

1 **Dynamic Modelling of Workforce Planning For Infrastructure**

2 **Projects**

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4 **Abstract**

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

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17 **Introduction**

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

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

26

27 In the absence of reliable workforce planning (WP), labor market requirements are inherently
28 uncertain and exposed to workforce perturbations that can oscillate erratically between surplus
29 and shortage (Sing et al. 2012a). To forecast and plan for labor requirements a plethora of
30 models (e.g., regression and econometric modelling) have been developed so that government
31 policy makers can adjust the type, number and size of training courses available to fulfill
32 demand (Mutingi and Mbohwa 2012). Despite progress in this area, inaccuracies with WP
33 continue to frustrate the industry’s attempts to effectively manage labor requirements (Sing et
34 al. 2014). Against this contextual backdrop, this paper reviews, compares and contrasts

35 between prominent WP models in construction. A novel system dynamics (SD) model is then
36 developed as a viable alternative approach to capture the dynamic nature of labor supply and
37 demand within the construction and civil engineering industry.

38

39 **Workforce Planning**

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

51 *Judgment Techniques*

52 Judgment techniques provide a simplistic means of estimating workforce requirements and
53 utilize industry experts' intuitive knowledge (Marshall and Rossman 1999). They are extremely

54 useful when historical data is either unavailable or of poor/ unsuitable quality (Richards and
55 Morse 2007). The Delphi technique provides a more structured process for collecting and
56 distilling expert knowledge via questionnaires interspersed with controlled opinion feedback
57 (Ziglio 1996). This iterative judgment process continues until consensus emerges amongst
58 group participants. However, forecasting reliability is questionable because of potential bias
59 introduced by experts involved (Meehan and Ahmed 1990); for example it was used by
60 Australia's engineering and mining industry but predictions made led to a considerable
61 shortage of skilled labor (PricewaterhouseCoopers 2012).

62

63 *Stock-flow Modeling*

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

67
$$x(t + 1) = x(t)P + N(t + 1)p \dots\dots\dots\text{Eq.[1]}$$

68

69 Where: $x(t)$ is the stock vector that is observed at time t ; $N(t+1)$ is the number of new entrants
70 at time $(t+1)$; p indicates entrants are distributed among the states of categories; and P is the
71 matrix of transition proportions among the categories and the expected stock vector at time $t+1$
72 is $x(t+1)$. The Markovian model produces an assessment of the number of employees with a

73 recruitment, wastage and promotion rule. It neglects, however, the complexities inherent within
74 aggregated workforce supply for an entire industry and is hence, limited in scope and
75 application (Anthony and Wilson 1990).

76

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

87

88 *Trend Projection and Time Series Forecasting Model*

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

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

105

106 *Econometric Model using Regression Techniques*

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

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

113

114 $MD_t = \beta_0 + \beta_1 Q_t + \beta_2 RW_t + \beta_3 MP_t + \beta_4 BR_t + \beta_5 LP_t, \dots \dots \dots \text{Eq.}[2]$

115

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

118

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

126

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

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

136

137 **System Dynamics Modeling**

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

142

143 Causal loop diagrams consist of cause and effect variables that are connected by arrows
144 denoting their causal influence. Each causal link is assigned a polarity, either positive (+) or
145 negative (-) to indicate the relationship (i.e. positive or negative) between the dependent and
146 independent variables. In addition, the feedback process within the loop can be simulated to
147 provide a delayed response; such a delay creates system inertia and oscillation within the
148 system. For example, significant delays that arise when assessing the workforce demand and

149 in changing the training policy for the supply of new entrants. The SD simulation is developed
150 in the form of stock and flow variables, where a ‘stock’ variable describes the system’s state
151 (such as the existing supply of workers) and the ‘flow’ variable represents the rate of system
152 changes. Examples of flows are the retirement and recruitment rates in the workforce supply
153 system. The workforce supply model is expressed as:

154

155
$$Stock(t) = \int_{t_0}^t [inflow(s) - outflow(s)] ds + stock(t_0) \dots \dots \dots Eq.[3]$$

156

157 Where: t_0 is the initial time; t is the current time; $stock(t_0)$ is the initial value of workforce stock,
158 $inflow(s)$ and $outflow(s)$ rates represent new graduates who become either in, or retired workers
159 who become out of stock at any time between the initial time t_0 to and current time t . $Inflow(s)$
160 and $outflow(s)$ have the units of $stock(t)$ divided by time.

