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Improving Services to Hospital Outpatient Clinics

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Abstract
The waiting time from referral to actual appointment to see a specialist doctor at the outpatient clinic is often long, can be many months. It is challenging to manage the number of patients from the waiting list whom can be seen with respect to retaining sufficient capacity to follow-up existing patients. The situation is often worse if some of the patients have to revisit clinic many times or, in some cases, throughout their lifetime. This study demonstrate how system dynamics can be used as an insightful strategic planning tool for an outpatient clinic to manage the increasing demands due to the constrained capacity and capability. An outpatient system dynamics model was built according to the principles of system dynamics. The simulation model includes the operational parameters as measures of capacities. A number of impact areas are identified and proposed to test the effectiveness of the model. Key indicators were set to enable the validation and evaluation of the proposed interventions. All the scenarios have been simulated 1000 times to generate a mean result for the validation. The model suggested that creating specialist clinic and patient orientated follow-up system would improve services to the outpatient clinics. Given the recommended interventions, the model generates an accurate prediction of outcomes. Following this intervention with the surgical outpatient services, the model has been used interactively with nearly all the outpatient services in the organisation. The model provides accurate forecasting scenarios that are validated with post-intervention data. It supports the service implementing the intervention with the consideration of system delays and provides a balanced solution to avoid any short-term or long-term disruption.

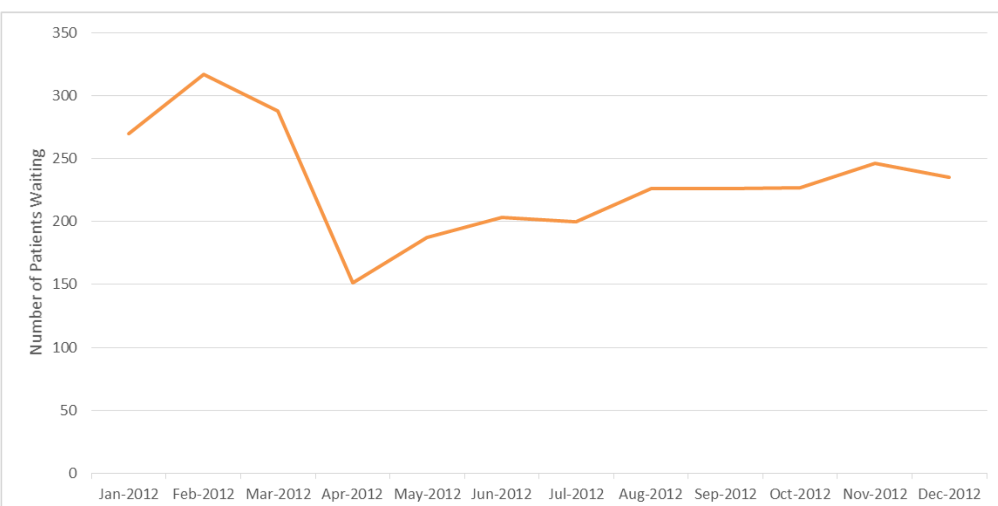
Introduction

Counties Manukau Health (CM Health) is a large publicly funded healthcare provider in South Auckland, New Zealand, providing services for a multi-ethnic population of just over 500,000 people. It encounters many of the same challenges as most publicly funded health organisations, with increasing demands for healthcare services but limited resources. In endeavouring to meet the pressure to deliver sustainable high-quality services, managers and decision makers are looking to adopt tools that can help with planning, optimising or even reforming service processes. This study demonstrates how system dynamics can be used as an insightful strategic planning tool to help manage the increasing demands due to the growing new patient referrals and follow-up (FUP) appointments for an outpatient clinic. Effective interventions are developed in the context of constrained capacity (e.g. facility) and capability (e.g. workforce).

Background

An important part of healthcare services for CM Health is the outpatient service; it is a common point for patients to access secondary healthcare services, on referral from their primary care ‘healthcare home’. The waiting time from referral to actual appointment to see a specialist doctor at the outpatient clinic is often long, can be many months. The ever-growing referrals to outpatient service have a major impact on the long growing waiting list. However, in addition to the newly referred patients, FUP patients—who have been seen previously at an outpatient clinic—are also requiring further clinic appointments. As the waiting list only records the newly referred patients, clinics struggle to manage those ‘invisible’ future demands by FUP patients. For instance, in order to reduce the waiting list for an outpatient clinic, the General Surgical service scheduled extra Saturday clinic sessions to see more new patients with minor anorectal disorders from the waiting list. In the short-term, this succeeded in reducing the waiting list for patients with minor anorectal disorders. However, the service was flooded with FUP patients a couple of months later. As a result, the extra capacity to see newly referred patients from the waiting list was subsequently limited. The waiting list quickly increased again when the 'extra' FUP patients began coming back to the clinic. This phenomenon can be observed in Figure 1. The waiting list dropped by more than 100 from March to April, but has steadily increased thereafter.

