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Workload-based manpower requirements determination using statistical time-series hierarchical modeling

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Abstract

Manpower requirements determination (MRD) analysis has been widely used in industry. However, previous manpower modeling in the literature has typically been limited to simple scenarios where all input variables are treated as fixed effects. In practice, input variables may exhibit random effects as well. This paper introduces random-effect input variables through statistical time-series hierarchical modeling, building upon the workload-based generic (naïve) modeling discussed in earlier MRD literature. Using this hierarchical time-series modeling approach, our objective is to develop a statistical methodology for determining the number of full-time equivalent (FTE) personnel required (REQD) to perform major tasks within a mission function in an organization. We demonstrate our methodology using a real-world dataset.

Keywords: Manpower modeling; manpower requirements determination (MRD); full-time equivalents (FTE); workload-based methods; time series; hierarchical modeling

Introduction

Past research ^[1-9] has discussed various approaches to calculating and determining manpower requirements, such as the ratio-based method, survey-based method, and hourly availability-based method. Although several non-workload-based manpower determination methods have been proposed, most organizations prefer workload-based methods, as they are considered the fairest, most scientifically sound, and justifiable approach to calculating staffing needs. Despite the numerous published articles proposing manpower calculation methods, none have developed workload-based methodologies—except for the most recent paper by Rahardja (2025) ^[10].

As a recap, Rahardja (2025) ^[10] presented a generic (naïve) manpower modeling equation. However, this model treated all input variables solely as fixed-effect variables. Since it did not distinguish between fixed and random effects, parameters and variables, or hierarchical and non-hierarchical modeling, it remains purely a mathematical model rather than a statistical one. Without the inclusion of any random variables, the model can only provide rough estimates of current manning requirements. It lacks the flexibility needed for deeper analyses—such as forecasting future manpower needs, performing model selection, controlling error rates, or refining accuracy. Ultimately, especially when budgets are tight, organizations seek reasonably assured and accurate projections of both current and future manning requirements.

In contrast, Rahardja (2025) ^[10] also notes that the input variable ‘Volume’—representing the volume of a task under an organization’s mission function—can naturally be treated as a random variable. As ‘Volume’ varies over time, it can be modeled as coming from a distribution, thereby transforming the model into a statistical one. Once ‘Volume’ is treated as a random variable, the previously generic (naïve) mathematical model becomes a hierarchical statistical model. With this expanded statistical framework, we can project both current and future manning needs more effectively.

Accordingly, this paper proposes a statistical methodology that employs time-series (TS) algorithms to enhance the workload-based, generic (naïve) model discussed in prior literature ^[10].

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In this enhancement, we hierarchize 'Volume' using TS algorithms. The remainder of the paper is organized as follows. Section 2 constructs the statistical methodology using a workload-based, time-series hierarchical manpower modeling equation to project required manning. Section 3 describes the data. Section 4 demonstrates the methodology on a dataset. Section 5 concludes the paper.

Methodology

The goal of this section is to develop a staffing methodology for determining manpower requirements. We build upon the workload-based manpower equation (1) in Rahardja (2025)^[10], applying hierarchical time-series (TS) modeling to the input variable Volume, which is treated as a random variable and depicted in Figure 1.

The staffing methodology comprises two scenarios for projecting final full-time equivalent (FTE) manning requirements: *Baseline (Estimations)* and *Endpoint (Forecasts)*.

Typically, the Baseline scenario involves collecting initial or baseline FTE manning numbers from the organization's systems of record (SOR) data and field surveys. These figures may include the number of onboard personnel (ONBD), assigned personnel (ASSGN), and/or authorized positions (AUTH). The purpose of collecting multiple baseline figures is to obtain different perspectives for comparison with the Endpoint numbers—namely, the current and future required (REQD) staffing levels.

