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A MODEL BASED SIMULATION TOOLKIT FOR EVALUATING RENAL REPLACEMENT POLICIES

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ABSTRACT

Renal failure concerns progressive loss of kidney function. Renal Replacement Therapy (RRT) is a costly, long-running process that includes several decision points in different stages. Small changes in the protocol can impact significantly the expenditures and healthcare outcomes. Unfortunately, policy makers have very little support for benchmarking improvement alternatives. The existing models are designed to fit certain applications with preset parameters and design choices which do not match with the requirements of a policy analysis. A generic approach is required to analyze the effects of different design options adjustable to finer scales. To remedy this, this paper describes a novel toolkit for evaluating renal replacement policies, containing a parametrized colored Petri-Net which can be configured for the specifics of local settings. The model is made available for open access to overcome the non-replicability issue of existing models.

1 INTRODUCTION

Systematic advancements in medicine and lifestyle support have extended human lifespan. At the cost of the clear benefits come great challenges from the healthcare economics side. Since citizens demand more care throughout their extended lifetime, governments and insurers are struggling to provide accessible healthcare to all citizens in an affordable manner. Among others, policy makers strive to demonstrate that planned capacity is able to meet expected demand, without waste. This prompts the need for decision support tools for Renal Replacement Therapy (RRT) policies as human life depends on the ability to treat every patient with adequate resources.

In this paper, we present a generic toolkit for evaluating renal replacement policies. The previous models described for RRT lack the generic structure that allows adaptation to local settings of the treatment process. The developed model overcomes this problem by a parametrized design which can be modified to analyze scenarios or regional variations without changing the structure of the model. The toolkit is available online for open access to be used in further applications.

Renal failure is a progressive loss of the kidney functions. Renal failure is mainly determined by a decrease in Glomerular Filtration Rate (GFR), the rate at which blood is filtered in the glomeruli of the kidney. There are five stages of renal failure depending on the values of the Estimated GFR (eGFR), and five possibilities for treatment: pre-dialysis (only for stages 1-4), Haemodialysis in a Centre (HDC), Haemodialysis at Home (HDH), Peritoneal Dialysis at home (PD), and kidney transplantation (for stage 5).

RRT is a long-running process that includes several decision points in different stages and resulting alternative pathways. The treatment is costly as well: for each patient, between 40,000€ 80,000€ is spent by the European Healthcare system (EKHA: European Kidney Health Alliance 2013). Fortunately, small changes in treatment protocols can yield great savings while improving healthcare outcomes too. For instance, a 10% rise in at-home dialysis (HDH and PD) for 5 years could result in a total savings of almost one billion euros in Europe (Joble and Laplante 2010). More broadly, several studies examined the renal treatment options and questioned the renal treatment policies considering costs, life expectancies, medical outcomes, and capacities. These studies include cost-effectiveness analyses of different treatment options (Haller, Gutjahr, Kramar, Harnoncourt, and Oberbauer 2011, Lemus, Cerezo, Bravo, and Jimenez Aranda 2013, Roberts, Gross, and Maxwell 1979), analyses of relations between several factors and RRT incidence rates (Caskey et al. 2011, Visser et al. 2012), and RRT demand predictions (Rodina-Theocharaki et al. 2012, Roderick et al. 2004) to support decision makers in healthcare policy evaluations.

Due to complexity of the process with several sources of uncertainty and multiple decision makers, simulation is a widely preferred method for RRT analysis, compared to more abstract optimization methods. One of the earliest studies uses the INS simulation language for a cost-effectiveness analysis where effectiveness is measured with quality-adjusted-life years (Roberts, Gross, and Maxwell 1979). The early studies demonstrate feasibility only, for example since they do not yet support all real-life treatment options. Simulation models in RRT studies are usually built for analyzing the health and cost effects of policy scenarios, which change the incidence rates of treatment modalities (Rodina-Theocharaki et al. 2012, Davies and Davies 1987, Liem et al. 2012). Davies and Davies (Davies and Davies 1987) create a generic simulation model using Pascal_SIM to be used for impact analysis of policy decisions on patient number. Simulation is also used for case-studies to determine future renal failure incidences in local districts. Davies and Roderick (Davies and Roderick 1998) expand the scope with discrete-event simulation to nation-wide RRT demand prediction for the UK. Their model is later updated with more risk factors and live transplants in addition to analysis of transfer between different dialysis options (Roderick et al. 2004). Other than discrete event simulation, Monte Carlo simulation is also used for demand prediction where treatment options are modeled as mutually exclusive states and the transfers among these states as a Markov Chain (Rodina-Theocharaki, Bliznakova, and Pallikarakis 2012).

