Dynamic Modelling of Workforce Planning For Infrastructure Projects

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Abstract

Workforce planning (WP) for infrastructure projects provides a readily available pool of skilled labor that can deliver a nation's societal needs. However, achieving a robust and reliable workforce prediction is a constant challenge, as a variety of variables and factors must be considered. Despite various forecasting techniques and approaches being developed, Government's worldwide continue to produce inaccurate forecasts and consequently fail to maintain a balanced workforce required to deliver infrastructure projects. To address this problem, a system dynamics (SD) model for the construction and civil engineering industry is developed, as traditional WP modelling approaches are static and unable to accommodate the changing complex dynamics that influence workforce supply and demand. The SD model is tested and used to formulate training policies that ensure workforce equilibrium and in turn, nurture sustainable infrastructure development.

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Keywords: Feedback, workforce planning, system dynamics model, policy analysis

Introduction

"The most reliable way to forecast the future is to try to understand the present (Naisbett 1982)."

The construction industry is inextricably linked within highly developed economies and contributes to approximately 7 to 10% of Gross Domestic Product (GDP) (Yiu et al. 2004) whilst, infrastructure produced for other productive industries (such as finance) further contributes to a country's economic development and prosperity (Goh 1998). Human resources represent the industry's most invaluable asset as a readily available pool of skilled and competent workers is a prerequisite requirement for successful project delivery (Schuster 1987; Bell and Brandenburg 2003).

In the absence of reliable workforce planning (WP), labor market requirements are inherently uncertain and exposed to workforce perturbations that can oscillate erratically between surplus and shortage (Sing et al. 2012a). To forecast and plan for labor requirements a plethora of models (e.g., regression and econometric modelling) have been developed so that government policy makers can adjust the type, number and size of training courses available to fulfill demand (Mutingi and Mbohwa 2012). Despite progress in this area, inaccuracies with WP continue to frustrate the industry's attempts to effectively manage labor requirements (Sing et al. 2014). Against this contextual backdrop, this paper reviews, compares and contrasts between prominent WP models in construction. A novel system dynamics (SD) model is then developed as a viable alternative approach to capture the dynamic nature of labor supply and demand within the construction and civil engineering industry.

Workforce Planning

Fundamentally, WP seeks to accurately forecast workforce requirements to ensure equilibrium between supply and demand; however, it is also politically influential in terms of shaping future industry and government training policy. From an operational perspective, WP represents an iterative process consisting of three core elements: (1) demand-side forecasting; (2) supply-side forecasting; and (3) identification of workforce surplus or shortage from these forecasts. This process may encapsulate judgment technique, trend projection, stock-flow modeling, labor multiplier modeling and econometric modeling. It seeks to secure labor equilibrium via a process of dynamic policy interventions in a fuzzy workforce environment (Mutingi and Mbohwa 2012). Prediction accuracy is subject to global and national economic performance, technological advances, demographic changes and so forth. Table 1 presents a summary of the workforce forecasting techniques developed.

Judgment Techniques

Judgment techniques provide a simplistic means of estimating workforce requirements and utilize industry experts' intuitive knowledge (Marshall and Rossman 1999). They are extremely useful when historical data is either unavailable or of poor/ unsuitable quality (Richards and Morse 2007). The Delphi technique provides a more structured process for collecting and distilling expert knowledge via questionnaires interspersed with controlled opinion feedback (Ziglio 1996). This iterative judgment process continues until consensus emerges amongst group participants. However, forecasting reliability is questionable because of potential bias introduced by experts involved (Meehan and Ahmed 1990); for example it was used by Australia's engineering and mining industry but predictions made led to a considerable shortage of skilled labor (PricewaterhouseCoopers 2012).

Stock-flow Modeling

Stock-flow modelling is based upon Markovian principles (Purkiss 1981) and has been used to study the movement of employees within an organization; where the probability of transition from one position to another can be expressed by Eq.[1].

$$x(t+1) = x(t)P + N(t+1)p \text{ ....Eq.[1]}$$

Where: *x(t)* is the stock vector that is observed at time *t*; *N(t+1)* is the number of new entrants at time *(t+1)*; *p* indicates entrants are distributed among the states of categories; and *P* is the matrix of transition proportions among the categories and the expected stock vector at time *t+1* is *x(t+1)*. The Markovian model produces an assessment of the number of employees with a recruitment, wastage and promotion rule. It neglects, however, the complexities inherent within aggregated workforce supply for an entire industry and is hence, limited in scope and application (Anthony and Wilson 1990).

To address the model's limitations, Sing et al. (2012b) developed a labor stock-flow model utilizing real-life databases of registered construction workers and information obtained directly from the workforce pertaining to their future aspirations and employment. The model is useful for training authorities who formulate training policies to meet industrial labor requirements. Unfortunately, many key parameters are more or less constant over time, even though for example, wastage rates change dynamically and will almost certainly be related to the state of the labor market (Gu and Chen 2010). The linear nature of a stock-flow model also fails in incorporating feedback mechanics between the key variables and workforce gap. For instance, a strong demand for workers during economic boom would simulate an influx of new entrants to the industry and reduce wastage rates (Rowings et al. 1996).

