Research article
DOI: https://doi.org/10.48554/SDEE.2023.3.5

Complex Modelling of Regional Tourism Systems

Aleksei Gintciak*, Zhanna Burlutskaya, Daria Zubkova, Alexandra Petryaeva

Peter the Great St. Petersburg Polytechnic University, Saint Petersburg, Russian Federation
Corresponding author: aleksei.gintciak@spbpu.com

Abstract

This study aimed to examine the prospects of various modelling tools in building complex models of regional tourism systems. It surveyed the international experience in forecasting tourist demands and modelling the tourism industry. It found that the hybrid approach – combining simulation modelling with econometric models to forecast tourist demands and deep learning models to process data from various sources – seems to be the most promising one. Simulation modelling is divided into two parts: system dynamics as a model of domestic tourism in terms of assessing state support's impact on the development of tourist infrastructure and agent-based modelling, which is used to form tourists' profiles and assess their needs as accurately as possible. Then, a more detailed study of the possibilities of using CGE models in the framework of integrated modelling of the tourism system, with an emphasis on sustainable development, was proposed. To reduce the level of uncertainty typical in a socio-economic system, integration into the CGE model of production functions was proposed. Thus, the potential applicability of using production functions for modelling tourism processes from the point of view of the state of the economy in a pandemic s being investigated. This study classified the production functions and adopted the function of constant elasticity of substitution to assess the income gained from the tourist products consumed by domestic tourists. Based on synthetic data, the possible income from tourist products were calculated using the income distribution in four groups of profitability. We performed the calculation using written code in the statistical programming language R. The formula we used considered the annual income of population groups, spending on rental housing and the consumer basket, as well as the elasticity of consumption of tourist services.

Keywords: simulation modelling, domestic tourism modelling, CGE model, production functions, CES function

Citation: Gintciak, A., Burlutskaya, Zh., Zubkova, D., Petryaeva, A., 2023. Complex Modelling of Regional Tourism Systems. Sustainable Development and Engineering Economics 3, 5. https://doi.org/10.48554/SDEE.2023.3.5

Научная статья
УДК 519.876.5
DOI: https://doi.org/10.48554/SDEE.2023.3.5

Комплексное Моделирование Региональных Туристических Систем

Алексей Гинцяк*, Жанна Бурлуцкая, Дарья Зубкова, Александра Петряева

Санкт-Петербургский политехнический университет Петра Великого, Санкт-Петербург, Российская Федерация
*Автор, ответственный за переписку: aleksei.gintciak@spbpu.com

Аннотация

Данная работа посвящена исследованию перспектив применения различных инструментов моделирования для построения комплексных моделей региональных туристических систем. В ходе исследования проводится изучение международного опыта прогнозирования туристического спроса и моделирования туристической индустрии. На основании проанализированной информации делается вывод о перспективности применения гибридного подхода, который сочетает имитационное моделирование с эконометрическими моделями для прогнозирования туристического спроса и моделями глубокого обучения для обработки данных из различных источников. Имитационное моделирование в концепции разделено на две части: системная динамика как модель внутреннего туризма с точки зрения оценки влияния государственной поддержки на развитие туристической инфраструктуры и агентно-ориентированное моделирование – для формирования профиля туриста и максимально точной оценки его потребностей. Затем предлагается более детальное изучение возможностей применении моделей CGE в рамках комплексного моделирования туристической системы с акцентом на устойчивое развитие. В рамках снижения типичного для социально-экономической системы уровня неопределённости предлагается интеграция в CGE модель производственных функций. Таким образом, исследуется возможность применимости использования производственных функций для моделирования процессов туризма с точки зрения состояния экономики в условиях пандемии. В ходе исследования проведена классификация проанализированных производственных функций и принята функция постоянной эластичности замещения для оценки доходов от туристических продуктов, потребляемых внутренними туристами. На основе синтетических данных, близких к реальным, были рассчитаны возможные доходы от туристических продуктов с распределением по четырем группам доходности. В дополнение, выполнен расчет с использованием написанного кода на статистическом языке программирования R. Формула учитывает годовой доход групп населения, расходы на аренду жилья и потребительскую корзину, а также эластичность потребления туристических услуг.

Ключевые слова: имитационное моделирование, моделирование внутреннего туризма, CGE модель, производственные функции, CES функция

Цитирование: Гинцяк, А., Бурлуцкая, Ж., Зубкова, Д., Петряева, А., 2023. Комплексное Моделирование Региональных Туристических Систем. Sustainable Development and Engineering Economics 3, 5. https://doi.org/10.48554/SDEE.2023.3.5

1. Introduction

The economic crisis caused by the pandemic has significantly affected the market of services and consumer goods (Hordofa et al., 2022). The business found itself in unusual conditions of isolation from consumers. In this continuously changing epidemiological situation, there is a need to use alternative measures to attract customers and analyse their new urgent needs. The governmental measures to restrict work and limit entry to public places and unpredictable consumer behaviour – all of it demands the need for flexibility and rapid adaptation to new conditions. Such an approach applies not only to the individual representatives of the industry but also to the industry as a whole. The tourism industry, the part of the economy most affected by the pandemic, needs flexible management methods, which can be provided only if there is a flexible forecasting system that can change along with the outside world. Since no part of the economy can exist separately from the outside world, it is necessary to consider the tourism industry by examining a country's general economic situation. The development of tourism infrastructure has fundamental importance for individuals – it is a tool to combat unemployment (new jobs) – for entrepreneurs –they can ensure the need for tourist products – and for the country's economy – tourism is an indicator that affects investment attractiveness and the level of people's well-being (Esfandiar et al., 2019). At the same time, uncontrolled development of tourist infrastructure can significantly harm the environment and culture (Berawi et al., 2016; Widaningrum et al., 2020). From this point of view, the issue of developing a general model of domestic tourism has been presented as the only competent approach to stimulate the tourism industry for sustainable development. This article examined the experiences of foreign researchers in modelling tourist flows. The articles that modelled domestic and international tourism were selected for analysis. In selecting the sources, emphasis was given to the articles' relevance in the field of tourism in general and in terms of the modern technologies and data used. The availability of reasonable results, considering the provision of data on statistical errors/deviations, was also emphasised.

This study also paid special attention to the prospects of using CGE models and, in particular, an approach to forecasting revenue from domestic tourism based on the income groups of the population. The revenue from domestic tourism is a key element of the domestic tourism model, which describes the relationship between the stabilisation of the region's economic indicators and the degree of development of domestic tourism. The model was developed using synthetic data, which is as close as possible to real data. The data obtained from the various open sources form a network that includes a region's economy, the level of citizen well-being, and the state of the regional tourism sector. This is the first study to offer results regarding an initiative project to develop a regional model of domestic tourism.

2. Literature review

Based on the research goals, we defined the basic rules for finding suitable sources. First, we limited the search queries to the field of tourism in general and the modelling of tourist processes in particular. We selected the sources from the Scopus database using the keywords "tourism" and "model". Next, we selected the most cited reviews (with at least 20 citations) in the last six years (2017–2022) that were most relevant to our topic. When we found a relevant article, we also analysed its lists of sources to evaluate the results of the described model that is based on several studies. As a result, we selected articles that described the model or approach most profoundly for further analysis. Thus, our review included articles from a much earlier period. For the analysis, it is worth noting that we considered articles that were not only about domestic tourism but also international tourism.

Among the variety of articles on modelling in the field of tourism, it was important to choose the most applicable ones for forecasting tourist flow. Accordingly, we repeated the procedure for selecting articles but changed the combination of the keywords: "tourism" and "demand".

The tourism sector includes varies types of tourism based on goals, types of tourists, and other classifications. Based on the United Nations World Tourism Organizations (UNWTO) methodology, we assumed the importance of models that allow us to predict the behaviour of tourists depending on their needs and preferences. At the next stage of the literature selection, we thus focused on examining tourist processes and analysing tourist behaviour. Thus, the review included articles modelling tourist routes or the satisfaction of a tourist from visiting attractions. It is important to note that the models of the Autoregressive Integrated Moving Average (ARIMA) and artificial neural networks (ANN) families were the most common among the analysed sources. To ensure diverse results, we tried to select the most typical articles describing these models, while the rest were not included. The final choice of the articles also depended on the availability of a comparison of the results within the same study, a requirement that was dictated by the complexity inherent in comparing different scientific papers.

The review included 36 articles: five articles discuss the mutual influence of economic growth and tourist infrastructure, and 31 articles describe the forecast models of tourist flow or other tourist processes. The selected models were divided into four types: simulation models (22%), econometric models (42%), deep learning models and neural networks (14%), and hybrid models (22%) (Table 1).