In addition to RRT processes, simulation modeling is widely used as a toolkit for policy analysis in other healthcare domains. Simulation is used for performance analysis and improvement in medical environments by providing tools for scheduling, capacity planning, patient flow modeling, etc (Diaz, Behr, and Britton 2015). Gunal and Pidd (Gunal and Pidd 2010) provide a brief review of discrete-event simulation applications in healthcare for performance evaluation and discuss that most models lack a generic approach.

The generic model for simulating the demand for the renal treatment that is described in this paper is based on Colored Petri-Nets ((CPNs) (Law and Kelton 1991)). CPNs are visual for the process and data flows while benefiting from the expressiveness of a full programming language for the details. The model introduces the configuration capability to RRT simulation studies as a critical contribution due to regional differences. By capturing the key variability through model parameters, we lower the barrier to applying the model in new regions. Another new aspect of the study is the expansion of process with the addition of details about the disease and treatment flow. The patients are defined with characteristics such as eGFR level and age which are essential for an accurate projection of future demand. This addition also allows for further extensions when treatments specific to age groups or eGFR levels are considered. The treatment process is expanded with options related to donor policy that allows people to choose to be a donor or not (i.e. Opting-In, Opting-Out). The key factors are defined in functions, thereby allows a easy modification for a scenario analysis or regional adaptation. The model and the CPN platform on which simulations are executed are made available at http://is.ieis.tue.nl/research/renalsim/. Although the aforementioned literature describes a variety of specific simulation models for the impact of RRT policy analyses, only Davies and Davies (Davies and Davies 1987) describe a generic model that can be used for

several applications. Yet, their model is only described and not provided publicly for further applications. Besides the genericity, our work is novel in the area of open access.

2 RESEARCH METHODS

In this study, we rely on version 4.0.0 of the CPN Tools software. CPN Tools is designed for modeling and simulating CPNs. CPNs extend classical Petri-nets with data types (so-called colors), time and hierarchy. We have designed a conceptual process and data model as further documentation to the already visual CPN. Our generic model is based on information gathered through renal failure therapy literature and medical experts. The generic approach is applied to a redesign study for the Dutch healthcare system. Data was collected from the Dutch End-Stage Renal Disease Registry, RENINE for the period between January 1st, 1998 and June 24th, 2013. Information on dialysis centers is retrieved from Hansmak Institute. The process details including referral to specialist, threshold eGFR levels, pre-dialysis and transplantation waiting lists are based on De Nierstichting (The Kidney Foundation) and Nierpatienten Vereniging Nederland (Kidney Patient Association Netherlands).

After the simulation model is developed, verification and validation analysis is done to check if the simulation runs perform as intended (Jensen and Kristensen 2009). To verify our executable model we have executed a state space analysis. However, we also used other techniques inspired by Kleijnen (Kleijnen 1995), specifically modular programming and animation. Model validation is done based on the results of "as is" situation by comparing the past values of key performance indicators (KPI) taken from RENINE data set with the simulation outputs.