161

162 With SD, the structure’s behavior over time is easily simulated (Morecroft 2007). Given its
163 inherent capabilities, SD has been widely applied to a number of problems, such as economic
164 behavior, supply chain management and health care modeling (Tako and Robinson 2010). The
165 application of SD to WP originated from a model developed by Parker and Caine (1996) who
166 focused predominantly on modeling staff promotion within a single organization. Based upon
167 this early work, Hafeez and Abdelmeguid (2003) developed an SD based model to illustrate

168 the relationship between recruitment, training, skills and knowledge in a causal loop form.
169 Mutingi and Mbohwa (2012) further combined fuzzy SD and optimization techniques to
170 develop training strategies for a single organization. Alvanchi et al. (2012) also applied SD
171 modeling to study the dynamics of construction workforce skill evolution and understand how
172 a company's human resource policy affects the project's performance and cost. The literature
173 indicates that whilst SD modeling is applicable to WP, past research is limited in scope and
174 application to a single organization only whilst the proposed model presented in this paper
175 would be the first attempt using SD to model workforce demand and supply over the whole
176 construction and civil engineering industry.

177

178 **Model Development**

179 To frame the scope of the SD model that is developed in this study, Figure 1 illustrates a
180 simplified CLD of the proposed WP system.. The system consists of: (a) demand sub-model;
181 and (b) supply sub-model. Each sub-model has their own feedback mechanism and closed-loop
182 (*B1* and *B2* as indicated in Figure 1) with an interaction of a variable, labeled as the 'workforce
183 gap'.The problem of workforce gap (e.g. shortage or surplus) could be resolved through a
184 detailed study on the variables laid within the feedback loop of *B1* and *B2*. For example, in
185 balancing loop *B1*, if the attractiveness of employment condition increases (e.g. pay rise due to
186 workforce shortage), the number of new entrants will then lead to an increase in the workforce

187 supply; this will eventually reduce the size of the workforce gap. Similarly, balancing loop *B2*
188 represents the workforce demand condition of construction workers. If the workforce gap
189 increases, the intention to commence a new construction project will be suppressed due to a
190 shortage of workers. This will again lead to a reduction of construction works that in turn
191 reduce demand for construction workers. A more comprehensive and holistic view of the
192 major causal loop dependencies that exist with the workforce demand and supply sub-models
193 are presented in the sub-sections below.

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

199

200 *Supply Sub-model*

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

206 bar-benders in the SD model.

207

208 Key factors affecting the workforce supply chain are identified in Table 1 (Briscoe and Wilson
209 1993; Sing et al. 2012b). Figure 2 presents the SD model for the supply of bar-benders and
210 illustrates the *training-work-retirement* work-life cycle on a temporal trajectory; this process
211 moves from: (a) recruitment of graduate trainee; (b) development of semi-skilled bar-benders
212 given exposure to industrial experience; and (c) following competence assessment, registration
213 as skilled bar-benders until retirement. The stock variables in the supply sub-model include the
214 workforce subgroups of: (a) age of bar benders; (b) number of new entrants; and (c) number of
215 retired workers. In this model, each equation in the workforce subgroup expresses the number
216 of workers progressing from first stock (*trainee entrants*) to last stock (*retirement*); unless the
217 individual leaves the construction industry, for example, when employability fails to provide
218 sufficient numeration to support their family living.