Table 1. Classification of the analysed models by type and size

Model type	City or less	Country	World
Simulation models	ABM (Santoso et al., 2020); Plog model (Litvin et al., 2016)	ABM (Li et al., 2021); System dynamics models (Mai et al., 2018); CGE (Blake, 2009)	Plog model (Griffith, 1996); Scienario-based modelling + TVP-PVAR model (Wu et al., 2021)
Econometric models	ARDL (Song et al., 2010); ARIMA, SARIMA (Millán et al., 2021)	Monte Carlo Forecasting + Polynomial-Fourier Series Model (Danbatta et al., 2021); Factor model + LARS-EN (Lourenço et al., 2021)	MIDAS method (Bangwayo-Skeete et al., 2015); Panel data model (Darani et al., 2018); SEM (Turner et al., 2001); GM, Verhulst, DGM (Nguyen et al., 2017); BGVAR (Assaf et al., 2018); Gravity model (Harb et al., 2018); KS-AR model, VAR, SARIMA (Nicholas et al., 2021); SARIMA, HW, GM (Sharma et al., 2020)
Deep learning models, neural network	DLM (Law et al., 2019); Latent dirichlet allocation (Wang et al., 2020); P-DBSCAN (Vu et al., 2015); MNL (Lubis et al., 2019)		

Simulation models

Simulation models allow replacing the system under study with a model that describes system's behaviours and its key indicators. This approach ensures the transparency of the processes occurring within the system, which means that it allows one to predict the development of the system by considering the changes in its various indicators. The analysed articles we analysed used two types of simulation models: system dynamics and agent-based modelling.

The system dynamic model is used as an alternative to forecasting models for the scenario-based planning of tourism destinations (Mai et al., 2018). The advantage of this model is its ability to consider a system's natural limitations, indicating that the classic approach, while capable of accurately predicting the growth rate, does not consider the possible negative consequences of excessive or too rapid development of a destination (overpopulation, flooding, shortage of drinking water sources, etc.).

Simulation models are ideal for analysing the risks and prospects of certain management decisions. The use of the computable general equilibrium (CGE) model adapted to the tourism sector allows for the assessment of the most promising investment directions in terms of the subsequent effect on the country's economy and the durability of the results (Blake, 2009).

Simulation modelling is often based on econometric models as an upper-level superstructure that allows the interpretation of the results and establishing logical connections (Wu et al., 2021). The time-varying parameter panel vector autoregressive (TVP-PVAR) model in combination with scenario modelling shows the results calibrated on historical data. This approach allows to evaluate the quality of the forecast and choose the optimal planning horizon.

Another approach to the simulation of tourist processes is agent-based modelling. The basis of research in such works is the study of behavioural factors that determine the rules of the behaviour of agents (tourists). In Li et al. (2021), there exists a parallel between the tourist's tendency to optimise and his tourist route.

The most common model created specifically for describing travel agents is the Plog model. The model describes tourists in terms of their psychotype and behaviour, distinguishing two types with intermediate subtypes: adventurers and psychocentrics. According to the typology of Plog, psychocentric people tend to visit popular proven places, while adventurers will explore local features and stay away from tourist areas. It is assumed that the number of visitors changes with the development of resorts (Griffith et al., 1996). Santoso et al. (2020) used behavioural factors to determine the degree of satisfaction tourists gained from visiting the main attractions in Indonesia. However, a limitation of the Plog's model is that it ignores the tourists' motivations, activities, and modes of transport (Litvin et al., 2016).

Econometric models

The better part of analysed models were econometric models. This type of model involves analytical tools based on mathematical and statistical modelling, allowing managers to make managerial decisions based on accurate forecasts. The largest number of the analysed articles used regression results, with the most typical representative of the regression models being the MIDAS model. The MIDAS model consists of only one equation, and while this does not allow the model to analyse the pairwise correlations between indicators, this makes it less prone to specification errors (Bangwayo-Skeete et al., 2015).

Regression is a productive and convenient tool for analysing the correlations between indicators. Song et al. (2010) used the autoregressive distributed lag (ARDL) to analyse the elasticity of tourists' demands in Hong Kong from a set of indicators (income level, search queries, and advertising costs). The study found a long-term relationship between demand, income, and prices, demonstrating that tourists' income levels are the most important factor determining tourism demand in the long term.

Econometric models may also be used to analyse bottlenecks. In Harb et al. (2020), the gravity model was used to confirm the need to use multi-lateral resistance to tourism (MRT) when assessing the attractiveness of a tourist destination. The classical models, the researchers noted that, did not consider the attractiveness of the alternative directions expressed in the MRT indicator. Integrating the gravity model with the common correlated effects (CCE) proved the need for analysing data to detect the magnitude of cross-sectional dependence and, when the latter is omnipresent, employing MRT-robust estimations.

Another approach is demonstrated in the study of tourist flows in Portugal, which used a factor model based on data processed by the Least-Angle Regression algorithm (LARS-EN) (Lourenço et al., 2021). For each country, the algorithm identified the most significant factors, which made it possible to increase the accuracy of forecasts. The researchers highlighted the usefulness of survey data in predicting tourism.

Inventive research was conducted on analysing the demand for dark tourism based on the statistical data on age, average income, and education level (Millán et al., 2021). The Seasonal Autoregressive Integrated Moving Average (SARIMA) model demonstrated the demand for visiting Cordoba with an error of 5%. SARIMA also surpassed the Grey model in forecasting tourist demands (Sharma et al., 2020). The Grey model family showed statistically significant results in forecasting tourism demand in Vietnam, but it demonstrated different accuracy for different countries (Nguyen et al., 2019). Some advantage over SARIMA was demonstrated by the KS-AR model, which combines kitchen sink (KS) modelling with the AR autoregressive model (Nicholas et al., 2021). It is worth noting that all the studies noted the applicability of one-dimensional models exclusively for short-term planning.

Though the VAR family of models is popular in short-term forecasts, it can also be adapted for long-term forecasting (up to four quarters ahead). The Bayesian global vector autoregressive (BGVAR) model tested in nine countries in Southeast Asia showed its ability to capture the spillover effects of international tourism demand in this region (Assaf et al., 2019).

As an alternative approach to forecasting tourist demands, it is worth considering the seasonally restacked multi-series structural time series model (M-STSM) (Chen et al., 2019). This model is similar to the multivariate method but includes a new data restacking technique: a quarterly tourism demand series is split into four component series, and the component series are then restacked to build a multi-series structural time series model. This method offers the best forecast accuracy compared with traditional univariate models (ARIMA, ETC).

Among the approaches to modelling tourist demand, we can distinguish panel data models that allow for tracking the dynamics of data changes, considering the assessment of elasticity, standard deviation, and other statistical indicators (Darani et al., 2018). This approach assumes that the demand for tourism depends on a country's macroeconomic indicators.

Danbatta et al. (2021) predicted tourist flow based on the data on the tourist's actual arrival by a mathematical model using a random variable generator. Thus, a model based on a Fourier series was received at the input, which was then processed by the Monte Carlo method based on the obtained data, and the probabilistic characteristics of the process under consideration were calculated. The forecast was considered statistically significant.

The most complete multidimensional analysis was presented in Turner et al. (2001). The SEM model implies modelling with structural equations (that is, conducting a multidimensional analysis based on regression analysis, path analysis, and factor analysis). Based on a multidimensional analysis of various indicators (GDP, income level, etc.), it can be concluded that there are significant differences between the independent variables that influence the demand for business, holidays, and tourist types. These results are of fundamental importance when building a model of tourist infrastructure.

Deep learning models, neural networks

A whole series of articles is devoted to the use of machine learning for predicting tourist demand and analysing its routes. Law et al. (2019) presented research results confirming the increase in forecast accuracy when using the Deep Learning Model (DLM) compared to using models such as ANN, ARIMAX, SVR, and so on. However, it is worth considering that these results were obtained with the short-term forecasting of demand and cannot be unambiguously used for long-term planning without additional research.

An alternative way to use machine learning models is to analyse the psychological perception of a tourist destination based on travel geotagged photos (Wang, 2020). Using Latent Dirichlet Allocation allowed categorising the analysed content into topics and then create a polynomial distribution model.

Vu et al. (2015) used social media photos to identify the most developed tourist routes. The data were clustered using the P-DBSCAN algorithm, and regions of interest were selected based on geographic data. Using the Markov chain, tourist trajectories were constructed.

Neural network models are also used to analyse the load of public transport. Lubis et al. (2019) presented the approbation of a Multinomial Logit model (MNL) for predicting high-speed rail (HSR) route loading. The developed model allows you to predict the load by considering alternative modes of transport.

Hybrid models

The last category highlighted in this study is hybrid models. Using various econometric models with each other or with machine learning models improves the accuracy of forecasts, because it considers both dynamically changing indicators and the impact of the macroeconomic situation.

Rafidah et al. (2020) used the support vector machine (WSVM) model and decomposition ensemble model (Benchmark EMD-SARIMA and EMD_WSVM) to predict tourist flow, obtaining results that revealed a greater efficiency of using the hybrid model than individual approaches.

The smallest measurement error was provided by a combination of MIDAS-SARIMA econometric models (Wen et al., 2021). Based on the data on search queries for specific keywords, the model predicted tourist flow with greater accuracy than the same models individually or the hybrid MIDAS-AR type.

A similar study on combining econometric models was conducted by Wen et al. (2019). The results obtained for the Hybrid Arimax / Narx Model were also almost one and a half times more accurate than when these models were used separately.