Trend Projection and Time Series Forecasting Model

Time series forecasting identifies historical patterns in data to extrapolate future trends (Chatfield 2013). The most widely used time series methods include: simple trend lines; moving averages; and the more complex autoregressive integrated moving average method

(ARIMA) (Chan 2002). For example, within Hong Kong, the Vocational Training Council (VTC) applied the exponential moving averaging (EMA) technique to forecast workforce requirements for over 20 industries since 1970. EMA is an infinite impulse response filter that applies a weightage that decreases exponentially and represents an advance upon the simplistic moving average technique (Montgomery et al. 1990). It facilitates greater insight into the current data rather than data from the distant past. The weightage of each data point must be specified; a difficult task given that the weightage must reflect the real data trend (Johnson and King 1988). There are considerable choices for the weightage selection, which in turn, seriously affect the forecast accuracy (Hanke et al. 2009). The underlying theory of time series projection is simple, and is both reliable and inexpensive (Smith and Bartholomew 1988). Nonetheless, time series modelling cannot capture the dynamic behaviour of the workforce supply - such as a reversal in the direction of the new entrant rate due to an industry downturn (Diaz et al. 2012).

Econometric Model using Regression Techniques

Regression techniques are applied to establish a causal effect relationship between a dependent and independent variable(s) through an examination of past data series (Warner 2013). The technique ‘multiple regression’ (MR) has been used to develop various econometric models to estimate construction workforce demand (Persad et al. 1995; Liu et al. 2014; Sing et al. 2015).

Variables entered into MR demand models have included: real wage; material price; interest price; and labor productivity. The general form of MR is shown in Eq. [2].

$$MD_t = \beta_0 + \beta_1 Q_t + \beta_2 RW_t + \beta_3 MP_t + \beta_4 BR_t + \beta_5 LP_t \text{ ....Eq.[2]}$$

Where: MD_t = manpower demand at time; t; Q = construction output; RW = real wage; MP = material price; BR = interest rate; and LP = labor productivity.

For supply-side modeling, Agapiou et al. (1995) developed an MR model to study how relative weekly earnings and construction output affected school graduates' intentions to pursue a construction career. Yet, MR is limited by the assumption that a fixed coefficient represents the correlation between the independent variable(s) and dependent variable. This inherent infalibility means that it cannot capture the dynamic relationship that exists between observed variables nor assess the impact of inevitable interventions such as changes of government policy (Wooldridge 2006; Sing et al. 2012c).

Various studies have failed to capture the dynamic complexity arising from the supply and demand deficit and are too static to establish the causal relationship between key variables. For example, workforce demand triggers supply and *vice-versa* in the real world (Park et al. 2007).

In this research, SD is utilized to understand the behavior of the labor market system over time and address internal feedback loops and time delays that affect the entire system's behavior. This knowledge is then used to develop a robust workforce planning model for the construction and civil engineering industry. Thus, key variables affecting the workforce such as training quota controllable by the training authorities and policy makers can be set as parameters to simulate different scenario on the workforce planning.

System Dynamics Modeling

SD modeling is an objected-oriented methodology where cause and effect variables are arranged into a causal loop diagram to represent the structure and interaction of principal feedback mechanisms in a system (Sterman 2001). The main diagramming tools used are the causal loop (CLD) and stock and flow diagrams.

Causal loop diagrams consist of cause and effect variables that are connected by arrows denoting their causal influence. Each causal link is assigned a polarity, either positive (+) or negative (-) to indicate the relationship (i.e. positive or negative) between the dependent and independent variables. In addition, the feedback process within the loop can be simulated to provide a delayed response; such a delay creates system inertia and oscillation within the system. For example, significant delays that arise when assessing the workforce demand and in changing the training policy for the supply of new entrants. The SD simulation is developed in the form of stock and flow variables, where a 'stock' variable describes the system's state (such as the existing supply of workers) and the 'flow' variable represents the rate of system changes. Examples of flows are the retirement and recruitment rates in the workforce supply system. The workforce supply model is expressed as:

$$Stock(t)=\int_{t_0}^{t}[inflow(s)-outflow(s)]ds + stock(t_0) \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\text{Eq.[3]}$$

Where: t_0 is the initial time; t is the current time; stock(t_0) is the initial value of workforce stock, inflow(s) and outflow(s) rates represent new graduates who become either in, or retired workers who become out of stock at any time between the initial time t_0 to and current time t. Inflow(s) and outflow(s) have the units of *stock (t)* divided by time.

With SD, the structure's behavior over time is easily simulated (Morecroft 2007). Given its inherent capabilities, SD has been widely applied to a number of problems, such as economic behavior, supply chain management and health care modeling (Tako and Robinson 2010). The application of SD to WP originated from a model developed by Parker and Caine (1996) who focused predominantly on modeling staff promotion within a single organization. Based upon this early work, Hafeez and Abdelmeguid (2003) developed an SD based model to illustrate the relationship between recruitment, training, skills and knowledge in a causal loop form. Mutingi and Mbohwa (2012) further combined fuzzy SD and optimization techniques to develop training strategies for a single organization. Alvanchi et al. (2012) also applied SD modeling to study the dynamics of construction workforce skill evolution and understand how a company's human resource policy affects the project's performance and cost. The literature indicates that whilst SD modeling is applicable to WP, past research is limited in scope and application to a single organization only whilst the proposed model presented in this paper would be the first attempt using SD to model workforce demand and supply over the whole construction and civil engineering industry.

Model Development

To frame the scope of the SD model that is developed in this study, Figure 1 illustrates a simplified CLD of the proposed WP system.. The system consists of: (a) demand sub-model; and (b) supply sub-model. Each sub-model has their own feedback mechanism and closed-loop (*B1* and *B2* as indicated in Figure 1) with an interaction of a variable, labeled as the 'workforce gap'.The problem of workforce gap (e.g. shortage or surplus) could be resolved through a detailed study on the variables laid within the feedback loop of *B1* and *B2*. For example, in balancing loop *B1*, if the attractiveness of employment condition increases (e.g. pay rise due to workforce shortage), the number of new entrants will then lead to an increase in the workforce supply; this will eventually reduce the size of the workforce gap. Similarly, balancing loop *B2* represents the workforce demand condition of construction workers. If the workforce gap increases, the intention to commence a new construction project will be suppressed due to a shortage of workers. This will again lead to a reduction of construction works that in turn reduce demand for construction workers. A more comprehensive and holistic view of the major causal loop dependencies that exist with the workforce demand and supply sub-models are presented in the sub-sections below.