3 RESULTS

3.1 Conceptual Model

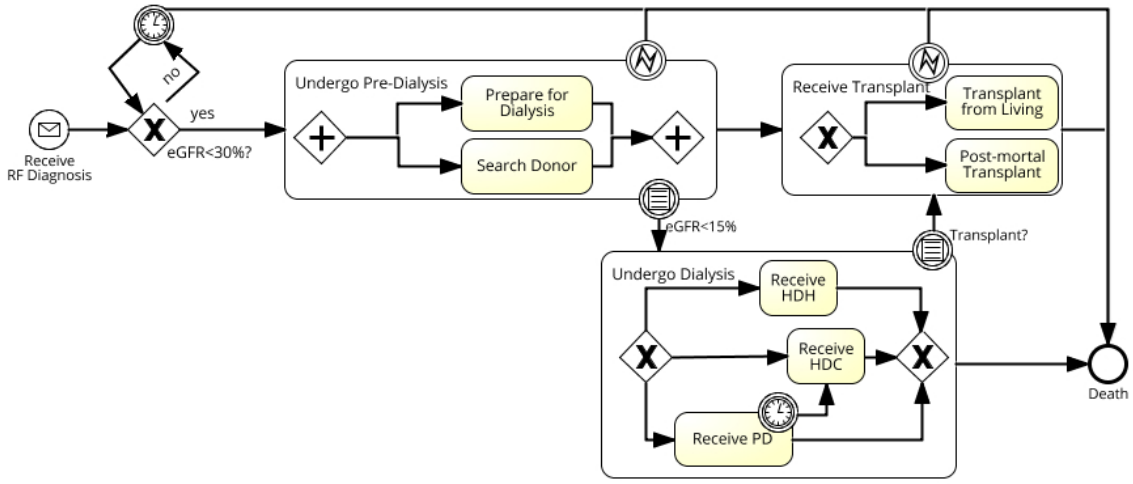

Figure 1: Conceptual process model describing the end to end flow for patient cases throughout simulation.

Figure 1 shows conceptual process model describing the end to end flow for patient cases. Patients enter the simulation process at the point they have been diagnosed with renal failure. In this phase eGFR is usually still above the pre-dialysis threshold and slowly decrease. Some people may die from other (natural) causes before their eGFR deteriorates to the pre-dialysis threshold. When the eGFR falls below a

certain threshold, the patients go to pre-dialysis where they will start to prepare for dialysis. Furthermore, they start looking for a potential living donor match. If they find a match and finish the procedure, which last several months, on time, they receive a transplant and continue to live with a donor kidney. Else, when their eGFR drops below a certain threshold, they start dialysis. At this stage, the treatment option is selected according to certain probabilistic parameters. When the patients choose PD, the peritoneum deteriorates over time, which causes the patient to switch automatically to HDC. There are two ways of exiting the dialysis phase. The first way is to get a transplant, from either a living donor that was already found during pre-dialysis, or a post-mortal donor. If a living donor is found but the patient does not match his blood group, he enters a cross-over program. In this program, donor kidneys are exchanged between patients with a donor from the wrong blood group. Since renal failure is irreversible, the only other way to finish dialysis for a patient is to die.

3.2 Setting The Model Parameters

The parameters that can be changed in the model to describe different scenarios and their input value in the "as is" model are specified in Table 1. Table 2 provides the output parameters of the model. The values of certain input parameters are dependent upon the age (A= a0_44,a44_65,a65_) and eGFR level (E=100_30,29_16,15_9,8_0) of the patient.

Table 1: Input parameters.

