DYNAMIC SIMULATION OF HEALTHCARE MANPOWER SYSTEMS: A MARKET-BASED PERSPECTIVE

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\textbf{ABSTRACT}
Health manpower supply decisions are highly critical in every growing society. In times of growing healthcare needs, the dynamics of the healthcare job market creates challenges for many training institutions when formulating policy structures for training and supply of healthcare professionals. Dynamic interactions between variables, time lags, and feedback effects need a cautious consideration in healthcare manpower planning. Poor policy structures have negative impacts, such as over- or under-investment in training capacity build-up which ultimately leads to unwanted imbalances in the labour market. A cautious approach is required when selecting the right information feedbacks that can assist in designing manpower policy structures. In this paper, we develop a system dynamics approach that utilizes a select set of indices which reflect trends in the labour market. The model demonstrates the dynamic influence between college recruitment, training, supply and demand in a causal loop form. Dynamic what-if analyses further expose the effects of modifying key policy parameters in a typical healthcare manpower system. Thus, strategic policies for manpower supply decisions can be developed and evaluated. The system dynamics model is a potential decision support tool to assist policy makers in formulating healthcare manpower decisions.

\textbf{KEY WORDS}
System dynamics; manpower systems; manpower planning; policy evaluation;

\section{1. Introduction}

Effective and timely supply of suitable health manpower is critical to every society for equitable provision of health services. Service delivery, in terms of cost, quality, and quantity, depends to a great extent on the effective deployment and use of personnel [1, 2].

The demand for the skilled manpower in the health sector has become so dynamic due to ever-growing healthcare needs. As such, unpredictable demand shocks in the labour market are inevitable. Consequently, maintaining a balance between manpower supply and demand is a challenging but crucial task. Under uncertain demand situations, policy makers have to adopt a cautious approach towards supply capacity building, for which tapping the right information at the right time becomes vital for ensuring reliability in manpower demand-supply planning.

The dynamics of the labour market creates many challenges to policy makers in training institutions when formulating policy structures for training and supply of human capital. Higher learning institutions are required to cope with uncertainties in manpower needs in the labour market [3]. Business sectors often lose critical human capital when trained employees leave for other sectors due to various reasons [4]. On the other hand, the supply of human capital by the training institutions cannot be instant due to training delay. Thus, college enrolment and training policies have to be adjusted in response to labour market status. In addition, policy makers need to consider the supply of foreign talent from the global market, subject to inherent time delays. System dynamics simulation is a potential tool in capturing the dynamic influence between enrolment, training, supply and demand from a systems perspective. By conducting time-based dynamic analysis, manpower policies can be evaluated, thus contributing to the policy scenario building and improvement on a continual basis. In this study, we anticipate that system dynamics modelling formalism [5] can serve as an effective aid for medium to long term manpower policy formulation. System dynamics is chosen for its capability to represent both information and physical flows, together with their respective delays, from an information feedback control perspective. In this respect, the identification of key information flows that provide the best handle for supply capacity adjustments is crucial.

In view of the above issues, the purpose of this paper is to develop a system dynamics model for health manpower systems. In particular, the objectives of this research are:

(i) to select a set of market-based indices that influence manpower supply dynamics;
(ii) to develop a systems dynamics model that simulates dynamics of health manpower; and
(iii) to carry out a what-if analysis by varying time-based and structural policy parameters

In this research, two real-world manpower demand patterns are assumed: (i) steady demand, with negligible growth, and (ii) steadily growing demand, often found in growing knowledge-based economies.

The rest of the paper is structured as follows. In Section 2, a review of relevant literature is given. Section
3 provides a dynamic model for health manpower dynamics involving interactive policy parameters. Simulation experiments and results are presented in Section 4. Finally, section 5 concludes this research.

2. Literature review

Adverse impacts of supply-demand imbalances of health professionals have been widely reported [2, 6]. Manpower imbalances in the health labour market have led to health crises in societies, sudden wage fluctuations, and leakages of skilled manpower into unintended destinations.

The earliest manpower planning model is the manpower requirements approach that seeks to prescribe an optimal match between supply and demand [7]. It is an open-loop strategy that relates planned economic growth forecast to the output of training institutions. Extant manpower forecasting models at industry level include steel manufacturing industry [8], health care [2], and construction industry [9]. However, these approaches lack consideration of dynamic forces involving technological and productivity changes, wage changes and skills leakages.

