Forecasting the Passenger Volume of Taiwan High Speed Rail by Amensalistic Lotka-Volterra Model

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***Abstract*—Forecasting passenger volume is crucial for transportation systems to effectively plan operations, determine ticket types, and set fare levels. To achieve this, a proposed aggregative model utilizes historical data from Taiwan's high-speed rail (HSR) passenger volume. The goal is to forecast passenger numbers without resorting to costly questionnaire surveys typically associated with discrete choice models. Instead, the study employs an amensalistic Lotka-Volterra model, integrating socio-economic variables such as gross domestic product (GDP), average income, average consumption, and population. Upon analyzing the results, it was discovered that utilizing average income as the sole socio-economic factor led to the most accurate forecasting of HSR passenger volume. This conclusion was drawn based on a mean absolute percentage error (MAPE) of approximately 5%, indicating a high level of forecasting accuracy. Furthermore, the coefficients of the model were interpreted consistently with general observations.**

***Index Terms*—amensalistic interaction, Lotka-Volterra model, high speed rail, passenger volume, socio-economic factor.**

I. INTRODUCTION

The advent of high-speed rail technology has wrought a profound transformation in transportation systems worldwide, particularly along major trunk routes. In Taiwan, the inauguration of the Taiwan High-Speed Rail (HSR) on January 5, 2007, marked a significant milestone. This system offers swift, high-volume passenger service along the west coast, linking the capital city Taipei with the southern city of Kaohsiung over a span of approximately 345 km. Boasting a top speed of 300 km/h, the HSR has dramatically slashed travel times, enabling residents of western Taiwan to complete a round trip within a single day.

Research has demonstrated that high-speed rail and air carriers are competitive modes of transportation for distances spanning 200 to 600 miles [1, 2]. Lin et al. [3] found that after the implementation of Taiwan HSR, about 50% of air trips, 20% of Taiwan Railway trips, and 15% of freeway coach trips would shift to HSR. Furthermore, other studies have indicated a notable shift from air travel, Taiwan Railway usage, and freeway coach commuting to HSR following its introduction [4].

According to forecasts by Lan [5], Wang and Liu [6], and Huang [7], the introduction of Taiwan HSR has had a significant impact on the three primary modes of intercity transportation, particularly domestic civil aviation services. While these studies predicted the influence of Taiwan HSR on the domestic air travel market, the actual impact surpassed the forecasts provided by related research. Due to the underestimated passenger volume of Taiwan HSR, domestic airlines failed to formulate adequate responses to compete effectively with the new rail service. Hence, the adoption of a robust forecasting model becomes imperative for transportation system operators to devise appropriate strategies and identify their niches to survive amidst intense competition. Previous studies on HSR have explored various facets such as operational planning [8, 9], optimization of ticket types and fare levels [10, 11], service quality [12], market share forecasting [13, 14], and the competitive dynamics between HSR and other transportation modes [15-17]. Understanding the growth rate of HSR passenger volume is pivotal for making informed marketing and managerial decisions, including those related to operational planning and pricing strategies.

Indeed, while regression and time series analysis serve as common forecasting techniques, they encounter challenges in elucidating how independent variables influence dependent variables, particularly within intricate systems like transportation modal choice. Furthermore, these methods may struggle to capture abrupt changes or external shocks to the system, such as the financial crisis of 2008 and the Covid-19 epidemic. To tackle these hurdles, individual choice models, such as logit or probit models, are widely employed for forecasting passenger volume by scrutinizing modal split [18-22]. These models leverage revealed and stated preference data acquired through questionnaire surveys. However, conducting such surveys can prove time-consuming and costly. Moreover, in the event of significant external changes, predictions from these models may exhibit substantial biases.

Essentially, while regression and time series analysis possess their strengths, they may not always be apt for forecasting modal choice, especially within dynamic environments characterized by complex interactions between variables. Individual choice models offer a more nuanced approach but entail their own set of challenges, particularly regarding data collection and adaptation to changing external conditions. Consequently, selecting the appropriate forecasting method hinges on the specific context and requirements of the transportation system under examination.

