SPATIAL DEMAND FORECASTING OF BROADBAND SERVICES: A REVIEW

ASIF GUL * & SYED JAMIL HASAN KAZMI**
Department of Geography, University of Karachi, Pakistan
asifschek@hotmail.com

ABSTRACT

A telecommunication utility service is demand driven business, where spatial demand forecast determines the future dimensions of required network (spread & capacity), allocation of associated resources (Human and capital) and support (marketing). This study intends to review the existing literature and puts an effort to find out factors influencing spatial diffusion and demand of broadband services particularly in urban areas, further the approaches and techniques applied and discussed in recent literature.

Study reveals the spatial service diffusion among society depends on the time of service growth cycle, subscriber composition of the area and market competition. Urban infrastructure and demographics of the area gets influenced by the urban migration, land use changes which results subscriber composition of the locality. Overall diversified patterns of demands are commonly aligned along socio economic inequalities.

To simplify complexity of demand the subscribers are segmented into spatial segments having relatively homogenous socio-economic characteristics with similar behavior to usage and adoption of telecom services. Commonly top-down and bottom-up approaches are applied depending on the availability of data and required accuracy, where if data is not available qualitative methods are used otherwise quantitative methods are opted. The selection of approach and the specific technique to be applied depends on data availability, relationships between factors and domain knowledge of forecaster.

INTRODUCTION

The Telecommunication utility services is a solely demand focused business where service operators have to deliver its network services at the doorstep of geographically distributed subscribers. So for any area the quantification of the expected number of subscriptions or connections during a time period with respect to space and time is of main concerns for any service operator, as this will be the base of many strategic, technical and commercial decisions. Further planners have to budget and align required resources according to forecasted demand and diffusion scenarios for each segment of business territory (Iwashitaa, Inoue, Kurosawa, & Nishimatsu, 2015; Li, Shakya, & Owusu, 2017; McBurney, Parsons, & Green, 2002).

For any Information and Communication Technologies (ICT) service or product every subscriber market goes through different phases of diffusion and during this process various segments of society or consumer

classes pose different patterns of demand. In urban areas the spatial aspects of broadband demand are associated with existing socio economic and demographic diversity of society at different spatial scales (macro and micro). On the other hand with involvement of multiple service operators the market competition grows and subscribers have multiple choices in terms of products, services and tariff.

This study has put an effort to find out the main factors influencing the broadband spatial diffusion and associated demand particularly in urban areas in related literature. Also this study covers the major techniques and methods applied by different authors for spatial demand forecasting and services diffusion.

The telecom service diffusion in any area depends on the socio economic composition of subscribers in the area and their purchasing power (Velickovic, Radojicic, & Bakmaz, 2016). The service growth life cycle of any ICT service or product generally follows "S" shaped curve path. Where after launch its initial phase is relatively slow and the early adopters are usually from wealthy class of subscribers, well informed and likes to adopt latest technology (McBurney, Parsons, & Green, 2002; Velickovic, Radojicic, & Bakmaz, 2016). The takeoff phase initiates from when the adoption is 10%-20%, the rate of adoption accelerates until it reaches peak (Meade & Islam, 2015). In saturation phase where due to substitution impact the service growth drops and flatten (McBurney, Parsons, & Green, 2002). So in forecasting demand of a service the timing and phase of service growth in a territory is very significant.

SPATIAL ASPECTS OF BROADBAND DEMAND

According to Tobler's first aw of Geography there exists a resemblance and connectivity between the nearby geographic units (Tobler, 1970).The urbanization of an area is shaped up as a result of different forces like economic, demographic, political, social, cultural, technological and environmental interacting at different geographical scales (Oriye, 2016; Knox & Pinch, 2010). The reorganization of internal urban functions and activities gradually evolves the urban structure over the time (Guanghui, Wenqiu, Deqi, Dingyang, Ruijuan, & Tao, 2017). Where along with new development and existing buildings also get modified and their land use also changes from residential to mixed or commercial (Knox & Pinch, 2010). Overall these changes bring urban compactness accompanied by increase in population density (Salvati, Zambonb, Chelli, & Serra, 2018).