Markov chain models have been applied in flow analysis of students and manpower. For instance, Shah and Burke [10] described in matrix notation a Markov chain model for investigating flows of an education system. The model provides a means for projecting the number of student graduates and dropouts. Other Markov chain applications at corporate level planning exist in literature [11, 12]. However, these models concentrate on the supply side of manpower planning.

From an economic stand point, several models explain the adequacy of manpower and the associated effect on economic development based on labour market and growth models. Toutkoushian [6] stresses that policy structure in the education market influences manpower supply and demand behaviour, which ultimately affects the variation of employment levels and wages in the labour markets. Employment and wage levels are determined by a combination of two forces: the demand for and the supply of workers.

A few artificial intelligence approaches have been employed in literature. For instance, Choudhury et al. [13] presented a model for forecasting engineering manpower using fuzzy associative memory neural networks. The main setbacks of earlier approaches is that they lack consideration of dynamic factors, time lags, delays, feedback effects, as well as wages and skills leakages in the labour market.

2.1 Manpower dynamics

Institutions of higher learning have long been viewed as unresponsive to human capital needs. Toutkoushian [3] showed that due to inaccuracy and unavailability of useful data, decision makers cannot design policies that would enable institutions to quickly respond to labour market needs. The substantial training delay required for college students to enter their professions creates an implementation lag by which time other market priorities may have emerged. Also, due to manpower leakage into unintended destinations, there is no foolproof way of mapping educational output to specific professions.

Castley [14] emphasised the need to consider a policy-focused approach to manpower planning. In the same token, Adams et al. [7] suggested a market-based manpower planning based on labour market signals arguing that labour market trends can provide a practical guide to strategic manpower policy formulation. Traditional forecasting approaches, such as the manpower requirements model, have since been widely criticised for their inaccuracies [15]; they fail to consider dynamic labour market forces involving wages, skills substitution and foreign talent inflows. Hafeez and Abdelmeguid [4] proposed a dynamic model to illustrate the dynamic relationship between recruitment, training, and skills at firm level. Park et al. [16] presented a system dynamics model for IT security manpower, arguing that system dynamics can offer various alternatives to achieve a stable labour market. In summary, health manpower systems are complex due to,

- dynamic unpredictable demand shocks;
- time lags and feedbacks;
- elastic foreign talent supply; and,
- shortage and inaccuracy of relevant data

In the presence of the above-mentioned complexities, dynamic simulation methods may provide better approaches to policy design and evaluation for manpower supply decisions.

2.3 Systems dynamics models

System Dynamics (SD) is a computer-aided approach, based on information feedback and delays, for simulating and analysing complex problems with a focus on policy analysis and design. Invented by Jay Forrester [17], system dynamics essentially consists of causal loop and/or stock flow diagrams. A causal loop diagram depicts causal hypothesis of a system in an aggregate form, while a flow diagram represents the system flow structure to facilitate mathematical modelling. Stock variables depict the state of the system, while flow variables describe the rates of change of the stocks. Mathematically, the net flow determines the rate of change of stocks represented thus;

\[
\frac{d}{dt} \text{(stock)} = \text{inflow}(t) - \text{outflow}(t)
\]

where \( \text{inflow}(t) \) and \( \text{outflow}(t) \) are the inflow and outflow values at time \( t \).

SD has been applied to a wide range of problems such as corporate planning and policy design, supply chain management, public management and policy evaluation, economic behaviour, and healthcare modelling [5, 18]. The application of SD in manpower systems has been
very limited. For instance SD models have been used to analyse personnel policy issues affecting training army personnel [19, 20]. Park, et al. [16] presented a dynamic manpower forecasting model specifically for local information security industry. The model emphasises on integrated dynamics of demand and supply, feedback, delay, and flexible saturation point. Though there is increased awareness of the dynamic aspects in manpower demand-supply planning, little attention has been given to use of market trends and global talent flows.

In view of the complexities prevalent in health manpower systems, the SD approach is a potential tool for a more effective policy-focused manpower planning, for varying values of time-based and structural policy parameters. We assume that the dynamic behaviour of a health manpower system is influenced by its entire structure, policies and traditions. Therefore, an SD-based approach can be useful for investigating the interactive influence of education and employment policies and labour market feedbacks.

