

In this study, the effect on the series prediction of the financial system of the central library has been investigated and analyzed accordingly. Four models have been conducted to analyze the series prediction of the library as well as to investigate the monthly income. These models included the Seasonal indexing model (SIM) and Prediction of ARIMA model (PARIMA). Furthermore, Poisson logarithmic linear model has been applied for all suggested models accordingly. The results based on the given models have been verified based on Heteroskedasticity Test. Six months have been included beginning with Jan and ending with Jun. According to the statistical analysis, the verification method used the Heteroskedasticity test. The results revealed that the three models have been verified and were ready to be employed in the next step of the procedure. A certain effective model was employed to predict time series for the used period (Jan to Jun). At these indexations, the lag value has reached a maximum of 0.98. In April, the correlation reached 0.344. Seasonal indexation values for the chosen time have been explained (six months). The figures shifted from month to month. According to the investigation, the highest degree of indexation occurred in April and the lowest level occurred in June. The linear Poisson logarithmic distribution has been explored and examined. At the SIM model, the standard error was reported within the maximum level of 0.3. From the beginning of the year through the end of the year, six months have been documented (X1 to X6). The month of March was the most deviant. In January, the residual Dif has achieved its greatest value of 0.092

Keywords: financial system, time series prediction, PFO, Poisson logarithmic, mathematical model

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IMPACT OF TIME SERIES PREDICTION TO THE ONLINE BOOKING SYSTEM (INTERNET) ON THE LIBRARIES EMPLOYING POISSON LOGARITHMIC LINEAR MODEL

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1. Introduction

The majority of people are interested in two variables that are mentioned in the news daily: weather and stock prices. Temperatures and stock prices both have one thing in common: they've been tracked over time. Time series data, such as daily temperature and stock prices, are defined as data points observed over evenly spaced time intervals, such as hourly, daily, monthly, quarterly, and yearly. Time series analysis is a statistical tool for extracting data features and relevant information from time-series data. Because time series data are generated and evaluated in a variety of disciplines, such as meteorology, economics, health science, engineering, and others, time series analysis is an essential subject in statistics. Time series analysis monographs are usually classified in the Library of Congress (LC) call number ranges QA280 and HA30.3. However, when looking for books on time series analysis, which is made up of several subfields, these call number ranges are rather large. As a result, this study delineates several sub-field categories that make up the field of time series analysis. The following are some of the subfields of time series analysis:

- 1) a practical or theoretical method,
- 2) a univariate or multivariate approach,
- 3) frequency or time domain,

- 4) frequentist or Bayesian,
- 5) linear or nonlinear,
- 6) parametric or nonparametric,
- 7) software applications, and
- 8) applications to many fields. Monographs were reviewed for inclusion in this selected, annotated bibliography based on these sub-field categories, which is intended for librarians as a guide to core scholarly resources on time series analysis and can be used for collection development to support teaching and research on time series analysis.

This type of subfield category development can be applied to time collection development.

Challenges «reach the complete range of a comprehensive university from the arts, humanities, and physical sciences to engineering, business, design, and the social sciences» in today's complex transdisciplinary problem environment [1]. Through ground-breaking efforts and disruptive innovations, higher education institutions extensively embark on new strategic movements and begin defining their future discourses.

Due to significant advances in artificial intelligence, embedded sensing, pervasive computing, and ubiquitous mobility, there is an emerging horizon of intelligent infrastructure within the framework of enterprise-wide academic innovation. The intelligent infrastructure sector, in particular, has an odd «fluidity» in its disciplinary borders, rapidly altering knowledge

bases and repeating research techniques. Virginia Tech (VT) is prepared to become a destination for global talents in this distinctive area of development, or the so-called Destination Area, where it already leads in many components of intelligent infrastructure and is motivated to expand on and connect these capabilities. Through an infrastructure-based area of development called Intelligent Infrastructure for Human-Centered Communities (IIHCC), this process leverages and integrates VT's existing programs in smart design and construction, robotics and autonomous vehicle systems, ubiquitous mobility, energy, and materials [2]. The university gathered together a variety of domain stakeholders to build a critical mass of researchers, practitioners, administrators, and developers who can then serve as a knowledge base and network engine for the IIHCC evolution.

