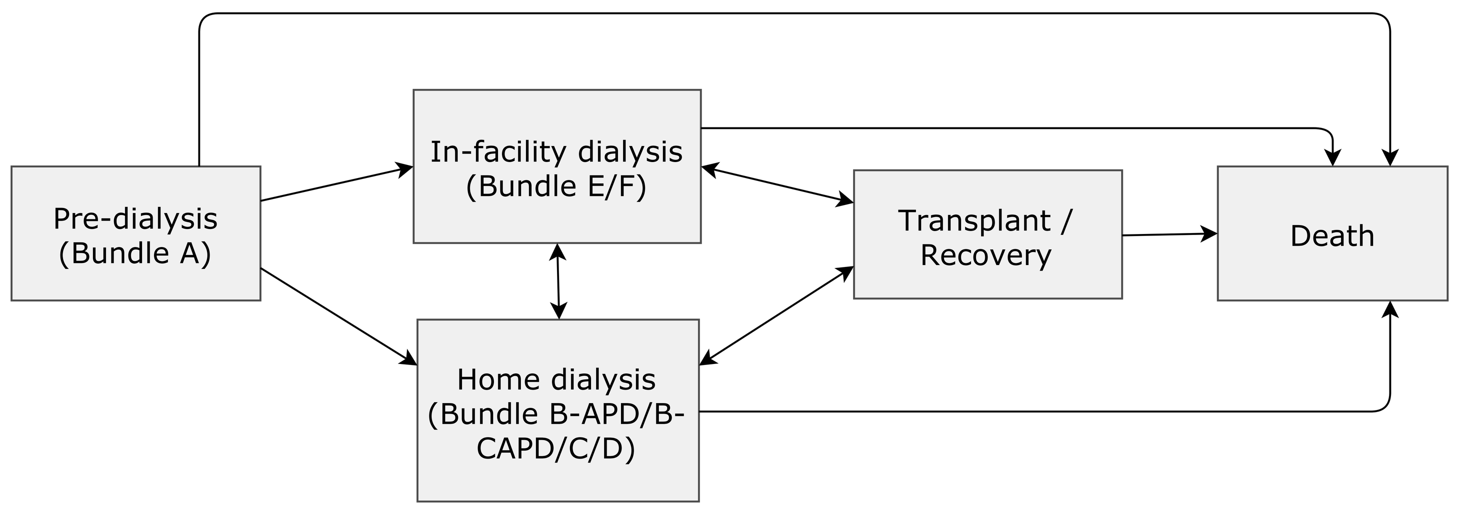

Figure 1: Simplified state transition schematic

Table 1: At any given time, a patient belongs to one of the following states:

State	Description
Acute	Acute episode
Bundle A	Pre-dialysis
Bundle B-APD	Home automated peritoneal dialysis (APD)
Bundle B-CAPD	Home continuous ambulatory peritoneal dialysis (CAPD)
Bundle C	Home hemodialysis (HD) daily/nocturnal
Bundle D	Home hemodialysis (HD) conventional
Bundle E	Ambulatory in-centre hemodialysis daily
Bundle F	Ambulatory in-centre hemodialysis conventional
AWAY	Lost to follow up or transfer out of province
RECOVER	Recovery
TRANS	Transplantation
DEATH	Death

Objectives & approach

- We wish to develop a model that forecasts annualized patient counts for each bundle.
- Instead of taking a discrete Markov modeling approach similar to that of Schaubel et al. (1998) we use continuous-time transition models since we have available Ontario Renal Reporting System (ORRS) data which has patient status updates by day.
- In contrast to the time series techniques employed by Quinn et al. (2009), we take a multi-state modeling approach which allows us to aggregate the patient time spent in each state and model state transitions based on the nature of disease progression.
- We use Statistics Canada population projections by age & gender to simulate state transitions for individual patients over a 5-year period.

Modeling state transitions & incidence

State transitions

We model transition rates per person-year between any two states using Poisson regression with age and gender as covariates and duration as an offset.

