Title: Resources management impact on neonatal services performance in the United Kingdom: A System Dynamics modelling approach

Short Title: Resources management in neonatal services: System Dynamics modelling

Reda Lebcir

Hertfordshire Business School. University of Hertfordshire. Hatfield AL10 9AB, UK

Email: M.R.Lebcir@Herts.ac.uk

Rifat Atun

T.H.Chan School of Public Health. Harvard University. Boston, MA 02115, USA.

Email: ratun@hsph.harvard.edu

Corresponding Author: Reda Lebcir

Funding: There is no funding for this study.

Conflict of interest: The authors declare no conflict of interest

Abstract: Demand for neonatal care in the United Kingdom (UK) has increased in recent years. This care is provided by neonatal services, which are chronically saturated due to years of budget austerity in the UK. The aim of this paper is to investigate the possible impact of increasing resources to these services to improve their operational performance and alleviate the pressure they are facing.

To achieve this aim, a System Dynamics (SD) simulation model was built and validated in a UK neonatal unit. The SD model was used initially to evaluate the impact of increasing resources on the unit performance and the results showed that this policy will have a limited effect on performance. The model was then extended to predict the effect of reducing the length of stay (LoS) in conjunction with increasing resources. These joint interventions will have a positive impact on the unit performance if LoS is reduced for all care categories and resources are slightly increased. Results' implications and SD's modelling usefulness to guide decision making in complex health settings are discussed.

Keywords: Neonatal Services; Resources Management; Length of Stay; Simulation; System Dynamics.

Introduction

Neonatal services in the United Kingdom (UK) are part of the National Health Service (NHS) and are tasked with treating new born babies with health complications, born prematurely (gestation period under 37 weeks), and with low weight (under 2500g) at birth (Lebcir and Atun, 2020; Demir et al, 2014). Due to a significant increase in demand in recent years, neonatal services have become saturated and strained (Boyle et al, 2015; Asaduzzaman et al, 2009) as admissions increased from 61,372 in 2007 to 94,145 and 110,997 in 2013 and 2015 respectively, and then to 115,462 in 2016 requiring a total of 1,185,400 care days (RCPCH, 2016; NDAU 2016, 2015, 2010). A recent report indicates that 1 in every 7 babies born in the UK needs neonatal care (RCPCH, 2020a). This increase is the consequence of (i) high birth rates in the UK in recent years and (ii) the introduction of new medical technologies, which make it possible to treat babies with complex medical conditions even if they are born very prematurely (Boyle et al, 2015; Battin et al, 2012).

The ability of neonatal services to respond to the increased demand and to provide high care quality to these vulnerable patients are affected by their chronic saturation. As an illustration, during a 6-month period in 2006-2007, neonatal units in the UK were closed to new admissions for an average of 24 days and 1 in 10 units exceeded their capacity for intensive care for more than 50 days during that period (Asaduzzaman et al, 2011). A report by the prenatal charity in the UK BLISS indicated that a third of neonatal units had an occupancy rate of 80% with 9% reaching 100% and 70% of intensive care neonatal units had an occupancy rate above the recommended safe level (BLISS, 2015). These pressures are still a serious concern as only 64% of neonatal shifts are numerically staffed according to national guidelines (RCPCH, 2019) and 18% of neonatal units have gaps in medical staffing (RCPCH, 2020b).

Given the vulnerability of the patients treated in neonatal services, these are heavily regulated. Informed by a long period of accumulated knowledge and agreed professional practices. The regulation covers many aspects of neonatal care including the definition of neonatal care categories, the medical conditions associated with each care category, the types of neonatal care units and which care categories of babies can be treated in the units, and the groups of clinical staff (doctors, nurses) allowed to deliver neonatal care (BAPM,2010; DoH, 2009).

Neonatal services regulation identifies three care categories and any baby admitted to unit is assessed and then allocated to one of the categories. These are, in an ascending order of severity, (i) Special Care (SC), those who cannot be provided with care at home and need to be in hospital for breathing and heart rate checks; (ii) High Dependency Care (HDC), those who need continuous monitoring because they require breathing help or intravenous feeding, and (iii) Intensive Care (IC), those with very complex health problems needing, for example, breathing through mechanical ventilation (DoH, 2009).

Although the regulation is detailed and provides a good level of clarity regrading areas such as the definition of care categories and the classification of neonatal care units, it does not, however, provide the same level of details in some other important dimensions of neonatal services management. For instance, issues regarding the management of resources in neonatal units and how these could be deployed to alleviate the relentless demand pressure are not clear. Beyond rules regarding the categories of doctors, nurses, and cots required for each of the three care categories and their associated ratios, there is not much else to guide neonatal units' managers on the best policies to achieve an efficient use of resources and respond to the increasing demand.

In addition to the lack of guidance on how to manage resources in neonatal units, the regulation creates constraints, which may have adverse effects on the ability of the units to treat babies and cope with demand. The strict rules regarding the categories of doctors, nurses, and cots required to treat specific categories of babies may reduce the number of babies treated in the unit if there is a shortage in a single resource given that the treatment cannot take place unless all resources are available (DoH, 2009; Mulcahy and Betts, 2005). Similarly, the required ratios of resources to babies is a further constraint as these cannot be relaxed regardless of the experience and seniority of the clinical staff. Furthermore, the Length of Stay (LoS), that is the treatment period, is regulated for every care category. LoS cannot be reduced even if extra resources are allocated to treat babies or if their clinical condition improve prior to the end of the regulated treatment phase (Demir et al, 2014; BAPM, 2011, 2010; DoH, 2009).

These difficulties create a need for further investigation on the best ways to manage resources in neonatal services especially that the NHS operates in a resources-constrained environment (Lafond and Charlesworth, 2016). Prolonged period of fiscal austerity in the UK left the NHS chronically underfunded affecting, as a result, neonatal care. The prenatal charity BLISS reported that 64% of neonatal units do not have enough nurses and two thirds do not have enough medical staff to meet national standards on safe staffing levels (BLISS, 2015). In another study by Mulcahy and Betts (2005), work pressure led to increased nurses' absenteeism, industrial action, and the closing of cots, and reduction of treatment capacity.

Although there has been a wealth of research in resources management in healthcare, there are still significant shortcoming and many aspects remain under-investigated. Most of the research focuses on the strategic management of human resources (Kabene et al, 2006) and the different organisational settings (primary care, community services, hospitals) these resources should be allocated to achieve the best clinical outcomes (Kakuma et all, 2011). Other studies covered some human resources factors and practices such as motivation, competence, availability, learning, and training and their effects on clinical staff attitudes and the functioning and operational efficiency of healthcare services (Moghadam et al, 2017; Cogin et al, 2016; Thomas et al 2009). However, this research ignores the management of non-human resources, which are critical to healthcare delivery. The importance of this type of resources stems from the fact that most healthcare activities require a mix of human and non-human resources and shortages of the latter may create bottlenecks affecting the operational performance of healthcare services (Demir et al, 2018; Lebcir et al, 2017). Shortages of hospital beds have been found to be associated with poor clinical outcomes and increased readmissions within 30 days following discharge (Song et al, 2020). Furthermore, healthcare managers are facing significant difficulties managing non-human resources capacity to meet increasing demand due to budget cuts, closure of hospitals and clinics, extended durations to approve investments in new capacity, and complicated procurements and planning procedures to acquire resources (Green 2012; Jack and Powers, 2009).