The reading pavilion of domestic university libraries has risen around 2,000. In just over 10 years, several domestic libraries have viewed the creation of a reading pavilion as a required feature. Reading Pavilion can give readers the reasonably independent area, which is convenient for seeking literature, deep study, academic discussion, etc. Nowadays, the management of the Reading Pavilion in the university library has gradually moved from the manual management stage to the network reservation. The user selects the room through the network to schedule an appointment. The system automatically reviews the user, prompts whether the appointment is successful, and the reservation result is timely. Students merely need to take the campus card and enter the door at the specified time to the agreed room [3]. Many university libraries have met various issues in their real operation [4].

Qualitative analysis and description were the main focus of conventional library research. Due to the rapid advancement of science and engineering, particularly machine learning and data mining in recent years, various library sciences have been further quantified. On the other hand, as the library's impact on university teaching and research grows, so does the amount of material students can borrow from it. As a result, the research of library borrowing flow has been separated from books management due to the wide variety of book classification retrieval methods and library application models. It is important for library capacity planning, open equipment access model design, resource management, and user behavior regulation that research, titled the prediction of library borrowing behaviorism, was conducted [5]. Prediction modeling utilizing statistical theory and stationary time series has been a major focus of library borrowing behaviorism study in recent years. A library borrowing volume forecasting model was developed by [6] using a grey model and linear regression [7] used wave-type time data to build a regression model of borrowing flow. Non-stationary time series were tackled using ARMA time series theory and artificial neural network, and they presented a seasonal model of a neural network to predict library borrowing amount [8]. However, there are a few downsides to this method. Time series models and regression methods such as linear regression are ineffective in dealing with library borrowing flow's complex non-linear dynamical process, which has a non-stationary characteristic and random variation in its internal relationships. A small variation in flow, for example, will have a detrimental impact on the prediction model. Neuronal networks have poor generalizability because of the local minimization challenge they produce when used for modeling [9].

Prediction methods that are commonly utilized include the moving smoothing method, exponential smoothing, re-

gression analysis method, and integration of numerous forecasting approaches [10]. The majority of these approaches concentrate on time series models or causality regression models. Without some information loss, the created models cannot accurately reflect the inherent structure and complexity of the expected dynamic data. Nonlinear mapping and the lack of prior knowledge of the item modeled are two of the numerous advantages of artificial neural networks as a parallel computing model compared to standard modeling methods [11]. If the object's input and output data are known, the network's learning process can simulate the nonlinear relationship between them. The number of books checked out by patrons and the quality of the library's services can both be gauged by looking at the number of books in circulation [12]. Book circulation is a useful tool for library staff, who can utilize it in a variety of ways to change the collection's structure and increase its use efficiency, as well as to improve service approaches and service quality. Many factors influence the circulation of books, including the quality of books, when the library first opened, the subjects and specialties it specializes in, the service quality of its librarians, and the degree of administration, to name a few [13].

Synthetically, a book's volume of duplications was established by taking into account the combined effects of seven primary elements. The linear relationship between circulation rate, borrow rejection rate, and average copy amount was examined using multiple regression analysis theory; the forecast approach for library book volume was explored using actual data. Managing a budget and allocating finances can be quite difficult. The library's use of literature money is influenced by a slew of variables whose interplay is nuanced and nonlinear [14]. It was possible to foretell library book purchases using a grey system hypothesis. The quality of books acquired has a direct impact on the quality and use of books in a library, making quality analysis of book purchases an important aspect of library procurement. An explanatory was used to evaluate the quality of books purchased.

Therefore, studies that investigate the impact of time series prediction to the online booking system (internet) on the libraries employing the system are of scientific relevance.

2. Literature review and problem statement

Scientific knowledge and information are no longer exclusively encoded in text formats like journal articles or book chapters. Non-textual formats like images, audio-visual content, computational models, and other numerical data sets are increasingly being considered. If significant data subsets can be recovered from often enormous and varied research data repositories, this body of non-textual data and information constitute a vital source of potentially undiscovered knowledge for scientists. The importance of such research data and its potential societal benefit are widely acknowledged [15]. Time series data is a common type of research data that can be found in climate research, medical treatment, and other fields. The time-varying behavior, in addition to the size and heterogeneity, adds another level of complexity to this type of research data. There are numerous research data repositories available today. Access to and re-use of this valuable type of research data can be facilitated by DLs. Library service support was always available for historic scientific discoveries based on experimental, theoretical, and computational science paradigms. The role of DLs may be more important

