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Workforce Forecasting for Nursing using System Dynamics Modelling

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Supervisor: Dr. Bahman Honari

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Abstract: Nursing workforce forms the backbone of the healthcare industry, which is an essential service for the population. As a consequence of the growing demand for such services for care and treatment, there has been an exponentially growing need for the nursing workforce in the present and the future. In order to meet this demand, it is crucial to forecast the supply of the nursing workforce. Furthermore, it is necessary to find ways to reduce the on-demand requirements of such a workforce during crises and emergencies.

This dissertation addresses the problem by building a simulation model to forecast the nursing workforce in the future. The stock-flow modelling approach is employed using the VensimPLE software to build the model. By collecting relevant nursing data from HSE and NMBI, the nursing workforce is modelled as a stock, and the underlying features of graduate nurses, immigrant nurses, returnees, attrition nurses and attrition returnees are modelled as flows and variables responsible for the nursing workforce estimation. Finally, the forecasts are computed for the upcoming ten years, and VensimPLE simulations are used to measure the impact of varying underlying features, on the nursing workforce stock.

Based on the simulation observations, appropriate graphs of results are presented to gather meaningful insights from the forecasting model. The model revealed that a gradual increase in graduate nurses and immigrant nurses over the next ten years could lead to an increase in the nursing workforce supply by almost 25%. Similarly, reducing the attrition rate and increasing the attrition returnee rate for employees to return to the public healthcare system enhances the workforce supply by almost 40%. Policymakers can consume these insights to make appropriate economic and organisational decisions to manage the workforce in the future. Future work includes the integration of demand forecasting with the proposed supply forecasting side of the model.

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1 Introduction

1.1 Motivation

The healthcare industry, being an essential service across the world, is mainly supported by its workforce. Among the various classes of workers that constitute the healthcare sector, Nursing and Midwifery are considered to be one of the most crucial departments. According to the World Health Organization reports, these personnel account for around 50% of the global healthcare workforce (1). Nurses play a significant role in promoting health, managing healthcare facilities and, most importantly, serving the patients with intensive care. In multiple instances during patients' illness or disease, care provided by nurses is adequate for the adequate treatment to improve their condition. The function of nurses includes critical decision-making about patients' clinical conditions. Additionally, their duty extends to providing the public with essential health and hygiene guidance, thus indulging in preventive care. A review conducted by Cochrane also proves that the primary care led by nurses led to better health results and brought about higher patient satisfaction compared to other instances (2). Some other crucial duties of nurses include combating rare diseases by identification of diseases and their symptoms, determining disease prevalence, preventing infections, and providing vaccinations.

From the above information, it is evident that the demand for the nursing workforce is exceptionally high in all parts of the world. However, due to various factors, this demand is not entirely met by the supply of the nursing workforce. Since 2020, COVID has been a massive contributor to the growing nursing demand. However, it was researched that the shortage of nurses was beginning to show even before COVID worsened the crisis. Other factors like change in the age dynamics in the population, retirement and burnout have also been major impacting factors. A survey by the American Nurses Foundation summarized that around half the nurses worldwide have considered stopping their practice, and about 89% of the participants reported staff shortages in their organization (3). This demand will only grow exponentially in the coming decades, causing an ever-expanding gap between supply and demand. Figure 1.1 shows the trend for demand for nursing, along with the estimated demand in the upcoming decade. This clearly shows that the estimated numbers are much farther than the actual trend observed historically. If this problem is not addressed, nursing shortage can directly lead to a high mortality rate among patients and error-prone treatment by workers, which may cause a requirement for additional corrective procedures.

The motivation behind the project at hand is to instantly address the problem by forecasting the nursing workforce supply, over the next couple of years. By building such a dynamic model, the various factors driving the workforce can be analyzed and tuned accordingly to study the model's behaviour. Hence, the intention behind the dissertation is not only to forecast the numbers, but also to discover various policies that can be applied to the system to match the growing demand.

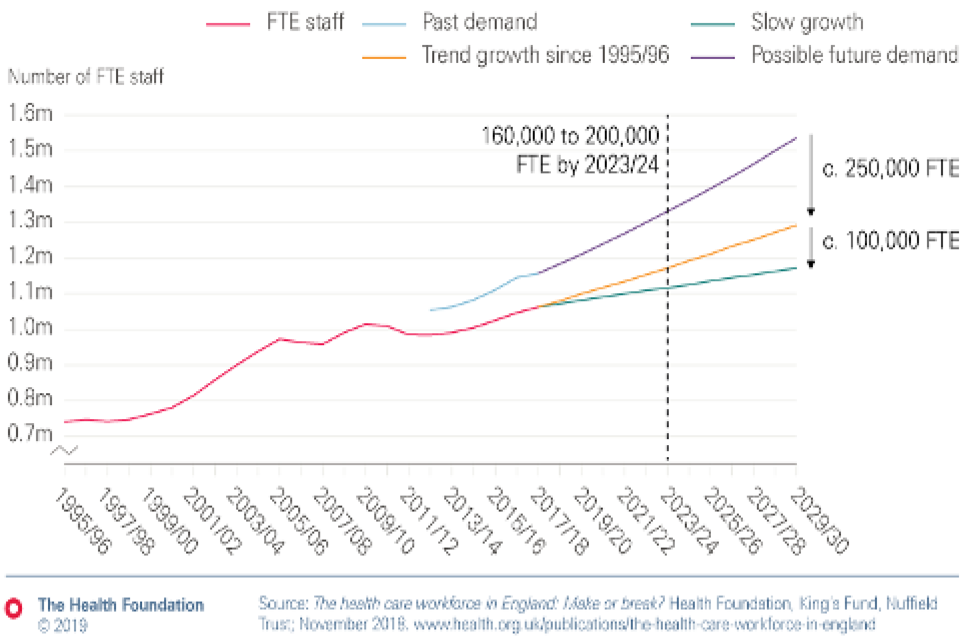


Figure 1.1: Demand for Nursing over the years

1.2 Problem Definition

As discussed above, the nursing workforce shortage is detrimental to all patients. In order to solve the impending issue, the project aims to build a model that forecasts the nursing workforce numbers. The aim is to build a model that will help policymakers make future decisions to uphold a system where the supply of the workforce is not lower than the demand. The problem can be divided into multiple components, which will be described below.

The beginning stage of the model is to find out the various factors that are responsible for constituting the workforce. These factors include both factors which are populating the numbers and factors that are reducing the number. The goal is to investigate and identify the factors that are most significant to the model design. This step relies on gathering multiple sources that shed light on the composition of the healthcare industry. Determining the relevant factors suitable for the project will pave the path toward the first step of data collection for the model. Further, the task involves gathering the historical trends for each individual factor.

Subsequently, the project aims to combine all these factors to architect a reliable workforce forecasting model using the Stock-Flow approach of System Dynamics Modelling. Once the factors are gathered and ready to interact, the model must maintain a system that considers the changes in individual factors and the nursing workforce numbers over time. In order to achieve this, a simulation model using system dynamics is a justifiable choice. System dynamics modelling assists in understanding the complexities of the workforce planning task (4), which will be further elaborated on in Chapter 2. The main objective of this step of the problem statement is to capture the current nursing workforce in a simulation model, considering all the assembled factors from the foremost task.

The main problem that the model attempts to solve is the forecasting of the nursing workforce in the next decade. After careful considering the underlying factors and utilizing these to design the workforce model, we apply this to predict the workforce supply over the next ten years. The workforce calculations are accomplished for every month over the timeframe considered. The dynamics of the model are assumed to vary every month, based on the trends of each variable. In doing so, the objective is to analyze the estimated workforce supply in the future years based on the past pattern observed.

The final stage of the problem is to identify pathways which can structure the future supply to match the demand. The intention is to build the model in such a way that the various factors can be modified, and the overall workforce trend can be observed in each of the scenarios using the help of simulations. By doing so, we achieve tweaks that can be incorporated by policymakers in the upcoming years. The goal is to provide numerous options for altering elementary factors to help reduce the on-demand requirement of employing workers when the situation arises. The main goal of the project is hence achieved in rigging up a dynamic stock-flow model that would produce results as per the simulation fed to the system.

1.3 Structure of Dissertation

The structure of the rest of the dissertation is described below. The next chapter focuses on the State of the Art (Chapter 2) which touches upon the foundations of Workforce Planning and the related research accomplished in the past(Chapter 2). It elaborates on the advantages and limitations of multiple approaches considered to solve the problem. Chapter 3 details the methodology and implementation used in building the model as part of the project. Chapter 4 shows the various experiments conducted, evaluations carried and the respective results observed. The final chapter(Chapter 5) sheds light on the conclusion, limitations of the project and possible improvements that can be adapted in the future.

2 State of the Art

This chapter focuses on background and related work needed to know to help understand the methodology used in the dissertation project. The chapter is divided into two parts, namely Background and Related Work, which will be detailed below.

2.1 Background

This section briefs about the foundational concepts required to be known in order to continue with the rest of the dissertation.

2.1.1 Workforce Planning

Workforce Planning is the process of aiding an organisation with the right amount of human and other resources to lead to efficient operations to achieve its mission and vision in the present and the future. An organisation is backed by its workforce, and effective workforce planning is the most crucial aspect of defining an industry or business. It is essential to analyse the current and past workforce of the organisation in order to evaluate and achieve the workforce required for the present and future of the organisation (5).

Achieving workforce planning involves comprehending the basic stages of the entire process. The National Institute of Health briefs about these in a systematic manner with respect to the healthcare industry (6).

- **Strategic Direction -** Defining strategy for an organisation not only includes identifying goals and missions but also determining the resources, skills and tools required to attain these goals. In order to plan human resources, it is vital to recognise what is expected for the resources to accomplish as being parts of the org (7).
- **Supply Analysis -** This stage refers to analysing the current state and estimated state of an organisation between now and a couple of years into the future. Examining the supply aspect involves analysing the number of employees, demographics, promotions, recruiting, attrition and other related statistics (8).

- **Demand Analysis -** The demand analysis is based on analysing the external factors that lead to the requirement of a fully functional organisation and its resources. While assessing the demand for any domain, it is elementary to consider all internal and external factors that give rise to the need for the product or service that the industry delivers (8). The demand analysing in case of nursing workforce will be analysing factors like population, trends if various diseases.
- **Gap Analysis -** This self-explanatory task is about figuring out how far the demand and supply aspects are from each other. By performing gap analysis, the strategies needed to align the supply with the anticipated requirements are planned. In this step, after doing a preliminary round of investigation, policymakers can revert back to the supply and demand analysis stages to strengthen the workforce planning process. Hence, using an iterative approach for the process would be beneficial in building a robust model for the future.
- **Solution Implementation -** Once these gaps are analysed, relevant procedures are needed in order to complete the workforce planning process. Arriving at solutions is not a one-step stage but rather a process in itself where each gap may have to be addressed in its own different way (9). Additionally, the implementation stage involves gathering data and metrics about the preferred techniques and methods. Further, the data gathered covers information regarding both the organisation's functional performance and its resources.
- **Monitoring Progress -** Keeping progress checks of the entire process at periodic times is highly necessary for making sure that the planning is proceeding in the right direction. The metrics discussed in the previous stage can be used to analyse and investigate if the objectives are fulfilled at every step of the process. By monitoring the organization's performance against both the short-term and long-term goals, a synopsis of the system state can be achieved at any point in time.

Figure 2.1 also summarises the information mentioned above in the form of a chart.

2.1.2 System Dynamics Modelling

System Dynamics Modelling is the process of capturing the critical business processes of a business and simulating how they impact the overall performance of the organisation. A System Dynamics model can be viewed as a computer simulation that generates realistic trend forecasts. From this simulation or model, we can obtain detailed insights into critical factors in an operation, such as resources, cycle times, lead time and capacity utilisation. Based on these insights, policymakers can then use our knowledge to make informed decisions for business improvement (10).

Figure 2.1: Systematic Approach to Workforce Planning

While designing dynamic systems, the definition of a "state" of a system has to be precisely established. Multiple factors are involved in this definition of a state. While modelling a dynamic system, the most critical characteristic is that the state of the system keeps changing and evolving over time (11). As mentioned in some of the information in the previous chapter (Chapter 1), multiple factors are involved in building up a system. In the example of the nursing workforce, factors like graduating nurses, immigrant nurses and attrition rate are responsible for the supply model, and factors like population, disease rate, and related factors constitute a demand model. The state of a system at a given instance is represented as s combination of such factors for the respective system. In a dynamic system, there are individual trends and changes in each of these constituting factors. Modelling the dynamics of each of these factors of the system individually and as a whole will help understand the behaviour of the system in detail.

With the application of System Dynamics Modelling in economic and business processes, the dynamic behaviour of managed systems can be observed and controlled. This can be accomplished with the use of simulations reflecting various scenarios of the system behaviour based on different conditions (10). The approach provides a way of mathematically modelling a system without the need to keep track of every component of a system manually. As mentioned before, since these systems evolve with time, the modelling provides possibilities to apply a time-based equation to variables of a system to observe the exact developing behaviour of the system (12).

System Dynamics Modelling can be classified into two types of approaches -

1. **Causal Loop Diagrams:** This approach is adapted to determine the fundamental cause-effect variables and feedback loops of a system. These causal variables can be related to each other in a positive way or a negative manner. Observe FIG 2.2 to understand this scenario (13). In the diagram, A and B have a positive causal relationship such that an increase in A leads to an increment in B. Whereas with the causal C-D relationship, an increase in C will have a negative decreasing effect on factor D.

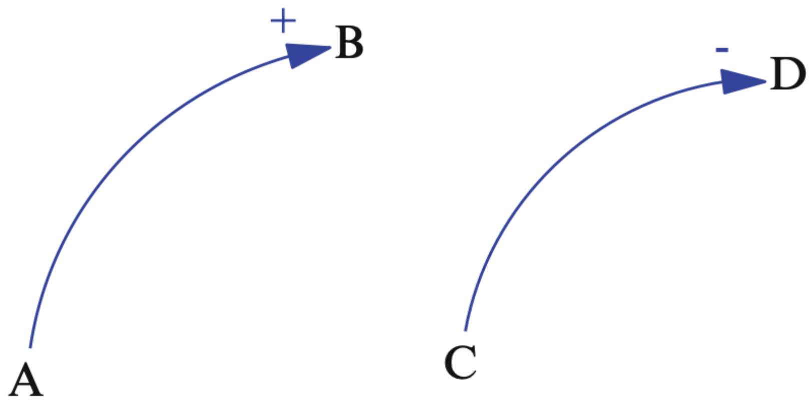


Figure 2.2: Cause and Effect Relationships in a Causal Loop Diagram

2. **Stock-Flow Modelling:** Stock-Flow Modelling approach is another mode of approaching the modelling of a managed system. In this case, the relationship among different variables can be modelled as quantifiable factors using simulations and stock-flow equations. Each variable is treated as a "stock", which evolves over time, and can be referred to as the "flow" of the model. When compared to causal loop diagrams, this approach offers a more detailed statistical analysis of the dynamic system assumed (14).

2.2 Related Work

This section describes the various related works of Workforce Forecasting using various approaches. There have been multiple classes of tools and methodologies used in the past to solve this problem. This chapter will be categorised into various subsections for each approach so as to understand their implementations, advantages and shortcomings.