The Hong Kong labor market, for example, encapsulates a large pool of diverse workers empowered with different specialized skill sets - over 60 skilled trades are listed and these include trades bar-bender and concreter. As the bar-bender was previously identified as being particularly problematic (Sing et al. 2012b), the workforce demand and supply of this trade is used to illustrate the application of the system dynamics model developed.

Supply Sub-model

The supply sub-model predicts the future availability of labor and is based upon the genetic structure of stock management of supply changes. As of 31st December 2014, there were 4483 registered bar-benders in Hong Kong and of these, 52% were categorized as skilled workers and 48% were semi-skilled workers. Given an absence of guidelines to regulate the percentage of skilled and semi-skilled workers, they are both classified into the workforce supply pool of bar-benders in the SD model.

Key factors affecting the workforce supply chain are identified in Table 1 (Briscoe and Wilson 1993; Sing et al. 2012b). Figure 2 presents the SD model for the supply of bar-benders and illustrates the *training-work-retirement* work-life cycle on a temporal trajectory; this process moves from: (a) recruitment of graduate trainee; (b) development of semi-skilled bar-benders given exposure to industrial experience; and (c) following competence assessment, registration as skilled bar-benders until retirement. The stock variables in the supply sub-model include the workforce subgroups of: (a) age of bar benders; (b) number of new entrants; and (c) number of retired workers. In this model, each equation in the workforce subgroup expresses the number of workers progressing from first stock (*trainee entrants*) to last stock (*retirement*); unless the individual leaves the construction industry, for example, when employability fails to provide sufficient numeration to support their family living.

Unlike traditional stock-flow models, the proposed supply sub-model incorporates feedback mechanisms. First, the rate of each career change from the supply pool (e.g., the intention of workers to leave the industry), depends upon the job opportunities (and level of renumeration) available; these consderiations are identified as representing a workforce gap in the model.

Using the survey data published by the Hong Kong Construction Industry Council (2014), 30% of bar-benders considered leaving the industry if income is deemed insufficient to support their family. To model this relationship in the supply model, their daily salary and average family income across the whole region is considered. According to the Census and Statistics Department (C&SD), the daily income for a bar-bender is approximately HK$1,500 for a 6 day week or HK$36,000 per month; whereas the average monthly income of a middle-class family in Hong Kong is HK$25000 (C&SD, 2012). Therefore, if their employability is ≥ 70% (that is, HK$25000/36000), then they are still capable of supporting their family. Thus, the feedback loop in this supply model assumes that if the workforce gap exceeds 30% (e.g. workforce surplus and employability is less than 70%), the supply pool will leave the industry as their monthly earning is insufficient to support their family.

In addition to stock and flow variables, the concept of delay is also considered in the supply sub-model. A delay is defined as time lags between inputs and outputs, for instance, places for trainee graduates that cannot be immediately adjusted to respond to changing demand. Hence, at time t_1, the local training authority amends its policy and increases the intakes onto bar-benders training courses. However, the training duration in Hong Kong is one year thus creating a (t_1+1) year lag before newly qualified trainees can enter the workforce pool. In the Loop *B3* of Figure 2, this lag is represented by the function of delay as defined in the SD modeling. A variable of 'delay: training duration' (e.g., t_1+1 years) has been inserted between the variables of 'number of trainee' and 'age group of 21-25 (e.g. new graduates)' to account of this time lag between intakes of trainees and their completion of training in the supply model. In the short term, it is possible to re-allocate the training quota to the most problematic trades without increasing the overall training capacity. For the long-term policy, strategic decisions would be required to build new (or expand) training centers, but such plans require extensive lead-times from budget approval to building completion.

Whilst importing labor represents an alternative policy to building new recruit training capacity, it also represents a short-term flexible measure for the government/ industry to meet labor demands (Golden and Skibniewski 2010). Lee (1999) postulated that the import of labor should only become operational when: (a) local workers have been given priority in filling job vacancies; and/ or (b) employers are genuinely unable to recruit local workers to fill these vacancies. In the proposed supply sub-model, the decision to import foreign workers is dependent upon the combined effect emanating from the workforce gap and the percentage of intake from the local training authority. The feedback mechanism between the workforce gap, imported labor and workforce supply is also represented by the Loop *B4* as indicated in Figure 2.

Demand Sub-model

The demand sub-model is a function of industry output (measured in Hong Kong dollars (HK$)). To estimate workforce demand, the model uses labor content per dollar multiplied by the predicted industry output. For each work trade, the labor content per dollar is derived from the number of workers employed and contract sum of the projects. For this study, 30 completed projects were collected from main contactors to generate the database of labor content per dollar and adopted in the SD model. The database then afforded a basis for assessing and aggregating the workforce demand for the Hong Kong construction industry (Eq.[4]).