However, if the source data is restricted to search queries, it is worth highlighting the DBEDBN model. Using a deep web of trust allows one to extract the most valuable information from the initial data. The resulting forecast is then processed by vector regression algorithms, which ensures minimum error in the results (Huang et al., 2021).

The integration of the AR model with a big data approach was introduced in Fronzetti Colladon et al. (2019). A specific web crawler was developed to extract information from the TripAdvisor travel forum. The crawler parsed HTML pages and extracted information of interest, with associated timestamps to allow a longitudinal analysis. The highest accuracy of the results was achieved for the one-month forecast (in comparison with AR, the accuracy for some cities exceeded by more than 30%), and the excess inaccuracy was no more than 5% for three months. It is important to note that the crawler produced a significant amount of incomplete or inconsistent data for some cities.

In Silva et al. (2019), the researchers used Singular Spectrum Analysis (SSA) to account for the seasonality of demand. The introduced DNNAR model showed better results than the NNAR model by 10%–30% for different countries. Improved results were obtained for all the planning horizons: from a month to a year. Compared to ARIMA and ETS forecasts, the DNNAR model showed better results for all horizons except the one-step-ahead forecast, indicating that seasonality is more problematic for NN models.

A more structured and complete data was supported by the VAR (P) model, which considers traditional structured data (ticket information) with unstructured data (web requests). The wide range of the data included data on infrastructure, weather conditions, and bookings in hotels, restaurants, theatres, and so on (Liu et al., 2018). This model forecasted the changes in tourism demand in conjunction with the intentions of tourists.

3. Materials and methods

The choice of the model depends on characteristics such as openness (it is necessary to consider the external links of the system with the world as the outflow of tourists to other countries or exchange rate) and the transparency of the results (it is important to establish the rules for the interaction of all the internal elements of the system to simulate the economic effect depending on changes in certain indicators). It seems that the most profitable approach is to combine the results of mathematical (econometric) tools for predicting tourist flow with machine learning tools for filtering and processing big data (Liu et al., 2018; Wen et al., 2019; Vu et al., 2015) and embed this into the simulation model (Fig. 1). At this stage of the study, it was difficult to choose between agent-based modelling (Li et al., 2021; Santoso et al., 2020; Griffith et al., 1996) and the system dynamics model (Mai et al., 2018; Blake, 2009), since both approaches are equivalent in the depth and prospects of the study. It is worth noting that scenario modelling corresponds to the goals of building a model of domestic tourism in terms of assessing the impact of state support on the development of tourist infrastructure in the country and increasing tourist flow. However, only agent-based modelling will help to form tourists' profile and assess their needs as accurately as possible. In this case, agent-based modelling is more complex and may be used in a longer perspective.

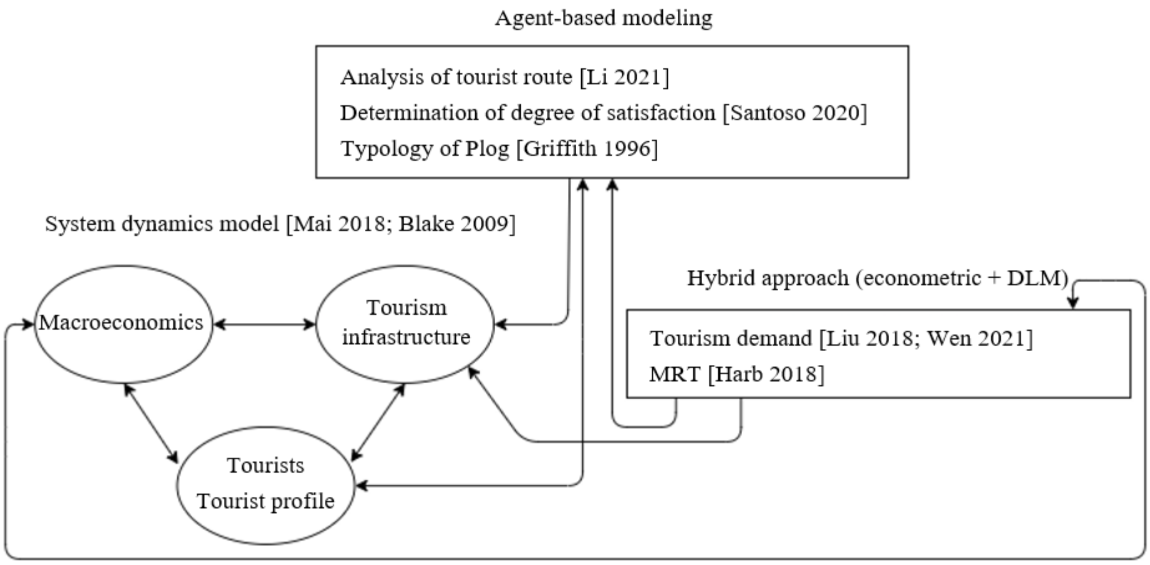

Figure 1. A possible approach to modelling domestic tourism

Consider the block with the system dynamics model. It is proposed to use the CGE model as a basis for modelling the tourism industry in the context of the region's sustainable development (Blake, 2009; Gintciak, 2022).

CGE models for the tourism sector

CGE models (computable general equilibrium models) are used to ensure the equilibrium between industries in economic modelling. The more industries, regions, and consumer types appear in the model, the more difficult it is to analytically solve the model, and numerical methods processed by computer capacities are used. CGE models are used in various economic sectors to assess the impact of investments on individual economic products (Blake, 2009). Among the most significant models based on the concept of CGE models, we can single out the MONASH model of the Australian economy and the similar USAGE model of the US economy.

Gül (2015) used a static CGE model to analyse the growth of demand in Turkey's tourism industry and detected the established prices, which made it possible to equalise supply and demand. The author was thus able to find that the data obtained showed an increase in the real runway with an increase in inbound tourism. Similarly, Blake (2006) showed that the CGE general equilibrium model, as it allows one to study the demand for tourism under various assumptions, can be used to measure the macroeconomic effects of internal and external shocks in a country. The authors found this model particularly useful for quantitatively assessing the effects of changes in demand or other possible scenarios. In contrast, the CGE model, Van Truong and Shimizu (2017) demonstrated, rarely detected the transport network's influence on the demand in tourism activities. However, the authors maintained that the CGE model is still quite effective despite this, which the authors advised to investigate in future studies. Since each of the above studies proved that it is reasonable to use general equilibrium models to analyse the processes of the tourism industry, we assume that this model can be successful used for the entire industry.

Review and classification of production functions

As part of the development of the prototype of the CGE model, we analysed international experience with using various production functions to describe economic processes using the model. In the course of the study, the most frequently used production functions for modelling the economic growth of the tourism industry were identified and classified.

The production functions were divided into the following:

- Microeconomic and macroeconomic;

- Static and dynamic;

- Single-factor and multi-factor;

- Additive and multiplicative.

According to the type of analytical forms, the production functions were divided into linear (additive) and nonlinear (multiplicative).

1. Leontief function (Yankovyi, 2021; Hu et al., 2020; Blake, 2006)

Characteristics: microeconomic, static, two-factor, and additive.

The Leontief function is a CES function with fixed proportions of factors and with an elasticity of substitution equals to 0, which means that it is impossible to replace the factors of production with each other. There is thus a restriction on deviating from the initial number of factors, which are strictly fixed for the production of a unit of output.

This function is determined by the minimum ratio of the number of resources spent to the constant values of production. Since it belongs to the static type of production functions, this function is intended to model certain technologies. It is thus often used to describe small-scale or fully automated productions.

2. Cobb-Douglas function, Cobb-Douglas-Tinbergen function (Sancho, 2009; Antoszewski, 2019; Chen and Haynes, 2015; Timilsina and Shrestha, 2008; Daniels and Kakar, 2017; Pratt, 2013)

Characteristics: macroeconomic, static, two-factor, and multiplicative.

The Cobb-Douglas function depends on the number of factors of production, their elasticity coefficients, as well as the scale of production and NTP. There is an addition called the Cobb-Douglas-Tinbergen function. It differs from the source in that it is dynamic, i.e. time-dependent.

It turns out that time dependence is added to the expression of the Cobb-Douglas-Tinbergen function. Moreover, the final number of products is influenced by the growth rate of other industries and factors that are not explicitly considered.

In this function, the NTP is stationary, which means that, every year, the final result will change the same number of times.

The Cobb-Douglas (Cobb-Douglas-Tinbergen) function is usually used to describe medium-scale or large-scale objects characterised by stable functioning. It is closest to real economic phenomena and processes (relative to the Leontief and Allen functions) and is easy to obtain the estimates of unknown parameters (relative to the CES function), although it is a CES function, which means a single elasticity of substitution.

The function has a small drawback, like the linear function: when capital intensity converges to infinity, labour productivity also tends to infinity, which is unrealistic.

3. Linear function (Yankovyi, 2021)

Characteristics: macroeconomic, static (dynamic), two-factor (multifactorial), additive, and heterogeneous.