In the context of neonatal services, research on resources management is surprisingly scarce given the challenges they face and the vulnerability of the patients treated. In a study by Nesbitt and Rosenblatt (1997), it was found that under-resourced neonatal units led to a higher risk of babies developing medical complications. Mulcahy and Betts (2005) investigated the sources of work pressure on neonatal nurses and the policies to alleviate these. Thomas et al (2009) studied the effect of implementing new hiring, training, and performance management policies on neonatal services performance. The level and mix of resources required for neonatal care were included in research to determine the impact of reducing LoS on the operational efficiency of neonatal services (Demir et al, 2014) and how doctors' ability to use their clinical judgment could simplify care pathways and increase admissions (Lebcir and Atun, 2020). However, these studies assumed resources to be a fixed input and did not cover whether changes to the management of resources including variations in their level and the relaxation of some of the rigid regulation regarding them could yield improvement to neonatal services performance.

Simulation modelling techniques have been used extensively to represent health contexts and evaluate the expected impact of alternative reconfigurations and changes to these contexts (Katsaliaki and Mustafe, 2011). The most popular simulation techniques applied to healthcare are Discrete Event Simulation (DES), System Dynamics (SD), and Agent Based Simulation (ABS). DES is generally used to model the evolution of individual entities (eg patients) over time where the transition of entities is determined by activities with stochastic durations and by resources constraints (Lebcir et al, 2017). SD is suitable to represent time related flows of sub-groups of elements (eg categories of patients) in contexts involving feedback (circular) processes, non-linear causality relationships, and interactions between the different components of the health context (Morecroft, 2015; Dangerfield, 2014; Sterman, 2000). ABS is a technique mainly applied to represent the behaviour of agents (eg patients, doctors) and how the interactions between the agents determine the health context outcomes (Currie et al, 2020}

DES and SD are both suitable techniques to evaluate the impact of alternative configurations involving changes to the level of resources and treatment processes on the operational efficiency of neonatal services. However, SD is selected as it is more aligned with the characteristics of these services and the evaluation objectives (Lebcir and Atun, 2000; Demir et al, 2014). Patients are divided into clear sub-groups represented by the care categories (SC, HDC, IC) and the operational efficiency of neonatal services is driven by the flows of babies in these sub-groups rather than by individual babies. Many circular (feedback) processes are present in neonatal services especially with regard to the transition of babies between the different care categories. Non-linear relationships such that the link between occupancy of cots and admissions are important features of these services. Furthermore, neonatal services include several mutually interacting elements (patients, doctors, nurses, cots, treatment protocols, clinical outcomes), which determine the performance of the services.

The above characteristics are not just present in neonatal services, but are exhibited by most health contexts (Taylor and Dangerfield, 2005; Dangerfield, 1999), hence the significant increase in the number and areas of SD applications in healthcare (Darabi and Hosseinichimeh, 2020; Chang et al, 2017). SD combines qualitative and quantitative tools to evaluate and predict possible outcomes of policies and to facilitate organisational learning and knowledge elicitation among policy makers (Thompson et al, 2016).

The aim of this paper is to evaluate the impact of changing the level of resources in neonatal units and relaxation of some of the regulations regarding treatment processes on neonatal services' operational performance. The paper's contribution is twofold: first, modelling of a strategic component affecting healthcare delivery and performance, and, second, exploring this in the context of neonatal services, an area of healthcare where research related to resources management is significantly limited. The paper starts with a literature review section followed by a description of the development and validation of the SD model. The following section focusses on the interventions and scenarios evaluated on the model and associated results and findings. The paper concludes with a section discussing the implications of the results from academic and health policy perspectives.

2. Literature Review

2.1 Organisation of neonatal care in the UK: Given the vulnerability and frailty of patients needing neonatal care, professional knowledge and consensus developed over a long period of time have been captured and converted into regulatory rules and policies (BAPM 2011, 2010; DoH, 2009). The regulation groups babies in 3 categories: (i) Special Care (SC) for babies who could not reasonably be looked after at home and may need to have their breathing and heart rate monitored, be fed through a tube, supplied with extra oxygen or treated for jaundice; (ii) High Dependency Care (HDC) for babies who need continuous monitoring such as those who weigh less than 1,000g , or are receiving help with their breathing via continuous positive airway pressure or intravenous feeding, and (iii) Intensive Care (IC) for babies with the most complex problems who require constant supervision and monitoring and, usually, mechanical ventilation. The regulation covers a number of areas and principles including organisation and types of neonatal units, transfer between units, family involvement, surgical services, clinical governance, data requirements, and staffing and resources. Regarding the latter, there are specific requirements regarding the academic and professional qualifications of clinical staff, ratios of clinical staff to babies for each care category, and resources required for every shift.

2.2 Resources management in healthcare and neonatal services: Healthcare cannot be delivered if human and non-human resources are not available. For this reason, significant research has taken place covering aspects such as strategic and operational management of human resources, capacity management, logistics management of non-human resources, factors affecting medical staff productivity and quality of care, and how resources impact the performance of healthcare services (Song et al, 2020; Shaikh Mohamed and Abdul Hameed, 2015; Kakuma et al, 2011). The relationship between resources and healthcare performance has been established in many frameworks including the one developed by Epping-Jordan el al (2004) for the management of chronic diseases. The framework identifies organisation of healthcare, community, policy environment, and resources as drivers of clinical and operational outcomes. Another framework stipulates that healthcare performance (clinical, operational, financial) is contingent upon the level of demand for healthcare, capacity management strategies, workforce management, and utilisation of resources (Jack and Powers, 2009)

However, there have been very few studies on resources management in the context of neonatal services. The mix of resources required for neonatal care was included in some studies representing the care pathways, but were assumed as fixed inputs reflecting the regulatory requirements (Lebcir and Atun, 2020; Demir et al, 2014). Other research covered some human resources aspects in neonatal units including the implementation process of new training and staff performance management (Thomas et al, 2009), cultural shifts to improve nurses' retention (Mulcahy and Betts, 2005) and the relationship between resources and clinical outcomes (Nesbitt and Rosenblatt, 1997).

2.3: Length of Stay and healthcare performance: LoS is an important driver of healthcare services performance and several studies investigated this relationship. In this context, performance of hospitals in the United States was found to be related to the LoS of patients (McDermott and Stock, 2007). Similarly, a study involving the top 100 integrated healthcare networks (IHNs) in the United States concluded that the performance score of the IHNs is negatively affected by the LoS (Wan and Wang, 2003). In the specific context of neonatal care, some studies determined that LoS influences the throughput of neonatal units (Lebcir and Atun, 2000; Adeyemi and Demir, 2019; Demir et al, 2014). Similarly, neonatal LoS was found in a research by Boyle et al (2015) to drive outcomes such as discharge, death, and transfer to other care wards.