than ever in the age of data-intensive science (also known as the fourth paradigm in scientific discovery [16]). A science and technology library's mission includes assisting scientists with methods that allow them to effectively use the available body of knowledge. This includes search and retrieval techniques as well as exploration techniques that take non-textual data into account. It also includes methods for indexing and citation for future reference. These DL functionalities should be tailored to the specific workflows of scientists to provide effective support. For example, scientists' specific requirements must be met when defining similarity for the underlying data content, calculating features for retrieval, or incorporating aggregation techniques for large data sets. While query-response technologies (as employed in traditional web search engines) are often used as lookup tools for fact retrieval and known-item search, ES intends to help scientific study and discovery, for example, by disclosing previously unseen and unconsidered aspects of information. Learning and decision-making are important parts of the information-gathering process, especially when dealing with complicated data types like time series research data. The visual-interactive features of ES tools are critical to their success. The visual overview of the data content, the visual query specification, and the visual display of retrieved objects are all important components. Scientists can use visual content overviews to explore massive collections of time series research data. The search procedure can be made more intuitive by using visual-interactive query definitions based on examples or sketches of time series curves. Enhanced visual result representations can be used as a testing ground for applying facets or learning new and potentially surprising information. Many scientists, however, continue to do at least some of their work with general-purpose software, most commonly Excel [17]. User-centered design approaches may aid in building trust in breakthrough technologies that address the aforementioned issues. Info is a web-based exploratory search solution for time series research data that we introduce. The following is our contribution: the user-centered design strategy is presented, which was implemented using a unique design research technique. We chose a user-centered strategy to best assist our users' scientific workflows while also increasing their trust [18]. Metadata related to research data papers also plays a significant function. Secondary data concerning test settings or geo-locations of scientific measurements are examples of metadata. The nature of research data, data use and re-use protocols, and applied methodology varied across several research disciplines [19]. Kehrer proposed a taxonomy of different forms of research data, with a focus on visualization and visual data analysis. The data life cycle [20] is a term used to describe the process of transferring research data through various stages. Data production, data processing, data analysis, data preservation, data access, and data re-use are common phrases. The info strategy is largely focused on the phases of data analysis, data access, and data reuse, to address the issues associated with search [21] and exploration. The relationship of VisInfo to scientific workflows and scientific workflow systems from a user- and task-centered perspective is emphasized. While there are numerous DL approaches for textual access to research data [22], there are relatively few DL approaches for non-textual access to research data. However, study domains such as information visualization [23], visual analytics, and ES focus on issues such as improved research data exploration and search interfaces. From the perspective of information visualization compare techniques [24]. Another researcher presented a review of efforts for visualizing climate change data.

Clustering methods are frequently used in exploratory analysis scenarios to group vast amounts of research data. Global overviews of the entire data collection, also known as content summaries, can be provided using such aggregation approaches. Geoscience, earth observation, energy consumption, human motion analysis, and cancer research are all promising examples. A metadata-based clustering technique is presented. Clustering was employed to uncover intriguing correlations between data content and metadata connected with research data material. It discusses visual query definition concepts for time series data, while presenting a comprehensive study of time series visualization [25]. Considers event data or climate data and presents research data-based methodologies on multivariate data changing over time. To the best of our knowledge, combination methodologies combining research data with content-based visual search in the DL context are limited, based on this review of related work.

Usability concepts and approaches advanced substantially, and they finally found their way into web-based apps and other applications [26]. They are considered to be one of the foundations of this period. Testing and developing in iterative cycles, doing heuristic evaluations, and conducting cognitive walkthroughs were all presented as concepts and models, respectively. A comprehensive overview of several ways is provided, also a study on usability testing activities in the time series context was conducted. He agreed that there are no assessment methodologies in time series, and he offered a conceptual framework for time series evaluation in his presentation. A formal study of the time series development process was done in the time series by Hill in the early 1990s [27]. The next sections [28] discuss the usability models and concepts that have been investigated and applied to the environment. In addition to usability testing, the Greenstone User and Developer Survey is one of the most recent findings of the time series' usability testing. Using an information visualization system and a text information retrieval system. Also compared usability research in 2010 to compare the user experiences of the two systems. As a result of their research, they discovered that visualization approaches can help improve the representation and arrangement of information in retrieval systems.

Thus, the impact of time series prediction on the online booking system (internet) on the libraries is investigated in this study, which applies the Poisson logarithmic linear model to use it in order to investigate it.

3. The aim and objectives of the study

The study aims to investigate the impact of time series prediction to the online booking system (internet) on the libraries employing the Poisson logarithmic linear model.

To achieve the aim, the following objectives are accomplished:

- to investigate the Heteroskedasticity approach;
- to predict time series;
- to determine the seasonal indexation;
- to investigate the Poisson logarithmic linear model.