The methodology for the Endpoint scenario follows a generalized approach discussed in Rahardja (2025)^[10], which is based on the workload-based manpower model described in Equation (1). As a recap, the outcome variable in Equation (1) estimates the number of FTE personnel required for the intended studied year. The input variables include yearly work Volume, average task Duration, the standard Work Year (e.g., 2080 hours/year) and Utilization Rate (UR).

$$\#FTE = \frac{\text{Volume} \times \text{Duration}}{\text{Work Year} \times \text{UR}} \quad (1)$$

Equation (1) is robust and can be applied across a broad range of scenarios. Each step in the process aims to balance timeliness with a reasonable level of assured accuracy, taking into account factors such as the rigor of the information or datasets collected, dataset partitioning, estimation methods, and available software.

The methodology and analysis are presented in both graphical and tabular formats in Figure 1 and Figure 2. Initially, the workload-based manpower model in Equation (1) serves as a simple, generalized model, where all input variables are treated as Fixed Effects^[10]. In this approach, analyses are performed at a basic level. To implement it, yearly data for each input component is gathered, substituted into Equation (1), and solved for the required FTE workforce. This calculation can be performed for each study year as necessary. We refer to this preliminary, coarse analysis as the Phase 1 Study.

In Phase 1, Equation (1) is used to calculate the FTE requirements (REQD) for the current and past several years, serving as input patterns for Phase 2. At this stage, we ensure the consistency of each step and data source. If inconsistencies arise, we identify the root causes and mitigate or address the data risks. Additionally, we compare the authorized or assigned FTEs (AUTH or ASSGN) with the actual number of onboard FTEs (ONBD). Based on these findings, we provide recommendations in Phase 1.

In the refined analysis of Phase 2, the model can be extended to a more detailed level, depending on resource availability and feasibility. By treating volume as a Random-Effect variable through Hierarchical Modeling and using Time Series (TS) statistical algorithms^[11-16], the manpower model is enhanced (refer to Figure 1 and Figure 2). This allows forecasting FTE requirements (REQD) from the current studied year into future studied years, expanding the original model's capabilities.