Figure 3 represents the CLD of workforce demand. In the demand sub-model, an increase in private investment generates growth and government funding on public projects which then produces a greater demand (denoting a positive relationship '+') for bar-benders from the workforce market (Eq.[4]). Contrastingly, an increase in the number of infrastructure projects that are abandoned (due to workforce shortages) will in turn reduce the demand for workers (denoting a negative relationship '-').

$$WF_{demand} = \underbrace{\sum_{i=1}^{p} CO_{private,i} \cdot SCW \cdot L_{private,i}}_{\text{Workforce demand in private sector}} + \underbrace{\sum_{i=1}^{q} CO_{public,i} \cdot SCW \cdot L_{public,i}}_{\text{Workforce demand in public sector}} \ldots\ldots\ldots\ldots\text{Eq.[4]}$$

Where: WF_{demand} = workforce demand; $CO_{private,\,i}$ = output of project type i in the private sector; $CO_{public,\, i}$ = output of project type i in the public sector; SCW = adjustment factor for the suspension of works due to labor shortages; $L_{private,\, i}$ = labor content per HK$ for project type i in private the sector; and $L_{public,\, i}$ = labor content per HK$ for project type i in the public sector.

Note that within the demand sub-model, two dichotomous groups are presented: (a) the private sector; and (b) public sector. For the private sector, residential and commercial building construction in the private sector output (measured by value HK$) accounts for circa 90% of the market (Rating and Valuation Department (2014). Given its predominance, infrastructure projects other than residential and commercial buildings will not be considered in the modeling work of private sector. To provide a projection on the forthcoming construction output in private residential and commercial building development that is used to determine workforce demand, the VAR model advocated by Sing et al. (2015) is used.

Contrastingly for the public sector, the initiation of infrastructure projects depends heavily on government policies. The first step is to retrieve the dataset for the government's planned expenditure for infrastructure projects. In Hong Kong, the government generally publishes its budget report annually to provide information on the ongoing programmes and expenditure pertaining to public services such as health, education and infrastructure projects. For the medium range and five-year forecast under the 2015-2016 *Budget* published by Hong Kong Special Administrative Region (HKSAR), the forthcoming Capital Works Reserve Fund for infrastructure projects will be HK$75,400 million and gradually increased to HK$103,800 million by year 2019. As part of the model development process, the number of projects to be included and the percentage of project types over the forecast year must be determined.

By carefully examining the budget report published by HKSAR, the project types within the public sector were identified as: schools, public housing, civil structure, highway construction, drainage and sewage, government building and facilities. The percentage of each project type over the whole government expenditures is calculated using a five-years moving average. In Hong Kong, contractors who carry out infrastructure site works are contractually required to submit a Form 527 (i.e. return on construction site employment) to the C&SD and record all deployment of labor involved within their project. Thus, hundreds of labor deployment records for infrastructure projects were obtained from the C&SD and used to compile the database of labor content per dollar.

Unlike traditional WP tools, a feedback loop is denoted in Figure 3. *B5 and B6* are identified as balancing loops, which means that the feedback loop will maintain the system stability and is depicted as:

[*Loop B5*] Workforce demand → (+) workforce gap → (+) shortage of labor → (+) suspension of the works by owners → (-) infrastructure projects being commenced →(-) workforce demand.

There is a strong correlation between the labor shortage and schedule overrun of the project, which in turn suppress the incentive of the invertor to initiate new projects. For instance, Love et al. (2013) found that the average schedule overrun to range from 10% to 30% of a project's original duration. The study from Assaf and Al-Hejji (2006) also identified that the key factor leading to schedule overrun is due to workforce shortages. The wage levels would ultimately rise owing to the labor shortages. As the labor cost is a large percentage of a project's cost, the incentive for commencing a new project is suppressed because of potentially low profit margins. For sake of simplicity, it is assumed that if the labor wages increase above 30%, the factor of SCW in Eq.[4] is randomly selected and will range from the numerical values of 0.1 and 0.3. Similarly, another balancing loop *B6* is used to represent the feedback mechanism of workforce demand in public sector

[*Loop B6*] Workforce demand → (+) workforce gap → (+) shortage of labor → (+) suspension of construction works by government → (+) adjustment on the government policy → (-)

expenditure in capital reserve fund.

Model Validation

Validation is required to build confidence in model predictions and generate a deeper understanding of WP. First, the proposed demand model was validated by comparing estimated values to historical data from 2009 to 2013. The number of construction workers recorded in the Quarterly Employment Survey of Construction Sites were adopted as a time series of historical workforce demand. According to Barlas (1994), a model is valid if the error rate is ≤ 5% (Eq.[5]). The comparison between the model and data extracted is computed in Table 3. As the error rate is only 2% and 4.3% for the private and public sector respectively, it confirms the fidelity of the proposed SD model.

$$\text{Error rate} = \frac{|\bar{E}-\bar{A}|}{|\bar{A}|} \quad \text{Eq.[5]}$$

where $\overline{\mathrm{E}} = \frac{1}{n}\sum_{i=1}^{n} E_i$, $\overline{\mathrm{A}} = \frac{1}{n}\sum_{i=1}^{n} A_i$;

When quality data is unavailable, preliminary models can still be developed on the basis of expert opinion/ judgement and using qualitative data (Burchill and Fine 1997). For the supply side of SD model, there was a lack of time series data on the number of workers available in the market from year 2009 to 2013 for backtesting the accuracy of the supply sub-model. As the supply sub-model is based onthe inflow and outflow of labor, it can be effectively captured the change of the labor supply model On the other hand, the accuracy of the supply sub-model should be dependent on whether the key variables affecting the inflow and outflow of labor has been carefully considered and also the quality and availability of the such data (i.e. current training capacity and trainee pass rate) for analysis.