4. Materials and method

4. 1. Research data

Initially, the data for this research was obtained from the national university's central library. Preprocessing is

required for data mining, which mostly includes lifting and sorting, unique inspection, and percentage sampling. Because the use of the reading pavilion fluctuated seasonally and cyclically, this study focused on the general semester, taking data from Jan-June as examples. This is also true for a few other months. We employ time-series stratified sample statistics to account for the influence of teaching and other factors during typical working hours as shown in Table 1.

Table 1

The data set of the research

Month	Name of Lib.	No. Taken products	Paid fees (financial) Dollars	Reputation
Jan	Central library	5,466	30,000	100
Feb	Central library	4,574	45,300	222
Mar	Central library	3,478	12,230	321
Apr	Central library	4,564	34,560	242
May	Central library	2,343	23,090	455
Jun	Central library	3,604	10,023	335

Six months were considered to be investigated starting from January to June. In the current study, the central library has been located accordingly. Taken products, paid fees and reputation have been analyzed statistically. The process of the whole work is shown in Fig. 1.

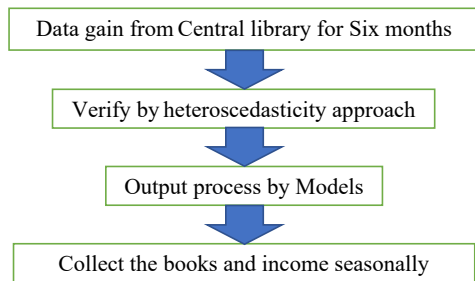


Fig. 1. Research flowchart

The research flow chart has shown the entire process of the current research by mentioning the data set and how will be confirmed. These data will be calculated and analyzed based on the proposed models. Outputs of the data are used to predict the income and allocations of the books seasonally. Chaotic time series and support vector machine methods are used in this paper to anticipate non-linear library borrowing traffic. With this approach, the embedding dimension and time delay of borrowing flow series are first calculated, and then an SVM single-step prediction model is established. International University Library’s monthly book borrowing volume has been tested, and the numerical results suggest that the proposed approach is effective in obtaining high prediction precision.

4. 2. Research sample

The number of literature books borrowed (66,397) is the largest, which indicates that students prefer reading literature, history, and geography books after class. Science students, as well as teachers and students in the fields of engineering and economic management, will benefit from taking courses in automation and computer technology. As a result, teachers and students alike enjoy TP novels. CET-4

and CET-6 should be taken by college students in their freshman year. English, on the other hand, is the primary means through which we may communicate with people around the world. Additionally, a lot of people who read English are preoccupied with teachers and students.

4. 3. Research Models

4. 3. 1. Seasonal indexing model (SIM)

The seasonal effect is a term used to describe a sequence that exhibits a regular periodic variation law. The seasonal index is typically required to analyze its seasonal variation rule. During a cycle, the difference between the moving average value and the annual average value is known as the «seasonal index». We employ the multiple moving average methods to minimize the impact of random elements and seasonal influences to obtain a more accurate seasonal index. Step-by-step instructions are provided below. It is supposed that the period of the original sequence t_x is m .

Step 1. To eliminate the influence of random factors on the current sequence value, the short-term composite moving average is used to estimate the current sequence value for the original sequence t_x .

The seasonal index applies to the following deterministic seasonal model.

$$Y = \dot{Y}_j B_j + I_j, \tag{1}$$

where \dot{Y}_j is the average value of periods j and j . I is a random factor.

4. 3. 2. Prediction of ARIMA model (PARIMA)

When the sequence contains long-term trends and seasonal effects, and the two effects are relatively independent, it can be assumed that they meet the additive relationship. By simple trend difference and seasonal difference, the sequence can be transformed into stability. Then, the ARMA model is established for the stable sequence, which is the construction principle of the ARIMA model. Its structure is as follows:

$$(1 - B^f)(1 - B)^f X_n = \frac{\beta(D)}{\lambda(D)}, \tag{2}$$

$$\text{PARIMA value} = (1 - B^f)(1 - B)^f / X_n \cdot C_n. \tag{3}$$

Among them, B is the delay operator, $(1 - B^f)d$ is the order difference. $(1 - B)^f$ is the seasonal difference with step D , and t is the white noise with zero means.

5. Results of research of time series prediction to the online booking system on the libraries

5. 1. Investigate Heteroskedasticity approach

In this paper, the hypothesis will be verified accordingly. In the verification process, Heteroskedasticity Test has been considered as the main indicator.