219

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

224

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

236

237 In addition to stock and flow variables, the concept of delay is also considered in the supply
238 sub-model. A delay is defined as time lags between inputs and outputs, for instance, places for
239 trainee graduates that cannot be immediately adjusted to respond to changing demand. Hence,
240 at time t_1 , the local training authority amends its policy and increases the intakes onto bar-
241 benders training courses. However, the training duration in Hong Kong is one year thus creating
242 a (t_1+1) year lag before newly qualified trainees can enter the workforce pool. In the Loop *B3*
243 of Figure 2, this lag is represented by the function of delay as defined in the SD modeling. A

244 variable of ‘delay: training duration’ (e.g., t_{l+1} years) has been inserted between the variables
245 of ‘number of trainee’ and ‘age group of 21-25 (e.g. new graduates)’ to account of this time lag
246 between intakes of trainees and their completion of training in the supply model. In the short
247 term, it is possible to re-allocate the training quota to the most problematic trades without
248 increasing the overall training capacity. For the long-term policy, strategic decisions would be
249 required to build new (or expand) training centers, but such plans require extensive lead-times
250 from budget approval to building completion.

251

252 Whilst importing labor represents an alternative policy to building new recruit training capacity,
253 it also represents a short-term flexible measure for the government/ industry to meet labor
254 demands (Golden and Skibniewski 2010). Lee (1999) postulated that the import of labor should
255 only become operational when: (a) local workers have been given priority in filling job
256 vacancies; and/ or (b) employers are genuinely unable to recruit local workers to fill these
257 vacancies. In the proposed supply sub-model, the decision to import foreign workers is
258 dependent upon the combined effect emanating from the workforce gap and the percentage of
259 intake from the local training authority. The feedback mechanism between the workforce gap,
260 imported labor and workforce supply is also represented by the Loop *B4* as indicated in Figure
261 2.

262

263 *Demand Sub-model*

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

271
 272 Figure 3 represents the CLD of workforce demand. In the demand sub-model, an increase in
 273 private investment generates growth and government funding on public projects which then
 274 produces a greater demand (denoting a positive relationship '+') for bar-benders from the
 275 workforce market (Eq.[4]). Contrastingly, an increase in the number of infrastructure projects
 276 that are abandoned (due to workforce shortages) will in turn reduce the demand for workers
 277 (denoting a negative relationship '-').

278
 279

280 $WF_{demand} = \sum_{i=1}^p CO_{private,i} \cdot SCW \cdot L_{private,i} + \sum_{i=1}^q CO_{public,i} \cdot SCW \cdot L_{public,i} \dots \dots \dots \text{Eq.[4]}$

281
$$\underbrace{\hspace{10em}}_{\substack{\text{Workforce demand} \\ \text{in private sector}}} \quad \underbrace{\hspace{10em}}_{\substack{\text{Workforce demand} \\ \text{in public sector}}}$$

282 Where: WF_{demand} = workforce demand; $CO_{private, i}$ = output of project type i in the private

283 sector; $CO_{public, i}$ = output of project type i in the public sector; SCW = adjustment factor for
284 the suspension of works due to labor shortages; $L_{private, i}$ = labor content per HK\$ for project
285 type i in private the sector; and $L_{public, i}$ = labor content per HK\$ for project type i in the public
286 sector.

287

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

296

297 Contrastingly for the public sector, the initiation of infrastructure projects depends heavily on
298 government policies. The first step is to retrieve the dataset for the government's planned
299 expenditure for infrastructure projects. In Hong Kong, the government generally publishes its
300 budget report annually to provide information on the ongoing programmes and expenditure
301 pertaining to public services such as health, education and infrastructure projects. For the

302 medium range and five-year forecast under the 2015-2016 *Budget* published by Hong Kong
303 Special Administrative Region (HKSAR), the forthcoming Capital Works Reserve Fund for
304 infrastructure projects will be HK\$75,400 million and gradually increased to HK\$103,800
305 million by year 2019. As part of the model development process, the number of projects to be
306 included and the percentage of project types over the forecast year must be determined.