2.4 Simulation modelling in healthcare settings: Simulation modelling applications in healthcare go as far back as the 1970s (England and Roberts, 1978) and have increased significantly in terms of disease categories, clinical services, and areas of applications. This is driven by the complexity of healthcare settings, significant developments in computer simulation tools and software, and the shift to a proactive evidence-based decision making in the healthcare sector (Darabi and Hosseinichimeh, 2020; Demir et al, 2018; Katsaliaki and Mustafe, 2011). These applications involved the use of the main simulation techniques (DES, SD, ABS) to address healthcare policy and management problems.

Examples of DES applications in healthcare include demand and capacity modelling for emergency services (Ordu et al, 2020a), resources management in hospitals (Ordu et al, 2020 b), reconfiguration of cataract surgery pathways (Demir et al, 2018), and prevention of mother to child HIV transmission (Rauner et al, 2005). SD was used to investigate antibiotics prescription in UK hospitals (Zhu et al, 2020), health seeking behaviour of pregnant women in Pakistan (Ahmad et al, 2019), planning of cardiovascular disease interventions in the United States (Hirsch et al, 2010) and evaluation of policies to reduce Tuberculosis and HIV infections in Estonia (Atun et al, 2007). ABS models have been less frequently applied in healthcare compared to DES and SD with examples including economic analysis of treatment protocols for patients with Epilepsy in India (Megiddo et al, 2016), patients' behaviour and its implications for Measles vaccination programmes in the United States (Liu et al, 2015), and optimisation of emergency departments in Spain (Cabrera et al, 2011).

2.5 System Dynamics modelling in neonatal services: SD gained significant popularity and importance in health management in recent times. This is due to increased awareness of the dynamism and complexity of health contexts, which make their response to policies and interventions, very often, counterintuitive (Homer and Hirsch, 2006; Dangerfield, 1999). This explains the recent upward increase in SD applications to provide robust evidence for policy making (Darabi and Hosseinichimeh, 2020; Chang et al, 2017; Brailsford et al; 2009). SD represents the structure of healthcare systems through qualitative Causal Loop Diagrams (CLDs) portraying the causality relationships between the system's elements. Simulation models of the contexts are then developed using appropriate software (for example STELLA) to evaluate, in a safe virtual environment, the likely effect of interventions and providing decision makers with the required evidence to determine the most promising policies to implement.

Despite this richness of SD applications in healthcare, models of neonatal services are limited. Demir et al (2014) developed an SD model of a neonatal unit in the UK to determine the impact of LoS on some operational performance indicators. In another study in Uganda, an SD model was developed to explore policy interventions aiming to reduce neonatal mortality (Rwashana-Semwanga et al, 2016). The findings suggested that the combination of two interventions, namely, the provision of clean free delivery kits and free transportation vouchers to health facilities during emergencies was the most effective in reducing neonatal mortality. In a recent study exploring simplification of neonatal pathways, through allowing doctors to use their clinical judgment when treating babies, it was found that combining this policy with a reduction in LoS could reduce the level of saturation and improve the operational efficiency of neonatal units without increasing the level of resources (Lebcir and Atun, 2020).

3. Development of the model

3.1 Model building process

The context for the development of the model is a neonatal unit located in region of the UK with a large population. The unit has highly skilled clinical teams and medically equipped to treat babies in all care categories. Most babies admitted to the unit come from the local catchment area with some transferred from other regional units if these are not equipped to treat babies with complicated medical conditions (mainly in the IC category). The unit was saturated most of the time due to its reputation for high quality of care, resulting in refusal of admission for many babies due to resources constraints.

The SD modelling process included two main steps in line with recommended SD modelling best practice (Sterman, 2000). First, the structure of the care pathways and the resources required over the different stages of the pathways was qualitatively mapped in the form of a CLD portraying the main cause-effect links between the neonatal unit's elements. Second, the structure of the CLD was converted into a computer simulation model using the icon-based user-friendly interface of the software STELLA (ISEE Systems, 2020). The model incorporated the processes of admission, initial clinical status check, assignment to a care category, treatment processes and outcomes, type of resources, mix of resources required for treatment of each category of care, and the rules regarding the evolution of babies in the unit. Model building was informed by regulatory documents and information provided by members of the clinical and management teams in the neonatal unit. The model went through a number of iterations of refinement and improvement until it was agreed by the members who provided the information to build the model.

3.2 Modelling of the care pathways and resources

The model represented the care pathways as recommended by the national rules and standards and neonatal care professional consensus (BAPM, 2011, 2010; DoH, 2009). Patients' journey start with admission to the unit. The admission rate, that is the number of babies admitted per day, depends on the daily demand for neonatal care and cot capacity constraint. Demand is driven by the number of babies born per day and the fraction of these needing neonatal care. Therefore, the admission rate is represented by the following equation:

$$ADR_t = BRN_t \times FNC \times ECAR \qquad (1)$$

Where

ADR_t: Admission rate per day [babies/day].

BRN_t: Number of babies born per day [babies/day].

FNC: Fraction of babies needing neonatal care [Dimensionless].

ECAR: Effect of cot availability on admission [Dimensionless].

The effect of cot availability on admission reflects the rule used by the unit managers to link the number of babies admitted per day to cot capacity constraint. This stipulates that babies are admitted normally up to a 60% cots occupation. If this threshold is exceeded in any day, admissions are reduced on that day. The scale of the reduction is more important in days when cots occupation is high and no baby is admitted in days when all cots are occupied (cots occupation of 100%). This managerial rule is represented by the following decreasing non-linear function (See Figure 1)

$$ECAR = f(FRCOT_t) \qquad (2)$$

Where

$FRCOT_t$: Fraction of cots used [Dimensionless].

$FRCOT_t$ represents the fraction of the number of cots used to the total number of cots available in the unit.

The first step following admission is to carry out a clinical check so that allocation to one of the three care categories (SC, HDC, IC) takes place. The baby then enters a treatment phase lasting for a period equal to the regulated care category LoS. There are a number of possible outcomes at the end of the treatment phase and these are: death, discharge home, transfer to hospital wards outside the unit, transfer to other neonatal units, or transition to another care category. Regarding the latter outcome, the possible transitions, depending on the clinical state at the end of the treatment phase, are from SC to HDC or IC, from HDC to SC or IC, and from IC to HDC or SC. The care pathways for babies in the SC state are given as an example in Figure 2 (as they appear on the STELLA software interface).

The treatment rate (the number of babies treated daily) depends on the LoS and the level of resources available to carry out treatment activities. The equation for this rate is given below

$$TRT_{t,j} = Min(TLOS_{t,j}, TRES_{t,j}) \qquad (3)$$
$$j \in \{SC, HDC, IC\}$$

Where

$TRT_{t,j}$: Treatment rate for babies in care category j [babies/day].