The heteroskedasticity test is used to find whether the data is homogeneous/contains the same variant as shown in Fig. 2. A heteroscedasticity test has been carried out for the selected models to investigate the validity of the chosen assumption. The main purpose of this test is to perform the given data and proceed for future analysis. As well as to confirm the validity of the time series where it has been analyzed accordingly.

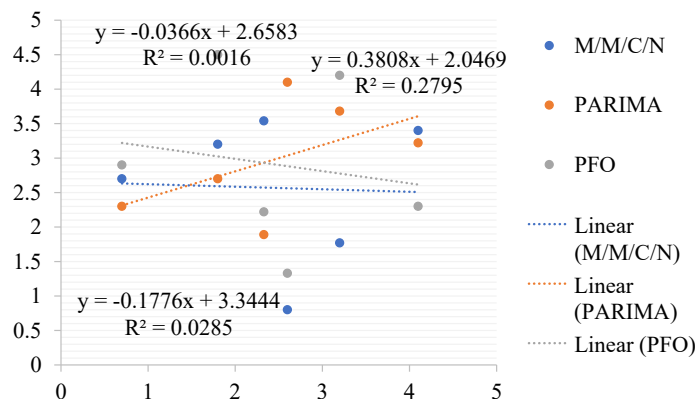


Fig. 2. Heteroscedasticity Test of the current hypothesis

According to Table 2, both models 1 and 2 passed the parameter and white noise tests, indicating that they are all reliable models. Model 1 is smaller than model 2, indicating that model 1 is better able to interpret data. However, is model 1 able to accurately anticipate the outcomes of a study? Therefore, we utilize data from Jan to June 2018 for modeling as a test set to evaluate the model’s ability to predict future events. The data used for modeling spans six years, from June 2013 to this year’s June. The model provides a prediction for 2018, and the actual value of 2018 is included before the model is run. The model then predicts a value of 2018. It is possible to derive each month’s forecasted value (the numbers in brackets represent the upper and lower ranges of confidence) in this manner for the six months spanning Jan 2018 to Jun 2018. The relative error and average relative error are determined about the actual value (Table 2).

and PACF) is observed. All of the projections are within the acceptable range, and none of them is outside of it. To get the prediction graph, set the upper and lower limits of the confidence intervals (UCL and LCL).

Table 3

Results of the lag and its correlation

Month	Lag	Covariance	correlation
Jan	0.54	Not varied	0.334
Feb	1.2	Not varied	0.134
Mar	0.66	Not varied	0.345
Apr	0.9	Not varied	0.344
May	1.3	Not varied	0.312
Jun	0.89	varied	0.109

Table 2

Prediction to the real values of the unit

Functions	Jan	Feb	Mar	Apr	May	Jun
Actual value	322	313	245	243	398	356
Predicted value	322	313.01	260	243	394.3	356
Error	00	0.001	0.002	00	0.003	00

Table 4

The UCL and LCL range for the months

-	Jan	Feb	Mar	Apr	May	Jun
LCL	12	22	19	11	9	14
UCL	23	26	29	24	12	26
ACF	0.1	00	0.12	0.18	0.11	0.14
PACK	00	00	0.01	0.034	00	0.12

Actual values along with the predicted values of the borrowed books were collected accordingly. For the six months from Jan to Jun, the maximum actual value is 398 for May. Furthermore, an error has been discovered accordingly for all these months.

5. 2. Prediction of the time series

The library’s current configuration plan is based on the results of the above operations. The library needs to plan for future growth to adjust the number of reading pavilions according to this design as time goes on and the impact grows. The time series-based exponential smoothing model is used to predict the monthly forecast value and the 95 percent confidence floating interval value for the following year. To know how to know the lag of the borrowed books and correlation between time series, ACF and PACF models have been discovered, as well covariance due to the given time series was explained. Table 3 contains the relevant statistics.

Further observations are required to reasonably anticipate future model results for the data in Table 4. To begin, the distribution of residual and partial autocorrelation (ACF

The upper limit and lower limit have been investigated for the period from Jan to Jun along with ACF and PACF. The results show that the maximum limit occurs in March with the value of 29. As well, the lower limit occurs in Feb with a value of 22. The main purpose of the UCL and LCL is to interpret the upper and lower borrowed books per month.

5. 3. Determination of the seasonal indexation

A deterministic factor decomposition approach. Seasonal adjustment models in SAS are the most widely utilized method for factor decomposition by global statistical and commercial organizations. Factor decomposition is employed in this study to derive the seasonal index for each period sequence using the X-11 seasonal adjustment model as shown in Fig. 3.