The geographical patterns of land use and its associated factors like number of tenancies, demography, socio economic conditions have a significant role to play in prediction of potential broadband subscription growth in future. Locally each land use class can have unique potential

regarding subscription growth (D.Melo, M.Carreno, & Padilha-Feltrina 2015; Gupta, 2003).

Knox and Pinch (2010) mentioned that provision of basic infrastructure in a locality and its distance to other facilities i-e education, health, markets and commercial areas may create social and economic disparities among urban neighborhoods. While Gilbert (2010) discussed that residential segregation in urban localities also cause disparities in education among society and these inequalities were also found apparent in use and adoption internet and telecom.

SOCIO-DEMOGRAPHIC & ECONOMIC ASPECTS OF BROADBAND SERVICES ADOPTION AND DEMAND

The use and adoption of ICT services among subscriber can be in disproportion based on consumer's segmentation in economic class, literacy, technological, social capacity of human capital, residential locality, gender and age (Sujarwoto, 2016; Perkins & Neumayer, 2011: Lengsfeld, 2011; Warf, 2012; Gilbert, 2010).

McBurney, Parsons, and Green (2002) mentioned overall the innovations in ICT technologies and deregulations by governments can significantly influence the growth potential in national or regional telecom markets. Particularly in post monopolistic phases after privatization there is increased market competition where diverse services availability along with aggressive marketing and tariff war which does increase the demand with subsequent consumer growth (Moutafides & Economides, 2010).

For service operators the demand forecasting of any telecom service is a complex problem due to involvement of many factors like heterogeneous geographical distribution of demography with varying socio economic conditions and different consumer choice of different classes (Moutafides & Economides, 2010). Fildes and Kumar (2002) discussed that changing trends of customer choices and services demand is associated with the role of telecom in the society.

Further subscriber behavior is sensitive to price variance and socio economic factors and in case of long term planning and demand forecasting economic factors related to infrastructure development should also be taken into account.

Due to advancement in ICT technologies there are variety of services and hardware available and based on the use and applications of these services the user choice and demand among different class of subscribers varies depending on their education, profession, economic group and age group as well (Fry, 2005; Madsen & Riaz, 2008). Also Driskell and Wang (2009)

discussed the affordability and lifestyle of individuals plays main part in technology adoption. Particularly in low income and less educated class of consumers there is substantial disparity of access to internet services facility and ICT equipment resulting digital divide among society.

While Mack (2015) and Perkins and Neumayer (2011) worked on internet penetration and identified a positive relationship with the countries having presence of knowledge based business hubs and business sector having interaction with international trade. While in urban area Torrens (2008) discovered the highly concentrated Wi-Fi access points in the areas with high density of residential and the commercial buildings in central business district.

Telecom service penetration among society is evolved along social (Fildes & Kumar, 2002) as well as spatial structures (Kellerman, 1999). There is broad based information needed to assess the consumer's behavior and their choices in terms of location/area, time, products & services, tariff (Li, Shakya, & Owusu, 2017). The spatial aspects of services demand, use and the consumer preferences plays significant role for development of future business strategies (Wang, Fan, & Gong, 2018).

Many authors have contributed in recent literature by working on the spatial association of ICT technologies' adaption and usage trends with demographics and socio-economics at different geographical scales. Torrens (2008) highlighted the social and spatial polarity in wired network services access leading to widen the digital divide among different segments of society while Driskell & Wang (2009) discussed the spatial disparities of services diffusion may spread from local area to national and regional scales. Anselin and Williams (2015) spatially assessed the role of digital neighborhoods in diffusion of telecom services at city level using social media users' locations. Moutafides and Economides (2010) by using users' profile data distinguished the use of broadband depending on users' place of accessing internet from i-e home, office, library, public place etc.

CONSUMER CHURN AND SWITCHING TO OTHER OPERATORS

Due to rapidly happening developments in ICT technologies in modern era the telecom goods and services have got more advanced in recent years and promptly implanted among society. So there is a trend of switching to updated services and technology (Knox & Pinch, 2010). This trend has been commonly observed in urban population and particularly in youth (Lengsfeld, 2011). Apart from new and advanced services the subscriber's intent to switch are also linked with the consistent experience of poor services (Peter & Lyons, 2017).