2.2.1 Time Series Approaches

Time series modelling is a predominantly applied technique for workforce planning and forecasting. Time series modelling uses historical data and patterns to analyse the behaviour and trends of a system in the present and future. In the case of Time series analysis, serially connected data are put into different time frames and analysed in depth to derive meaningful insights about the workforce system (15). Among these models, some of the different methods include ARIMA modelling, Box-Jenkins, Exponential Smoothing and Vector Error Correction (16). This section will effectively research and present multiple works around these methods in the domain of workforce forecasting (16).

Box-Jenkins method is one of the earliest used approaches applied to solving workforce forecasting using Time Series analysis. Box-Jenkins uses the Autoregressive Moving Average (ARMA) technique in its implementation (17). Wong, Chan And Chiang were the researchers able to achieve this by trialling it on the construction labour market in Hong Kong. In this paper, the authors used a quarterly time-series ARMA model to analyse five indicators related to the construction workforce industry. The evaluation of the proposal is done by using MAPE and Theil's U statistics. The work was able to achieve reasonably good predictive performance between the time period of 1983 to 2002. However, it was observed that they could have enhanced the performance accuracy by applying multivariate structural forecasting instead of a univariate approach (18). Figure 2.3 shows the various stages involved in the Box-Jenkins algorithms implementation.

There has been similar research on the Box-Jenkins method to evaluate the feasibility of the tool in the demand forecasting of the construction worker industry (19). This research adapts data that reflects continuous fluctuation of the economic trends, resulting in confusing variations of the demand analysis. After applying a customised Box-Jenkins approach to this data and comparing it with a multiple regression model, it was concluded that the technique predicted medium-term construction demand with good accuracy (19).

Another work published in 2008 had a newly proposed method to develop combination algorithms which could be used in economic forecasting models. The idea is to integrate Box-Jenkins methods with simulation-based implementations using the MATLAB tool. A complex set of steps was identified and applied, in which the most significant steps involved logarithm transformation, normal and seasonal differencing, ACF and PACF calculation, t-test and Q-test for evaluation, forecasting and inverse differencing for evaluating the comprehensive algorithms. The designers used the simulation software to stimulate the automated execution of the Box–Jenkins model by developing a Simphony SPS template (20). This work marked a key advancement in developing methodologies which combined various approaches toward workforce forecasting.

Autoregressive Integrated Moving Average (ARIMA) are extensively used in forecasting applications. Santric-Milicevic, Vasic and Marinkovic employed such a method to model the numbers for physicians and nurses in the public health sector in Serbia between the years 1961 to 1982 and 1983 to 2008. They used several econometric and societal variables like national population, GDP, inpatient discharges, outpatient numbers,

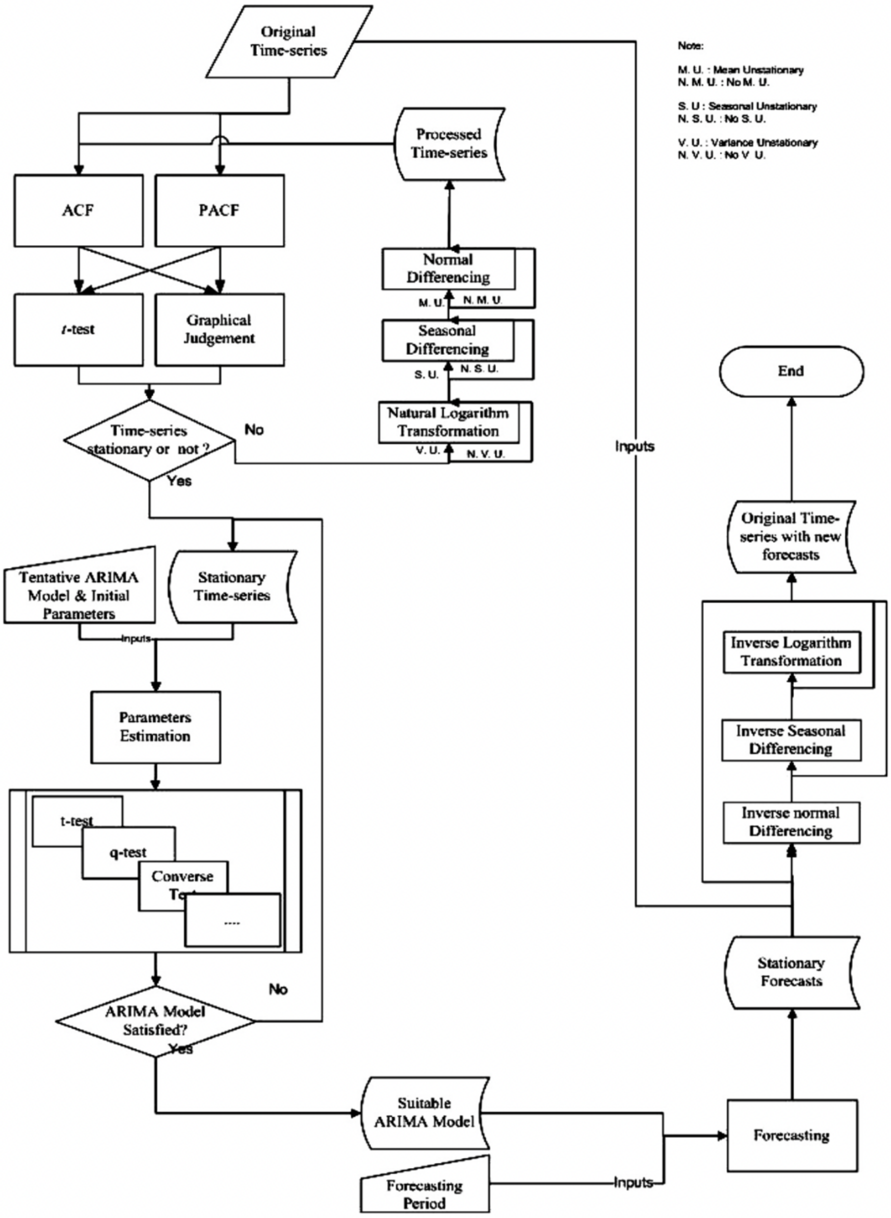


Figure 2.3: Box-Jenkins Algorithm Flow Chart

and medical and nursing students enrolled and graduated. After applying ARIMA/TF (Transfer Function) models, they were able to achieve a performance reflecting R2 squared score of 0.71 for physicians and R2 squared of 0.92 for nurse workforce supply. It was concluded that population and GDP are the best indicators for predicting workforce numbers (21).

Another methodology employs a weighted moving average where historical insights are applied to weights over time in an exponential manner. These weights can be modified to accommodate numerous scenarios to forecast the patterns in the future. Hsu, Chein and Hsein have worked on using this in the industry of energy technology. As per their research, the manpower supply was observed to increase gradually between the years 2009 and 2013, which was an almost precise indication of the true observed trend (22).

Error Correction is another class of time-series method used to analyse the long-term dynamics using the help of the short-term dynamics and the present system state. Wong, Albert, and Chiang got together again in an attempt to improve their previously derived forecasting model. They dug deep into the econometric modelling techniques and observed the interrelation between economic variables and the construction workforce industry. The correlation between factors like prices of construction material, employee productivity, daily wages and bank-related variables were taken into account. Subsequently, a Vector Error Correction model was designed to predict the manpower demand trend. It was concluded with decent accuracy that labour productivity and construction output are the most impactful parameters in the model (23).

There have also been considerable attempts at observing the application of time-series estimation to model the unemployment rate in various countries. Even though this domain is very different from the modelling workforce, there are common aspects between the two domains. The primary factors used in the latter industry are greatly used in determining the former trends as well. Rothman was one of the first few researchers to explore this concept by comparing linear and non-linear time series models applied to assess the USA's unemployment rate. He applied models like exponential autoregressive (EAR), self-exciting threshold autoregressive, smooth threshold autoregressive, generalised autoregressive (GAR), time-varying autoregressive, and bi-linear models. EAR and GAR were observed to perform the best out of the others mentioned. It was concluded that the relative forecasting performance of the linear and non-linear models was dependent on whether the time series was converted to a stationary model or not. However, it was observed that non-linearities enhanced the performance of the models (24). Montgomery had a similar observation about the inclusion of non-linearities while forecasting the US unemployment rate (25). Johnes, in 1999 had the same conclusion from his work on predicting unemployment in the UK using time series and neural network models (26).

A few years into the future, Tommaso Proietti attempted the same US unemployment problem where the forecasting model is assessed using the rolling-origin procedure, where model performance is linked with its time domain properties, to notice underlying correlations. It was concluded in this research that structural time series models would be a powerful forecasting tool for such systems (27). Not so later, Perloff and Golan used a non-parametric method using a higher dimensional simplex approach to model unemployment rates. It was interpreted that non-parametric methods outperformed the popularly known structural and economic-theory-based models (28). Chua, Lim and Tsiaplias propose a structure economical-theory-based model for the forecasting problem. They exploited time series properties but attempted to satisfy the economic relationships reflected in Okun's law and the Phillips curve. The model performance was evaluated

Vector-Autoregressive (VAR) and Bayesian Vector-Autoregressive (BVAR) models. The model outperformed the traditionally used time series models in the past (29).

2.2.2 Markov Modelling Approaches

Moscovice, Bass, and Brooks were among the first authors to publish work on using a Markov-based approach to forecasting workforce. A semi-Markov model is used in predicting the supply of healthcare providers (physicians and nurses) in selected regions in the USA. Real national health data was used while developing this model. The results showed a 30% increase in the estimate for physicians between 1982 and 1990. It was also validated that the method was a reasonable approach to the healthcare workforce problem statement (30). Zeffane and Mayo apply models with additional complexity. The core model is based on the Markov theory and has a preliminary matrix consisting of the fundamental features. However, this is paired up with peripheral matrices, which consider various internal and external constraints that impact the system directly or indirectly. The result showed that there was scope for improvement of the model performance. Nevertheless, the simplicity of the model was a highly beneficial aspect of the project (31).

Years later, Kinstler, Richter, Kocher and Johnson used the Markov model to analyse the supply of navy nurse corps. The model used promotion and attrition rates primarily to develop the prediction prototype. They also investigated the flow of staff from junior levels to medium and high levels within the agency. It was found that the attrition and retention rates were not very strong indicators of the workforce supply (32). Belhaj and Tkiouat presented an employee forecasting model in an HR system which covered both supply and demand bases. The model assumed limited promotion probabilities of all the participating employees. A stochastic model with the traditional Markov approach of using a transition matrix combined with suitable factors was developed. The model estimated a substantial gap between the forecasts and organisational expectations (33).

A semi-Markov model was built by Yadavalli and Natarajan by assuming a single-grade only system. This means that the system's internal flows and processes were ignored to reduce the elaborateness. As part of the model, wastage and recruitment factors are considered where wastage is modelled as a Poisson process, and the latter is modelled by taking instantaneous quantity values at the required point of time (34).

Recent research was done by Mohammad M AlDurgam in which a semi-Markov stochastic model with an integrated dynamic lot-sizing approach is built. The production concept is applied to this model during implementation. This process was observed to be working for both time-homogeneous and heterogeneous demand systems. The model resulted in aiding the decision-making process, especially during uncertainty. The biggest limitation of the project was the assumption of a neutral decision-maker, which resulted in a challenging estimation of a few fundamental factors of the model (35). A related study in the domain of manufacturing and service processes was conducted by Tamás Bányai, Christian Landschützer and Ágota Bányai. The prototype assembled as part of the study presents a Markov-chain simulation of the human resources development processes, with the assistance of promotional matrices. Human resource organisational data with six levels of career promotion was used as input to the model. It was observed that rates of recruitment and promotion have a powerful impact on the structure of future employees of the assessed organisation (36).

2.2.3 Statistics and Regression models

A statistical model is a deterministic system that is used to estimate the probability distributions of various outcomes that can be arrived at by the managed system by the historical data and observations. This is done by varying the different underlying inputs over time and obtaining the statistical results. Statistical and regression techniques are classified as prediction methods and have been vastly used in forecasting applications. Dexter and Liam applied these analytical methods to the healthcare sector by attempting to forecast the operating room staffing's optimum capacity in case of urgent medical procedures. With the help of statistical analysis, the authors were able to accomplish a hierarchy which helped with the prediction (37).

Ben-Gal, Wangenheim and Shtub consider factors such as absences, allowances, occupancy levels, employee duties and patient services to predict the physician staffing requirements (38). After rigorous statistical analysis, a standardisation model was developed for the system, which can be represented using the formula below:

$$J = [(P_d \times w_d \times z_d + P_s \times w_s + P_c \times w_c \times z_c) \times (1 + a) + P_o + R] \times (1 + e)$$

J - the required physician staffing in the department

P_d - the effective required presence of physicians in the department area.

P_s - the effective required presence of physicians in the operating rooms

P_c - the effective required presence of physicians in hospital outpatient clinics

P_o - the effective required presence of physicians in external areas

R - the average number of doctors performing roster duties every day of the week and therefore are absent the next day because of leave after roster duty

w_d - the standardization factor to normalize work capacity observed at the time of the study in the department according to average yearly occupancy.

w_s - the standardization factor to normalize work capacity observed at the time of the study in the operating rooms according to average yearly occupancy.

w_c - the standardization factor to normalize work capacity observed at the time of the study in the outpatient clinics according to the average yearly occupancy.

z_d - the standardization factor to reflect the perceived level of service for the patients at the department area. The factor is neutralized in the model by setting its value at one.

z_c - the standardization factor to reflect the perceived level of service for the patients at outpatient clinics. The factor is neutralized in the model by setting its value at one.

a - the percentage of allowance (personal, fatigue, and unavoidable delays).

e - the percentage of necessary professional absences.

Regression analysis was also used to predict workforce demand in Indian construction projects. The real-estate workforce demand forecasting used regression coefficients to bind the various factors in play. As a result of the research, it was found that construction output was the most sensitive and significant factor in the model (39). In Australia, statistical analysis was used to scrutinise the disaster mental health workforce. State-level data across multiple professions was used as the dataset for the same. The results showed that merely about 40% of service providers were able to provide best practice assistance. The huge gap in the supply resulted in better decision-making in the mental healthcare industry in Australia (40).

2.2.4 Stock-Flow Approaches

Stock and Flow system dynamics models illustrate the workforce as quantifiable stocks which can evolve over time, represented by flows. This kind of model relies on inflow and outflow variables for the stock and uses these values to build a dynamic model around the problem statement. Wilson used the stock-flow approach to describe workforce planning for both supply and demand. This model takes multiple underlying factors into account.

Few of these include employee competition, technology changes, productivity fluctuations, governmental conditions, and societal norms (41). Briscoe and Wilson presented a bunch of employment functions covering nine different industries in the engineering sector in the UK. A stock-flow model built on the basis of co-integrating regressions resulted in a model that explained the past and future trends of employment in various industries. It was also observed that real wage terms and hours worked hugely impacted the forecasts (42). The same authors worked on enhancing their stock-flow model with the construction industry.

Sing, Love and Tam further worked on using a pragmatic stock-flow approach to develop a model for workforce forecasting for construction workers in Hong Kong. The model had inflow and outflow variables which were gathered by conducting a telephone survey that provided reliable output, as compared to a regression-based approach. The primary factors used in the model were trade classification lists, estimates for new entrants, attrition ratio, retirement rate, career progression data, construction workforce numbers working overseas, age-related statistics, and the ratio of general and skilled workers. The designed model produced forecasts for the workforce for the upcoming decade. Additionally, the ageing distribution trends were also derived from the sentiment analysis of the results. However, it was concluded that the accuracy of the proposed model would be highly dependent on the quality of the data collected (43). The authors further worked on an endeavour to improve the proposed model, which had an uncertain performance. A triangulation method was used on the forecasting model, thus enhancing the accuracy and reliability of the model (44).