The linear function, in addition to the number of factors of production, has dependencies on the time and coefficients of the marginality of products related to the resources used. Most often, the linear function is used in large-scale systems where income or output is the result of the simultaneous interaction of a large number of different technologies or where the number of costs will be proportional to the final result.

An important role in the production linear function is played by the hypothesis of the constancy of marginal production factors or unlimited elasticity of substitution, which is not the most realistic scenario. Of course, the factors may be interchangeable, but most likely not in the tourism industry.

4. The Allen function (Yankovyi, 2021)

Characteristics: microeconomic, static (dynamic), two-factor, and multiplicative.

The Allen function is used to describe the processes in which the excessive growth of one of the factors of production leads to a negative change in output or income. This production function is usually intended for small production systems in which there exists no possibility of replacing the resources used because the elasticity of substitution is 0. Moreover, if the model is based on data that changes over time (for example, several years at the same enterprise), the Allen dynamic production function is used. It depends on time, factors of production, various coefficients, and has a degree of uniformity equal to 2.

5. CES function or constant elasticity substitution function (Sancho, 2009; Chen and Haynes, 2015; Daniels and Kakar, 2017; Pratt, 2013; Willenbockel, 1999; Klump and Preissler, 2000)

Characteristics: macro-and microeconomic, dynamic (static), two-factor (three-factor), and multiplicative.

There are various specifications of the CES function: the Solow specification, the Pitchford generalisation, and the Barro and Sala-y-Martin specification, which, since it is inconsistent and redundant, is rarely used in practice.

The CES function is used when there exists no accurate information about the level of interchangeability of production factors, i.e. the exact value of the elasticity of substitution is unknown but greater than 0. However, it is assumed that this level will not change much if the resources used are increased or decreased, i.e. there is a property of stability at certain proportions of factors.

The CES function is more reasonable, because with capital intensity tending to infinity, labour productivity will be limited. This indicates a more realistic description of economic systems. However, it is difficult to obtain the estimates of unknown parameters. To do this, one needs to conduct a logarithm analysis, and the estimates will most likely be only approximate. The CES function can be used to model systems of any level and is universal.

6. LES function or function with linear elasticity of factor substitution (Gül, 2015)

Characteristics: macro-and microeconomic, static, multifactorial, multiplicative.

The LES function, also called the consumer utility function, is a measure of the ratio between the volumes of goods consumed and the level of utility, i.e. the satisfaction obtained from the consumption of a specific set of goods by a specific consumer. Its final result is influenced by the minimum required amount of each of the factors and the coefficient of the importance of the product for the consumer.

This production function is most often used to describe processes in which the possibility of replacing the factors used strongly depends on their proportions.

Macroeconomic production function (MPF) (Kamaletdinov and Ksenofontov, 2018).

Characteristics: macroeconomic, static, two-factor, and multiplicative.

The macroeconomic production function is similar to the Cobb-Douglas function, but instead of the labour factor, labour productivity is used, which is the ratio of GRP and the number of the employed population.

The MPF can be used for a formalised description of the work of the state, taking into account various taxes, investments, and other expenses and fees.

7. Solow or Hilhorst function (Miao and Vinter, 2021; Attar, 2021; Ilyash, 2021)

Characteristics: macro-and microeconomic, static, multifactorial, multiplicative, and heterogeneous.

The Solow function differs from the CES function only in the property of uniformity (this function is inhomogeneous). Due to this fact, the Solow function is used when the uniformity property appears optional. Since the Solow function differs from the CES function in terms of the assumptions about uniformity, it can similarly be used in modelling systems of any scale.

8. Quasi-linear production of functions (Wu, 2021; Tanaka, 2022)

Characteristics: macro-and microeconomic, static, multifactorial, multiplicative, and heterogeneous.

In a quasi-linear function, one parameter changes linearly and the other non-linearly. If there is no linearly changing factor, i.e. its quantity will be equal to 0, then production will continue, despite the lack of linear resources.

This function is typical for firms with large volumes of nonlinear factors. Such productions can use a larger or smaller amount of linear factor, i.e. they do not particularly depend on their quantity. Small fluctuations in the value of the linear factor will not affect the final result, while fluctuations in the value of the nonlinear parameter change the output values.

9. The Tornquist function (Issin, 2017)

Characteristics: macro-and microeconomic, static, multifactorial, and multiplicative.

The Tornquist function is called the demand function; it shows the dependence of the volume of production on goods and services.

This function has three types. Its basic formula reflects that the amount of demand for essential goods decreases with income growth and has a limit. The formula for the demand for secondary goods and services is used when income reaches a certain mark. However, the volume of demand also has a limit. As a result, the formula for elite services or luxury goods is used when an even higher threshold in affluence is reached. However, it no longer has a limit – only the rapid growth of the function graph.

To solve the selected problem, the CES function was selected from the other considered functions.

This function offers the most realistic description of economic systems. It is also used when there exists no accurate information about the level of interchangeability of the factors of production.

Consider the general view of the CES function (formula 1):

$$Y=\left(A0*e^{\wedge}\left(wt\right)\right)*\left(A1*K^{\wedge}\left(-p\right)+\left(1-A1\right)*L^{\wedge}\left(-p\right)\right)^{\wedge}\left(-\frac{\gamma}{p}\right), \quad (1)$$

where Y – quantity of output; K – capital; L – labour; $A0$ – factor productivity; $A1$ – weighting; p – replacement ratio; γ – uniformity; w – production growth rate due to all other factors except K and L; t – time.

Calculation formula (2) of p:

$$p=\frac{1-\sigma}{\sigma}, \quad (2)$$

where σ is the elasticity of substitution.

4. Results

Improvement of the traditional CES function

It is worth considering that the production functions were not initially adapted for calculating the tourist indicators. However, we decided to consider the possibility of using them when calculating the possible revenue from domestic tourism. Since the incomes of the different population groups of a country can differ significantly, we decided to divide the population into four groups according to the data found in open sources. We assumed that the financial capabilities of tourists can be considered as the difference in their income after taxes and spending on rent and the consumer basket, considering elasticity. It is obvious that tourists do not spend this amount entirely on trips but we assumed that the calculation aimed to estimate the maximum possible income from tourism.

Therefore, our next task was to calculate a tourist's maximum possible spending. This required adapting the production function to the tourism industry. We calculated the financial opportunities for each tourist separately depending on their standard of living.

If, for production in the CES function, the important parameters were K (capital) and L (labour) and Y (the quantity of products produced), then, for the tourism industry, the parameter Y will be responsible for the total income of a person, K for constant and necessary expenses, including spending on housing area, food, transport, and other necessities, and L for the final part of the funds that the agent can set aside for future travel.

The following formula (3) was used to calculate the data on the tourism industry.

$$Y=\left(K^{\wedge}\left(-p\right)+L^{\wedge}\left(-p\right)\right)^{\wedge}\left(-\frac{\gamma}{p}\right), \quad (3)$$

where K – permanent (necessary) expenses, which include spending on rental housing and the consumer basket; L – the maximum possible amount of money a person is willing to save (postpone) for travel; and Y – annual income, including taxes. In this case, the unknown parameter will be *L, and the distribution of funds will depend on the trend of spending tourists.*

Accordingly, the formula 4 for obtaining an estimate of the maximum possible expenses of one tourist, taking into account their standard of living, is as follows:

$$L=Y\left(^{1}_{\gamma}\right)-K, \quad (4)$$

The calculation formula (5) of σ using the ratio of the number of tourists in different years to their tourism expenses is as follows:

$$\sigma = \left(L0 - L1\right) / \left(population0 - population1\right), \tag{5}$$

where *L0, L1* – travel expenses of tourists in 2018 and 2019, respectively; population0, population1 – the number of tourists in 2018 and 2019, respectively.

Unfortunately, at this stage, we were limited by the lack of high-quality source data necessary for validating and refining the formula. Since work is currently underway to collect and analyse data on the tourism industry as part of a project to develop a model of domestic tourism, at the next stage, all the results obtained will be verified based on real data.

Initial data

The process of data collection and analysis requires separate coverage. No single unified system exists in any country for collecting and analysing the tourism industry data. The methodological recommendations for collecting and analysing the data on the tourism industry are presented in the Methodology of the United Nations World Organisation from 2008. However, each country follows its own approach to this process. Therefore, within the framework of this model, the data obtained from various open sources were used (Botavina et al., 2020), which could affect its quality. It is difficult to find real, openly accessible data to make calculations. Real data, in most cases, has private access. In turn, open sources contain data that differ in its content, since collecting tourist data is not bound by any uniform requirements. Since we considered only the first experiments within the framework of the project on modelling domestic tourism, we made assumptions about the possibility of using synthetic data, which is close to real data.

It is worth noting that, during the development and testing of the prototype model, no emphasis was placed on the use of data on any particular country, as the model is assumed to be a unified solution for any object of research. In this case, it was necessary to focus on a developed country with stable economic indicators and with a minimum number of tourist zones. The latter requirement was due to the inability to obtain reliable results based on the average for different points of attraction. Based on the stated requirements, the choice of the country for the study settled on Austria for a number of the following reasons:

- Relative completeness of data in comparison with other countries;

- Stable contribution of the tourism industry to the country's GDP (about 6%);

- Developed domestic tourism (at least 40% of the tourist flow);

- Stability of economic indicators;

- Relative limitations at the tourist points of attraction.