Input Parameter	Description	Value	Input Value
Patient distribution	Distribution of input patients among different patient classes based on eGFR level (E) and age category (A)	(E,A)	(100_30,a0_44) (29_16,a0_44) (15_9,a0_44) (100_30,a44_65) (29_16,a44_65) (15_9,a44_65) (100_30,a65_) (29_16,a65_) (15_9,a65_)
Patient arrivals	Average number of patients per week.	λ	4.063846 patients per week
Length diagnosis phase	Deterministic time in weeks (t_D) based on eGFR level.	t_D (E)	(5 year ,0 year,-,-)
Mortality Rate	Percentage of patients (MR) that die per five years due to natural causes.	MR (A)	(0.08%;0.18%;4.08%)
Length pre-dialysis phase	The average length of the pre-dialysis in weeks t_PD based on the eGFR level of the patient.	t_PD(E)	(-,178 weeks,44 weeks,22 weeks)
Treatment distribution	The percentage of patients that choose a specific dialysis treatments (HDH, HDC, PD).	HDH, HDC, PD (A)	(3.41%;17.12%;79.47%) (3.33%;19.22%;77.45%) (3.59%;12.80%;83.61%)
Life expectancy dialysis	The average life expectancy in weeks for patients receiving dialysis LE_HDH, LE_HDC, LE_PD.	LE_HDH, LE_HDC, LE_PD (A)	(1336 weeks,478 weeks,179 weeks) (1336 weeks,478 weeks,179 weeks) (1336 weeks,478 weeks,179 weeks)
Length PD treatment	The maximum duration of the PD treatment in weeks (t_PDSWITCH).	t_PDSWITCH	4 year
Living donor	The chance of finding a living donor P_LD.	P_LD (A)	(86.18%;18.36%;14.34%)
Living donor Match	The chance that the living donors matches with the patient.	P_MLD	90%
Diagnosis time living donor	The time that it takes to diagnose the person that wants to donate his kidney in weeks t_LD.	t_LD	22 weeks
Post mortal donor	The number of post mortal donors that become available per year S_PMD.	S_PMD(Y)	37.99
Life expectancy living donor	The average life expectancy of a living donor in years.	LE_LD	25 year

Life expectancy post mortal donor	The average life expectancy of a post mortal donor in years based on Exponential Distribution.	LE_PMD	15 year
HDC Capacity	Total capacity of Hemodialysis clinics in number of patients that can be treated in parallel.	S_HDC	954

Table 2: Output parameters.

Output parameter	Description
HDC Patients	Number of patients that receive HDC at any moment in time.
HDH Patients	Number of patients that receive HDH at any moment in time.
PD Patients	Number of patients that receive PD at any moment in time.
Donor Patients	Number of patients that receives a donor kidney.
Utilization HDC capacity	The utilization of the hemodialysis clinic capacity.

3.3 Executable Model

The executable model is built in CPN Tools, a package for discrete event simulation. The previously defined input parameters are either used in functions or, in the case of patient attributes, within the color set patient. Figure 2 shows the hierarchy levels of the model. Each subsequent part of the model uses the output of the previous phase as input. Furthermore, pages lower in the hierarchy form the sub processes of pages higher in hierarchy. This favors the overall readability of the model compared to a variant without hierarchy.

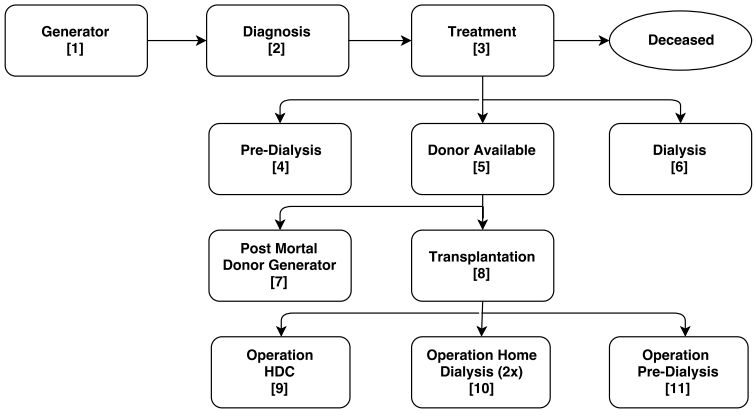

Figure 2: Model Hierarchy

3.3.1 Functions

In CPN tools, functions are necessary to translate the input parameters to practical outputs in the executable model. Table 3 shows a list with functions used, their respective page in the model, the relevant input parameters, the distribution that used to determine values and the output that follows from the execution of the function.

Table 3: Explanation of formulas used in specific pages (submodels) of the executable model.