Fraher, Knapton et al. applied the dynamic stock-flow modelling approach for forecasting the supply of surgeons in the United States. The projection model not only produced overall forecasted numbers but also provided information on the estimates by age, gender and speciality. The model predicted that the surgeon supply will decline by 18% between 2009 and 2028 in all surgeon specialities, except pediatric, colorectal, vascular, and neurological surgery. This model was proven to be highly crucial for the government, healthcare training institutions and professional healthcare associations (45). Crettenden et al. also applied the stock-flow modelling methodology for predicting the healthcare sector workforce in Australia. The sensitivity of the model was analysed with respect to parameters like immigration, reform, and innovation. These insights were used to investigate the future workforce supply and demand. The results showed that the healthcare workforce was not sustainable in satisfying the requirements and needs in the future (46).

2.2.5 Summary of Related Work

Time series models are the most popular class of methods used for forecasting applications. Under this approach, many algorithms are available based on the problem being dealt with. Time series models also consider underlying trends, historical patterns and cycles for future prediction. However, the models can only work well in a limited time frame. As the time frame is extended, the accuracy of the models declines. Another disadvantage is that time series models require a high volume of data to make informed decisions with good performance. The approaches also assume that past trends reflect future systems' behaviour, which may not always be true (16).

The need for historical data could be solved with the use of low-order Markov models. Markov models also have very simple designs, which mostly involve transition matrices with probabilities for each transition instance. However, Markov models are entirely built on several assumptions which are not practical in real-world forecasting applications. One of these assumptions is that the probabilities in the transition matrices stay the same throughout the course of the problem. Another assumption is that all system participants are defined by the same matrices, which is far from reality. Finally, Markov models do not allow the option of feedback in the systems, which is most likely to occur in managed systems (16).

These limitations can be solved by using the Stock-Flow modelling approach. Stock-flow modelling approach is suitable for dynamic managed systems, as it captures the essence of all the factors evolving with time, along with the system they are part of. Stock-flow models do not demand the need for huge volumes of historical data to forecast the feature. This approach's main characteristic is the option of incorporating feedback loops into the managed systems. With simulations in place, stock-flow models also allow the opportunity to manage and control underlying variables in order to observe multiple possibilities of future instances and the respect model behaviour.

2.3 Summary of Chapter

This chapter gives an overview of the related work in the workforce planning domain which was carried out in the past by various researches. The summary section encapsulates the various characteristics of each approach and the reason Stock-Flow modelling was finalised for proceeding with the Nursing workforce project.

3 Methodology

The following chapter describes the entire methodology used in building the Stock-Flow model. The chapter starts with the strategy and approach used in solving the problem. Further, the data collection, architecture design and implementation stages of the project are explained in detail.

3.1 Strategy and Approach

Based on the analysis and review from the previous chapter (Chapter 2), the Stock-Flow approach was finalised for the nursing workforce model. There are different stages in which the model was designed and implemented. These stages are -

1. Analysing all the requirements of the nursing workforce model.
2. Research, analysis and collection of relevant data, tools and features.
3. Architecting the design and implementation of the model.
4. Prototyping and testing the model.
5. Evaluation, results and performance evaluation.

Figure 3.1 depicts the stages mentioned above in a flow diagram.

Once the required research and data were gathered, VensimPLE, which is a simulation software, was used to design and build the model for the nursing workforce. Even the design phase of the model was done in various phases, starting with a basic model, which was further shaped into an advanced model capturing the impact of all the underlying features of the model.

3.2 Requirements of the System

Requirement Specification is a complete description of the behaviour of the system to be developed. It includes the system requirements, which indicate what functions the software should perform, and its overall properties (47). This section contains all the software

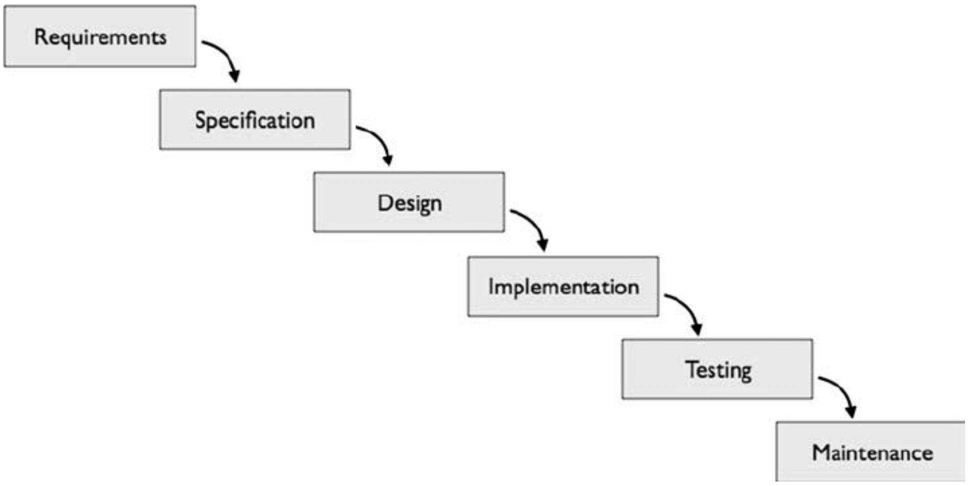


Figure 3.1: Strategy for Designing the Workforce Model

and platform requirements sufficient to design a system to satisfy those conditions, and it also helps to design their test cases to verify them to check whether the system satisfies those requirements or not. It also talks about both the functional and the non-functional requirements for the system to be constructed. The functional requirements describe what exactly the software must do, and the non-functional requirement includes the constraint on the design or implementation of the system. A function is defined as a set of inputs, behaviour, and outputs. A non-functional requirement is something that specifies measures and standards that could be used to judge the function of a system rather than specific behaviours.

3.2.1 Overall Description of the Model

This section describes the general factors which affects system and the requirements. The model developed should be able to analyze data usage, determine patterns, generate periodic reports and ultimately detect anomalies based on the usage patterns. This section also deals with user characteristics, constraints on using the system and dependencies of the system on other applications.

3.2.1.1 Model Perspective and Functions

The model is meant to analyse the flow of the Nursing Workforce using the relevant underlying features and use the input data to forecast the supply of the nursing workforce for the next decade. The functions can be separately defined as shown below:

1. Analyse the relevant features required to define the nursing workforce statistics.
2. Model the trends of each of the extracted features/variables using simulations.
3. Design the forecasting model using the variables mentioned above, which is meant

to forecast the workforce numbers for the next ten years.

4. Use simulations to identify different ways to operate the underlying parameters so that the required demand is satisfied by the forecasting supply model.

3.2.1.2 User Characteristics

The consumers of the system designed are mostly policymakers in the public healthcare sector in Ireland. The users are meant to have two roles as part of the system. The first role is to consume the model for the nursing forecasts for the upcoming years. The second role is to use simulations and attempt to generate various scenarios where different parameters are controlled to analyse the observations. Hence, the users of the system possess both active and passive roles in the system.

3.2.2 Specific System Requirements

This section covers all specifications of the system to that level of detail which is sufficient for the designing of the project. It also outlines performance, functionality and supportability along with the design constraints. The requirements covered in the previous section are not sufficient for understanding the actual requirements needed. The specific requirements are agreed upon by both users and the system designer. The final product is expected to satisfy all the requirements specified in this section.

3.2.2.1 Functional Requirements

The functional requirements of the model include the set of functions that need to be performed by the model in order to primarily satisfy its definition. The requirements include :

- Analysis of the data to extract relevant factors and variables that impact the model most significantly.
- Utilisation of these variables to constitute the stock-flow model, which forecasts the nursing workforce numbers.
- Usage of the stock-flow model to forecast the workforce trends for the next ten years, calculated on a monthly basis.
- Simulation of the model, which allows the user to manage and set changes to the variables in order to observe the behaviour of the system under various conditions.

3.2.2.2 Non-Functional Requirements

These are the requirements that denote the performance of the product. They are used as criteria to evaluate or judge the operation of the system rather than specific behavior and are not directly concerned with the functionalities delivered by the system.

- Efficiency : The system shall perform at best possible efficiency in all scenarios and instances.
- Accuracy : A high accuracy is expected as the stock-flow approach uses pure mathematical modelling of variables. This approach cannot lead to discrepancies unless designed incorrectly.
- Uniformity : The system must perform on all environments uniformly, with no disparities.
- Speed : The system must have a short latency period and must be responsive to all simulations.

3.2.2.3 Software Requirements

The model needs two different platforms for different functionalities:

1. **VensimPLE:** a simulation software for designing the model and running simulations for forecasting the Nursing Workforce
2. **Google Colab:** a platform which provides Python notebooks which is used for plotting the observations from the VensimPLE simulations.

3.3 Data Collection and Feature Extraction

This section focuses on the finalisation of data and relevant features which were fed as input to the Nursing Workforce Stock-flow model.

3.3.1 Data Collection

This section elaborates the dataset consumed and the tools and techniques used in the process of data extraction for the model usage.

3.3.1.1 Dataset

The objective of the project is to build a stock-flow dynamic model for forecasting the nursing workforce in the public health sector in Ireland. The data required to make the model should be pertaining to the objective of the project. Hence, it is clear that data regarding the healthcare sector in Ireland is necessary for being fed as input to the model. Based on this, two primary sources of data were chosen and utilised.

1. **Health Service Executive (HSE):** The HSE is an organisation responsible for the provision of all the public health services in the Republic of Ireland. The organisation has access to all the data regarding public health care services and the personnel recruited to provide these services. This includes the Nursing and Midwifery department, which is referred to as the Office of the Nursery and Midwifery Services Director (ONMSD). Its function is to strategically lead and support nurses and midwives to deliver safe, high-quality, patient-centred care. The HSE publishes monthly reports about the personnel and staff numbers that work as part of the organisation. These monthly reports were used in building the model. The ***Health Service Personnel Census December 2021*** was used for the nursing workforce.

   Figure 3.2 shows the monthly report format from where the data was extracted for the workforce reporting.

2. **Nursing and Midwifery Board of Ireland (NMBI):** The NMBI is another regulatory board for nurses and midwives in Ireland. The nurses in Ireland have to register with this board in order to practice in the country. Hence, all the numbers of registered nurses and midwives can be obtained from this board. The data that is available from NBMI is also categorised into the different types of nurses based on their origin in their practice. For example, the exact number of nurses who joined the system as graduates, immigrants, returnees, and so on.

   Figure 3.3 shows an example of how data reports can be found on NMBI. In this chart, there are monthly numbers of graduates registered as nurses in the respective month in the years 2019 and 2020.

3.3.1.2 Data Extraction

The data required for the model was mostly available as tabular reports on both HSE and NMBI websites. Hence, the data was downloaded in the form of Comma Separated Value (CSV) files. The required values from the reports were extracted with the help of the Python package *numpy* by utilising the *dataframe* tool in the package. These extracted values were loaded as lookups and initial values onto the VensimPLE simulation software.

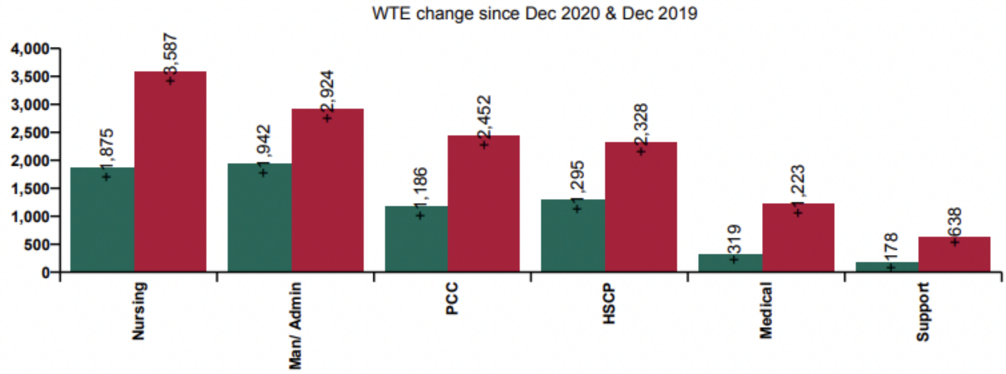
3.3.2 Feature Extraction

In the context of System Dynamics Modelling, feature extraction can be explained as the process of selecting variables and parameters that act as an integral part of the system. The trends observed for each of the variables directly impact the nursing workforce.

Health Service Employment Report: January 2022

Employment by Staff Group

January 2022	WTE Dec 2019	WTE Dec 2020	WTE Dec 2021	WTE Jan 2022	WTE change since Dec 21	WTE change since Dec 20	% change since Dec 20	WTE change since Dec 19	% change since Dec 19	No. Jan 2022
Overall	**119,817**	**126,174**	**132,323**	**132,969**	**+645**	**+6,794**	**+5.4%**	**+13,152**	**+11.0%**	**152,438**
Consultants	3,250	3,458	3,608	3,610	+2	+152	+4.4%	+360	+11.1%	3,951
Registrars	3,679	3,876	4,104	4,121	+16	+245	+6.3%	+441	+12.0%	4,542
SHO/ Interns	3,116	3,594	3,587	3,545	-42	-50	-1.4%	+429	+13.8%	3,915
Medical/ Dental, other	812	833	814	804	-10	-29	-3.5%	-8	-0.9%	1,140
Medical & Dental	**10,857**	**11,762**	**12,113**	**12,080**	**-33**	**+319**	**+2.7%**	**+1,223**	**+11.3%**	**13,548**
Nurse/ Midwife Manager	7,984	8,344	8,852	8,884	+32	+540	+6.5%	+900	+11.3%	9,733
Nurse/ Midwife Specialist & AN/MP	1,996	2,299	2,481	2,499	+18	+200	+8.7%	+503	+25.2%	2,800
Staff Nurse/ Staff Midwife	25,693	26,763	27,850	27,772	-78	+1,009	+3.8%	+2,079	+8.1%	31,820
Public Health Nurse	1,537	1,557	1,523	1,519	-4	-38	-2.4%	-18	-1.2%	1,818
Nursing/ Midwifery Student	644	592	526	774	+248	+183	+30.9%	+130	+20.2%	1,667
Nursing/ Midwifery other	350	362	344	343	-1	-19	-5.3%	-7	-2.0%	391
Nursing & Midwifery	**38,205**	**39,917**	**41,576**	**41,792**	**+215**	**+1,875**	**+4.7%**	**+3,587**	**+9.4%**	**48,229**
Therapy Professions	5,234	5,565	5,947	5,981	+34	+416	+7.5%	+747	+14.3%	6,891
Health Science/ Diagnostics	4,500	4,731	4,918	4,923	+5	+192	+4.1%	+423	+9.4%	5,468
Social Care	2,710	2,909	3,127	3,148	+21	+240	+8.2%	+438	+16.2%	3,640
Social Workers	1,165	1,238	1,296	1,308	+12	+69	+5.6%	+143	+12.3%	1,469
Psychologists	1,004	1,066	1,095	1,095	-0	+29	+2.7%	+91	+9.1%	1,242
Pharmacy	1,038	1,164	1,292	1,287	-4	+124	+10.6%	+249	+24.0%	1,435
H&SC, Other	1,123	1,134	1,324	1,360	+37	+226	+19.9%	+238	+21.2%	1,664
Health & Social Care Professionals	**16,774**	**17,807**	**18,999**	**19,102**	**+103**	**+1,295**	**+7.3%**	**+2,328**	**+13.9%**	**21,809**
Management (VIII & above)	1,842	1,969	2,216	2,253	+37	+283	+14.4%	+411	+22.3%	2,316
Administrative/ Supervisory (V to VII)	5,199	5,821	6,705	6,805	+100	+984	+16.9%	+1,606	+30.9%	7,252
Clerical (III & IV)	11,805	12,038	12,661	12,712	+51	+674	+5.6%	+907	+7.7%	14,509
Management & Administrative	**18,846**	**19,829**	**21,583**	**21,770**	**+188**	**+1,942**	**+9.8%**	**+2,924**	**+15.5%**	**24,077**
Support	8,234	8,676	8,813	8,859	+46	+183	+2.1%	+625	+7.6%	10,237
Maintenance/ Technical	1,182	1,200	1,197	1,195	-2	-5	-0.4%	+13	+1.1%	1,235
General Support	**9,416**	**9,876**	**10,010**	**10,054**	**+44**	**+178**	**+1.8%**	**+638**	**+6.8%**	**11,472**
Health Care Assistants	17,396	18,554	19,326	19,373	+47	+819	+4.4%	+1,976	+11.4%	22,249
Home Help	3,569	3,543	3,546	3,608	+63	+65	+1.8%	+39	+1.1%	5,207
Ambulance Staff	1,828	1,877	1,936	1,926	-9	+49	+2.6%	+99	+5.4%	1,985
Care, other	2,925	3,011	3,234	3,263	+28	+252	+8.4%	+337	+11.5%	3,862
Patient & Client Care	**25,719**	**26,985**	**28,042**	**28,170**	**+128**	**+1,186**	**+4.4%**	**+2,452**	**+9.5%**	**33,303**