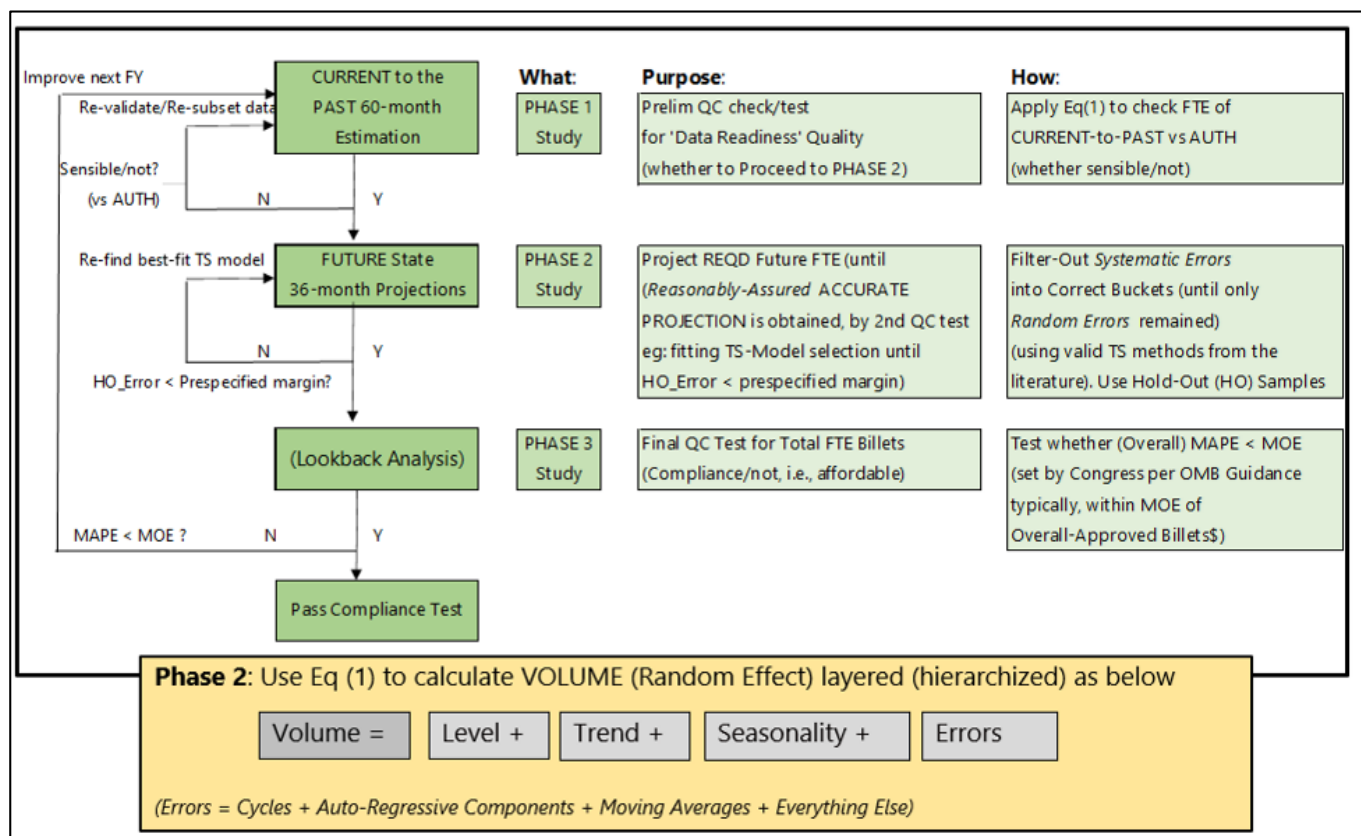


Fig 1: Methodology & Analysis graphic

Note that in the literature ^[11], there are three-family category of TS models/algorithms: the Exponential Smoothing Model (ESM) family, the Auto-Regressive Integrated Moving Average (ARIMA) model family, and the Unobserved Component Model (UCM) family.

Subsequently, the random variable *Volume* (V_t) can be hierarchized (layered) and modeled as one of the three-family categories of TS models/algorithms as follows.

ESM-family model

$$V_t = l_t + b_t + s_t + \varepsilon_t, \varepsilon_t \sim N(0, \sigma_t^2) \quad (2)$$

with different time-varying smoothing weights for each term on the right-hand side of Equation (2), including the level (l_t) smoothing weight, trend (b_t) smoothing weight, seasonal (s_t) smoothing weight, and the white noise error term with the corresponding variance, as listed in Table 1 of Rahardja (2020) ^[11]. Additionally, there are eight different sub-hierarchical equations (models) under ESM family, as formulated in Table 1 of Rahardja (2020) ^[11].

ARIMA-family model

$$V_t = I + \alpha_1 V_{t-1} + \alpha_2 V_{t-2} + \dots + \alpha_p V_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \dots + \theta_q \varepsilon_{t-q} \quad (3)$$

for a *generalized ARIMA*(p, d, q) family model, with the predictors on the right-hand side of Equation (3), is as follows: *I* is the *Integrated* term, followed by the *Auto-Regressive* (AR) terms, and the *Moving-Average* (MA) terms.

UCM-family model

$$V_t = \mu_t + \gamma_t + \psi_t + r_t + \alpha_1 V_{t-1} + \alpha_2 V_{t-2} + \dots + \alpha_p V_{t-p} + \beta_1 x_{1t} + \beta_2 x_{2t} + \dots + \beta_m x_{mt} + \varepsilon_t \quad (4)$$

for a generalized UCM family model with the components on the right-hand side of Equation (4) as follows: level or intercept (μ_t), trend (γ_t), seasonality (ψ_t), cycle (r_t), auto-regressive components ($\alpha_p V_{t-p}$), regression terms ($\beta_m x_{mt}$), and the white noise error term (ε_t). For more details, see Rahardja (2020) ^[11]. Using available software ^[12-17] in an organization (such as EXCEL, R, and various SAS products), projections (forecasts) for Phase 2 (Future State) can be implemented and obtained using statistical TS algorithms ^[11-17].