Application of the System Dynamics Modeling

The methods and application of SD modelling for policy analysis can assist in designing/ augmenting policies that balance workforce demand and supply. A number of scenarios can be performed to explore the impact of the interconnections and feedback loops on the workforce condition for infrastructure projects. Scenario development is a predictive method where the present data is used to develop various alternative future scenarios (Ruge et al. 2009). For instance, a supply model allows policy makers to manipulate relevant data within each year to produce alternative scenarios such as the number of students admitted to the training program and the immigration rate. The developed SD model provides assistance in simulating the consequences of different policies, which aim to solve the cyclical workforce imbalance and support sustainable development for delivering infrastructure projects.

Scenario A: Baseline Resource Held Constants

A baseline model infers that training resources are in-line with the existing government policy and that no improvement in provision is required. In anticipation of increasing demand for workers, the government often attempts to augment the industry's image as a means of attracting new recruits. By providing higher training allowances and placement services, around 300 new trainees eventually entered the bar-bender trade in year 2014; the drop-out rate was around 10%. The above value is set to the initial value of the training capacity and drop-out rate in the supply SD model. Several key assumptions are listed in Table 4. For the demand side, the private industry output is based upon key economic indicators as discussed in Sing et al. (2015) while the public sector is based on the forecasting expenditure captured from Government statistics. The forecast workforce demand and supply on bar-benders is illustrated in Figure 4. It is noted that the deficit of this trade will grow from 2016-2020 and will be between 1.5% and 4.9%. This forecasted shortfall is caused by the strong growth in the private sector and increase in volume of public infrastructure projects over the next five years from 2016. This dearth will eventually drive the salary rise of workers, which may have a detrimental impact on the future delivery of infrastructure projects. This feedback mechanism (which is due to the shortage of workers) can be traced back in the loops *B5* and *B6* as identified in the demand sub-model (see Figure 3).

Scenario B: Change on the government policy and public investment

Owing to a policy response to the workforce shortage, policy intervention could be implemented, for example to: (a) slow down the commencement of public sector construction projects and avoid the adverse effects ensuing from a foreseeable labor shortage as reflected in Loop *B6* of Figure 3; (b) lower the eligibility criteria of foreign workers importation as reflected in the supply sub-model (see Loop *B4* in Figure 2); and (c) increase trainee places within further education but with time delay (see Loop *B3* in Figure 2). Figure 5 presents the outcomes of the workforce gap from slowing down the infrastructure projects by 5%, 10% and 15% respectively. In Hong Kong, any changes in government policy require approval from the Public Works Subcommittee of Legislative Council; an administrative procedure that normally takes around one year to complete. From the SD model perspective, this delay affects the entire system's behavior. It is reasonable to assume that investment in infrastructure projects would slow down from the 2nd year (i.e. 2017) when the system has detected a labor shortage during the 1st year (year 2016). Refering to Figure 5, it is foreseeable that only the policy with 5% reduction in infrastructure spending could help to maintain the workforce balance (i.e. where the workforce gap is $\leq$ 1.6%). If investment in infrastructure decreases by 15%, it will cause a significant surplus of workers (i.e. the workforce gap will be up to 13% at year 2020). Notably, the workforce gap in both scenarios is less than 20%, and thus reliance upon foreign workers should not be considered.

As illustrated in the Figure 5, the model represents a useful planning tool to simulate the effect of regulatory changes for infrastructure projects. However, the supply model will be only make realistic forecasts when entry parameters (i.e. places for trainee) are realistic. Fortunately, the SD model allows the modification of these parameters, which can provide policy makers with invaluable insights to examine ‘what if’ scenarios to enable an equilibrium between supply and demand to be obtained.

Conclusion

Reliable WP is essential for providing a sufficient pool of appropriately skilled workers to support infrastructure development. A review of the literature examined, compared and contrasted existing models that have been used to forecast WP supply and demand. The dynamic relationship between workforce supply and demand associated with WP for delivering infrastructure projects requires an understanding of a system’s stock and flow and feedback mechanisms. By using SD, the dynamics influencing the supply and demand of labor were modelled; a number of simulations were also performed to explore the impact of the interconnections and feedback loops influencing the workforce. The developed SD model can assist in designing better policies to maintain workforce capacity and support the sustainable delivery and development of infrastructure investments.

Although the model is useful for planning and policy development, its limitations need to be acknowledged. The demand and supply sub-model that were created are influenced by the parameters, which govern its assumption; the complexity of the real-world in this instance is simplified. However, further research is required to better understand the dynamics of the key parameters such as the intention of construction workers leaving the industry. The SD workforce model presented in this paper should be extended to model other skilled trades as well as explore interconnectedness between them. The above information would be useful to solve the long-standing workforce problem such as skill mismatch in the construction industry world-wide.

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Table 1 Workforce forecasting techniques

Category	**Key factors to be considered**	**Modeling Techniques**	**Authors**
(1) Judgment forecasting	Experience of the focus groups or expert	It is achieved simply by asking the group of experts in the area to identify their workforce needs. It involves the valued judgment of individuals who are highly knowledgeable in the field and who possess some intuitive senses related to their problems	Drandell (1975); Meehan and Ahmad (1990); Marshall and Rossman (1999)
(2) Stock-flow modeling	Inflow and outflow of the workforce, e.g. number of new entrants and retired workers	The creation of a stock-flow commences with determining the existing workforce. A labor inventory is then subjected to 'new entrants', 'retired labor' and other key variables such as 'labor mobility'. It can be used to forecast the labor supply for the next 5-10 years	Briscoe and Wilson (1993);Sing et al. (2012b)
(3) Trend projection and time series forecasting model	The past figures of workforce demand and supply	A time series forecasting identifies the historical patterns in the data to extrapolate the future trend of workforce requirement and supply	Persad et al. (1995); Bell and Brandenburg (2003); Hanke et al. (2009)
(4)Econometric modeling using regression model	Establish a causal effect relationship between demand (or supply) and independent variables	For demand sides, the independent variables can be: forecast construction output, real wage, material price, interest rate and productivity; For supply sides, the independents variables can be weekly earning, number of school leavers.	Agapious et al., 1995; Briscoe and Wilson, 1993.