Figure 1: Historical waiting list trend



It is challenging to manage the number of patients from the waiting list whom can be seen with respect to retaining sufficient FUP capacity. The situation is often worse if some of the FUP patients have to revisit clinic many times or, in some cases, throughout their lifetime. This means that clinicians have to decide carefully which patients truly need outpatient clinic follow-up and which might be managed appropriately by their primary care healthcare home; and managers need to understand the dynamic between new referrals and FUPs. Managing this complex situation requires managers and decision makers to have a fully understanding of the dynamics of system relationships and behaviours so they can foresee the short term and long term effect of their decisions.

Initially developed from the work of Jay Wright Forrester in the late 1950s, system dynamics was formally introduced in 1960s as "Industrial Dynamics" (1961), which is linked to various system philosophies. It is a method to enhance learning in complex systems (Forrester, 1961, 1969, 1994, 1998, 1999, 2007a, 2007b). System dynamics is grounded in the field of nonlinear dynamics and feedback control (Forrester, 1961, 1969; Sterman, 2000), which helps to understand the behaviour of complex systems. System dynamics simulation models can be used to design and manage improved policies, operational procedures and ultimately organisations (Maani & Cavana, 2007; Sterman, 2000). It allows decision makers to experience the long-term effects of decisions, develop an understanding of complex systems and design structures and strategies for improvement (Maani & Cavana, 2007; Sterman, 2000). The system dynamics modelling approach has been recognised as "a mature and powerful tool" for the health system "to test how different factors may improve efficiency, effectiveness and equity in situations where it is not possible to conduct real-world experiments" (Gray et al., 2006, p. 453). It has been successfully used in many health environments, primarily in hospital and residential services (Homer, Hirsch, Minnitii, & Pierson, 2004; Kim & Goggi, 2005; Taylor, Dangerfield, & Grand, 2005). Although system dynamics modelling "provides a method of conducting policy experiments at low risk and cost with instant results" (Gray et al., 2006, p. 456), it is not yet being utilised to its full potential. In the literature, only one study (Thomas R. Rohleder, Bischak, & Baskin, 2007) has been found using a system dynamics simulation model to help with outpatient clinic management, although a lot of simulation work has been done for outpatient services (Michael Thorwarth, 2012; Rau et al., 2013; Thomas R Rohleder, Lewkonia, Bischak, Duffy, & Hendijani, 2010). Using system dynamics models for this study has two key advantages that are not generally found in other study methods. Firstly, it can directly analyse the complicated programmatic and behavioural interactions that abound in the system; secondly, it permits detailed and flexible analyses of the distributional impacts of interventions.

Methodology

At the beginning of this project, the General Surgery outpatient service was selected for detailed analysis because surgeons from this service were willing to test out how system dynamics could help them to improve the service. As mentioned earlier, Per Rectal (PR) bleeding service failed to achieve long-term reductions in the waiting list due to FUP patients. This particular service is chosen to validate the proposed interventions based on the results of the simulation. Different techniques had been used to gather information about the processes: interviewing surgeons and managers about the process and situation; a brainstorming workshop to determine the project boundaries; a preliminary simulation model to test out which data methods to choose; and statistical data mining methods to analysis the data output. Key indicators were set to enable the validation and evaluation of the proposed interventions. A standard process map was proposed.

System dynamics software iThink was used to develop the simulation model. Descriptive statistical analysis was performed by using Statistical Analysis System (SAS) to determine the preferred summary statistics input for the model. Mean, standard deviation and interquartile range of the model parameters were used inthe preliminary simulation model (see Table 1). Based on the validation of forecasted data with actual collected historical data, the non-parametric method based on the random values between the 25th to 75th quintiles of historical records has been found to produce the 'best match' to the historical trend (see Figure 4, Figure 5, and Figure 6). The other parametric method such as normal, lognormal, beta and Poisson distributions for the key variables were also tested in the simulations.

