Policy Approximation for Optimal Treatment Planning

INDUSTRIAL & OPERATIONS ENGINEERING
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1 Abstract

Markov decision process (MDP) models are powerful tools which enable the derivation of optimal treatment policies, but may incur long computational times and decision rules which are challenging to interpret by physicians. To reduce complexity and enhance interpretability, we study how Poisson regression may be used to approximate optimal hypertension treatment policies derived by a MDP for maximizing a patient's expected discounted quality-adjusted life years (QALY).

2 Background

Cardiovascular (CV) Disease

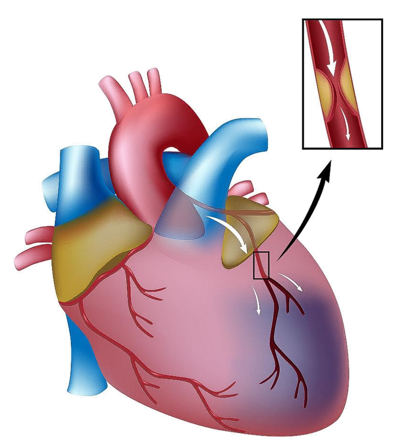

Figure 2.2

Coronary heart disease (CHD) accounted for 53% of the deaths related to cardiovascular diseases.[1]

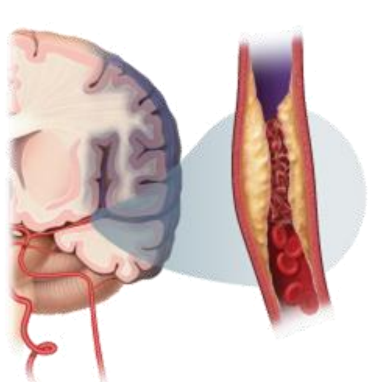

Figure 2.2

Stroke is considered among the top five leading causes of death in the U.S.[2]