Human Resources
Leaders in People Services

Building a Better Health Service

Figure 3.2: HSE Personnel Census Report Example

Hence, this variable selection is the most consequential stage of the design. In the past, while dealing with similar forecasting problems, extensive research was conducted in order

Figure 3.3: NMBI Data on Graduates Registered as Nurses in 2019-20

to pick the right features for the workforce planning model. The parameters shown in Table 3.1 were considered by the engineers in the previously designed stock-flow models. The research and works of these engineers are briefed in the State of the Art (Chapter 2) chapter.

Parameter	**Description**
Age	The age distribution of the workforce
Current Stock of Labour	Current count of workforce
Attitude Rate	Retention rate of the organization
New Entrants	Potential and Recruited New Employees
Promotion Procedure	System in place for promotions within org
Retirement Rate	Annual rate of retirement for employees
Workforce Skill Mix	Different classes of Employees

Table 3.1: Parameters considered for Workforce Planning in the past

Similar to these parameters, the variables for the Stock-Flow model of this project will be considered. The data source of NMBI reports was referred to find relevant parameters for the nursing scenario in Ireland. Based on this data and the numbers from the HSE monthly reports, the following parameters/variables were finalised for the VensimPLE model:

- **Nursing Graduates**: A myriad of students join courses to get trained to serve the public in the healthcare service industry. When they graduate from the courses, these students enter the nursing system in Ireland. These graduate numbers have been analysed on a monthly basis and reported by NMBI. Table 3.2 shows the data for Graduates being part of the system.

Month	**Workforce (in WT)**
January	5.5
February	36.8
March	31.3
April	6.3
May	3.1
June	3.1
July	3.1
August	0.8
September	47.8
October	330.4
November	197.3
December	19.6

Table 3.2: Nursing Graduates Monthly Input Data

From table 3.2, we can observe that the graduate output of nurses joining the system is very high during the last quarter of the year.

- **Immigrant Nurses**: The primary source of new entrants to the system is the immigrants that enter Ireland and attain licenses to practice nursing and midwifery. These immigrants, too, have to register with NMBI to practice legally in the country. Similar to the above parameter, the immigrant data is also calculated annually and documented. Refer to Table 3.3 for the month-wise data of immigrant nurses in Ireland.

- **Returnees**: A percentage of the overall nursing workforce temporarily leaves the national nursing system for just a brief time. These nurses enter back into the system in a couple of months or years. There is a considerable amount of these returnees, as reported by the NMBI. The table 3.4 shows the monthly data for returnee nurses in Ireland.

- **Attrition**: Attrition is referred to as the rate at which an organisation's employee count reduces over time. In the case of the current workforce model, attrition comprises several underlying variables like retired employees, fired employees, employees who quit, employees who migrated to a different country. The attrition rate is provided by NMBI on a quarterly basis, which is represented in Table ()

- **Attrition Returnees**: Attrited employees are calculated for every individual leav-

Month	Workforce (in WT)
January	47.0
February	51.2
March	89.9
April	95.2
May	89.9
June	63.6
July	86.0
August	48.7
September	66.3
October	60.4
November	77.5
December	55.5

Table 3.3: Immigrant Nurses Monthly Input Data

Month	Workforce (in WT)
January	13.9
February	25.4
March	56.4
April	38.6
May	23.7
June	10.1
July	14.6
August	9.0
September	5.2
October	5.9
November	7.3
December	11.5

Table 3.4: Returnee Nurses Monthly Input Data

Quarter	Workforce (in WT)
First Quarter	1.43
Second Quarter	1.15
Third Quarter	2.10
Fourth Quarter	1.82

Table 3.5: Returnee Nurses Monthly Input Data

ing an organisation in the public health sector in Ireland. A percentage of these employees return to the public health sector but join a different organisation. These employees returning to the system must be incorporated into the forecasting model as feedback.

These are the variables chosen to be part of the nursing workforce model, as per NMBI registrations for Ireland's public health services. The modelling and equations for each of these variables will be described in the Design and Implementation section (Section 3.4) of this chapter.

Note: *Whole Time Equivalent (WT) will be used as a unit to measure the nursing workforce for the stock-flow model designed in this project.*

3.4 Design and Implementation

This section of the chapter explains the model designing process and the steps followed while implementing the model in VensimPLE.

3.4.1 Design and Architecture

The nursing workforce stock-flow model can be thought of as continuously evolving with inflow and outflow of workforce WT. In the first stage of design, the model was built to incorporate this fundamental design. Figure 3.4 shows the data flow diagram of the first phase of the model design.

Figure 3.4: Nursing Workforce Model: First Phase Design

From the first phase, it is evident that the primary functionality of the project is achieved in this design, where there is an inflow of workforce and there is an outflow of the workforce. However, the different variables and parameters finalised in the previous stage of the methodology is not taken into account. For accommodating this, a model with higher complexity must be designed, incorporating all variables that were mentioned above. The next phase of design incorporated all the variables - Graduate Nurses, Immigrant Nurses, Returnees, Attrition and Attrition Returnees, all measured in WT. While designing the model, there has to be a differentiation between the inflows and the outflows of the model. The variables Graduate Nurses, Immigrant Nurses, and Returnees classify as the inflows to the model. The Attrition nurses classify as the outflow. However, the Attrition Returnees, arising from the Attrition nurses classify as inflow to the model again. The best design to incorporate this function is the use of a feedback loop.

Figure 3.5 shows the detailed design of the model, which is the second and final stage of the design phase of the model.

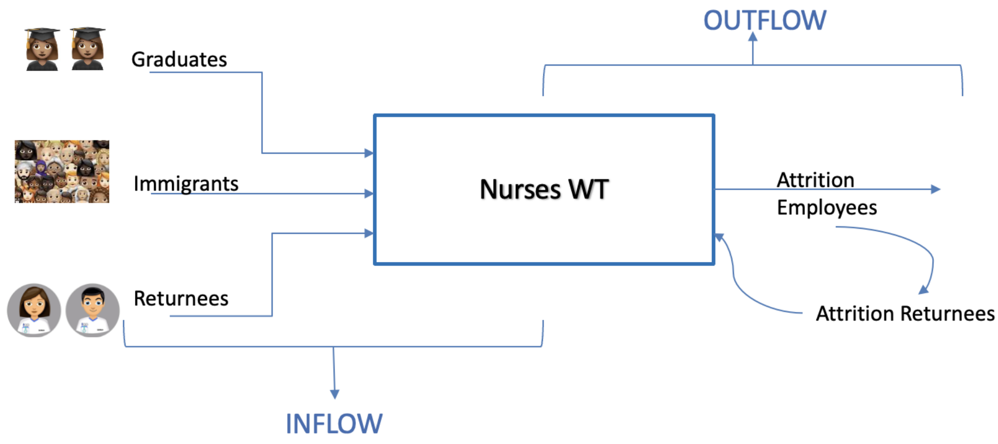


Figure 3.5: Nursing Workforce Model: Final Phase Detailed Design

As you can see in Figure 3.5, the detailed functionality of the model is satisfied in the advanced design presented here. This model has further details to its design for accommodating the simulation parameter valves and lookup data, which will be explained in the implementation sub-section of this section.

3.4.2 Implementation

VensimPLE was used to implement the stock-flow model into a fully functional dynamic simulation model.

3.4.2.1 VensimPLE Know-How

VensimPLE is a simulation software used for System Dynamics Modelling implementations. The fully functional software was released to enhance the performance of real dynamic systems in the real world. The tool helps in conceptualising, simulating, documenting and optimising dynamic systems in a simple yet flexible manner. This can be done by using causal loop diagrams or using stock-flow diagrams. Vensim allows for the use of multiple tools within the software to define various parameters designed as part of the model. Some of the important concepts and terminologies as part of the software are explained below:

1. Auxiliary Variable: These are the kind of variables where the current value does not depend on the previous value, and are represented as absolute values by themselves.
2. Level: Level variables, most commonly referred to as "Stocks" are the ones that accumulate over time, on top of their previously calculated values. These Stocks are

an outcome of some underlying factors, which include auxiliary variables, constants and rates.

3. Rate: Rate, commonly referred to as "Flow", is the speed at which the respective factor changes per unit time. The unit of Time can be set to the suitable option by the model designer. It is represented by a double-lined arrow, which will be shown in the implemented model later in the chapter.

4. : Lookup: These are variables that have a pre-defined set of values, in the form of a graph or a table, with key and value pairs. In this case, based on the key value of the factor, the respective value will be assigned to the lookup variable at hand.

5. Constant: A constant is a variable that has a fixed value assigned to it, which never changes during the course of the model being executed.

6. Arrow: An arrow is used to represent a cause-effect relationship between different variables in the model. This functionality is represented by a single-lined arrow in the software.

7. Function tool: This tool is used to assign equations, initial values, lookups and units to each and every entity of the stock-flow model. The

3.4.2.2 Implementation of Model using VensimPLE

The step-wise implementation of the stock-flow model using VensimPLE will be described in this section. The variables considered, equations assigned to each of them and the data/lookups they are associated with will be depicted in full detail in this section.

The first step of the model involves setting up the Time related features in the model. The following VensimPLE window depicted in Figure 3.6 shows the settings and options used in our model.

From Figure 3.6, we can see that:
Unit used for Time = *Month*
Time Period for Model = *119 - 0 = 119 Months = 10 Years*
Time Step = *1 (denotes the per unit time at which results get saved)*

These settings can be modified using the *Model -> Settings* option in the software.

The next stages of the model design include gathering the underlying features identified in the previous sections. The following methodology depicts setting up each of the variables individually, with the respective data and equations:

Immigrant Nurses: Immigrant nurses that enter the Ireland nursing system, having worked in other countries have a commonly monthly trend which is incorporated as a

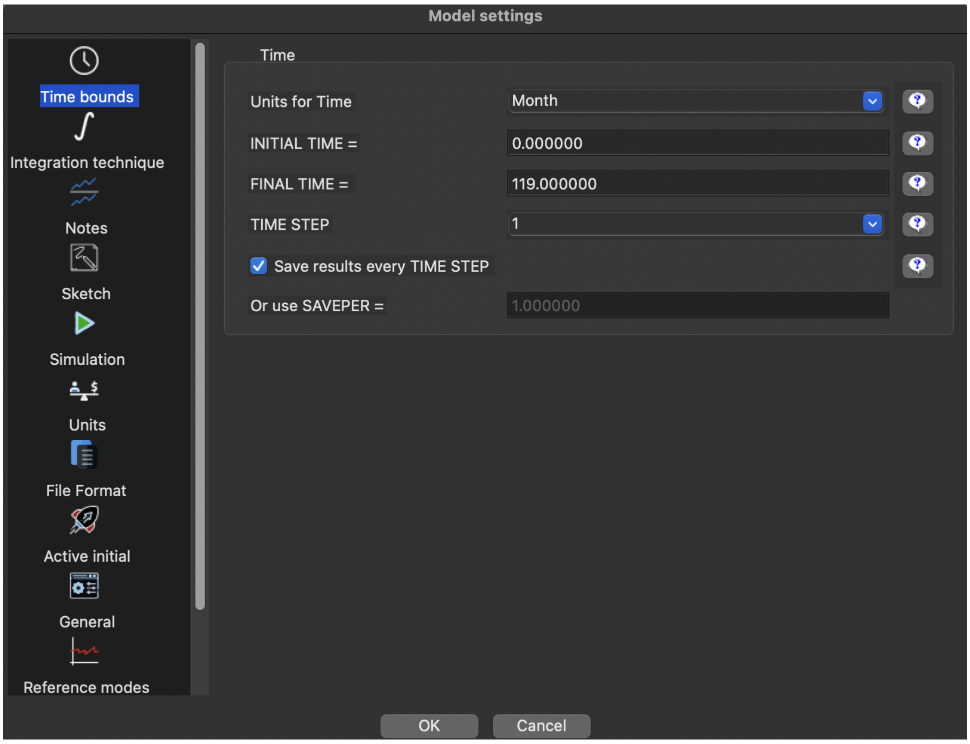


Figure 3.6: Time settings for Nursing Workforce Model

lookup in the model. While designing the model, it is necessary to keep track of the current Time (in Month) that the model is experiencing, the lookup data for immigrant nurses, and the rate at which this monthly data varies annually. Refer Figure 3.7 to see the design for the immigrant nursing variable, which is part of the inflow for Nursing Workforce WT.

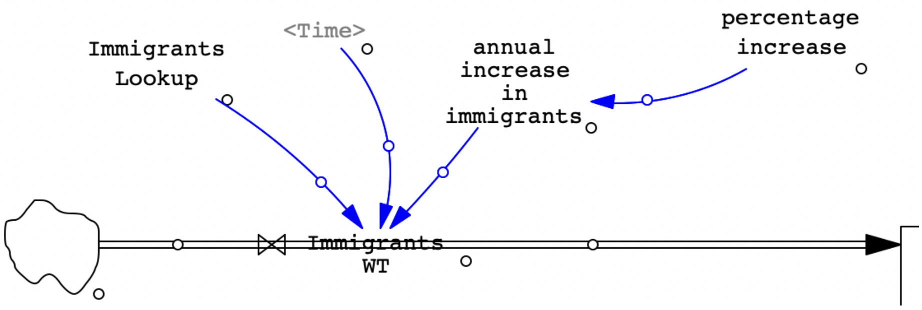


Figure 3.7: Nursing Workforce Model: Immigrant Nurses

Figure 3.7 shows all the above mentioned underlying variables required to define the *Immigrants WT* rate feature. The *Immigrants Lookup* is used to store the monthly lookup values provided by the dataset. The *<Time>* variable is a shadow variable that is used to evaluate the current Time value when evaluation the *Immigrants WT* feature. The *percentage increase* auxiliary variable denotes the variable used to provide a range of values between 10% to 40%. This value defines the amount by which the *Immigrants Lookup* value increases to at the end of ten years. In order to accommodate an annual increase in the Immigrant Nurses number, which is more practical for the model, the auxiliary variable *annual increase in immigrants* is defined, in order to calculate the annual percentage increase according the overall percentage increase and the year.

