Finanziato dall'Unione europea NextGenerationEU
Ministero dell'Università e della Ricerca
Italiadomani PIANO NAZIONALE DI RIPRESA E RESILIENZA
Università Ca'Foscari Venezia

Algorithmic Innovations in Tourism Flow Modelling and Forecasting: A Survey

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iNEST Spoke 6 “Tourism, Culture and Creative Industries”
RT: 1   Sub. RT: 3

Abstract

This study explores the transformative role of algorithms in the tourism industry, a key driver of global economic growth. It delves into the application of algorithms in analyzing travel data to discern patterns and behaviours, thereby enabling businesses to customize their services to customer needs. We discuss the use of algorithms in managing tourist flow, ensuring an even distribution of tourists across various attractions to prevent overcrowding. A significant focus is on the role of algorithmic-assisted approaches in sustainable tourism management strategies. By analyzing data on tourist behaviour and environmental impact, these strategies aim to strike a balance between catering to tourists’ needs and preserving natural and cultural heritage sites. This study provides a comprehensive overview of how these algorithmic solutions are revolutionizing the tourism industry. It discusses their benefits and challenges, and contemplates future trends in this field. The overarching theme is the potential of algorithms to enhance the efficiency and effectiveness of tourism management, contributing to sustainable and responsible tourism.

Text

Tourism is one of the most important promoters of global economic growth. As such, efficient and effective solutions to the management of touristic flow are high in demand. In practice, several application topics cover this subject. Algorithms can be used to analyze travel data and mine frequent patterns and behaviours, helping businesses tailor their offerings to meet the needs of their customers. They can also aid in the management of tourist flow, ensuring that popular sites are not overcrowded and that tourists are evenly distributed across various attractions. Moreover, algorithmic-assisted approaches are at the centre of sustainable tourism management strategies (Xu et al., 2020; Yekimov et al., 2022). By analyzing data on tourist behaviour and environmental impact, these solutions can help devise strategies that balance the needs of tourists with the preservation of natural and cultural heritage sites. This study will explore these topics in detail, providing an overview of how algorithmic solutions are revolutionizing the tourism industry.

In this paper, we delve into the primary methodologies of algorithmic tourism, which include advanced algorithms and data analysis techniques aimed at enhancing the effectiveness and efficiency of tourism operations. Our discussion is centred around four prominent research areas that address different yet complementary challenges in the field of tourism. We thus begin by discussing *tourism demand forecasting* as one of the simplest yet most effective and studied approaches. We then discuss *visitor trajectory tracking*, another important application in this context. Building on these notions we discuss *trajectory modelling*, an important analytical approach to extract further insight from the trajectory of tourists. Lastly, we discuss some *simulation and modelling* approaches.

Tourism Demand Forecasting

Tourism forecasting (or *demand modelling, demand forecasting*) is one of the most widely studied and important topics of tourism management. It deals with the prediction of the future volume of visiting tourists, which can be done at different scales (Attanasio et al., 2022; Sun et al., 2023). The literature identifies three main types of forecasting approaches. (i) Econometric-based methods forecast tourism demand based on explanatory variables such as income and tourism price. (ii) Time-series-based methods forecast tourism demand according to historical trends and patterns. Lastly, (iii) Artificial Intelligence (AI) based methods leverage machine learning to extract information from complex and nonlinear data. Each of these methods offers a unique approach to predicting tourism demand.

Econometric-based methods are causal models that forecast tourism demand through the combination of stochastic variables. The variables are most commonly economic (concerning both the destination and the tourists), usually a combination of sales data with information on outside forces that affect demand. These may include things like the GDP of the country of origin, tourist expenses, accommodation prices for hotels, transport expenses of travelling, etc. Indeed, the main difference with time-series-based models is their ability to use such explanatory variables. The usage of Big Data extracted from Internet sources such as search engines is a recent trend in these types of methods (Höpken et al., 2019; Jiao and Chen, 2019; Song, 2022; Song et al., 2003). Examples of econometric models include most standard statistical regression models, such as *Linear Regression Models* and *Generalized Linear Models*. Some recent econometric models applied to the tourism domain include the *vector autoregressive model (VAR)* (Gunter and Önder, 2016), the *error correction model (ECMs*) (Moore, 2010), the *autoregressive distributed lag model* (ADL) (Wan and Song, 2018), and the *time-varying parameter model* (TVP) (Song et al., 2011). *Dynamic factor models* (DFM) have also been used (Hu et al., 2023; Li et al., 2017).