$TLOS_{t,j}$: Treatment rate allowed by the LoS for babies in care category j [babies/day].

$TRES_{t,j}$: Treatment rate allowed by resources for babies in care category j [babies/day].

$TLOS_{t,j}$ reflects the fact that clinical regulations and established processes require that babies stay in the treatment phase for the whole LoS independently of the level of resources available in the neonatal unit. As a result, the $TLOS_{t,j}$ equation is as follows:

$$TLOS_{t,\,j} = \frac{NBAB_{t,\,j}}{LoS_j} \qquad (4)$$

$$j \in \{SC, HDC, IC\}$$

Where

$NBAB_{t,j}$: Number of babies in care category j needing treatment [babies].

LoS_j: Length of stay for babies in care category j [days].

$TRES_{t,j}$ represents the treatment rate allowed by resources and, as such, reflects the number of patients, who can be treated daily within the level of resources available in the unit. Resources required for treatment include nurses, doctors, and cots (BAPM 2011, 2010). There are 3 categories of doctors: consultants, specialist registered, and senior officer, who can treat babies in all three care categories but with different ratios of doctors to babies. Similarly, nurses are grouped into support nurses, who can treat SC babies only, non-specialist nurses, who can treat SC and HDC babies, and specialist nurses, who can treat babies in all the three care categories. As it is the case for doctors, the ratio of nurses to babies is also regulated for every category of nurses. There are two types of cots: (i) SC cots adequate for SC category only and (ii) IC cots adequate for all categories.

For example, the treatment rate allowed by resources for HDC babies is presented in equation (5).

$$TRES_{t,\,HDC} = Min(NUR_{t,\,HDC}, DOC_{t,\,HDC}, COT_{t,\,HDC}) \qquad (5)$$

Where

$TRES_{t,HDC}$: Treatment rate allowed by resources for HDC babies [babies/day].

$NUR_{t,HDC}$: Nurses treatment rate for HDC babies [babies/day].

$DOC_{t,HDC}$: Doctors treatment rate HDC babies [babies/day].

$COT_{t,HDC}$: Cots treatment rate HDC babies [babies/day].

$NUR_{t,HDC}$ represents the total number of HDC babies, who can be treated every day as determined by the nurses treatment capacity. Similarly, $DOC_{t,HDC}$ and $COT_{t,HDC}$ represent the same number for doctors and cots respectively. The minimum condition in equation (5) reflects the fact that the treatment rate allowed by resources, which represents the daily treatment capacity, is determined by the least available resource in the unit.

As an illustration, $NUR_{t,HDC}$ is determined by the total number of nurses in the unit, the daily fraction of time allocated by nurses to treatment activities (this is because nurses may have other administrative and managerial responsibilities), the maximum number of babies a single nurse can treat (nurse to baby ratio), and the fraction of the total treatment capacity allocated to HDC babies (as some of the total treatment capacity is also allocated to treat SC and IC babies). The equation for $NUR_{t,HDC}$ is, consequently, as follows

$$NUR_{t,\,HDC} = \sum_{i=1}^{2} (A_i \times B_i \times C_{i,\,HDC} \times D_{t,\,HDC}) \quad (6)$$

$$i \in \{SPE, NSP\}$$

Where

A_i: Total number of nurses of category i in the unit [Nurses].

B_i: Daily fraction of time allocated by nurses of category i to treatment activities [fraction/day].

$C_{i,\,HDC}$: Ratio of nurses of category i to HDC babies [babies/nurse].

$D_{t,HDC}$: Fraction of nurses treatment activities allocated to HDC babies [dimensionless].

SPE: Specialist nurses.

NSP: Non specialist nurses.

The model captures the performance of the unit through a set of performance indicators representing the throughput from the unit (the number of babies leaving the neonatal unit following treatment), and the unit ability to cope with demand represented by the number of cases of refused admission due to unit capacity constraints.

4. Model parameters and validation

The data used to populate the model was collected from national regulatory sources and from the neonatal unit statistical services. National regulatory sources provided data such as doctors and nurses ratios to babies. The unit statistical services provided information on admissions, the number of babies in each care category, LoS, the number of doctors, nurses, cots in the unit, the fraction of time allocated by doctors and nurses to treatment activities, and the rules governing admission to the unit.

Once the data was inputted, the model was subjected to the required validation tests in line with the SD literature (Sterman, 2000). Tests were divided into three categories: First, the qualitative structure of model represented by the CLD was checked by members of the clinical and management teams in the unit and went through some adjustments until it was agreed by all members. For example, doctors commented on the loop representing the treatment of HDC babies and provided advise on how it should be linked to the loops representing the treatment of SC and IC babies through some of the clinical outcomes of HDC treatment (transfer from HDC to IC in case of worsening and from HDC to SC in case of improvement). Second, the simulation model was validated through a rigorous check of the equations for dimensional consistency. In addition, a list of the variables included in the model was presented to members in the unit to make sure that every model variable was meaningful in the real world and that no dummy (virtual) variables were included in the model. Third, the model ability to generate plausible results and replicate past real-world observations was validated. Results plausibility was tested by subjecting the model to extreme conditions (for example the death of all babies following treatment) and the model generated results consistent with expectations. The model ability to replicate past observation was tested by comparing the simulation results with real data on a number of variables and the model results were very close to real world observations (See Table 1)

5. Scenario Analysis and Results

5.1 Selection of simulation scenarios

Given that the neonatal unit was saturated most of the time and rejecting new admissions, the main concern was to find new ways of alleviating this chronic situation so that the unit can cope with demand for its care services. This process was not, however, straightforward as most aspects of neonatal care are constrained by regulation and established professional practices. In this context, a number of options were considered by the clinical and management teams including non-admission of babies outside of the hospital where the unit is located, admission of IC babies only from other neonatal units in the region, reducing treatment duration for SC babies (the less severe care category), adding resources to other SC specialised neonatal units in the region to treat HDC babies, and increasing resources to the unit. After a review of these options, the latter was considered to be the best for a number of reasons. First, it is not subject to regulatory constraints as these focus on the mix of resources required to treat a single baby and their ratios to babies. Second, it was possible to make a case for more investment in resources if this was backed by evidence from the model findings.

Therefore, the scenarios selected for simulation on the model represented an incremental increase of 10% in the level of all resources up to a maximum of 50%.

5.2 Simulation results

The neonatal unit performance is measured by its throughput and ability to cope with demand. Throughput represents the number of babies leaving the unit following successful treatment and is reflected by the performance indicators “Cumulative Number of Babies Discharged Home (BDH)”, “Cumulative Number of Babies Transferred to Other Units (BTO)”, and “Cumulative Number of Babies Transferred to other Wards in the Hospital (BWH)”. The unit ability to cope with demand is represented by the “Cumulative Number of Babies Refused Entry (BRE)”. A positive performance is reached if the throughput (BDH, BTO, BWH) is high and BRE is low.