Table 1: Descriptive statistics of key model variables

Parameters used in the model	Definition of the operational parameters	Minimum	Maximum	Mean	Std. Deviation	Skewness
FSA	First Specialist Appointment	19.0	186.0	59.233	28.1254	2.398
FUP	Follow-up existing patients	9.0	76.0	50.535	13.4206	-.640
FSA to Other (services)	Ratio of patients referred from FSA to other services	.00%	33.93%	10.3872%	10.18140%	.810
FSA to Surgery	Ratio of patients referred from FSA to surgery	.00%	37.84%	12.2706%	10.47596%	.211
FSA to FUP	Ratio of patients referred from FSA to follow-up appointment	6.41%	65.31%	42.6567%	15.93902%	-.710
FSA to DNA	Ratio of patients whom did not attend FSA	.00%	14.04%	3.5311%	2.80809%	1.577
FSA to Discharge	Ratio of patients been discharged from their first appointment	16.22%	53.93%	31.1543%	9.45246%	.539
FUP to Other	Ratio of patients referred from follow-up appointment to other services	.00%	22.22%	6.8766%	6.35073%	.832
FUP to Surgery	Ratio of patients referred from follow-up appointment to surgery	.00%	22.22%	9.0760%	6.70054%	.152
FUP to FUP	Ratio of existing patients having follow-up appointments	16.67%	45.24%	31.3091%	7.40485%	-.039
FUP to DNA	Ratio of patients whom did not attend follow-up appointment	.00%	8.33%	2.3181%	2.38647%	.790

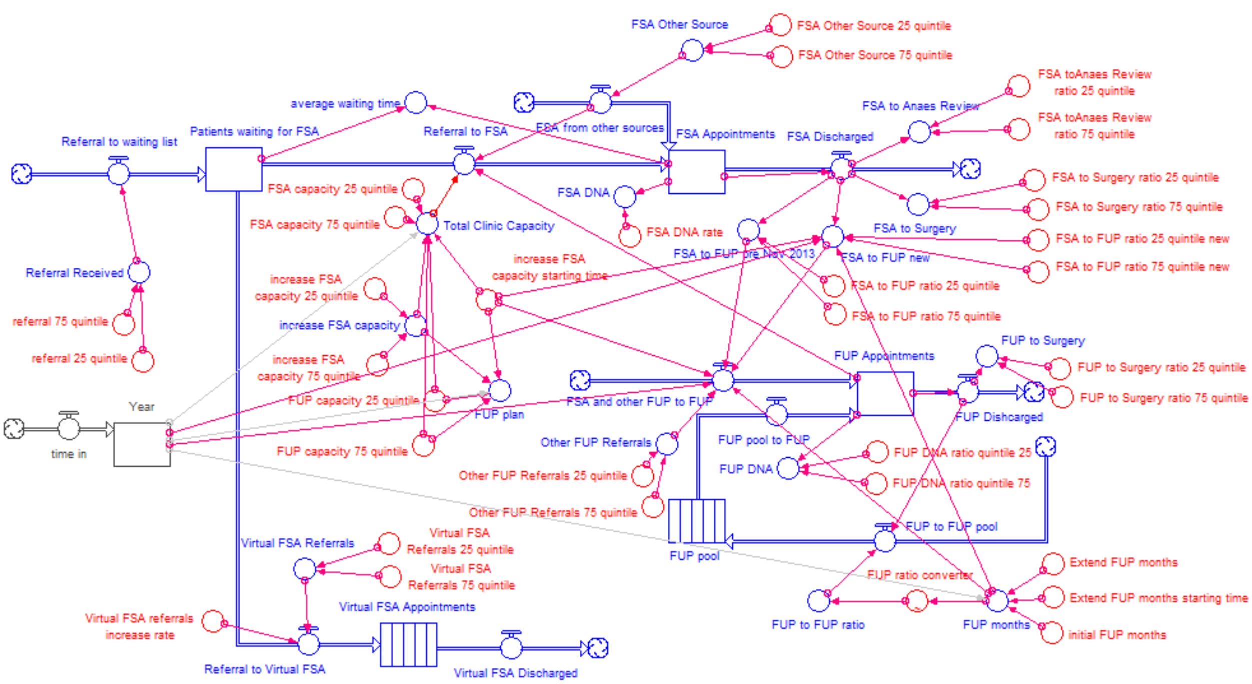
Parameters used in the model	Definition of the operational parameters	Minimum	Maximum	Mean	Std. Deviation	Skewness
FUP to Discharge	Ratio of existing patients been discharged	32.35%	66.67%	50.4202%	7.86531%	-.020

Total number validated is 43 of each parameter.