Table 2 Key model parameters

Parameters	Authors
Current stock of labor	Green (1990)
Attitude rate	Harvey and Murthy (1988); Martin (1990)
Potential new entrants, training policy	Agapiou et al. (1995); Green (1990)
Recruitment rate	Ugwuowo and McClean (2000)
Retirement rate	Harvey and Murthy (1988)

Table 3 Comparison between the estimated and actual value of the workforce demand on bar-bender

Year	**Workforce Demand from Private Sector**		**Workforce Demand from Public Sector**	
	Actual, A_i	Estimated, E_i	Actual, A_i	Estimated, E_i
2009	4350	4180	4460	5330
2010	4060	3610	4230	4450
2011	3920	3690	3420	3630
2012	3730	3720	3250	3180
2013	3680	4060	3170	3060
	$\bar{A}$ = 3948	$\bar{E}$=3850	$\bar{A}$=3710	$\bar{E}$=3930
		Error rate=2.5%		Error rate=5.9%

Table 4 Key assumptions of the baseline scenario

Variables	Key assumptions
Training capacity	300 trainee quota per year
Drop-out rate	1.5%
Career-change	If the workforce gap>0.3, 30% of the workers will leave the construction industry
Adjustment on training policy	If the workforce gap >0.3 for consecutive years, the government would consider to construct a training center for increasing the number of training quota.
Time delay#1	Time interval between the adjustment on training policy and completion of new training center
Government policy on labor importation scheme	If the (workforce gap>0.3) and (Δ number of new entrants<0.1), the government would lower the eligible criteria for importing the foreign workers
Time delay #2	Time interval between the release of foreign labor scheme and the 1st foreign labor arrived Hong Kong