The set of equations and data representing each of the variables described above are:

Immigrants Lookup = [(0,0)-(86,100)],(0,47),(1,51.2),(2,89.9),(3,95.2),(4,89.9),(5,63.6),(6,86),(7,48.7),(8,66.3),(9,60.4),(10,77.5),(11,55.5)

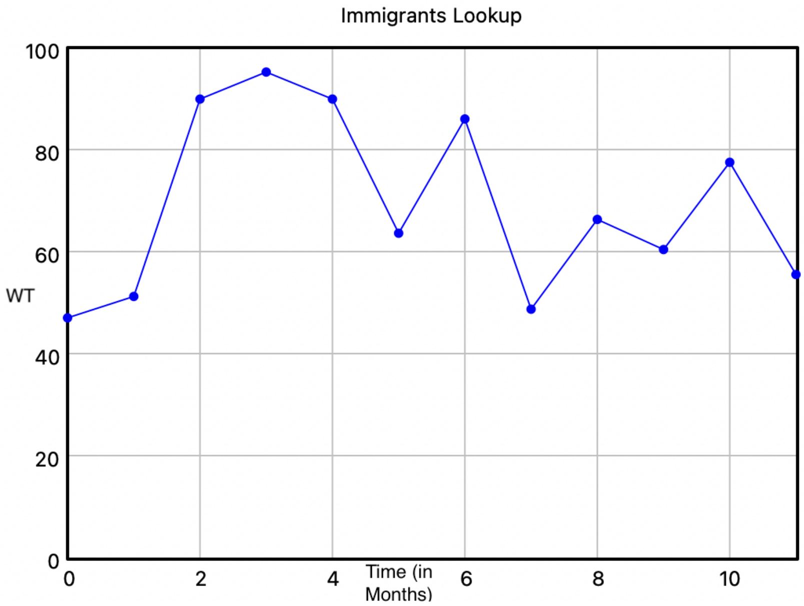


Figure 3.8: Immigrants Lookup Graph

Figure 3.8 shows the lookup in terms of a graph trend.

percentage increase = 5 (this value can be set between 10 and 40 during simulation)
*annual increase in immigrants = (POWER((1 + percentage increase/100), 1/9) * 100) - 100*

*Immigrants WT = Immigrants Lookup(MODULO(Time, 12)) * POWER(1 + annual increase in immigrants/100, INTEGER(Time/12))*

Further on the above equations, the *annual increase in immigrants* equation is calculated using the given formula because of the ten year time period considered. The formula was computed based on this note. In the *Immigrants WT* equation, we calculate the value based on the Lookup variable which is represented as a function of Time, and from incorporating the annual increase in immigrants.

To show the impact of *percentage increase* and *annual increase in immigrants* variables, refer to graph in Figure 3.9 which shows the trend of Immigrants WT, considering the overall increase to be 30%.

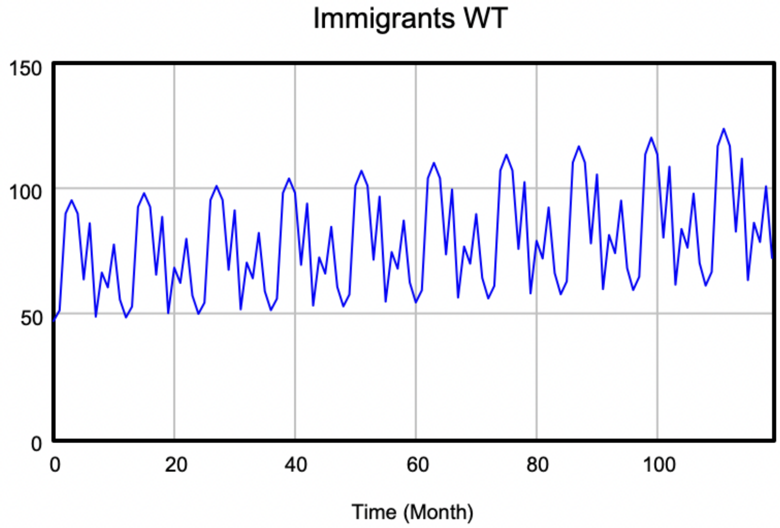


Figure 3.9: Immigrants WT Incremental Graph

Graduate Nurses: Graduate nurses that join the nursing system after graduating from their degree or course. The data provided by NMBI is also incorporated as a lookup in the model. While designing the model, it is necessary to keep track of the current Time (in Month) that the model is experiencing, the lookup data for graduate nurses, and the rate at which this monthly data varies annually. Refer Figure 3.10 to see the design for the graduate nursing variable, which is part of the inflow for Nursing Workforce WT.

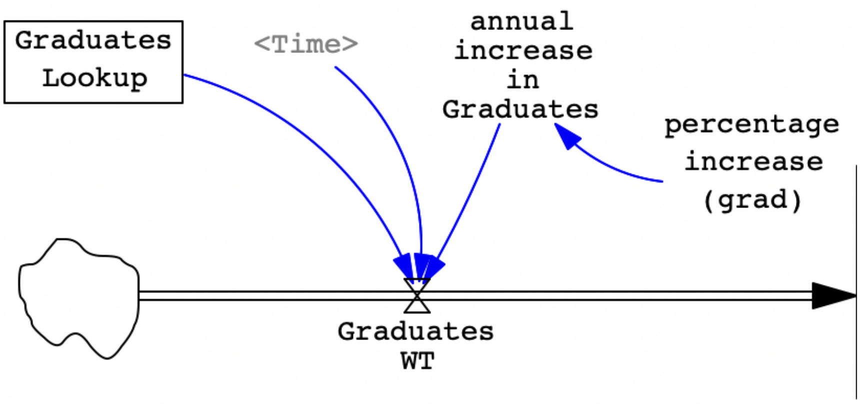


Figure 3.10: Nursing Workforce Model: Graduate Nurses

Figure 3.10 shows all the above mentioned underlying variables required to define the *Graduates WT* rate feature. The *Graduates Lookup* is used to store the monthly lookup values provided by the dataset. The *<Time>* variable is a shadow variable that is used to evaluate the current Time value when evaluation the *Graduates WT* feature. The *percentage increase (grad)* auxiliary variable denotes the variable used to provide a range of values between 10% to 40%. This value defines the amount by which the *Graduates Lookup* value increases to at the end of ten years. In order to accommodate an annual increase in the Graduates Nurses number, which is more practical for the model, the auxiliary variable *annual increase in Graduates* is defined, in order to calculate the annual percentage increase according the overall percentage increase and the year.

The set of equations and data representing each of the variables described above are:

Graduates Lookup = [(0,0)-(11,400)],(0,5.5),(1,36.8),(2,31.3),(3,6.3),(4,3.1),(5,3.1),(6,3.1),(7,0.8),(8,47.8),(9,330.4),(10,197.3),(11,19.6)

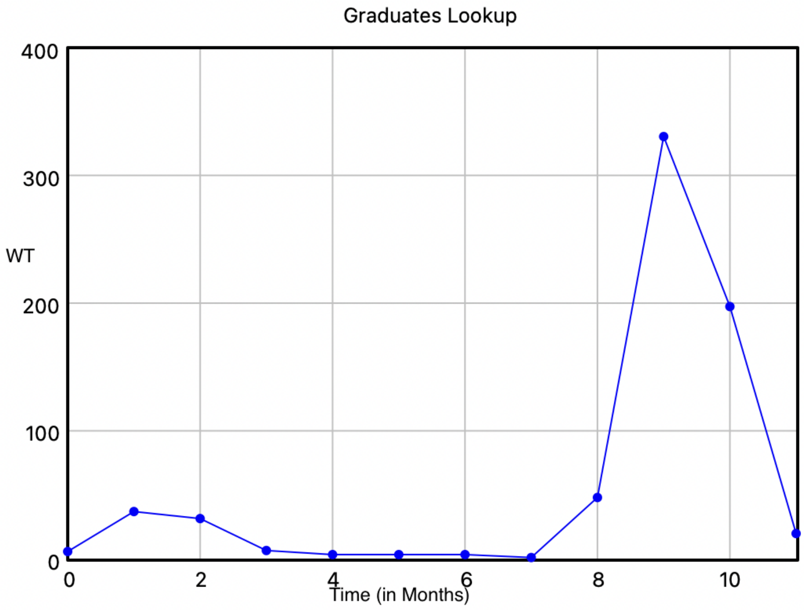


Figure 3.11: Graduates Lookup Graph

Figure 3.11 shows the lookup in terms of a graph trend.

percentage increase (grad) = 5 (this value can be set between 10 and 40 during simulation) *annual increase in Graduates = (POWER((1 + percentage increase (grad)/100), 1/9) * 100) - 100*

*Graduates WT = Graduates Lookup(MODULO(Time, 12)) * POWER(1 + annual increase in Graduates/100, INTEGER(Time/12))*

Further on the above equations, the *annual increase in Graduates* equation is calculated using the given formula because of the ten year time period considered. The formula was computed based on this note. In the *Graduates WT* equation, we calculate the value based on the Lookup variable which is represented as a function of Time, and from incorporating the annual increase in graduates.

To show the impact of *percentage increase (grad)* and *annual increase in Graduates* variables, refer to graph in Figure 3.9 which shows the trend of Graduates WT, considering the overall increase to be 30%.

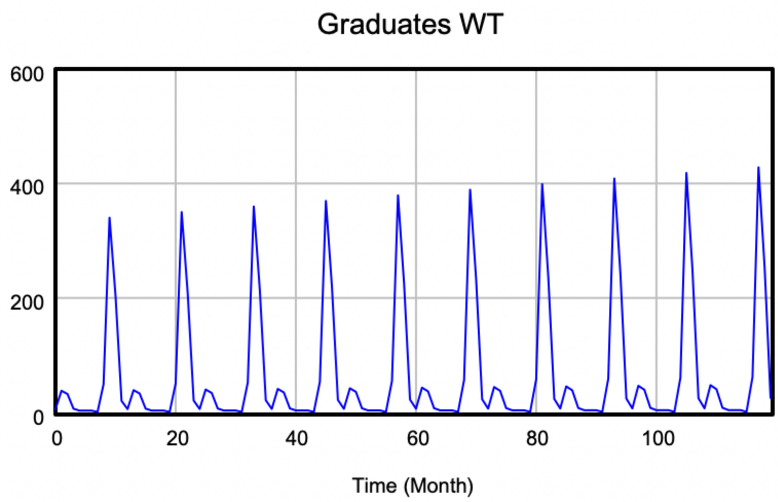


Figure 3.12: Graduates WT Incremental Graph

Returnee Nurses: Returnees to the nursing system, after a brief or long break, are also incorporated as a lookup in the model. While designing the model, it is necessary to keep track of the current Time (in Month) that the model is experiencing, the lookup data for returnees, and the rate at which this monthly data varies annually. Refer Figure 3.13 to see the design for the returnees variable, which is part of the inflow for Nursing Workforce WT.

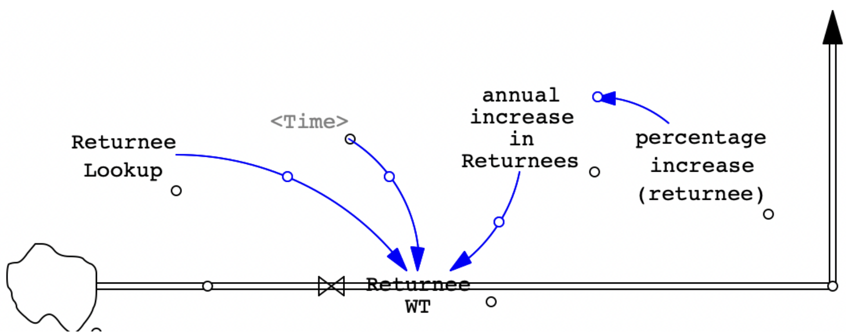


Figure 3.13: Nursing Workforce Model: Returnees

Figure 3.13 shows all the above mentioned underlying variables required to define the *Returnees WT* rate feature. The *Returnee Lookup* is used to store the monthly lookup values provided by the dataset. The *<Time>* variable is a shadow variable that is used to evaluate the current Time value when evaluation the *Returnees WT* feature. The *percentage increase (returnee)* auxiliary variable denotes the variable used to provide a range of values between 10% to 40%. This value defines the amount by which the *Returnee Lookup* value increases to at the end of ten years. In order to accommodate an annual increase in the Returnee Nurses number, which is more practical for the model, the auxiliary variable *annual increase in Returnees* is defined, in order to calculate the annual percentage increase according the overall percentage increase and the year.

The set of equations and data representing each of the variables described above are:

Returnee Lookup = [(0,0)-(11,60)],(0,13.9),(1,25.4),(2,56.4),(3,38.6),(4,23.7),(5,10.1), (6,14.6),(7,9),(8,5.2),(9,5.9),(10,7.3),(11,11.5)

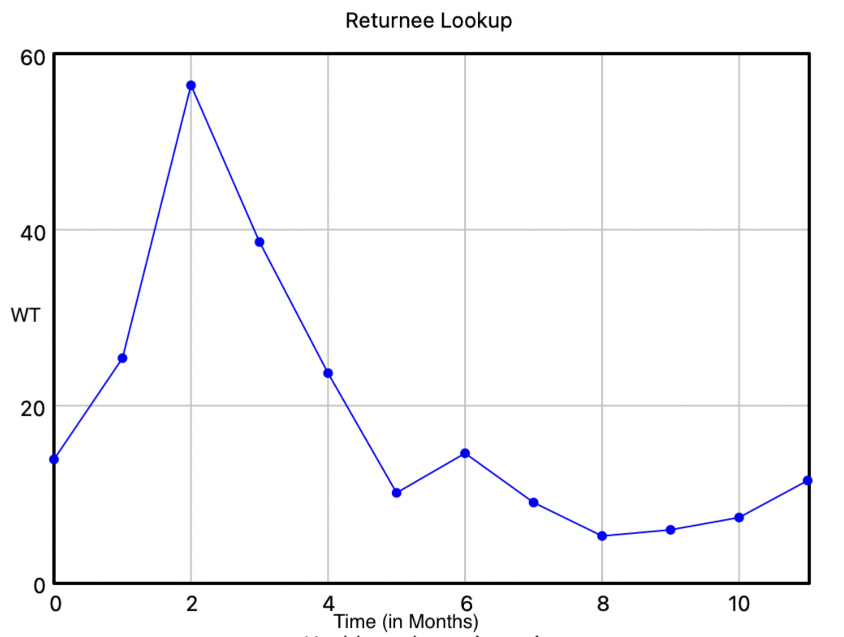


Figure 3.14: Returnees Lookup Graph

Figure 3.14 shows the lookup in terms of a graph trend.

percentage increase (returnee) = 5 (this value can be set between 10 and 40 during simulation) *annual increase in Returnees = (POWER((1 + percentage increase (returnee)/100), 1/9) * 100) - 100*

*Returnees WT = Returnee Lookup(MODULO(Time, 12)) * POWER(1 + annual increase in Returnees/100, INTEGER(Time/12))*

Further on the above equations, the *annual increase in Returnees* equation is calculated using the given formula because of the ten year time period considered. The formula was computed based on this note. In the *Returnees WT* equation, we calculate the value based on the Lookup variable which is represented as a function of Time, and from incorporating the annual increase in returnees.