Experiments

Considering pensioners, the working population was divided into four income groups. For each group, the maximum amount of money that could be spent on holidays in the country was calculated. It is worth noting that the results turned out to be logically acceptable, as they did reveal an increase in the difference in income after taxes and spending on rental housing and grocery baskets. Elasticity smoothed the distribution of funds between the necessary expenses and tourist products, allowing us to count on high-quality results after experimenting with real data.

Table 2 shows the results of calculating the possible revenue from tourists categorised by income groups. The income from one tourist is the share of the salary that remains with them after paying for all the vital needs. The data on the salary of one tourist per year, depending on the income group, is based on articles of a recommendatory nature. The approximate expenses of one tourist for the consumer basket and the cost of housing and other necessary expenses were also calculated depending on the income group. Knowing the values of the parameters Y and K, the elasticity variable γ was selected, which offered a realistic estimate of the residual amount for travel. The revenue from one tourist was calculated according to formula (4). The authors compiled the data using open sources.

Table 2. Revenue from one tourist based on the income group

Group	Predictable waste, €
1	1056
2	3796
3	7582
4	8657

In addition to revenue, it was necessary to calculate the maximum number of trips per year to predict tourist flow. For each of the profitability groups, the cost of vacation was determined depending on its class based on the studied materials from open sources. To unify the data for a unit of vacation, we took 14 days. We took the average cost of a vacation by category for 14 days from open sources. We then calculated the possible number of trips for each income group using the following formula:

$$Number\ of\ possible\ trips = Predictable\ waste\ /\ Recreation\ coast \tag{6}$$

We then rounded the resulting values to integers. Table 3 shows the results.

Table 3. Maximum number of trips per year for one tourist based on income group

Group	Predictable waste, €
1	1056
2	3796
3	7582
4	8657

It is worth noting that prices in Austria are among the highest, so tourists can afford a vacation in most other countries for a similar cost. For most countries, an additional reason for choosing domestic tourism instead of outbound tourism is to save money.

All the calculations were implemented in code written in the statistical programming language R.

5. Discussion

Modelling domestic tourism based on the concept of CGE models is not a new solution (Deepak et al., 2001; Blake, 2009; Gül, 2015; Blake, 2006; Van Truong et al., 2017). However, in the conditions of a pandemic (Hordofa et al., 2022), the development of a general equilibrium model is becoming relevant again, since it allows us to assess the object of the investigation from the point of view of the impact on this system, and it also takes into account the mutual influence of all elements of the system on each other. Thus, significant changes in the needs and opportunities of tourists correlate with changes at the state level, and the model continues to develop in a coordinated manner. Since increasing the scale of the research object increases the complexity of building a model, it is necessary to formalise the behaviour of all the elements of the system as much as possible. A mathematical description of the dynamics of consumer spending will allow us to assess the trends towards savings as well as to understand the natural limitations in the possible income from tourist products.

The resulting solution allowed us to assess the financial capabilities of the population and its propensity to spend on necessities and recreation and to divide the population groups by profitability, which is necessary at the next stage of developing the model to determine the revenue from one tourist. It is impossible to estimate the prospects of obtaining revenue from tourism without the distribution of profitability groups, indicating that it is impossible to predict tourism's contribution to the GDP.

6. Conclusion

In this article, we reviewed the approaches to modelling tourist flows and tourist processes. We classified the analysed models based on their type and scale. We also created a list of the most popular indicators for analysing the tourism industry: geotagged photos, the GDP, the annual tourist's income, the actual arrivals of tourists, the search queries (general information about the country), the search queries regarding planning (restaurants, hotels, and shops), and the psychotype and behaviour of tourists. After analysing the articles, we selected the most promising approaches to modelling domestic tourism. It formed the basis of a general model of domestic tourism, combining the advantages of mathematical methods for predicting tourist flow, neural networks for data processing, and simulation models for fully accounting for all the infrastructure elements and their mutual influence. Moreover, we analysed the production functions for the subsequent calculation of the income of tourists from various income groups. Based on our analysis, we selected the CES function to forecast revenue from the tourist products consumed by domestic tourists. We adapted this function to consider the profitability indicators, the cost of essential goods, and the elasticity of demand for tourist services for four income groups. We conducted the analysis on Austria's synthetic data, which was close to the real data. Our results reveal the estimated maximum amounts of revenue gained from one tourist for the four groups of profitability, as well as the estimated number of trips per year, considering the recommended type of vacation for each of the groups. Our study contributes to the initial stage of the development of the CGE model for modelling tourism processes by considering the relevance of general equilibrium models in the context of the economic crisis caused by the pandemic.

Acknowledgements

The research was funded by the Ministry of Science and Higher Education of the Russian Federation (contract No. 075-03-2023-004 dated 13.01.2023).

References

Antoszewski, M., 2019. Wide-range estimation of various substitution elasticities for CES production functions at the sectoral level. Energy Economics 83, 272–289. https://doi.org/10.1016/j.eneco.2019.07.016

Assaf, A.G., Gang, L., Song, H., Tsionas, M.G., 2019. Modeling and forecasting regional tourism demand using the Bayesian Global Vector Autoregressive (BGVAR) Model. Journal of Travel Research 58(3), 383–397. https://doi.org/10.1177/0047287518759226

Attar, M., 2021. Growth, distribution and dynamic inefficiency in Turkey: An analysis of the naïve neoclassical theory of capital. Structural Change and Economic Dynamics 59, 20–30. https://doi.org/10.1016/j.strueco.2021.07.008

Bangwayo-Skeete, P.F., Skeete, R.W., 2015. Can Google data improve the forecasting performance of tourist arrivals? Mixed-Data Sampling Approach. Tourism Management 46, 454–464. https://doi.org/10.1016/j.tourman.2014.07.014

Berawi, M.A., 2016. Accelerating sustainable infrastructure development: Assuring well-being and ensuring environmental sustainability. International Journal of Technology 7(4), 527. http://dx.doi.org/10.14716/ijtech.v7i4.3829

Blake, A., 2009. The dynamics of tourism's economic impact. Tourism Economics 15, 615–628. https://doi.org/10.5367/000000009789036576

Blake, A., Durbarry, R., Eugenio-Martin, J.L., Gooroochurn, N., Hay, B., Lennon, J., Sinclair, T., Sugiyarto, G., Yeoman, I., 2006. Integrating forecasting and CGE models: The case of tourism in Scotland. Tourism Management 27 (2), 292–305. https://doi.org/10.1016/j.tourman.2004.11.005.

Botavina, E.B., Churzina, E.Y., 2020. Tourist potential of Austria. Bulletin of the University 6, 70–76. https://doi.org/10.26425/1816-4277-2020-6-70-76

Chen, J.L., Gang, L., Doris, C. W., Shujie, S., 2019. Forecasting seasonal tourism demand using a multiseries structural time series method. Journal of Travel Research 58, 1 (January 2019), 92–103. https://doi.org/10.1177/0047287517737191

Chen, Z., Haynes, K., 2015. Spatial impact of transportation infrastructure: a spatial econometric CGE approach. Regional Science Matters, 163–186. https://doi.org/10.1007/978-3-319-07305-7_10.

Colladon, A. F., Guardabascio, B., Innarella, R., 2019. Using social network and semantic analysis to analyze online travel forums and forecast tourism demand. Decision Support Systems 123, 113075. https://doi.org/10.1016/j.dss.2019.113075

Danbatta, S. J., Asaf V., 2021. Monte Carlo forecasting of time series data using polynomial-fourier series model. International Journal of Modeling, Simulation, and Scientific Computing 12(03), 2141004. https://doi.org/10.1142/S179396232141004X

Daniels, G., Kakar, V., 2017. Economic growth and the CES production function with human capital. Economics Bulletin 37(2), 930–951. http://dx.doi.org/10.2139/ssrn.2878578

Deepak, M., Taylor West, C., Spreen, T., 2001. Local government portfolios and regional growth: Some combined dynamic CGE/optimal control results. Journal of Regional Science 41, 219–254. http://dx.doi.org/10.1111/0022-4146.00215

Esfandiar, K., Mohamad S. T., Stephen, P., Levent A., 2019. Understanding entrepreneurial intentions: A developed integrated structural model approach. Journal of Business Research 94, 172–182. https://doi.org/10.1016/j.jbusres.2017.10.045

Gintciak, A.M., Bolsunovskaya, M.V., Burlutskaya, Zh.V., Petryaeva, A.A., 2022. High-level simulation model of tourism industry dynamics. Business Informatics 16(3), 53-67. https://doi.org/10.17323/2587-814X.2022.3.53.67

Griffith, D. A., Albanese, P. J., 1996. An examination of plog's psychographic travel model within a student population. Journal of Travel Research 34(4), 47–51. https://doi.org/10.1177/004728759603400407

Gül, H., 2015. Effects of foreign demand increase in the tourism industry: A CGE approach to Turkey. Anatolia 26(4), 598–661. http://dx.doi.org/10.1080/13032917.2015.1044016