3. System dynamics model

In this section, we outline the system dynamics model to support the health manpower planning to meet the projected demand for health manpower. The aim is to enhance formulation of manpower supply policies by utilising system dynamics formalism to represent the information and physical flows in a health manpower system. The model seeks to answer what-if analysis questions through structural modifications with variations in the assumptions and the parameters used in the model. In this study, we consider a health manpower system under two types of manpower demand; (i) a steady manpower demand; and (ii) a steadily growing demand with an S-pattern. The system considers manpower flows involving training, leakage of trained manpower, natural attrition, and foreign talent supply. We assume that the potential supply of student cohorts and foreign talent are large. Also, we assume that leakage of manpower into unintended professions is influenced by the labour market status defined in terms of labour market indices.

3.1 System dynamics model development

The model approach uses influence diagrams to represent relationships describing the dynamics of a health manpower system. Current education/training needs are adjusted in proportion to the labour market information in a feedback loop path. Thus, the actual manpower supply and the training performance are managed by the introduction of the feedback loop. The future training needs are represented as a function of labour market indices which reflect the current stocks of employment, unemployment and vacancies. A positive demand-supply gap due to unfilled vacancies triggers manpower inflow from supply sources, that is, local unemployed and foreign talent. Sufficient supply suppresses immediate demand.

It is useful to describe the individual building blocks of the dynamic simulation model. For ease of understanding of the model logic, only major highlights of the building blocks will be presented. In this connection, the major stock variables are;

**Notations**

- \( C \) Student/trainee cohorts
- \( U \) Unemployment (unemployed local talent)
- \( E \) Employment (employed local talent)
- \( F \) Employed foreign talent
- \( V \) Vacancies

### 3.1.1 Education and training dynamics

The training sub-model captures the flow of students under training in healthcare in anticipation of meeting demand for health manpower in the labour market. Consequently, the proposed model primarily relies on feedback information from market trends in form of (i) vacancy ratio \( v \), (ii) unemployment ratio \( u \), and (iii) relative demand, \( R \). The vacancy and the unemployment ratios determine the desired admission \( DA \), and the admission capacity \( C \). Students enter training at a rate admission, and eventually join the unemployed at a rate graduation after a training time \( T \).

![Figure 1: The education sub-model](image)

Students accumulate according to admission, graduation and dropout rates. The graduation and dropout rates are obtained by averaging the admission rate over \( T \) using the first order smoothing function. The expressions for the subsystem are as follows;

\[
\frac{d}{dt}(C) = \text{admission} - \text{graduation} - \text{dropout} \quad (2)
\]

where, the admission, graduation and dropout rates are defined by the following expressions;

\[
\text{admission}(t) = \text{MIN}(DA,C) \quad (3)
\]

\[
\text{graduation}(t) = f[\text{admission}(t), T_t] \cdot \text{turnover} \quad (4)
\]
\[
dropout(t) = f[\text{admission}(t), T_c] \cdot (1 - \text{turnover}) \tag{5}
\]

where \( f \) represents the smoothing function; \( DA \) is the desired admission rate; and \( C \) is the admission capacity.

The desired capacity is defined in terms of current labour market status. The actual admission capacity is then obtained by anchoring on the current admission capacity, then adjusting it according to the desired capacity, with a capacity expansion delay. The capacity adjustment sub-model is provided in the next section.

### 3.1.2 Capacity adjustment dynamics

The capacity adjustment sub-model in Figure 2 shows various information elements for capacity adjustment. A factor \( h \) is introduced to control the desired admission \( DA \);

\[
h = v - u \tag{6}
\]

where, \( v = V/(V + E) \); and \( u = U/(U + E) \).

![Figure 2: Capacity adjustment sub-model](image)

Since \( DA \) is assumed to be influenced by factor \( h \), the current value of \( DA \) is a function of \( h \) and the previous value of \( DA \);

\[
DA(t) = f[(g(h) - 1) \cdot DA(t-1), T_c] \tag{7}
\]

where \( g(h) \) is a heuristic function of \( h \) representing the effect of \( h \) on admission as shown in Figure 3.

![Figure 3: Effect of labour market status factor \( h \) on admission](image)

The desired capacity \( C \), in turn, is adjusted over time \( T_c \) based on the current value of \( DA \). In this regard,

\[
C(t) = C(t-1) + [DA(t) - C(t-1)]/T_c \tag{8}
\]

where, \( C \) depicts the admission capacity of is the training sub-model.