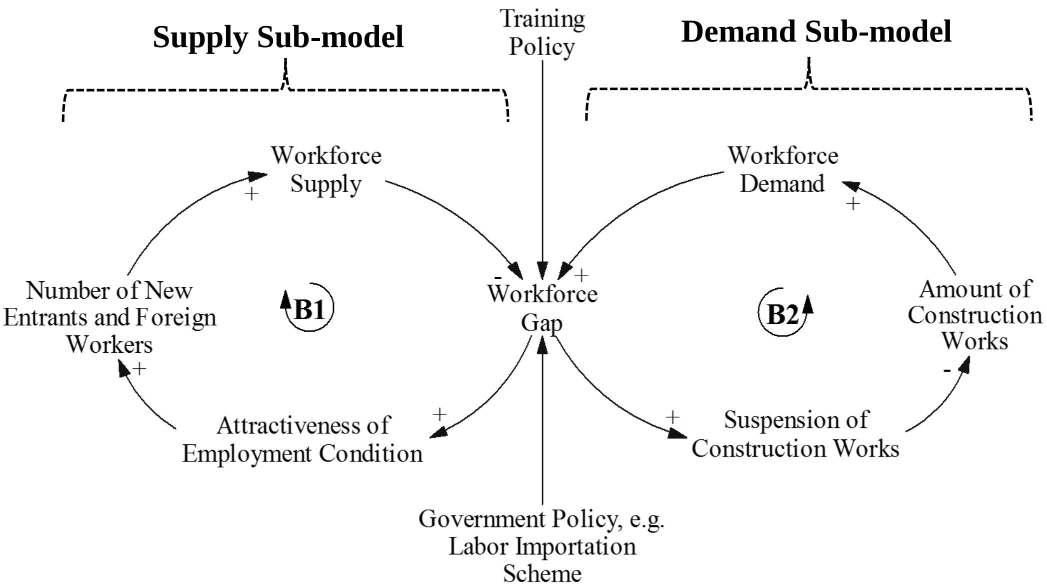

Figure 1 Causal loop diagram of the workforce planning model

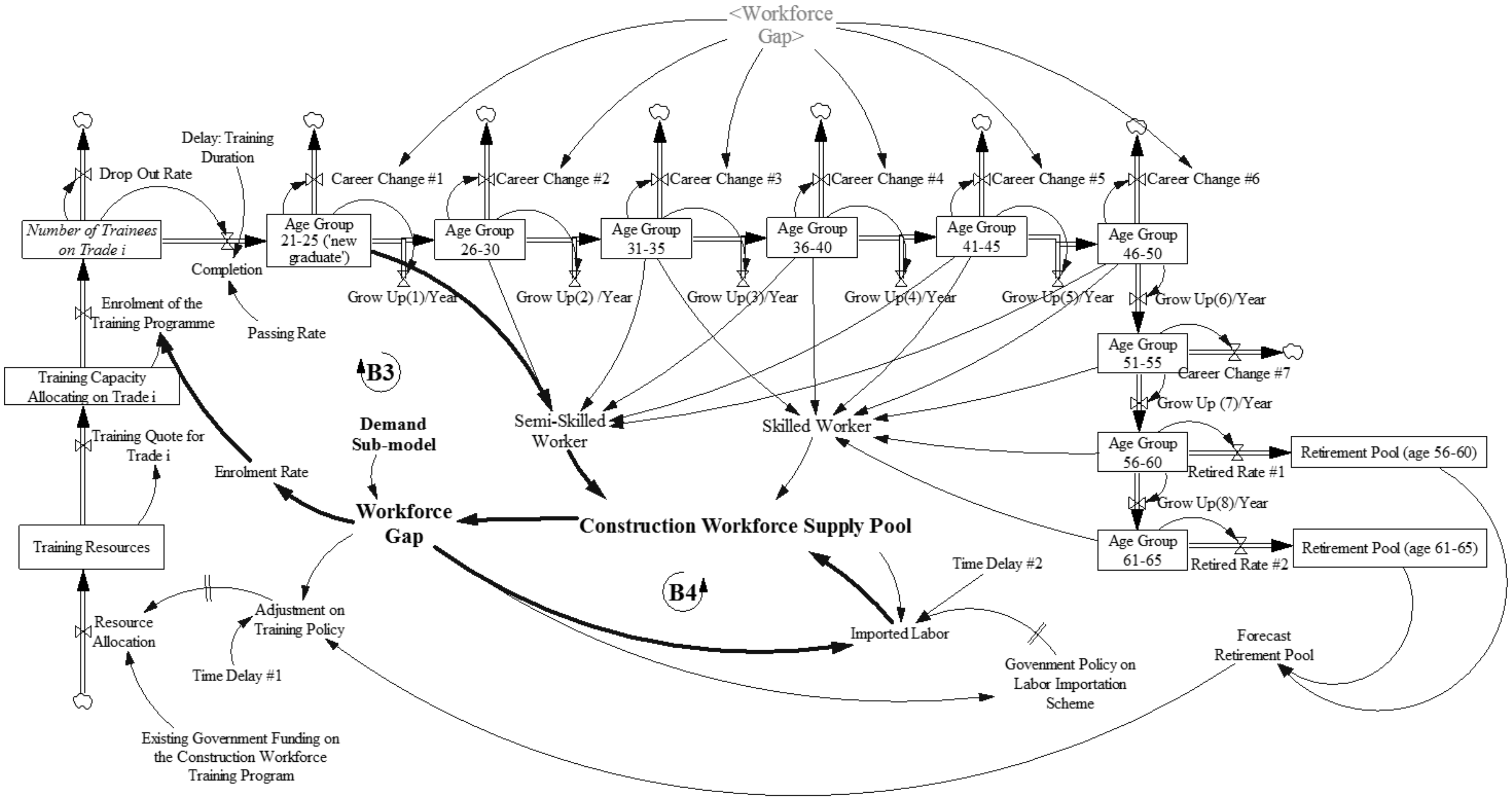

Figure 2 Supply sub-model for the workforce

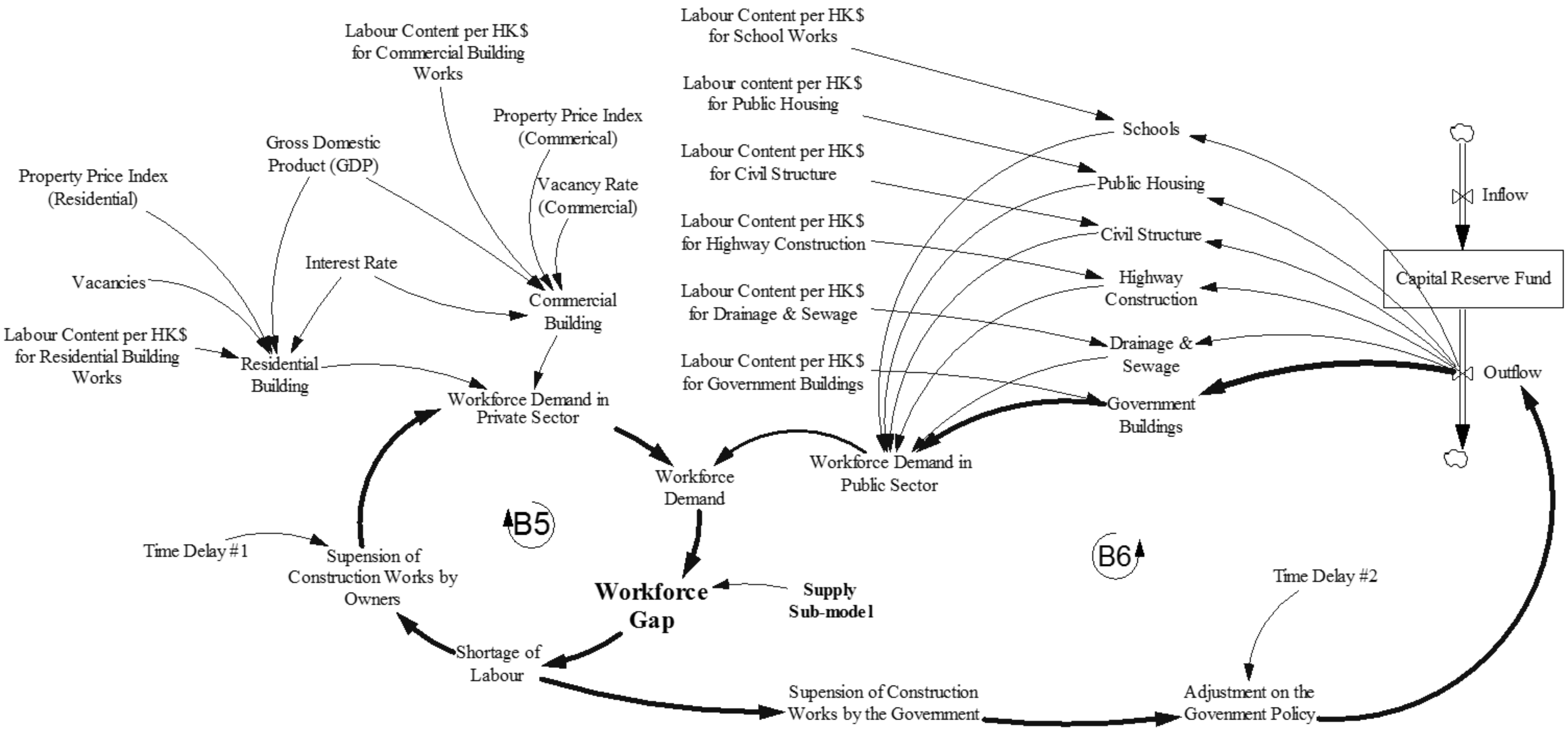

Figure 3 Demand sub-model for the workforce

(remarks: each government works contracts (such as school and public housing) would have a separate closing loop B6 for representing the feedback mechanism