Time series-based forecasting methods are statistical models that use historical trends and patterns to make their predictions. Such models can be applied in the tourism domain by analyzing historical data on tourist arrivals, expenditures, and other relevant variables. One of the most widely used time series models is the *Autoregressive Integrated Moving Average* (ARIMA) and its many variants. *State Space Models* and *Exponential Smoothing* approaches are also popular, while *Singular Spectrum Analysis* (SSA) is a relatively new non-parametric model being explored. Numerous neural network-based approaches have also been proposed in the latest years (Kim et al., 2021; Kumar and Raubal, 2021). Time series may also be augmented with explanatory variables, most commonly ones based on Big Data (Jiao and Chen, 2019).

The *AI-based* category involves methods based on machine learning approaches. These types of approaches have gained great popularity because of their ability to handle complex and nonlinear data that often does not have stability assumptions.

This class of methods is often divided into two further categories: *shallow* and *deep methods*. Shallow methods include more traditional machine learning approaches, such as *Radial Basis Function (RBF) networks*, *Support Vector Machines (SVMs)*, *Graph Neural Networks (GNNs)*, and shallow neural networks (NN), such as *Multilayer Perceptrons (MLPs)* with few layers (Chang and Tsai, 2017; Han et al., 2023; Kumar and Raubal, 2021). On the other hand, deep methods include more recent approaches based on deep NN with numerous layers and much greater numbers of parameters. These include both *Recurrent Neural Networks (RNNs)*, which are well suited to sequential data such as time series, but also *Convolutional Neural Networks (CNNs)* (Sun et al., 2023), which can allow the integration of other types of data (e.g., spatial information).

As one would expect, *hybrid methods* are also a possibility. Hybrid approaches combine one or more methods in hopes of combining their advantages and minimizing their limitations. This is common practice in the field of AI approaches, and multiple AI approaches are often combined to create a hybrid model. Hybridization may also be achieved between different classes of models; for instance, authors of (Nor et al., 2018) utilize a hybrid method which uses an equally weighted combination of Box-Jenkins (a time series analysis approach that uses ARIMA internally) and a NN.

Visitor Trajectory Tracking

Visitor trajectory tracking is a technique used to gather information about the movements and behaviour of tourists in a destination. This information can be used by destination managers to understand and manage tourism flows and to find locations that may need intervention. Areas that may be suffering from negative phenomena such as over-tourism and congestion may be identified this way, allowing stakeholders to take action (Padrón-Ávila and Hernández-Martín, 2020).

Visitor trajectory tracking primarily focuses on observing tourist behaviour and interpreting the patterns that emerge. Once the data is collected, it can be utilized in numerous ways to enhance and manage tourism. For instance, the data can provide insights into why specific locations are visited, the timing of these visits, and the profiles of the visitors (Edwards and Griffin, 2013). This information enables stakeholders to plan and manage tourism more effectively. Furthermore, the data can be used to pinpoint areas of concern, such as locations experiencing over-tourism and congestion (Kumar and Raubal, 2021). It can also support various policy decisions aimed at promoting sustainable development. Concurrently, it can facilitate the digital transformation of the tourism business in a region, a concept that aligns with the idea of smart cities (Ivars-Baidal et al., 2023). This type of data can be used to construct various models. These models could be analytical methods designed to gain a deeper understanding of visitor behaviour or predictive models that forecast the future movements of tourists.

An example of its application is in managing over-tourism. Over-tourism is defined as a surge in tourist numbers at such high volumes that it negatively impacts residents, visitors, and the environment (Gu et al., 2021; Hardy et al., 2020). This phenomenon is not homogeneous, meaning destinations do not face over-tourism as a whole but rather suffer from congestion issues in a few areas (points of interest, POI), while most parts of the territory are mainly used by the local population. It's also important to note that tourists visit attractions and POIs during specific times, leaving them less frequented during most parts of the day. As over-tourism can have severe negative effects on natural and cultural spaces, tourist tracking techniques are a prime tool to identify locations suffering from this issue (Domènech et al., 2020). This data can then be used to make prudent decisions to avoid unsustainable developments. This comprehensive use of data underscores the importance and potential of visitor trajectory tracking in the field of tourism.