In this study, a modified model based on the Lotka-Volterra (LV) model [23, 24] is proposed for forecasting the passenger volume of the HSR. Originally devised to depict

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the dynamics of predator-prey interactions in ecological systems, the LV model has been adapted to analyze diffusion phenomena and reciprocal competition between two entities. While earlier models, such as those by Fourt and Woodlock [25], Mansfield [26], Bass [27, 28], and Bass et al. [29], primarily focused on the life cycle of single products, they often neglected competitive factors in the market. Similarly, Fisher and Pry [30] developed a substitution model assuming that a new technology would supplant an older established technology, yet it did not fully account for competitive dynamics. Norton and Bass [31] sought to address this by amalgamating aspects of both the Bass model and the Fisher and Pry model to illustrate the substitution effect, particularly in forecasting the diffusion of new technologies.

In contrast, the LV model furnishes a more comprehensive framework for analyzing competitive dynamics by elucidating interactions between two entities [32-35]. Referred to as the predator-prey model due to its portrayal of two-species biological dynamics, the LV model has been employed in scenarios involving correlated populations. Moreover, the LV model transcends the limitation of analyzing only two entities; it can be expanded to scrutinize systems with multiple interacting components, as exemplified by Jackson [36] and Meadows [37] in their technology system dynamics models.

In this study, we undertake a comparison of forecasting results obtained from models with and without socio-economic factors, along with an assessment of two distinct types of interaction. Our aim is to recommend the most effective model for forecasting the passenger volume of HSR. The paper is structured as follows: Section 2 delves into the modeling process and the integration of socio-economic factors. In Section 3, the numerical results are presented and compared. Finally, Section 4 provides conclusions along with a brief summary and discussion.

II. Amensalistic Lotka-Volterra Model

The Lotka-Volterra model is derived from the single-species population model, which considers the growth rate of population to be proportional to the population itself. Let $N(t)$ denote the function of population, t be time and α be the proportionality constant. Then, we have $dN(t)/dt = \alpha N(t)$. If the initial condition is given, the model can be solved analytically. According to the model, N increases exponentially with t, it can only be applied to short-term forecasting because when t increases. The result is unreasonable and unrealistic. Actually, the population growth is also proportional to the capacity of the system, and thus we have $dN(t)/dt \propto (M-N(t))$, where M is a constant representing the capacity of the system. Thus, the one-species population model is given by

$$\frac{dN(t)}{dt} = a_1 N_1^2(t) + b_1 N_1(t), \tag{1}$$

where a_1 and b_1 are coefficients. Equation (1) is a diffusion equation and can be solved by separation of variables. The solution is in the logistic form, which is given by

$$N(t) = M \Bigg/ \left[1 + \left(\frac{M - N_0}{N_0}\right) e^{-\alpha M t}\right]. \tag{2}$$

Under the closed system assumption, Eq. (2) can be represented in a general form, which is $dN(t)/dt = F(N,t)$. $F(N,t)$ is the growth function. If two population species are considered, the model will consist of two equations with interaction terms, such as $dN_1(t)/dt = F_1(N_1, N_2, t)$ and $dN_2(t)/dt = F_2(N_1, N_2, t)$, where N_1 and N_2 are two species, and F_1 and F_2 are the growth function of N_1 and N_2, respectively. The most famous model in this form is the Lotka-Volterra (LV) model, which is given by

$$dN_1(t)/dt = a_1 N_1^2(t) + b_1 N_1(t) + c_1 N_1(t) N_2(t), \tag{3}$$

$$dN_2(t)/dt = a_2 N_2^2(t) + b_2 N_2(t) + c_2 N_1(t) N_2(t), \tag{4}$$

where a1, a2, b1, b2, c1 and c2 are coefficients. Table 1 shows types of the model, which is determined by the combination of c_1 and c_2.