### 3.1.3 Labour market dynamics

Figure 3 shows the labour market dynamics sub-model, comprising four stocks: Unemployed (\( U \)), Employed (\( E \)), Foreign Talent (\( F \)) and Vacancies (\( V \)). The unemployed is replenished by new entrants from the education sector at graduation rate and depleted by leakage and hiring rates. The dynamics of the stocks is given by,

\[
\frac{d}{dt} U = \text{entrance} - \text{hiring} - \text{leakage} \tag{9}
\]

where, \( \text{entrance} \) rate is equivalent to graduation rate; \( \text{hiring} \) is a function of \( U \), \( V \), and foreign talent policy \( Q' \); \( \text{hiring rate} = (1 - Q') \cdot \text{MIN}(U/\text{hiring time}, V) \tag{10} \)

where \( \text{hiring time} \) is the average recruitment time.

Here, leakage rate is influenced by base leakage fraction and the effect of relative demand, \( g(R) \). The heuristic relationship between \( R \) and effect \( g(R) \) is shown in Figure 3. Hence the leakage rate is determined as \( \text{leakage} = g(R) \cdot \text{leakage fraction} \cdot U \).

![Figure 4: Effect of relative demand on leakage](image)

\[
\frac{d}{dt} V = \text{vacancy creation} - \text{vacancy closure} \tag{11}
\]

where \( \text{vacancy creation} \) is obtained by averaging manpower from attrition, manpower need, over vacancy adjustment time vacancy \( AT \), that is;

\[
\text{vacancy creation} = f(\text{manpower need} + \text{growth}, \text{vacancy AT}) \tag{12}
\]

Here, \( \text{vacancy closure} = \text{hiring} + F\_hiring \).
The employment stocks \( E \) is replenished by the hiring and naturalisation rates, and reduced by the attrition rate according to the following equation.

\[
\frac{d}{dt} (E) = \text{hiring} + \text{naturalising} - \text{attrition}
\]  

(13)

where, naturalisation depicts the rate of conversion of foreign talent to local talent \( E \); attrition is given by the expression \( E/\text{attrition time} \).

The foreign talent \( F \) is influenced by \( F_{\text{hiring}} \) and diminished by \( F_{\text{attrition}} \) and naturalisation. Therefore,

\[
\frac{d}{dt} (F) = FT_{\text{hiring}} - F_{\text{attrition}} - \text{naturalisation}
\]  

(14)

where, the rates \( F_{\text{hiring}} = \text{hiring} \cdot Q'/(1-Q') \); and \( F_{\text{attrition}} = F/F_{\text{attrition time}} \).

### 3.1.4 Demand growth dynamics

In this research, demand is assumed to follow an S-shaped pattern, which is typical of health manpower demand in a steadily growing economy. As such, demand growth can be simulated dynamically using expression (see Figure 6);

\[
growth = b \cdot D \cdot (L - D)/L
\]  

(15)

where \( b \) is a parameter controlling the shape of the S-curve; \( D \) is \( \text{Growth Demand} \) cumulated due to growth; and \( L \) is the growth limit. (Here, \( b \) is assumed to be 0.07).

### 3.1.5 Labour market performance indices

Figure 7 provides causal linkages between variables that interact with labour market indices: (un)employment ratio, vacancy ratio, and relative demand.

**Figure 5: Labour market dynamics sub-model**

**Figure 6: Demand growth sub-model**

**Figure 7: Labour-market performance indices**
In particular, the market indices of interest are defined by the following expressions:

\[ v = V / (V + E) \]  
\[ u = U / (U + E) \]  
\[ r = V / U \]  

4. Simulation experiments

The proposed system dynamics model was simulated on two case examples. In particular, our experiments involved the following:

(i) base experiments with a steady demand input;
(ii) base experiments with steadily growing demand;
(iii) dynamic what-if analysis experiments

The performance metrics chosen for our simulation are demand-supply planning reliability (REL), root mean square error (RMSE), and final capacity. The RMSE and REL are defined by the following expressions:

\[ REL = \left[ 1 - \frac{1}{n} \sum_{t=1}^{n} |V_t - V| \right] \times 100 \% \]  
\[ RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^{n} (D_t - S_t)^2} \]  

where, \( n \) is the planning horizon.

4.1 Steady demand: Case example of South Africa

Simulation runs were performed based on a steady demand input, with a case example of South Africa. During the period of 2004 to 2007, the total vacancies for nursing professionals hovered around 2000 per annum, which, on average, translates to 500 per quarter [6]. For simulation purposes, assume that the initial workforce is 60,500 and the education sector has to cope with manpower losses due to 5% student dropout, leakage into unintended destinations, and natural attrition.

Figure 8 shows that supply closely follows demand, with a low RMSE = 5.37 and a high REL = 90.39%.

As illustrated by Figure 9, admission capacity slightly increased to 500 and remained constant over the planning period. This shows the utility of labour market indices in healthcare human resources planning in a dynamic environment.