Finally, when the *Future* actual observations become available in the organization's SOR, we can conduct a *Lookback Analysis*, using the same testing technique as Hold-Out samples method ^[17]. This will allow us to test whether the overall error rate (for example, using the mean absolute percentage error, or MAPE) is less than the prespecified margin of error (MOE). This is considered Phase 3 of the Study.

PHASE	PURPOSE	HOW
PHASE 1 (CURRENT-to-PAST 60-month ESTIMATION)	DATA READINESS QC (whether to go PHASE 2)	Apply Eq(1) to check #FTE (CURRENT-to-PAST) vs AUTH (whether sensible/not).
PHASE 2 (FUTURE STATE of 36-month Estimate)	Estimate Future REQD #FTE (until reasonably-accurate estimate is obtained), by 2nd QC test. Eg: fitting TS-Model Selection until HO Error < prespecified margin.	Filter-Out Systematic Errors into Correct Buckets (until only Random Errors remained), using valid TS Methods in the literature. Use Hold-Out (HO) samples.
PHASE 3 (Lookback Analysis)	Final QC test for Total FTE Billets (compliance/not, i.e., overspent/not), when the Future Actual Observations become available in the CBP SOTR	Test if Overall MAPE < MOE (set by Congress per OMB Guidance, typically, within MOE of Overall-Approved Billets).

Fig 2: Methodology & Analysis table

Data

The input data here are the TS dataset for the 'Volume' as a random variable, as displayed in Equation (1). The rest of the input data are the Duration, Man-Year, and UR, which are assumed to be fixed variables in Equation (1) and can typically be obtained from a work study (WS). The outcome variable (#FTE) is on the left-hand side of Equation (1).

Example

Work studies are an integral part of the Staffing Methodology. In this section, we present a detailed example of workload-based manpower hierarchical modeling using statistical TS algorithms, demonstrated through a case study of shuttle-van

driver WS. The following example outlines the study's scope, constraints, assumptions, data sources, and analysis process, following the methodology described in Section 2.

Following the example used in Rahardja (2025) ^[10], we demonstrate our statistical methodology described in Section 2 using monthly airline passenger volume data from 1949 to 1960, obtained from the well-known Box-Jenkins (1976) dataset in Time Series Analysis: Forecasting and Control (p. 531) ^[18].

As a recap, the data consist of the monthly passenger volumes (in counts) for a U.S. airline of 144 months, from 1949 to 1960 (see Figure 3). This dataset is also publicly available online via a simple Google search.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1949	112	118	132	129	121	135	148	148	136	119	104	118
1950	115	126	141	135	125	149	170	170	158	133	114	140
1951	145	150	178	163	172	178	199	199	184	162	146	166
1952	171	180	193	181	183	218	230	242	209	191	172	194
1953	196	196	236	235	229	243	264	272	237	211	180	201
1954	204	188	235	227	234	264	302	293	259	229	203	229
1955	242	233	267	269	270	315	364	347	312	274	237	278
1956	284	277	317	313	318	374	413	405	355	306	271	306
1957	315	301	356	348	355	422	465	467	404	347	305	336
1958	340	318	362	348	363	435	491	505	404	359	310	337
1959	360	342	406	396	420	472	548	559	463	407	362	405
1960	417	391	419	461	472	535	622	606	508	461	390	432

Fig 3: The 'Airline Passengers' dataset.

For demonstration purposes, in this particular dataset, suppose that for a Shuttle-Van company, a major (main) task within one of the company's Essential Mission Functions (EMF) was to transport all airline passengers shown in Figure 3—from each passenger's pick-up point to their drop-off point at the airport. The company aimed to determine both the current and future projected number of FTE drivers required to perform this EMF. Specifically, the drivers' main duties under this EMF are to manage, verify, and transport airline passengers to and from the airport and their destinations.