Table 1 The relationship according to the signs of c_1 and c_2

coefficient c_1	c_2	Type	Explanation
+	+	Pure competition	Both species suffer from each other's existence.
–	+	Predator-prey	One of them serves as direct food (N_2) for the other (N_1).
–	–	Mutualism	It is the case of symbiosis or a win-win situation.
–/+	0	Amensalism	One (N_1) suffers from the existence of the other (N_2), who is impervious to what is happening.
0	0	Neutralism	There is no interaction.

Let $E_i(t)$ represent the socio-economic factors, where i is the indicator that denotes different factors. Before substituting the socio-economic factors into Eqs. (3) and (4), the forecasting equation of socio-economic factors is discussed. Two types of the equation are presented. The first one assumes that the growth rate of socio-economic factors is proportional to their present values, which is given by

$$\frac{dE_i(t)}{dt} = a_2 E_i(t), \tag{5}$$

where a_2 is the coefficient. The second one assumes that the growth rate of socio-economic factors increases linearly, which is given by

$$\frac{dE_i(t)}{dt} = a_2 \,. \tag{6}$$

In this study, we assume that an individual's modal choice is influenced by their purchasing power. Hence, we consider gross domestic product (GDP), average income, and average consumption as the socio-economic factors. GDP serves as a measure of a country's economic performance, representing the total monetary value of all finished goods and services produced within its borders over a specified period. Average income, in this context, refers to income stated without adjustments for inflation, deflation, or other economic factors. Average consumption is utilized to gauge individual purchasing power and living standards.

In 2012, domestic airlines ceased providing air services from Taipei to Kaohsiung, while the HSR began offering high-quality, albeit high-cost, services to passengers. A Taipei-to-Kaohsiung ticket on the HSR is priced at NT$1,530 (US$50), exceeding the cost of a Taiwan Rail Administration (TRA) ticket at NT$843 (US$28) and a freeway coach ticket at NT$580 (US$16). Broadly speaking, an increase in GDP and average income suggests a rise in individuals' disposable income, potentially leading to more people opting for the

HSR as their transportation mode. Regarding the correlation between individuals' annual consumption and their inclination to travel via HSR, a higher standard of living may result in increased HSR ridership alongside rising annual consumption. In Taiwan, the average income surpasses the average consumption, implying that more individuals may opt for the HSR as their consumption rises. Additionally, the population in Taiwan naturally influences HSR passenger volume. Table 2 presents historical data for these four factors.

Table 2 Data of socio-economic factors from 2007 to 2016.

year	GDP (10^6\$US)	average income per year (\$US)	average consumption per year (\$US)	population (10^4 persons)
2007	408,254	15,401	9,564	2,296
2008	416,961	15,388	10,009	2,304
2009	392,065	14,398	9,405	2,312
2010	446,105	16,650	10,237	2,316
2011	485,653	17,982	11,410	2,322
2012	495,845	18,125	11,657	2,332
2013	511,614	18,872	11,869	2,337
2014	530,519	19,724	12,084	2,343
2015	525,196	19,540	11,701	2,349
2016	529,910	19,626	11,886	2,354

Two types of socio-economic influences are considered and Eq. (3) is modified to Eqs. (7) and (8). Equation (7) means that the socio-economic factors will directly influence the growth rate of passenger volume directly. The interaction term $E_i(t)N(t)$ in Eq. (8) illustrates that the socio-economic factors will act on the passenger volume and then influence the growth rate. The comparison of forecasting results will be presented in the next section.

$$\frac{dN(t)}{dt} = a_1 N^2(t) + b_1 N(t) + c_1 E_i(t), \tag{7}$$

$$\frac{dN(t)}{dt} = a_1 N^2(t) + b_1 N(t) + c_1 E_i(t) N(t), \tag{8}$$

where d_1 is a coefficient. Equations (5) and (6) are the socio-economic equations, whereas Eqs. (7) and (8) are the passenger volume equations. The models we have proposed consist of one socio-economic equation and one passenger volume equation. The systematic equations are in the form of Lotka-Volterra model with amensalistic interaction. That is, the socio-economic factors will influence the passenger volume of HSR; nevertheless, the passenger volume of HSR will not influence the socio-economic factors.