307

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

317

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

321

322 [Loop B5] Workforce demand \rightarrow (+) workforce gap \rightarrow (+) shortage of labor \rightarrow (+) suspension
323 of the works by owners \rightarrow (-) infrastructure projects being commenced \rightarrow (-) workforce
324 demand.

325

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

337

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

340 expenditure in capital reserve fund.

341

342 **Model Validation**

343 Validation is required to build confidence in model predictions and generate a deeper
344 understanding of WP. First, the proposed demand model was validated by comparing estimated
345 values to historical data from 2009 to 2013. The number of construction workers recorded in
346 the Quarterly Employment Survey of Construction Sites were adopted as a time series of
347 historical workforce demand. According to Barlas (1994), a model is valid if the error rate is \leq
348 5% (Eq.[5]). The comparison between the model and data extracted is computed in Table 3. As
349 the error rate is only 2% and 4.3% for the private and public sector respectively, it confirms the
350 fidelity of the proposed SD model.

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

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

353

354 When quality data is unavailable, preliminary models can still be developed on the basis of
355 expert opinion/ judgement and using qualitative data (Burchill and Fine 1997). For the supply
356 side of SD model, there was a lack of time series data on the number of workers available in
357 the market from year 2009 to 2013 for backtesting the accuracy of the supply sub-model. As
358 the supply sub-model is based on the inflow and outflow of labor, it can be effectively captured

359 the change of the labor supply model On the other hand, the accuracy of the supply sub-model
360 should be dependent on whether the key variables affecting the inflow and outflow of labor has
361 been carefully considered and also the quality and availability of the such data (i.e. current
362 training capacity and trainee pass rate) for analysis.

363

364 **Application of the System Dynamics Modeling**

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

375

376 *Scenario A: Baseline Resource Held Constants*

377 A baseline model infers that training resources are in-line with the existing government policy

378 and that no improvement in provision is required. In anticipation of increasing demand for
379 workers, the government often attempts to augment the industry's image as a means of
380 attracting new recruits. By providing higher training allowances and placement services,
381 around 300 new trainees eventually entered the bar-bender trade in year 2014; the drop-out rate
382 was around 10%. The above value is set to the initial value of the training capacity and drop-
383 out rate in the supply SD model. Several key assumptions are listed in Table 4. For the demand
384 side, the private industry output is based upon key economic indicators as discussed in Sing et
385 al. (2015) while the public sector is based on the forecasting expenditure captured from
386 Government statistics. The forecast workforce demand and supply on bar-benders is illustrated
387 in Figure 4. It is noted that the deficit of this trade will grow from 2016-2020 and will be
388 between 1.5% and 4.9%. This forecasted shortfall is caused by the strong growth in the private
389 sector and increase in volume of public infrastructure projects over the next five years from
390 2016. This dearth will eventually drive the salary rise of workers, which may have a detrimental
391 impact on the future delivery of infrastructure projects. This feedback mechanism (which is
392 due to the shortage of workers) can be traced back in the loops *B5* and *B6* as identified in the
393 demand sub-model (see Figure 3).

394

395 *Scenario B: Change on the government policy and public investment*

396 Owing to a policy response to the workforce shortage, policy intervention could be

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

414

415 As illustrated in the Figure 5, the model represents a useful planning tool to simulate the effect

416 of regulatory changes for infrastructure projects. However, the supply model will be only make
417 realistic forecasts when entry parameters (i.e. places for trainee) are realistic. Fortunately, the
418 SD model allows the modification of these parameters, which can provide policy makers with
419 invaluable insights to examine ‘what if’ scenarios to enable an equilibrium between supply and
420 demand to be obtained.