Page	Function	Input	Distribution	Output
1	TakeTime()	-	None	Current model time
1	patientarrivals()	?	Arrivals: Poisson	Tokens for new patients (per week)
1	loadPatientTypes()	(E,A)	None	Tokens for each patient-class
1	Uniform(u)	-	Uniform	Tokens with a uniform value (to match patients with patient-class)
1	definePatient(id:ID, egfr:EGFRLEVEL, a:AGE, p:PROVINCE)	Patient-class, value [0,1], ID	None	Individual patient
2	survivediagnosis(p)	MR (A)	Chance: Uniform	Chance of dying during diagnosis
2	setefrdiagnosis (p)	E	Fixed: None	New eGFR level for patient (from 100-30 to 29-15)
4	dettreat(p)	HDH,HDC,PD (A)	Chance: Uniform	Treatment type
4	setegfrpredialysis (p)	E, t_PD(E)	Fixed: None	New eGFR level for patient (if end stage renal failure is not reached)
4	predialysistime (p)	t_PD(E)	Time: Exponential	Time till next eGFR deterioration based on eGFR level
4	livingdonor(p)	P_LD (A)	Chance: Uniform	Yes or no value whether patients will find a living donor
6	UpdateSwitchtime(p,k)	t_PDSWITCH	Fixed: None	The time the patient needs to switch from PD to HDC
6	deceasedialysis(p)	LE_HDH, LE_HDC, LE_PD (A)	Time: Exponential	Time when patient deceases
9 , 10 , 11	donordetoriation(p)	LE_LD, LE_PMD	Time: Exponential	Time after which patient with donor kidney will die.
7	genpostmortal()	S_PMD(Y)	Arrivals: Poisson	Post-mortal donors (per week)
5	diagnosedonor(p)	P_MLD	Chance: Uniform	Value to determine if patient needs cross-over

3.3.2 Process Description

For each page (i.e. hierarchical submodel), a short overview of the process is defined as follows:

- **Generator.** Patients are created in the generator. The inter arrival time per province determines the number of patients generated. Each patient receives a unique ID number and is assigned to a predefined patient class according to input ratios.
- **Diagnosis phase.** At the diagnosis page, patients arrive with a certain eGFR as determined in the generator. During this phase, patients with an eGFR $>$ T1 can pass away according to a pre-defined mortality rate. This is represented by a number from the uniform distribution which is different for every age group since mortality changes over age groups. With an eGFR $<$ Tq, the patient directly flows to pre-dialysis.
- **(Pre-)Dialysis.** The treatment page consists of several hierarchical phases which are mentioned below. At the start of the pre-dialysis page, it is determined if a patient will find a living donor, based on an input probability, which is different for every age group. The length of the time in pre-dialysis depends on the patient's initial eGFR and the rate of deterioration, which is based on an exponential distribution. At the end of the pre-dialysis phase, a treatment-type is determined for each patient based on the distribution as specified in the input parameters. During pre-dialysis a percentage of the patients, specified in the inputs, will receive a living donor. At the start of the dialysis page (Figure 3), the life expectancy of the patient is determined, and in case of a PD treatment, the time

at which the patient should switch to HD treatment (due to peritoneum deterioration) is set. In addition, the patient is subscribed on the waiting list for post-mortal donors. HDC, HDH and PD are modeled individually. Each province has a certain capacity. If capacity is short, a patient is sent to the "dialysis in other province" place where it waits until capacity is available. Patients can leave the treatment place due to deceasing or receiving a donor kidney. Therefore, the treatment places are hierarchical and connected to the donor process. This is also the reason why the patients don't receive an updated timestamp for their decease time but an updated value for an attribute. With a timestamp, patients would not be able to exit the dialysis phase because of the arrival of a post-mortal donor. Figure 3 makes the flow of patients through dialysis visually explicit for an easier extension when new treatment options are to be introduced.