4.2 Growing demand: Case example of South Africa

The system dynamics model was run based on a steadily growing S-shaped demand input, with a case example of South Africa. According to the report in [6], demand growth for health professionals was projected to steadily rise from 1679 to 11549 for the period 2006 to 2015. In this model, we assume that during rapid demand growth, additional health manpower may be obtained from foreign talent inflows. For the purpose of simulation, assume that initial employment in the labour market is 68,500.

The simulation model was run over a period of 100 quarters. Figure 10 provides the results of the simulation experiment. Simulated manpower supply follows manpower demand closely, with RMSE value of 27.97 and REL value of 70.35%. As shown in Figure 12, by using feedback information from the labour market indices, admission, training and supply decisions can be adjusted dynamically so that supply will match future demand.

Further simulations experiments involving capacity policies were carried out considering limitations on...
admission capacity adjustments. Three simulation experiments were designed:

1) Unlimited admission capacity – the requisite capacity is readily available
2) Limited admission capacity without adjustment
3) Limited admission capacity with adjustments

Figure 11: Variation of capacity versus a growing demand

Figure 11 provides the behaviour of some of the essential model parameters under the base case, limited capacity with capacity adjustments. It is evident that the actual admission capacity lags behind the desired capacity. The capacity growth stops in year 12 after the peak of the desired capacity, and the final capacity reached 872.

Table 1: Performance behaviour under different strategies

<table>
<thead>
<tr>
<th>Strategy</th>
<th>REL</th>
<th>RMSE</th>
<th>Capacity</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Unlimited capacity</td>
<td>85.6</td>
<td>14.64</td>
<td>755</td>
</tr>
<tr>
<td>2. Limited capacity with no adjustment</td>
<td>60.51</td>
<td>57.23</td>
<td>600</td>
</tr>
<tr>
<td>3. Limited capacity with adjustment</td>
<td>70.35</td>
<td>28.97</td>
<td>872</td>
</tr>
</tbody>
</table>

Table 1 presents the performance of the two strategies in comparison with the base scenario (limited admission with adjustment). Unlimited capacity gives the best results in terms of RMSE and REL values. Therefore, capacity should lead demand in a dynamic environment.

4.3 Dynamic what-if analysis

Dynamic analysis involved experimental variation of policy parameters, that is, the controllable model variables which represent the system policy structures and traditions. By these, the model should be able to shed light on the conditions for optimum performance of the manpower system. Table 2 summarises the key policy parameters that affect health manpower dynamics.

Table 2: A summary of key policy parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_c$</td>
<td>Time to adjust admission capacity</td>
</tr>
<tr>
<td>$T_a$</td>
<td>Time to average desired admission</td>
</tr>
<tr>
<td>$T_t$</td>
<td>Training lead time, or time to graduation</td>
</tr>
<tr>
<td>$Q$</td>
<td>Desired foreign talent proportion (quota)</td>
</tr>
</tbody>
</table>

In this analysis, the values of the parameters are varied while other parameters are maintained at the base level. The fourth column provides the base case results. From the simulation results of what-if analysis in Table 3, certain observations are in order. By decreasing the $T_a$, the manpower policy structure becomes more reliable, hence decreasing unwanted transients and fluctuations. As expected the RMSE decreases with decreasing $T_a$. Similarly, the RMSE decreases with decreasing $T_c$ due to improved response time to demand changes. However, unwanted fluctuations may be introduced as $T_c$ values continue to decrease. Variations in the quota policy $Q$ bring about marginal influences to the reliability of the policy structure. However, increased $Q$ may lead to unwanted fluctuations in the labour market. We infer from Table 3 that $Q$ increases continually with REL, which shows the utility of foreign talent in times of turbulent demand growth.

The reliability of the system increases significantly with decreasing training delay ($T_t$). Thus, training delay generally decreases the response of the system. On other hand, decreasing training delay will demand more investment to build up capacity. The implication in this dynamic analysis is that, for informed decisions, policy designers should pay more attention to information loops regarding (i) vacancy ratio, (ii) unemployment ratio, and (iii) employment ratio, and (iv) foreign talent policy, with possible structural changes to education and training programs to reduce training lead time.