Harb, G., Bassil, C., 2020. Gravity analysis of tourism flows and the 'multilateral resistance to tourism'. Current Issues in Tourism 23(6), 666–678. https://doi.org/10.1080/13683500.2018.1544612

Hordofa, T.T., Liying, S., Mughal, N., Arif, A., Vu, H.M, Kaur, P., 2022. Natural resources rents and economic performance: Post-COVID-19 era for G7 countries. Resources Policy Elsevier 75(C), 102441. http://dx.doi.org/10.1016/j.resourpol.2021.102441

Hu, C., Lai, S., Lai, C., 2020. Investigations to the price evolutions of goods exchange with CES utility functions. Physica A: Statistical Mechanics and its Applications, Elsevier 549(C), 123938. http://dx.doi.org/10.1016/j.physa.2019.123938

Huang, B., Hao H., 2021. A novel two-step procedure for tourism demand forecasting. Current Issues in Tourism 24(9), 1199–1210. https://doi.org/10.1080/13683500.2020.1770705

Ilyash, O., 2021. Models of efficiency of functioning in trading enterprises under conditions of economic growth. Bulletin of Geography 51, 7–24. http://dx.doi.org/10.2478/bog-2021-0001

Issin, M., 2017. Approximate formulas for elasticity of the Tornquist functions and some their advantages, in: Proceedings of the international conference «Functional analysis in interdisciplinary applications» (FAIA2017) 1880(1). http://dx.doi.org/10.1063/1.5000660

Kamaletdinov, A., Ksenofontov, A., 2018. Modeling of income of socio-economic system on the basis of the production function. Finance: Theory and Practice 22(1), 118–127. https://doi.org/10.26794/2587-5671-2018-22-1-118-127

Klump, R., Preissler, H., 2000. CES production functions and economic growth. Scandinavian Journal of Economics 102, 41–56. https://doi.org/10.1111/1467-9442.00183

Law, R., Li, G., Fong, D.K.C., Han, X., 2019. Tourism demand forecasting: A deep learning approach. Annals of Tourism Research 75, 410–423. https://doi.org/10.1016/j.annals.2019.01.014

Li, S., Yang, Y., Zhong, Z., Tang, X., 2021. Agent-based modeling of spatial spillover effects in visitor flows. Journal of Travel Research 60(3), 546–563. https://doi.org/10.1177/0047287520930105

Litvin, S. W., Smith, W.W., 2016. A new perspective on the plog psychographic system. Journal of Vacation Marketing 22(2), 89–97. https://doi.org/10.1177/1356766715580187

Liu, A., Wu, D.C., 2019. Tourism productivity and economic growth. Annals of Tourism Research 76, 253–265. https://doi.org/10.1016/j.annals.2019.04.005

Liu, Y.Y., Tseng, F.M., Tseng, Y.H., 2018. Big data analytics for forecasting tourism destination arrivals with the applied vector autoregression model. Technological Forecasting and Social Change 130, 123–134. https://doi.org/10.1016/j.techfore.2018.01.018

Lonfgren, H., Cicowiez, M., Diaz-Bonilla, C., 2013. Chapter 4–MAMS–A computable general equilibrium model for developing country strategy analysis. Handbook of Computable General Equilibrium Modeling, 159–276. https://doi.org/10.1016/B978-0-444-59568-3.00004-3

Lourenço, N., Gouveia, C.M., Rua, A., 2021. Forecasting tourism with targeted predictors in a data-rich environment. Economic Modelling 96, 445–454. https://doi.org/10.1016/j.econmod.2020.03.030

Lubis, H.A., Pantas, V.B., Farda, M., 2019. Demand forecast of Jakarta-Surabaya high speed rail based on stated preference method. International Journal of Technology 10(2), 405. https://doi.org/10.14716/ijtech.v10i2.2442

Mai, T., Smith, C., 2018. Scenario-based planning for tourism development using system dynamic modelling: A case study of Cat Ba Island, Vietnam. Tourism Management 68, 336–354. https://doi.org/10.1016/j.tourman.2018.04.005

Miao, K., Vinter, R., 2021. Optimal control of a growth/consumption model. Optimal Control Applications and Methods 42(6), 1672–1688. https://doi.org/10.1002/oca.2754

Millán, M.G.D., Millán Vázquez de la Torre, M.G., Hernández Rojas, R., 2021. Dark tourism in southern Spain (Córdoba): An analysis of the demand. International Journal of Environmental Research and Public Health 18(5), 2740. https://doi.org/10.3390/ijerph18052740

Nguyen, N.T., Tran, T.T., 2019. Optimizing mathematical parameters of grey system theory: An empirical forecasting case of Vietnamese tourism. Neural Computing and Applications 31, 1075–1089. https://doi.org/10.1007/s00521-017-3058-9

Nicholas, A., 2021. Forecasting US overseas travelling with univariate and multivariate models. Journal of Forecasting 40(6), 963–976. https://doi.org/10.1002/for.2760

Pratt, S., 2013. Estimating tourism impact using CGE models: A historical review and future developments. Handbook of Tourism Economics: Analysis, New Applications and Case Studies, 471–492. https://doi.org/10.1142/9789814327084_0021

Rafidah, A., Shabri, A., Suhaila, Y., Mazuin, E., 2020. Forecasting Indonesia tourist arrivals to Malaysia based on nonlinear and linear model. Journal of Critical Reviews 7(8). https://doi.org/10.31838/jcr.07.08.19

Rafiei Darani, H., Asghari, H., 2018. Study of international tourism demand in Middle East by panel data model. International Journal of Culture, Tourism and Hospitality Research 12(1), 80–88. https://doi.org/10.1108/IJCTHR-03-2017-0030

Roy, J., 2004. Regional input-output analysis, data and uncertainty. The Annals of Regional Science 38, 397–412. https://doi.org/10.1007/s00168-003-0153-x

Sancho, F., 2009. Calibration of CES functions for real-world multisectoral modeling. Economic Systems Research 21, 45–58. https://doi.org/10.1080/09535310902731270

Santoso, T.A.P., Yusuf, R., Irawan, K., Juhana, A., Elindriyani, R.V., Dermawan, K.F., 2020. Agent-based modeling on traveler behavior and travel destination development with case study of Indonesian tourism, in: Proceedings of the 6th International Conference on Interactive Digital Media (ICIDM'20), 1–6. Bandung, Indonesia: IEEE. https://doi.org/10.1109/ICIDM51048.2020.9339680

Sharma, H.K., Kumari, K., Kar, S., 2020. A rough set theory application in forecasting models. Decision Making: Applications in Management and Engineering 3(2), 1–21. https://doi.org/10.31181/dmame2003001s

Silva, E.S., Hassani, H., Heravi, S., Huang, X., 2019. Forecasting tourism demand with denoised neural networks. Annals of Tourism Research 74, 134–154. https://doi.org/10.1016/j.annals.2018.11.006

Song, H., Kim, J.H., Yang, S., 2010. Confidence intervals for tourism demand elasticity. Annals of Tourism Research 37(2), 377–396. https://doi.org/10.1016/j.annals.2009.10.002

Tanaka, Y., 2022. Boundedness and finite-time blow-up in a quasilinear parabolic-elliptic chemotaxis system with logistic source and nonlin-

ear production. Journal of Mathematical Analysis and Applications 506(2), 125654. https://doi.org/10.1016/j.jmaa.2021.125654
Timilsina, G., Shrestha, R., 2008. A general equilibrium analysis of potential demand side management programs in the household sector in Thailand. International Journal of Energy Sector Management 2(4), 570–593. https://doi.org/10.1108/17506220810919072
Truong, N.V., Shimizu, T., 2017. The effect of transportation on tourism promotion: Literature review on application of the Computable General Equilibrium (CGE) Model. Transportation Research Procedia 25, 3096–3115. https://doi.org/10.1016/j.trpro.2017.05.336
Turner, L.W., Witt, S.F., 2001. Factors influencing demand for international tourism: tourism demand analysis using structural equation modelling, revisited. Tourism Economics 7(1), 21–38. https://doi.org/10.5367/000000001101297711
Vu, H.Q., Li, G., Law, R., Ye, B.H., 2015. Exploring the travel behaviors of inbound tourists to hong kong using geotagged photos. Tourism Management 46, 222–232. https://doi.org/10.1016/j.tourman.2014.07.003
Wang, J., Li, Y., Wu, B., Wang, Y., 2021. Tourism destination image based on tourism user generated content on internet. Tourism Review 76(1), 125–137. https://doi.org/10.1108/TR-04-2019-0132.
Wen, L., Liu, C., Song, H., 2019. Forecasting tourism demand using search query data: A hybrid modelling approach. Tourism Economics 25(3), 309–329. https://doi.org/10.1177/1354816618768317
Wen, L., Liu, C., Song, H., Liu, H., 2021. Forecasting tourism demand with an improved mixed data sampling model. Journal of Travel Research 60(2), 336–353. https://doi.org/10.1177/0047287520906220
Widaningrum, D.L., Surjandari, I., Sudiana, D., 2020. Analyzing land-use changes in tourism development area: A case study of cultural world heritage sites in Java Island, Indonesia. International Journal of Technology 11(4), 688–697. https://doi.org/10.14716/ijtech.v11i4.4097
Willenbockel, D., 1999. On apparent problems with the use of the Armington aggregator in computable general equilibrium models. Applied Economics Letters 6(9), 589–591. https://doi.org/10.1080/135048599352664
Wu, D. C., Cao, Z., Wen, L., Song, H., 2021. Scenario forecasting for global tourism. Journal of Hospitality & Tourism Research 45(1), 28–51. https://doi.org/10.1177/1096348020919990
Wu, S., 2021. Boundedness in a quasilinear chemotaxis model with logistic growth and indirect signal production. Acta Applicandae Mathematicae 176(9), 1–14. https://doi.org/10.1007/s10440-021-00454-x
Yankovyi, O., 2021. Modeling sustainable economic development using production functions. Studies of Applied Economics 39(5), 1–14. https://doi.org/10.25115/eea.v39i5.5090