5.2.1 Increase in the level of resources

The model was run for a period of 1 year and the simulation results are presented in Table 2 and Figure 3 for BRE. The simulation results are extremely surprising as they indicate a limited effect of the policy on the throughput indicators. An increase in resources will not translate in any significant improvement regardless of the level of increase in resources. Regarding BRE, there is a reduction of the magnitude of around 30% if resources go up by 10% with no further improvements under the remaining scenarios. In fact, BRE value is the same under scenario 1 (10% increase) and scenario 5 (50% increase). Furthermore, BRE is lower under scenarios 2 (20% increase), 3 (30% increase), and 4 (40% increase) than under scenario 5 (50% increase). The modeller, who facilitated the workshop, explained that these results are not uncommon as health contexts are dynamic complex systems and these tend to behave in a counterintuitive manner (Homer and Hirsch, 2006).

To overcome the confusion and enhance confidence in the model, the modeller used a high level CLD (Figure 4) representing babies in the HDC category to explain the unexpected results (HDC was selected just as an example to simplify the unit’s complexity). The CLD includes 4 balancing loops from which B1 to B3 portray the journey of babies in the neonatal unit from admission to discharge or transfer and B4 represents the impact of resources on the treatment process. The journey is divided into three main phases: (i) admission, health check status, and allocation to the HDC care category (loop B1), (ii) the progress of babies through the treatment phase (loop B2), and (iii) discharge and transfer to other wards in the hospital or unit (loop B3). If these loops are powerful, babies' journey is speedy leading to a higher throughput and a lower refusal of admissions.

The intervention of increasing the level of resources impacts directly on loop B4, which become more powerful increasing the HDC resources treatment rate (this reflects the availability of more resources to treat babies). This, in turn, strengthen loops B2 and B3 leading to a higher number of babies treated, discharged, and transferred, and freeing cots to admit more babies explaining the enhanced performance under scenario 1. Adding more resources increases further the power of loop B4, but this is not transmitted to loop B2 as the HDC treatment rate is constrained by the impact of HDC LoS on HDC process treatment rate (LoS was not changed under the scenarios to increase resources). Consequently, the power of loop B2 remains unchanged leading to the same number of babies treated, hence the virtually similar performance under scenarios 2 to 5. This is a vivid example of counterintuitive behaviour of dynamically complex systems where the effect of an intervention (increased resources to treat babies) is counteracted and "defeated" by other processes in the system (babies staying in the treatment phase for the whole duration of the LoS).

5.2.2 Reduction of LoS

The simulation results above and the CLD indicated that LoS is a constraint preventing the expected improvement in neonatal unit performance from increasing resources. Therefore, the model was adjusted to test the impact of reducing LoS in conjunction with increasing resources. The set of scenarios regarding LoS reduction were taken from past published research (Lebcir and Atun, 2020) as these were deemed feasible by the unit management (See Table 3).

The results are presented in Table 3 for all performance indicators and in Figure 5 for BRE. They show that reducing LoS has a positive impact on performance only if this is reduced by 3 days for the three care categories simultaneously. If the decrease is limited to a single care category, then there is no significant change in performance. This trend is valid under all scenarios on increasing resources. For example, BRE is reduced from 18 if LoS is not reduced to a minimum of 12 if LoS is reduced by 3 days for the three care categories under no resources increase. If resources are increased by 10%, the same thing is observed as BRE is reduced from 15 if LoS is not reduced to a minimum of 11 if LoS is reduced by 3 days for the three care categories. Under 30% resources increase, BRE goes down from 14 if there is no LoS reduction to a minimum of 11 if LoS is reduced by 3 days for all care categories.

However, it is interesting to note that the policy of increasing resources is not matched by a similar trend in performance improvement. There is a certain improvement when resources are increased by 10%, but performance remains the same if resources are increased further up to 50% and this finding is consistent across all scenarios regarding LoS reduction. As an illustration, in the case of LoS reduction by 3 days for SC babies, BDH increases from 235 if there is no increase in resources to 237, 236, 237, 237, and 238 under increased resources scenarios 1, 2, 3, 4, and 5 respectively. These results indicate that increasing resources beyond 10% is not recommended as LoS will restrict any benefits expected from additional resources (as explained above through the CLD in Figure 4). They also indicate that, under any resources' configuration, if LoS is to be reduced, the best option is to do it by 3 days for all the 3 care categories. In summary, the results mean that a combination of LoS reduction and resources increase will generate the best improvements in neonatal performance, but a high scale deployment of resources on its own (which would be costly) is not recommended given the constraining effects of LoS.

6. Discussion and Conclusion

This paper focusses on an important area of health management, that is the management of resources in contexts of high demand and limited capacity. Neonatal services are a typical example of such contexts as they are characterised by a chronic shortage of resources and high treatment costs (BLISS, 2015; Demir et al, 2014; Asaduzzaman et al, 2009). This research is also relevant as neonatal services have not attracted much interest from the research community despite the clinical complexity of the treatment they provide and the management challenges they face.

The research findings indicate that the intuitive policy of increasing resources to improve operational performance and alleviate pressure on neonatal services will not yield the expected results. It is surprising that adding 10% or 50% of resources will generate the same performance level. However, the latter scenario is more costly to the NHS and implementing it would have constituted a significant waste of scarce financial resources. Similarly, reducing LoS, another intuitive and costly policy, is not translated into better performance especially if the reduction is associated with a single care category. These results highlight the difficulty of policy making in the healthcare sector and how to determine the most effective interventions to improve its performance (Homer and Hirsch, 2006). These challenges are more acute as these interventions are not cost neutral and require significant investments to implement them.

A practical consequence of this research is that improving performance of neonatal services requires a combination of LoS reduction and an increase in resources. This is a good example on the need to deploy a number of policies simultaneously to achieve the objective and it is in line with what has been reported in recent research that a single intervention do not always lead to the expected outcomes (Lebcir and Atun, 2020). This is a known characteristic of dynamically complex systems (such as health systems), which behave in unexpected manners and defeat what may be considered logical and reasonable policies (Morecroft, 2015).

The qualitative map (CLD) explaining why adding more resources was not matched by the same level of performance improvement highlighted the role of the LoS in limiting the positive impact of extra resources. This is a consequence of the rigid regulation and pathways of neonatal care, which requires that babies spend the whole LoS in the treatment phase regardless of the level of available resources. This is even more problematic if at the end of the treatment phase, babies are transferred to another care category on the pathway spending a further full LoS in the unit. These constraints negated any positive impact of increasing resources and is a vivid example of situations where one element of the system (organisation of care and patients' pathways) is acting another part of the system (resources deployed for treatment). This is a major cause of what is known in SD as "policy resistance" where the structure of a system acts against a policy intervention and prevents it from achieving its intended outcome (Sterman, 2000).

From a methodological perspective, the current research strengthens the argument for a holistic approach to investigate and analyse healthcare settings. Systems Thinking approaches, including SD, are adequate methodologies to enable this, which explains the significant increase in their applications in healthcare (Darabi and Hosseinichimeh, 2020). These methodologies provide tools to qualitatively map the complexity of healthcare contexts (Eg CLDs), predict and quantify the consequences of interventions (Eg Simulation models), and provide explanations of results and findings (Chang et al, 2017). The combined use of these tools has been found to improve the quality of policy and decision making and enhance individual and organisational learning (Thompson et al, 2016; Rouwette et al, 2011).