A WS is conducted using a workload-based approach (i.e., manpower hierarchical modeling) to gather monthly passenger volume data (i.e., number of airline passengers) and the average duration of driver activities. This data is sourced from both the organization's system of record (SOR) and/or field surveys, covering all shuttle-van company locations. A review of this staffing projection WS should occur at the minimum every three years, or more frequently at the organization's discretion, based on variations in passenger volume.

The scope of the WS is as follows:

This example captures and analyzes airline passenger volume data from calendar years (CY) 1949 to 1960, with the objective of projecting current and future driver manning requirements for CY61-CY63.

The constraints are as follows

Timeliness, accuracy, and funding are key constraints for any study, including this shuttle-van drivers WS. Therefore, an initial analysis is essential to assess the feasibility of the study and strike a balance among these constraints.

Key assumptions for this example WS include:

- Assumed passengers Volume is a Random Effect variable for the Hierarchical Modeling
- Assumed the rest of input variables or components are Fixed Effect variables

- Assumed average Durations was 3 hour/case for field's van driver, assumed per fields survey following previous example^[10]
- Assumed Work Year is 2080 hours/year following previous example^[10]
- Assumed utilization rate (UR) is 0.64 following previous example^[10]
- Utilized an average past 3y estimates & future 3y forecasts for current & future required staffing following the organization's discretion on updates

The data analysis process goes as follows:

Following the methodology discussed earlier, the Baseline Analysis is conducted. For illustration purposes, assume that, based on the company's current records, the total number of ONBD drivers is 10 FTEs (see Table 1 in the Results and Recommendations section), while the number of funded positions—i.e., the total authorized (AUTH) drivers—is 11 FTEs. In the Phase 2 Study, using available software (Excel, 2021)^[13], the overall projected endpoints were calculated to be 12 and 15 FTEs for the current and future states, respectively (see Figure 4).

The right-hand side panel of Figure 4 shows the projected current and future requirements of 12 FTE and 15 FTE, respectively. The top panel displays the patterns—such as level, trends, seasonality, and cycles—of the monthly volume of passengers transported, while the bottom panel illustrates the annual patterns of the number of FTE drivers. Blue represents historical data, red indicates future forecasts, green represents the estimated Current REQD, and yellow denotes the forecasted Future REQD.

There are clear monthly patterns in level, trend (i.e., an increasing incline in the volume patterns, as shown in the top panel of Figure 4), and 12-month seasonality. Therefore, it makes sense that the total projected Current and Future REQD would increase (in this case, from 12 to 15 FTEs).