Список источников

Antoszewski, M., 2019. Wide-range estimation of various substitution elasticities for CES production functions at the sectoral level. Energy Economics 83, 272–289. https://doi.org/10.1016/j.eneco.2019.07.016
Assaf, A.G., Gang, L., Song, H., Tsionas, M.G., 2019. Modeling and forecasting regional tourism demand using the Bayesian Global Vector Autoregressive (BGVAR) Model. Journal of Travel Research 58(3), 383–397. https://doi.org/10.1177/0047287518759226
Attar, M., 2021. Growth, distribution and dynamic inefficiency in Turkey: An analysis of the naïve neoclassical theory of capital. Structural Change and Economic Dynamics 59, 20–30. https://doi.org/10.1016/j.strueco.2021.07.008
Bangwayo-Skeete, P.F., Skeete, R.W., 2015. Can Google data improve the forecasting performance of tourist arrivals? Mixed-Data Sampling Approach. Tourism Management 46, 454–464. https://doi.org/10.1016/j.tourman.2014.07.014
Berawi, M.A., 2016. Accelerating sustainable infrastructure development: Assuring well-being and ensuring environmental sustainability. International Journal of Technology 7(4), 527. http://dx.doi.org/10.14716/ijtech.v7i4.3829
Blake, A., 2009. The dynamics of tourism's economic impact. Tourism Economics 15, 615–628. https://doi.org/10.5367/000000009789036576
Blake, A., Durbarry, R., Eugenio-Martin, J.L., Gooroochurn, N., Hay, B., Lennon, J., Sinclair, T., Sugiyarto, G., Yeoman, I., 2006. Integrating forecasting and CGE models: The case of tourism in Scotland. Tourism Management 27 (2), 292–305. https://doi.org/10.1016/j.tourman.2004.11.005.
Botavina, E.B., Churzina, E.Y., 2020. Tourist potential of Austria. Bulletin of the University 6, 70–76. https://doi.org/10.26425/1816-4277-2020-6-70-76
Chen, J.L., Gang, L., Doris, C. W., Shujie, S., 2019. Forecasting seasonal tourism demand using a multiseries structural time series method. Journal of Travel Research 58, 1 (January 2019), 92–103. https://doi.org/10.1177/0047287517737191
Chen, Z., Haynes, K., 2015. Spatial impact of transportation infrastructure: a spatial econometric CGE approach. Regional Science Matters, 163–186. https://doi.org/10.1007/978-3-319-07305-7_10.
Colladon, A. F., Guardabascio, B., Innarella, R., 2019. Using social network and semantic analysis to analyze online travel forums and forecast tourism demand. Decision Support Systems 123, 113075. https://doi.org/10.1016/j.dss.2019.113075
Danbatta, S. J., Asaf V., 2021. Monte Carlo forecasting of time series data using polynomial-fourier series model. International Journal of Modeling, Simulation, and Scientific Computing 12(03), 2141004. https://doi.org/10.1142/S179396232141004X
Daniels, G., Kakar, V., 2017. Economic growth and the CES production function with human capital. Economics Bulletin 37(2), 930–951. http://dx.doi.org/10.2139/ssrn.2878578
Deepak, M., Taylor West, C., Spreen, T., 2001. Local government portfolios and regional growth: Some combined dynamic CGE/optimal control results. Journal of Regional Science 41, 219–254. http://dx.doi.org/10.1111/0022-4146.00215
Esfandiar, K., Mohamad S. T., Stephen, P., Levent A., 2019. Understanding entrepreneurial intentions: A developed integrated structural model approach. Journal of Business Research 94, 172–182. https://doi.org/10.1016/j.jbusres.2017.10.045
Gintciak, A.M., Bolsunovskaya, M.V., Burlutskaya, Zh.V., Petryaeva, A.A., 2022. High-level simulation model of tourism industry dynamics. Business Informatics 16(3), 53-67. https://doi.org/10.17323/2587-814X.2022.3.53.67
Griffith, D. A., Albanese, P. J., 1996. An examination of plog's psychographic travel model within a student population. Journal of Travel Research 34(4), 47–51. https://doi.org/10.1177/004728759603400407
Gül, H., 2015. Effects of foreign demand increase in the tourism industry: A CGE approach to Turkey. Anatolia 26(4), 598–661. http://dx.doi.org/10.1080/13032917.2015.1044016
Harb, G., Bassil, C., 2020. Gravity analysis of tourism flows and the 'multilateral resistance to tourism'. Current Issues in Tourism 23(6), 666–678. https://doi.org/10.1080/13683500.2018.1544612
Hordofa, T.T., Liying, S., Mughal, N., Arif, A., Vu, H.M, Kaur, P., 2022. Natural resources rents and economic performance: Post-COVID-19 era for G7 countries. Resources Policy Elsevier 75(C), 102441. http://dx.doi.org/10.1016/j.resourpol.2021.102441
Hu, C., Lai, S., Lai, C., 2020. Investigations to the price evolutions of goods exchange with CES utility functions. Physica A: Statistical