Simulation

The outpatient system dynamics model was built according to the principles of system dynamics. Figure 2 presents the model's structure. Patient stocks are indicated as rectangles and the flows into and out of these stocks are indicated as tabs with arrows (flow directions). All other variables in the diagram directly or indirectly affect the flows, through causal relationships indicated with red arrows. Red circle variables are time-series input to the model, each of which requires an estimate of that variable's behaviour from the model initial time (August 2012) to the present, as well as assumptions about its future trajectory. The result of any alternative scenario one might want to consider would be represented in the model through manipulation of one or more of these time-series inputs. Blue circle variables are for the purpose of calculating certain indicators.

Figure 2: Outpatient system dynamics model overview



Outpatients newly referred by general practitioners or other services are initially put onto the waiting list for a face-to-face appointment where that is requested. The 'referral received' variable is a random value generated by the model in the range of the historical records between quintile 25 and 75. The 'referral increase rate' may change over time (its initial value is set at 0% per year) as affected by the population growth, which can be changed by users accordingly. Referrers can also request a virtual FSA where the specialist reviews the information provided and provides advice back to the referrer. Similarly to requests for face-to-face referral, 'virtual FSA referrals' also generates a random value from the historical quintile 25 to 75 range. The 'virtual FSA referrals increase rate' specifies the proposed increase rate with an initial value of 0%.

Referral to FSA is dependent on the availability of Total Clinic Capacity. It is calculated as follows:

Referral_to_FSA = (Total_Clinic_Capacity-FUP_Appointments*2/3)-FSA_from_other_sources

FSA from other sources includes acute FSA for some other services. The value is based on historical trends. The model assumes FUP appointments has higher priority than the FSA appointments. It constrains the availability of FSA appointments. Furthermore, the average FUP appointment time is shorter than that of the FSA appointment as it takes about 2/3 of an FSA appointment time. This means that each FUP appointments converts into 2/3 FSA appointment for calculation.

FUP appointments have two main sources: one is post-FSA patients (this includes post-FSA from other sources or specialties), and the other is FUP patients who booked the appointment during their last FUP visit.

The FSA to FUP ratio is a random value based on historical records between quintile 25 and 75. The FUP to FUP ratio is influenced by the frequency of the follow up. In general, the longer the follow-up period, the smaller the FUP to FUP ratio. Also the less follow up repeats, the smaller the FUP to FUP ratio. An FUP ratio converter is built to reflect this relationship in the model. Based on the historical trends, a graphical assumption is used to illustrate the relationship between changing FUP months and FUP to FUP ratio. The actual FUP to FUP ratio calculated as follow:

FUP to FUP ratio = RANDOM(1-FUP_ratio_converter-0.03,1-FUP_ratio_converter+0.03)

The FUP pool holds all the booked follow-up patients, which will vary by changing of follow-up time periods and actual discharged follow up patients.

This model is simulated by specifying a set of initial conditions for the model's population stocks, and then stepping forward by computing through the entire set of equations every simulated ¼ month. In each computation step, the model's stock variables—written as difference equations—are firstly updated based on the previous period's inflows and outflows. All other variables are then recalculated based on the updated stock variables and based on the current values of time-series inputs. The initial conditions have been specified in a way that allows for replication of historical trends.

Results

This model was initially finished in November 2013. It provided simulated results from August 2012 to October 2013 that were validated by comparison with the actual historical records. Then, the model forecast results up to August 2017. Workshops were held with clinicians and managers to develop and test scenarios in the model. This forms a learning environment for all the participants. A number of impact areas are identified and proposed to test the effectiveness of the model:

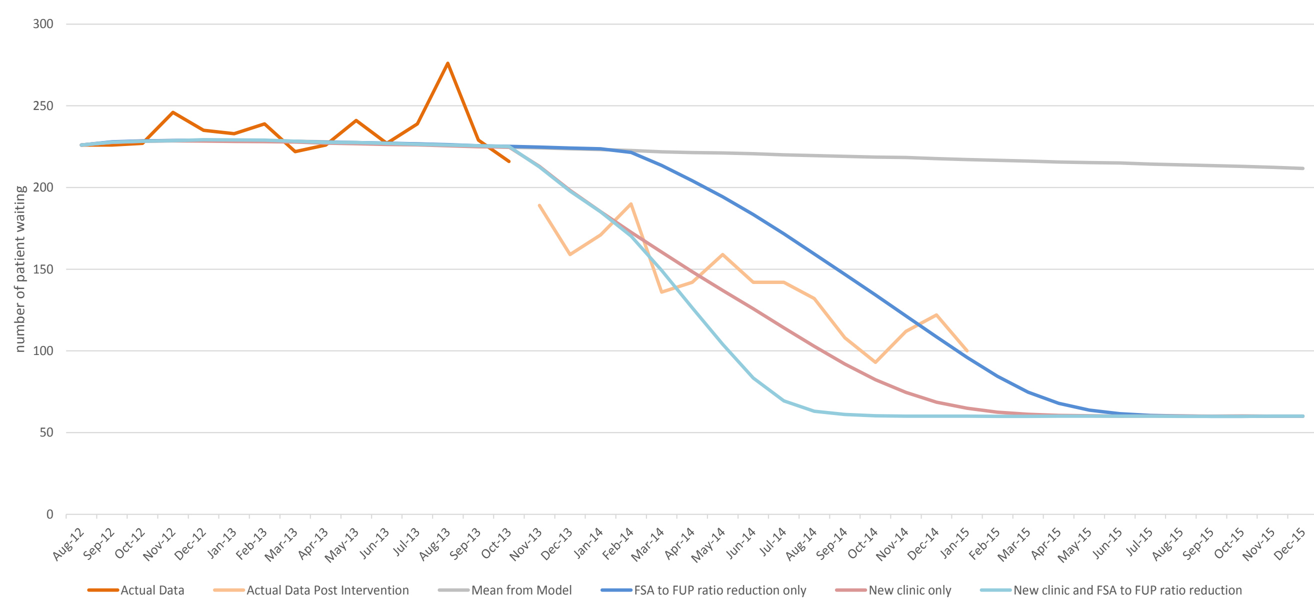
1. Reduce the referrals by providing specialist support to general practitioners.

2. Increase capability to see more patients, e.g. extra clinic sessions.
3. Reduce FUP patients without compromising the quality of care by:
   A. Reducing unnecessary FUP organised by junior doctors
   B. For some simple cases, change doctor organised FUP to patient organised FUP. This means that patients only revisit the clinic if their circumstances change.
   C. For some simple cases, doctor or nurse specialist makes phone call to FUP patient.
   D. Extend the period for patients to come back for FUP, e.g. in some instances, instead of clinic revisits every three months, it may be possible to change to every 4 or 5 months.

After presenting the simulation results (details given below), the service decided to have an extra clinic once a month to see PR bleeding patients only. The additional clinic was to be run by a senior surgeon to reduce unnecessary FUP organised by junior doctors. In addition, the FUP method was changed to patient organised (patients call in if their circumstances changes).

This paper was written in February 2015. The service implemented the recommendations and collected the historical data from November 2013 to January 2015. It hence provides the additional data to validate the model's forecasting results. The model takes random values from each variable. All the scenarios have been simulated 1000 times to generate a mean result. Figure 3 summarises all the mean projections and historical records of the waiting list.