To show the impact of *percentage increase (returnee)* and *annual increase in Returnees* variables, refer to graph in Figure 3.15 which shows the trend of Returnees WT, considering the overall increase to be 30%.

Attrition and Attrition Returnees: While all the previously designed features constitute the inflow of the Nursing Workforce WT model, Attrition is responsible for the outflow function of the model. *Attrition* data is provided on a quarterly basis which

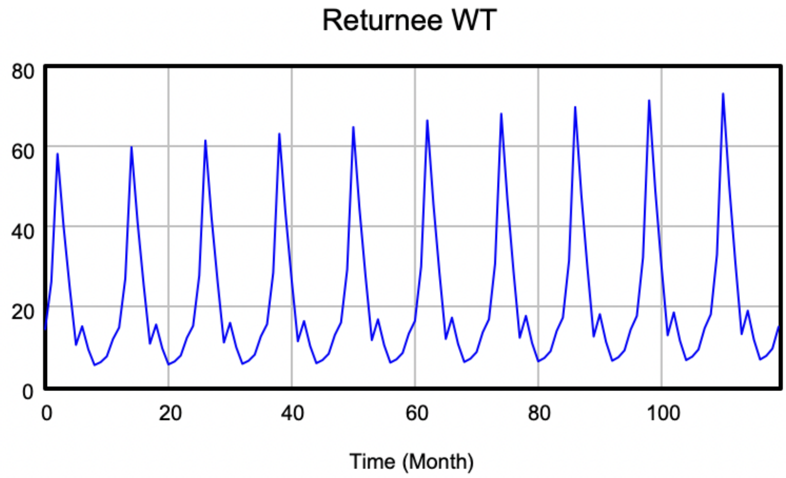


Figure 3.15: Returnees WT Incremental Graph

was shown in the data collection section. *attrition rate* provides the rate at which attrition occurs, based on which quarter of the year it is. The *attrition rate lookup* variable is used to set quarterly lookup data for attrition.

Another variable, *Attrition Returnees* is crucial for the model. This parameter refers to a portion of nursing WTs that were part of *Attrition*, but joined back the public health sector in Ireland, which is represented by *Attrition Returnees*. The*attrition returnee rate* depicts the change in the returnee return rate on an annual basis.

Figure 3.16 depicts the modelling of *Attrition* and *Attrition Returnees* of the model.

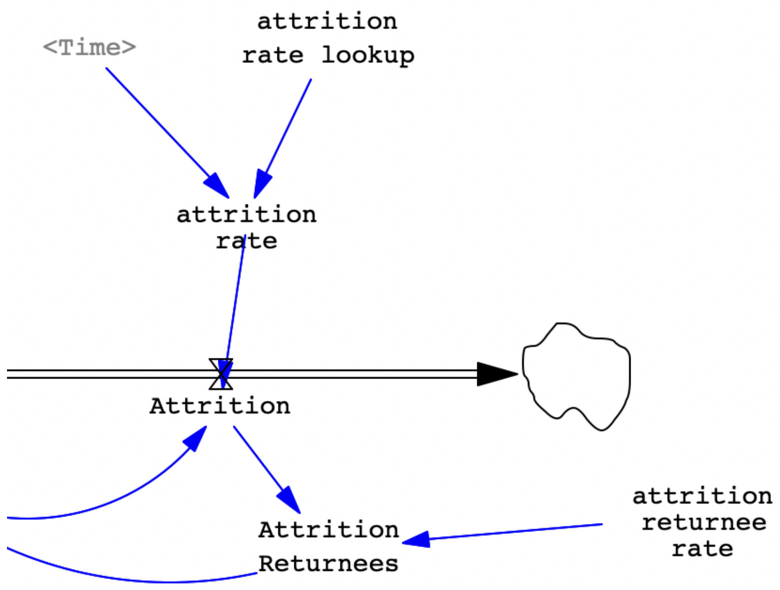


Figure 3.16: Attrition and Attrition Returnees Modelling

The equations for each entity which is part of this section of the model is shown below:

attrition rate lookup = [(0,0)-(11,10)],(0,1.43),(1,1.43),(2,1.43),(3,1.15),(4,1.15),(5,1.15),(6,2.1),(7,2.1),(8,2.1),(9,1.82),(10,1.82),(11,1.82)

attrition rate = attrition rate lookup(MODULO(Time, 12))

*Attrition = Nurses WT * attrition rate/100*

attrition return rate = 50 (this value can be set between 40 and 60 during simulation)

*Attrition Returnees = Attrition * attrition returnee rate/100*

The equations for all the features are now defined according to their functionality assigned. Now, the final model with all the components which lead to the calculation of ***Nursing Workforce WT*** can be designed and computed.

The final implementation of the fully functional Nursing Workforce Stock-Flow model is shown in Figure 3.17

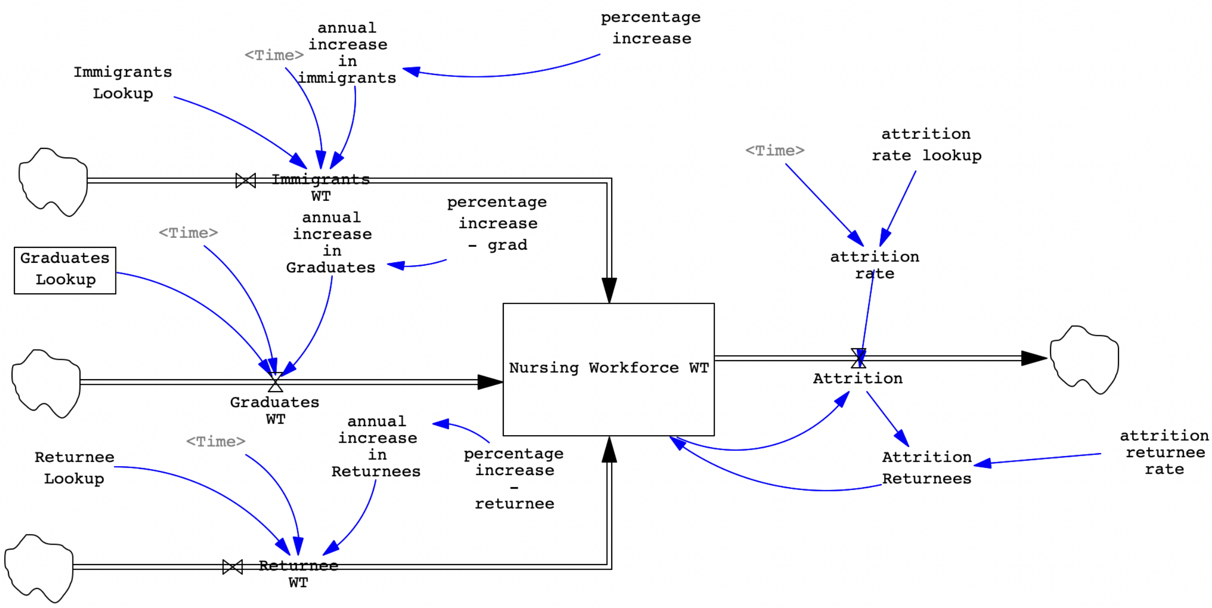


Figure 3.17: Nursing Workforce Stock-Flow Model

The final Nursing Workforce equation that was assigned was :

Nursing Workforce WT = (Graduates WT + Immigrants WT + Returnee WT) (Attrition) + (Attrition Returnees)

Initial Value of Nursing Workforce WT = 30380

Thus, the designed model is implemented using VensimPLE software. The inflows and outflows of the managed system were successfully integrated with the main stock i.e., *Nursing Workforce WT*. All the features are incorporated in the form of *rates* or *flows*. The simulations of the model will be depicted in detail in the upcoming chapter named Evaluation and Results.

3.5 Summary

The specific requirements and constraints that must be kept in mind while building the model have been detailed in this chapter. These include the software requirements, functional requirements and nonfunctional requirements for stock-flow modelling. Also, this chapter cites the various assumptions being made by the developer of the system for the dynamic managed system model. All these have to be managed while building and running the system.

4 Testing, Evaluation and Results

This chapter is focused on the evaluation of the stock-flow model designed to forecast the Nursing Workforce WT supply. The chapter is divided into different sections for testing, evaluation and the results obtained from the model simulations.

4.1 Testing

As mentioned above, the testing process is a crucial step in order to make sure that the workforce model is in place to produce the results required.

4.1.1 Unit Testing of Modules

Unit testing refers to the testing of each of the module of the model separately. The functionality of the chosen module is tested for errors and exceptions. The unit testing of each of the modules is carried out using the *"Check Syntax"* option in the *"Function"* tool on the Menu Bar in VensimPLE.

Figure 4.1 shows an example for the using this checker for Immigrants module using the Function tool. The option provided helps check if the equations of the module are correctly assigned, and if all the required parameters are included in the equation of the module. The result *"Equation OK"* shows that the module has been validated.

The upcoming sub-sections show the design of the test case, and the result achieved for each of the modules.

4.1.1.1 Immigrants Module

The unit test case design and the outcome of the unit testing is represented in the form of a table for each of the modules. Table 4.1 shows the unit testing details for Immigrants Module in the stock-flow managed system.

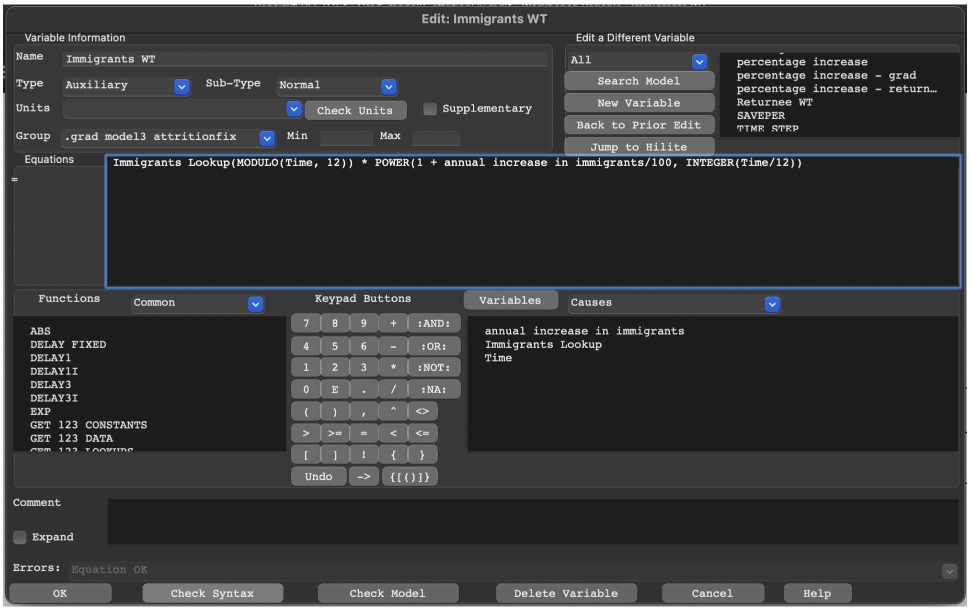


Figure 4.1: Unit Testing: Check Syntax Tool

Name of Test Case	Immigrants Module
Feature Being Tested	Rate of Immigrants WT tested for correct equation and output
Sample Input	Immigrants Lookup, <Time>, annual increase in immigrants
Expected Output	Equation OK, Expected forecasts for Immigrants WT
Actual Output	Equation OK, Matching forecasts for Immigrants WT
Testing Remarks	Test Successful

Table 4.1: Unit Testing of Immigrants Module

4.1.1.2 Graduates Module

Table 4.2 shows the unit testing details for Graduates Module in the stock-flow managed system.

Name of Test Case	Graduates Module
Feature Being Tested	Rate of Graduates WT tested for correct equation and output
Sample Input	Graduates Lookup, <Time>, annual increase in Graduates
Expected Output	Equation OK, Expected forecasts for Immigrants WT
Actual Output	Equation OK, Matching forecasts for Immigrants WT
Testing Remarks	Test Successful

Table 4.2: Unit Testing of Graduates Module

4.1.1.3 Returnees Module

Table 4.3 shows the unit testing details for Returnees Module in the stock-flow managed system.

Name of Test Case	Returnees Module
Feature Being Tested	Rate of Returnees WT tested for correct equation and output
Sample Input	Returnee Lookup, <Time>, annual increase in Returnees
Expected Output	Equation OK, Expected forecasts for Returnees WT
Actual Output	Equation OK, Matching forecasts for Returnees WT
Testing Remarks	Test Successful

Table 4.3: Unit Testing of Returnees Module

4.1.1.4 Attrition Module

Table 4.4 shows the unit testing details for Attrition outflow module in the stock-flow managed system.

Name of Test Case	Attrition Module
Feature Being Tested	Attrition workforce exiting the system
Sample Input	attrition rate
Expected Output	Equation OK
Actual Output	Equation OK
Testing Remarks	Test Successful

Table 4.4: Unit Testing of Attrition Module

4.1.1.5 Attrition Returnee Module

Table 4.5 shows the unit testing details for Attrition Returnee module in the stock-flow managed system.

Name of Test Case	Attrition Returnee Module
Feature Being Tested	Attrition workforce joining back the system
Sample Input	Attrition
Expected Output	Equation OK
Actual Output	Equation OK
Testing Remarks	Test Successful

Table 4.5: Unit Testing of Attrition Returnee Module

4.1.1.6 Nursing Workforce Stock Module

The final module to test is the Nursing Workforce Stock module, which comprises of both the inflows and outflows of the model, and is the fundamental module responsible for forecasting. Refer Table 4.6 for details on the unit testing for this module.

All the unit tests performed on each of the modules produced successful results, Hence, the further phase of integration testing was performed following this stage.

Name of Test Case	Nursing Workforce Stock Module
Feature Being Tested	Stock of Nursing Workforce WT that forecasts supply
Sample Input	Immigrants WT, Graduates WT, Returnees WT, Attrition, Attrition Returnees, Nursing Workforce WT
Expected Output	Equation OK, Expected forecasts
Actual Output	Equation OK, Matched forecasts
Testing Remarks	Test Successful

Table 4.6: Unit Testing of Nursing Workforce Stock Module

4.1.2 Integration Testing

The integration testing is performed with the use of the *"Check Model"* tool, as part of the *"Model"* tab in the VensimPLE window. Figures ?? and 4.3 show the tool and the result window if the integration test of the model is successful.