421 **Conclusion**

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

432

433 Although the model is useful for planning and policy development, its limitations need to be
434 acknowledged. The demand and supply sub-model that were created are influenced by the

435 parameters, which govern its assumption; the complexity of the real-world in this instance is
436 simplified. However, further research is required to better understand the dynamics of the key
437 parameters such as the intention of construction workers leaving the industry. The SD
438 workforce model presented in this paper should be extended to model other skilled trades as
439 well as explore interconnectedness between them. The above information would be useful to
440 solve the long-standing workforce problem such as skill mismatch in the construction industry
441 world-wide.

442

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570

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 1 st foreign labor arrived Hong Kong |

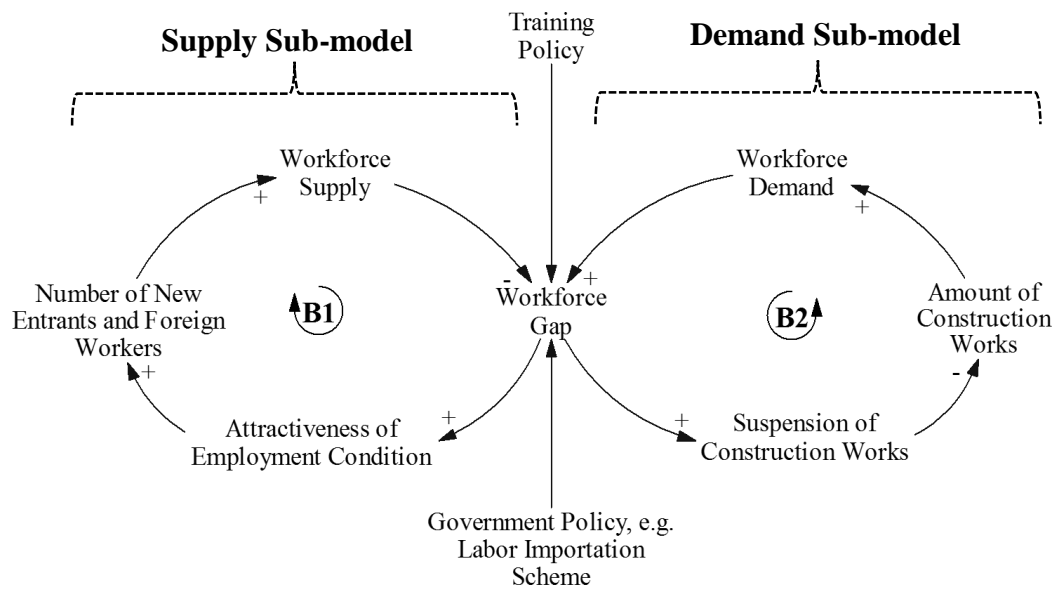


Figure 1 Causal loop diagram of the workforce planning model

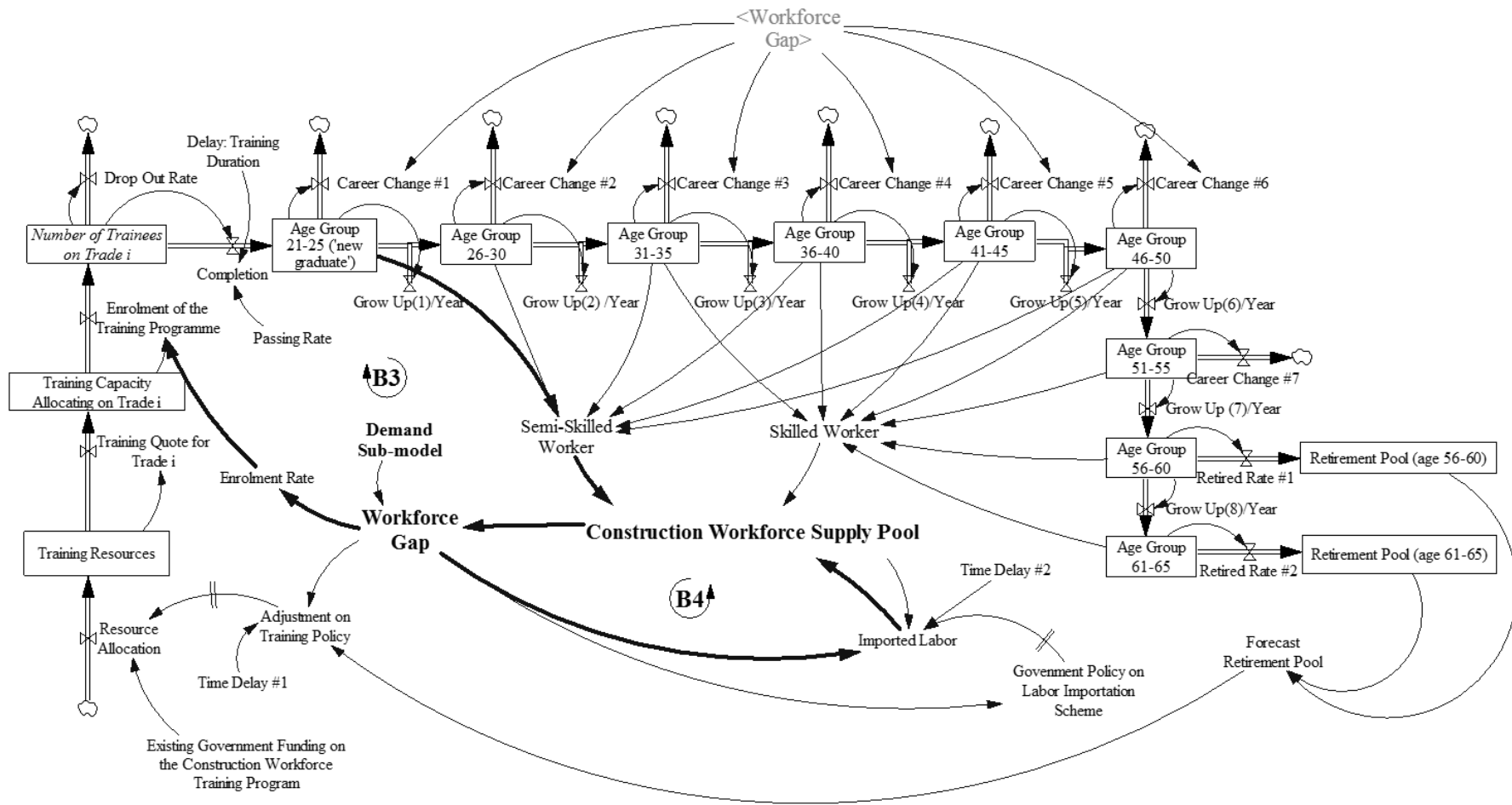


Figure 2 Supply sub-model for the workforce

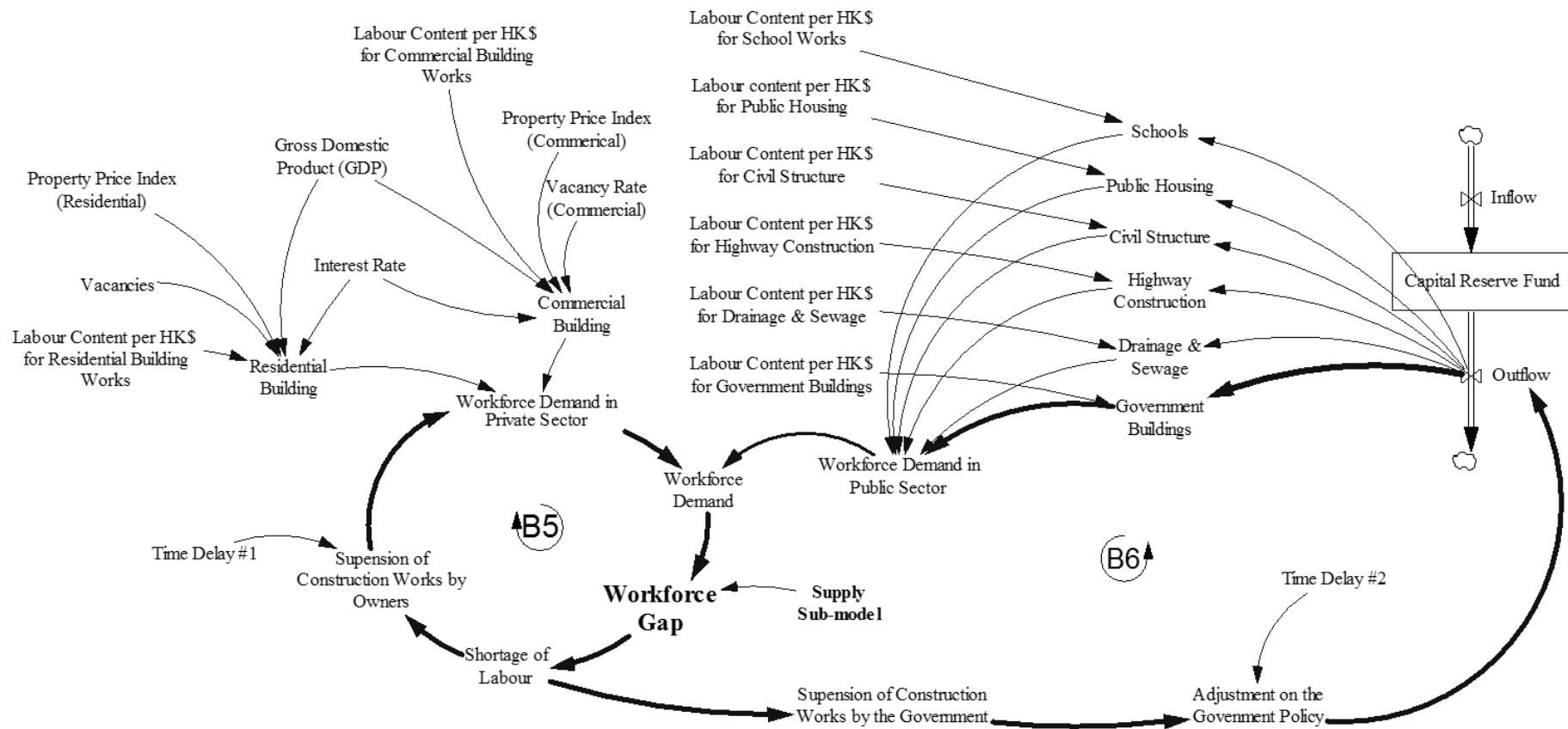


Figure 3 Demand sub-model for the workforce

(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.