Figure 3: Patients waiting for FSA



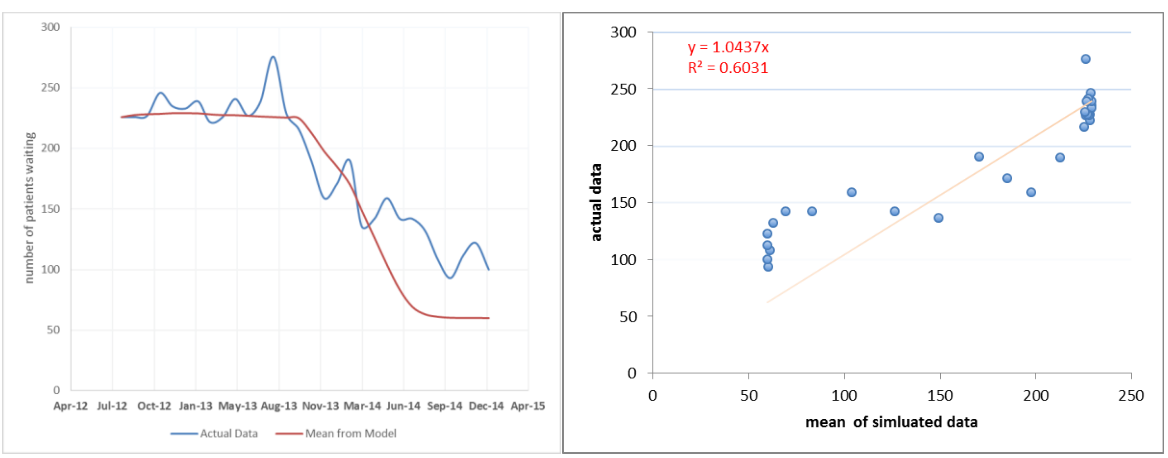
1. Grey colour—Do Nothing Scenario, which assumes the clinic carrying on as usual without any interventions. However, in this scenario, the population growth rate has not been applied yet, which would give a 1.4% annual increase of the demand if applied.
2. Blue colour—Reduction of FSA to FUP ratio. Compared to the grey line, the waiting list starts to reduce from February 2014 if this intervention started from November 2013. This intervention shows a clear

delay effect, as the follow-up period for patient revisit clinic is about three months. This intervention requires discussion with clinicians on how to do it safely without compromising quality of care.

3. Red colour—New Clinic Scenario. It assumes an extra clinic operating monthly, but no change of follow-up ratio. However, this new clinic will take both new patients and follow-up patients instead of new patients only, which happened historically. Following the pre-set configuration the model can automatically allocate new patients and follow-up patients to the new clinic. This is a critical function provided by the model, as the results can be exported and given to the clinic to implement the change and to avoid unintended consequences, e.g. if the clinic only uses the extra capacity to see new patients, it will cause a delayed follow-up patient surge.
4. Light Green colour—New clinic with reduction of FSA to FUP ratio. As a combination scenario, it reduces the waiting list faster than other interventions; hence it is the preferred scenario.
5. Dark Orange colour—historical data from August 2012 to October 2013. The model almost replicates the historical data, except for a few spikes of the historical data.
6. Light Orange colour—Post intervention data from November 2013 to January 2015. It reflects the effect of the interventions, of introducing an extra clinic and reducing follow-ups from November 2013.

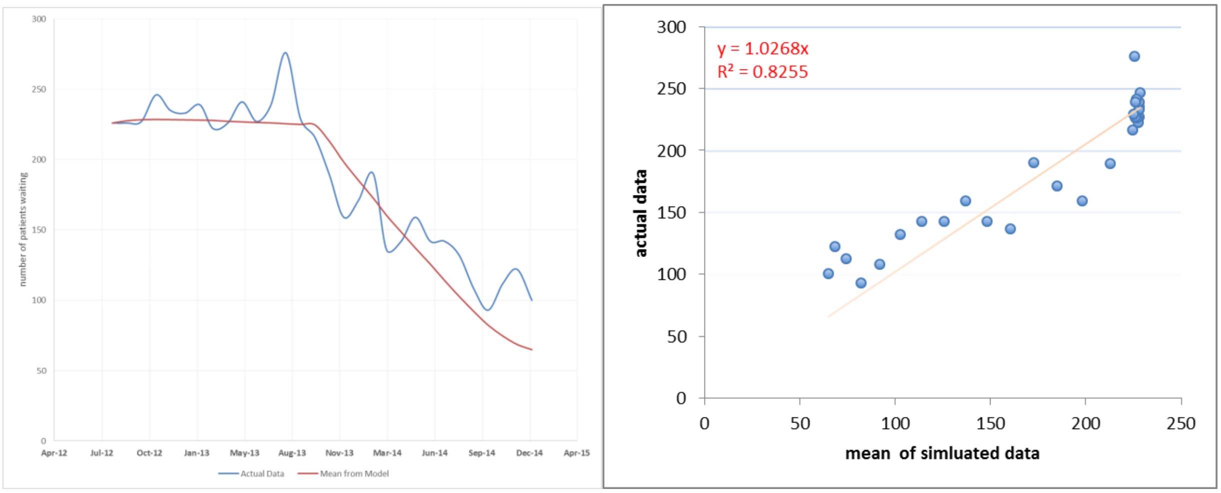
In Figure 4, the left graph demonstrates the relation between the actual historical data (blue line) against the mean of 1000 simulations results (red line). The right graph presents a fitted regression line for the mean simulated data vs. the actual historical data. The fitted regression has an R square of 0.6031 and a linear slope of 1.0437. The R square with a range of 0 and 1 is a statistical measure of how much variation of the actual data explained by the predicted values; higher R squares indicated a better fit with the simulated values. The R square of 0.6031 indicates that 60% of the variations have been explained by the simulation. The linear slope of 1.0437 which is close to 1, indicates that the simulated values have a reasonable fit with the actual data.