Improving the operational performance of neonatal units in the UK will remain an important challenge and a priority for the foreseeable future given the high demand for this care and the financial constraints on the NHS. In addition to the policies of reducing LoS and increasing resources investigated in this study, there are other possible policies to help achieve this objective. These include, for example, increased flexibility on the pathways through allowing doctors to use their clinical judgment (Lebcir and Atun , 2020), rapid exchange of information and cross-learning among medical staff in neonatal units of the same network (Shah et al, 2013), transferring babies with less severe medical conditions for treatment in SC focused units, training of nurses and doctors so that they able to treat babies in all care categories, and use of Artificial Intelligence tools to better predict the post-treatment clinical outcomes and reduce the cycles a baby goes through in the unit before discharge (Nuffield Council on Bioethics, 2018).

This study can be expanded in a number of ways. The SD model could be widened to evaluate the impact of the policies of adding resources and reducing LoS on a network of neonatal units. Another possibility is to investigate the processes of implementing these policies in a highly regulated context. Further research could explore the effect of relaxing the rigid regulations of the care pathways and allowing a degree of flexibility in decision making by clinical staff. Finally, it would be important to determine the impact of these policies on quality of care and readmissions.

The assumptions included in the SD model developed for this research create some limitations, which can be relaxed and explored through further research. The level of resources is assumed constant and the model does not take account of the changes in resources' level through, for example, investment in clinical staff and cot capacity. The admission policy is based on cots' utilisation only and more complex policies could be explored where admission is based on the availability of all resources not just cots. The model scope is limited to a single neonatal unit and this can be expanded to include, for example, the hospital maternity services feeding babies to the unit. Last, factors affecting productivity and quality of care can be included in the model.

This research demonstrates the potential of modelling techniques such as SD to capture the complexity of health systems, identify the adequate policies to improve their performance, and avoid costly implementation of non-effective interventions. It also provides evidence of the ability of SD to enhance individual and organisational learning and provide evidence for designing policies. This can only be welcomed in a sector where improving efficiency and quality of care are expected to be the most important priorities in the future.

References

Adeyemi S, Demir E. Modeling the neonatal system: A joint analysis of length of stay and patients pathways. Intl J Hlth Plan & Mgt. 2019; DOI: 10.1002/hpm.2928.

Ahmad R, Zhu N, Lebcir R, Atun R. How the health-seeking behaviour of pregnant women affects neonatal outcomes: findings of System Dynamics modelling in Pakistan. BMJ Glob Hlth. doi:10.1136/bmjgh-2018-001242.

Asaduzzaman MD, Chaussalet TJ, Robertson NJ. A loss network model with overflow for capacity planning of a neonatal unit. Anls Ops Res 2009;178:67–76.

Asaduzzaman MD, Chaussalet TJ. An overflow loss network model for capacity planning of a perinatal network. J Roy Stat Soc 2011; A 174:403-417.

Atun RA, Lebcir MR, McKee M, Habicht J, Coker RJ. Impact of joined-up HIV harm reduction and multidrug resistant tuberculosis control programmes in Estonia: system dynamics simulation model. Hlth Pol 2007;81:207-217

Battin MR, Knight DB, Kuschel CA, Howie RN. Improvement in mortality of very low birthweight infants and the changing pattern of neonatal mortality: The 50 year experience of one perinatal centre. J Paed & Chi Hlth 2012;48:596-599.

BLISS. Bliss baby report 2015: Hanging in the balance. 2015; Available at http://www.bliss.org.uk/babyreport. Last accessed 17 September 2019.

Boyle EM, Johnson S, Manktelow B, Seaton SE, Draper ES, Smith LK, Dorling J, Marlow N, Petrou S, Field DJ. Neonatal outcomes and delivery of care for infants born late preterm or moderately preterm: a prospective population-based study. Achv Dis Chi – Fet & Neo Edit 2015;100:F479-F485

Brailsford SC, Harper PR, Patel B, Pitt M. An analysis of the academic literature on simulation and modeling in healthcare. J Sim 2009;3:130-140.

British Association of Perinatal Medicine (BAPM). Service standards for hospitals providing neonatal care, 3rd edition. 2010; Available at https://www.bapm.org/resources/service-standards-hospitals-providing-neonatal-care-3rd-edition-2010. Last accessed 27 September 2019.

British Association of Perinatal Medicine (BAPM). Categories of care. A BAPM framework for practice. 2011; Available at https://www.bapm.org/resources/34-categories-of-care-2011. Last accessed 30 March 2020.

Cabrera E, Taboada M, Iglesias ML, Epelde F, Luque E. Optimization of Healthcare Emergency Departments by Agent-Based Simulation. Procedia Computer Science 2011;4:1880-1889.

Chang AY, Ogbuoji O, Atun R, Verguet S. Dynamic modelling approaches to characterize the functioning of health systems: A systematic review of the literature. Soc Sci & Med 2017;194:160-167.

Cogin JA, Ng JL, Lee I. Controlling healthcare professionals: how human resources management influences job attitudes and operational efficiency. Hum Res Hlth 2016; Available at https://human-resources-health.biomedcentral.com/articles/10.1186/s12960-016-0149-0. Last accessed 26 March 2020.

Currie CSM, Fowler JW, Kotiadis K, Monks T, Ongoo BS, Robertson DA, Tako AA. How simulation modelling can help reduce the impact of COVID-19. J Simul 2020;14:83-97.

Dangerfield BC. System dynamics applications to European health care issues. J Ops Res Soc 1999; 50: 345–353.

Dangerfield BC. Systems thinking and system dynamics: a primer. In: Brailsford et al (Eds). Discrete event simulation and system dynamics for management decision making. Chichester: Wiley; 2014. 342 p.

Darabi N, Hosseinichimeh N. System Dynamics modelling in health and medicine: A systematic literature review. Syst Dynm Rev 2020; DOI: 10.1002/sdr.1646.

Demir E, Southern D, Rashid S, Lebcir R. A Discrete Event Simulation model to evaluate the treatment pathways of patients with cataract in the United Kingdom. BMC Hlth Ser Res 2018:18:933. Available at https://bmchealthservres.biomedcentral.com/articles/10.1186/s12913-018-3741-2

Demir E, Lebcir R, Adeyemi S. Modelling Length of Stay and patients flows: Methodological case studies form the UK neonatal services. J Ops Res Soc 2014;65:532-545.

Department of Health (DoH). Toolkit for High Quality Neonatal Services. 2009. Available at http://www.londonneonatalnetwork.org.uk/wpcontent/uploads/2015/09/Toolkit-2009.pdf. Last accessed 27 September 2019.

Epping-Jordan JE, Pruitt SD, Bengoa R, Wagner EH. Improving the quality of healthcare for chronic conditions. BMJ Qual Saf 2004;13:299-305.