Sequential Decision Making

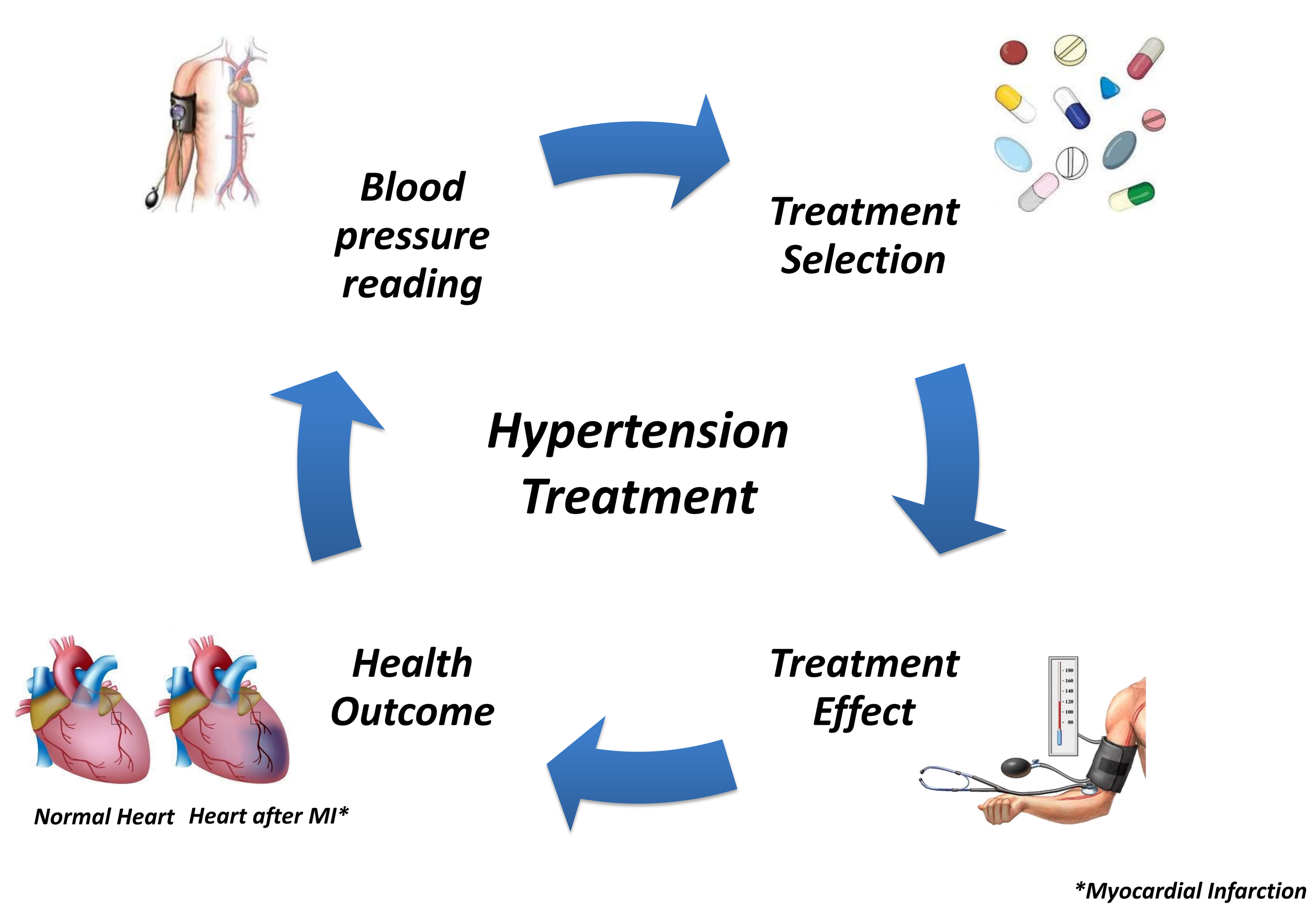

Figure 2.1

Hypertension treatment can be translated as a sequential decision making problem. Treatment selection will vary according to the health status of the patient.

3 Methodology

Markov Decision Process

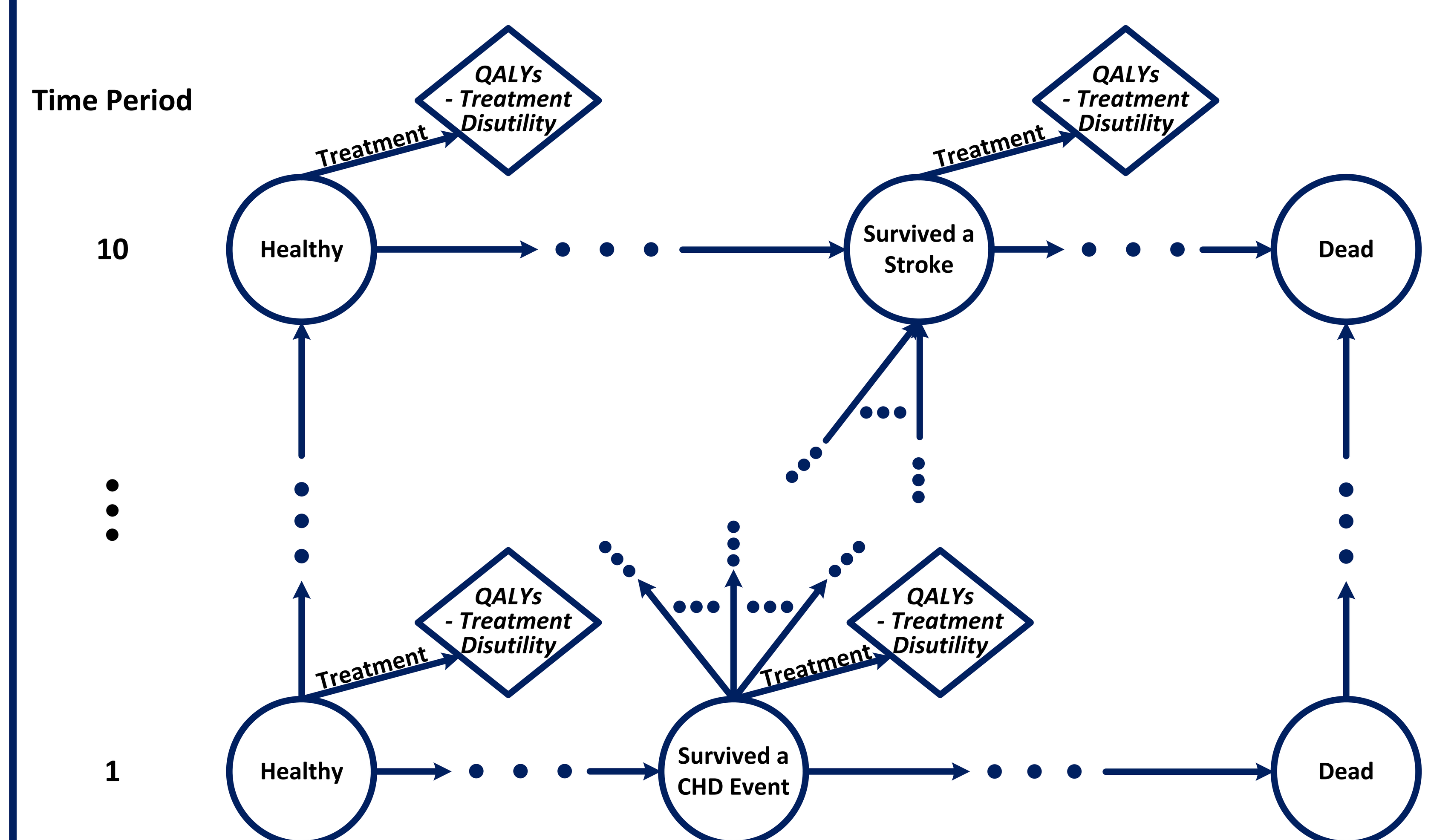

Figure 3.1

The optimal number of medications per patient at each decision period was obtained using a MDP.