III. Results and Analyses

The two-stage least squares method (2SLS), which is an estimation method for simultaneous equations is employed to calibrate the model. In the first stage, 2SLS uses instrumental variables that are uncorrelated with the error terms to estimate the problematic predictor(s). Then, the results are estimated by a linear regression model in the second stage. After obtaining the values of coefficients, the model is solved by the Broyden algorithm [38], which is a numerical method for solving systematic ordinary equations. Tables 3 and 4 provide the forecasting results and the absolute percentage error of socio-economic factors from Eqs. (5) and (6), respectively. The absolute percentage error (*APE*) and mean absolute percentage error (*MAPE*) are given as follows.

$$APE = \frac{|n(t) - N(t)|}{n(t)} \times 100\%, \tag{9}$$

$$MAPE = \frac{1}{T}\sum_{t=1}^{T} \frac{|n(t) - N(t)|}{n(t)} \times 100\%, \tag{10}$$

where $n(t)$ is the actual data at time t of the passenger volume and T is the number of data.

In fact, Eq. (5) represents an exponential fitting curve of the socio-economic factors, while Eq. (6) depicts a linear fitting curve of these factors. Tables 3 and 4 illustrate that both exponential and linear models exhibit a good fit with the historical data. Let's designate Model 1 as the combination of Eq. (5) and Eq. (7), and Model 2 as the combination of Eq. (6) and Eq. (7). Tables 5 and 6 present the forecasting results and errors for Model 1 and Model 2, respectively. The study period spans from 2007 to 2016. We utilize data from 2007 to 2015 for coefficient calibration and forecast HSR passenger volume from 2008 to 2016. Extrapolative forecasting yields the passenger volume for 2016.

Models incorporating socio-economic factors demonstrate better alignment with historical data compared to the single-equation model. Notably, all models produce highly accurate forecasting results (MAPE<10%). There exists no significant disparity between Model 1 and Model 2.

To maintain model simplicity and computational ease, we couple Eq. (6) with Eq. (8) to derive an interaction model, conforming to the standard format of the amensalistic Lotka-Volterra model. This model elucidates that one species (or player) exerts a positive or negative influence on another species (or player), which can only withstand the impact within a two-species system. In this study, we consider socio-economic factors influencing the passenger volume of HSR, wherein the HSR passenger volume cannot reciprocally influence the socio-economic factors. Let the amensalistic model be Model 3. Table 7 presents the results and errors, with coefficients calibrated using data from the 2007-2015 interval.

Only the model incorporating population as the socio-economic factor yields accurate forecasting results (with 10% < MAPE < 20%); models incorporating other socio-economic factors offer highly accurate forecasting. While MAPE serves as a reliable measure for forecasting precision, it's also essential to consider the trend of the forecasting curve. Figures 1 to 3 illustrate the actual data curves alongside results from the single-equation model and Models 1 to 3. All curves exhibit an upward trend. However, in Figs. 1 and 3, the curve from the single-equation model deviates from the actual data curves. Extrapolating forecasting over an extended period may exacerbate errors in passenger volume estimation.

The coefficients of Models 1 to 3 are detailed in Tables 8 and 9. According to the Lotka-Volterra model's derivation, a_1 is expected to be negative due to market capacity limitations, while b_1 should be positive for high-quality services or products, as increased usage tends to attract further adoption. As for c_1, it represents the influence of socio-economic factors on HSR passenger volume. In this study, we investigate several socio-economic factors—namely GDP, average income, average consumption, and population—all of which are anticipated to positively impact HSR passenger volume. In essence, as GDP, average income, average consumption, and population increase, so does HSR passenger volume. A negative value for c_1 would render the model's physical interpretation untenable.