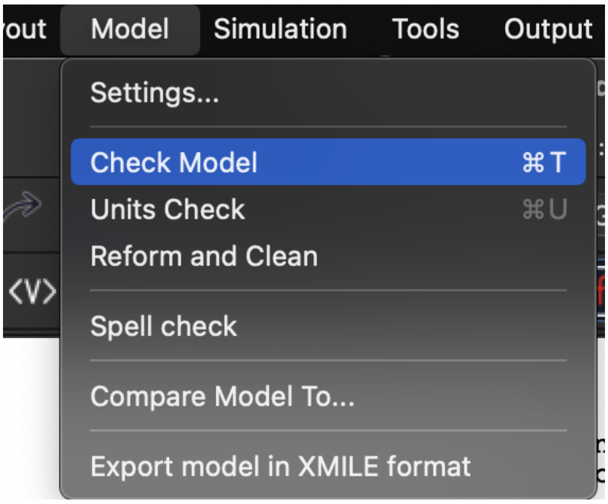


Figure 4.2: Check Model Tool

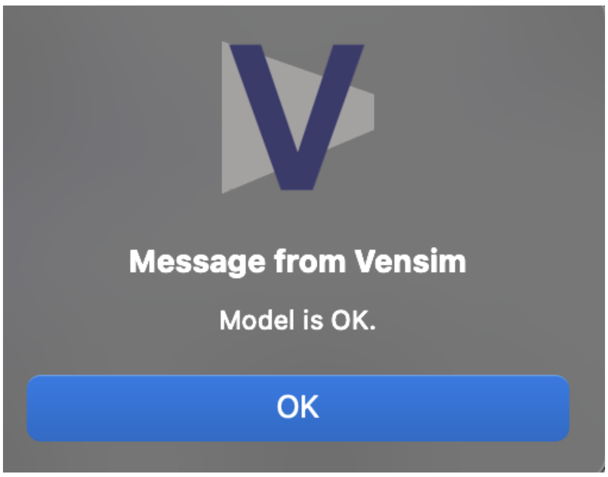


Figure 4.3: Model Validated Message

These tools are used to validate the entire model to e fully operational for forecasting the nursing workforce.

4.2 Evaluation

This sections shows the metrics and methods used to evaluate the performance of the model. The simulations available in VensimPLE are used to perform the evaluations. **Sensitivity Analysis** is performed using simulations observations for various scenarios designed. Sensitivity analysis refers to the process of determining the impact of underlying variables in a model on the target variable, based on the conditions applied in the simulation.

Figure 4.4 shows the full stock-flow model along with the simulation options for the various controllable variables in the model. Simulated results for range of values for all inflow and outflow parameters, and observations are plotted for the results section which will be described later.

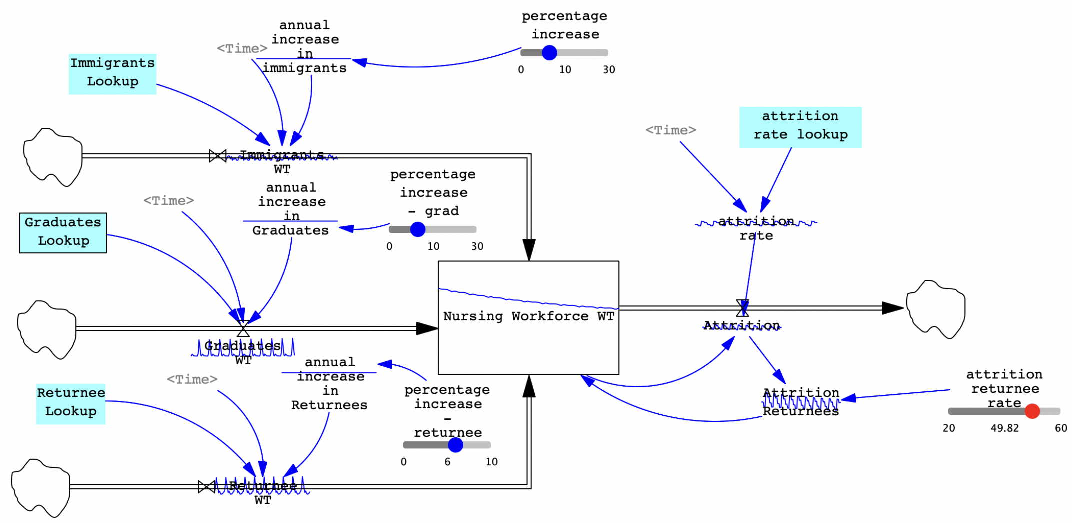


Figure 4.4: Simulation Example for Nursing Workforce Model

The scroll bar for the percentage change variables indicates the options for different simulations. The results will be depicted in the next section(Section 4.3) of the chapter.

4.3 Results

As mentioned above, the results were generated using simulations such that, the different parameters are adjusted to analyse the outcome on the forecasting numbers of nursing workforce. As seen in the simulation model in the previous section, the variables that can be experimented with most are graduates, immigrants, attrition and attrition returnees.

Based on the feasibility of adjusting these parameters in real life, the following experiments were conducted and the associated results were displayed.

- **Increase the Graduates WT numbers, keeping Returnees WT and Immigrants WT at a constant rate** From the policymakers perspective, the feasibility of controlling and managing the Graduates and Immigrants parameters, over time, is more feasible. Hence the returnees rate increase is kept constant at a rate of 1% over the ten years, and the other two inflow values are varied over simulations. Figure 4.5 shows the tabular values of the Nursing Workforce WT forecasts, annually for the considered period of ten years, when Returnee percentage change is set at 1%.

Time (Month)	0	12	24	36	48	60	72	84	96	108	119
Nurses WT : Immigrants=10% increase, Graduat	30380	31149.7	31925.3	32706.7	33493.7	34286.2	35084.1	35887.1	36695.2	37508.1	38332.7
Nurses WT : Immigrants=10% increase, Graduat	30380	31143.9	31908.1	32672.7	33437.7	34203	34968.8	35735	36501.6	37268.6	38043.8
Nurses WT : Immigrants=10% increase, Graduat	30380	31137.7	31889.7	32636.3	33377.6	34113.9	34845.3	35572	36294.2	37012.1	37734.5
Nurses WT : Immigrants=10% increase, Graduat	30380	31127.4	31859.4	32576.2	33278.6	33966.9	34641.7	35303.4	35952.4	36589.2	37224.5
Nurses WT : Immigrants=20% increase, Graduat	30380	31149.7	31937.6	32743.5	33567.3	34408.6	35267.3	36143.2	37036.1	37945.9	38872.4
Nurses WT : Immigrants=20% increase, Graduat	30380	31143.9	31920.4	32709.5	33511.2	34325.4	35152	35991	36842.5	37706.4	38583.6
Nurses WT : Immigrants=20% increase, Graduat	30380	31137.7	31902	32673.1	33451.1	34236.2	35028.5	35828.1	36635.2	37449.9	38274.2
Nurses WT : Immigrants=20% increase, Graduat	30380	31137.7	31889.7	32636.3	33377.6	34113.9	34845.3	35572	36294.2	37012.1	37734.5
Nurses WT : Immigrants=30% increase, Graduat	30380	31149.7	31945.1	32766.1	33612.6	34484.6	35382.1	36305	37253.3	38227.2	39221.9
Nurses WT : Immigrants=30% increase, Graduat	30380	31143.9	31927.9	32732.1	33556.5	34401.4	35266.8	36152.8	37059.7	37987.7	38933.1
Nurses WT : Immigrants=30% increase, Graduat	30380	31137.7	31909.5	32695.6	33496.5	34312.3	35143.3	35989.9	36852.4	37731.2	38623.7
Nurses WT : Immigrants=30% increase, Graduat	30380	31131	31889.6	32656.4	33431.8	34216.3	35010.3	35814.4	36629.1	37454.9	38290.6
Nurses WT : Immigrants=40% increase, Graduat	30380	31149.7	31952	32787.2	33655.4	34556.9	35491.9	36460.6	37463.6	38501.1	39564.3
Nurses WT : Immigrants=40% increase, Graduat	30380	31143.9	31934.8	32753.2	33599.4	34473.7	35376.5	36308.5	37270	38261.6	39275.5
Nurses WT : Immigrants=40% increase, Graduat	30380	31137.7	31916.4	32716.8	33539.3	34384.5	35253.1	36145.6	37062.7	38005.1	38966.1
Nurses WT : Immigrants=40% increase, Graduat	30380	31127.4	31886.1	32656.8	33440.3	34237.6	35049.5	35876.9	36720.9	37582.2	38456.2

Figure 4.5: Nursing Workforce WT Forecast

Figure 4.6 shows the graphs plotted of the Nursing Workforce WT, when returnees is constant at 1% increase rate, Immigrants at 10% increase rate, but varying Graduates percentage increase between 10% and 40%.

From Figure 4.6, we can observe that the forecasts of the nursing workforce increase, with the increase in the percentage change of the Graduate workforce lookup data. This is expected behaviour. A more subtle detail is to realise that with time, the gap between the workforce numbers increases which implies that the impact of the percentage increase in Graduates WT on the Nursing Workforce WT, is sort of exponential in nature.

- **Increase the Immigrants WT numbers, keeping Returnees WT and Graduates WT at a constant rate** Figure 4.7 shows the graphs plotted of the Nursing Workforce WT, when returnees is constant at 1% increase rate, Graduates at 10% increase rate, but varying Immigrants percentage increase between 10% and 40%.

  From Figure 4.7, we can observe that the forecasts of the nursing workforce increase, with the increase in the percentage change of the Immigrants workforce lookup data. This is expected behaviour. Similar to the previous scenario, with time, the gap between the workforce numbers increases which implies that the impact of the percentage increase in Immigrants WT on the Nursing Workforce WT, is sort of

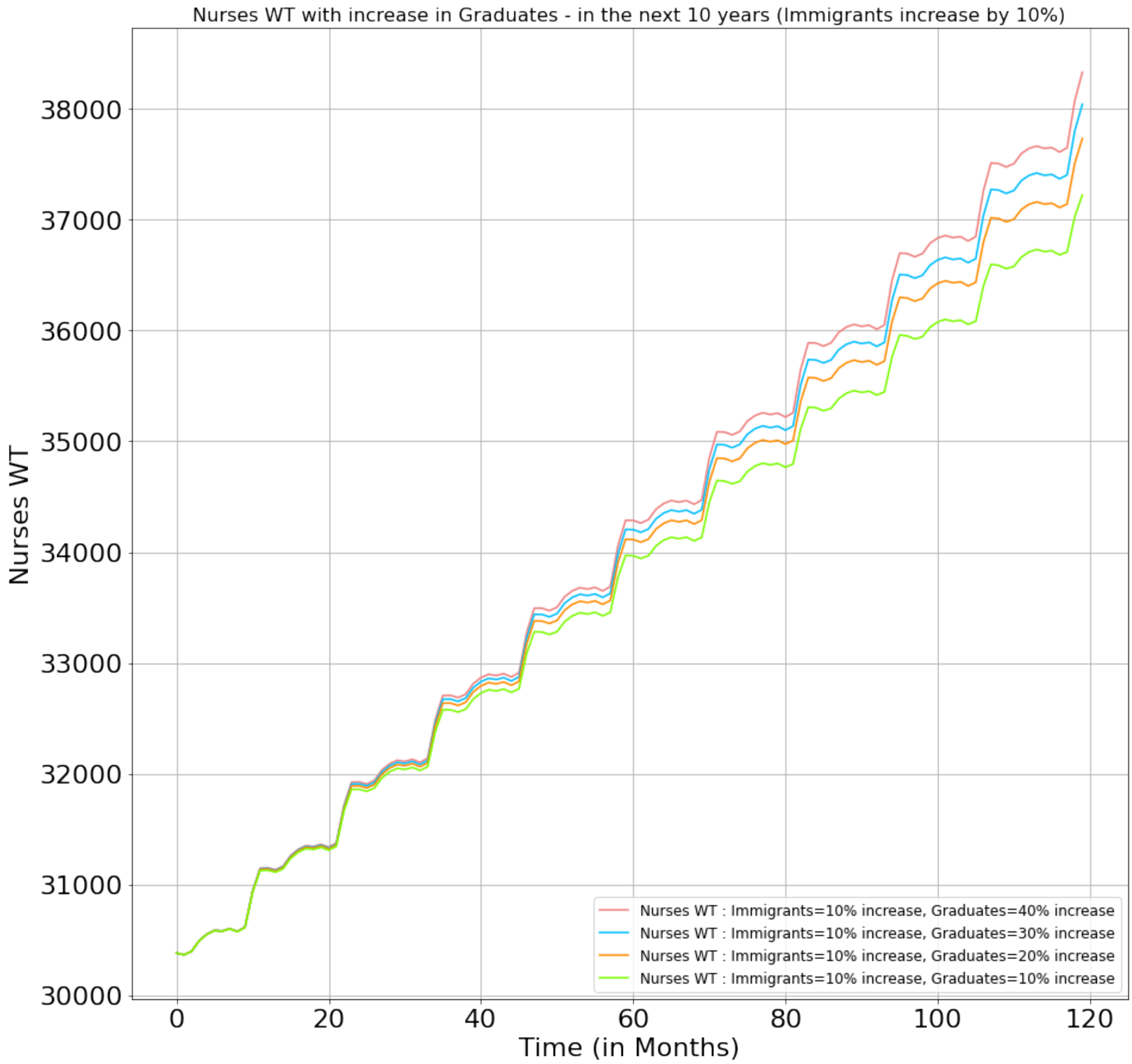


Figure 4.6: Nursing Workforce Plot: Varying Graduates WT annually

exponential in nature.

- **Increasing both Graduates WT and Immigrants WT, with Returnees WT at a constant rate** Figure 4.8 shows a similar plot, but varying both immigrants and graduates by the same range, over eight different scenarios. The Returnees change percentage is again set at 1% over the decade.

  Figure 4.8 has an interesting observation, apart from the fundamental ones listed in the previous two scenarios. When we increase both the Graduates WT and Immigrants WT by a range of percentage values, we can see that the resultant forecasts are almost overlapping, which means that there is similar outcome.