Using ORRS data, we fit the following Poisson regression models where A_{ij} is the event that a patient transitions from bundle i to bundle j:

$$\log\left(\frac{\mathbf{E}(A_{ij})}{\text{duration}}\right) = \log(\lambda_{ij}) = \beta_{0ij} + \beta_{1ij}\text{Age} + \beta_{2ij}\text{Gender} \quad (1)$$

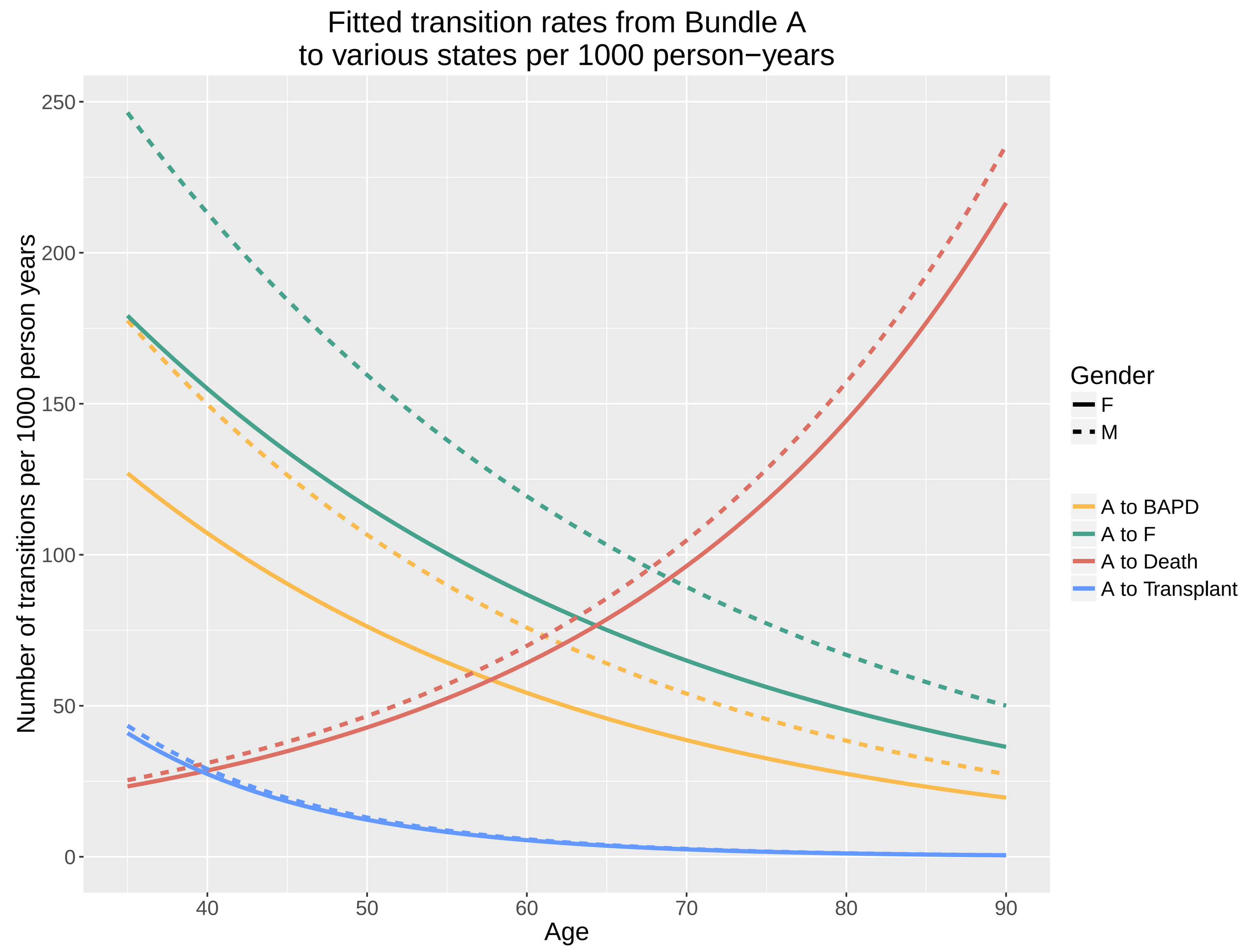

Figure 2: Fitted state transition models

Incident patients

Similarly, using historical data from ORRS, we fit the following Poisson regression models where N_i is the number of incoming bundle i patients of a specified age and gender given the subpopulation of healthy persons that belong to that age/gender group:

$$\log\left(\frac{\mathbf{E}(N_i)}{\text{subpopulation}}\right) = \log(\lambda_i) = \beta_{0i} + \beta_{1i}\text{Age} + \beta_{2i}\text{Gender} \quad (2)$$

We can now determine the incidence rate per person-year by age and gender for each bundle. Using these rates along with population projections by age and gender from Statistics Canada, we can simulate incoming patients with exponentially distributed start times.

Simulation & results

We then create a cohort consisting of all prevalent patients as of the last day of data collection (Nov. 30, 2015) and all expected incoming patients over the simulation period (2016-2020).

Simulation & results cont'd

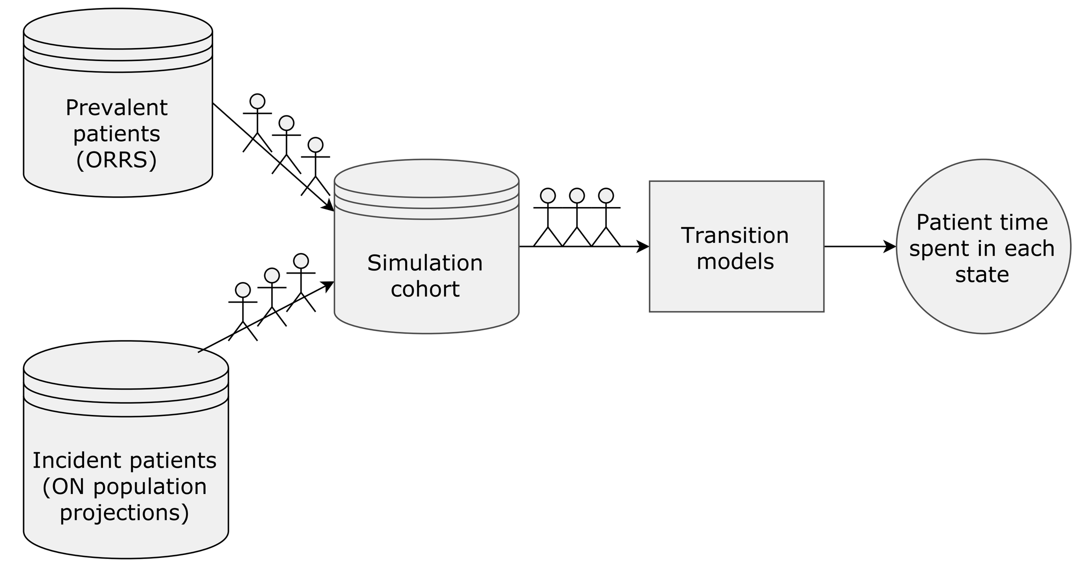

Figure 3: Flowchart illustrating the creation and simulation of the cohort

Given Poisson regression models like those in equation (1), the simLexis function from the Epi package can be used to simulate a cohort of patients with the appropriate covariates. We use this function to simulate our cohort for a 5-year period.