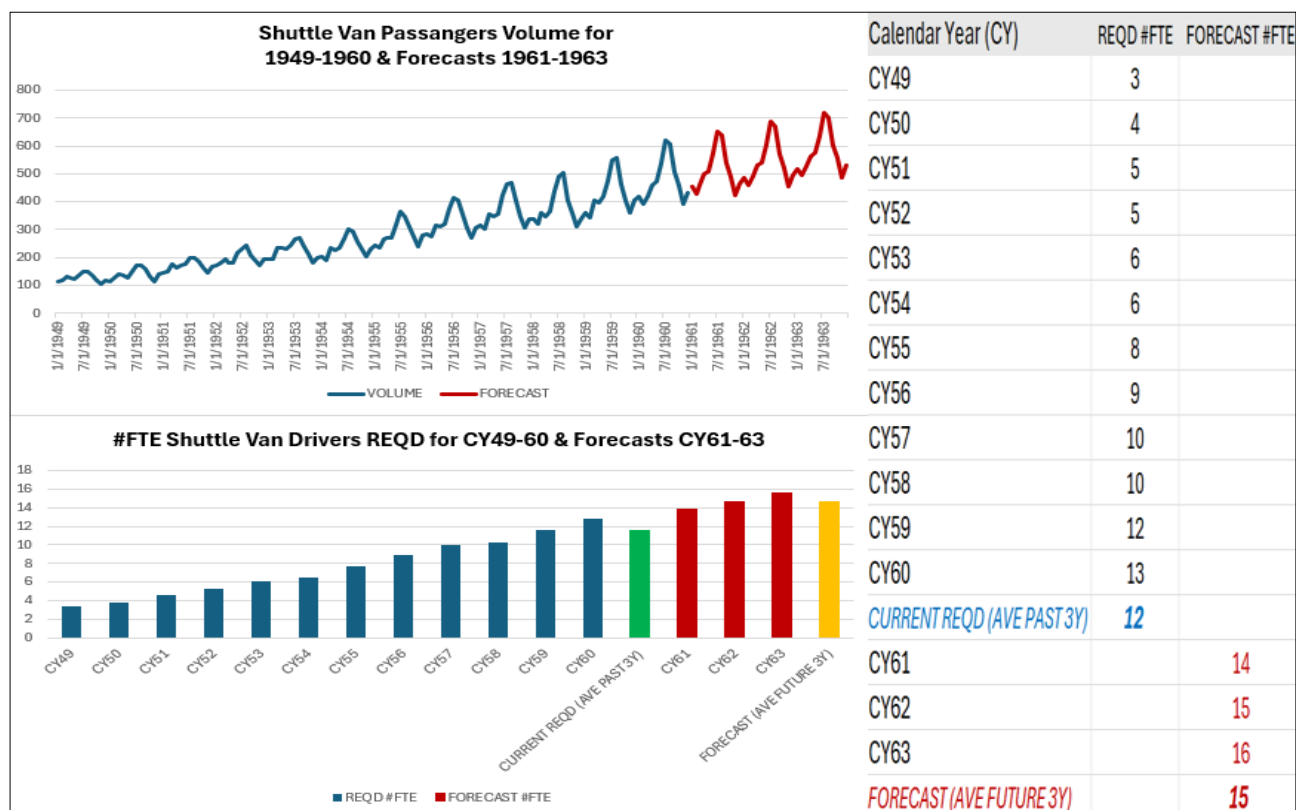


Fig 4: The #FTE Shuttle Van Drivers projections

Results and Conclusions

The results of this study were obtained in accordance with the methodology and analysis process described in the previous section. Both the baseline and endpoint scenarios were analyzed using the outlined methodology, with the results presented in Figure 4 and Table 1. The baseline scenario reflects the initial FTE numbers (AUTH and ONBD), while the endpoint scenario projects the staffing requirements (REQD) for the current and future states, based on the study's scope and all acquired data.

Accordingly, the findings from Figure 4 are summarized in Table 1 below.

Table 1. Projections of #FTE Drivers for the Shuttle-Van Company

Est. Type	Staffing Type	Source	#FTE
BASELINE	AUTH	System of Records	11
BASELINE	ONBD	System of Records	10
ENDPOINT	Current REQD	Stat Methodology	12
ENDPOINT	Future REQD	Stat Methodology	15

Finally, based on the above results, the following summarizes the key findings. The Endpoint Analysis results for this WS scope align with the Initial Analysis from the Passenger Volume plots (see the blue curve in the top panel of Figure 4), which indicate that the passenger volume trend is steadily increasing with 12-month seasonality. Consequently, the projected volume and the corresponding need for additional FTEs are reflected as follows: 12 and 15 drivers for the current and future requirements, respectively, increasing from 10 and 11 current onboard and authorized drivers.

Therefore, although the organization currently has only 10 onboard drivers (slightly below the funded position of 11), the actual required number of drivers to perform the EMF is 12 FTEs, with a forecasted future requirement of 15 drivers. By proactively calculating and determining these current and future staffing needs, the shuttle-van company can strategically manage and maintain its operations.

We conclude that, in this paper, we have developed a workload-based staffing methodology using statistical time-series hierarchical modeling to determine the manpower requirements for an organization's EMF. This methodology expands upon the generic (naïve) modeling introduced earlier in Rahardja (2025)^[10]. We have also provided a walkthrough example case for illustration. This developed staffing methodology will be highly useful for practitioners and researchers across various applied fields (e.g., business, human resources, social sciences, psychology, manufacturing, medicine, industry, government, healthcare, etc.) to determine both the current and future staffing needs to perform an EMF within an organization. The implementation of this staffing methodology for each EMF in an organization can be updated every three years or as determined by the organization's management.