Table 3 Forecasting results and the absolute percentage error of socio-economic factors from Eq.(5).

year	GDP		average income		average consumption		population	
	10^6\$US	APE	\$US	APE	\$US	APE	10^4persons	APE
2008	421527	1.10%	15889.68	3.26%	9805.178	2.04%	2302.434	0.06%
2009	435231.5	11.01%	16393.87	13.86%	10052.44	6.88%	2309.051	0.13%
2010	449381.6	0.73%	16914.06	1.59%	10305.93	0.67%	2315.687	0.02%
2011	463991.8	4.46%	17450.75	2.95%	10565.82	7.40%	2322.342	0.01%
2012	479076.9	3.38%	18004.48	0.66%	10832.26	7.08%	2329.016	0.11%
2013	494652.5	3.32%	18575.77	1.57%	11105.42	6.43%	2335.71	0.07%
2014	510734.4	3.73%	19165.19	2.83%	11385.47	5.78%	2342.422	0.04%
2015	527339.2	0.41%	19773.31	1.19%	11672.58	0.24%	2349.154	0.00%
2016	544483.9	2.75%	20400.73	3.95%	11966.93	0.68%	2355.905	0.08%
MAPE	3.43%		3.54%		4.13%		0.06%	

Table 4 Forecasting results and the absolute percentage error of socio-economic factors from Eq.(6).

year	GDP		average income		average consumption		population	
	10^6\$US	APE	\$US	APE	\$US	APE	10^4persons	APE
2008	422871.8	1.42%	15918.38	3.45%	9831.125	1.78%	2302.507	0.05%
2009	437489.5	11.59%	16435.75	14.15%	10098.25	7.37%	2309.179	0.12%
2010	452107.3	1.35%	16953.13	1.82%	10365.38	1.25%	2315.85	0.02%
2011	466725	3.90%	17470.5	2.84%	10632.5	6.81%	2322.522	0.00%
2012	481342.8	2.92%	17987.88	0.76%	10899.63	6.50%	2329.193	0.10%
2013	495960.5	3.06%	18505.25	1.94%	11166.75	5.92%	2335.865	0.06%
2014	510578.3	3.76%	19022.63	3.56%	11433.88	5.38%	2342.536	0.04%
2015	525196	0.00%	19540	0.00%	11701	0.00%	2349.207	0.00%
2016	539813.8	1.87%	20057.38	2.20%	11968.13	0.69%	2355.879	0.08%
MAPE	3.32%		3.41%		3.97%		0.05%	

Table 5 Forecasting results and the absolute percentage error of Model 1 and Eq.(1).

year	actual data	Eq.(1)		with GDP		with income		with consumption		with population	
		persons	APE	persons	APE	persons	APE	persons	APE	persons	APE
2008	30581261	23346390	23.66%	30083270	1.63%	30345740	0.77%	28640920	6.34%	27995140	8.46%
2009	32349260	30894290	4.50%	35686950	10.32%	36456290	12.70%	34432440	6.44%	34463110	6.53%
2010	36939596	37203760	0.72%	38636470	4.59%	39691980	7.45%	37592250	1.77%	38487670	4.19%
2011	41629303	41957380	0.79%	40803860	1.98%	41968890	0.82%	39768980	4.47%	41379240	0.60%
2012	44525754	45297580	1.73%	42789930	3.90%	43960640	1.27%	41598860	6.57%	43735080	1.78%
2013	47486859	47540430	0.11%	44800580	5.66%	45915470	3.31%	43342870	8.73%	45893530	3.36%
2014	48024758	49003330	2.04%	46915860	2.31%	47931480	0.19%	45116310	6.06%	48120170	0.20%
2015	50561954	49940130	1.23%	49176730	2.74%	50053610	1.01%	46977340	7.09%	50756580	0.38%
2016	56586210	50533160	10.70%	51614410	8.79%	52308780	7.56%	48963000	13.47%	54614890	3.48%
MAPE		5.05%		4.66%		3.90%		6.77%		3.22%	

Table 6 Forecasting results and the absolute percentage error of Model 2 and Eq. (1).