Areas where existing service is in higher penetration ratio will give negative impact on the diffusion of any new service or arrival of competitor service operator (Ding, Haynes, & Li, 2010). On the other hand same new service grows rapidly in dry areas where no other services reached before (Ramachander, 2016). Peter and Lyons (2017) stated that despite the market competition the long standing subscribers who never switched were more resistant to switch.

The factors associated with the consumer's switching to other operators and services may differ as the market evolves through different growth stages. While from service provider point of view in saturated stage the operators keep more focus on existing consumer retention by offering differentiated services rather than to attract wholly new consumers (Lee, Kwak, & Lee, 2015; Peter & Lyons, 2017).

METHODS AND APPROACH IN LITERATURE

Meade and Islam (2015) mentioned three main areas of forecasting and modeling in telecommunication and ICT domain which are time series forecasting, diffusion modeling and technological forecasting.

There are many demand assessment models based on correlation of telecom services demand with different demographic and socio-economic characteristics of subscribers. On the other hand there are discrete choice models which involve the subscriber's preferences for different characteristics of products and services under study (Moutafides & Economides, 2010).

Market research based on primary data involves direct data collection from consumers through questionnaire and interviews, this approach relatively consumes more time and it is labor intensive (McBurney, Parsons, & Green, 2002; Wang, Fan, & Gong, 2018). In Teleocm utility organizations commonly qualitative methods are in practice, where experts opinion, conjoint analysis and inrerviews with sales persons and the subscribers are used to forecast future demand (Fildes & Kumar, 2002). Due to complex relationship among variables and availability of big data structured judgmental methods are applied (Green & Armstrong, 2015) which may include Delphi, scenario analysis, structured scenario analysis (McBurney, Parsons, & Green, 2002).

The geographical time series data is the information recorded over a time scale reading the individual's actions occurring in a geographical space (Leonard & Samy, 1998; Huddleston, Porter, & Brown, 2015) almost all utility business collect and utilize the spatial information of their subscribers, sales, and assets. While methods using time series data extrapolate past trends to forecasting demand assuming that some aspects

of past trends may continue (Hyndman & Athanasopoulos, 2013). While in case of long spanned temporal data the recent values get more weight as compare to older records (Green & Armstrong, 2015).

Velickovic, Radojicic, and Bakmaz (2016) highlighted the importance to evaluate the market diversity along different dimensions like demography and socio-economic factors, While McBurney, Parsons and Green (2002) segmented the consumers into homogenous categories of residential, business, students and professionals to assess their common behaviors, attitudes, and preferences for different buying decisions and consumption behaviors.

The multi-dimensionality of demand assessment and its forecasting makes it a complex scenario, normally in such problems decomposition approach is applied to break it down into relatively simple segments where information about the elements and their relationships are known. At each segment the demand is modeled and aggregated (Fildes & V.Kumar, 2002; Green & Armstrong, 2015). Huddleston, Porter and Brown (2015) mentioned dividing the geographic territory for sake of decomposition is termed as Bottom-up approach while in case of Top- bottom method the modeled forecast at top level is divided into subdivisions as per their weights.

Many authors in recent literature adopted decomposition approach and formed similar classes to resolve complexities. For instance, Salvó and Piacquadio (2017) decomposed the electricity demand into space and time and categorized consumers into land use and demographics to forecast future electricity demand. Fildes and Kumar (2002) segmented the consumers into   business and residential classes to forecast traffic load. Whereas Velickovic, Radojicic and Bakmaz (2016) used municipality boundaries to divide the study area and made further segmentation based on socio-economic indicators, topology and population density.

CLUSTERING ALGORITHMS
Wang, Fan and Gong, (2018) discussed the clustering algorithms classify and aggregate the data into homogenous clusters based on their characteristics. The density based spatial clustering of application with noise (DBSCAN) considers the objects concentration in a certain area, K-means clustering takes distance as a reference between objects for clustering, while Expectation-Maximization is a statistical model applied to find local maximum likelihood parameters in such a data where latent variables are involved and data is incomplete.