England W and Roberts S. Applications of computer simulation in healthcare. In Higland HJ, Hull LG, and Neilsen NR (Eds). Proceedings of the 1978 Winter Simulation Conference. Miami Beach, USA, 4-6 December 1978: 665-676.

Green LV. The vital role of operations analysis in improving healthcare delivery. Manu Ser Ops Man 2012;14:488-494.

Homer JB, Hirsch GB. System dynamics modelling for public health: background and opportunities. Amr J Pub Hlth 2006;96:452-458.

Hirsch G, Homer J, Evans E, Zielinski MS. A System Dynamics model for planning cardiovascular disease interventions. Amr J Pub Hlth 2010;100:616-622.

ISEE Systems. STELLA Architect 2020. Available at https://www.iseesystems.com/store/products/stella-architect.aspx

Jack EP, Powers TL. A review and synthesis of demand management, capacity management and performance in healthcare services. Intl J Man Rev 2009;11:149-174.

Kabene SM, Orchard C, Howard JM, Soriano MA, Leduc M. The importance of human resources management in health care: a global context. Hum Res Hlth 2006. Available at https://human-resources-health.biomedcentral.com/articles/10.1186/1478-4491-4-20. Last accessed on 26 March 2020.

Kakuma R, Minas H, Van Ginneken N, Dal Poz MR, Desiraju K, Morris JE, Saxena S, Scheffler RM. Human resources for mental healthcare: current situation and strategies for action. Lancet 2011;378:1654-1663.

Katsaliaki K, Mustafee N. Applications of simulation within the healthcare context. J Ops Res Soc 2011;62:1431-1451.

Lafond S, Charlesworth A. A perfect storm: an impossible climate for NHS providers' finances? The Health Foundation. 2016. Available at https://www.health.org.uk/publications/a-perfect-storm-an-impossible-climate-for-nhs-providers%E2%80%99-finances. Last accessed on 8 August 2019.

Lebcir R, Demir E, Ahmad R, Vasilakis C, Southern D. A Discrete Event Simulation model to evaluate the use of community services in the treatment of patients with Parkinson's Disease in the United Kingdom. BMC Hlth Ser Res 2017:17:50. Available at https://bmchealthservres.biomedcentral.com/articles/10.1186/s12913-017-1994-9

Lebcir R, Atun R. Should doctors use their judgment? How a System Dynamics model elicited knowledge in neonatal care services. J Ops Res Soc 2020;71:1113-1123.

Liu F, Enanoria WTA, Zipprich J, Blumberg S, Harriman K, Ackley SF, Wheaton WD, Allpress JL, Porco TC. The role of vaccination coverage, individual behaviors, and the public health response in the control of measles epidemics: an agent-based simulation for California. BMC Pub Hlth 2015;15:447.

McDermott C, Stock GN. Hospital operations and length of stay performance. Intl J Ops Prd Man 2007;27:1020-1042.

Megiddo I, Colson A, Chisholm D, Dua T, Nandi A, Laxminarayan R. Health and economic benefits of public financing of epilepsy treatment in India: An agent-based simulation model. Epilepsia 2016;57: 464-474.

Moghadam MN, Amiresmaili M, Sadeghi V, Zeinalzadeh AH, Tupchi M, Parva S. A qualitative study on human resources for primary healthcare in Iran. Intl J Hlth Plan & Mgt 2017;33:e38-e48.

Morecroft JDW. Strategic Modelling and Business Dynamics. A feedback systems approach. (2nd eds). Chichester: Wiley; 2015. 504 p.

Mulcahy C, Betts L. Transforming culture: an exploration of unit culture and nursing retention within a neonatal unit. J of Nur Mgt 2005;13:519-523.

Nesbit TS, Rosenblatt RA. Access to maternity care in rural Washington: Its effect on neonatal outcomes and resource use. Amr J Pub Hlth 1997;87:85-90.

Neonatal Data Analysis Unit (NDAU). Report: Care days and reason for admission of term babies. 2010. Imperial College London. Available at http://www.imperial.ac.uk/medicine/research/researchthemes/reprodscience/paediatrics/neonatalmedicine/ndau/. Last accessed on 15 August 2019.

Neonatal Data Analysis Unit (NDAU). 2015 report. 2015. Imperial College London. Available at https://www.imperial.ac.uk/media/imperial-college/medicine/dept-medicine/infectious-diseases/neonatology/NDAU-Annual-Report-2015.pdf. Last accessed on 15 August 2019.

Neonatal Data Analysis Unit (NDAU). 2016 report. 2016. Imperial College London. Available at https://www.imperial.ac.uk/media/imperial-college/medicine/dept-medicine/infectious-diseases/neonatology/NDAU-2016-Report-v1.1-(002).pdf. Last accessed on 18 November 2020.

Nuffield Council on Bioethics. Artificial intelligence (AI) in healthcare and research. Bioethics Briefing Note 2018. Available at https://www.nuffieldbioethics.org/publications/ai-in-healthcare-and-research. Last accessed on 24 November 2020.

Ordu M, Demir E, Tofallis C. A decision support system for demand and capacity modelling of an accident and emergency department. Hlth Syst, 2020a;9:31-56.

Ordu M, Demir E, Tofallis C, Gunal MM. A novel healthcare resource allocation decision support tool: A forecasting-simulation-optimization approach. J Ops Res Soc 2020b. DOI: 10.1080/01605682.2019.1700186

Rauner MS, Brailsford SC, Flessa S. Use of Discrete-Event Simulation to Evaluate Strategies for the Prevention of Mother-to-Child Transmission of HIV in Developing Countries. J Ops Res Soc 2005;56:222-233

Rouwette EAJA, Korzilius H, Vennix JAM, Jacobs E. Modeling as persuasion: the impact of group model building on attitudes and behaviour. Syst Dynm Rev 2011;27:1-21.

Royal College of Paediatrics and Child Health (RCPCH). National neonatal audit programme 2016 annual report on 2015 data. 2016. Available at https://www.rcpch.ac.uk/improving-child-health/quality-improvement-and-clinical-audit/national-neonatal-audit-programme-nnap. Last accessed on 17 September 2019.

Royal College of Paediatrics and Child Health (RCPCH). National neonatal audit programme 2019 annual report on 2018 data. 2019. Available at https://www.rcpch.ac.uk/resources/national-neonatal-audit-programme-annual-report-2019. Last accessed on 18 November 2020.

Royal College of Paediatrics and Child Health (RCPCH). National neonatal audit programme 2020 annual report on 2019 data. 2020a. Available at https://www.rcpch.ac.uk/sites/default/files/2020-11/nnap_report_2020_final_pdf2.pdf. Last accessed on 18 November 2020.

Royal College of Paediatrics and Child Health (RCPCH). A snapshot of neonatal services and workforce in the UK. 2020b. Available at https://www.rcpch.ac.uk/sites/default/files/2020-09/a_snapshot_of_neonatal_services_and_workforce_in_the_uk_2.4.pdf. Last accessed on 18 November 2020.