Generalized Linear Mixed Effects Model

Demographic and risk[3] information · *Patient identification* · *Residual*

$$y = X\beta + Z\gamma + \varepsilon$$

Optimal medication count (from the MDP policy) · *Fixed effect coefficients* · *Random effect*

Equation 3.1

The policies derived from the MDP were approximated using a Poisson regression model, parameterized on 20,000 patients[4] through linear mixed-effects modeling. This allows for the interpretation of the effect of each regression coefficient.

Treatment Policies Description

MDP	Full Interaction	Risk Only	JNC 7
Optimal Policy[5]	Demographic Information** 5-year CV risk[3] Interaction between demographics and 5-year CV Risk[3]	5-year CV Risk[3]	Current Practice[6]

***Demographic information include the following factors: age, sex, smoking status, diabetes status, pretreatment systolic blood pressure, pretreatment diastolic blood pressure, high density lipoprotein, and total cholesterol.*

4 Results

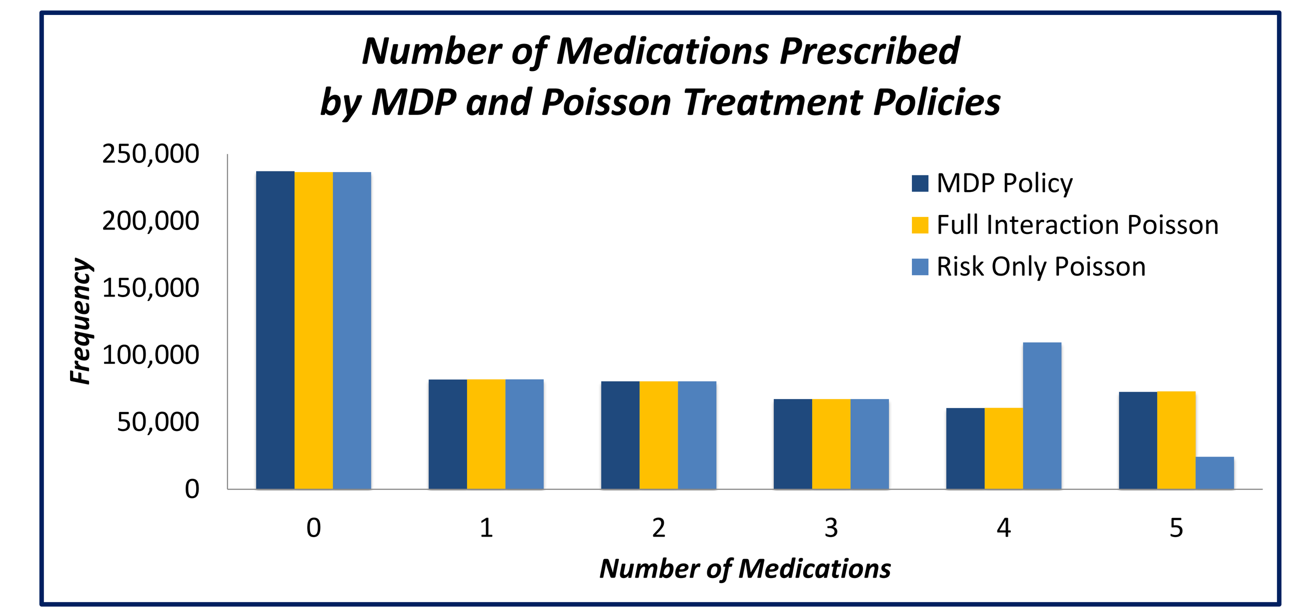

Figure 4.1

Policies were tested on a cohort of 60,000 patients.[4] The Poisson policies were able to accurately approximate the policies determined by the MDP model.

Treatment Policy	*Expected Discounted QALYs Saved per 1000 Patients*	*Expected Number of CV Events Prevented per 1000 Patients*
MDP	271.88	47.41
Full Interaction Poisson	271.88	47.42
Risk Only Poisson	266.52	46.41
JNC7	162.66	29.47

Table 4.1

The MDP policies were also accurately matched by the Poisson policies in terms of the expected health outcomes.

5 Additional Analyses Performed

- Evaluation of treatment policies using a distinct risk calculator.[7] Differences between the optimal policy and the Poisson policies remained under 2.5%.
- Assessment of treatment policies under ±25% risk calculator calibration error. The approximations were not highly affected by the calibration error.

6 Summary and Conclusions

- By building upon large longitudinal datasets to derive policy approximations, our algorithms provide fast, interpretable, reliable and software-free decision support.
- While first developed for hypertension treatment planning, our methodology could be applied to derive treatment plans for patients with other chronic conditions.

7 Acknowledgments

- Rackham Graduate School
- University of Michigan Health System

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8 References

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