between the workforce gap and government policy. Only the closing loop of government buildings is shown on above diagram for the sake of clarification.)

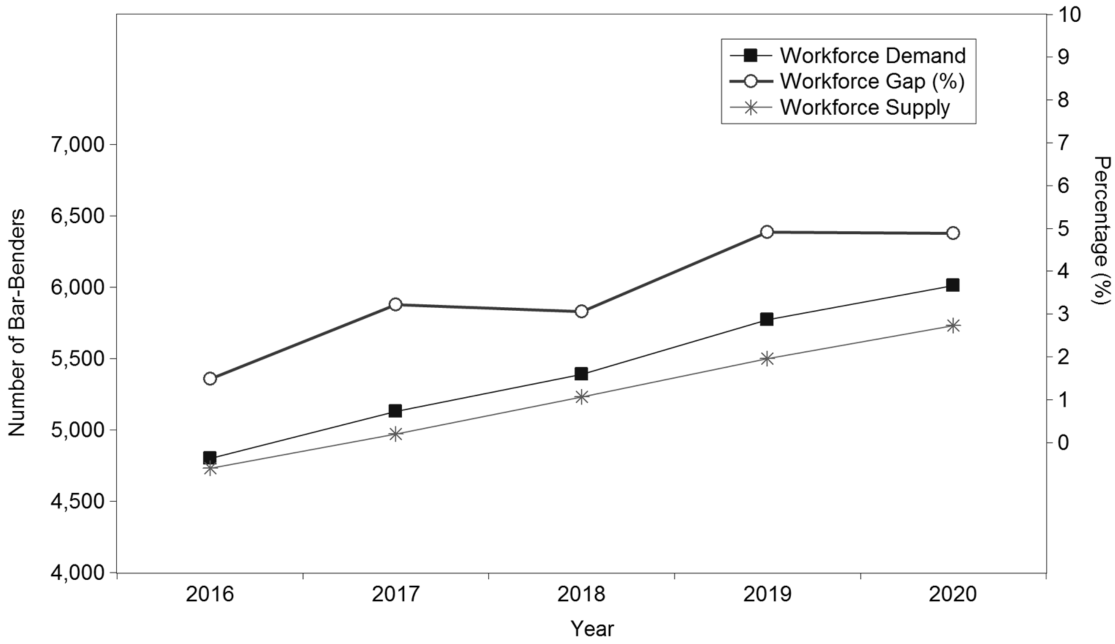

Figure 4 Workforce demand and supply of bar-bender
(Baseline model- Scenario with the existing training resources)

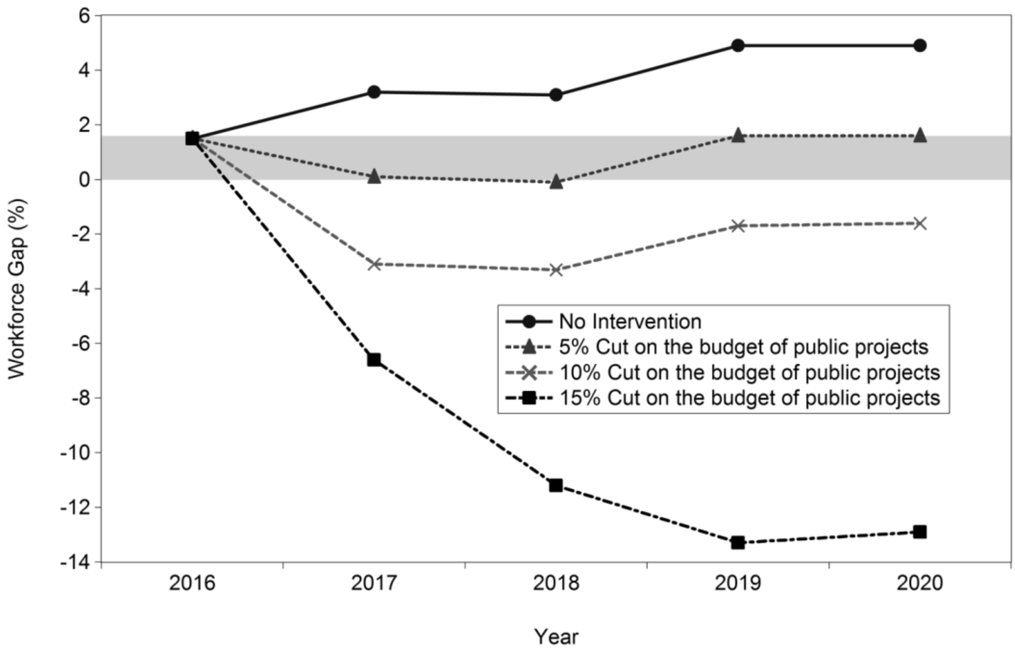

Figure 5 Policy analysis for cutting the budget of infrastructure projects