SPATIAL DIVISION

Wang, Fan and Gong (2018) discussed three methods for spatial division of the territory grid diagrams, spatially weighted voronoi diagrams and Delaunay triangulation.

To reveal the geographic patterns of subscribers and their mian concentration centers different authors have applied kernal density, central place theroy and distance attenuation (Rabinovich, Rungtusanatham, & Laseter, 2008; Oppewal & Holyoake, 2004; Silverman, 1986; Paralikas, Fysikopoulos, Pandremenos, & Chryssolouris, 2011).

Spatial autocorrelation measures geographical proximity and correlation between variables and its most common test Moran's I statistic estimate the intensity of spatial dependence among variables (Fischer & Getis, 2010; Fischer & Wang, 2011; Tian, Song, & Li, 2014). Cabral, Legey, and de Freitas Cabral (2017) used Moran's I static in panel data for extrapolation analysis and (Luyao Wang, 2018) applied spatial autocorrelation based on spatial consumer demand to estimate potential purchasing strategies.

UNIVARIATE MODELS

In case of univariate time series data of smaller geographic areas Leonard and Samy (1998) discussed first order ARIMA and its higher orders, regression models, moving average models, seasonal models and combination of these can also be applied to each separate zones, while some other techniques applied by different authors are exponential smoothing (Green & Armstrong, 2015), SARIMA, Grey Neural networks (Wang, Fan, & Gong, 2018) and naïve method (Huddleston, Porter, & Brown, 2015).

Green and Armstrong (2015) have stated in favor of simpler models against complex as these can provide better understanding of model to all stake holders and can reduce likelihood of errors. While Moutafides and Economides (2010) mentioned that as these models are repeatedly applied in organization's formal systems so simpler models or less complex models need to be preferred.

Armstrong and Green (2005) mentioned that it has been witnessed in many cases that incorporating the judgmental and statistical methods give better accuracy. This integration is effective when experts' judgments are collected in a systematic manner and then used as inputs to the quantitative models.

CONCLUSION

The telecom services penetration among a society highly depends on the socio-economic composition of subscribers. The timing and phase of diffusion plays very important role for determination of demand potential and subscriber's behavior toward the use of services. In recent years rapid advancements have been witnessed in ICT technologies and on the other hand in many countries governments have de-regularized the local markets to increase market competition among multiple service operators, which brought alternative to consumers in terms of services and product with aggressive marketing.

At individual level the use of different services and applications of telecommunications depends on the subscriber's education, profession, economic group and age group as well. So generally consumers are categorized into economic class, literacy, technological and social capacity of human capital, residential locality, gender and age.

Spatially each locality and neighborhood may have its own socio-economic conditions and urban structures. It keeps evolving particularly in metropolitan areas due to reorganization of internal urban functions. The residential segregation causes educational and socio-economic disparities among societies creating digital divide. So at different geographical scales spatially there is diversity of subscribers classified in heterogeneous demographic distribution with diverse socio-economic conditions and having different choices and behaviors in terms of location/area, time, products, services and tariff.

As all telecom service operators manage geographical data of subscribers, sales and assets in any form. For spatial forecast of demand apart from discrete choice approach focused on sample of individuals' preferences, commonly subscribers are categorized into general classes having relatively homogenous socio-economic characteristics (i-e land use, residential, business, demography, population density, and topology) which can be spatially demarcated in areas or neighborhoods. Further Top down or Bottom up approaches is applied depending on the availability of detailed data and accuracy required. Generally bottom up approaches in spatial demand forecasting are more detailed where local area situations are better translated into results. It is common in telecom organizations that judgmental (qualitative) methods are used with structured approach. In case of geographical time series data the applied techniques to extrapolate previous trend found in recent literature are ARIMA, exponential smoothing and regression models, SARIMA and Grey Neural networks. Overall the demand forecasting method selection depends upon the data availability, relationships between factors and the experimental

as well as basic domain knowledge of forecaster. Further incorporation of judgmental inputs to quantitative models gives better results.

REFERENCES

Anselin, L., & Williams, S. (2015). Digital neighborhoods. *Journal of Urbanism: International Research on Placemaking and Urban Sustainability, 9*(4).