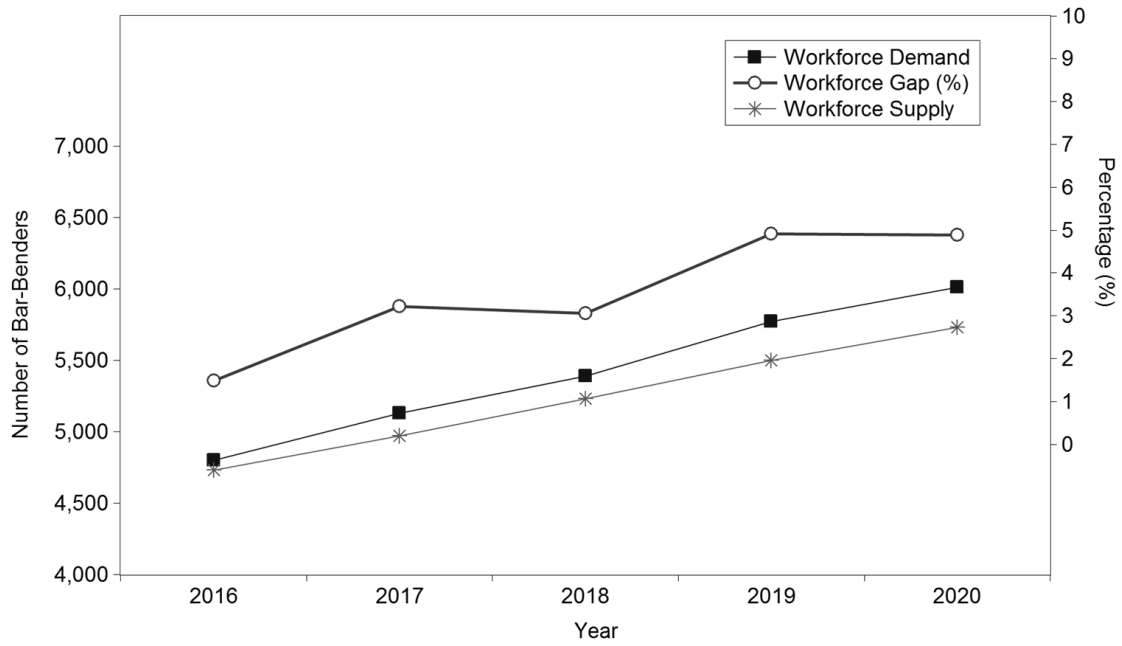


Figure 4 Workforce demand and supply of bar-bender
(Baseline model- Scenario with the existing training resources)

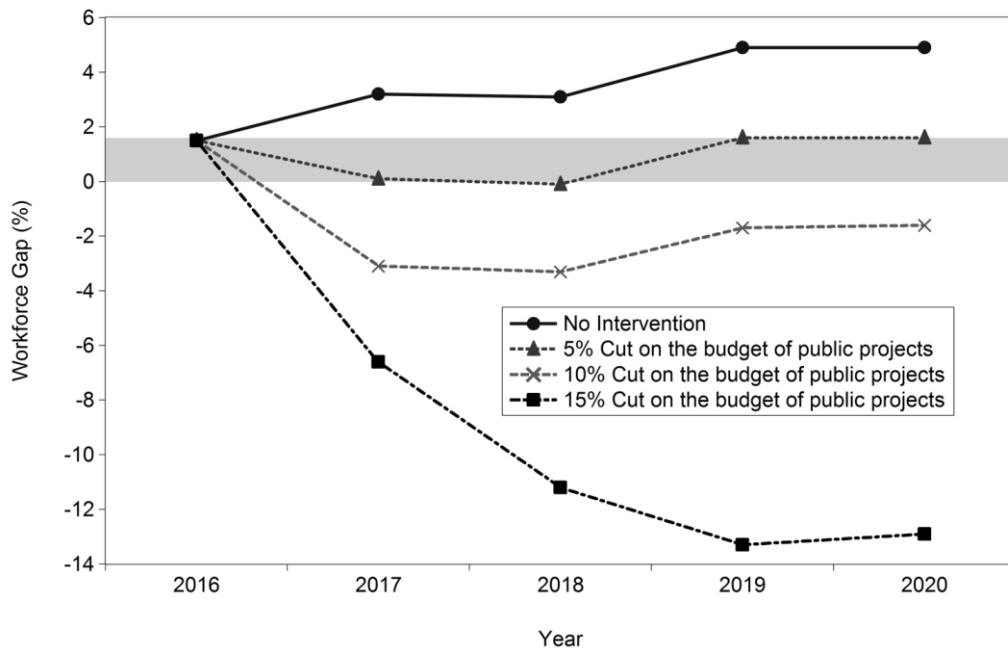


Figure 5 Policy analysis for cutting the budget of infrastructure projects