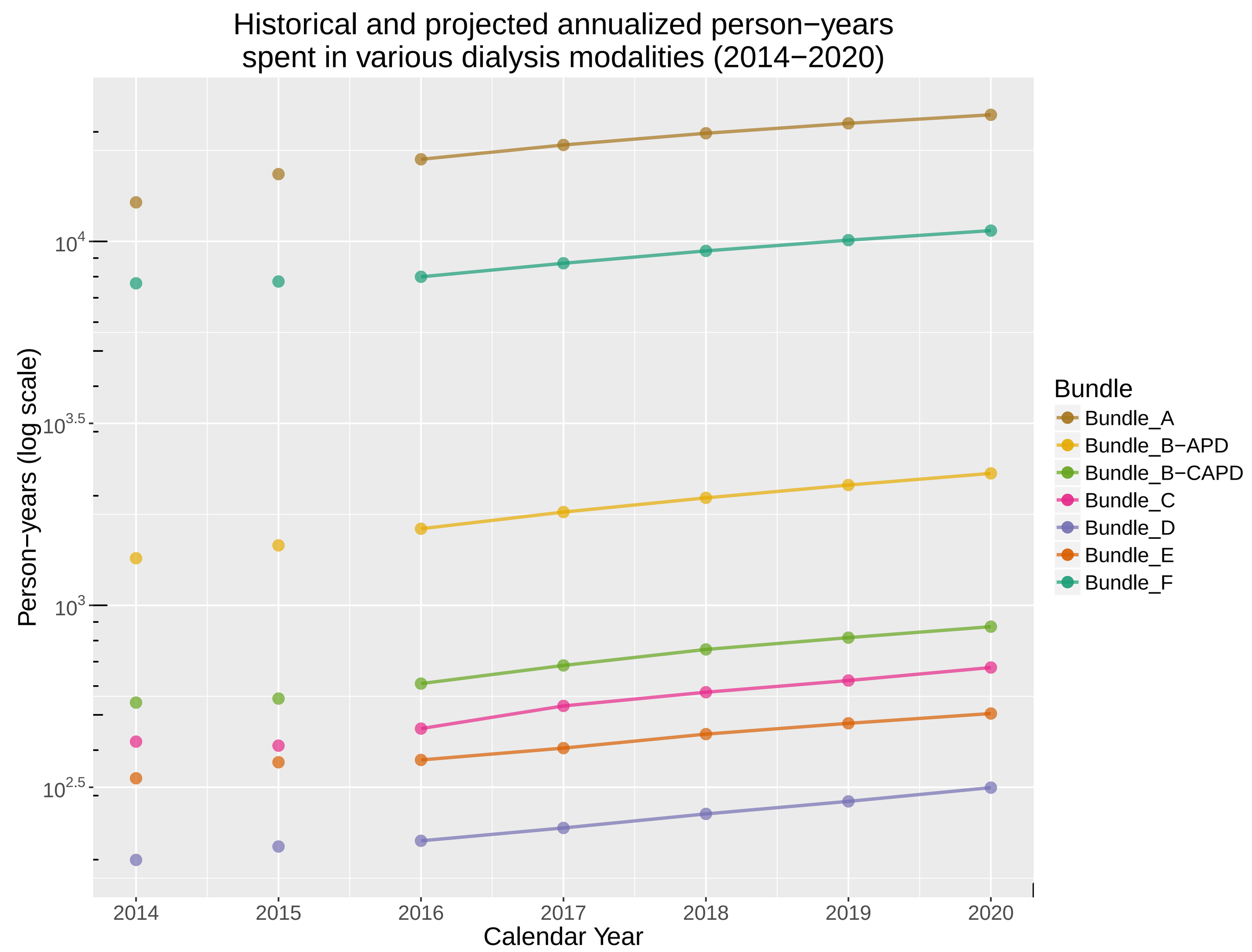

Figure 4: Simulation results

Conclusions & next steps

- The multistate model is a patient-level approach; it captures disease progression from healthy to pre-dialysis to various dialysis modalities to attrition.
- This model could be improved by modeling the effects of dialysis duration and/or other aspects of treatment history and modeling calendar time trends.

References

[1] Quinn, R. R., Laupacis, A., Hux, J. E., Moineddin, R., Paterson, M., Oliver, M. J. (2009), "Forecasting the Need for Dialysis Services in Ontario, Canada to 2011," *Healthcare Policy | Politiques De Santé*, 4(4). DOI:10.12927/hcpol.2009.20684

[2] Schaubel D. E., Morrison H. I., Desmeules M., Parsons D., Fenton S. S. (1998), "End-stage renal disease projections for Canada to 2005 using Poisson and Markov models," *International Journal of Epidemiology*, **27**(2), 274–281.

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