Suggested models were applied to investigate the fluctuation of the income and stability of the borrowed book with the month. All variables have been subjected to the same criteria accordingly. As known books are borrowed seasonally, by applying the discovered models, the maximum and minimum number of borrowed books per season is shown.

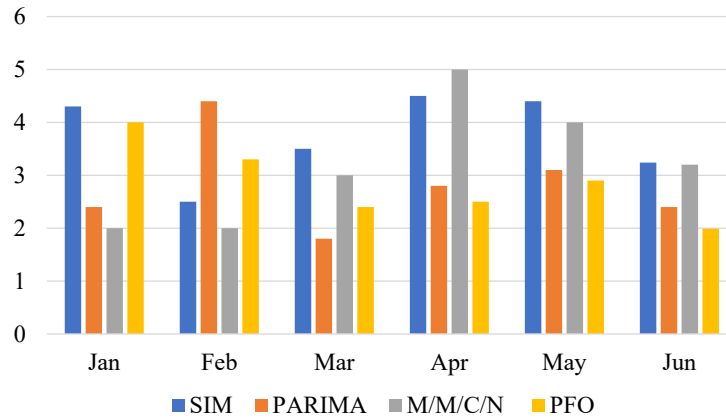


Fig. 3. Application of the assumed models to months

5. 4. Investigation of Poisson logarithmic linear model

The deviation of the SIM model is 0.2, with 0.03 degrees of freedom. The residual deviation of SIM (9) is 00. For the M/M/C/N model, the deviation is 00 with 00 degrees of freedom with a probability of 0.1. The PARIMA is 0.1 with an F value of 0.87, and the dispersion parameter is 0, indicating that no dispersion has occurred. The likelihood ratio test (Table 5) is used to compare whether the difference between the PFO model and the SIM model is significant. The following output results show that the models are significantly better than the PRIMAL model. Once again, it shows that the influence of grade and gender on borrowing quantity is very significant.

Table 5

Results of the Poisson logarithmic linear model

MODELS	Estimated value	STD.ERR	F Value	Probability
SIM	00	0.03	0.02	0.1
PARMA	00	0.01	0.87	0.1
M/M/C/N	00	000	00	0.1
INFO	00	0.02	0.2	0.1

Whether there is a significant difference in the amount of borrowing by boys and girls in different grades will be investigated. Accordingly, more than 27,000 students were selected from the whole school. Considering the equilibrium of indicators at all levels, 200 boys and girls the mean value $\ln Y$ of the positive real number will be logarithmically transformed into the whole real number field, and then a linear regression will be established as shown in Table 6. Therefore, the structure of the Poisson logarithmic linear model is as follows:

$$\ln Y = C + C1X1 + C2X2 + C3X3 + C4X4 + C5X5 + C6X6, \quad (4)$$

where Y is the mean value of Poisson distribution,

$$\ln Y = 0.453 + 0.345X1 + 0.387X2 + 0.353X3 + 0.45X4 + 0.67X5 + 0.78X6. \quad (5)$$

Six months have been considered as ($X1$ to $X6$) to be analyzed by the proposed model. Residual and deviance along with chi. sq values have been obtained mathematically.

The main function of the Poisson logarithmic linear model is to investigate the standard error of each month and the probability of the books that have been borrowed per month.

Table 6

Residual values along with deviance of the central lib based on the applied models

Months	Residual dif	Dev. Value	df	Deviance	CHLSQ
Jan ($X1$)	0.092	0.1	0.32	00	0
Feb ($X2$)	0.093	0.1	0.31	00	0
Mar ($X3$)	0.023	0.2	0.30	1	0
Apr ($X4$)	0.034	0.4	0.34	00	0
May ($X5$)	0.021	0.1	0.34	00	0
Jun ($X6$)	0.023	00	0.45	00	0

6. Discussion of time series prediction to the online booking system on the libraries

The study explains the investigation of the Heteroskedasticity approach to assure the results of the prediction that has been collected. Furthermore, time series have been predicted using the ARIMA model that has been employed accordingly. Moreover, the seasonal indexation has been determined using a specific model. Finally, the Poisson logarithmic linear model has been investigated accordingly.

All of the results that have been achieved are based on the statical analysis performed using the three mathematical models that have been proposed. The proposed methods have been thoroughly tested in this regard. On the basis of the proposed models, these numbers will be produced and examined. Results of the data analysis are used to forecast income and allocations of books on a seasonal basis.