year	actual data	Eq.(1)		with GDP		with income		with consumption		with population	
		persons	APE	persons	APE	persons	APE	persons	APE	persons	APE
2008	30581261	23346390	23.66%	30179230	1.31%	30397910	0.60%	28714300	6.10%	27996140	8.45%
2009	32349260	30894290	4.50%	35889620	10.94%	36555270	13.00%	34601200	6.96%	34465760	6.54%
2010	36939596	37203760	0.72%	38918930	5.36%	39805620	7.76%	37851450	2.47%	38492450	4.20%
2011	41629303	41957380	0.79%	41121920	1.22%	42051530	1.01%	40098800	3.68%	41386490	0.58%
2012	44525754	45297580	1.73%	43089730	3.23%	43958360	1.27%	41970920	5.74%	43745020	1.75%
2013	47486859	47540430	0.11%	45020170	5.19%	45767370	3.62%	43722830	7.93%	45906420	3.33%
2014	48024758	49003330	2.04%	46984290	2.17%	47569320	0.95%	45464310	5.33%	48136450	0.23%
2015	50561954	49940130	1.23%	49011940	3.07%	49400600	2.30%	47247240	6.56%	50777720	0.43%
2016	56586210	50533160	10.70%	51120100	9.66%	51277830	9.38%	49100800	13.23%	54647570	3.43%
MAPE		5.05%		4.68%		4.43%		6.44%		3.22%	

Table 7 Forecasting results and the absolute percentage error of Model 3 and Eq. (1).

year	actual data	Eq.(1)		with GDP		with income		with consumption		with population	
		persons	APE	persons	APE	persons	APE	persons	APE	persons	APE
2008	30581261	23346390	23.66%	27236160	10.94%	27480230	10.14%	24869880	18.68%	20907670	31.63%
2009	32349260	30894290	4.50%	34817610	7.63%	35341370	9.25%	32509210	0.49%	26743410	17.33%
2010	36939596	37203760	0.72%	39291050	6.37%	39965740	8.19%	37903850	2.61%	32630400	11.67%
2011	41629303	41957380	0.79%	42111670	1.16%	42813030	2.84%	41512900	0.28%	38068760	8.55%
2012	44525754	45297580	1.73%	44166480	0.81%	44814860	0.65%	43963370	1.26%	42572940	4.39%
2013	47486859	47540430	0.11%	45888900	3.37%	46440590	2.20%	45734430	3.69%	45750440	3.66%
2014	48024758	49003330	2.04%	47472080	1.15%	47904940	0.25%	47128530	1.87%	47358170	1.39%
2015	50561954	49940130	1.23%	48997940	3.09%	49301440	2.49%	48320210	4.43%	47326090	6.40%
2016	56586210	50533160	10.70%	50500190	10.76%	50669580	10.46%	49405450	12.69%	45748880	19.15%
MAPE			5.05%		5.03%		5.16%		5.11%		11.57%

Table 8 Coefficients of Model 1, Model 2 and the single-equation model.

coefficient	Eq.(1)	with GDP	with income	with consumption	with population
a_1	-1.18×10^{-8}	1.71×10^{-8}	1.22×10^{-8}	1.59×10^{-8}	2.84×10^{-8}
b_1	0.610187	-3.286505	-2.678092	-2.588156	-2.726916
c_1	-	232.2578	5336.253	7560.173	28890.4
Model 1					
a_2	-	0.031488	0.030755	0.024597	0.002866
Model 2					
a_2	-	14617.75	517.3750	267.1250	6.671425

Table 9 Coefficients of Model 3.

coefficient	with GDP	with income	with consumption	with population
a_1	-3.45×10^{-8}	-3.24×10^{-8}	-2.09×10^{-8}	-5.36×10^{-10}
b_1	-0.09044	0.001628	0.159108	12.22355
c_1	3.45×10^{-6}	8.3×10^{-5}	7.47×10^{-5}	-0.005193
a_2	14617.75	517.3750	267.1250	6.671425