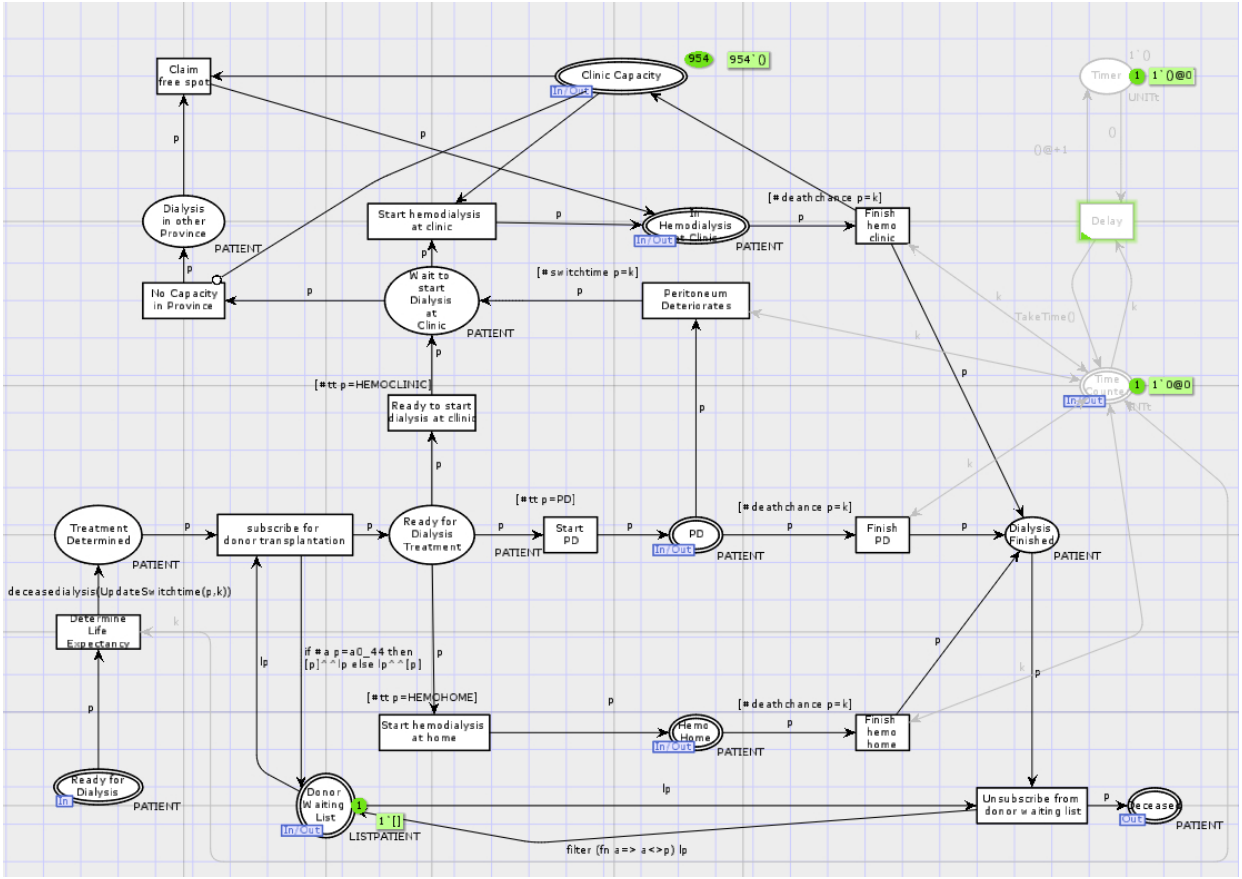

Figure 3: The dialysis page of the executable model in CPN Tools.

- **Donor Process.** When a living donor is found, it is instantly checked if the donor matches the patient, the remaining others will find a match after 3 months in the cross-over program. Patients with deteriorated donor kidneys will not flow back into the normal pathway, but considered in the inflow at the generator. Four situations are modelled; one for each situation where it is possible to receive a donor kidney, which means one for HDC, HDH, PD and Pre-Dialysis.

Verification. According to the manual techniques, such as checking intermediate results before adding extra complexity and manual simulations to check whether the tokens followed the intended path, the model

performs as intended. Conducting a state space analysis is the final verification step after the whole model is finished. However, the state space analysis is done with only one patient since the model is relatively complex. Therefore the generator was disabled. In this way, it is possible to get a full state space report. First, the upper and lower bounds are checked which are as expected. For example, the timer works as intended, there is always one token in this place. If we look at the best upper and lower multi-set bounds we can check that the patient is in pre-dialysis with three different eGFR levels, from 29 to 8, when he has to leave to dialysis. This also performs as intended. When checking the Liveness properties, the dead markings are as expected since they are associated with the deceased patient. At that point, there are of course no Live transition instances. One patient cannot take all three treatment types and the dead transitions are the transitions not fired when a patient receives a post-mortal donor after HDC. Furthermore, since there is only one patient, there are no infinite occurrence sequences. Based on the state space analysis and the results of the other verification techniques, we can conclude that the simulation computer program performs as intended and does not contain any bugs.