The results have been acquired through simulation using the Heteroskedasticity technique, which is represented in Fig. 2. In addition, as demonstrated in Tables 3, 4, the proposed models have been utilized to predict time series, which is a first for the field. As seen in Fig. 3, a seasonal index was also discovered in this study over a period of six months, as indicated by the arrow. Additionally, Table 6 illustrates the Poisson logarithmic linear

function, which is based on the mean value of the Poisson distribution.

This paper makes a significant contribution to the prediction of library borrowing materials during a time series with annotations of the lag and income during this length, and it is well worth reading. In contrast to [13], where the prediction of the time series was accomplished using a new strategy while maintaining the same methodology.

This study is limited to using one place and it is (a central library) with certain months starting from Jan to Jun. Two main models were used to obtain the results. The disadvantage of the current study is the difficulty to predict the borrowing of books per month.

In the future, the developed model with newly invented software can be used to predict the exact borrowed items with expenses.

The electronic systems can be used with intelligent networks for the distribution of books and other items. In this research, mathematical difficulties in the calculation of the items and estimated income have been encountered.

7. Conclusions

1. The statistical investigation has revealed that the verification process employed the Heteroskedasticity test. The results showed that the three models have been verified accordingly to be used for further process.

2. Time series has been predicted of the used period for Jan to Jun using the certain effective model. The lag value at these indexes has reached the maximum level of 0.98. The correlation reached 0.344 in April.

3. Seasonal indexation values have been explained for the selected period (six months). The values were varied from month to month. The maximum level of indexation occurred in April and the minimum level in June.

4. Linear Poisson logarithmic model has been investigated and analyzed accordingly. The standard error recorded within the maximum level at the SIM model is 0.3. Six months have been recorded from (X1 to X6). Maximum deviance occurred in March. The residual Dif has reached the maximum and it is 0.092 in January.

References

1. Yan, H., Ouyang, H. (2017). Financial Time Series Prediction Based on Deep Learning. *Wireless Personal Communications*, 102 (2), 683–700. doi: <https://doi.org/10.1007/s11277-017-5086-2>
2. Niu, H., Wang, J. (2013). Financial time series prediction by a random data-time effective RBF neural network. *Soft Computing*, 18 (3), 497–508. doi: <https://doi.org/10.1007/s00500-013-1070-2>
3. Zhang, Y., Wang, X., Tang, H. (2019). An improved Elman neural network with piecewise weighted gradient for time series prediction. *Neurocomputing*, 359, 199–208. doi: <https://doi.org/10.1016/j.neucom.2019.06.001>
4. Wang, J., Wang, J., Fang, W., Niu, H. (2016). Financial Time Series Prediction Using Elman Recurrent Random Neural Networks. *Computational Intelligence and Neuroscience*, 2016, 1–14. doi: <https://doi.org/10.1155/2016/4742515>
5. Bai, Y., Jin, X., Wang, X., Su, T., Kong, J., Lu, Y. (2019). Compound Autoregressive Network for Prediction of Multivariate Time Series. *Complexity*, 2019, 1–11. doi: <https://doi.org/10.1155/2019/9107167>
6. Moews, B., Herrmann, J. M., Ibikunle, G. (2019). Lagged correlation-based deep learning for directional trend change prediction in financial time series. *Expert Systems with Applications*, 120, 197–206. doi: <https://doi.org/10.1016/j.eswa.2018.11.027>
7. Wen, J., Yang, J., Jiang, B., Song, H., Wang, H. (2021). Big Data Driven Marine Environment Information Forecasting: A Time Series Prediction Network. *IEEE Transactions on Fuzzy Systems*, 29 (1), 4–18. doi: <https://doi.org/10.1109/tfuzz.2020.3012393>
8. Sapankevych, N., Sankar, R. (2009). Time Series Prediction Using Support Vector Machines: A Survey. *IEEE Computational Intelligence Magazine*, 4 (2), 24–38. doi: <https://doi.org/10.1109/mci.2009.932254>
9. Ahlmann-Eltze, C., Huber, W. (2020). glmGamPoi: fitting Gamma-Poisson generalized linear models on single cell count data. *Bioinformatics*, 36 (24), 5701–5702. doi: <https://doi.org/10.1093/bioinformatics/btaa1009>
10. Alanaz, M. M., Algarni, Z. Y. (2018). Proposed methods in estimating the ridge regression parameter in Poisson regression model. *Electronic Journal of Applied Statistical Analysis*, 11 (2), 506–515. doi: <https://doi.org/10.1285/i20705948v11n2p506>
11. Xu, T., Demmer, R. T., Li, G. (2020). Zero-inflated Poisson factor model with application to microbiome read counts. *Biometrics*, 77 (1), 91–101. doi: <https://doi.org/10.1111/biom.13272>
12. Gao, G., Wang, H., Wüthrich, M. V. (2021). Boosting Poisson regression models with telematics car driving data. *Machine Learning*, 111 (1), 243–272. doi: <https://doi.org/10.1007/s10994-021-05957-0>
13. Tamba, S. P., Batubara, M. D., Purba, W., Sihombing, M., MuliaSiregar, V. M., Banjarnahor, J. (2019). Book data grouping in libraries using the k-means clustering method. *Journal of Physics: Conference Series*, 1230 (1), 012074. doi: <https://doi.org/10.1088/1742-6596/1230/1/012074>
14. Black, A. (2018). The British Soldier and his Libraries, c. 1822–1901. By Sharon Murphy. *The Library*, 19 (2), 247–250. doi: <https://doi.org/10.1093/library/19.2.247>
15. Askew, B., Brown, A., Christy, M., Gomez, A., Gooch, M., Kubicki, J. M. et. al. (2020). Georgia libraries respond to COVID-19 pandemic. *Georgia Library Quarterly*, 57 (3). Available at: <https://digitalcommons.kennesaw.edu/glq/vol57/iss3/10/>
16. Stepanova, O. (2019). PLRE.Folger: Private Libraries in Renaissance England. *Renaissance & Reformation/Renaissance etReforme*, 42 (4), 176–179.