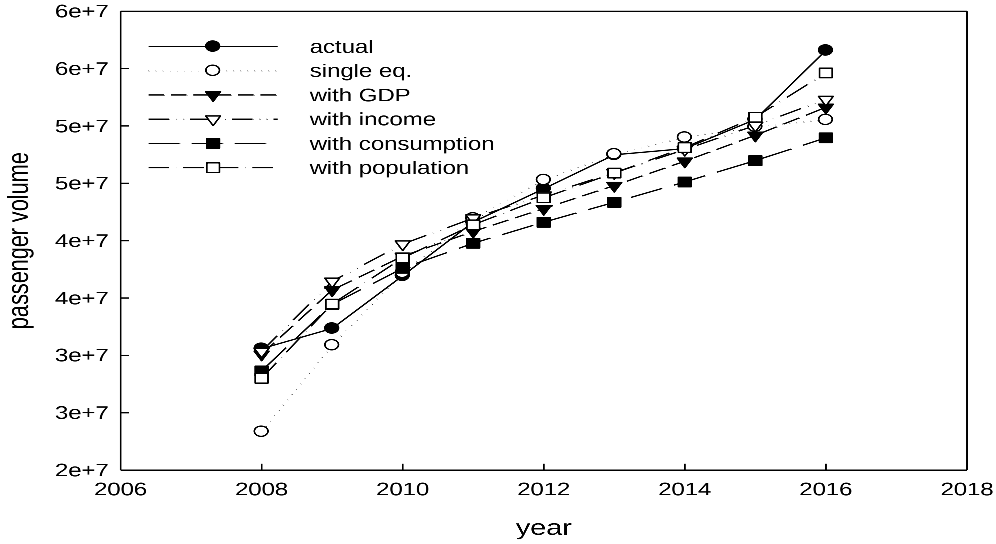

Fig. 1 Comparison of actual data, forecasting results of the single-equation model and Model 1 with socio-economic factors.

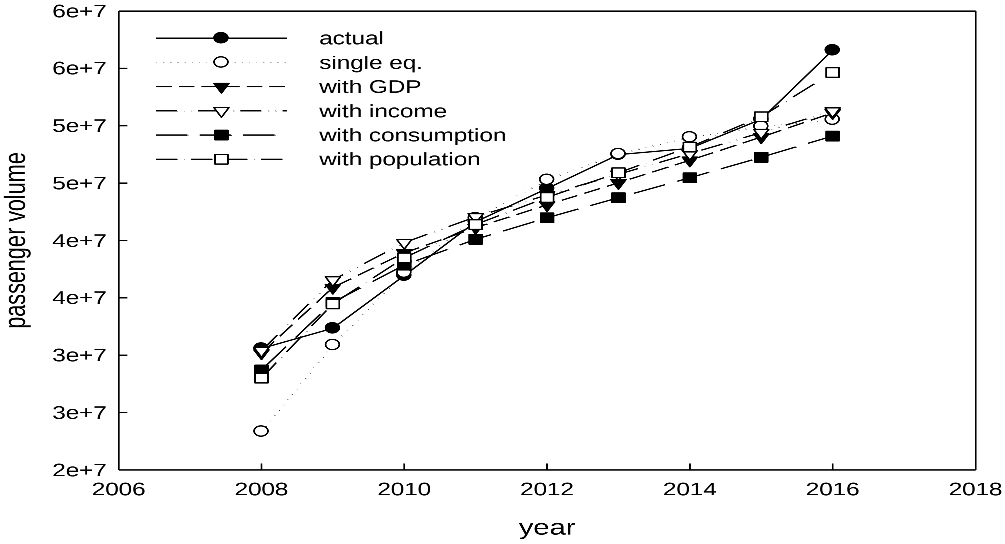

Fig. 2 Comparison of actual data, forecasting results of the single-equation model and Model 2 with socio-economic factors.