Table 3: Performance under policy parameter variations

<table>
<thead>
<tr>
<th>Time to adjust admission capacity, $T_c$ (Quarters)</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>REL</td>
<td>73.71</td>
<td>72.89</td>
<td>71.98</td>
<td>71.01</td>
<td>70.00</td>
<td>69.01</td>
</tr>
<tr>
<td>RMSE</td>
<td>24.18</td>
<td>25.13</td>
<td>26.22</td>
<td>27.97</td>
<td>28.73</td>
<td>30.07</td>
</tr>
<tr>
<td>Capacity</td>
<td>865</td>
<td>867</td>
<td>870</td>
<td>872</td>
<td>896</td>
<td>899</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Time to average desired admission, $T_a$ (Quarters)</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>REL</td>
<td>70.85</td>
<td>69.08</td>
<td>70.09</td>
<td>70.35</td>
<td>71.70</td>
<td>72.21</td>
</tr>
<tr>
<td>RMSE</td>
<td>25.95</td>
<td>27.73</td>
<td>27.64</td>
<td>27.97</td>
<td>27.27</td>
<td>27.16</td>
</tr>
<tr>
<td>Capacity</td>
<td>1066</td>
<td>955</td>
<td>908</td>
<td>872</td>
<td>864</td>
<td>851</td>
</tr>
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</table>

<table>
<thead>
<tr>
<th>Training lead time, $T_t$ (Quarters)</th>
<th>10</th>
<th>12</th>
<th>14</th>
<th>16</th>
<th>18</th>
<th>20</th>
</tr>
</thead>
<tbody>
<tr>
<td>REL</td>
<td>77.20</td>
<td>75.19</td>
<td>73.07</td>
<td>70.35</td>
<td>69.17</td>
<td>67.54</td>
</tr>
<tr>
<td>RMSE</td>
<td>19.91</td>
<td>22.15</td>
<td>24.74</td>
<td>27.97</td>
<td>29.99</td>
<td>32.40</td>
</tr>
<tr>
<td>Capacity</td>
<td>843</td>
<td>855</td>
<td>867</td>
<td>872</td>
<td>895</td>
<td>908</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Desired foreign talent proportion, $Q$ (%)</th>
<th>5%</th>
<th>10%</th>
<th>15%</th>
<th>20%</th>
<th>25%</th>
<th>30%</th>
</tr>
</thead>
<tbody>
<tr>
<td>REL</td>
<td>33.79</td>
<td>48.48</td>
<td>61.10</td>
<td>70.35</td>
<td>78.40</td>
<td>83.91</td>
</tr>
<tr>
<td>RMSE</td>
<td>81.18</td>
<td>56.63</td>
<td>39.22</td>
<td>27.97</td>
<td>19.53</td>
<td>14.42</td>
</tr>
<tr>
<td>Capacity</td>
<td>1139</td>
<td>1017</td>
<td>936</td>
<td>872</td>
<td>841</td>
<td>811</td>
</tr>
</tbody>
</table>

5. Conclusion and Summary

In today’s highly unpredictable healthcare labour markets where policy makers are faced with the decision of matching health human resource supply with demand, it is
essential to understand the dynamics of the manpower supply. This study presents a system dynamics-based approach for designing a health personnel training policy structure for healthcare systems based on labour-market indices, under steady and growing demand patterns. The model can assist training institutions in developing informed dynamic policies based on information feedback from labour market indices. For instance, a decision maker can put in place college admission policies based on trends in the labour market. As demonstrated by the results, dynamic policies can provide manpower plans with high levels of demand-supply planning reliability.

The system dynamics-based model enables manpower policy makers to design manpower policy structures based on time-based parameters. By heuristic proportional control of time to average admission ($T_a$), capacity adjustment time ($T_c$), training lead time ($T_l$), and foreign quota policy $Q$, planners should be able to evaluate the desired training patterns, considering manpower needs. Adherence to the design set of policy parameters is essential in order to avoid unwanted oscillations and transients in the overall manpower system. Unfavourable transients will lead to human capital loss through leakage to unintended professions. The implication of the training lead time $T_l$ is that it is possible to minimize the current and the future manpower gaps by designing or redesigning appropriate training programmes. Indeed, it is evident that the foreign quota policy can be used to quickly curb manpower shortages in the short-term and to average out unwanted rises in wages. In addition, the model also provides a conceptual framework to better understand the interaction of key factors on manpower supply and demand.

The system dynamics model can assist in providing training time estimates against immediate and long term manpower shortages. Thus, the framework provides planners with an interactive decision support system for making informed health human capital decisions from a systems perspective. Therefore, the model is useful for investigating the interactive influence between education and employment policies and the labour market status. System dynamics can be used as a decision modelling tool for healthcare manpower decision modelling.

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