17. Jin, Z. (2018). Research on Chinese Electronic Book Retrieval in University Libraries. Proceedings of the 2018 2nd International Conference on Education Science and Economic Management (ICESEM 2018). doi: <https://doi.org/10.2991/icesem-18.2018.125>
18. Kirichenko, L., Radivilova, T., Bulakh, V. (2019). Binary Classification of Fractal Time Series by Machine Learning Methods. Lecture Notes in Computational Intelligence and Decision Making, 701–711. doi: https://doi.org/10.1007/978-3-030-26474-1_49
19. Pala, Z., Atici, R. (2019). Forecasting Sunspot Time Series Using Deep Learning Methods. Solar Physics, 294 (5). doi: <https://doi.org/10.1007/s11207-019-1434-6>
20. Zhang, X., Lin, Q., Xu, Y., Qin, S., Zhang, H., Qiao, B. et. al. (2019). Cross-dataset time series anomaly detection for cloud systems. 2019 USENIX Annual Technical Conference, 1063–1076. Available at: <https://www.usenix.org/system/files/atc19-zhang-xu.pdf>
21. McClary, T., Rawlins, S. (2020). Libraries = Success: NJ Libraries and Schools Conquer Library Card Sign-Up Month. Children and Libraries, 18 (2), 19–21. doi: <https://doi.org/10.5860/cal.18.2.19>
22. Hicks, D., Cavanagh, M. F., VanScoy, A. (2020). Social network analysis: A methodological approach for understanding public libraries and their communities. Library & Information Science Research, 42 (3), 101029. doi: <https://doi.org/10.1016/j.lisr.2020.101029>
23. Pebesma, E. (2018). Simple Features for R: Standardized Support for Spatial Vector Data. The R Journal, 10 (1), 439. doi: <https://doi.org/10.32614/rj-2018-009>
24. Campos-Taberner, M., García-Haro, F. J., Martínez, B., Izquierdo-Verdiguier, E., Atzberger, C., Camps-Valls, G., Gilabert, M. A. (2020). Understanding deep learning in land use classification based on Sentinel-2 time series. Scientific Reports, 10 (1). doi: <https://doi.org/10.1038/s41598-020-74215-5>
25. Lim, B., Zohren, S., Roberts, S. (2019). Enhancing Time-Series Momentum Strategies Using Deep Neural Networks. The Journal of Financial Data Science, 1 (4), 19–38. doi: <https://doi.org/10.3905/jfds.2019.1.015>
26. Torres, J. F., Galicia, A., Troncoso, A., Martínez-Álvarez, F. (2018). A scalable approach based on deep learning for big data time series forecasting. Integrated Computer-Aided Engineering, 25 (4), 335–348. doi: <https://doi.org/10.3233/ica-180580>
27. Boman, C. (2019). An exploration of machine learning in libraries. Library Technology Reports, 55 (1), 21–25. Available at: <https://journals.ala.org/index.php/ltr/article/view/6911/9309>
28. Ross, C. S., McKechnie, L. E., Rothbauer, P. M. (2018). Reading still matters: What the research reveals about reading, libraries, and community. ABC-CLIO.