Armstrong, J. S., & C.Green, K. (2005). *Demand Forecasting : Evidence based Methods Working paper 24/05.* Working Paper , Monash university Austrailia, Department of Econometrics and Business Statistics.

Cabral, J.D.A.; Legey, L.F.L.; de Freitas Cabral, M. Electricity consumption forecasting in Brazil: A spatial econometrics approach. *Energy, 126*, 124-131.

D.Melo, J., M.Carreno, E., & Padilha-Feltrina, A. (2015). Estimation of a preference map of new consumers for spatial load forecasting simulation methods using a spatial analysis of points. *International Journal of Electrical Power & Energy Systems, 67*, 299-305.

Ding, L., Haynes, K. E., & Li, H. (2010).Modeling the Spatial Diffusion of Mobile Telecommunications in China. *The Professional Geographer, 62*(2), 248-263.

Driskell, L., & Wang, F. (2009). Mapping digital divide in neighborhoods: Wi-Fi access in Baton Rouge, Louisiana. *Annals of GIS, 15*(1), 35-46.

Fildes, R., & Kumar, V . (2002). Telecommunications demand forecasting – a review. *International Journal of Forecasting, 18*(4), 489-522.

Fischer, M., & Getis, A. (2010). *Handbook of applied spatial analysis: software tools, methods and applications.* Berlin, Germany: Springer;.

Fischer, M., & Wang, J. (2011). *Spatial data analysis: models, methods and techniques.* Heidelberg: Springer.

FRY, C. (2005). GIS in Telecommunication. In P. A. Longley, M. F. Goodchild, D. J. Maguire, a. D. Rhind, P. A. Longley, M. F. Goodchild, D. J. Maguire, & a. D. Rhind (Eds.), *Geographical Information Systems: Principles, Techniques, Management and Applications* (2nd ed., Vol. 2, pp. 819-826). Wiley.

Gilbert, M. (2010). Theorizing Digital And Urban Inequalities. *Information, Communication & Society, 13*(7), 1000-1018.

Green, K., & Armstrong, J. S. (2015). Simple versus complex forecasting: The evidence. *Journal of Business Research, 68*(8), 1678-1685.

Guanghui, J., Wenqiu, M., Deqi, W., Dingyang, Z., Ruijuan, Z., & Tao, Z. (2017). Identifying the internal structure evolution of urban built-up land sprawl (UBLS) from a composite structure perspective: A case study of the Beijing metropolitan area, China. *Land Use Policy, 62*, 258-267.

Gupta, L. (2003). *Telecommunications Access Networks (Structure,Planning and Technologies).* Retrieved from http://www.angelfire.com/nt/access1/index.html

Huddleston, S. H., Porter, J. H., & Brown, D. E. (2015). Improving forecasts for noisy geographic time series. *Journal of Business Research, 68*(8), 1810-1818.

Hyndman, R. J., & Athanasopoulos, G. (2013). *Forecasting: principles and practice.* http://otexts.org/fpp/.

Iwashitaa, M., Inoue, A., Kurosawa, T., & Nishimatsu, K. (2015). Efficient method to determine microarea with high potential demand for broadband services. *Procedia Computer Science, 60*, 1728-1737.

Kellerman, A. (1999). Geospatial Apsects of Telecommunication: An Overview. In G. A. Harmeet Sawhney, *Advances in Telecommunications* (Vol. 15, pp. 217-220). Greenwood Publishing Group.

Knox, P., & Pinch, S. (2010). *Urban Social Geography: An Introduction* (6th ed.). Pearson Education Limited.

Lee, C., Kwak, N., & Lee, C. (2015). Understanding consumer churning behaviors in mobile telecommunication service industry: Cross-national comparison between korea and china. *Thirty Sixth International Conference on Information Systems, Fort Worth 2015.*

Lengsfeld, J. H. (2011). An econometric analysis of the sociodemographic topology of the digital divide in Europe. *The information society, 27*(3), 141-157.