  However, the fascinating result can be observed by comparing two lines in the plot: (1) Dark Blue plot with Immigrants percentage increase = 30%, Graduates

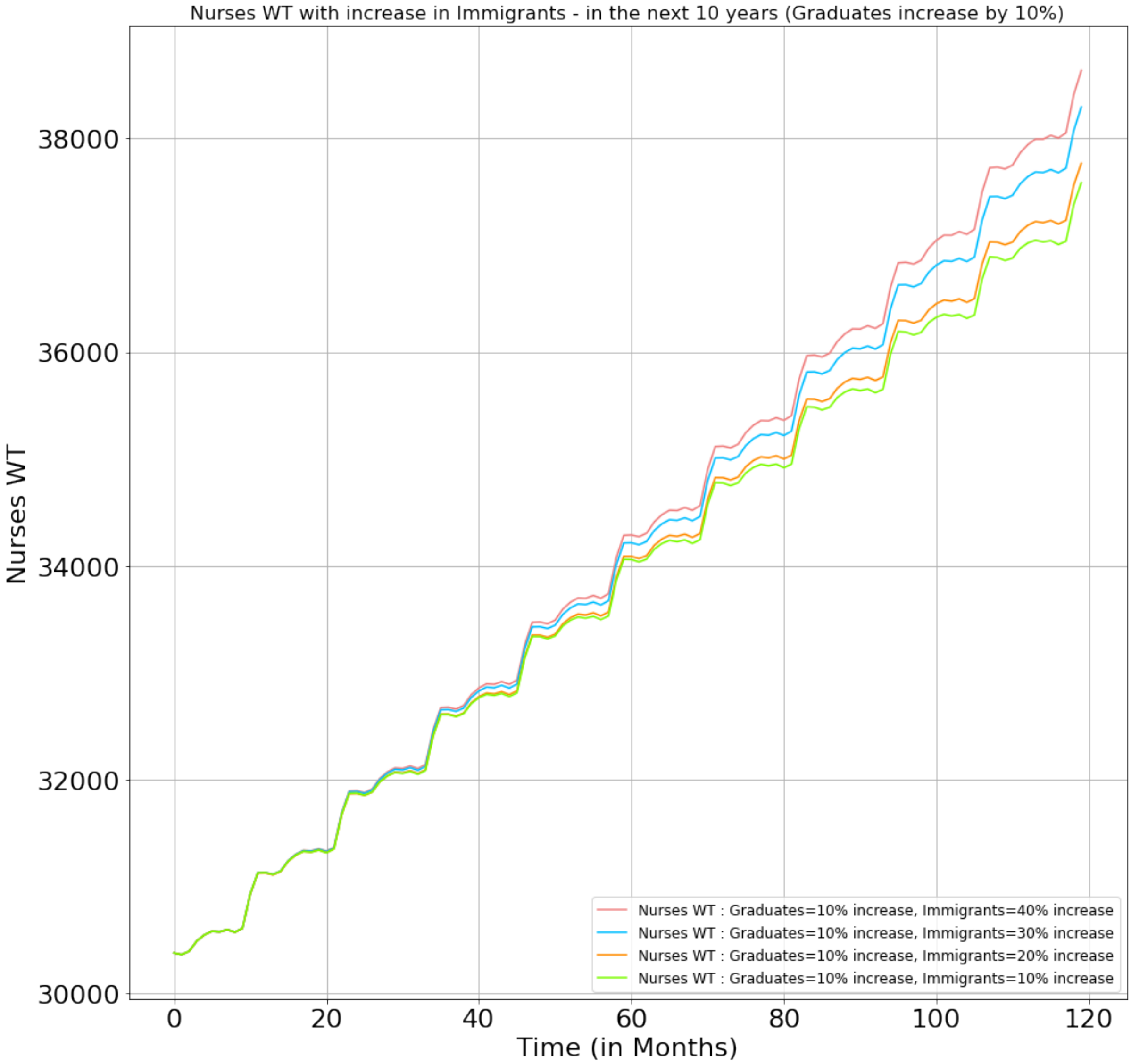


Figure 4.7: Nursing Workforce Plot: Varying Immigrants WT annually

percentage increase = 30% and (2) Coral Pink plot with Immigrants percentage increase = 20%, Graduates percentage increase = 40%. By comparing these two plot lines, we can see that the blue line is forecasting higher numbers over time as compared to the coral pink plot line, even though the Graduates WT percentage increase is higher than the former. This implies that he impact of Immigrants WT feature is stronger than the impact of the Graduates WT feature, on the Nursing Workforce WT forecasts.

- **Reducing Attrition Rate** Figure 4.9 shows the plot with the impact of decreasing the annual attrition rate is brought down to 4.5% by 6.5%, on the Nursing Workforce WT forecasts.

Figure 4.9 shows that percentage decrease in annual Attrition rate by even 2% can make a huge positive impact on the Nursing Workforce WT. These results will be

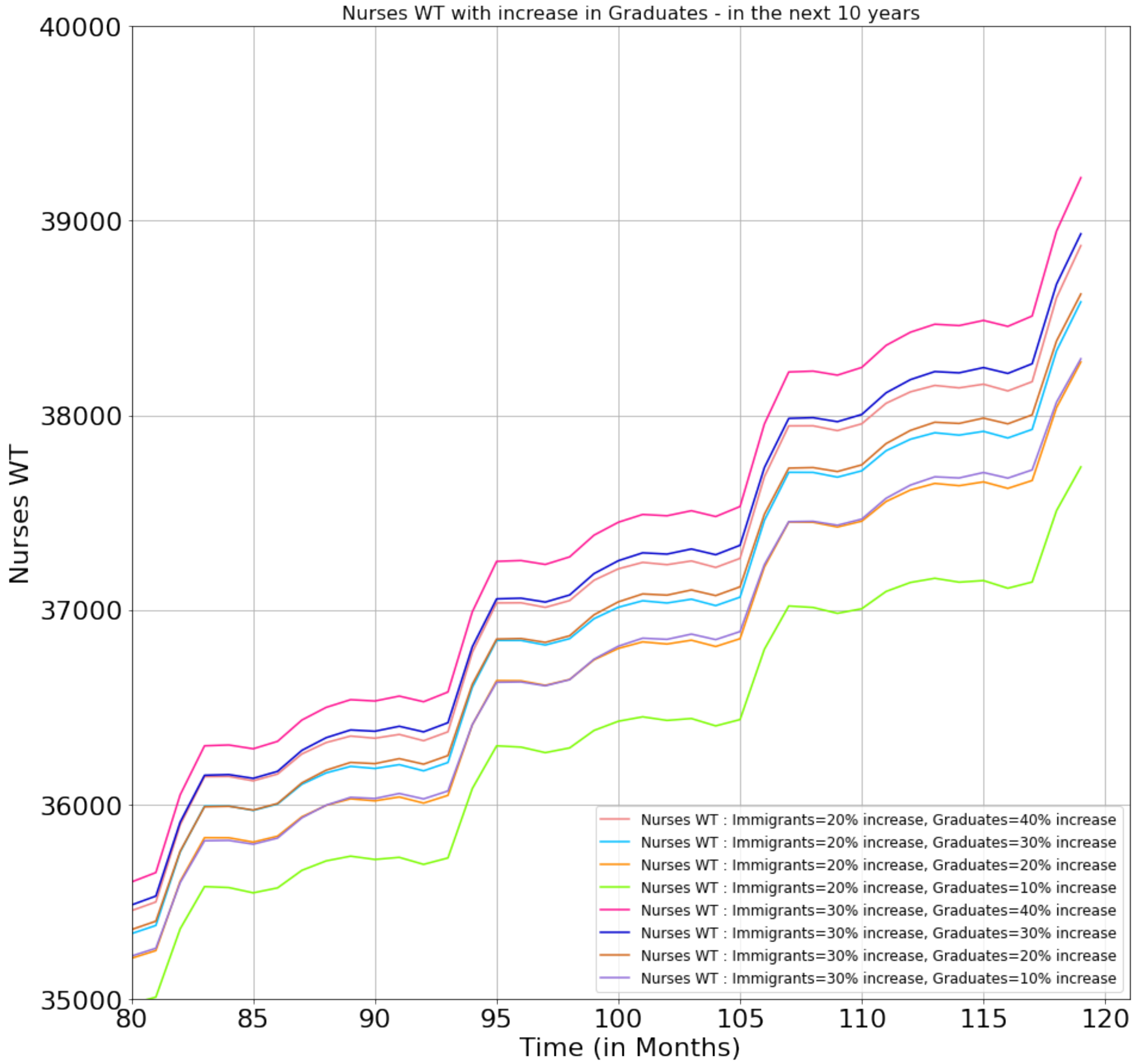


Figure 4.8: Nursing Workforce Plot: Varying Graduates WT and Immigrants WT annually

further explained in the Conclusions chapter (Chapter 5).

4.4 Summary

This chapter wraps up the final stage of the model, which primarily involves testing the model and computing the results of the model. The various evaluation techniques and the observations capture were listed and plotted, along with meaningful insights for the same.

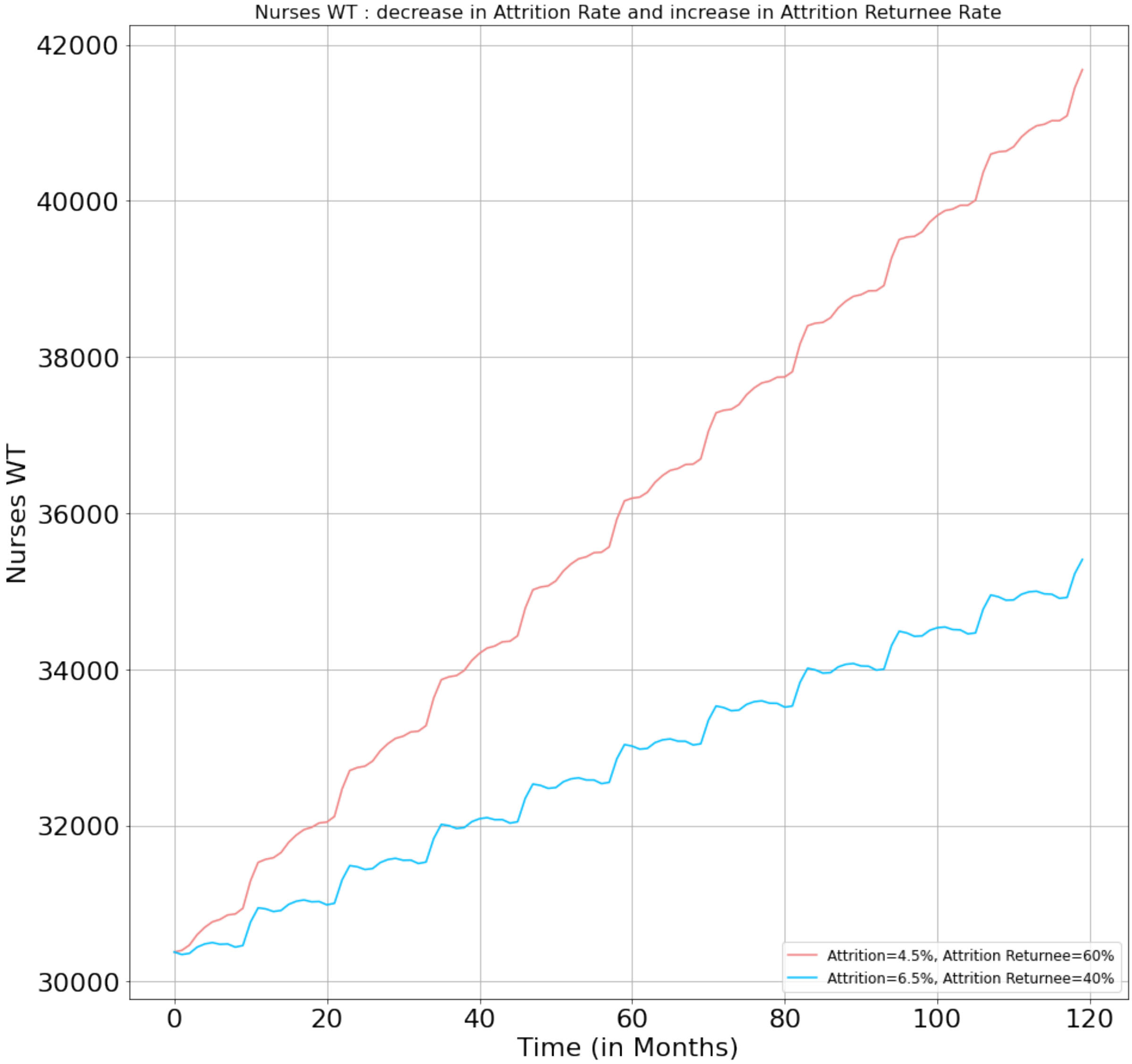


Figure 4.9: Nursing Workforce Plot: Decreasing Annual Attrition Rate

5 Conclusion and Future Work

5.1 Conclusion

The objective of the project was to build a model to forecast the supply of Nursing Workforce in the public healthcare sector in Ireland. Based on comprehensive research performed on various approaches for solving the problem statement, the stock-flow modelling methodology was finalised. This preference is justified as the behaviour of the managed system that was to be designed significantly resembled the concept and procedure required for System Dynamics Modelling.VensimPLE software was used to implement the same, with underlying features of Graduate nurses, Immigrant Nurses, Returnees, Attrition employees and Attrition returnees. The implemented VensimPLE model gives a holistic overview of the projection of the Nursing Workforce in the next decade. A simulation model was designed so as to allow the opportunity for policymakers to experiment with various possible scenarios to match the future nursing supply with the growing demand in the upcoming years.

When the forecasts were generated using simulations from VensimPLE, various insights were gathered about the underlying features of the model. From the observations and results, it was evident that increasing the *Graduates WT* numbers by 40% over the next ten years could improve the supply of *Nursing workforce WT* by 26.17%. Further, increasing the *Immigrant Nursing WT* by 20% over the next decade could improve the *Nursing WT* numbers by 24.21%. Additionally, reducing the *Attrition rate* by a meagre 2% and increasing *Attrition Returnee rate* by around 10% can instantly shoot up the nursing workforce supply by 37.19%. These insights are greatly valuable for policymakers in the healthcare domain to make crucial decisions that could change the course of the nursing workforce in the upcoming years. For example, in order to increase attrition returnee rate, appropriate incentives and benefits can be provided for employees. Therefore, the objective of reducing the on-demand requirement for the healthcare workforce can be reduced with the help of the forecasting model and suitable experimentation.

The stock-flow modelling approach has proven to be highly advantageous because of the presence of simulations and feedback loops, using which managed systems can be defined most precisely. However, there are some limitations of the project at this stage. The model does not consider the impact of maternity leave activity and temporary workforce statistics. Currently, these factors are considered to be an internal problem dealt with by individual organisations. However, the incorporation of these factors into the model would enhance the accuracy further. Another limitation is the restricted capability of testing the model using multiple simulations at one go. The VensimPLE software permits only a limited amount of datasets to be loaded simultaneously, thus confining the comparison degree among various simulations.

5.2 Challenges Faced and Solutions Employed

During the course of the entire process, there were several challenges faced and the respective solutions employed to solve the same, will be discussed in this section.

1. The system demanded usage of the "Time bias" feature of the VensimPLE software, which was not available in the VensimPLE version. This model allowed the usage of monthly lookups in an annual model, which is the exact design of the nursing workforce forecasting model.

2. VensimPLE has a limitation of loading only a limited number of datasets from the simulations generated, which restricts the ability to plot all the simulations together using the VensimPLE visualisations.

3. Testing and Validation – The model currently uses manual simulation and the "Model Check" tool in VensimPLE, which may not be sufficient enough to do a thorough integration testing of the whole system.

The solutions adapted to overcome these challenges were:

1. Utilisation of shadow variables for representing "Time", which was combined with the Vensim equations to provide the same effect as the "Time bias" feature.

2. The data generated as part of the simulations were collected and stored as CSV files, which were extracted by a Python file to produce *matplotlib* visualisations.

3. Proposed solution in future – A future fix to this challenge would be to integrate the VensimPLE model with Monte-Carlo simulations. This will lead to the generation of a higher range of simulations, and hence increase the reliability of the observations.

5.3 Future Work

The nursing workforce model designed is fully operational and satisfies all the objectives intended to satisfy. However, there is scope for improvement in the design, approach, and performance of the model. This can be achieved as part of the future work for the project. Immediate future enhancements include the incorporation of finer features into the model. These include temporary workforce and maternity leave-related features in the dynamic system. Another refinement would be to research and extract monthly attrition data instead of quarterly to enhance the performance of the model. There could also be more observations and plots generated to achieve a better understanding of the behaviour of the model.

Multiple long-term advancements can be achieved to better the forecasting model. The testing phase of the model can be intensified by integrating the implementation with Monte-Carlo simulations to allow the generation of numerous test simulations and their comparison with each other. Another level of upgrading can be attained by having a model for forecasting the demand of the workforce. The two models can be combined to produce a comprehensive workforce planning system. The use of neural networks along with simulation models to predict the different rates and flows of the underlying factors could be a great addition to the existing model.

5.4 Summary

The final chapter of the dissertation which gives an overview of the entire project, in terms of approach used and results achieved. The chapter also describes the challenges faced during the course of the project, along with respective solutions employed to address these challenges. The final section of the chapter dives into the possible work that could be done in the future, to enhance the model even further.

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A1 Appendix

A1.1 Appendix numbering

1. HSE Dataset: https://www.hse.ie/eng/staff/resources/our-workforce/workforce-reporting/