Rwashana-Semwanga A, Nakubulwa S, Adam T. Applying a system dynamics modelling approach to explore policy options for improving neo natal health in Uganda. Hlth Res Poly Syst 2016. DOI 10.1186/s12961-016-0101-8.

Shah V, Warre R, Lee SK. Quality improvement initiatives in neonatal intensive care unit networks: Achievements and challenges. Acad Pedit 2013;13:S75-S83.

Shaikh Mohamed N, Abdul Hameed S. The impact of human resources management on healthcare quality. Intl J Man 2015;6:603-612.

Song H, Tucker AL, Graue R, Moravick S, Yang JJ. Capacity pooling in hospitals: The hidden consequences of off-service placement. Man Sci 2020;66:3825-3842.

Sterman JD. Business dynamics. Systems thinking and modeling for a complex world. Singapore: Mc-Graw Hill: Singapore; 2000. 768 p.

Taylor K, Dangerfield BC. Modelling the feedback effects of reconfiguring health services. J Ops Res Soc 2005;56:659-675

Thomas A, Kumar V, Bhandari M, Ahuja RC, Singh P, Baqui AH, Awasthi S, Santhosam M, Darmstadt GL. Neonatal health program management in a resource-constrained setting in rural Uttar Pradesh, India. Intl J Hlth Plan & Mgt 2009;24:173-184.

Thompson JP, Howick S, Belton V. Critical learning incidents in system dynamics modelling engagements. Eur J Ops Res 2016;249:945-958.

Wan TTH, Wang BBL. Integrated healthcare networks performance: A growth curve modelling approach. Hlth Care Man Sci 2003;6:117-124.

Zhu N, Ahmad R, Holmes A, Robotham J, Lebcir R, Atun R. System dynamics modelling to formulate policy interventions to optimise antibiotic prescribing in English hospitals. J Ops Res Soc 2020. https://doi.org/10.1080/01605682.2020.1796537

Table 1: Simulation results versus real world observation replication test.

Outcome Variable	Real World	Simulation	Difference Real World and Simulation	Difference (Percentage)
Babies transferred to other units IC	117	108	9	7%
Babies transferred to other units HDC	10	10	0	0%
Babies transferred to other units SC	84	70	14	16%
Babies discharged home IC	9	7	2	22%
Babies discharged home HDC	5	4	1	20%
Babies discharged home SC	196	202	-6	-3%
Babies transferred same hospital IC	14	12	2	14%
Babies transferred same hospital HDC	1	1	0	0%
Babies transferred same hospital SC	122	123	-1	-0.8%
Babies deaths IC	37	31	6	16%
Babies deaths HDC	0	0	0	0%
Babies deaths SC	0	0	0	0%

Table 2: Simulation results for different levels of resources

Scenario	BDH	BTO	BWH	BRE
Scenario 0: Baseline	230	187	136	18
Scenario 1: Increase Resources by 10%	235	183	139	15
Scenario 2: Increase Resources by 20%	236	183	139	14
Scenario 3: Increase Resources by 30%	236	183	139	14
Scenario 4: Increase Resources by 40%	236	183	140	13
Scenario 5: Increase Resources by 50%	235	183	139	15

BDH: Cumulative Number of Babies Discharged Home.

BTO: Cumulative Number of Babies Transferred to Other Units.

BWH: Cumulative Number of Babies Transferred to other Wards in the Hospital.

BRE: Cumulative Number of Babies Refused Entry.

Table 3: Simulation results under the combined policies of reducing LoS and increasing resources

		No Change				10%		
Description	**BDH**	**BTO**	**BWH**	**BRE**	**BDH**	**BTO**	**BWH**	**BRE**
Baseline (Current Situation)	230	187	136	18	235	183	139	15
Reduce LoS by 1 day for SC Babies	234	182	138	18	235	183	139	15
Reduce LoS by 3 days for SC Babies	235	182	139	17	237	184	140	12
Reduce LoS by 1 day for HDC Babies	234	182	138	18	236	183	140	13
Reduce LoS by 3 days for HDC Babies	233	181	138	20	236	183	139	15
Reduce LoS by 1 day for IC Babies	233	181	138	21	234	182	138	18
Reduce LoS by 3 days for IC Babies	234	181	138	20	236	182	139	16
Reduce LoS by 1 day for SC, HDC, and IC Babies	236	182	139	16	236	183	139	14
Reduce LoS by 3 days for SC, HDC, and IC Babies	240	185	139	12	237	184	140	11
		20%				**30%**		
Description	**BDH**	**BTO**	**BWH**	**BRE**	**BDH**	**BTO**	**BWH**	**BRE**
Baseline (Current Situation)	236	183	139	14	236	183	139	14
Reduce LoS by 1 day for SC Babies	236	183	139	14	236	183	140	13
Reduce LoS by 3 days for SC Babies	236	183	139	13	237	184	140	12
Reduce LoS by 1 day for HDC Babies	235	182	139	17	236	183	139	14
Reduce LoS by 3 days for HDC Babies	236	183	139	15	236	183	139	15
Reduce LoS by 1 day for IC Babies	236	183	139	15	235	183	139	15
Reduce LoS by 3 days for IC Babies	235	182	139	16	236	183	140	13
Reduce LoS by 1 day for SC, HDC, and IC Babies	237	184	140	13	237	184	140	12
Reduce LoS by 3 days for SC, HDC, and IC Babies	237	184	140	11	237	184	140	11
		40%				**50%**		
Description	**BDH**	**BTO**	**BWH**	**BRE**	**BDH**	**BTO**	**BWH**	**BRE**
Baseline (Current Situation)	236	183	140	13	235	183	139	15
Reduce LoS by 1 day for SC Babies	236	183	139	14	237	184	140	13
Reduce LoS by 3 days for SC Babies	237	184	140	12	238	184	140	12
Reduce LoS by 1 day for HDC Babies	237	184	140	13	237	183	140	12
Reduce LoS by 3 days for HDC Babies	236	183	140	13	236	183	140	13
Reduce LoS by 1 day for IC Babies	236	184	140	13	236	183	140	13
Reduce LoS by 3 days for IC Babies	236	183	139	15	237	184	140	12
Reduce LoS by 1 day for SC, HDC, and IC Babies	236	183	140	13	237	184	140	12
Reduce LoS by 3 days for SC, HDC, and IC Babies	237	184	140	11	238	184	140	11

BDH: Cumulative Number of Babies Discharged Home.

BTO: Cumulative Number of Babies Transferred to Other Units.

BWH: Cumulative Number of Babies Transferred to other Wards in the Hospital.

BRE: Cumulative Number of Babies Refused Entry.

Figures Legend

Figure 1: Graphical representation of the effect of cot availability on admission (ECAR).

Figure 2: Structure of the care pathways for babies in the SC care category.

Figure 3: Simulation results for the BRE under the policy of increasing resources.

Figure 4: Causal Loop Diagram for the policy of increasing resources.

Figure 5: Simulation results for BRE under the combined policies of reducing LoS and increasing resources.