Validation. The model is validated by comparing the actual values of four Key Performance Indicators (KPIs) in 2013 taken from RENINE with the simulation outputs for these four KPIs for the province of Limburg. The four KPIs used for validating the model are the number of new patients that go to dialysis, the number of patients in dialysis, the number of post mortal donor transplantations and the patient distribution over the different treatment options. The warm up period is set with Welch's method based on the number of patients in dialysis which reaches the steady state latest among other parameters. The actual values provided by RENINE of the number of new patients in dialysis and the number of post mortal donor operations are almost equal to the simulation results and are within the 95% confidence interval of the simulation results. The actual values for the patient distribution are different from the simulation results. This is due to the fact that the treatment distribution provided by RENINE is implemented as an initial treatment preference for patients in the simulation model. The number of patients in PD in the simulation model will be lower due to the PD switch that will occur after four years and the relative high percentage of young people in PD treatment which get a donor transplant.

4 DEMONSTRATION OF USABILITY

To demonstrate the usability of the generic model on a concrete case study, this section presents an application of the toolkit to a policy evaluation study for the Dutch province Limburg for the period 2013-2050. Limburg is the province with the highest average number of dialysis patients per inhabitant which makes it an interesting region to test the toolkit.

4.1 Renal Failure Pathway In Limburg

In the Netherlands, patients spend quite some time in the diagnosis phase, where they are regularly checked by a GP. When dialysis starts a patient can choose between three different types of treatments: HDC, which is the most popular treatment, mainly among elderly, HDH and PD, which both face higher popularity by younger patients. Furthermore, the patient is subscribed to the donor waiting-list where patients younger than 44 years get priority. Post-mortal donor kidneys become available if donors, which are subscribed opting-in, die unexpectedly while their kidneys still are in good shape, e.g. due to a traffic accident.

4.2 Analyzing Scenarios

In the first scenario we investigate the effects of earlier detection and therefore better treatment before the end stage renal failure phase. Effectively, we will enlarge the average time that a patient will be in the diagnosis phase from 5 to 10 years. This will give more insight into the effects of earlier renal failure detection. In the second scenario we changed the preference for treatment types which makes home dialysis a more adapted choice according to the numbers in Table 4. These values are based on research that shows nephrologists and nurses prefer home dialysis over HDC (Ledebo and Ronco 2008, Schiller, Neitzer, and

Doss 2010). In the third scenario, becoming a donor is based on an opting-out principle instead of the current opting-in principle. This will increase the percentage that is a registered donor from 25.8% to an estimated 61.17% (extrapolation based on current data) (**?**).

4.3 Input Parameters

Table 2 displays the values for each input parameter in the "as is" situation. The input parameters that are changed for the three different scenarios are described in Table 4.

Table 4: Input parameters scenarios.

Scenario	Input Parameter	Value	Input Value
Diagnosis 10 years	Length diagnosis phase	t_D (E)	(10 year , 0 year,-,-)
Changed treatment distribution	Treatment distribution	HDH, HDC, PD (A)	(32.77%;24.83%;42.40%) (31.67%;27.35%;40.98%) (35.38%;18.84%;45.78%)
Opting Out	Post mortal donor	S_PMD(Y)	90.74

4.4 Results

The results of the simulation study are presented in Figure 4 and Table 5.

Table 5: Average patient distribution in Limburg in 2013-2050.