Mechanics and its Applications, Elsevier 549(C), 123938. http://dx.doi.org/10.1016/j.physa.2019.123938
Huang, B., Hao H., 2021. A novel two-step procedure for tourism demand forecasting. Current Issues in Tourism 24(9), 1199–1210. https://doi.org/10.1080/13683500.2020.1770705
Ilyash, O., 2021. Models of efficiency of functioning in trading enterprises under conditions of economic growth. Bulletin of Geography 51, 7–24. http://dx.doi.org/10.2478/bog-2021-0001
Issin, M., 2017. Approximate formulas for elasticity of the Tornquist functions and some their advantages, in: Proceedings of the international conference «Functional analysis in interdisciplinary applications» (FAIA2017) 1880(1). http://dx.doi.org/10.1063/1.5000660
Klump, R., Preissler, H., 2000. CES production functions and economic growth. Scandinavian Journal of Economics 102, 41–56. https://doi.org/10.1111/1467-9442.00183
Law, R., Li, G., Fong, D.K.C., Han, X., 2019. Tourism demand forecasting: A deep learning approach. Annals of Tourism Research 75, 410–423. https://doi.org/10.1016/j.annals.2019.01.014
Li, S., Yang, Y., Zhong, Z., Tang, X., 2021. Agent-based modeling of spatial spillover effects in visitor flows. Journal of Travel Research 60(3), 546–563. https://doi.org/10.1177/0047287520930105
Litvin, S. W., Smith, W.W., 2016. A new perspective on the plog psychographic system. Journal of Vacation Marketing 22(2), 89–97. https://doi.org/10.1177/1356766715580187
Liu, A., Wu, D.C., 2019. Tourism productivity and economic growth. Annals of Tourism Research 76, 253–265. https://doi.org/10.1016/j.annals.2019.04.005
Liu, Y.Y., Tseng, F.M., Tseng, Y.H., 2018. Big data analytics for forecasting tourism destination arrivals with the applied vector autoregression model. Technological Forecasting and Social Change 130, 123–134. https://doi.org/10.1016/j.techfore.2018.01.018
Lonfgren, H., Cicowiez, M., Diaz-Bonilla, C., 2013. Chapter 4–MAMS–A computable general equilibrium model for developing country strategy analysis. Handbook of Computable General Equilibrium Modeling, 159–276. https://doi.org/10.1016/B978-0-444-59568-3.00004-3
Lourenço, N., Gouveia, C.M., Rua, A., 2021. Forecasting tourism with targeted predictors in a data-rich environment. Economic Modelling 96, 445–454. https://doi.org/10.1016/j.econmod.2020.03.030
Lubis, H.A., Pantas, V.B., Farda, M., 2019. Demand forecast of Jakarta-Surabaya high speed rail based on stated preference method. International Journal of Technology 10(2), 405. https://doi.org/10.14716/ijtech.v10i2.2442
Mai, T., Smith, C., 2018. Scenario-based planning for tourism development using system dynamic modelling: A case study of Cat Ba Island, Vietnam. Tourism Management 68, 336–354. https://doi.org/10.1016/j.tourman.2018.04.005
Miao, K., Vinter, R., 2021. Optimal control of a growth/consumption model. Optimal Control Applications and Methods 42(6), 1672–1688. https://doi.org/10.1002/oca.2754
Millán, M.G.D., Millán Vázquez de la Torre, M.G., Hernández Rojas, R., 2021. Dark tourism in southern Spain (Córdoba): An analysis of the demand. International Journal of Environmental Research and Public Health 18(5), 2740. https://doi.org/10.3390/ijerph18052740
Nguyen, N.T., Tran, T.T., 2019. Optimizing mathematical parameters of grey system theory: An empirical forecasting case of Vietnamese tourism. Neural Computing and Applications 31, 1075–1089. https://doi.org/10.1007/s00521-017-3058-9
Nicholas, A., 2021. Forecasting US overseas travelling with univariate and multivariate models. Journal of Forecasting 40(6), 963–976. https://doi.org/10.1002/for.2760
Pratt, S., 2013. Estimating tourism impact using CGE models: A historical review and future developments. Handbook of Tourism Economics: Analysis, New Applications and Case Studies, 471–492. https://doi.org/10.1142/9789814327084_0021
Rafidah, A., Shabri, A., Suhaila, Y., Mazuin, E., 2020. Forecasting Indonesia tourist arrivals to Malaysia based on nonlinear and linear model. Journal of Critical Reviews 7(8). https://doi.org/10.31838/jcr.07.08.19
Rafiei Darani, H., Asghari, H., 2018. Study of international tourism demand in Middle East by panel data model. International Journal of Culture, Tourism and Hospitality Research 12(1), 80–88. https://doi.org/10.1108/IJCTHR-03-2017-0030
Roy, J., 2004. Regional input-output analysis, data and uncertainty. The Annals of Regional Science 38, 397–412. https://doi.org/10.1007/s00168-003-0153-x
Sancho, F., 2009. Calibration of CES functions for real-world multisectoral modeling. Economic Systems Research 21, 45–58. https://doi.org/10.1080/09535310902731270
Santoso, T.A.P., Yusuf, R., Irawan, K., Juhana, A., Elindriyani, R.V., Dermawan, K.F., 2020. Agent-based modeling on traveler behavior and travel destination development with case study of Indonesian tourism, in: Proceedings of the 6th International Conference on Interactive Digital Media (ICIDM'20), 1–6. Bandung, Indonesia: IEEE. https://doi.org/10.1109/ICIDM51048.2020.9339680
Sharma, H.K., Kumari, K., Kar, S., 2020. A rough set theory application in forecasting models. Decision Making: Applications in Management and Engineering 3(2), 1–21. https://doi.org/10.31181/dmame2003001s
Silva, E.S., Hassani, H., Heravi, S., Huang, X., 2019. Forecasting tourism demand with denoised neural networks. Annals of Tourism Research 74, 134–154. https://doi.org/10.1016/j.annals.2018.11.006
Song, H., Kim, J.H., Yang, S., 2010. Confidence intervals for tourism demand elasticity. Annals of Tourism Research 37(2), 377–396. https://doi.org/10.1016/j.annals.2009.10.002
Tanaka, Y., 2022. Boundedness and finite-time blow-up in a quasilinear parabolic-elliptic chemotaxis system with logistic source and nonlinear production. Journal of Mathematical Analysis and Applications 506(2), 125654. https://doi.org/10.1016/j.jmaa.2021.125654
Timilsina, G., Shrestha, R., 2008. A general equilibrium analysis of potential demand side management programs in the household sector in Thailand. International Journal of Energy Sector Management 2(4), 570–593. https://doi.org/10.1108/17506220810919072
Truong, N.V., Shimizu, T., 2017. The effect of transportation on tourism promotion: Literature review on application of the Computable General Equilibrium (CGE) Model. Transportation Research Procedia 25, 3096–3115. https://doi.org/10.1016/j.trpro.2017.05.336
Turner, L.W., Witt, S.F., 2001. Factors influencing demand for international tourism: tourism demand analysis using structural equation modelling, revisited. Tourism Economics 7(1), 21–38. https://doi.org/10.5367/000000001101297711
Vu, H.Q., Li, G., Law, R., Ye, B.H., 2015. Exploring the travel behaviors of inbound tourists to hong kong using geotagged photos. Tourism Management 46, 222–232. https://doi.org/10.1016/j.tourman.2014.07.003
Wang, J., Li, Y., Wu, B., Wang, Y., 2021. Tourism destination image based on tourism user generated content on internet. Tourism Review 76(1), 125–137. https://doi.org/10.1108/TR-04-2019-0132.
Wen, L., Liu, C., Song, H., 2019. Forecasting tourism demand using search query data: A hybrid modelling approach. Tourism Economics 25(3), 309–329. https://doi.org/10.1177/1354816618768317

Wen, L., Liu, C., Song, H., Liu, H., 2021. Forecasting tourism demand with an improved mixed data sampling model. Journal of Travel Research 60(2), 336–353. https://doi.org/10.1177/0047287520906220

Widaningrum, D.L., Surjandari, I., Sudiana, D., 2020. Analyzing land-use changes in tourism development area: A case study of cultural world heritage sites in Java Island, Indonesia. International Journal of Technology 11(4), 688–697. https://doi.org/10.14716/ijtech.v11i4.4097

Willenbockel, D., 1999. On apparent problems with the use of the Armington aggregator in computable general equilibrium models. Applied Economics Letters 6(9), 589–591. https://doi.org/10.1080/135048599352664

Wu, D. C., Cao, Z., Wen, L., Song, H., 2021. Scenario forecasting for global tourism. Journal of Hospitality & Tourism Research 45(1), 28–51. https://doi.org/10.1177/1096348020919990

Wu, S., 2021. Boundedness in a quasilinear chemotaxis model with logistic growth and indirect signal production. Acta Applicandae Mathematicae 176(9), 1–14. https://doi.org/10.1007/s10440-021-00454-x

Yankovyi, O., 2021. Modeling sustainable economic development using production functions. Studies of Applied Economics 39(5), 1–14. https://doi.org/10.25115/eea.v39i5.5090

Камалетдинов А.Ш., Ксенофонтов А.А., 2018. Моделирование доходов социально-экономических систем на основе производственной функции. Финансы: теория и практика 22(1), 118–127. https://doi.org/10.26794/2587-5671-2018-22-1-118-127

The article was submitted 13.07.2023, approved after reviewing 28.08.2023, accepted for publication 01.09.2023.

Статья поступила в редакцию 13.07.2023, одобрена после рецензирования 28.08.2023, принята к публикации 01.09.2023.

About authors:

1. Aleksei M. Gintciak, Head of Laboratory of Digital modelling of Industrial systems, Peter the Great St. Petersburg Polytechnic University, Saint Petersburg, Russian Federation. https://orcid.org/0000-0002-9703-5079, aleksei.gintciak@spbpu.com

2. Zhanna V. Burlutskaya, Junior Researcher of Laboratory of Digital modelling of Industrial systems, Peter the Great St. Petersburg Polytechnic University, Saint Petersburg, Russian Federation. https://orcid.org/0000-0002-5680-1937, zhanna.burlutskaya@spbpu.com

3. Daria A. Zubkova, Junior Researcher of Laboratory of Digital modelling of Industrial systems, Peter the Great St. Petersburg Polytechnic University, Saint Petersburg, Russian Federation. https://orcid.org/0000-0003-1106-5080, daria.zubkova@spbpu.com

4. Alexandra A. Petryaeva, Junior Researcher of Laboratory of Digital modelling of Industrial systems, Peter the Great St. Petersburg Polytechnic University, Saint Petersburg, Russian Federation. https://orcid.org/0000-0002-2028-7251, alexandra.petryaeva@spbpu.com

Информация об авторах:

1. Алексей Михайлович Гинцяк, заведующий лабораторией «Цифровое моделирование индустриальных систем», Санкт-Петербургский политехнический университет Петра Великого, Санкт-Петербург, Российская Федерация. https://orcid.org/0000-0002-9703-5079, aleksei.gintciak@spbpu.com

2. Жанна Владиславовна Бурлуцкая, младший научный сотрудник лаборатории «Цифровое моделирование индустриальных систем», Санкт-Петербургский политехнический университет Петра Великого, Санкт-Петербург, Российская Федерация. https://orcid.org/0000-0002-5680-1937, zhanna.burlutskaya@spbpu.com

3. Дарья Андреевна Зубкова, младший научный сотрудник лаборатории «Цифровое моделирование индустриальных систем», Санкт-Петербургский политехнический университет Петра Великого, Санкт-Петербург, Российская Федерация. https://orcid.org/0000-0003-1106-5080, daria.zubkova@spbpu.com

4. Александра Андреевна Петряева, младший научный сотрудник лаборатории «Цифровое моделирование индустриальных систем», Санкт-Петербургский политехнический университет Петра Великого, Санкт-Петербург, Российская Федерация. https://orcid.org/0000-0002-2028-7251, alexandra.petryaeva@spbpu.com