Disclaimer Statement

This research represents the authors own work and opinion. It does not reflect any policy nor represent the official position of the U.S. Department of Defense nor any other U.S. Federal Agency.

References

1. Schoo AM, Boyce RA, Ridoutt L, Santos T. Workload capacity measures for estimating allied health staffing requirements. *Aust Health Rev.* 2008;32(3):548-558.
2. Lee M, Kim SE, Jeong JH, Park YH, Han HW. Development of service standards and manpower calculation criteria for hospital clinical pharmacies in South Korea: a survey-based study. *BMC Health Serv Res.* 2024;24(118):1-11.
3. Popoola BG. Manpower forecasting in education. *Educ Plan.* 2023;6:70-89.
4. Kurniawan H, Yulianah, Shaura RK. Workload analysis using the Full Time Equivalent (FTE) method to optimizing labor. *Enrich J Manag.* 2022;12(4):3058-3066.

5. Doulati SP, Shahgoli JF, Jahanbin H, Kousha A, Tabrizi JS. The assessment of needed workload for manpower approximation in health houses in Iran's villages. *Eur J Sci Res.* 2013;114(1):139-148.
6. Rani R, Sharma SK, Gupta MK. Standard workload-based estimation of nursing manpower requirement in the ICU of a tertiary care teaching hospital: A time and motion study. *J Educ Health Promot.* 2023;12(2):1-9.
7. Sharma K, Zodpey P, Gaidhane A, Quazi SZ. Methodological issues in estimating and forecasting health manpower requirement. *J Public Adm Policy Res.* 2014;6(2):25-33. doi:10.5897/JPAPR2011.067.
8. Noviandani N, Indartono A, Hardiyanti F. Manpower optimization needs with workload approach using NASA-TLX method. *Adv Soc Sci Educ Humanit Res.* 2019;354(2):325-328.
9. Wahyuni N, Gunawan A, Ferdinand PF, Fitriyanti E. Designing employee workload calculation based on Java-based full time equivalent method. *IOP Conf Ser Mater Sci Eng.* 2019;673:012098. doi:10.1088/1757-899X/673/1/012098.
10. Rahardja D. Workload-based manpower requirements determination via generic (naïve) modeling. *J Res Appl Math.* 2025;11(2):44-48. doi:10.35629/0743-11024448.
11. Rahardja D. Statistical methodological review for time-series data. *J Stat Manag Syst.* 2020;23(8):1445-61. doi:10.1080/09720510.2020.1727618.
12. Rahardja D. Statistical computing for time-series forecasts via SAS Forecast Studio. *Int J Appl Sci Math.* 2021;8(4):38-45.
13. Rahardja D. Statistical time-series forecast via Microsoft Excel (FORECAST.ETS) built-in function. *J Res Appl Math.* 2021;7(11):69-73.
14. Rahardja D. Univariate time-series forecast computing via R 'auto.arima()' function. *J Res Appl Math.* 2023;9(5):46-50.
15. Rahardja D. Computational statistics for time-series forecasts via SAS/ETS 9.4 drop-down menu. *J Stat Manag Syst.* 2023;26(4):787-800. doi:10.47974/JSMS-877.
16. Rahardja D. Advantages and disadvantages comparison of time-series forecast computing via Microsoft Excel and three different SAS products. *J Stat Manag Syst.* 2024;27(4):769-784. doi:10.47974/JSMS-983.
17. Rahardja D. Statistical time-series forecast error and bias assessment using hold-out samples and a single benchmark (data-reduction) scoring metric. *J Stat Manag Syst.* 2024;27(3):569-578. doi:10.47974/JSMS-974.
18. Box GEP, Jenkins GM. *Time Series Analysis: Forecasting and Control.* Hoboken (NJ): John Wiley & Sons; 1976.