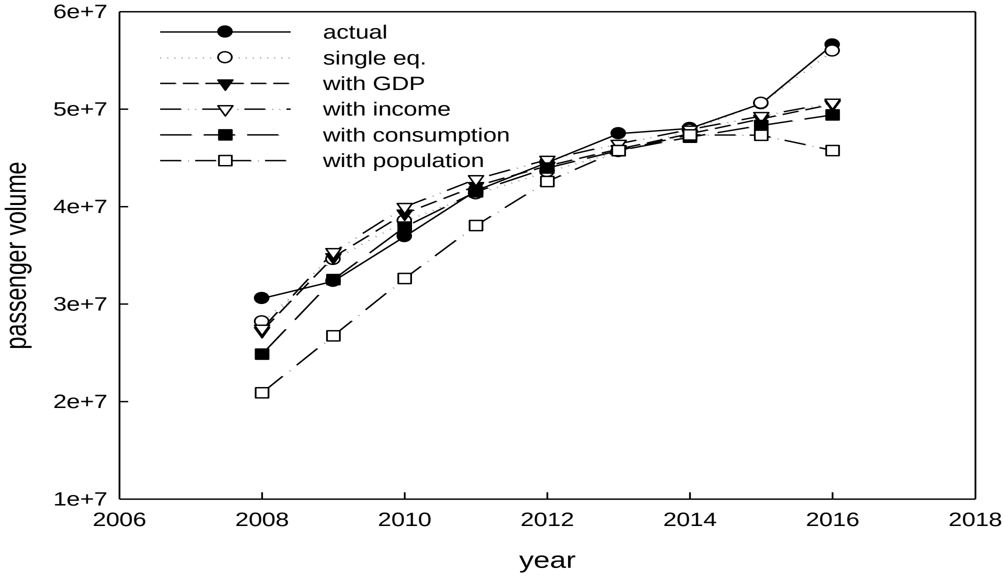

Fig. 3 Comparison of actual data, forecasting results of the single-equation model and Model 3 with socio-economic factors.

Among the models examined, the coefficients of the single-equation model and Model 3 appear reasonable. This consistency lends credibility to these models' ability to capture the relationship between socio-economic factors and HSR passenger volume. However, in Model 3, with population as the socio-economic factor, c_1 is negative, contradicting general observations. Upon comparing Figs. 1-3, we advocate for the use of Model 3 with average income as the socio-economic factor for forecasting Taiwan HSR passenger volume, as data on average income are more readily available. In Taiwan's western corridor, primary public transportation services include Taiwan Railway, freeway coaches, and the HSR. Among these, the HSR stands out for its superior quality and relatively higher prices. Therefore, it is expected that coefficients b_1 and c_1 would be positive, aligning with our initial hypothesis. The calibration results indeed confirm this expectation.

IV. Conclusion and Perspectives

Forecasting models with social-economic factors of the passenger volume of Taiwan HSR are proposed and compared in this study. While all models examined yield accurate forecasting results, the curve generated by the single-equation model diverges from the actual data curve. Given that the operation of transportation systems is intricately linked to external factors, incorporating socio-economic variables into forecasting models is imperative. Among the models considered, the one integrating average income as a socio-economic factor demonstrates reasonable coefficients and consistently stable forecasting results. Therefore, we recommend adopting a model that couples Eq. (6) with Eq. (8), resembling an amensalistic Lotka-Volterra model, for forecasting purposes. This model exhibits a MAPE of approximately 5%, indicating high forecasting accuracy.

Traditionally, the Lotka-Volterra model delineates cooperative or competitive relationships between two species, with socio-economic factors typically viewed as external influences. However, in this study, average income is approached differently; it is integrated into the model as a species itself. This innovative approach allows for the simultaneous utilization of socio-economic factors and passenger volume for forecasting purposes.

In summary, the incorporation of socio-economic factors, particularly average income, into forecasting models for HSR passenger volume yields more accurate and stable results. By adopting a coupled model resembling the Lotka-Volterra framework, this study presents a robust forecasting approach that comprehensively considers the intricate interplay between socio-economic factors and transportation demand.

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