Tracking Methods

The collection of data from tourists and visitors is a crucial aspect of visitor trajectory tracking. Accurate data enables more effective decision-making and improved analysis. This data can reveal why certain places are visited, the timing of these visits, and the demographic profile of the tourists. Historically, data was collected through face-to-face interviews and direct observation of tourists (Domènech et al., 2020; Padrón-Ávila and Hernández-Martín, 2020). However, these methods were found to be largely inadequate for understanding the motivations and intentions behind tourist decisions. In recent years, a variety of tracking techniques have been employed to study tourist movement. These techniques encompass mobile positioning data, Global Positioning System (GPS) data, Bluetooth data, user-generated data, credit card data from ticket sales, and geo-referenced photos uploaded to the internet. GPS devices have been predominantly used for local-scale studies, while mobile phone data is often used for studying movement across larger areas. These two types of data are argued to enable more precise and efficient studies due to their superior spatial and temporal accuracy. However, the use of these data types raises ethical and legal concerns related to user data protection. While GPS and mobile data are precise and accurate, they also present certain challenges. For instance, GPS data requires a constant internet connection. Additionally, the use of mobile devices is less common among older individuals, which can result in a skewed sample. These data types also do not reflect motivations or preferences, prompting some researchers to supplement them with surveys (Padrón-Ávila and Hernández-Martín, 2020). To address these issues, researchers have started to incorporate other types of Big Data sourced from the internet, such as quantitative data from TripAdvisor, information on attractions and views from Wikidata, and data from social networks.

Trajectory Modelling

Trajectory modelling in tourism involves the analysis of the paths or routes that tourists take during their visits. This can provide valuable insights into tourist behaviour, preferences, and patterns. Two methods used in trajectory modelling are the *sequence alignment method* (SAM) (Shoval et al., 2015) and *frequent trajectory mining* (FTM) (Wang et al., 2021).

The *Sequence Alignment Method* (SAM) is a dynamic programming method used to identify patterns of tourist behaviour from a large dataset of tourist trajectories and cluster groups of tourists. SAM is often applied to classify sequences of tourists' movements and understand similarities in their patterns (Zheng et al., 2022). SAM works by comparing sequences of data and finding the best alignment between them. A score is assigned to each possible alignment based on how well the sequences match and the best alignment is then chosen.

Frequent Trajectory Mining (FTM) is a technique used to identify common patterns in the movement of objects, such as people or vehicles, by analyzing their trajectories (Park et al., 2020). One approach to FTM involves using a line simplification technique such as the Douglas-Peucker trajectory compression algorithm to transform the sequence segments into directed line segments (Gao et al., 2019; Zheng et al., 2022). These segments are then grouped based on their shape and proximity in space. Several studies have tried to divide the space into grids (Batista e Silva et al., 2018; Yao et al., 2021) characterizing trajectories with the sequences of grids they pass through, and then mining the frequent trajectory patterns. However, this approach can be problematic due to the smoothing effect that can prevent the discovery of useful trajectory information.
Clustering approaches have also been used in FTM (Huang et al., 2016; Kádár and Gede, 2021; Qin et al., 2019). One approach involves clustering local POIs into ROIs (regions of interest), and then using trajectory mining to characterize the trajectories that pass through these ROIs. Trajectories are sometimes modelled as sequences of GPS points or ROIs, and an a-priori-like algorithm can be used to discover frequent trajectory patterns.
Differently from SAM, which focuses on identifying the commonalities of sequences of tourists to obtain features, FTM extracts high-frequency tourist movement and identifies the connections between attractions and their combination patterns. FTM provides a more microscopic perspective by analyzing patterns among two, three, or even more attractions (Zheng et al., 2022).

Tourism Simulation and Modelling

Tourism systems are complex adaptive systems. There are many modelling approaches, and we describe the most important (Baktash et al., 2023).