Figure 4: Validation of the Model-new clinic and reduction of FSA to FUP ratio



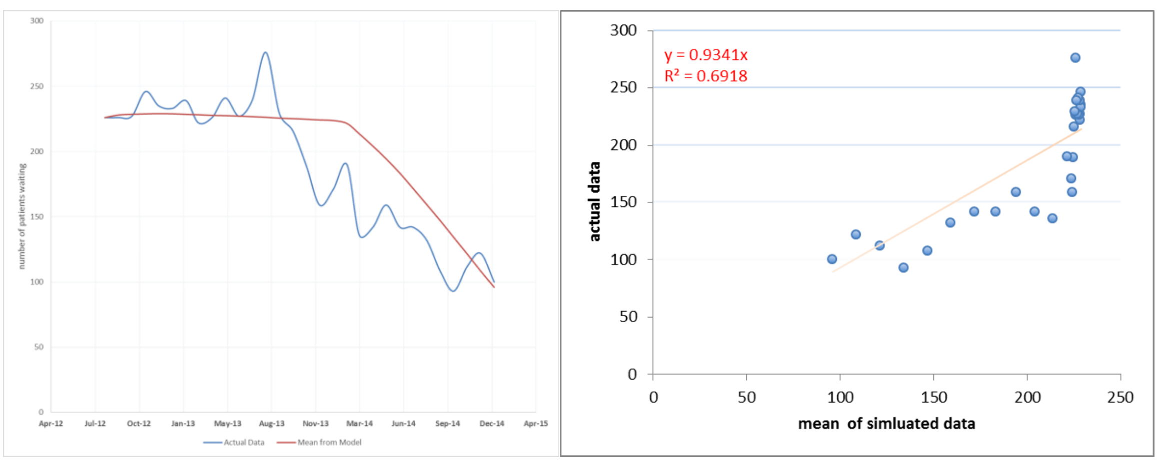
In Figure 5, the fitted regression has an R square of 0.8255 and a linear slope of 1.0268. The largely improved R square indicates that more variations in the actual data have been explained by the simulation. The smaller linear slope of 1.0268 also indicates that the simulated values have a better fit with the actual data.

Figure 5: Validation of the Model-new clinic only



In Figure 6, which simulates a scenario that only includes the reduction of FSA to FUP ratio, the fitted regression has an R square of 0.69 and a slope of 0.93. Both statistics suggest that the simulated result does not match well with what had actually happened.

Figure 6: Validation of the Model-Reduction of FSA to FUP ratio only



In Figure 4 and Figure 5, the forecasted results closely match to the historical data. Although the real intervention includes both the new additional monthly clinic and reduction of the FUP ratio, because the parameter of the FUP ratio reduction is estimated from all patients instead of from patients in the new clinic, a better matched was observed in Figure 5. The ideal changes will be to implement the reduction of FUP ratio for all patients. If using an FUP ratio reduction that has taken into account what has actually happened in real life, the discrepancy between the observation and the simulation results should be smaller. Following this intervention with the surgical outpatient services, the model has been used interactively with nearly all the outpatient services in the organisation.

Conclusion

The outpatient model was developed in partnership with the clinicians and managers of the hospital outpatient services. The outpatient system dynamics modelling project began in February 2013 primarily as a result of the concern about the growing waiting list for surgical outpatient clinics. The system dynamics model was deemed to be an appropriate technique to look for intervention options and considering their relative effectiveness over the short and long term. Part of the appeal of system dynamics was its flexibility and ability to deal in an integrative and transparent way incorporating the many interdependent factors that affect waiting list control. In this study, the model provides accurate forecasting scenarios that are validated with post-intervention data. It supports the service implementing the intervention with the consideration of system delays and provides a balanced solution to avoid any short-term or long-term disruption (e.g. what happened in Figure 1).

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