Scenario	% patients of all patients entering dialysis receiving a living donor	% patients of all patients entering dialysis receiving a post mortal donor	% patients in home dialysis	% patients in HD clinic	# patients in Dialysis
as is	15.6%	27.7%	14.2%	85,8%	600.65
Diagnosis 10 years	16.8%	29.8%	13.7%	86,8%	539.8
Change in treatment distribution	15.5%	27.9%	49.4%	50,6%	584.6
Opting-Out	15.3%	51.8%	18.0%	82%	390.6

From the results of the "as is" situation, it is clearly visible that while utilization increases for the first few upcoming years, it will start declining after 2020. The increase is probably the consequence of the fact that the incoming patients remain stable, but the mortality rate decreased last years. The decrease after 2020 is caused by an increase in the number of post-mortal donors, strengthened by a shift in age distribution of patients to more elderly patients. This causes a higher mortality and results in a shorter average time spent in the dialysis phase.

From Figure 4 it follows that each redesign decreases the utilization of clinics. However, a longer diagnosis phase just decreases the percentage of patients that really needs dialysis, and therefore the utilization follows a trend similar to the "as is" situation. By changing the distribution of patients over the treatments such that home dialysis is more frequently used, a decrease in utilization is directly visible as it can be implemented immediately. The third scenario, where 'Opting-Out' is applied and more people will donate their kidney, shows a steep decrease in utilization for the upcoming years, but flattens out eventually.

In Table 5 the patient satisfaction measures are given. A first finding is that the percentage of patients receiving a living donor does not change much over the different designs. This is as expected, since this

Input	Age group	% New dialysis patients per age group	Absolute number of patients per category
	0-44	12.633%	265.805926
	45-64	32.355%	680.755016
	65+	55.011%	1157.439058
		100.00%	2104.00

eGFR level of patient after first diagnosis per age category				
100-30	0-44	45-64	65+	
	90%	75%	60%	75%
30-15	0-44	45-64	65+	
	8%	20%	32%	20%
15-9	0-44	45-64	65+	
	2%	5%	8%	5%
9-0	0-44	45-64	65+	
	0%	0%	0%	
	100%	100%	100%	

Province	% Dialysis patients per province of total number of patients
Brabant	14.14%
Drenthe	3.27%
Flevoland	1.99%
Friesland	3.79%
Gelderland	11.48%
Groningen	3.87%
Limburg	8.83%
Noord-Holla	17.09%
Overijssel	7.22%
Utrecht	6.48%
Zeeland	1.93%
Zuid-Holland	19.92%
	100%

Patient characteristics		
Age group	eGFR level inflow	Value
0-44	100-30	0.11370025
	30-15	0.01010669
	15-9	0.00252667
45-64	100-30	0.24266457
	30-15	0.06471055
	15-9	0.01617764
65+	100-30	0.33006817
	30-15	0.17603636
	15-9	0.04400909
		1.00

Figure 4: Utilization HD clinics in Limburg.

scales with the number of patients in pre-dialysis. However, as expected the number of post mortal donors increases to a large extend by introducing an opting-out system (51.8% instead of 27.7%), leading to enhanced patient satisfaction. Furthermore, stimulating patients to choose for home dialysis increases the percentage of patients receiving home dialysis treatment (from 14.2% to 49.4%). In addition, the opting out redesigns seems to perform a little bit better on this aspect as well (18%). If we look at the number of patients in dialysis, we note that this is much lower in the opting out system. This can be explained by the fact that people receive a post mortal donor faster, and due to a prolonged stay in the diagnosis phase fewer patients will be using dialysis.

Concluding, we see clear improvements for each scenario compared to the "as is" scenario. Furthermore, each scenario indicates improvements as expected, which could indicate that the toolkit is valid representation of reality.

5 CONCLUSIONS

We described the parametrized CPN-model for simulating the demand on renal treatment. CPN tools is selected as the simulation tool since it is widely used for modeling processes defined by Petri Nets. Renal Replacement Therapy (RRT) is a costly, long-running process that includes several decision points in different stages and resulting alternative pathways. Small changes in treatment paths can result in great savings in addition to healthcare outcomes. The developed simulation model can be used to try different scenarios and predict future demands for healthcare in this domain, and therefore influence the strategy planning of the healthcare. Our parametrized model can accessed online http://is.ieis.tue.nl/research/renalsim/ to be used for further analysis of several scenarios.

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