System dynamic-based methods to study the macro-level behaviour of a complex system. In tourism, this could involve modelling how changes in one part of the tourism system affect other parts of the system. Such models use a series of differential equations to reflect changes in stock variables of interest (e.g., touristic presence, average expenditure), flows between these stocks, and information that determines the values of the flows. The behaviour of individual entities (tourists) is not modelled, and aggregated variables such as (average) density and (average) flow are used instead (Gazoni and Silva, 2022; Sedarati et al., 2019).

Methods in the *network-based* family of methods are more suitable to account for micro-level interactions between entities and to understand relationships between entities. A wide range of methods can be used to analyze these networks, depending on their complexity, including community detection and measures coming from graph theory (closeness, betweenness, etc.). Among these, Exponential Random Graphs Models (ERGMs) are a popular approach to modelling complex networks. Multiplex/Multilayer network analysis is a particular subcategory that models multiple types of relationships and interactions (Baggio and Baggio, 2020).

Agent-based approaches use computer-based simulations to model individual agents and their interactions. This can be used to understand complex and emergent behaviours and assess the impact of specific changes on some entities. This family of methods is quite flexible, combining elements from system dynamics modelling and network analysis; as such, it can be integrated with other theories such as game theory, spatial models and evolutionary programming to understand both micro- and macro-dynamic processes and reveal the possible causal or correlational relationships through dynamic simulation (Kazil et al., 2020; Majic et al., 2023; Qiu et al., 2016).

Finally, we encompass other methods in the class of *statistical models*, comprising simpler statistical techniques used in modelling systems of limited complexity. These techniques are used to understand patterns and trends within tourism data mainly to predict future trends. Each of these methods has its strengths and applications, and they can often be used in combination to provide a more comprehensive understanding of tourism systems (Mahdi and Esztergár-Kiss, 2023; Sabashi et al., 2022). The survey provides several examples of use cases for these methods.

Flow Modelling

Much of the reviewed research is focused on modelling the flow of visitors or traffic in tourist destinations. These methods can be considered a specific application of simulation approaches, but we describe them separately due to their popularity in the literature. Generally speaking, an entity flow is defined as the number of entities passing a reference point per unit time (Kumar and Raubal, 2021). Common applications of flow modelling in urban settings have been applied to traffic and transport monitoring systems (Cheng et al., 2023, 2023; van Wageningen-Kessels et al., 2015). Besides being applied to model tourism and visitor flows, flow modelling is particularly applied to predict traffic flows in urban environments and related tasks, like congestion detection. We will not discuss such approaches, limiting our analysis to the ones with more direct application to the tourism domain.

Several studies focus on using crowd-sourced data, particularly geo-tagged images to find regions and landmarks of tourist interest (Kádár and Gede, 2021; Qin et al., 2019). These articles are usually interested in studying tourist movements in specific regions, determining frequent trajectories, and correlations between hotspots. Hence, they are interested in a more qualitative evaluation of the tourist flow, usually with coarse-grained temporal resolution. Conversely, flow modelling studies interested in the prediction of the touristic presence make use of historical volumetric data measuring the volume of tourists (or passengers, vehicles) passing through a monitored control station. Data are usually payment data collected in Automatic Fare Collection (AFC) systems (Chen et al., 2020; Li et al., 2019; Yang et al., 2021), images and video coming from surveillance cameras (Kumar and Raubal, 2021) and census or econometrics data sourced from specific agencies (Ma and Zhou, 2023; Sevtsuk et al., 2021). The former is quite common in public transport systems, while the latter may include the positioning of urban assets, like parks, parking lots, stadiums, weather information and a series of political and econometrics variables (Kim et al., 2021; Sevtsuk et al., 2021). Additionally, statistical models are commonly used in the regression of tourist flow (Chen et al., 2020; Li et al., 2019; Rosselló Nadal and Santana Gallego, 2022; Yang et al., 2021), including ARIMA and some nonlinear variants, like NARMAX.

Gravity models have also been on the rise in recent years. These models were originally introduced to describe the patterns in international trade and have since been applied to other domains including tourism flows. (Rosselló Nadal and Santana Gallego, 2022) describe a theoretical foundation for applying gravity formulations to the study of tourism demand function. More recently (Arshad et al., 2023; Dropsy et al., 2020; Hsu et al., 2020) proposed the usage of gravity equations with variables such as GDP and the distance between origin and destination to explain the change in the flow of tourists.