Leonard, M., & Samy, R. (1998). Forecasting Geographic Data. *The International Symposium on Forecasting.*

Li, Y., Shakya, S., & Owusu, G. (2017). Integrated Forecasting & Planning for Strategic & Operational Telecom Field Service Delivery. *2017 Computing Conference.* London: IEEE.

Mack, E. A. (2015). Variations in the Broadband-Business Connection across the urban heirarchy. *Growth and Change, 46*(3), 400-423.

Madsen, O. B., & Riaz, T. M. (2008). *Planning Broad band network insfrastructure, A Refrence model.* Aalborg University, Department of Control Engineering. Aalborg,Denmark: European Broadband Portal.

McBurney, P., Parsons, S., & Green, J. (2002). Forecasting market demand for new telecommunications services: an introduction. *Telematics and Informatics, 18*(3), 225-249.

Meade, N., & Islam, T. (2015). Forecasting in telecommunications and ICT—A review. *International Journal of Forecasting, 31*(4), 1105-1126.

Moutafides, G. M., & Economides, A. A. (2010). Demand for broadband access in Greece. *Telematics and Informatics, 28*(2), 125-141.

Oppewal, H., & Holyoake, B. (2004). Bundling and retail agglomeration effects on shopping behavior. *Journal of Retailing and Consumer Services, 11*(2), 61–74.

Oriye, O. (2016). Uncontrolled Urban Expansion, Population Growth and Urban Development in Ado-Ekiti, Nigeria. *International Journal of Architecture and Urban Development, 6*(4), 5-12.

Paralikas, J., Fysikopoulos, A., Pandremenos, J., & Chryssolouris, G. (2011). Product modularity and assembly systems: An automotive case study. *CIRP Annals, 60*(1), 165-168.

Perkins, R., & Neumayer, E. (2011). Is the Internet Really New After All? The Determinants of Telecommunications Diffusion. *The Professional Geographer, 63*(1), 55-72.

Peter, D., & Lyons, S. (2017). Consumer switching intentions for telecoms services: evidence from Ireland. *University Library of Munich, Germany*.

Rabinovich, E., Rungtusanatham, M., & Laseter, T. M. (2008). Physical distribution service performance and Internet retailer margins: The drop-shipping context. *Journal of Operations Management, 26*(6), 767-780.

Ramachander, S. (2016). The Price Sensitivity Of Mobile Use Among Low Income Households In Six Countries of Asia. *Telecommunications Policy, 40*(7), 673-691.

Salvati, L., Zambonb, I., Chelli, F. M., & Serra, P. (2018). Do spatial patterns of urbanization and land consumption reflect different socioeconomic contexts in Europe? *Science of the Total Environment, 625*(1), 722–730.

Salvó, G., & Piacquadio, M. (2017). Multifractal analysis of electricity demand as a tool for spatial forecasting. *Energy for Sustainable Development, 38*, 67-76.

Silverman, B. (1986). Density estimation for statistics and data analysis. *Chapman Hall, 37*, 1–22.

Sujarwoto, S. G. (2016). Spatial Inequality And The Internet Divide In Indonesia 2010–2012. *Telecommunications Policy, 40*(7), 602-616.

Tian, W., Song, J., & Li, Z. (2014). Spatial regression analysis of domestic energy in urban areas. *Energy, 76*(1), 629-640.

Tobler, W. R. (1970). A computer movie simulating urban growth in the detroit region. *Economic Geography, 46*, 234–240.

Torrens, P. M. (2008). Wi-Fi Geographies. *Torrens, P. M. (2008). Wi-fi geographies. Annals of the Association of American Geographers, 98*(1), 59-84.

Velickovic, S., Radojicic, V., & Bakmaz, B. (2016). The effect of service rollout on demand forecasting: The application of modified Bass model to the step growing markets. *Technological Forecasting & Social Change, 107*, 130-140.

Wang, L., Fan, H., & Gong, T. (2018). The Consumer Demand Estimating and Purchasing Strategies Optimizing of FMCG Retailers Based on Geographic Methods. *Sustainability, 10*, 466.

Warf, B. (2012). Contemporary Digital Divides In The United States. *Tijdschrift voor Economische en Sociale Geografie, 104*(1), 1-17.