Theoretical Concepts Influencing Tourist Models

The application of algorithms to monitor and predict tourist movements merges various concepts borrowed by other disciplines. It draws upon theories and models from geography, economics, and consumer behaviour to analyze and predict patterns in tourism. In this section, we briefly mention some of these disciplines and concepts, which are also mentioned in (Zheng et al., 2022).

Time geography is a theoretical foundation for understanding tourist time-space behaviours. It considers how tourists move through space and time through their travels, and how their movements are influenced by factors such as transportation, attractions, and the availability of resources. Time geography can be used to analyze tourist flows and identify patterns in tourist behaviour. The *core-periphery model* suggests that geographical regions have core areas and several peripheral areas. When applied to tourism, the central regions are characterized by a high density of well-known attractions, while the outlying areas are marked by a sparse visitor presence. This model can be used to analyze the distribution of tourist flows within a destination and identify development opportunities. The concept of *cumulative attraction* refers to the idea that clusters of attractions or destinations can attract more tourists who stay longer than sites with single attractions or destinations that are not part of and do not connect to a cluster. This is because visiting destinations that are closely interconnected saves time, effort, costs, and other resources. Cumulative attraction can be used to optimize the distribution of attractions within a destination to improve the tourism experience. Tourism attractions may be scattered around a destination (Edwards et al., 2008): some are large, primary attractions, while others are small, secondary ones. According to *gravity theory,* primary attractions exert a stronger gravitational pull on visitors due to their larger size, compared to secondary ones. The presence of a group of primary attractions, when coupled with secondary attractions, can boost the overall appeal and competitiveness of the destination. A theoretical foundation for the usage of gravity models in the context of tourism is discussed in (Morley et al., 2014). Among spatial effects that affect tourism demand, *spatial spillover* and *spatial heterogeneity* are the most discussed in the literature (Li et al., 2022). The *spillover effect* describes how neighbouring destinations' tourism industries indirectly and unintentionally impact the tourism demand in a destination.

The effects could be both positive and negative. On the other hand, *spatial heterogeneity* presents the idea that different destinations have unique characteristics that affect their tourism demand. These characteristics can include factors such as natural and cultural attractions, infrastructure, and accessibility. Both of these effects should be considered by destination managers when tailoring marketing and development strategies.

Finally, *consumer behaviour theories* try to explain how tourists make their travel decisions. According to random utility theory, tourists strive to optimise their benefits when deciding on their travel plans: they opt to visit and spend their time at those attractions that offer them the highest value. Tourists use cognitive representations of the destination but are not entirely rational, given the limitations of information, time, and cognitive capabilities. Tourist cognitive representations are usually biased or distorted; as an example, tourist cultural background plays a crucial role in tourist choices of transport mode. A survey by (Lew and McKercher, 2006) gives an excellent overview of the variables involved in tourist decision-making. These include the type of origin and accommodation where the tourist starts planning, the level of isolation of attractions and the presence of similar attractions. Interests and the psychometric profile of the tourist are also important, as well as the emotional value of a destination. The authors also empirically determine three movement profiles for tourists, accounting for the personal tendency to prefer point-to-point movement, circular patterns, radial movement, etc. Such considerations are important in the definition of comprehensive modelling of tourists' behaviour. However, in practice, much simpler models with fewer conjectures are proposed to solve real problems. This is partially due to the lack of enough data that encompasses all activities related to tourism.

Conclusion

In conclusion, this paper has provided a comprehensive exploration of the role of algorithmic solutions in revolutionizing the tourism industry. We have delved into the primary methodologies of algorithmic tourism, including advanced algorithms and data analysis techniques, and discussed their application in enhancing the effectiveness and efficiency of tourism operations. From tourism demand forecasting and visitor trajectory tracking to trajectory modelling and simulation approaches, we have examined how these techniques address different yet complementary challenges in the field of tourism. As we move forward, these algorithmic-assisted approaches will continue to be at the forefront of sustainable tourism management strategies, balancing the needs of tourists with the preservation of natural and cultural heritage sites. The future of tourism lies in leveraging these innovative solutions to promote global economic growth while ensuring the sustainability of our precious heritage.

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